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DISSERTATION

Advanced Resilience-Oriented Control of Multi-Microgrids

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Kurzfassung

Die dringend gebotene Dekarbonisierung des Energiesystems und verwandter Sektoren wie der Mobilität erfordert, den Anteil der volatilen erneuerbaren Erzeugung drastisch zu erhöhen und gleichzeitig die Systemresilienz zu bewahren oder sogar zu verbessern. Microgrids und Multi-Microgrids werden gemeinhin als Maßnahme zur Erhöhung der Widerstandsfähigkeit des Stromsystems und zur engmaschigen Integration erneuerbarer Energiequellen propagiert. Proaktive Scheduling-Algorithmen, die den Betrieb des Multi-Microgrids im Voraus optimieren, können einen Teil dieser Multi-Microgrids darstellen, es fehlt allerdings an einer gemeinsamen Vorgehensweise zur Implementierung der Algorithmen, die die Systemkomplexität vollständig abbildet. Um die Publikationen zu bestehenden Scheduling-Ansätzen aufzubereiten, werden zunächst eine detaillierte, systematische Klassifikation eingeführt und mehrere Modellannahmen anhand eines meteorologischen Langzeitdatensatzes bewertet. In weiterer Folge stellt die Arbeit einen auf hybrider Optimierung basierenden Schedulingalgorithmus vor, der es erlaubt, komplexe Netzbedingungen abzubilden. Weiters wird eine Methode entwickelt und angewendet, die es erlaubt, den Nutzen und die Notwendigkeit proaktiver Schedulingverfahren im Langzeitbetrieb zu beurteilen.

Die anfängliche Literaturstudie zeigt ein breites Spektrum resilienter Multi-Microgrid-Scheduling-Ansätze mitsamt deren Einschränkungen. Die fehlende Berücksichtigung komplexer Regelinfrastruktur sowie eine beschränkte Skalierung können jedoch durch den neuartigen Algorithmus überwunden und somit Probleme gelöst werden, die mit konventionellen Methoden unlösbar sind. Die umfangreiche Auswertung verschiedener Algorithmen zeigt weiters, dass selbst auf dem speziell konzipierten Testsystem 87% bis 99% der Fehlerzeit bereits ohne resiliente Schedulingalgorithmen bewältigt werden können. Die verbleibenden Energieausfälle werden jedoch um bis zu 41% deutlich durch resiliente Algorithmen reduziert. Daher kann es durchaus gerechtfertigt sein, sich auf rein wirtschaftliche Aspekte zu konzentrieren, ohne die Systemresilienz beim Scheduling zu berücksichtigen. Bei kritischen Anwendungen können solche Algorithmen, einschließlich der neuartigen hybriden Optimierungstechnik, jedoch einen deutlichen Beitrag zur Steigerung der Resilienz leisten. Diese Arbeit bietet Werkzeuge, um geeignete Algorithmen auszuwählen und Schedulingalgorithmen weiter zu verbessern.

Abstract

Driven by the urgent need of decarbonizing the power system and related sectors such as mobility, it is necessary to drastically increase the share of volatile renewable generation while maintaining the same or even an improved system resilience. Microgrids and multi-microgrids are commonly presented as a measure to increase the power system resilience and to tightly integrate renewable energy sources alike. One lever in such systems are proactive scheduling algorithms that optimize the multi-microgrid operation in advance. Still, no common pathway towards the implementation of resilient scheduling that fully admires the complexity of such systems is known.

To increase the accessibility and comparability of existing scheduling approaches, first a detailed, systematic classification is introduced. Additionally, several modeling assumptions are assessed on a meteorological long-term dataset and a first estimation on the effects of common simplifications is given. Based on identified research gaps, a novel hybrid optimization algorithm that enables the inclusion of complex grid constraints in resilient scheduling is presented. To further address the value and need of proactive scheduling formulations, an extensive evaluation method is proposed and applied.

The initial literature study reveals a broad spectrum of available resilient multi-microgrid scheduling approaches and common limitations. It is shown that the novel algorithm overcomes limits in scalability and in considering low-level controls at scheduling time, even when a state-of-the-art reference fails to deliver any feasible solution. The extensive evaluation of various scheduling formulations further demonstrates that even on the specifically designed test system, a large share of 87% to 99% of the incident duration can already be handled without considering resilience at scheduling-time. Nevertheless, when it comes to the remaining unsupplied energy, a considerable reduction by up to 41% can be reached by proactive scheduling.

The results demonstrate that in some cases, it can be well justified to focus on economic aspects without considering system resilience in day-ahead scheduling. However, in critical applications, such algorithms including the novel hybrid optimization technique can add further value. This work provides engineers and researchers with tools to select suitable algorithms and to push the limits of proactive resilient scheduling even further.

Contents

Chapter 1

Overview

1.1 Motivation and Problem Statement

A rapid decarbonization of the power system according to international policies [1] avoiding most hazardous impacts on humans, society and ecosystems is urgently needed [2, 3]. At the same time, the resilience of critical infrastructure needs to be strengthened to mitigate increasing risks such as those induced by extreme weather events that cannot be mitigated by decarbonization anymore [2, 3, 4]. Microgrids are commonly introduced as a measure to tackle both issues by a tight integration of highly volatile Renewable Energy Sources (RES) and by extended fault mitigation techniques that strengthen the resilience of the electricity network [5, 6, 7, 8, 9, 10]. Other commonly listed benefits include economic payoffs, efficiency gains, and the option to locally overcome upstream grid limitations. Although there are several competing definitions that also include fully isolated power systems without any main-grid connection [10], microgrids are herein defined as tightly integrated electrical networks that can be operated in grid-connected and islanded mode [4, 11, 12].

Although microgrids show a great potential in integrating volatile RES, several microgrid designs still heavily rely on fossil-fueled generation such as gas-fired micro turbines and diesel engines [7]. Recent literature gives priority on integrating high shares of RES and on reducing or even eliminating greenhouse gas emissions [6]. Still, several technical challenges in providing a high level of reliability and resilience while facing increased shares of volatile load and generation exist. For instance, storage reserves need to be managed to find adequate balances on operating costs and system resilience. One measure to meet upcoming challenges and to raise economic benefits even further is the introduction of multi-microgrids that coordinately operate individual microgrids [4, 11, 13]. In contrast to single microgrids, multi-microgrids as illustrated in Figure 1.1 allow sharing reserves and balance volatility even in case of contingencies. Neverthe-

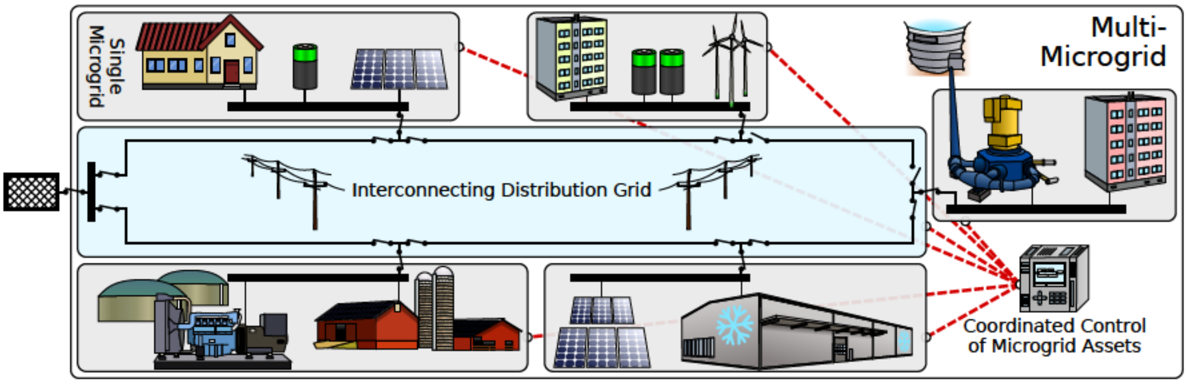

Figure 1.1: Multi-microgrid scheme connecting single microgrids.

less, advanced fault mitigation techniques such as partial islanding in multi-microgrids significantly increase the complexity and call for adequate control architectures [9, 13].

One element in such control architectures that can be found in single-microgrid and multi-microgrid setups is proactive scheduling [14]. On top of several low-level controls such as local voltage control, scheduling algorithms optimize the (multi-)microgrid operation beyond the boundaries of individual assets according to a common set of objectives. For instance, proactive resilient algorithms optimize the operation in advance such that a certain set of failures can be tolerated with minimal impact. Note that this work follows a broad definition of resilience [15] that permits a degraded operation in case of failures but also includes a fully robust reaction without triggering any degradation. Even in resilient scheduling, economic objectives play a major role in balancing the operation costs and the value of resilience measures [16, 17]. Nonetheless, no common pathway towards resilient multi-microgrid scheduling is known and a multitude of competing algorithms implementing diverse approaches are available. As such, the broad spectrum of formulations without adequate categorization and guidance can hinder an efficient engineering and application in real-world systems. Despite the broad availability of scheduling literature, only few approaches specifically focus on the interaction with low-level controls. Several questions, for instance on the value of resilient scheduling in the overall system operation and the level of detail that needs to be considered are still open to be discussed before a widespread application of proactive resilient algorithms.

1.1.1 Related Work

Since microgrids are intensely studied for decades, the basic operating principles, for instance, on frequency droop control, are well understood and several textbooks are available that well concentrate the settled body of knowledge [18, 11, 19]. Nevertheless, several areas that are related to microgrids such as coordinated control of individual microgrids and advanced scheduling formulations are still subject to heavy research activity addressing a plethora of open research questions [7, 20, 21].

Resilient Microgrid and Multi-Microgrid Operation

Even in the context of power systems, no commonly used and accepted definition of resilience is found [22, 23, 15, 24]. However, [22] found several common elements such as the ability to withstand and recover from adverse impacts that are often connected to resilience. A resilient power system may degrade, for example, by load shedding, but may not entirely fail in case of unexpected contingencies [23, 15, 24]. On the contrary, robustness commonly focuses on tolerating a given set of contingencies without permitting a reduced quality of service. Still, several mismatches, for instance, whether a robust behavior that does not show a reduced performance is also a resilient reaction exist among different definitions [24]. An attempt towards a common definition of resilience is given in [15] that further describes different operating phases concerned with a resilient operation.

A multitude of operation measures is presented that target resilience and robustness of microgrids, multi-microgrids, and the power system in general [25, 26]. For instance, [27] proposes an adaptive load shedding scheme that avoids blackout scenarios by disconnecting low-priority loads in case of contingencies. Other measures such as proactive resilient scheduling prepare the network before any contingency is encountered to reduce the potential impacts of such disturbances [28, 29, 30]. As such, [29] presents an Electrical Energy Storage (EES) operation scheme that manages storage reserves in preparation of potentially disruptive events. Although the publication considers the inherent uncertainties of variable loads and generation, the impact of grid constraints and low-level controls is not covered in detail. Likewise, several other publications such as [30, 31] formulate resilient scheduling without taking topological aspects into account. Other work including [32] extend the classical scheduling formulations by more detailed constraints on the physical grid operation but still rely on the limited fault mitigation options of single microgrids.

Although [33] does not consider a detailed grid model, it describes scheduling of provisional microgrids that exceed the borders of single grids. In contrast to microgrids that can be independently islanded, provisional microgrids require a coupled microgrid for voltage and frequency control and hence do not have to implement excessive local reserves. In contrast, [34] formulates a common scheduling problem of connected microgrids that can be individually islanded but does not consider detailed grid reconfiguration options. In classical distribution grids, such topological changes can restore power on isolated sections by automatically isolating faults within the system and closing redundant tie-lines [35]. Research work extends common fault reconfiguration by utilizing microgrids to power isolated sections of the grid and to participate in grid restoration after blackout scenarios [36]. For instance, [8] shows a load restoration scheme based on distributed microgrids. Although reconfiguration actions are commonly conducted in response to failures, also proactive reconfiguration techniques such as loss reduction measures are available [37, 38]. Some publications such as [39, 40, 41] even actively consider reconfiguration options in proactive scheduling. However, the value in considering such measures to adjust reserve requirements is only loosely evaluated without considering a broad range of operating scenarios.

Grid and Control Constraints in Scheduling

First results on voltage and reactive power impacts indicate that scheduling decisions that affect available reserves can have a significant influence on the safe and reliable microgrid operation [42]. To limit such impacts, several microgrid and multi-microgrid scheduling approaches consider network constraints such as the permissible voltage band [43, 44, 45]. For instance, [32] and [45] linearized the highly nonlinear Alternating Current (AC) power flow equations to consider grid constraints in scheduling. Other publications avoid the simplification step via a heuristic search procedure that supports nonlinear models. For instance, [43] implemented a genetic algorithm to solve the nonlinear optimization problem. Other heuristics include particle swarm optimization [46] and imperialist competitive algorithm [47].

Despite the ability of solving nonlinear problems, traditional meta heuristics do not utilize highly developed mathematical programming solvers [48]. Few authors therefore proposed hybrid scheduling strategies that efficiently join mathematical programming and heuristics [49, 50]. Notably, [49] considers nonlinear power flows in an inner Mixed Integer Linear Programming (MILP)-based problem by iteratively updating a power loss constant. In case a schedule turns out to be infeasible, the entire inner problem is solved by an Optimal Power Flow (OPF) solver. Since most candidate schedules are assumed to be feasible, less emphasis is put on the nonlinear OPF implementation. In contrast, [50] specifically focuses on constraint handling and automatically approximates nonlinear power flow equations by iteratively adding sensitivity-based constraints to the outer quadratic problem. Hence, [50] successfully demonstrates the application of a hybrid optimization algorithm. However, the nonlinear constraints are only considered at a single time interval of the multi-period scheduling task and scalability issues are not studied in detail.

Although several approaches include physical constraints [43, 44, 45], only very few of them actively take the impact on low-level controls and their contribution in managing reserves into consideration. The formulation published in [51] includes droop-based active power control and corresponding reserve requirements that enable a successful islanding. Nevertheless, voltage control and reactive power requirements are not considered in detail. Although [51] takes multiple low-level control strategies for active power into account, it is yet to be studied to which extent these strategies need to be included at scheduling and whether it is sufficient to focus on active power control, only.

Related Reviews and Classifications

Several authors already summarized the vast body of microgrid-related literature [7]. Initial developments, first practical experiences and field tests are covered by [10, 52, 53, 54]. Several broad reviews of various microgrid and multi-microgrid related aspect including economics and protection are available at [7, 21]. More specifically, [6] discusses major challenges in microgrid control and [16, 17, 55] focuses on energy management aspects in the context of microgrids. Notably, [16] lists a broad range of optimization types, objective functions, solution approaches and related tools. Despite a first detailed categorization of several aspects such as model formulations and objective functions, resilience aspects and the scientific evaluation of the reviewed approaches are not covered in detail. Review [20] gives an extensive categorization of optimization objectives and constraints but only considers purely islanded grids for review. Additionally, resilience, multi-microgrid systems, and implementation-related aspects are not covered in detail.

In addition to various other aspects, review [14] specifically covers stability and reliability aspects of microgrids and virtual power plant scheduling. Additionally, the publication includes a comparative review of several aspects such as considered Distributed Energy Resource (DER) types and the way uncertain inputs are addressed, but multi-microgrids are beyond the scope of the review. A broad overview on multi-microgrids and related concepts is given in [56, 57] and [58] specifically focuses on multi-microgrid architectures. Nevertheless, no in-depth analysis of scheduling and resilience-related aspects in multi-microgrids is given. Other reviews such as [22, 26, 59] target power-system resilience in a broader context but do not specifically focus on scheduling-related aspects. Resilience-oriented microgrids are particularly discussed in [25]. Although the authors described various resilience mechanisms including emergency control strategies, proactive scheduling and its impacts on the emergency operation is only loosely covered.

Assessment of Scheduling Algorithms

Testbeds provide vital facilities to assess various microgrid-related aspects such as islanding, synchronization and stability [60, 61]. Depending on the questions at hand, a broad variety of methods ranging from purely simulation-based assessments to real-world implementations is applied. Transient phenomena in fully inverter-based grids, for instance, are targeted by the purely simulation-based testbed presented in [62], but a long-term assessment is beyond the scope of the facility. In [63], a laboratory-scale testbed that specifically focuses on scheduling applications is used to study the performance of an energy management heuristic and an optimal scheduling approach. Although the study provides several valuable insights into economic benefits of optimal scheduling, only 15 operating scenarios derived from five dedicated measurement days are applied. Additionally, only small, single-bus grids were studied and no focus was put on grid reconfiguration actions and physical grid constraints.

Dynamic transient simulations are successfully applied in the assessment of low-level controls [60, 64], but a high computational burden is put on the assessment of long-term phenomena. Steady-state power flow computations are successfuly applied in various studies that focus on the long-term grid operation, but classical formulations do not support islanded microgrids well [65, 66]. Nevertheless, several methods such as the balanced formulation [65] already support distributed voltage and frequency control without introducing a dedicated slack node that models the upstream grid connections. Likewise, [66] introduces a distributed frequency and voltage control but supports both balanced and unbalanced grids. In particular for unbalanced networks, an extended Newton Raphson algorithm is proposed that improves the convergence of the power flow computations. Although significant efforts were conducted in representing islanded networks in power-flow equations, outage detection, detailed device capabilities and various control heuristics such as dynamic droop curves of EES are rarely considered.

It was noted that microgrid assessment requires new metrics that well cover resilience-related aspects [67]. A framework to define resilience metrics as a function of time that reflects the system state is given in [24]. Most resilience and robustness metrics rely on a proper definition of considered failure modes. In conventional power systems, the well-known (N-1)-criterion stating the grid must be robust to the loss of any single system component is applied [4]. The reliability of islanded microgrids is specifically targeted by [68] that approximates several reliability indices via broadly available capacity factors. Other studies such as [69] follow Monte-Carlo-based methods to approximate the reliability metrics in the presence of highly stochastic phenomena. Nevertheless, a strong focus is put on reliability and robustness without specifically considering resilience.

1.1.2 Problem Statement

As scheduling decisions that influence the amount of available reserves can have an impact on the resilience of microgrids and multi-microgrids [42], several proactive resilient scheduling approaches are proposed [30, 31]. These algorithms prepare the system before an incident is encountered and at the same time balance vital aspects such as the computational costs to avoid an overly conservative operation. Since in general, proactive scheduling will require additional resources compared to a purely economic operation, it is either enabled on first early warning signs or always secures the most critical applications [29]. Despite the broad body of scheduling-related literature, there is no comprehensive guidance that leads engineers towards appropriate proactive resilient scheduling implementations. First, a comprehensive categorization that increases the accessibility of current work is missing. Several research gaps hinder efficient engineering workflows and prevent detailed consideration of low-level control aspects in scheduling. Although most approaches show a first validation [28, 45, 70], replication and scalability is scarcely covered in detail. Finally, the impact of proactive scheduling on the resilient system operation is only loosely studied and not fully quantified.

Missing Guidance in Proactive Resilient Scheduling

A huge amount of scheduling-related literature and several approaches that specifically address resilient scheduling in microgrids and multi-microgrids is already available [7, 16, 17, 55]. Additionally, several reviews cover scheduling-related topics and introduce a first categorization of related work [16, 20, 14]. It is evident that several approaches use common techniques such as MILP to formulate and solve scheduling problems. Nevertheless, presented algorithms and implementations such as [70] are far away from a unified approach to proactive scheduling. Even related reviews do not fully provide an efficient overview on major design options such as considered failure modes, fault mitigation strategies and validation efforts. Additionally, only a minority covers scheduling of multi-microgrids [56, 57, 58] and none of them provides great details in resilient multi-microgrid scheduling.

A solid foundation is needed to quickly make necessary engineering decisions such as the appropriate type of scheduling and available implementation options without the need of an extensive literature review. Since a broad spectrum of scheduling approaches that specifically focus on individual aspects are proposed and no common method is currently on the horizon, additional engineering support is needed. Also, subsequent research activities call for such supportive guidance in selecting the best available scheduling and verification techniques to quickly enhance the State-of-the-Art (SotA). To establish an efficient comparability among scheduling approaches, a fine-grained categorization including modeling, engineering, and validation aspects is needed. Such a classification may be based on related reviews [16, 20, 14, 25] to further strengthen comparability by a step towards a common scheduling nomenclature.

Common Limitations of Optimized Scheduling

Despite the broad range of optimization-based scheduling literature (cf. Section 2.1), one can observe several simplifications in scheduling that are commonly introduced but rarely evaluated. For instance, [43, 71] model meteorological inputs such as wind and solar irradiation as temporally independent distributions. Nonetheless, related work [72] indicates a considerable interdependence of meteorological inputs within typical scheduling horizons of 24 hours. Similar discrepancies can be found in several forecasting error models that are used to quantify unavoidable deviations to deterministic weather predictions. For instance, [49] assumed that forecasting errors follow a temporarily independent Gaussian distribution, but [73] gives strong indication that the assumption does not hold in practice. Yet, the impact of such simplifications on the scheduling outcome and the system resilience is not well quantified.

Other widespread simplifications concern the representation of AC power flow models in optimization problems. To efficiently compute the scheduling outputs (e.g., via off-the-shelf MILP solvers), the highly nonlinear AC power-flow equations are commonly linearized or directly formulated as linear model [32, 45]. However, only very few publications discuss and quantify the impacts of the simplification [32]. Other approaches such as [43, 46, 47] rely on heuristic techniques to directly solve the nonlinear optimization problem, but commonly, such techniques cannot fully exploit the linear relationships within the model. Notably, [50, 49] presented hybrid optimization approaches that join mathematical programming and heuristic optimization techniques. Still, scalability and replicability of the hybrid approaches are not well studied and some algorithms may be prone to considerable overapproximation of nonlinear constraints.

Although some work on resilient scheduling acknowledges a common control hierarchy [43], low-level controls such as voltage and frequency droop are rarely considered in scheduling. Nevertheless, work on grid resilience [42] indicates a considerable impact of scheduling decisions on the islanded grid operation and consequently on the feasibility of fault mitigation techniques. At the same time, low-level controls such as real-time grid reconfiguration techniques [35] may compensate adverse scheduling decisions and reduce the need of online reserves. Including these control aspects in scheduling may further improve decisions and avoid outages caused by insufficient control reserves.

Only few scheduling formulations such as [50, 74] reference external models. The majority explicitly states the problem formulation without relying on proven and well optimized implementations (cf. Section 2.1). From an engineering point of view, a reimplementation of grid models creates additional overhead both in implementation and parametrization of the scheduling algorithm. Such an overhead even increases with the complexity of scheduling models, for example, in case detailed low-level controls and device constraints need to be considered. However, limited information that is exposed to a solver and considerable execution time of external models impose significant challenges to optimization. Advanced algorithms are needed to fully support complex external grid models in scheduling.

Need to Quantify Impacts of Proactive Scheduling

Although most contributions on scheduling algorithms present an evaluation thereof [43, 32, 50], the impact of proactive scheduling on the overall system resilience remains unclear. In particular, the impact of scheduling decisions on low-level controls and consequently on the system resilience is not well quantified, yet. Hence, it is not well understood to which extent such low-level controls can induce resilient system behavior on their own and to which extent scheduling needs to consider aspects such as grid and control constraints. Such questions on the share of proactive scheduling become even more prevailing, in case grid reconfiguration and secondary control heuristics are deployed that mitigate potential disturbances after an impact is registered. Due to the missing evaluation work, only few testbeds specifically focus on the interaction of scheduling algorithms and the physical power grid [63].

Commonly, proactive scheduling operates on a set of forecasts and modeling assumptions that describe relevant inputs ahead of time whereas low-level control operates on real-time measurements only [50]. Nevertheless, the distinctions between information that is available ahead of time and corresponding measurements is rarely found in the validation of scheduling algorithms [28, 30, 43]. Often, relevant metrics are directly calculated from the scheduling outputs and no independent verification of these outputs is performed. However, such an assessment step is needed to assess the quality of inevitable simplifications without relying on the same set of input assumptions. Additional shortcomings in the assessment of (multi-)microgrids arise from the high share of stochastic inputs that can be expected in zero-emission grids entirely based on RES [6]. Most attempts to quantify the performance of proactive resilient scheduling rely on a very limited set of input conditions and operating scenarios. Large-scale simulations that address the long-term operation and a broad range of failures are needed in a comprehensive resilience assessment.

It is expected that the need for proactive resilient scheduling highly depends on the specific grid and system requirements. Hence, an efficient per-case assessment of scheduling algorithms is needed that allows to quickly determine the eligibility of candidate algorithms. To further support a fluent engineering workflow, such assessment methods need to be well integrated into existing tool chains and procedures. For instance, simulation results should be connected to the inputs such as parameters of the algorithms under test to support iterative development cycles. Special attention needs to be put on handling the high computational strains of a large-scale assessment method and associated system complexity.

1.2 Research Question and Goals

Given the identified research gaps in resilient microgrid and multi-microgrid scheduling, an overarching research question is formulated as follows [75].

> *How can a multi-microgrid that includes a high share of volatile RES be optimally operated, such that a large set of failures can be withstood without triggering a critical multi-microgrid fault?*

Due to the broad focus on optimal operation, interactions between low-level controls and high-level scheduling are well covered. The scope of microgrid scheduling is thereby extended to multi-microgrids and studied approaches need to be capable of managing the increased complexity of such networks. Nonetheless, the scope of multi-microgrids is not understood exclusively, i.e. scheduling approaches that address both, microgrids and multi-microgrids are included in the research question as well. To generalize the distinction between resilience and robustness, the research question introduces a minimal robustness criterion on the most critical faults without defining the behavior beyond these incidents. However, the following research work will specifically emphasize a resilient behavior that limits the impact of failures on the system performance beyond avoiding the most critical failures.

The research question is addressed by four goals that broadly reflect required research efforts from a categorization of existing literature, the development of advanced scheduling and assessment methods up to the quantification of benefits gained from proactive scheduling. Figure 1.2 illustrates the main research goals and the relationship among them. Despite considerable scientific advancements that are needed to answer the main research question, all goals specifically address the impact on current engineering practice. In particular, the objectives are formulated as follows.

- *Guide to Resilient Scheduling:* First, a comprehensive guide is to be created that describes the spectrum of available proactive resilient multi-microgrid scheduling approaches. To provide added value for engineering and research alike, the guide shall introduce a broad classification of presented scheduling techniques and support a comparative analysis among the algorithms. In contrast to related work, further information on testing and validation efforts concerning the identified key literature needs to be collected. In case classification schemes from related reviews

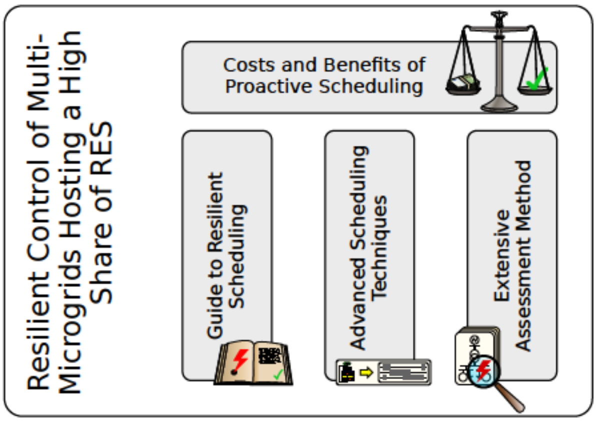

Figure 1.2: Overview on the individual research objectives.

are applicable, own classifications should be based on these schemes to improve comparability beyond the scope of resilient multi-microgrid scheduling.

- *Advanced Scheduling Techniques:* A novel scheduling approach needs to be developed that allows to proactively consider the impacts of scheduling decisions on low-level controls and consequently on grid constraints. The algorithm should support efficient engineering by accessing external grid and control models without the need of manually transforming or implementing these models in the optimization environment. At the same time, the approach should exploit synergies with classical mathematical programming approaches to efficiently solve or approximate highly nonlinear scheduling problems.

- *Extensive Assessment Method:* Another goal is to overcome the prevalent limitations of current assessments in covering the long-term impact of scheduling in highly stochastic environments. An assessment method is to be developed that is capable of quantifying the impact of scheduling algorithms on the long-term multi-microgrid operation. A dedicated focus needs to be put on the system resilience and the interaction of scheduling with commonly deployed low-level heuristics. Therefore, accurate device models including the effects of a real-time control hierarchy and detailed device constraints should be implemented. In addition, a clear distinction between scheduling-time information including forecasts and data such as measurements that are available at real-time only, is to be made. To address highly stochastic RES and loads, the method needs to be capable of handling a large amount of operating conditions and input scenarios. Given the assessment methods it should be possible to efficiently address questions in engineering such as the level of detail that needs to be considered at scheduling time for a particular multi-microgrid system.

- *Value of Proactive Scheduling:* The advanced assessment method is to be demonstrated on a case study that estimates the value of proactive resilient scheduling considering common low-level controls and grid constraints. The evaluation should include both, the economic costs of scheduling and the impact of the algorithms on the system resilience. Furthermore, the influence of forecasting deviations on the system performance should be covered. Given the results of the case study, first recommendations on the implementation of proactive scheduling should be given and further research needs should be identified.

1.3 Methodology

The main research question and the related goals on proactive, resilient multi-microgrid scheduling are addressed by several consecutive studies that follow the way towards thoughtfully validated advanced scheduling including novel hybrid optimization methods. First, the extensive body of literature is processed by a systematic review and classification that paves the way for advanced research and future engineering tasks alike. Following the classification, several common modeling assumptions are identified and independently verified by an initial study on RES modeling and forecasting. As another piece towards advanced proactive scheduling, a novel hybrid optimization approach is presented that for the first time allows to efficiently consider complex control and grid constraints in proactive multi-microgrid scheduling. To fill the validation gap, first an extensive assessment method allowing to independently address the impacts of scheduling decisions on the long-term operation and resilience of multi-micorgrids is proposed. Given the newly developed scheduling algorithm as reference, the developed testbed is applied to give an initial estimation on the value of proactive resilient scheduling. Additional engineering measures further target an efficient case-specific assessment of scheduling algorithms in practice.

1.3.1 Comprehensive Classification of Resilient Scheduling

The comprehensive classification of proactive scheduling follows a method based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [76] to reduce the risk of bias and missing out relevant contributions (cf. Section 2.1). At first, structured database searches are conducted to find relevant publications. Afterwards, the extensive list of 404 candidates is condensed to 20 key contributions by an integrated screening and eligibility test step. The key contributions are then iteratively reviewed to extract a comprehensive fact sheet that describes each contribution in detail. In contrast to the original PRISMA method that focuses on medical studies, this work targets modeling aspects and solution methods instead of achieved results. In addition, the screening and eligibility test steps were merged to transparently access the full text in case the abstract does not provide sufficient information for a founded decision.

Before screening the literature, detailed eligibility criteria based on the research question were defined. Each key contribution needs to be available in full text, needs to describe a scheduling algorithm that focuses on normal operation, needs to cover resilience aspects, needs to include a minimal set of assets, and needs to incorporate the (multi-)microgrid topology. Note that none of the criteria explicitly states that the publication needs to focus on multi-microgrids because a scheduling algorithm that is originally designed for single microgrids may work as well for multi-microgrids. Nevertheless, based on [77, 42] it is assumed that the geographic extent of resilient, highly loaded multi-microgrids needs to be considered either by the algorithm itself or in an evaluation step. Consequently, an eligibility criterion on topological constraints is added.

To allow for a unified description and detailed comparison of scheduling approaches, the information from all key contributions is recorded in a comprehensive fact sheet on resilient scheduling. A first template that defines the initial set of features to be extracted was set up based on related schemes [16, 14, 25, 20]. The broad range of objective functions given in [16] was further put into a set of more generic categories to enable a broad comparison among the formulations. Such objective categories target the individual terms such as DER operating costs in the objective but abstract the detailed formulation of each term. In addition to aspects covered in related reviews, the template was substantially refined to include detailed information on resilience measures, model formulations and validation actions. Hence, the goal on compatibility to related reviews is achieved by the basic set of common features and a detailed picture that is needed for further research and development work is provided by the extensions. The initial version of the template that specified the main aspects of the review was iteratively refined as new categories and aspects were encountered.

1.3.2 Initial Verification of Common Modeling Assumptions

Based on the initial literature review presented in Section 1.1.1 and the systematic study in Section 1.3.1, several common modeling assumptions in scheduling and validation can be identified. To guide following development and validation efforts, an initial study on common simplifications on RES models in scheduling is conducted and presented in [78]. Depending on the implemented modeling approach, uncertain inputs are commonly represented as stochastic distributions [43, 71], intervals of possible realizations [28, 33], or point estimates based on the best known forecast [74, 50]. Such inputs are often derived based on historic measurements and, if available, external models such as numerical weather prediction [73, 72]. Nevertheless, assumptions such as temporal independence of meteorological inputs and forecasting deviations are commonly found in literature [49].

Based on an exemplary site and two extensive datasets, the impacts of several modeling assumptions regarding wind and solar irradiation inputs on the operation of scheduling approaches is studied. Due to the broad data availability and several closely located measurement sites, long-term measurements [79] that cover solar irradiation and wind speed data near Denver, Colorado are selected. A consecutive period of seven years serves as training data to fit corresponding stochastic models and another seven years worth of data is used in validation. To additionally cover the impact of numerical weather predictions, the reforecast dataset [80] is matched with the particular location. Measurements and sampled data are aggregated over a typical scheduling horizon of one day to estimate the effects of several modeling assumptions on scheduling problems independently of the particular asset model. Exemplary Wind Turbine (WT) and Photovoltaics (PV) models further estimate the effects on electricity generation via static turbine curves [81] and an ecliptic model that calculates the in-plane irradiation at the PV array [82], respectively.

In the following, typical assumptions on RES generation are covered by simplified models and evaluated on the validation dataset. Such models include temporally independent parametric models that are commonly used to represent the continuous nature of the stochastic observations and temporally independent discrete models that avoid mismatches in the shape of the parametric distribution but still allow to study the effects of independence assumptions. As references modeling temporal dependencies among observations, a set of Markov models is included in the evaluation. For each model, the goodness of fit is assessed by the Cumulative Density Functions (CDFs) of the accumulated observations and the corresponding generation.

Additional scheduling-time forecasts are covered by extended distributions that output the probability of certain wind speed and solar irradiation values given the most recent forecast. Again, Markov models are introduced to cover dependencies among forecasting errors, but these errors are not well quantified by the studied CDFs. To additionally cover the forecasting quality in terms of prediction errors, for each distribution, a deterministic counterpart that returns the expected value given available inputs such as the most recent numerical weather predictions is modeled. Prediction errors with respect to observed measurements are further contextualized by naive forecasts that serve as well-studied references. Since the observed forecasting errors are stochastic in nature themselves, the Mann-Whitney U test is applied to compare the performance of individual forecasts.

1.3.3 Hybrid Optimization for Proactive Scheduling

Following identified research gaps in proactive scheduling, the effective integration of complex physical and control models into multi-microgrid scheduling is studied (cf. Section 2.2). First, a comprehensive scheduling model is defined as optimization problem. In contrast to related work that commonly linearizes the highly nonlinear grid constraints, a formulation that separates the linear part of the scheduling model and the nonlinear grid constraints is found [50]. The separation is then used to formulate two hybrid optimization algorithms that solve the problem at hand in a way that automatically extends the MILP problem by constraints derived from the nonlinear equations. The first algorithm extends a procedure from literature that iteratively adds linear constraints [50]. Furthermore, a novel technique that utilizes more powerful decision trees instead of purely linear approximations is implemented. In a detailed case study, the performance of both approaches in solving several scheduling formulations is assessed.

Proactive Scheduling Model

To support the development of novel optimization methods, first the generic representation of the problem formulation is defined (cf. Section 2.2). The definition follows an implicit partitioning of related work [50] into linear $\vec{g}^{\mathrm{l}}(\vec{x})$ and nonlinear constraints $\vec{g}^{\mathrm{n}}(\vec{x})$. Given the linear single-objective function $c(\vec{x})$, the problem of finding an optimal schedule $\vec{x}$ is defined as (1.1) with $\vec{x}$ being a mixed-integer vector.

$$\begin{aligned} \min_{\vec{x}} c(\vec{x}) \quad & \text{s.t.} \\ & g_i^{\mathrm{l}}(\vec{x}) \leq 0 \quad \forall i = 1, \ldots, \left|\vec{g}^{\mathrm{l}}\right| \\ & g_i^{\mathrm{n}}(\vec{x}) \leq 0 \quad \forall i = 1, \ldots, \left|\vec{g}^{\mathrm{n}}\right| \end{aligned} \tag{1.1}$$

Consequently, the problem induced by $c(\vec{x})$ and $\vec{g}^{\mathrm{l}}(\vec{x})$ can be directly solved by MILP techniques, whereas on using $\vec{g}^{\mathrm{n}}(\vec{x})$, the problem cannot directly be solved by off-the-shelf procedures. To support an efficient engineering process, the nonlinear constraints may be implemented by an external simulation tool such as a power system simulator. Hence, computing the nonlinear constraint function $\vec{g}^{\mathrm{n}}(\vec{x})$ may require the execution of external solvers and corresponding computational overhead. The performance of the overall procedure can therefore highly depend on the number of samples drawn from $\vec{g}^{\mathrm{n}}(\vec{x})$. Furthermore, it is assumed that only limited static information beyond dynamic

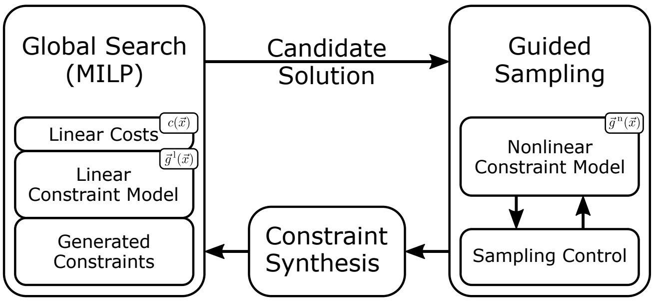

Figure 1.3: Generalized hybrid optimization scheme (cf. Section 2.2).

samples of $\vec{g}^{\mathrm{n}}(\vec{x})$ is available. In particular, $\vec{g}^{\mathrm{n}}(\vec{x})$ does not have to be exposed in closed form and no derivative information may be available.

The linear base model stated in Section 2.2 follows a deterministic single-bus formulation. To focus on computational aspects of scheduling, only the most essential assets identified in the preceding literature study are covered without introducing specific models such as Electric Vehicle (EV) and mobility constraints. In particular, the formulation includes volatile load and generation, as well as generation that can be freely scheduled within its operating range and storage units that are additionally restricted by their storage state. Since the base formulation focuses on the normal operation only, a connection to the upstream grid that allows to sell and buy energy according to a predetermined day-ahead price is included as well. The objective function aggregates the overall operating costs of main grid transfers and controllable generation within the scheduling horizon.

The impact of additional constraints beyond the basic set of equations on the performance of scheduling approaches is studied by extensions that introduce further operating constraints such as startup restrictions and linear reserve models. Although the reserve ensures that all nominal loads can be supplied by scheduled reserves until further generation is started, stochastic deviations are beyond the scope of the linear model. In contrast, the nonlinear grid model that implements a balanced AC power flow and first control models introduces several static scenarios. Hence, the model covers manually defined extreme-case deviations of volatile load and generation forecast. Failure scenarios extend the deviation set to consider the detailed system behavior in case of outages. The nonlinear constraint function $\vec{g}^{\mathrm{n}}(\vec{x})$ is thereby defined as the directed distance to voltage and asset loading limits for each individual scenario.

Hybrid Optimization Methods

By a polynomial time reduction from scheduling to the Knapsack problem [83] it is shown that the (multi-)microgrid scheduling problem is at least weakly NP-hard and the nonlinear constraints $\vec{g}^{\mathrm{n}}(\vec{x})$ may further encode arbitrary decision problems (cf. Section 2.2). To manage the resulting computational complexity of the problem at hand, this work develops and studies heuristic methods. These approaches allow the utilization of highly-developed algorithms to efficiently solve practical MILP and power flow instances without the need of directly solving monolithic nonlinear optimization problems. The basic operation of the hybrid schemes is extracted from related work [50] that implicitly follows the procedure illustrated in Figure 1.3. A MILP problem consisting of the linear base model $c(\vec{x})$ and $\vec{g}^{\mathrm{l}}(\vec{x})$ is iteratively extended by synthesized constraints that approximate the nonlinear function $\vec{g}^{\mathrm{n}}(\vec{x})$. Therefore, the linear problem is solved and $\vec{g}^{\mathrm{n}}(\vec{x})$ is sampled near the candidate solution. Given the previously drawn samples, the approximating linear constraints are updated and the procedure is repeated until the termination criterion is met.

The sensitivity-based method that was extended from related work [50] numerically approximates the Jacobean near the current candidate solution and adds a linearized approximation of each failing nonlinear constraint. The Jacobean approximation is conducted by systematically introducing small perturbations on the scheduling variables. To improve the performance and stability of problems that exceed the original scope of a single scheduling interval, a heuristic is introduced limiting the number of samples. Additionally, the permitted region defined by the planar constraints is strengthened by an ϵ-term to further support convergence. Since constraints are never revoked, the feasible region is always confined and the procedure stops as soon as no nonlinear constraint is violated anymore or the linear problem is reported to be infeasible.

Since constraints in the sensitivity-based method are never revoked and globally valid, over-approximation may occur. To study the effects of the approximation model and to allow for more complex approximations, a model based on decision trees is developed. In contrast to the globally valid planar approximation, the novel tree-based method exploits the recursive decision structure and supports more complex boundaries. As a consequence, all known samples are directly used to approximate the decision trees and the entire approximation can be replaced in subsequent iterations. To efficiently sample the nonlinear constraint function, a randomized local search technique is deployed that aims at drawing samples near the current local optimum of the complete optimization problem. In a subsequent step, off-the-shelf machine learning methods are applied to grow the decision trees and an extended method of [84] is used to transform the trees into MILP form. If needed, the recursive conversion procedure thereby adds additional discrete variables to the basic MILP problem that encode the active path within the tree. Hence, the procedure supports more complex approximations than the sensitivity-based method.

Case Study on Proactive Scheduling Algorithms

The performance of both scheduling algorithms is assessed by a detailed case study further described in Section 2.2 that specifically focuses on varying levels of model complexity. Due to the widespread application in related scheduling literature (cf. Section 2.1), an extended Baran testfeeder [37] that hosts several additional assets such as local generation and storage units is taken as a common base. Several variations such as a reduced amount of storage units and limited constraint sets are introduced to observe the scheduling performance with respect to the model complexity. Additionally, one scheduling run that solely includes the linear economic formulation without incorporating any nonlinear grid constraints is conducted. The most reduced run serves as a reference in terms of operating performance, costs and the amount of grid constraint violations that occur without appropriate scheduling measures.

To give detailed insights into the behavior of the algorithms, each constraint function sample and each candidate solution is recorded. Given this information, the convergence of the novel tree-based algorithm with respect to the operating costs and distance to the best known solution can be evaluated and related to the sensitivity-based reference. In addition to the final operating costs, the number of samples that are needed to find the first feasible schedule is evaluated. To further generalize the results, to provide detailed insights into the runtime performance, and to support efficient implementations, the execution time of various sub-tasks is traced in detail. Since the tree-based method depends on randomized decisions for local search and the timing of both approaches is influenced by stochastic effects, all experiments are repeatedly executed and corresponding statistics are listed.

1.3.4 Extensive Assessment of Microgrid Scheduling

The hybrid scheduling algorithms that allow to incorporate complex physical models and even the effects of low-level controls in scheduling are thoughtfully validated with respect to their performance in solving the problem at hand. However, the necessity and value of such algorithms in complex multi-microgrids are still open for discussion. It is not well understood which level of detail needs to be considered at scheduling time and which effects can solely be addressed by the real-time control architecture below day-ahead scheduling. To close the research gap, first, an extensive simulation-based method that allows to assess multi-microgrid scheduling approaches in great detail and under a broad range of operating scenarios is introduced (cf. Section 2.3). The method itself targets a microgrid-specific assessment of scheduling approaches. Nevertheless, a case study is conducted to demonstrate the assessment method and to

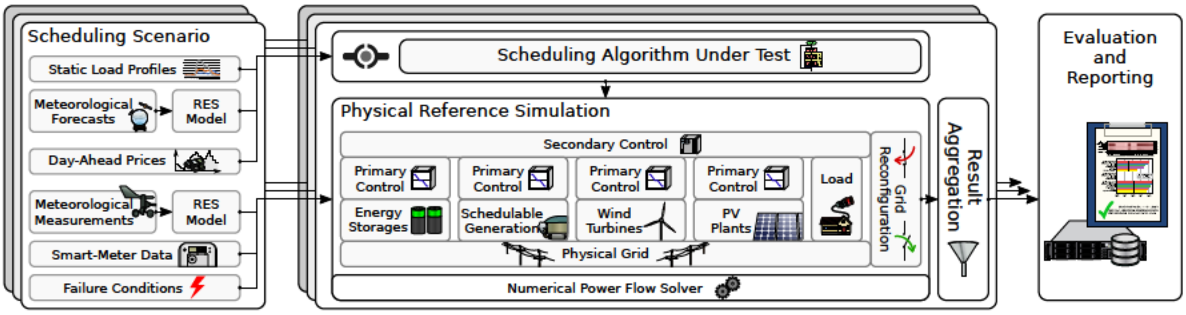

Figure 1.4: Structure of the multi-microgrid testbed (cf. Section 2.3).

give first generalized results on the value of proactive resilient scheduling. A portfolio of scheduling algorithms is created that covers various levels of details ranging from purely economic scheduling to complex grid-aware formulations solved by the novel hybrid algorithm. The case study then evaluates the impact of each algorithm on the system performance of an exemplary multi-microgrid to give detailed insights into the value of prototypical scheduling.

Comprehensive Problem Formulation

The system model is separated into scheduling-time models that operate on forecasts only and those models that can incorporate the latest measurements in the control decision and device outputs (cf. Section 2.3). Both types are linked by matching forecasts and measurement information as well as the scheduling outputs that are taken as high-level setpoints for the low-level controls. Figure 1.4 illustrates the problem decomposition and the testbed that implements the assessment method. Scheduling-time information is either directly modeled by input profiles such as standard load profiles and day-ahead prices or via RES models that transform meteorological forecasts into the wanted generation predictions. Based on the scheduling-time information, the algorithm under test then computes the inputs of the independent reference simulation that covers the real-time performance of the system. Due to the independent reference, it is not necessary to rely on metrics that are directly exposed by the scheduling algorithms.

The reference simulation covers a two-layer control architecture consisting of a central control for reserve management and fault mitigation as well as distributed primary control. All controls are embedded in a grid simulation based on the well-known balanced power flow equations. In contrast to classical power flow models that assume a single slack node modeling the upstream grid connection, an extended formulation that supports islanded and partly islanded systems is used [65, 66]. For each island in the grid, active and reactive power are dispatched according to primary P-of-f and Q-of-U droop, respectively, without the need of a central slack. Nevertheless, the power flow model well exceeds related work [65, 66] by detailed device constraints such as apparent power limits, an outage model that allows to detect insufficient supply, and dynamic droop schemes considering the state of storage units.

It is assumed that in islanded mode, all active schedulable generation and storage units fully participate in primary control. However, to balance out storage states, it is further assumed that such units gradually reduce their frequency droop gain in case storage limits are reached. Additionally, all volatile RES generation units fully participate in primary voltage control, but similar to [85], only reduce their generation, in case the frequency of the corresponding island exceeds a given emergency threshold. Outages are modeled by virtual power sources that inject active power in case critical frequency deviations are encountered. Hence, nonconverging power flows can be distinguished from outage situations and an indication on the amount of short or excessive active power can be given. To further cover secondary control actions that counteract faults and deviations manifesting in the real-time operation, two heuristics are implemented. The first one manages generation reserves based on predefined thresholds and the second one implements a simple grid-reconfiguration scheme that connects separated parts of the network, if possible.

Extensive Benchmark and Case Study

Another case study is conducted to demonstrate the assessment method and to study the value of proactive scheduling. Similar to the study covered in Section 2.2, the study in Section 2.3 is based on a modified Baran testfeeder [37]. Since the study specifically focuses on highly loaded grids with a high share of volatile RES, the amount of PV and wind generation is significantly increased. To quantify the system performance in a broad range of operating conditions, an extensive set of input scenarios is introduced. The load, meteorological and market information is thereby taken from long-term recordings without the need of introducing common stochastic assumptions such as temporally independent distributions in the assessment. System resilience is covered by introducing an extensive set of failure conditions. In addition to scenarios that are directly covered by some algorithms under test, failure modes that are not considered by any of the approaches are included. To avoid quantification of rare events and corresponding modeling errors, performance metrics are recorded per failure class without the need of specifying incident probabilities.

Several cases covering a broad spectrum of scheduling algorithms are distinguished. First, purely economic scheduling is introduced as a deterministic reference that does not include any resilience aspects. Reserve constraints within the realm of a single-bus MILP formulation are considered by an extended version of MILP reserve constraints first formulated in the study on hybrid optimization (cf. Section 2.2). In contrast to the initial constraint set, both upwards and downwards reserve as well as multiple extreme-case deviation scenarios instead of deterministic predictions are covered. The hybrid scheduling approach considering tree-based approximation is further used to consider grid constraints and the complex control hierarchy in scheduling. To cover the more advanced grid model, the original formulation is replaced by the grid and control architecture used in the evaluation step. Nevertheless, information available at real-time only is replaced by the corresponding scheduling-time forecasts to still maintain a separation of inputs. To build a common base, all algorithms are executed and evaluated on the same set of input scenarios.

1.3.5 Engineering Support for Extensive Assessments

Following the assessment method presented in Section 2.3 requires considerable engineering efforts in implementing and applying the assessment facilities. The high computational workload of several hundred thousand scenarios needs to be efficiently managed and distributed to multiple machines. To guide the selection and development of multi-microgrid scheduling approaches, repeated testing and validation runs are needed to assess the impacts of changes in the algorithms under test. Such repeated assessments can lead to a multitude of result sets that need to be properly stored and managed. To reduce engineering efforts, a software architecture that handles the computational workload and tightly integrates the assessment into a common development tool chain is presented in [86].

Testbed Architecture For Distributed Computing

The testbed illustrated in Figure 1.4 is split into a scenario generation facility, the actual scheduling and validation logic as well as a central evaluation and reporting infrastructure [86]. Due to the separation of scenario generation and validation facilities, a common set of input scenarios can be generated and applied in the assessment of multiple scheduling algorithms without the need of frequent and deterministic scenario generation. Figure 1.5 further illustrates the detailed architecture of the scenario generation utility that accesses a broad variety of input data sources and composes a comprehensive scenario set. To temporally align the observations and forecasts, first a common set of study periods is selected. Since the meteorological information also needs to be spatially aligned, both forecasts and measurements are processed centrally before the individual RES models are applied. Similarly, a central load scenario selection component matches the appropriate forecasting profiles and scales them according to the available meta information.

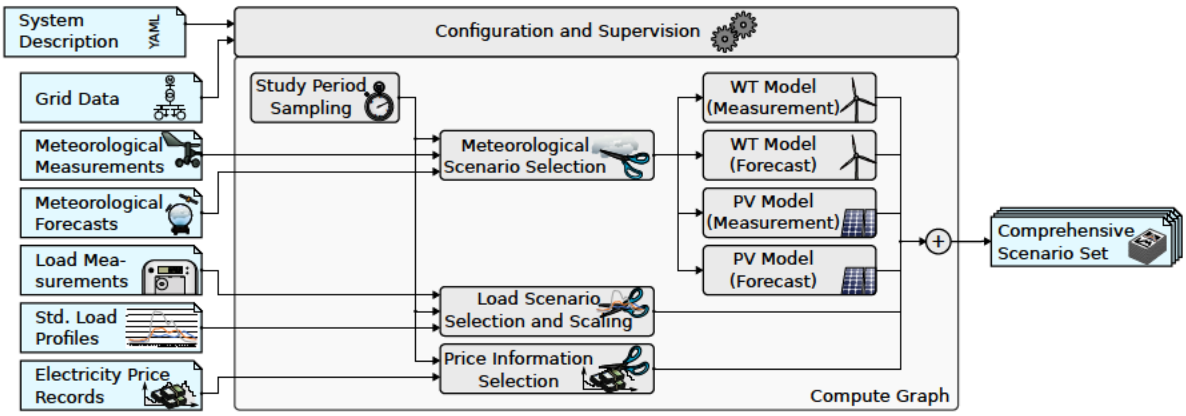

Figure 1.5: System architecture for scenario generation based on [86].

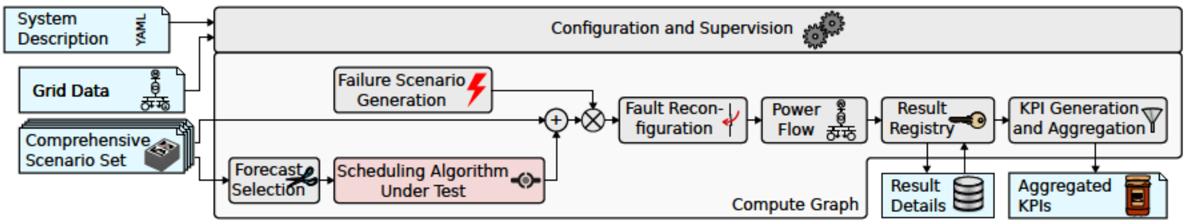

Figure 1.6: System architecture for scheduling assessments based on [86].

The detailed assessment workflow is illustrated in Figure 1.6. Note that although the failure scenarios are logically part of the input scenario set as illustrated in Figure 1.4, the failure scenario generation is conducted on demand in the assessment infrastructure. Such a separation significantly limits the amount of scenarios that need to be stored and processed by the scheduling algorithm under test. For each scenario executed in a simulation run, a unique identifier is generated and managed by the result registry and the connected database. Although the registry can also store detailed simulation results for debugging, a dedicated Key Performance Indicator (KPI) generation and aggregation component is implemented that utilizes the distributed computing resources of the remaining testbed. Still, the unique identifier allows recalling associated details for any KPI outcome.

The flow-based architecture given in Figures 1.5 and 1.6 is directly mapped to a compute-graph that encodes individual tasks as nodes and input data requirements as edges [87]. To exploit the embarrassingly parallel nature of the problem, each component is split into multiple tasks that operate on a subset of the input data and dynamically distributed to multiple workers. Since the graph management and execution is already implemented in dedicated computing framework [87], the implementation effort of the testbed is mainly reduced to the domain logic.

Integrated Development and Validation Workflow

A user interface that focuses on a tight integration into existing development and validation workflows is created [86]. First, the complex system description is managed in an established text-based format that can be well integrated into common version control systems. The main description links the auxiliary information such as long-term measurements that cannot be efficiently encoded in the text-based syntax and provides a common anchor to control the testbed execution. A reference mechanism that recursively includes external information allows to create a hierarchy of single input files and to share information among related configurations. Since the auxiliary files are not subject to frequent changes, but are an integral part of the input description, it is proposed to integrate the auxiliary files into the version control process via appropriate tools that manage large binary files as well.

Frequent regression tests that assess the quality of scheduling algorithms and allow to evaluate the impact of algorithmic changes on the system resilience are supported by a tight integration into Continuous Integration (CI) systems. Therefore, the testbed provides a user interface that can be easily accessed by external software. For instance, all tools can be executed without a graphical user interface and advanced configuration options allow a CI system to dynamically inject information without the need of directly accessing configuration files. In addition, results can be exported to and managed by the CI system to efficiently trace impacts on the system resilience and scheduling performance. To validate the proposed software architecture and the integration into the engineering process, the proposed workflow was applied in the studies described in Sections 2.2 to 2.3 and reviewed afterwards.

1.4 Overview on Results

Following the described methodology presented in Section 1.3, a broad range of insights into proactive resilient scheduling can be given. Such results cover the spectrum of available resilient multi-microgrid scheduling approaches, include quantitative evidence on the performance and value of several scheduling algorithms, and support efficient engineering of resilient multi-microgrid scheduling.

1.4.1 Comprehensive Classification for Engineering Support

Although none of the eligibility criteria formulated in the systematic classification of existing literature (cf. Section 1.3.1) explicitly stated that the scheduling algorithm must follow an optimization-based approach, all key-contributions utilize optimization techniques (cf. Section 2.1). In consequence, none of the contributions directly formulates heuristic operation procedures. Despite the common aspect, a very broad variety of problem formulations, optimization approaches and evaluation measures are found. By definition, all key contributions included EES units, Distributed Generators (DGs), and volatile RES. Most of the publications implement generic asset models of controllable and volatile generation without considering specifc assets in detail. For instance, only one contribution specifically addressed combined heat and power [45] and one publication specifically included microturbines [43] in their formulations. Nevertheless, a minority of six contributions considered specifics of WT and PV models such as turbine curves and solar irradiation characteristics (such as [43, 88]).

Selected key contributions also demonstrate the spectrum of handling uncertainties in the energy management problem by listing deterministic [47], stochastic [88, 70] and robust formulations [32, 33]. In most cases, uncertainties of loads and volatile RES are considered by stochastic and indeterministic formulations and only few approaches simplify these models by a purely deterministic representation. To represent multi-microgrid topologies and topological constraints, engineers find a spectrum of several methods ranging from connection graphs [88, 39, 89] to detailed balanced and unbalanced network equations [90, 44, 74]. Most scheduling formulations are concerned with steady-state phenomena. Nevertheless, one publication specifically constraints the transient response of the grid [74].

Similar to the model formulations, a broad spectrum of optimization objectives is found. Although all key contributions include economic costs as one or the primary objective, a versatile set of terms including the costs of main grid transfers [70, 43], DG operation costs [29, 33, 70] and the value of lost load [49, 91] is formulated. Following from the broad range of model formulations, an extensive set of methods is used to handle the complexity of optimal scheduling. For instance MILP techniques are found as a common method of choice [70, 45]. Other approaches include genetic algorithms [43, 49] and particle swarm optimization [46, 40]. To give an indication on relevant solution approaches, in addition to the detailed tables that categorize available model formulations, a comprehensive classification of methods is derived. One can note that several measures such as linearization [32, 89, 41], problem decomposition [28, 45] and scenario reduction [43, 40] are applied to reduce the computational burden and make the problem tractable.

One of the main concerns of resilient scheduling are failures and corresponding mitigation options that are considered at scheduling time. Given the broad variety of potential failures that can occur in a microgrid [62], it can be observed that the key contributions actively address a small subset only. Main grid outages are considered by a majority of 17 key contributions such as [90, 88, 91] and eight approaches include the possibility of line-outage events (for instance, [90, 43, 89]). Other failure modes include tripping generators [90, 44, 45], bus-related faults [92] and even detailed short circuits [74], but several failure modes such as communication failures [62] are rarely reflected in detail [39]. Three main mitigation techniques and their feasibility with respect to a given schedule are considered in the key contributions. A majority of 18 contributions disconnects from the main grid to mitigate external faults [46, 45, 40]. Grid splitting and partial islanding [45, 91, 44] as well as grid reconfiguration that isolates the fault and establishes alternative paths [39, 90, 89] are also found.

As validation and testing efforts are main aspects towards a successful implementation, this work categorizes major validation efforts presented in the key contributions. One can observe that all approaches are validated by numerical simulations such as [33, 45, 74]. Only one publication additionally presents laboratory tests [70] and no key contribution reported field trials of proactive resilient scheduling. To aid a quick implementation of future validation efforts, detailed information on common test systems and input profiles is collected. Although no single universal benchmark system is observed, some test grids such as the Baran testfeeder [37] are regularly found [28, 43, 92]. Despite the broad range of contributions, shortcomings in testing and validation, as well as limits in scheduling that were identified in the initial literature review could also be observed in the systematic study.

1.4.2 Validity of Common Modeling Assumptions

Following the methodology of the initial verification study described in Section 1.3.2, Figure 1.7 shows the CDF of the validation dataset and three stochastic models that operate without any additional scheduling-time information such as numerical weather forecasts [78]. In addition to the meteorological observables (i.e., the wind speed and global horizontal solar irradiation), the corresponding CDF values after applying the RES output models are given. For both observables, exemplary parametric models (hourly fit Beta-distributions for solar irradiation and one Weibull model representing wind speed) are taken. To further cover any mismatches in the parametric models and to focus on the impact of the assumption on temporarily independent observables, discrete but temporarily independent distributions are fit as well. It can be observed that all independent models systematically underestimate the probability of days with exceptionally low and high RES generation.

Temporal dependencies between hourly observations are introduced by an additional set of discrete Markov models. For solar irradiation, it is assumed that an observation

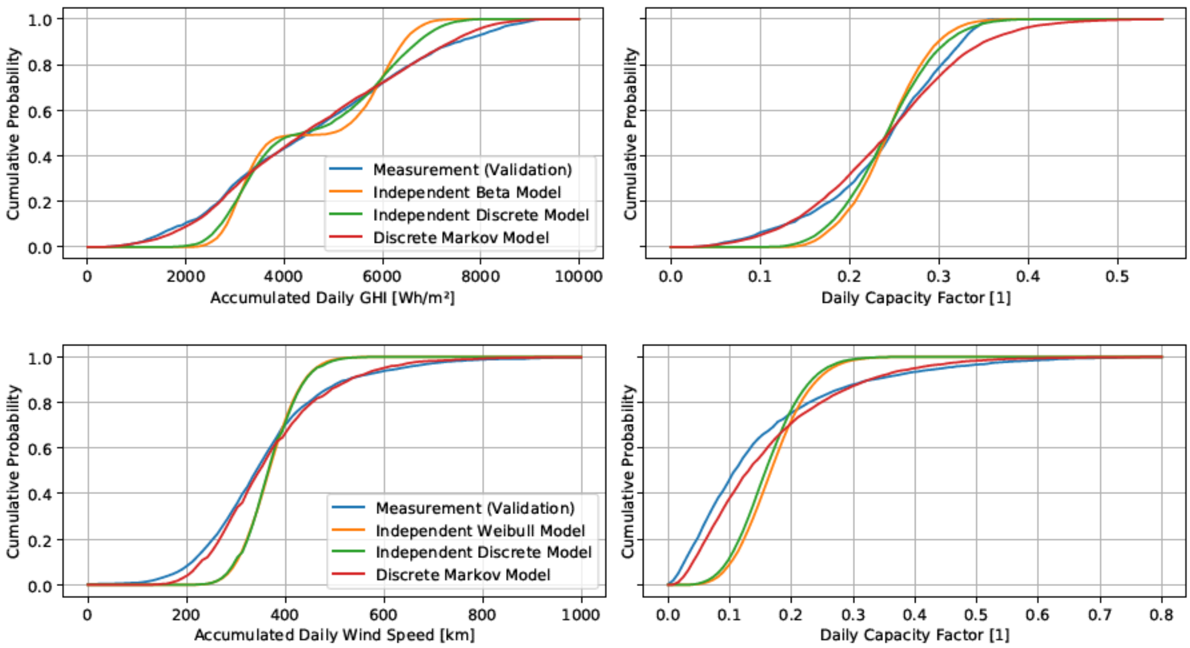

Figure 1.7: CDF plots of the accumulated observations in a one-day scheduling horizon without using any scheduling-time information [78].

depends on the current time of day, the seasons, as well as the last observation. For wind speed, no dependency on the time of day and no seasonal influence is included. One can observe that both Markov models follow the reference distribution more closely than the temporally independent distributions. Nevertheless, the daily capacity factors as calculated by the RES models, still show a deviation from the reference that is considerably stronger than for the input distributions.

The effects of scheduling-time information on the accuracy of stochastic characterizations is studied by taking numerical weather prediction information into account. Figure 1.8 shows the CDF plots for three different modeling approaches and the reference distribution. Again, the figure hosts wind-speed and irradiation distributions as well as the corresponding RES model outputs. All models are discrete in nature to avoid the assumptions associated with continuous parametric models. At first, temporally independent distributions that model the observations given the current forecast are fit. Unlike the single wind-speed distribution, an ensemble of one distribution per hour is used for solar irradiation measurements. One can observe that again, all independent distributions considerably underestimate the probability of extreme infeed situations.

Temporal dependencies among forecasting errors are also addressed by discrete Markov models that express an observation given the previous realization and the current forecast. For solar irradiation, additionally, the dependence on the time of day is included.

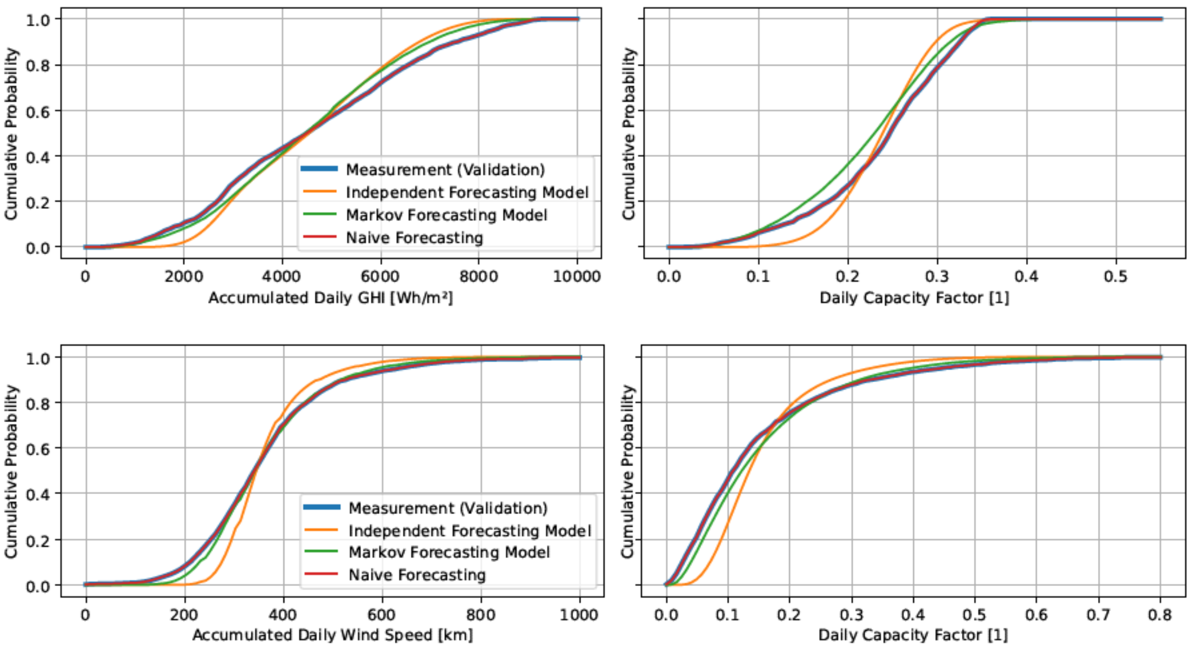

Figure 1.8: CDF plots of the accumulated observations in a one-day scheduling horizon that use any scheduling-time information [78].

Both Markov models closely fit the reference distribution, but for solar irradiation, still a considerable underestimation of high-generation days is observed.

In addition to the goodness of fit that well influences the performance of stochastic approaches, deterministic prediction errors are studied. Therefore, the expected values of all stochastic distributions are compared with the reference values. The resulting forecasting errors are illustrated in Figures 1.9 and 1.10. Note that the box plots mark mean values by green triangles and medians by orange bars. As a reference, one naive forecast that persists all measurements from the previous days is introduced for each

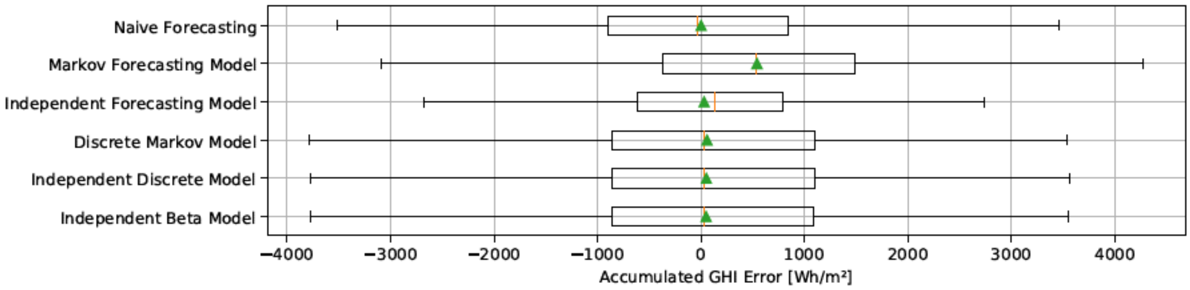

Figure 1.9: Daily prediction errors given a deterministic irradiation forecast based on the expectation [78].

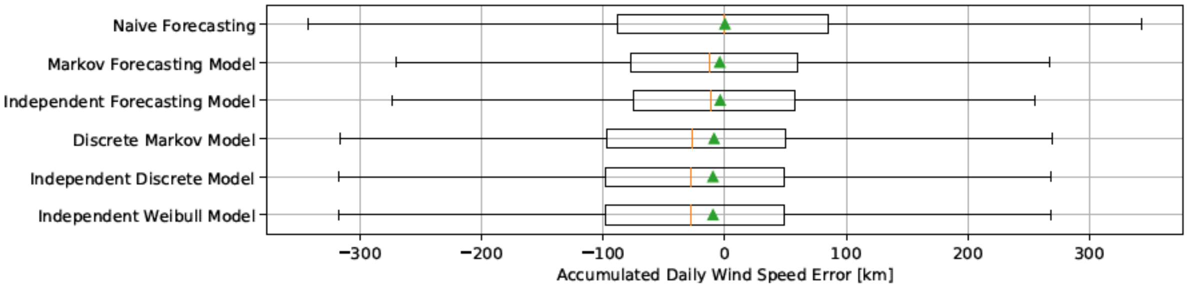

Figure 1.10: Daily prediction errors given a deterministic wind speed forecast based on the expectation [78].

observation. Due to the definition of naive forecasts, the forecasting CDFs converge to the references and the average errors are asymptotically zero.

The bias values of all irradiation and wind speed models that solely depend on past measurements can be directly tracked down to a corresponding bias in the validation dataset. Following the Mann-Whitney U test with a significance level of 5%, it can be observed that all distributions that utilize additional scheduling-time information show a significantly reduced absolute error compared to the models that do not include such information. On considering the RES models, the same conclusion does not hold anymore because Markov forecasting is outperformed by several independent models. Nevertheless, the independent forecasting-based model still significantly outperforms all other models including naive forecasts.

1.4.3 Hybrid Scheduling Performance

The performances of the extended reference algorithm and the novel tree-based approach are assessed on a detailed case study (cf. Sections 1.3.3 and 2.2). The first case focuses on the MILP formulation and excludes the nonlinear grid model. It can be seen that although the linear resilience constraints are enabled, several violations in the nonlinear model are encountered. Even at failure modes that are directly addressed by the MILP constraints, several nonlinear constraints are violated. In a next case, both hybrid algorithms are executed on a simplified test system without any operational constraints. Figure 1.11 illustrates the resulting convergence behavior of the tree-based method and relates it to the sensitivity-based approach. It is observed that the simpler sensitivity-based algorithm on average outperforms the tree-based one both by the number of samples until convergence is reached and by the achieved operating costs. The same observation can be drawn from the recorded execution time values that are largely dominated by the evaluation of nonlinear constraints.

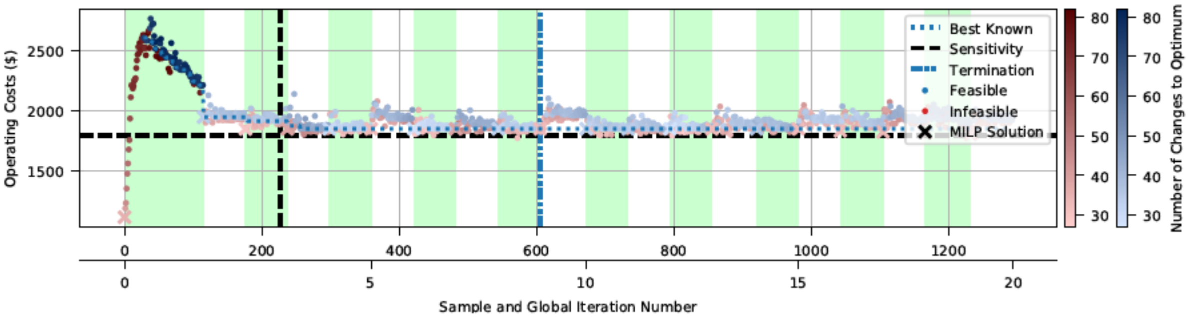

Figure 1.11: Exemplary convergence of the tree-based method on a simplified system that excludes operational constraints (cf. Section 2.2). Note that global iterations are marked by green and white stripes.

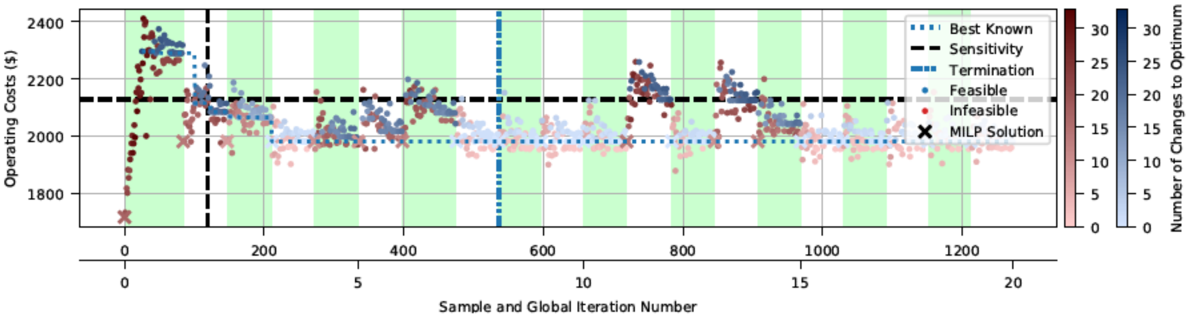

Figure 1.12: Exemplary convergence of the tree-based method on a simplified system that includes operational constraints (cf. Section 2.2). Note that global iterations are marked by green and white stripes.

The third study case repeats the experiments with the same simplifications in the benchmark grid but enables the optional operational and resilience constraints. Figure 1.12 again illustrates the convergence of the tree-based approach and indicates the performance of the sensitivity-based method. In contrast to the previous case, the tree-based algorithm always outperforms the sensitivity-based one in terms of operating costs. Considering the same number of samples that are needed until the sensitivity-based approach terminates, the average operating costs of both methods only marginally differ and the increased overall execution time of tree-based scheduling can be attributed to the improved operating costs. The final study case focusing on hybrid scheduling includes the test grid without any simplifications and with all optional constraints. One can observe that the sensitivity-based method does not converge to a feasible solution and eventually reports the problem to be infeasible. Still, the tree-based approach manages to compute schedules that satisfy all linear and nonlinear constraints.

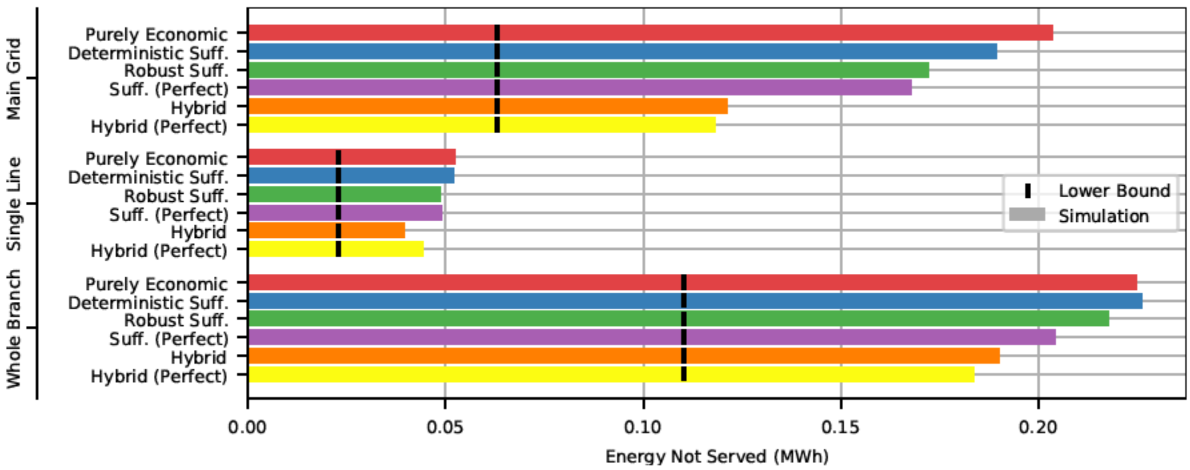

Figure 1.13: Average energy that cannot be supplied (cf. Section 2.3).

1.4.4 Proactive Microgrid Scheduling Needs and Gains

The extensive assessment method that targets the impact of scheduling algorithms on the system resilience is applied in a case study on the needs and benefits of proactive resilient scheduling (cf. Sections 1.3.4 and 2.3). First, an economic MILP scheduling formulation that does not include any resilience constraints or grid limitations is established as a baseline. Since the test network is designed to host all generation assets and loads in normal operation, no loss of load is encountered in such situations. Nevertheless, due to intentionally limited grid capacity reserves, a considerable amount of constraint violations such as line overloading and resulting loss of load are encountered on all failure modes. For each class of failures, Figure 1.13 plots the energy that cannot be supplied due to constraint violations and corresponding outages. In addition, the plot includes a hypothetical lower bound that encodes the best known schedule of all approaches. Single-line failures that can be directly mitigated by grid reconfiguration actions show significantly less Energy Not Supplied (ENS) than main grid and whole branch failures that require the networks or parts thereof to operate in islanded mode. Despite the fact that lost load is encountered for all failure modes, one can observe that even with economic scheduling a high share of events can already be handled without any loss of load. In particular, 87% of the entire fault duration of partly islanded systems facing whole branch faults do not show unserved energy. Following the trend shown in Figure 1.13, this fault mitigation rates even reach 94% and 99% for main grid and single line faults, respectively.

In the next cases, the purely economic formulation is extended by a set of linear resilience constraints that ensure sufficient generation reserves to counteract main grid failures until secondary control actions take effect. To study the impact of forecasting deviations on the system resilience, multiple sufficiency-based variations are assessed. First, a deterministic formulation does not consider any forecasting deviation and a robust formulation incorporates several extreme-case deviations. As a further reference, a hypothetical perfect forecast is assumed to bound the effects of improved forecasting capabilities. While the deterministic sufficiency-based model slightly reduced the ENS on main grid failures by 7.0%, compared to purely economic scheduling, the robust variation already achieved a reduction of 15.5%. Notably, only a minor improvement of 2.5% compared to the robust counterpart is seen, for perfect forecasts.

For the last study cases, the hybrid scheduling approach that includes detailed grid constraints is deployed in a robust variation and a reference that assumes perfect forecasts. Given the robust hybrid approach, an ENS reduction on main grid failures of 40.5% compared to the purely economic case can be achieved. Similar to the sufficiency-based formulation, improvements on the forecasting quality only yielded a marginal reduction of lost load. Notably, only 35% of all main grid outage scenarios that show loss of load in the perfect reference show infeasible solutions to the scheduling run. All other cases terminate with a feasible solution but simplifications such as whole-day outages that are introduced to keep the problem computationally tractable still lead to loss of load.

For all study cases, performance improvements on faults such as single-line outages that are not considered in the scheduling formulation are less significant or not observed at all. The observed resilience improvements come with a cost increase of 0.7% and even 30.8% for robust sufficiency and hybrid scheduling, respectively. Despite the limited impact of forecasting improvements on the system resilience, a considerable potential is indicated by an average cost reduction of 19.8% for hybrid scheduling when assuming perfect forecasts. Hence, improvements on the forecasting quality can significantly reduce the cost associated with reserve provisioning.

1.4.5 Engineering Support Experiences

The integrated development and validation methodology introduced in Section 1.3.5 and in the own contribution [86] is applied in the case studies for further validation. The multi-microgrid testbed implementation of the presented assessment follows the proposed graph-based architecture. Hence, it is demonstrated that the software design easily scales to several hundred thousand of scenarios per simulation run and over 120 workers that process the computational workload. Due to the graph-based design, the parallelization logic could be largely delegated to an external framework [87] and the testbed implementation mainly focuses on the domain logic. Still, the additional

Table 1.1: Qualitative comparison of assessment methods

Criteria	Integrated Assessment	Stand-Alone Workflow
Traceability of results	provided	missing
Manual assessment effort	low	medium
Assessment granularity	fine	coarse
Computational resources	high	medium
Implementation complexity	medium	low

engineering overhead needs to be considered in case a fully distributed execution is not needed to handle the computational workload. The data management strategy including the result registry proved to be an effective measure to connect aggregated KPIs and detailed debugging information. Nonetheless, care must be taken to avoid bottlenecks in the central database due to excessive access of debug information.

Both case studies tightly integrate the simulation runs into a SotA software development and CI platform [86]. It is demonstrated that an automatic assessment of code changes in the system description and the algorithms themselves is feasible. To further relate the proposed methodology to a hypothetical stand-alone workflow without an automatized integration, Table 1.1 gives a quantitative comparison. Due to the tight integration into the software development platform, results are closely connected to the source configuration. Hence, a high level of traceability can be achieved that cannot be provided by stand-alone workflows without such records. The high level of automation in the integrated assessment workflow further reduces manual efforts of a single simulation run and can consequently lead to more fine-grained assessments.

Nevertheless, the frequent test runs triggered by the integrated assessment method require a considerable amount of computational resources. Both, machines that handle the assessment workload and storage resources that manage evaluation results need to be provided. Since the integration into SotA CI systems shifts the workload from the development workstation to dedicated servers, impacts on the local workflow such as blocked workstations can still be reduced. Benefits of the integrated assessment in automatized testing and validation come with the cost of an increased implementation complexity. Tooling needs to provide interfaces that can be well accessed by the CI system and results need to be exposed in a way that can be efficiently managed by the external software. Still, existing tool chains well support such integration tasks, for example, by providing facilities that handle even large input files.

1.5 Summary of Scientific Publications

Publication A

The chronologically first publication (cf. Section 2.1) handles the extensive body of literature related to multi-microgrids and presents a comprehensive classification of proactive resilient scheduling. Originating from the need for an accessible listing and comparison of resilient scheduling approaches, a systematic literature study is conducted. The study first defines multiple eligibility criteria and performs an extensive search to identify several key contributions that are classified in detail. To establish comparability among diverse approaches, a high-dimensional classification covering model formulations, computational methods, resilience features, and validation aspects is introduced. Although all key contributions follow an optimization-based approach, it is shown that a broad variety of scheduling formulations and techniques are available. Nevertheless, several shortcomings of current methods and research needs could be identified that guide the following scientific studies and future research efforts.

Publication B

One shortfall of existing methods in efficiently integrating nonlinear grid constraints into the optimization procedure is addressed by the second publication (cf. Section 2.2). In contrast to related work that commonly requires grid models to be simplified, a novel hybrid optimization approach allowing to access detailed nonlinear grid constraints as provided by external simulation tools is introduced. To fully exploit linear substructures within the optimization problem, the formulation is split into a linear and nonlinear subset. The nonlinear constraints are then approximated within the MILP problem by an iteratively refined tree structure deduced from dynamically drawn samples of the nonlinear constraint function. It is shown that the approach allows to utilize both highly developed MILP solvers and specialized power system simulators without the need of relying on purely heuristic optimization techniques. A case study relates the novel algorithm to a refined reference from literature. Although the modified reference showed better results in the most simplified cases, the novel algorithm outperformed the reference on more complex optimization models and even provided feasible solutions when the reference method failed.

Publication C

The third publication (cf. Section 2.3) addresses research needs on the impact and necessity of proactive and resilient day-ahead scheduling from a system resilience perspective. Therefore, an extensive simulation-based assessment method is proposed that allows to quantify the impact of scheduling on the long-term operation of multi-microgrids. In contrast to related publications, this work considers the impacts of a control hierarchy that can balance fluctuations and mitigate faults in real time but may be influenced by scheduling decisions as well. The method covering a large amount of operating scenarios is applied in a detailed case study that includes a broad variety of scheduling formulations. It turned out that even on the exemplary multi-microgrid which is specifically designed to challenge the algorithms under test, a large share of faults can already be mitigated by low-level controls without considering resilience at day-ahead scheduling. Nevertheless, the remaining share can be well influenced by day-ahead measures at the cost of additional operating expenses. It is demonstrated that the proposed method supports balancing these costs and to find the limits of proactive resilient scheduling.

1.6 Scientific Contributions of this Work

This work advances the design, implementation and validation of proactive and resilient multi-microgrid scheduling. First, a novel hybrid optimization approach that allows the inclusion of grid constraints in unprecedented detail is provided. An extensive evaluation method assessing the value of proactive scheduling, and detailed decision support further advance the engineering process. Given the achievements of this work, the spectrum of proactive and resilient scheduling algorithms is well categorized and significantly extended by a novel hybrid optimization approach. This groundwork enables detailed assessments considering the need of proactive scheduling and the impacts of several algorithms on the system resilience. In particular, the following scientific contributions are achieved.

Classification of Resilient Scheduling

This work condenses the extensive body of scheduling-related literature into a comprehensive classification of proactive and resilient scheduling (cf. Section 2.1). In contrast to related reviews, this work follows a systematic review method to identify a set of key contributions. Based on related schemes, a fine-grained classification is developed to establish comparability among scheduling approaches and to showcase the spectrum of available methods. Nevertheless, both the scope and granularity of the high-dimensional classification exceed related work by far. In addition to modeling and solution aspects, the classification includes detailed information on the validation of presented approaches. Hence, the study contributes an extensive guide to support engineering decisions without the need of extensive literature reviews. Finally, a detailed analysis on research gaps and future perspectives is conducted that discusses the key contributions with respect to related research disciplines.

Hybrid Optimization

This work on hybrid scheduling (cf. Section 2.2) first proves that even the MILP formulation without the generalized constraint function that may encode arbitrary decision problems is at least weakly NP-hard. Given the motivating observation, a sensitivity-based hybrid scheduling algorithm that heuristically includes nonlinear constraints in MILP is significantly extended to serve as a reference for hybrid scheduling. In contrast to the initial publication [50], multiple heuristics are introduced to efficiently scale the algorithm from a single-period problem to a multi-period optimization. Furthermore, this work presents a novel hybrid scheduling algorithm based on decision-trees to overcome identified limitations of the sensitivity-based method.

A case-study assesses both hybrid methods and gives detailed insights into the eligibility of both of them. It is demonstrated that sensitivity-based scheduling performs well on simplified formulations but fails to deliver good or even any feasible results on more complex systems. It is further demonstrated that the tree-based method outperforms the reference in the more extensive cases. Additionally, this work delivers detailed insights into the convergence behavior of both algorithms and the role of individual algorithmic steps in the optimization procedures. In contrast to related work that commonly state the overall execution time only, a fine-grained timing analysis shows the computational effort of individual actions.

Assessment of Multi-Microgrid Scheduling

Finally, several contributions in the long-term assessment of resilient multi-microgrid scheduling can be reported (cf. Section 2.3). An extensive evaluation method that addresses the impact of scheduling on the system resilience is presented. In contrast to related work, the method specifically addresses the effects of day-ahead scheduling considering a comprehensive control hierarchy and detailed device constraints in a long-term operation. Therefore, a strict separation of scheduling-time information that is available to the scheduling algorithm under test and information that is available to real-time controls only, is introduced. Additionally, power flow models of islanded microgrids are significantly extended to reflect the impact of dynamic low-level controls and device constraints. Furthermore, an outage model is introduced to clearly distinguish outage conditions from non-converging power flows.

Based on the extensive assessment method, first detailed insights into the need and value of proactive scheduling on top of a comprehensive control architecture are given. Therefore, this work introduces a broad portfolio of scheduling algorithms to represent various levels of detail and the impact of forecasting deviations on the system resilience. For the first time, it is demonstrated that even in the test grid that is specifically designed to challenge algorithms under test, a high share of failures can already be mitigated without considering them in scheduling. Nevertheless, it is also demonstrated that the remaining faults in the test system can be well influenced by day-ahead scheduling. Due to the independent validation that exceeds related work by far, further insights into the cost of resilient scheduling formulations and the impacts of forecasting deviations can be provided. In addition to the potential of proactive scheduling, such insights also include limitations of SotA algorithms and motivate future research.

1.7 Concluding Remarks

The main research question on the resilient operation of multi-microgrids including a high share of volatile RES is tackled by detailed studies on proactive multi-microgrid scheduling. The problem is addressed from different angles including design, implementation and validation of resilient scheduling algorithms. To support the multi-microgrid design phase, a broad spectrum of resilient scheduling algorithms is identified and categorized in detail. The typical proactive resilient algorithm follows an optimization-based design that reduces the operating costs and adds several constraints targeting successful fault mitigation. However, a broad variety in modeling and solving the optimization problem is found. The detailed, multidimensional classification therefore targets the efficient selection of suitable approaches without the need to review the extensive body of scheduling-related literature in a typical engineering process. Due to the classification, comparability among heterogeneous approaches is established. Combining the systematic research and classification, the guide to resilient scheduling as requested by the first research goal is established. Although the presented guide documents the broad spectrum of resilient scheduling, several research gaps such as restricted grid models and limited validation can be identified and leave room for further improvements.

Most scheduling algorithms strongly simplify the grid model that typically includes nonlinear power flows and several low-level controls. Nonetheless, the impacts of such simplifications on the system resilience is not well studied in related literature. To create a reference that allows to largely reduce simplifications in the grid model, hybrid scheduling approaches are investigated. It is successfully demonstrated that the hybridization of mathematical programming and heuristic optimization techniques can be used to efficiently include complex nonlinear grid constraints in proactive scheduling. It is shown that the novel tree-based algorithm allows solving problems that cannot be solved by a reference extended from literature. Given the advanced capability of proactively including complex grid and low-level control constraints, the research goal on creating a novel scheduling technique is achieved. Still, the reference algorithm benefits from simplicity and delivers excellent results on some reduced problems. Hence, both algorithms can play a role in considering complex grid constraints as needed in theoretical studies and practical implementations alike.

The study on available scheduling approaches further reveals that most algorithms are validated on simple simulation-based test grids without considering long-term operation. Additionally, most contributions do not independently validate the effects of low-level controls and forecasting deviations on the system resilience. To close the gap according to the third research goal, a comprehensive assessment method is presented that allows to quantify the impacts of day-ahead scheduling decisions on the system resilience in presence of other real-time fault mitigation measures. Therefore, an improved power flow model enables the assessment of day-ahead scheduling algorithms in presence of a complex control architecture that may impact the performance and necessity of scheduling-time measures. Still, the assessment method covers long-term operation under a broad range of operating scenarios without the limits imposed by transient simulations. Hence, the need to model few representative scheduling scenarios and corresponding impacts on the significance of results is drastically reduced. Additionally, strong simplifications on applied grid and control models are avoided, which can improve the quality of validation studies even further. Given the significant advancements in assessing the long-term operation of scheduling algorithms, the research goal on the extensive assessment method is fully met.

Following the assessment method, a case study on the value of proactive scheduling is conducted. Even in the challenging test grid, a large share of events can already be handled by low-level controls and real-time fault mitigation measures without considering them at scheduling time. Hence, it is expected that dedicated scheduling-time measures are not needed in case the application can tolerate the remaining share of outages. Consequently, it can be justifiable that day-ahead scheduling solely focuses on the economic operation without actively considering resilience aspects. Nevertheless, it is also demonstrated that scheduling time algorithms can have an impact on the remaining share of events which makes resilient scheduling a viable option for the most critical applications.

In addition to benefits, the case study also reveals the limits of current proactive scheduling approaches. It could be shown that due to necessary simplifications of failure modes even the hybrid approach with a hypothetical perfect forecast cannot fully avoid outage conditions. Given the perfect reference, it is also shown that only little improvements on the resilience of the test system can be expected by a further improved forecasting quality. Nevertheless, a considerable influence of prediction errors on the operating costs is observed. However, in case the assumptions on temporally independent forecasting deviations which are invalidated in this work are directly used to compute the extreme case deviations, a negative impact on the system resilience cannot be excluded.

In fulfillment of the fourth research goal, this work therefore provides initial guidance in selecting suitable levers to further improve scheduling results. Still, a case-specifc evaluation of day-ahead scheduling is needed. The demonstrated assessment method provides necessary tooling to seamlessly integrate the extensive validation efforts into the development process and to give one answer to the research question on how to optimally operate multi-microgrids.

1.8 Outlook

The thoughtful analysis of existing key contributions, hybrid optimization approaches and impacts of proactive scheduling led to significant insights into a resilient multi-microgrid operation. Nevertheless, several additional research perspectives could be identified. Such work includes studies on the robustness of asset models with respect to inevitable parameter deviations, an improved asset coverage, the scalability of optimization approaches, and on common benchmark systems. Furthermore, it is still open to demonstrate the feasibility of proactive and resilient scheduling in extensive laboratory setups and practical field trials.

Despite the good performance of the tree-based hybrid optimization algorithm, further improvements by using more complex tree structures and by deploying advanced termination criteria may be achieved. Until now, the algorithm is only applied in resilient scheduling problems. However, the procedure follows a generalized structure beyond scheduling problems. It is still open to discuss the eligibility of the novel hybrid optimization approach in related fields of application such as active distribution systems and grid capacity management.

The case study on the value of proactive scheduling shows a considerable number of infeasible optimization runs. To reduce that number, the application of soft-constraints that permit a certain degradation and additional flexibility can be considered in future research work. More advanced models such as protection, upstream grid and extended fault mitigation may further refine the assessment results. To support such models, additional improvements on the convergence of the power flow computations may be needed. Until now, gained evidence on the detailed assessment of proactive scheduling is limited on a single test grid. Future work includes a broad evaluation on a large variety of test grids to gain more general, quantitative insights into the need and value of proactive scheduling. It is expected that the presented work lays the foundation of such future research work.

Chapter 2

Publications

2.1 Publication A

M.H. Spiegel, E.M.S.P. Veith, and T.I. Strasser
The Spectrum of Proactive, Resilient Multi-Microgrid Scheduling: A Systematic Literature Review
Energies, MDPI, vol. 13, no. 17, p. 4543, 2020.

Own contribution

The conceptualization of this study was carried out by the applicant as well as the second and third author. Additionally, the second author as well as the applicant developed the presented methodology including the selection of suitable definitions. The investigation including the review of related literature, analysis, validation, data curation, visualization, and draft-writing were carried out by the applicant. Review, editing, and supervision were undertaken by the second and third author. Project administration and management of resources were conducted by the third author.

energies MDPI

Review

The Spectrum of Proactive, Resilient Multi-Microgrid Scheduling: A Systematic Literature Review

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Abstract: Multi-microgrids address the need for a resilient, sustainable, and cost-effective electricity supply by providing a coordinated operation of individual networks. Due to local generation, dynamic network topologies, and islanding capabilities of hosted microgrids or groups thereof, various new fault mitigation and optimization options emerge. However, with the great flexibility, new challenges such as complex failure modes that need to be considered for a resilient operation, appear. This work systematically reviews scheduling approaches which significantly influence the feasibility of mitigation options before a failure is encountered. An in-depth analysis of identified key contributions covers aspects such as the mathematical apparatus, failure models and validation to highlight the current methodical spectrum and to identify future perspectives. Despite the common optimization-based framework, a broad variety of scheduling approaches is revealed. However, none of the key contributions provides practical insights beyond lab validation and considerable effort is required until the approaches can show their full potential in practical implementations. It is expected that the great level of detail guides further research in improving and validating existing scheduling concepts as well as it, in the long run, aids engineers to choose the most suitable options regarding increasingly resilient power systems.

Keywords: asset scheduling; proactive scheduling; multi-microgrid; networked microgrid; microgrid; resilience; fault mitigation; systematic review

1. Introduction

Several decades ago, electrical networks called microgrids that can be both operated in a grid-connected and islanded mode were established. Such networks are often constructed to meet advanced power quality and reliability requirements which cannot be achieved by the main grid alone. Additional incentives include the economic interest in a tight integration of Renewable Energy Sources (RES), lowered purchase costs, as well as an increased efficiency by local generation [1]. Since the introduction of microgrids, several topics ranging from low-level voltage and frequency control up to high-level economic and reliable operation schedules of microgrid assets have been addressed [2,3].

A few years ago, the concept of multi-microgrids was introduced and has since attracted attention [4–6]. In most cases, multi-microgrids are defined as power systems, which incorporate multiple coordinated microgrids. Main driving forces in implementing multi-microgrids include resilience enhancements by supplying microgrid-external loads in case of contingencies as well as economic performance gains by sharing backup capacity and jointly optimizing normal operation. Following the diverse incentives and requirements, various multi-microgrid network topologies and coordination schemes [7] were presented. For instance, several microgrids can be connected via a common distribution system and a high-level controller may coordinate a jointly islanded operation of multiple connected microgrids in case the upstream grid fails. Furthermore, the distribution system may be split into multiple separate islands that are powered by connected microgrids within the island to circumvent distribution system faults. However, sharing backup capacity, in particular, requires a grid operation as one single or many parallel unconnected islands, which is not feasible in standard distribution systems.

As the local backup capacity is decreased and the extent of multi-microgrid setups is increased, the operation of a local microgrid may be affected by a drastically increased number of failures. Although for small independent microgrid installations it may be reasonable to consider main-grid failures only, additional failure modes such as line or generator tripping within a multi-microgrid gain in importance. Some techniques such as grid reconfiguration that mitigate the effect of various failures are already available. Nevertheless, most work on optimal, resilient microgrid and multi-microgrid operation only considers a limited set of failure modes and mitigation options [2]. Traditionally, the problems of optimal asset scheduling in normal operation and fault mitigation are discussed separately. However, several authors already started to incorporate advanced fault mitigation options and their side effects into their resilient scheduling approaches [8].

An exemplary multi-microgrid is depicted in Figure 1. Each of the three individual microgrids consists of various assets, such as controllable Distributed Energy Resources (DERs), energy storage units, volatile RES, and mixed-critical loads that may or must be supplied in case of contingencies. A deployed scheduling algorithm needs to control the microgrid assets before any contingency such that a resilient and cost-effective operation is achieved. A conventional scheduler, although it may consider the inherent stochasticity of loads, RES, and main-grid failures, may not consider the weak line L2-3. Even though the multi-microgrid can successfully tolerate main-grid outages, tripping L1-3 may cause an overload of the weak line L2-3 in case the power exchange between MG3 and the other microgrids exceeds the line capacity. To circumvent this situation, more generation needs to be scheduled at MG3, locally.

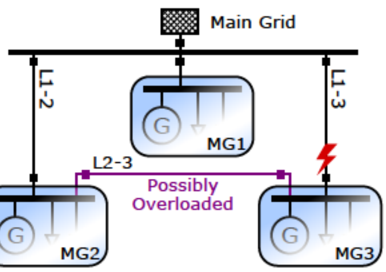

Figure 1. Exemplary multi-microgrid.

A broad variety of both fault mitigation techniques and targeted failure modes needs to be taken into account to ensure that microgrids and multi-microgrids are operated cost-effectively and yet at a guaranteed level of resilience. Such targeted failure modes include communication faults, as well as line- and generator tripping. Additionally, the inherent uncertainty of volatile RES generation, fluctuating loads and forecasting deviations need to be considered by a resilient schedule. The quality of the deployed models and probabilistic input assumptions calls for special attention, because inaccuracies may easily degrade the operation or increase the risk of faults.

Several competing methods which deal with the resilient operation and schedule various microgrid configurations are already available [2,3,8]. Similarly, various review papers which study multi-microgrid aspects were published [7,9]. Although some of them already introduce various resilience-related topics, none of them gives details on proactive asset scheduling that optimizes the normal operation while considering the influence on the system resilience. A sound overview of design decisions, implementation options, as well as the expected performance is needed to efficiently guide future research and to conduct the practical implementation of existing algorithms. For instance, several approaches to enhance resilience are summarized in [3], but an in-depth analysis of resilient multi-microgrid scheduling approaches, which also analyzes modeling and implementation details is still missing.

It is expected that a systematic study that covers aspects, such as modeling and validation approaches, will assist engineers and researchers likewise in selecting suitable methods for resilient multi-microgrid scheduling. This work addresses the concerns by first establishing a common view based on related literature in Section 2. The subsequent section specifically focuses on resilient pre-contingency scheduling in multi-microgrid setups. Section 3 presents the systematic methodology for selection and in-depth analysis of the identified key contributions. Results of the systematic review are stated and discussed in Section 4. Based on the review and contributions from related fields, an outlook on future research opportunities and engineering challenges is given in Section 5. Finally, the paper is concluded with Section 6.

2. Work Related to a Resilient and Economic Multi-Microgrid Operation

Substantial work has been contributed in related microgrid topics such as scheduling resources in microgrids, multi-microgrid forming and analyzing failure scenarios in power grids. Additionally, several contributions target the complexity of optimal asset scheduling in systems which face various sources of uncertainty (e.g., induced by volatile RES). At the same time, the approaches ensure that the microgrids can withstand certain failures [2,10].

2.1. Failure Modes and Resilience Metrics

Despite the lack of a common definition of resilience in the context of power systems [8,11–13], some properties such as the ability to withstand and to recover from disruptive events are regularly associated with the term [8]. For instance, [11] that studies the definition of resilience in detail, defined the term with respect to an unexpected set of disturbances as "the system's ability to reduce the magnitude and duration of the disruption". The related term robustness is declared as "the ability of a system to cope with a given set of disturbances and maintain its functionality" [11]. A resilient system is associated with the ability of downgrading the performance while a robust one maintains the desired performance in the presence of potentially disruptive events. A review of 12 resilience definitions is given in [8]. The authors noted that in addition to restoration aspects, several definitions also include the avoidance of degraded states that others associate with robustness, only [13].

One attempt towards a common definition of power system resilience was made in [12] which relates resilience to various other terms such as reliability and robustness. Reliability, i.e., the probability of a functional system, reflects the performance under given conditions and over a long period of time, while resilience emphasizes the time-varying conditions in a contained time frame. The authors concluded that new metrics are needed to reflect resilience and presented a generalized framework to define such metrics. Similarly, a framework for resilience metrics is proposed in [13], which considers resilience as a function of time that reflects the recovery from a disruptive event. The framework was applied to assess the resilience of a road network.

Special attention must be drawn to the definition of considered failure modes. To secure the operation of conventional power systems, often the $(N-1)$ robustness criterion—which states that an operation strategy has to withstand the outage of any single system component—is applied [4]. Nevertheless, more detailed failure scenarios and other reliability indices may be used as well to secure the operation of microgrids and multi-microgrids. For instance, fault tree analysis, a method which is commonly used in risk assessment, was applied in [14] to identify critical components and to estimate the reliability of microgrids.

To assess the reliability of isolated microgrids without the need for a detailed stochastic characterization of volatile energy sources, [15] uses easily available capacity factors to approximate various reliability metrics. Alternative assessment strategies include Monte-Carlo-based methods, which sample a large number of scenarios to approximate the joint distribution of all uncertainties [16]. Although these methods primarily target robustness and reliability aspects, they may also be incorporated into scheduling problems to improve the resilience of a particular schedule.

2.2. Resilience-Aware Microgrid Scheduling

A solution for the economic dispatch problem in single microgrids that ensures a stable islanded operation was presented in [17]. The authors considered the effects of the primary control strategy on the scheduling decision in detail, but only static security margins were used to reflect forecasting errors. To guarantee that critical loads can be supplied in islanded mode, Ref. [18] presented a scheduling method that is based on robust optimization. One deterministic worst-case scenario is found to define the resilient operation. An optimal normal operation schedule is revised in case it lacks sufficient online capacity for switching to an islanded operation. Hussain et al. [19] studied scheduling in multi-microgrids and proposed a robust optimization-based approach to incorporate inherent uncertainties. Although they also considered the islanded operation schedule, no detailed physical network model and no grid-reconfiguration options are included.

Some work also directly deploys stochastic optimization. For instance, in [20], a two-stage stochastic optimization approach that takes various network constraints and the required spinning reserve into account was presented. The expected cost under the presence of stochastic phenomena was optimized by mapping the problem into a deterministic linear optimization. Demand-response actions in a stochastic scheduling problem were studied in [21]. The presented approach also considers reserve requirements for compensating fluctuations.

2.3. Multi-Microgrid Forming

Conventional outage management systems are designed to automatically locate faults and restore healthy portions of a distribution grid [22] but an islanded operation is rarely considered. The role of microgrids in enhancing resilience was highlighted in [23], which describes the option that these microgrids provide surplus power to restore parts of the distribution grid. A particular method to control the supply of external loads was presented in [24] considering that the time loads can be expectedly supplied with available energy reserves.

A Mixed Integer Linear Programming (MILP) formulation of the grid partitioning problem, which forms each radial partition by a single generator, is additionally given in [25]. Supplied loads are maximized and switching operations are minimized in [26] by partitioning healthy but islanded sections of distribution networks into self-sustainable microgrids. Although some of the outlined approaches study both normal and emergency operation, the impact of grid-reconfiguration options on local reserve requirements in normal operation mode is not considered. Nevertheless, presented fault mitigation and reconfiguration options may be used to refine reserve estimation in asset scheduling problems.

2.4. Resilience-Aware Multi-Microgrid Scheduling

Some work specifically targeting resilience-aware scheduling in multi-microgrid environments is already available. To reduce the high share of dispatchable DERs, the concept of provisional microgrids, i.e., less critical microgrids that rely on other microgrids for islanding, was introduced [27]. Notably, an uncertainty-constrained optimal scheduling model that also includes islanding constraints is given. In particular, the concept and formulation of provisional microgrids may be used in the planned work as well. A risk-based model of optimal energy exchange scheduling between networked microgrids is given in [28]. Multiple strategies to deal with inherent risks connected to the stochastic nature of load

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and generation are presented and evaluated. The presented risk measure may be as well applied to manage risks in other multi-microgrid setups that cover an extended range of failure scenarios.

2.5. Related Reviews

Since the introduction of microgrids decades ago, a vast amount of work has been contributed [2]. Several authors already presented review papers which summarize the State-of-the-Art (SotA) and systematize various microgrid-related aspects [2,3,7,9,10,29–41]. Table 1 gives an overview of selected related reviews and their main topic. First developments and initial field test of microgrids were covered by [29–31], which describe several experimental sites and practical experiences. In [39], further developments and test sites with a strong focus on the United States are listed. Major challenges in including RESs into microgrids, such as scheduling under uncertainty, reliable and economic operation, as well as market-model designs are identified in [32]. The authors highlighted that microgrids can benefit from hierarchical control schemes allowing for a compromise between fully centralized and fully decentralized controls and summarized the SotA in the context of the three-layer scheme. A comprehensive review of various microgrid-related aspects including economics, protection, grid-supporting functions and clustered microgrids is given in [2]. Broad and condensed overviews of microgrids [36] and microgrid management systems [37,41] are also available. The application of multi-agent control in microgrids and microgrid clusters was specifically reviewed in [34,35] studied differences in control architectures.

Table 1. Overview of related reviews.

Ref.	Publication Date	Main Topic
[29]	2007-06-02	Microgrid-related research, development and demonstration effort
[30]	2008-05-02	Testing experiences in experimental microgrids
[31]	2010-10-01	Experimental and simulation-based microgrid test installations
[32]	2014-04-20	Microgrid control strategies
[42]	2015-05-12	Power system resilience
[2]	2015-06-10	Broad review of microgrid-related topics
[10]	2016-02-02	Optimization-based energy management in microgrids
[33]	2016-09-16	DERs scheduling for microgrids and virtual power plants
[9]	2017-06-30	Overview of multi-microgrids and available demonstration platforms
[34]	2017-10-09	Distributed control and optimization of microgrids and multi-microgrids
[7]	2017-12-22	Multi-microgrid architectures
[35]	2018-03-22	Microgrid management system architectures
[36]	2018-04-03	Recent microgrid-related developments and regulations
[37]	2018-04-05	Microgrid energy management systems
[38]	2018-06-11	Resilience of microgrids and multi-microgrids
[39]	2018-06-18	Microgrid achievements in the United States
[40]	2018-11-15	Networked microgrids
[8]	2018-12-10	Impact of microgrids on power system resilience
[43]	2018-12-13	Power system resilience
[3]	2019-02-13	Resilience aspects in microgrids
[41]	2019-03	Energy management in microgrids
[44]	2019-12-09	Optimal planning and operation of islanded microgrids

In [10], a detailed review of energy-management approaches for microgrids is presented. The authors specifically listed related review work and practical implementations. Additionally, aspects such as objectives, constraints, solution approaches, as well as tools were reported. Although the work does not specifically evaluate resilience aspects such as failure modes and modeling assumptions, it is used as one basis for classifying optimization types and objectives. Similarly, [44] reviewed and categorized objectives, constraints and variables of optimization problems in islanded microgrids. The study focuses on islanded systems without considering multi-microgrid, resilience, and implementation-related aspects in detail, but results are used in the own research as another basis of classification and to provide a broad context. Scheduling approaches for microgrid and virtual power plant concepts are reviewed in [33]. Among other aspects, they addressed scheduling problems that are associated with reliability and stability issues and listed various reliability metrics. A comparative review of features such as supported DER types, type of formulation and solving methods is used as another basis to formulate a common feature set. Multi-microgrids or networked microgrids are addressed by [9,40], who gave a broad overview of that topic and summarized several contributions related to planning and operation of multi-microgrids. A detailed study of multi-microgrid architectures and their impact on various aspects including costs, protection, as well as business models is given in [7]. One can observe that there are already some reviews targeting specific multi-microgrid and scheduling topics. However, resilience-relevant scheduling details such as modeled DERs and grid parameters as well as failure modes and effects are not covered in detail [2,7,9,30,31,33–36,39–41,44].

Resilience in the broader context of power systems was studied by [42,43], but few details on resilient scheduling were given. In [8], a study on the definition of power system resilience is given and the strategies to increase power system resilience via microgrids are briefly discussed. Microgrid and multi-microgrid concepts that specifically focus on resilience aspects were reviewed in [38]. The authors introduced mechanisms for a resilient operation such as control strategies for an emergency operation, and briefly categorized common optimization terms. Although the categorizations are successfully used as a basis for own refinements, the link between pre-event operation and post-event fault mitigation techniques is weakly described. Significant details such as considered failure modes and validation approaches of pre-event scheduling algorithms are missing as well. Work presented in [3] specifically focuses on resilience-related aspects in microgrid operation. They covered a broad range of topics such as disaster modeling, outage management, and proactive scheduling. One research gap that was identified in [3] is the need for proactive scheduling approaches.

2.6. Contributions of This Paper

This paper refines findings of [3] and targets the identified research gap by systematically studying relevant technical details of work related to proactive, resilient multi-microgrid scheduling. It does so by applying a systematic review methodology that first assesses a large amount of candidate contributions and condenses a set of most relevant key contributions. A thoughtful analysis of the key contributions categorizes various details of the algorithms including modeling, optimization, validation and resilience aspects. This paper identifies the main design options that were exploited in resilient multi-microgrid scheduling approaches and highlights the development stage of these algorithms. It shows the wide variety of optimization-based contributions and illustrates that the work is on an early development stage that merely exceeds simulation-based validation. Given the detailed breakdown, this paper may be used to quickly identify related work and select suitable design options for upcoming research and engineering activities. The extensive outlook on research perspectives further discusses research gaps and related work that may be successfully applied in proactive resilient scheduling as well.

3. Systematic Review Method

As review studies always have a chance of giving biased results, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [45] is used as a basis for the systematic review process. By following the recommendations, a reduction of bias and an increased transparency in the quality of the presented study is targeted. Figure 2 outlines the review procedure. At first, review candidates are identified and screened. Afterwards, eligible literature is iteratively reviewed. Finally, results from all reviewed papers are discussed and evaluated.

Due to the strong focus of the PRISMA methodology on medical studies, the process was slightly adapted to the needs of engineering studies. For instance, instead of focusing on achieved results and performance metrics, strong emphasis was put on the methodology such as modeling aspects and solution methods. Additionally, it was decided to merge the screening step that filters work according to the abstract and the eligibility test that accesses full-text articles in favor of a combined selection step that individually meets the review requirement to evaluate the selection criteria, i.e., full-test articles are accessed as soon as the selection criteria cannot be checked based on the abstract alone. Despite these modifications from the original PRISMA methodology, the overall process description was taken from [45].

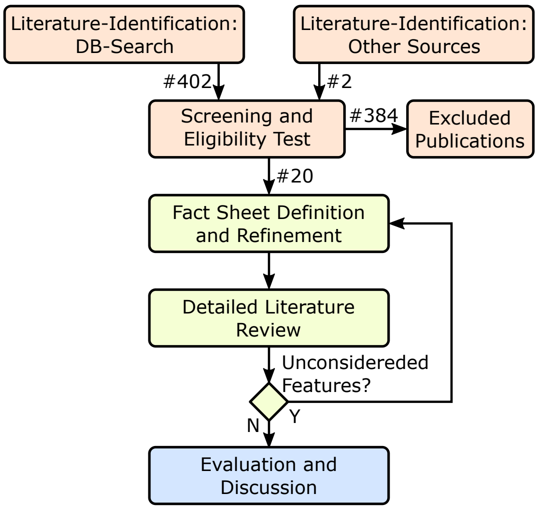


Figure 2. Review methodology workflow based on [45].

First, definitions and the research question are stated in Sections 3.1 and 3.2, respectively. Based on the study objectives, a broad literature screening was conducted. Section 3.3 describes the literature identification, screening and initial selection process in detail. For the detailed review of selected key contributions, a fact-sheet template was developed and in combination with the selection criteria, iteratively refined. Details on the fact sheet are presented in Section 3.4. The protocol including the identification steps and screened literature is published as supplementary material.

3.1. Definitions

Resilience is often used in the literature to characterize a system's capability of sustaining and recovering from hazardous impacts without an entire loss of functionality [8]. In opposition to other concepts such as robustness, which do not fully reflect a graceful degradation and service restoration, this publication defines the term resilience as "the ability to reduce the magnitude and/or duration of disruptive events" [12]. However, it must be emphasized that no common sense of resilience is established [11–13]. For instance, [13] defined resilience with respect to a delivery function as the ratio of recovery at a certain time to the loss at a disruptive event. An event is considered disruptive if and only if the magnitude of the delivery function is reduced. With respect to microgrids and the definition of [13], one can argue that a system is robust but not resilient, when no loss of load is encountered in case of a potentially disruptive event. An algorithm may be able to sustain potentially disruptive events without encountering a loss of load and consequently would be considered robust but not resilient with respect to that event. However, deploying that robust algorithm may still have the potential to increase the security of power supply in the presence of extreme events and failures. Furthermore, the strict definition may or may not include mitigation techniques, depending on their impact on the target metric.

In contrast to [13] and to mitigate problems of definition, the systematic review uses the term resilience in a broader context presented by [12]. This paper explicitly includes approaches which try to avoid power delivery failures of any kind. Nevertheless, considered algorithms may also permit a degraded performance in case of disruptive events. Hence, this paper refers to resilience-oriented multi-microgrid scheduling as "short-term resource planning, which is not restricted to avoiding outages entirely, but which also considers rapid recoverability in case of power shortages" [46]. Figure 3 illustrates the definition of resilience and the point in time, where normal and emergency mode scheduling decisions are taken.

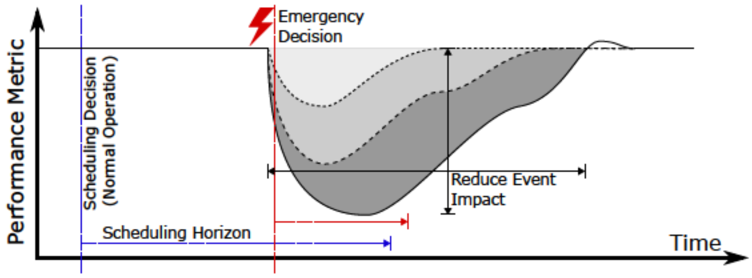


Figure 3. Resilient scheduling based on [12,13].

Similar to the definition of resilience, several definitions of microgrids do exist [32]. Some definitions include isolated microgrids which do not have a connection to a main grid and permanently operate in islanded mode. Since the work focuses on interconnected multi-microgrids, islanded grids are considered to be beyond the scope. Hence, microgrids are herein understood as electrical power systems that "can be operated in a non-autonomous way, if interconnected to the grid, or in an autonomous way, if disconnected from the main grid" [5] (p. 4).

3.2. Research Questions

The given review requires definition and assessment of a large amount of features that potentially impact the performance of scheduling algorithms. In order to contain the scope of the work and to select the most relevant aspects for review, the research question is explicitly defined, first. Starting from the motivation of achieving a resilient and economic operation of multi-microgrids and choosing suitable approaches for practical implementation and further research, the following main research questions emerges.

Which types of resilience-oriented scheduling functions for multi-microgrids do exist and how do they differ from one another?

To highlight the spectrum of resilient multi-microgrid scheduling functions, several sub-questions need to be answered. In particular, the following sets of sub-questions are used to guide the selection of extracted features.

1. Which aspects were modeled in SotA approaches? Such aspects include the type of DERs and their models, topological assumptions, failure modes, as well as the formulation of the objective functions. Additionally, sources and representations of uncertainty that are covered by presented models are addressed.
2. Which type of proactive actions and fault mitigation techniques are considered to increase resilience and efficiency? For instance, shiftable loads and controllable generation may be scheduled such that certain types of faults can be tolerated. Other actions may include grid-reconfiguration measures and in case of post-fault actions various islanding schemes [3].
3. How are these functions tested and evaluated? Which methodology is used to evaluate given approaches? Which input conditions (e.g., test networks, load and DER profiles) are used and do they differ in the degree of detail from the models used for optimization? Is there a common set of benchmarks? Which types of metrics are used to evaluate the performance of scheduling algorithms?

From a practical perspective, several design decisions need to be taken before implementing a resilient multi-microgrid scheduling approach. Figure 4 illustrates the main design decisions that are covered by the research question. The graphic divides the set of decisions into five categories such as modeling aspects and resilience features. Each design decision is linked to the other decisions. For instance, multi- and single-objective formulations must be solved differently.

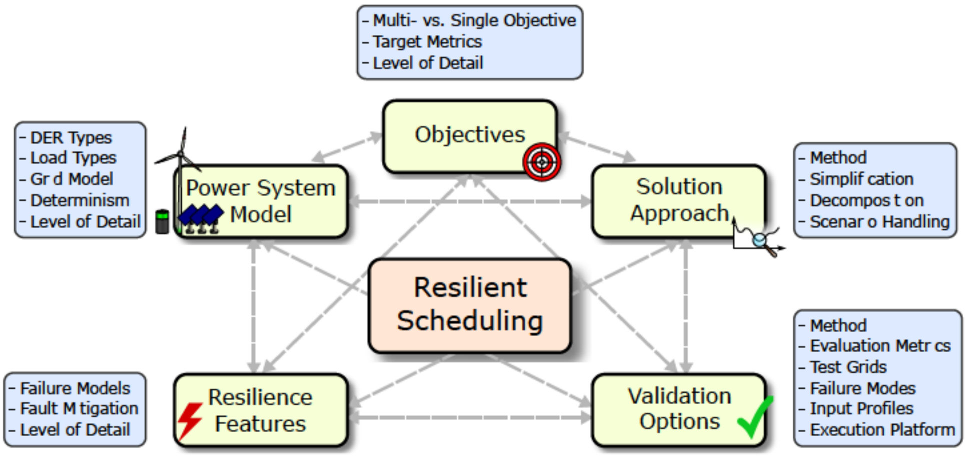


Figure 4. Resilient multi-microgrid scheduling: Design decisions.

3.3. Literature Identification and Screening

The primary literature was identified by several database searches. Due to the large coverage that includes numerous major databases and the subsequent manual selection process that tolerates less significant results, Google Scholar was selected as search engine. Since the relevance of displayed matches dropped considerably according to their ranking, a limit of 80 entries per search term was found to be appropriate. An initial search was conducted at the end of 2018 which was updated and extended in the first quarter of 2020. Further details including the list of search terms, matches and screening results can be found in the supplementary materials. Including several matches that were generated by multiple search terms, 404 publications were identified and screened for eligibility, in total. A list of criteria was defined to filter relevant publications that can be used to answer the research question. Each publication which was considered for the detailed review must fulfill the following criteria. Please note that a paper from the identification step can be rejected by multiple reasons. Consequently, the sum of rejections is bigger than the sum of rejected papers. No two papers which describe the very same approach were identified and no paper which describes multiple approaches is included. Hence, the number of papers corresponds to the number of studied approaches.

- *Full-Text Availability*: One of the basic formal criteria for including the paper in the systematic study is its availability. A paper was included if and only if the full content is available in English or German language. Six papers out of 404 were excluded due to their availability.
- *Scheduling Algorithm Available*: For further evaluation, a scheduling algorithm which covers essential technical details must be given. Scheduling algorithm is thereby understood as an algorithm which computes the set-points of controllable assets such as gensets, battery storage, and controllable loads in advance. Algorithms and papers which focus on long-term resource planning or placement, e.g., for optimizing strategic investment, and therefore not only consider set-points but also asset variations are considered to be out of scope. In the screening step, 140 papers were excluded because they do not describe a scheduling algorithm.
- *Focus on Normal Operation*: By definition, a microgrid or multi-microgrid is considered to be in normal operation if it is connected to the main grid. Hence, algorithms which solely cover an islanded or emergency operation were rejected for review. Additionally, if an approach focuses on resilience parameters such as critical load supply only, without considering operation metrics

such as costs relevant in normal operation, it is not considered for review. In total, 75 papers were excluded because they focus on emergency operation only.

- *Resilience Aspects Covered*: To answer the research question on resilient scheduling, only approaches which tackle resilience aspects need to be covered. Work is herein considered in case one failure mode during normal operation is taken into account in a way that tolerance of this failure mode is ensured (i.e., robustness) or the impact of these failures is minimized (i.e., resilience). Such failure modes include (main-)grid failures, communication failures, or generation faults. An approach is not considered to be resilient scheduling, in case it does not actively shape resilience and only operates on static security margins without deriving them form the microgrid properties or validating them in an independent simulation. Such static margins include spinning reserve requirements are not actively adapted to the microgrid state. While screening, 98 papers were found to neglect resilience aspects considerably.
- *Covered Technology*: To guarantee a broad applicability of the reviewed approaches and to be able to compare several detailed aspects, a minimum set of modeled assets is defined [30,31]. In particular, each approach must at least be able to handle a schedulable energy storage, non-schedulable, stochastic loads, stochastic generation, and in accordance with the microgrid definition, an interruptible connection to the main grid. In particular, non-schedulable generation covers a wide range of RES which can be subsumed under this term [2]. In total, 46 papers do not cover the required technology and are therefore not considered for further review.
- *MG Topology and Topological Constraints*: A distribution system, which connects multiple, coordinated microgrids or which forms multiple, coordinated islands may not be able to handle every configuration without voltage and current violations [26]. It is, therefore, expected that network constraints such as topological constraints gain an increasing importance in multi-microgrids, compared to geographically contained single microgrids. Even if an algorithm does not actively alter the network topology, controls and scheduling decisions can have a considerable impact on a reliable operation [47].

  Since the study focuses on a resilient operation of multi-microgrids, it is decided that included work must take topological constraints into account. In particular, power-flow limits and the topology of the microgrid or multi-microgrid must be taken into account. An algorithm which assumes a single-bus microgrid is not considered to be multi-microgrid scheduling, even if power transfer constraints to the main grid are modeled. From the initial set of identified publications, 31 papers do not consider network constraints at all and 15 papers only model a single-bus microgrid with limited transfer capabilities to the main grid. Similarly, four papers were excluded because they only model Alternating Current (AC)/Direct Current (DC) converter assets without considering transmission constraints within the network.

3.4. Fact Sheet and Feature Extraction

A detailed template was developed to guide the systematic review of selected papers and to answer the research questions given in Section 3.2. Based on related studies, a basic set of relevant features that should be extracted from each paper was recorded. The classification of optimization types such as MILP, and the classification of constraints including storage constraints were taken from [10]. The initial classification from [10] was further extended by the features of [33,38,44] such as the additional DER and objective types.

The basic features from literature were substantially refined and new features which are needed to answer the research question were added. Results listed in [10,33,44] were used to validate findings from this study. Although [10] lists the formulation of several objective functions in detail, it was decided to provide a categorized view, thereby easing the comparability of various approaches and the readability of the study. Hence, the fact-sheet template that defines recorded features was designed such that most of the features can be specified by assigning a category. For instance, it can be specified for each considered DER, whether it was modeled deterministically, indeterministically, stochastically, or not at all.

The fact sheet is structured in four feature groups. The first group covers model-related aspects such as details on DER, and in addition to related reviews, aspects related to the grid and load models. The optimization-related group covers the objectives and solution-related facts. One group specifically addresses resilience-related facts such as considered failure modes and fault mitigation techniques, and the last group lists various details on validation-related aspects. Although the overall structure was defined beforehand, the open-ended research questions such as the one on applied objective functions require an adaptive approach that allows the evaluation of features which were not considered beforehand. The fact-sheet template as well as reviewed facts were therefore iteratively refined as soon as new, relevant features were identified.

4. Results and Discussion of the Systematic Review

Based on the initial screening and eligibility test, the key contributions listed in Table 2 were selected for a detailed review. The first key contribution that leads towards resilient multi-microgrid scheduling dates back to September 2012. Although [48] already integrated dynamic grid-reconfiguration options into the resilient scheduling formulation, no dedicated multi-microgrid setup which potentially distributed ownership and independent islanding capabilities was addressed. A next step towards the integration of multiple independent microgrids was presented in [27]. The paper introduced the concept of provisional microgrids that use the grid-forming capabilities of a coupled independent microgrid in case of emergencies.

Table 2. Selected key contributions.

Ref.	Publication Date	Main Topic
[48]	2012-09-28	Integration of dynamic topology option into economic microgrid operation
[49]	2014-04-09	Optimal scheduling of DER considering the risk of outages
[27]	2014-09-26	Interaction of microgrids with and without independent islanding capabilities
[50]	2016-06-13	Value of reconfigurable microgrids in integrating Electric Vehicles (EVs)
[20]	2016-08-10	Resilient scheduling of microgrids affected by uncertainty
[51]	2016-08-26	Multi-objective scheduling of microgrids considering normal operation costs and the risk of load curtailment
[52]	2016-10-15	Microgrid scheduling considering operating costs, emissions, and reserve requirements
[53]	2017-08-17	Robust formulation of the optimal proactive scheduling problem for microgrids
[28]	2017-12-13	Risk-based strategies for multi-microgrid scheduling considering stochastic RESs
[54]	2018-02-16	Optimal scheduling for hybrid AC/DC multi-microgrids
[55]	2018-02-20	Integration of Demand Response (DR) programs and grid reconfiguration into microgrid asset scheduling
[56]	2018-03-26	Resilient asset scheduling in reconfigurable microgrids
[57]	2018-05-11	Security-constrained dispatch for microgrids using multi-objective optimization
[58]	2018-08-17	Resiliency enhancements by optional scheduling of networked microgrids
[59]	2018-12-28	Impact of scheduling discrepancies on interconnected microgrids
[60]	2019-04-18	Microgrid scheduling combining flexible time frame DER scheduling and single time interval-based optimal dispatch
[61]	2019-07-02	Resilient scheduling of networked multi-microgrids using a three-stage approach
[62]	2019-08-07	Proactive, resilient scheduling of interconnected microgrids
[63]	2019-08-16	Distributed energy management of interconnected microgrids considering adversarial actions
[64]	2020-01-06	Optimal, resilient operation of dynamic multi-microgrids

The first selected key contribution that specifically addresses multi-microgrid setups is [28] that was published at the end of 2017. Evidently, the authors did not present the first multi-microgrid setup, ever [7,28], but a significant contribution was made in considering resilience aspects in multi-microgrid scheduling. Since then, several authors also directly considered multi-microgrid setups in resilient scheduling formulations [54,58,61–64]. Although only in very recent years identified key contributions show a tendency to explicitly cover multi-microgrids, literature that focuses on independent microgrids may be applicable in the extended setting as well.

None of the eligibility criteria directly states that a scheduling approach needs to be explicitly formulated as an optimization problem. A scheduling algorithm may be as well formulated as some simple heuristic rules that eliminate the need for an online optimization procedure [37]. For instance, [65] presented a heuristic EV charging strategy that does not require any optimization steps. The key contributions show a wide variety of different models, resilience features, and optimization approaches including heuristic optimization. However, every selected publication follows an optimization-based framework.

4.1. Selected Literature

The screening of identified literature and the eligibility test were performed in an interleaved process. In case the paper abstracts did not provide sufficient information to classify the work with certainty, a more detailed screening was conducted. Although the authors tried to define the eligibility criteria as precisely as possible, some border cases still had to be handled. For instance, the early work [17] that studies a scheduling problem of distributed generators considering main-grid faults was excluded due to the fact that energy storage units were insufficiently tackled. Although the work gives valuable insights into reserve commitment, Electrical Energy Storages (EESs) such as battery storage systems are considered to be a canonical part of future multi-microgrids. Similarly, the work in [21] that specifically tackles reserve scheduling was excluded due to the limited consideration of failure modes. Judging from the formulation, managed reserves are used to balance RES and load fluctuations only, without considering failure scenarios such as main-grid outages and their mitigation. Although the paper provides valuable insights into the effects of DR programs, it was excluded from the list of key contributions because it violates the resilience criteria.

No obvious classification was found for [57] either, which describes a security-constrained optimal dispatch approach. Although the stochastic behavior of RESs and loads is not explicitly taken into account, terms in one objective function penalize main-grid transfer and storage usage. Hence, available reserves that are used to balance fluctuations are systematically maximized and the paper is considered to be a key contribution. A similar border case is given by [27] that introduces the concept of provisional microgrids. The provisional microgrid is modeled as a single bus only, but the topological constraint that provisional microgrids cannot be islanded independently of a coupled microgrid, is given. The connection to the coupled microgrid including its power-flow limitations is also modeled in addition to the main-grid connection. Despite the single-bus limitation, some topological constraints that supplement the main-grid connection are provided and the paper was selected.

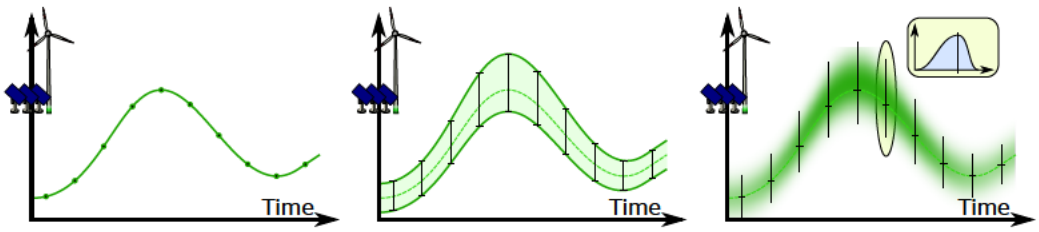
In [66], a proactive scheduling approach of hybrid AC/DC microgrids was described. The microgrid was modeled by two buses, one connecting the AC assets and the main grid as well as one connecting the DC facilities. Since the paper focuses on independent hybrid microgrids, no topological constraints, despite one interlinking converter that couples both buses and main-grid transfer constraints, were given. Unlike [27,66] does not study the scheduling approach in the context of other microgrids and was therefore not selected as a key contribution. A similar border case was given by [67] that provides valuable insights into the resilient operation of networked hybrid AC/DC microgrids. However, the publication does not include any topological constraints such as line capacity constraints and was therefore not selected as a key contribution either.

4.2. Modeling Approaches and Modeled Assets

Each of the key contributions models a set of controllable and uncontrollable microgrid assets. Some of them use generic models such as generic unschedulable DERs (e.g., [27,52,64]) while others specifically model the properties of some assets such as Wind Turbines (WTs) including their turbine characteristics (e.g., [28,58]). Table 3 summarizes modeled DER parameters and classifies common DER constraints. In case only a generic model is considered, no specific model is listed although the specific asset may be covered by the generic model as well. Some publications such as [64] explicitly use the term battery energy storage but no significant difference to the formulation of generic EESs including [28,62] was found. Hence, these battery energy storage models were classified as generic EESs as well.

Most of the key contributions stick to generic DER and EES models without specifically focusing on more specific assets. Only one paper also considers Combined Heat and Power (CHP) plants and the thermal needs of a microgrid [62]. Similarly, one out of 20 papers specifically targets Micro Turbines (MTs) [28] and two contributions take EVs into account [20,50]. None of the contributions directly considered hydro turbines, pumped storage, fuel cells or hydrogen storage. Although there are papers such as [68] that consider hydrogen infrastructure in scheduling problems, none of the screened work meets all eligibility criteria for resilient multi-microgrid scheduling. In particular, [68] provided valuable insights into the operation of reconfigurable microgrids considering reliability and degradation effects caused by asset use. However, due to the lack of resilience features such as islanding, it was excluded from the detailed analysis.

In addition to the principal DER classes, Table 3 also indicates the level of determinism. Deterministic (D) formulations that do not incorporate any uncertainty, stochastic (St) models that include probabilistic information, and indeterministic (ID) formulations that do not use any probabilistic assumptions on the distribution of uncertain values are explicitly highlighted. Figure 5 illustrates the levels of determinism via a single deterministic curve, and two ensembles of curves that are defined by indeterministic intervals and probability density functions, respectively. One can observe that all generic controllable assets, i.e., EESs and DERs are modeled in a deterministic fashion. Intuitively, this makes sense because the low-level control of most controllable assets will ensure a proper operation according to the set-points. However, some publications such as [69] that considers frequent but random outages of a fuel cell in a scheduling formulation, also report stochastic phenomena of controllable assets.



(a) Purely deterministic

(b) Indeterministic, but not probabilistic

(c) Stochastic, including probabilistic information

Figure 5. Observed model and input types.

Although EVs that actively participate in a microgrid can be controlled while they are plugged in, the user behavior, in particular departure and arrival time, as well as State of Charge (SoC) requirements, is highly uncertain [20,50]. Both key contributions that consider EVs presented a stochastic EV model. However, also deterministic simplifications of driving patterns can be observed in some scheduling approaches [67].

For unscheduled DERs, most key contributions use a stochastic or robust formulation without purely relying on a forecast and optimizing security margins. Although for generic unscheduled DERs several authors including [27,53,54,62] chose to follow an indeterministic formulation, most of the contributions that tackle the specifics of uncontrollable or partly controllable generation such as Photovoltaics (PV) and wind power plants, deploy stochastic asset models. Most of the specific asset models describe the conversion of the primary energy source, into electric energy [28,58]. For solar irradiation and wind speed, detailed studies on their distribution are available [70–72] and used in scheduling problems [28,58]. However, for an indeterministic robust model, the input distribution reduces to a set [19] that is often generalized to the set of expected unscheduled power generation [53,54,62].

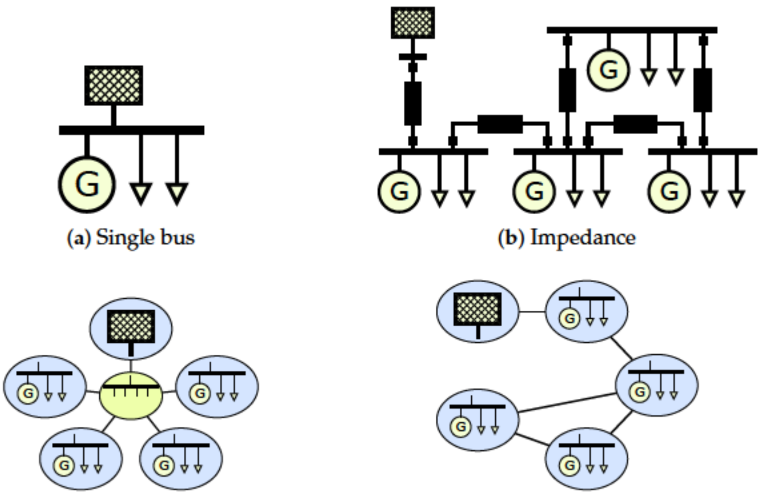
Diverse levels of detail are found for the DER models and are briefly summarized in Table 3. Every key contribution considered active power generation limits for the controllable assets. However, other limitations such as reactive and apparent power constraints are far less common. For instance, only eight out of 20 key contributions including [53,56,62,64] explicitly considered reactive or apparent power constraints. For one publication, [49], not enough details were given to clearly categorize the constraint. In addition to various power constraints, 12 publications such as [27,51,60] also include ramping constraints that limit the rate of change of the generated power. In order to avoid frequent start-up operations, eight key contributions (e.g., [28,52,58]) considered minimum up- and down-time constraints.

The common EES is modeled as a finite power and capacity constraint storage that accumulates the charged and discharged energy into a time-dependent SoC. In particular, only three key contributions did not constrain the energy that can be fed into or drawn from the energy storage [28,49,55]. Eighteen contributions model a constant storage efficiency that limits the energy that can be discharged. Although most of them assume that, like in [20,64], losses are encountered while charging and discharging only, one contribution also considers self-discharge of the energy storage unit [63]. None of the key contributions modeled the storage efficiency as a non-linear relationship of charging/discharging power or the SoC. However, one paper considers the non-linear charging curve of EVs by modeling the maximum charging and discharging power with respect to the current SoC [20]. A minority of five contributions constrained the minimum charging- and discharging time of an EES [27,52], but most of the contributions did not include any constraints to limit the battery degradation.

In addition to DER types and parameters, Table 3 also lists the implemented load models. One can see that all the papers consider constant power loads, while only one paper considers voltage-dependent loads [20]. One type of assets that is commonly found in microgrids is sheddable loads as discussed in [53,54]. To differentiate sheddable loads from loads that may be unserved by accident, only loads that can be controlled by the scheduling approach are considered. In case a load is interrupted because, for instance, line protection trips that load is not considered to be sheddable load. In addition to loads, that can be interrupted based on a signal from the microgrid controller, shiftable loads that can be deferred [27,54,56,58] and price-based DR programs [55] are modeled. However, these load types are only considered in a minority of five papers.

Similar to generic unscheduled DERs, most contributions consider load uncertainties via indeterministic (e.g., [20,27]) or stochastic (like in [58,59]) models. In contrast, only three out of 15 papers consider an uncertain amount of sheddable loads as well [53,61,64]. Similar observations can be made for price-based DR loads and shiftable loads as well. No contribution was found that considers stochastic effects in the latter two load types.

Table 4 lists the evaluated features regarding the grid model and Figure 6 illustrates the listed model types. The model itself is categorized into several different types of formulations. In the simplest case, the topology is reduced to one single bus and only energy balances are taken into account. As described in Section 4.1, there is only a single paper that uses a single-bus model and that still meets the eligibility criteria of resilient multi-microgrid scheduling. To cover topological constraints without requiring a detailed physical model, three publications use arbitrary connection graphs [54,58,63] and one publication restricts that graph to a star topology of microgrids that are connected via a distribution system [61]. For each node in the graph model, a power balance equation is stated and the power that is transferred from or to an adjacent grid can be constrained. However, power flows that result from the physical properties of the network and that may not be fully controllable, are beyond the scope of the model.



(a) Single bus **(b)** Impedance **(c)** Star **(d)** Connection graph

Figure 6. Observed types of grid models.

One key publication [59] extended the basic graph model by considering the efficiencies of power lines and the resulting power losses. However, no detailed model that covers the impact of reactive power flows on the line efficiencies was given. To cover the power flows as they appear by the physical properties of the system, several contributions formulated the grid model as steady-state power-flow model based on the line impedance (e.g. [48,55,57]). Despite the common framework of using a steady-state power-flow model, various differences in the particular formulations can be observed. Some publications directly model the power-flow equations as non-linear relationship between the voltage magnitudes and angle differences of connected buses [55]. Others directly present a linearized version [48] or include a linearization procedure [56]. Notably, some publications indirectly reference the power-flow model by using an external solver in their scheduling approach [51,57,60], but the majority explicitly states the power system model.

Nearly all publications that use impedance-based models also stated voltage constraints (e.g., [52,56,62]). Only [48] did not explicitly constrain the bus voltage. Hence, one additional value of the impedance-based model beyond realistic power flows is the containment of voltage problems caused by improper scheduling. In contrast, more detailed transient models that allow the assessment of the microgrid in switching or failure states are only used by [57]. Although the publication demonstrates the impact of scheduling on the short-circuit performance in terms of frequency response and voltage transients, scheduling models are mostly concerned with steady-state phenomena.

Another set of a commonly considered constraints are line capacity constraints (e.g., [48,56,59]). Only three key contributions did not consider the limited capacity of distribution lines. However, there is not a single formulation to address the line capacity given. Observed constraints include steady-state active [63], reactive [62], and apparent power-flow [50] constraints, as well as steady-state current limitations [60]. A majority of 13 key publications including [27,48,54] model main-grid transfer via a single point of common coupling. However, some publications such as [62] explicitly consider multiple connections to one or several utility grids as well [7]. Similar to the power line constraints, main-grid transfer is often restricted by active [20], reactive [48], and apparent [53] power constraints.

Table 3. Modeled load and DER types (✓ Implemented, ? Not reported, St Stochastic, D Deterministic, ID Indeterministic)

	DER Types									DER Parameters									Load Types				
Ref.	WT	PV	CHP	**Thermal**	EVs	MTs	EESs	**Generic Unscheduled DERs**	**Generic Schedulable DERs**	**DER Ramp-Up/Down Constraints**	**DER Up/Down-Time Constraints**	**DER Operating P Constraints**	**DER Operating Q Constraints**	**DER Operating S Constraints**	**EV Charging Curve**	**Storage Capacity Constraints**	**Minimum Charge/Discharge Time**	**Constant Storage Efficiency**	**P(Q)-Loads**	**Z-Loads**	**Price-based DR Loads**	**Sheddable (Interruptible) Loads**	**Shiftable Loads**
[48]							✓(D)	✓(St)	✓(D)			✓	✓			✓		✓	✓(St)			✓(D)	
[49]	✓(D)	✓(D)					✓(D)	✓(D)	✓(D)			✓		?					✓(D)			✓(D)	
[27]							✓(D)	✓(ID)	✓(D)	✓	✓	✓				✓	✓	✓	✓(ID)			✓(D)	✓(D)
[50]					✓(St)			✓(St)	✓(D)			✓				✓		✓	✓(St)				
[20]	✓(St)				✓(St)		✓(D)		✓(D)			✓	✓		✓	✓		✓	✓(ID)	✓(ID)		✓(D)	
[51]							✓(D)	✓(St)	✓(D)	✓		✓				✓		✓	✓(St)			✓(D)	
[52]							✓(D)	✓(St)	✓(D)	✓	✓	✓	✓			✓	✓	✓	✓(St)				
[53]							✓(D)	✓(ID)	✓(D)	✓	✓	✓		✓		✓		✓	✓(ID)			✓(ID)	
[28]	✓(St)	✓(St)				✓(D)	✓(D)			✓	✓	✓					✓	✓	✓(St)				
[54]							✓(D)	✓(ID)	✓(D)	✓	✓	✓				✓		✓	✓(ID)			✓(D)	✓(D)
[55]	✓(St)	✓(St)					✓(D)		✓(D)	✓		✓						✓	✓(D)		✓(D)		
[56]							✓(D)	✓(St)	✓(D)	✓	✓	✓	✓			✓	✓	✓	✓(St)			✓(D)	✓(D)
[57]							✓(D)	✓(D)	✓(D)			✓				✓		✓	✓(D)	?		✓(D)	
[58]	✓(St)	✓(St)					✓(D)	✓(St)	✓(D)	✓	✓	✓				✓	✓		✓(St)			✓(D)	✓(D)
[59]							✓(D)	✓(D)	✓(D)			✓				✓		✓	✓(St)			✓(D)	
[60]							✓(D)	✓(D)	✓(D)	✓	✓	✓	✓			✓		✓	✓(D)			✓(D)	
[61]	✓(St)						✓(D)		✓(D)			✓				✓		✓	✓(St)			✓(St)	
[62]			✓(ID)	✓(D)			✓(D)	✓(ID)		✓		✓	✓			✓		✓	✓(ID)			✓(D)	
[63]							✓(D)	✓(St)	✓(D)			✓				✓		✓	✓(St)				
[64]							✓(D)	✓(St)	✓(D)	✓		✓	✓			✓		✓	✓(St)			✓(St)	

Table 4. Grid model (✓ Implemented, ? Not reported)

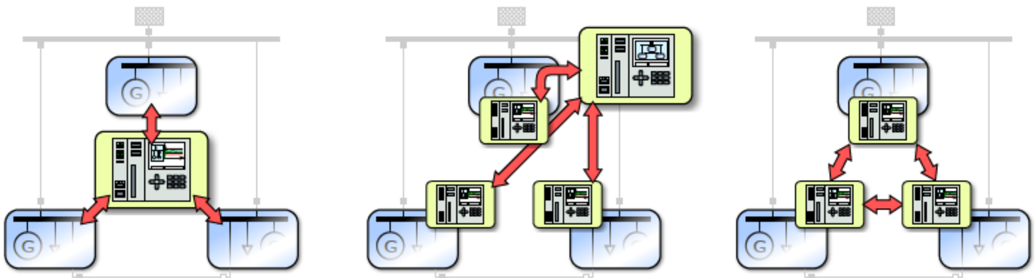
Ref.	Line Model	AC Links	DC Links	Bus-Voltage Model	Bus-Voltage Constraints	Bus-Voltage Transient Constraints	Voltage Angle Constraint (Bus or Line)	Frequency Constraints	Line-Active Power-Flow Constraints	Line-Reactive Power-Flow Constraints	Line-Apparent Power-Flow Constraints	Line-Current Constraints	Line/Main Grid-P/Q/S Fluctuation Constraints	Main Grid P (Min/Max) Constraints	Main Grid Q (Min/Max) Constraints	Main Grid S (Min/Max) Constraints	Single Main Grid Point of Common Coupling (PCC)	Static Transformer	VAR Compensator (Q)	Dynamic AC/DC or DC/DC or AC/AC Converter	Constant Converter Efficiency	Remote Switches	Switching Operation Constraints	Radial Topology Constraint
[48]	Res /Admittance	✓		✓							✓			✓	✓		✓					✓		
[49]	?	✓		?	✓						✓					?	✓							
[27]	Single Bus	✓							✓					✓			✓							
[50]	Res /Admittance	✓		✓	✓						✓			✓			✓					✓	✓	✓
[20]	Res /Admittance	✓		✓	✓						✓			✓			✓		✓					
[51]	Res /Admittance	✓		✓	✓				?	?	✓	?					✓							
[52]	Res /Admittance	✓		✓	✓									✓	✓		✓							
[53]	Res /Admittance	✓		✓	✓						✓			✓		✓	✓							
[28]	Res /Admittance	✓		✓	✓							✓					?							
[54]	Connection Graph	✓	✓						✓				✓	✓			✓			✓	✓			
[55]	Res /Admittance	✓		✓	✓							✓					?					✓	✓	✓
[56]	Res /Admittance	✓		✓	✓							✓		✓	✓							✓		✓
[57]	Res /Admittance	✓	?	✓	✓	✓		✓				✓		✓			✓	✓	?	?	?			
[58]	Connection Graph	?	?											✓										
[59]	Line Efficiencies	?	?						✓					✓			?							
[60]	Res /Admittance	✓	?	✓	✓							✓					✓	✓	✓	?	?			
[61]	MMG Star	?	?											✓			✓							
[62]	Res /Admittance	✓		✓	✓		✓		✓	✓				✓	✓									
[63]	Connection Graph	?	?						✓					✓										
[64]	Res /Admittance	✓		✓	✓				✓	✓				✓	✓		✓					✓		✓

Although most of the key contributions focus on static grid models that consist of lines that connect DERs, loads and the main grid, few also consider controllable assets such as VAR compensators [20] and dynamic converters to control power flows [54]. Similarly, static transformer models are reported by two contributions only [57,60]. Five papers considered remote switching capabilities to dynamically alter the topology of a microgrid (e.g., [48,55]). Only one of these contributions, [48], considered meshed topologies. Every other publication that included dynamic topologies formulated constraints that always guarantee a radial topology [50,55]. Although some approaches including [57,60] may directly support other grid assets such as tap changer transformers as well, none of the contributions reported their application.

A similar set of models and constraints can also be found in other related domains such as islanded microgrids [44]. In particular, DER output, ramping, power flow and balance constraints appear most frequently in microgrid operation and panning problems [10,33,44]. However, other constraints such as financial budgets and placement options are primarily found in planning problems. Although voltage and frequency control strategies may have a significant impact on the feasibility of mitigation techniques [57], few key contributions included detailed frequency constraints. Voltage constraints, in contrast, are far more often found in resilient normal operating problems. Considering recent publications on islanded microgrids, both voltage and frequency constraints are frequently found [44].

4.3. Optimization Objective and Methods

The typical resilient scheduling approach such as [20,48,56] sketches a central controller that uses a mathematical solver such as a MILP solver to obtain the optimal schedule with respect to a single-objective function. However, there are various notable exceptions that follow a different approach. Table 5 summarizes the results regarding used optimization procedures. In addition to mathematical approaches that usually pass the problem on to a MILP solver, some heuristic optimization techniques such as genetic algorithms [28,51], Particle Swarm Optimization (PSO) [52,64], Imperialist Competitive Algorithm (ICA) [49], Clonal Selection Algorithm (CSA) [50], Exchange Market Algorithm (EMA) [55], and Pareto Concavity Elimination Transformation (PaCcET) [57] can be found [73]. Two contributions demonstrated an alternative to the central control paradigm in which one controller gathers all information and decides on the next schedule [54,63]. Publication [54] demonstrated a hierarchical architecture where single independent microgrid controllers are coordinated by a central supply-level controller. A fully distributed approach is presented by [63] which does not need a central entity at all. Figure 7 gives an overview of all three control paradigms and shows the controllers as well as the main points of interaction.



(a) Central (b) Hierarchical (c) Distributed

Figure 7. Control architectures.

Before the model is solved, it is regularly preprocessed. Nine contributions directly formulate the model as MILP or Mixed Integer Programming (MIP) models (e.g., [20,51,62]) that can be directly solved by commercial solvers. Other models such as [52,57,60] are initially formulated without any restrictions or based on a quadratic formulation [53,63]. After stating the model, linearization is often applied to reduce the computational burden and to allow the usage of external solvers [20,54,56,62]. One contribution also applied an intermediate convexification step before linearizing the problem [56]. One may note that [62] is listed as MILP model and as presenting a linearization, because the power-flow model is stated in its linearized version only, but the linearization procedure is quickly sketched.

Table 5. Optimization approaches (✓: Implemented, ?: Not reported) .

Ref.	Method	Location	Formulation	Model Type	Linearization	Convexification	Problem Decomposition	Independent Sampling	Correlated Sampling	Scenario Reduction
[48]	Mathematical	Central	Stochastic	MIP			✓		✓	✓
[49]	ICA	Central	Stochastic	Unconstrained						
[27]	Mathematical	Central	Deterministic	MIP			✓			
[50]	CSA	Central	Stochastic	Unconstrained				✓		✓
[20]	Mathematical	Central	Stochastic	Unconstrained	✓			?	?	✓
[51]	Genetic+Mat.	Central	Stochastic	MILP			✓	✓		✓
[52]	PSO+Mat.	Central	Stochastic	Unconstrained			✓			
[53]	Mathematical	Central	Deterministic	Quadratic	✓		✓			
[28]	Genetic	Central	Stochastic	MIP					✓	✓
[54]	Mathematical	Hierarchical	Deterministic	Unconstrained	✓		✓			
[55]	EMA	Central	Stochastic	MIP					✓	
[56]	Mathematical	Central	Stochastic	Unconstrained	✓	✓	✓		✓	
[57]	PaCcET	Central	Stochastic	Unconstrained						
[58]	Mathematical	Central	Stochastic	MIP				?	?	
[59]	Mathematical	Central	Deterministic	MILP						
[60]	Mathematical	Central	Deterministic	Unconstrained	✓		✓			
[61]	Mathematical	Central	Stochastic	MILP					✓	
[62]	Mathematical	Central	Deterministic	MILP	✓		✓			
[63]	Mathematical	Distributed	Stochastic	Quadratic			✓	✓		
[64]	PSO	Central	Stochastic	Unconstrained			✓	✓	✓	✓

One common measure to increase the computational tractability of the scheduling problem [53,62], to develop sub-problem-specific solution procedures [51], and to account for the inherent structure of the scheduling problem [27,54], is to decompose the whole problem into several sub-problems. Eleven out of 20 papers decompose the scheduling such that the partial problems can be solved individually and will then be combined into the complete problem. Since the sub-problems are usually not fully independent, iterative approaches like in [27,52,54] that refine the individual problems are commonly seen.

Robust and stochastic formulations are by far the most common methods to deal with uncertainty in scheduling problems. None of the key contributions considered other means such as fuzzy sets to directly represent uncertainty. In Table 5, the optimization is considered stochastic, in case the optimum is defined with respect to some probabilistic information. In case a robust algorithm computes a single worst case, the optimization procedure itself is categorized as deterministic. Although in some cases, probabilistic models may be optimized without sampling a set of scenarios first [49,52], most papers that follow a stochastic approach report sampling-based methods to generate a certain set of scenarios (e.g., [50,51,64]). These samples are either drawn independently [51], or in an approach which establishes a correlation that is not covered by the sampled distribution and which thereby reduces the number of scenarios that need to be considered [55]. To contain the number of samples and to decrease the computational burden, correlated sampling approaches that directly limit the number of samples [61] or scenario reduction techniques that reduce a large amount of scenarios [28] are commonly observed.

On a common ground, all key contributions minimize the operating costs of the controlled microgrids. Except some common terms such as the cost of controllable DERs; however, a wide variety of objective terms is observed and summarized in Table 6. The high prevalence and diversity of cost-based objectives can also be found in other areas of microgrid-related research [10,44]. Despite some broadly used terms including DER operation expenses, some costs such as fees for lost loads are more specific to resilient and islanded microgrid problems. Other terms including investment cost are commonly found in planning problems but do not play a major role in operation. All but four key contributions directly state a single-objective function without considering a multi-objective formulation, first. Three of the papers that consider a multi-objective formulation apply fuzzy decision making to obtain a single schedule automatically [28,51,57]. Herein, the decision maker's satisfaction with each single-objective value is encoded as fuzzy membership function and used to select the best compromise solution in the Pareto front. However, uncertainties in the power system are not modeled as fuzzy sets.

In addition to linear (e.g., [27,59,66]) or non-linear (e.g., [63,64]) generation costs of schedulable DERs, start-up and shut-down costs like in [60] are frequently considered. Similar to the DER generation cost, the cost of energy that is sold to or purchased from the main grid (e.g., [28,59]), as well as the value of lost load (e.g., [51,61]) are included by a majority of 19 and 14 contributions, respectively. For instance, [53] considered the value of lost loads via elastic load prices while [51] directly included the value in the unscheduled islanding scenarios. The costs of Vehicle to Grid (V2G) or EES operation is considered by ten key contributions such as [28,50,51,60]. Presented cost terms include cost of the charged and discharged energy [53], constant start-up, shut-down and operation fees [60], as well as detailed EV battery degradation models [50].

In contrast to regularly considered tariffs of transferring energy from or to an external main grid, trading energy between independent microgrids is considered by a minority of five key contributions including [27,58]. Other rarely used cost terms include maintenance costs [28], the cost of power losses [55], the cost of scheduling additional load, for instance in DR programs [20,61], costs or benefits gained by selling energy to customers [28,53], costs for committing operational reserves without actually scheduling them [52], and cost terms that penalize uncertainty or security margins [57,62]. Two out of the four contributions that considered remote switches also considered the cost of operating them [50,55]. Although one key contribution [52] directly considered the emission of pollutants, no publication added emission costs such as the cost of CO_2 emissions.

Table 6. Objective terms (✓ Implemented)

Ref.	Multi-Objective Formulation	Fuzzy Decision Making	Cost - DER Production Cost (Linear)	Cost - DER Production Cost (Non-Linear)	Cost - Start-up	Cost - Shut-down	Cost - Main-Grid Transfer	Cost - Energy Trading (Transfer) to Adjacent Microgrids	Cost - Maintenance	Cost - EES or V2G Operation	Cost (Income) - Energy Sold to Customers	Cost - Power Losses	Cost - Value of Lost Load/Energy not Supplied	Cost - Scheduling of Additional Load	Cost - Demand-Response Reserve Commitment	Cost - Generation Reserve Commitment	Cost - EES Capacity Reserve	Cost - Grid Capacity Reserve	Cost - Switching (Topology Changes)	Cost - Deviation from a (High-Level) Schedule	Cost - Uncertainty or Security Margins	Emissions (Directly)	Lost Load/Energy not Supplied (Directly)
[48]			✓		✓	✓	✓						✓										
[49]			✓		✓	✓	✓			✓			✓										✓
[27]			✓		✓	✓	✓	✓															✓
[50]			✓				✓			✓			✓						✓				
[20]			✓		✓		✓				✓		✓	✓	✓					✓			
[51]	✓	✓	✓		✓	✓	✓			✓			✓										✓
[52]	✓			✓	✓	✓	✓									✓						✓	
[53]			✓		✓	✓	✓			✓	✓		✓							✓			
[28]	✓	✓	✓				✓		✓	✓	✓	✓	✓										
[54]			✓		✓	✓	✓	✓	✓	✓			✓							✓			
[55]			✓						✓	✓		✓	✓	✓					✓				
[56]			✓				✓					✓											
[57]	✓	✓		✓			✓						✓				✓	✓			✓		
[58]			✓				✓	✓					✓										
[59]			✓				✓	✓															
[60]			✓		✓	✓	✓			✓										✓			
[61]			✓		✓		✓						✓	✓	✓					✓			
[62]			✓				✓		✓	✓			✓							✓	✓		
[63]				✓			✓	✓		✓													
[64]				✓			✓						✓										

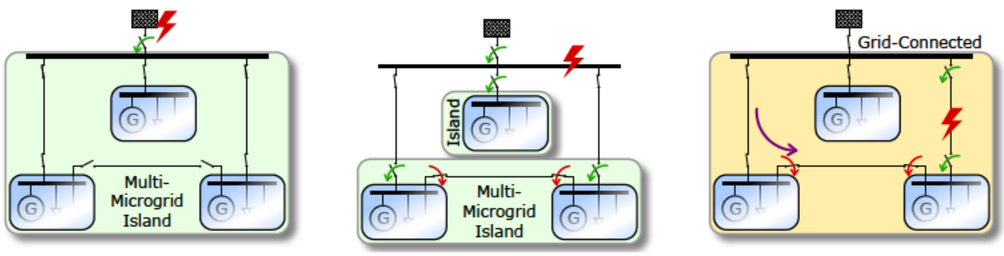
4.4. Resilience Features

Although a microgrid and multi-microgrid may be impacted by a wide variety of failures [14] such as communication faults, misbehaving circuit breakers, and degraded batteries, only a small subset of these failure modes is commonly considered. Table 7 summarizes the observed failure modes and mitigation techniques. A great majority of 17 key contributions including [48,58,61], incorporated main-grid outages and nine publications such as [51,60] considered this mode as the only source of unplanned disturbances. Eight contributions hardened their scheduling approaches by considering line tripping events (e.g., [48,54,74]) and three publications assumed that a generator may fail [48,55,62].

Notably, [50] generically considered bus faults or disconnections and corresponding fault isolation and rerouting actions. Generic deviations from the scheduling decision are addressed by [63] in which an adversary model that includes intentional attacks as well as faults of the scheduled assets is formulated. A detailed, transient short-circuit model is used by one key contribution, [57], that assessed each candidate schedule by a set of transient simulations. Following the eligibility criteria, all failures are either considered to be stochastic phenomena given a stochastic failure model [61] or as indeterministic phenomena that could either happen all the time or in exceptionally vulnerable situations [27,53].

Depending on the currently active schedule, a multi-microgrid may have several options to mitigate the effects of a failure. All mitigation techniques that were found in the key contributions are illustrated in Figure 8. When an external fault happens, most of the scheduling approaches consider the disconnection from the main grid as the primary mitigation measure. In particular, eighteen contributions such as [52,62,64] include islanding options in their schedule. Ten of these publications including [27,49,59], solely focus on islanding and do not actively consider other fault mitigation techniques in their scheduling approaches.

Other fault mitigation options are also found in the literature. Grid splitting, for instance, which refers to the division into several independent sections which are not electrically connected, is considered by seven key contributions (e.g., [55,61,62]). In addition, a failure may be compensated by establishing another connection to islanded or disconnected parts of the network [48,54,63]. Rerouting is considered by a minority of six publications as an alternative method of compensating failures.



(a) Islanding **(b)** Grid splitting **(c)** Rerouting

Figure 8. Observed mitigation schemes.

Table 7. Resilience features (✓: Implemented, ?: Not reported, St: Stochastic, D: Deterministic, ID: Indeterministic) .

	Failure Modes						**Mitigation**		
Ref.	**Main-Grid Failure**	**Generator Tripping**	**Line Tripping**	**Bus Fault or Disconnection**	**Short-Circuit Fault (Detailed Model)**	**Deviated Schedule (Generic)**	**Main-Grid Disconnection**	**Fault Isolation and Rerouting**	**Grid Splitting**
[48]	✓(St)	✓(St)	✓(St)				✓	✓	
[49]	✓(ID)		✓(St)				✓		
[27]	✓(ID)						✓		
[50]				✓(St)				✓	
[20]	✓(St)						✓		
[51]	✓(St)						✓		
[52]	✓(ID)						✓		
[53]	✓(ID)						✓		
[28]	✓(St)		✓(St)				✓	?	✓
[54]	✓(ID)		✓(ID)				✓	✓	
[55]	✓(St)	✓(St)	✓(St)				✓		✓
[56]	✓(ID)						✓	✓	✓
[57]	✓(ID)				✓(St)		✓		
[58]	✓(ID)						✓		
[59]	✓(ID)						✓		
[60]	✓(ID)						✓		
[61]	✓(St)		✓(St)				✓		✓
[62]	✓(ID)	✓(ID)	✓(ID)				✓		✓
[63]						✓(St)		✓	✓
[64]			✓(St)				✓	✓	✓

4.5. Validation Approaches

Another aspect in the construction of a resilient scheduling approach is its validation. Table 8 summarizes the validation approaches of each key contribution. One can see that all key contributions are validated by numeric simulations. However, only one single key contribution, [59], also includes a laboratory test setup and none of these publications reported any field tests or real-world deployments. Most of the publications assessed the performance in one or multiple failure conditions, either explicitly based on single scenarios [27,57,62] or via some performance metric that aggregate multiple failure conditions [20,51]. Following the modes summarized in Table 7, mostly main-grid failures such as in [27] are assessed. However, other failures such as tripping generators [62], line failures [28], deviated schedules [63], deviations from forecasts or from input parameters [59], as well as short-circuit events [57] were also included.

Table 8. Validation approaches (✓: Implemented, ?: Not reported) .

		Type		Failure Modes					Test-Grid			
Ref.	**Test Case ID**	**Numerical Simulation**	**Laboratory Test**	**Main-Grid Failure**	**Generator Tripping**	**Line Tripping**	**Deviated Schedule (Generic)**	**Parameter or Forecasting Deviations**	**Specification**	**No. of Buses**	**No. of DER (total)**	**No. of Schedulable DER**
[48]	Standard	✓		✓	✓	✓			IIT Standard MG	10	2	2
[48]	HRDS	✓		✓	✓	✓			IIT HRDS MG	12	2	2
[49]		✓							CIGRE	12	6	3
[27]	Base Case	✓		✓					-	1	2	1
[27]	Extension	✓		✓					-	1	3	2
[50]		✓							IEEE 33-bus	32	8	5
[20]		✓		✓					IEEE 33-bus	33	11	6
[51]		✓		✓					Listed in [75]	34	5	3
[52]		✓							Listed in [76]	38	19	9
[53]		✓		✓					IEEE 33-bus	33	14	6
[28]		✓		✓		✓			IEEE 33-bus	33	10	5
[54]		✓		✓		✓			-	4	4	1
[55]		✓							PG&E 69-bus	69	11	5
[56]	Case 0	✓							IEEE 33-bus	33	0	0
[56]	Case 0	✓							IEEE 69-bus	69	0	0
[56]	Case 1-3	✓		✓					?	32	7	5
[57]		✓							-	6	4	3
[58]		✓		✓					-	3	17	12
[59]		✓	✓	✓				✓	-	3	6	3
[60]	Case 1	✓							IEEE 34-bus	34	7	7
[60]	Case 2	✓							IEEE 123-bus	123	15	15
[61]		✓		✓		✓			-	3	4	2
[62]		✓		✓	✓	✓		✓	IEEE 13-bus + 34-bus	47	12	10
[63]		✓					✓		PG&E 69-bus	69	24	16
[64]		✓		✓		✓			IEEE 33-bus	33	?	9

In most cases, one single test grid is used to assess the scheduling methodology. Exceptions include [48], which uses multiple variations of a single network and [60] which uses two different test networks. Six times, including [28,50,53], the assessment was based on a grid called Baran or IEEE 33-bus test feeder [77]. Other test systems include the official IEEE 34-bus, and 123-bus test feeders [60], as well as some CIGRE benchmark systems [49]. To be able to test assets that were not considered in the initial test network, one commonly observed practice is the extension by various DERs [53,60]. The sizes of assessed networks range from one bus systems that host up to three DERs [27] to 123-bus grids [60] and networks that host up to 24 DERs [63].

Typically, the scheduling algorithm is executed once per day and the next schedule is calculated. In particular, 16 key contributions such as [49,54,59], configure a scheduling horizon of 24 h. For [48], the schedule of a whole year is assessed, but no other information on the scheduling horizon was given. The observed time resolution ranges from minutely scheduling intervals [59] to hourly set-points like in [52,57] that are used in 14 key contributions.

A minority of two publications implements a scheduling scheme that updates or installs set-points before the end of one scheduling horizon. A scheduling function that updates parts of the optimization both in real time and as soon as new forecasts are available, is presented by [60]. A fully cyclic

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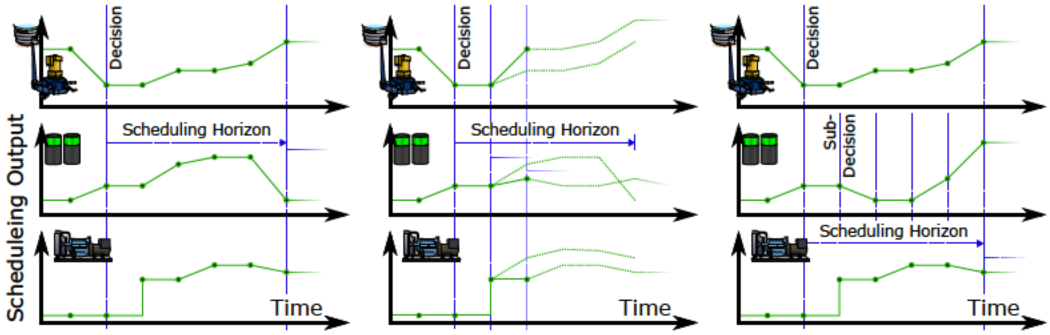
approach that outputs the first set-point of each scheduling horizon only, is presented in [63]. Figure 9 illustrates the observed scheduling schemes and shows an exemplary scheduling output for three controllable assets. Table 9 summarizes the main features of the validation platforms and the execution parameters. One can see that only few publications give hints as to the computational complexity of their algorithms by presenting the execution time [20,54,60,61]. However, the software tools such as MILP solvers and hardware platforms are listed more commonly.



(a) Run Once **(b)** Fully Cyclic **(c)** Interleaved

Figure 9. Observed scheduling schemes.

To validate a schedule, several input profiles such as load and RES generation are needed. Table 10 summarizes type and source of load, energy price, PV and wind generation, as well as EV charging profiles. For wind and PV profiles, both electricity generation [51,66] and primary energy source profiles [28] are subsumed. For [27,52], generation of volatile RES is considered in a generic way, either as negative loads or as generic generation. In the first case, only load profiles are listed in Table 10, while in the second case, the RES profile is listed for both PV and wind generation.

Since most related models are stochastic or indeterministic in nature, profiles are often not only given as single deterministic curves, but as distribution or set of feasible values. Most papers such as [53,57,64] base their undetermined inputs on a deterministic forecast and model the forecasting errors in addition. In terms of forecast errors, both stochastic formulations including [50,58] and indeterministic ones such as [51,66] are regularly observed. One can see that most of the publications that use a stochastic model assume that the observables or forecasting errors are temporally independent, i.e., one sample does not depend on any previous sample.

A rich set of evaluation metrics, as summarized in Table 11, is used to assess the performance of scheduling algorithms. The most common terms are operation costs or their stochastic expectation (e.g., [56,57]) that is used by 15 key contributions. Eleven publications such as [28,60] published results regarding energy transfer either between different microgrids or to the main grid. Half of the key contributions including [55,62] provided information on bus voltages and seven listed the expected energy that cannot be supplied (e.g., [51,58]). In addition to the frequent metrics, several metrics such as network losses [51], the system average interruption duration index [48], and pollutant emissions [52] were given.

Table 9. Validation platform (? Not reported)

Ref.	Execution Parameters: Test Case ID	Time Horizion [h]	Step-Size [min]	Scheduling Scheme	Execution Time [s]	Reported Execution Platform
[48]	Standard	8760 (?)	60	Run-Once		
[48]	HRDS	8760 (?)	60	Run-Once		
[49]		24		Run-Once		MATLAB implementation
[27]	Base Case	24	60	Run-Once		CPLEX 11 0, 2 4GHz PC
[27]	Extension	24	60	Run-Once		CPLEX 11 0, 2 4GHz PC
[50]		24	60	Run-Once		
[20]		24	60	Run-Once	22 59	Intel Core i7 CPU, 3 20 GHz, 4GB RAM, IBM ILOG CPLEX 12 4, GAMS IDE
[51]		24	60	Run-Once		MATPOWER
[52]		24	60	Run-Once		MATPOWER (MINOPF)
[53]		24	60	Run-Once		Intel Core i7 CPU, 3 20 GHz, 4GB RAM, IBM ILOG CPLEX 12 4, GAMS IDE
[28]		24	60	Run-Once		MINLP model, NSGAII algorithm, MATLAB 2016a
[54]		24	15	Run-Once	124 37	MATLAB, YALMIP toolbox, CPLEX 12 4, 32-bit PC, 2 10GHz CPU, 2GB RAM
[55]		24	60	Run-Once		
[56]	Case 0	-	-	Run-Once		CPLEX 11 0, 2 4-GHz PC
[56]	Case 1-3	24	60	Run-Once		CPLEX 11 0, 2 4-GHz PC
[57]		5	60	Run-Once		Win7, E5420 CPU, 2 Cores, 2 5 GHz, 16 GB RAM
[58]		24	60	Run-Once		GAMS, BARON
[59]		24	1	Run-Once		IBM CPLEX
[60]	Case 1	24	30	Interleaved	9 8	OpenDSS + OPTI Toolbox + MATLAB, Windows, Intel Core i5-4300M, 2 60GHz, 8 GB RAM
[60]	Case 2	24	30	Interleaved	36 9	OpenDSS + OPTI Toolbox + MATLAB, Windows, Intel Core i5-4300M, 2 60GHz, 8 GB RAM
[61]		24	60	Run-Once	0 06	GAMS DIE, CPLEX 12 4, Intel Core i7 CPU, 3GHz, 12 GB RAM
[62]		6	15	Run-Once		Python 2 7, GUROBI 8 0 0, Intel Core i7-7700, 4 2 GHz, 16GB RAM
[63]		1	15	Fully Cyclic		MATLAB with YALMIP, Intel Core i7, 2 6 GHz, 16GB RAM
[64]		24	60	Run-Once		

Table 10. Input profiles (Det Deterministic, Dist Distribution, Int Interval, Dev Deviation, TI Temporally Independent, ID Indeterministic, N A Not Applicable, UnAv Source is Unavailable, - Source is not listed)

Ref.	Load Type	Source	Main-Grid Energy Prices Type	Source	PV/Irradiation Type	Source	Wind Type	Source	EV Charging Type	Source
[48]	Det	-	Det	UnAv	N A	-	N A	-	N A	-
[49]	Det	-	Det	UnAv	Det	-	Det	-	N A	-
[27]	Det + TI Dist	-	Det + TI Dist	-	N A	-	N A	-	N A	-
[50]	Det + TI Dist	-	Det + TI Dist	-	Det + TI Dist	-	Det + TI Dist	-	Det + TI Dist	-
[20]	Dist	[78]	Dist	[78]	N A	-	TI Dist	[79]	TI Dist	-
[51]	Det + TI Dist	[80]	Det	-	Det + TI Dist	[80]	Det + TI Dist	[80]	N A	-
[52]	Det + TI Dist	-	Det	[81]	Det + TI Dist	-	Det + TI Dist	-	N A	-
[53]	Det + Det Dev	[20]	Det + ID Int	[20]	N A	-	N A	-	N A	-
[28]	Det + TI Dist	-	Constant	-	TI Dist	-	TI Dist	-	N A	-
[54]	Det + ID Int	-	Det	-	Det + ID Int	-	Det + ID Int	-	N A	-
[55]	Det	-	Det	-	Dist	-	Dist	-	N A	-
[56]	Det + Dist	-	Det + Dist	-	N A	-	Det + Dist	-	N A	-
[57]	Det	-	Det	-	Det	-	N A	-	N A	-
[58]	Det + TI Dist	-	Det	-	Det + TI Dist	-	Det + TI Dist	-	N A	-
[59]	Det + Det Dev	[82]	Det	-	Det + Det Dev	[83]	N A	-	N A	-
[60]	Det	-	Det	-	Det	-	Det	-	N A	-
[61]	Dist	[84]	Dist	[84]	N A	-	Dist	[84]	N A	-
[62]	Det + ID Int	[85]	Det	[86]	N A	-	Det + ID Int	[87]	Constant	[88]
[63]	Det + TI Dist	UnAv	Constant	-	Det + TI Dist	UnAv	N A	-	N A	-
[64]	Det + TI Dist	-	Det + TI Dist	-	Det + TI Dist	-	Det + TI Dist	-	N A	-

Table 11. Evaluation metrics (✓ Implemented)

Ref.	Test Case ID	(Expected) Energy Not Supplied	System Average Interruption Frequency Index	System Average Interruption Duration Index	Customer Average Interruption Frequency Index	Customer Average Interruption Duration Index	Loss of Load Expectation	(Expected) Operating Cost	Emission (e.g., CO2)	(Expected) Energy Transfer or Trading (Main Grid, Intra-MG)	Power factor (Single line or min/max)	Network Losses (Single line, cumulative)	Voltage (Single Bus or min/max)	Current (Single Line or min/max)	Voltage Angle (Single Bus or min/max)	Frequency	Accumulated Reserve Capacities	Countermeasure Success/Failure Rate	Deviation to Expected Case	Value at Risk	Conditional Value At Risk
[48]	Standard	✓	✓	✓	✓	✓	✓	✓		✓								✓			
[48]	HRDS	✓	✓	✓	✓	✓	✓	✓		✓								✓			
[49]		✓						✓													
[27]	Base Case							✓		✓											
[27]	Extension							✓		✓											
[50]								✓				✓	✓								
[20]								✓					✓								
[51]		✓						✓				✓									
[52]								✓	✓	✓	✓		✓				✓				
[53]								✓	✓	✓	✓		✓					✓	✓		
[28]		✓						✓		✓		✓	✓	✓						✓	✓
[54]		✓						✓		✓											
[55]								✓		✓			✓								
[56]	Case 0											✓	✓		✓				✓		
[56]	Case 1-3							✓				✓									
[57]								✓					✓			✓					
[58]		✓						✓		✓											
[59]		✓								✓									✓		
[60]	Case 1	✓								✓			✓								
[60]	Case 2	✓																			
[61]		✓						✓		✓											
[62]								✓		✓			✓						✓		
[63]																		✓	✓		
[64]								✓		✓							✓				✓

5. Future Perspectives

Several key publications, as summarized in Table 2, demonstrated the feasibility of resilient scheduling in multi-microgrids or provided significant contributions that may also be applied in such an environment. Several design choices were successfully explored, and a broad spectrum of scheduling approaches was presented. However, none of the key contributions reported a field implementation. Additionally, practical aspects such as the availability and quality of input data are rarely discussed. To guide future research towards practical implementation and alternative options that may be applied as well, a list of open points is given.

5.1. Modeling Approaches and Modeled Assets

Although one can observe a broad variety of asset models, there are various research opportunities to refine knowledge of the effects of modeling assumptions. These opportunities include the following perspectives on modeling approaches and asset models.

- *Level of Abstraction*: Most assets such as loads, generation and grid facilities were modeled by different levels of abstraction. For instance, some papers consider a graph model and active power-flow constraints, only [54], while others include a detailed grid model [20] that considers reactive and apparent power flows, as well. Choosing the right level of abstraction may drastically influence the system performance [56], but few papers present the impact of simplification on a resilient schedule in detail.
- *Hidden Aspects*: To get a concise view on the required level of abstractions, several aspects, that are usually not modeled but that may impact an algorithm, should be considered. For instance, storage losses are commonly modeled via constant efficiencies. However, battery storage systems including their power electronics converters show various non-linear effects that strongly depend on the point of operation [89,90]. A more detailed model may cover system effects that potentially hamper supply security in critical part-load situations [3]. Similarly, few papers consider the effects and reserve requirements of low-level controls such as Q-of-U and P-of-f droop curves that may implement short-term power sharing and voltage control [17].
- *Stochastic Effects*: Following one of the eligibility criteria, all key contributions trivially consider stochastic effects such as volatile load and RESs. Some of these contributions directly use stochastic models of meteorological observables and forecasting deviations. On a common basis, errors and the observables themselves are assumed to be independently distributed as concerns points in time, i.e., one sample does not depend on previous samples. Such assumptions may be valid for yearly assessments, but may fail at short-term horizons [70] of scheduling problems. Work [91] studies forecasting errors and indicates that a commonly assumed normal distribution does not fit either. Some research is needed to quantify the effects on the performance of a resilient scheduling algorithm and to study alternative models.
- *Robustness of the Asset Models*: Asset models may be subject to parameter deviations and degradation. For RESs and loads, such phenomena are commonly considered, but for controlled assets, the effects of parameter deviations such as EES capacities are hardly covered. Future work may tackle the robustness of asset models by studying the effects of inevitable parameter deviations. A feedback mechanism may be included to assure a sufficient model quality [92] and further insights regarding the impact of inaccuracies may be gained.
- *Covered Assets*: Current scheduling algorithms focus on a specific set of assets such as generic DER, EES, and constant power loads. Other components such as transformers that are equipped with On-Load Tap Changers (OLTCs) are not included in the key contributions. However, these assets may impact the system performance and may even be actively controlled by the scheduling algorithms, e.g., to support voltage control via OLTCs [93]. In case specific plant types such as hydro turbines and hydrogen-based EES may be subsumed by generic models, the eligibility of these models needs to be assessed as well.

- *Engineering Aspects*: One open point that is beyond the scope of all key contributions is the efficient engineering of scheduling approaches. All approaches require a large amount of input information such as network and DER parameters that may not be easily available. Methods that inherently include a system and model identification process such as reinforcement learning [94], as well as common data sources and engineering support systems [95] may be used to assist practical implementation.

5.2. Optimization Objectives and Methods

Optimization procedures and objectives are an integral part of each key contribution. Due to that relevance, significant impact may be gained by refining optimization-related aspects and by applying findings from related fields.

- *Distributed Optimization*: Out of 20 contributions, only a single one followed a fully distributed approach [63]. Most other publications implemented a centralized approach that requires extensive knowledge of the assets of various microgrids. Future work may include resilience aspects in distributed scheduling approaches more often [34] or may distribute centralized algorithms to tackle privacy, fault tolerance, and governance issues [35].
- *Hybrid Optimization*: Traditionally, optimization approaches either use mathematical programming or heuristics to obtain a feasible and possibly optimal solution [73]. However, there is a class of algorithms called hybrid optimization that tries to combine several complementary methods, for instance both mathematical programming and heuristic procedures. Some key contributions already successfully use hybrid approaches, e.g., for problem decomposition [27,53] or to interface external solvers [51,57]. Future work may improve the interaction between different solvers and study the application of hybrid optimization methods in detail. A particular focus may be put on the integration of detailed models that are solved by external tools.
- *Scalability*: Some papers such as [53] indicate that techniques to improve the performance are needed, but as listed in Table 9, few publications actually assess the execution time. Furthermore, no systematic scalability study is given that relates the execution time to the system size and complexity. It is still open to assess the scalability of scheduling approaches and to document the performance limits with respect to practical systems. A fine-grained evaluation may highlight performance trade-offs and assist future engineering work.
- *Regulatory Frameworks*: Although the key contributions include a wide variety of cost terms, including resilience and operating costs, few references to regulatory regimes that imply certain cost structures are given. Such frameworks may dictate when price information is available, how prices are determined and whether a market can be accessed [96]. Furthermore, energy transfer and trading within multi-microgrids or local energy communities may be restricted by various regulations that need to be considered in the design and operating phase. Some key contributions already consider regulatory measures by assuming certain market price structures [20,62], but a broad discussion is missing.

5.3. Resilience Features

One major aspect of this review is the resilience of scheduling algorithms that manage normal operation. As such, all key contributions already consider some failure modes and fault mitigation techniques. However, the analysis revealed several research opportunities that may increase the resilience and robustness of microgrids even further.

- *Extended Failure Modes*: In most key contributions, only a few failure classes that must be withstood are considered. Typically, main-grid faults [27,52] and line tripping events [28,64] are tackled. Few papers also include other modes such as short-circuit failures [57] and no paper directly considers faulty DER set-points, invalid switching actions, or load disconnections. Open research includes the systematic identification of relevant failure modes that need to be considered in the scheduling problem. Additionally, the flexibility of algorithms in considering new and previously unknown failures may be assessed. Future work may further rely on the integration of external simulation tools to tackle both flexibility and the level of detail.

- *Generic Failure Modes*: Some failure modes may be subsumed by another class. For instance, main grid failures may be covered by a fault in the line that connects the point of common coupling [28,55]. However, a systematic study of prototypical failure modes in scheduling problems is still open. In particular when increasing the number of considered failure modes, a proper generalization may be needed to contain the computational effort of finding an optimal solution.
- *Effects of Low-Level Controls*: Low-level controls such as voltage and frequency control that are installed to provide immediate action in terms of disturbances [5] are commonly beyond the scope of key contributions. However, a high-level schedule may impact the feasibility of certain control actions, e.g., in case a generator is already close to a limit, and may hamper a successful mitigation action. Some emergency actions such as fault rerouting can also be implemented by a dedicated controller to guarantee a fast response. Future work may focus on the interaction of low-level controls and the scheduling algorithm to ensure a consistent behavior and a valid emergency response. Insights into the proper abstractions of low-level controls may decrease the complexity of the scheduler without impacting the resilience of the system.
- *Fault Mitigation Techniques*: The key contributions deploy three different classes of fault mitigation techniques: Main-grid disconnection [27], rerouting [48], and grid splitting [28]. However, practical issues such as protection, inertia, grid-forming, and legal requirements [36] are hardly considered on assessing mitigation options. Some work may be conducted to increase the knowledge of feasibility aspects of mitigation techniques and to explore further options such as mobile generators and batteries that may quickly replace other units [97].

5.4. Validation Approaches

The key contributions mostly focus on simulation-based validation, only. Considerable work is needed until the reviewed algorithms can be safely and efficiently applied in real-world setups. The following research opportunities target the progression of technological readiness.

- *Common Benchmark System*: All key contributions include a simulation-based validation, but each of them uses different benchmark systems or diverging configurations to demonstrate their approaches. One of the most common test feeders is the Baran test feeder [77]. However, to demonstrate the algorithms, several independent modifications were introduced to account for DERs that were not considered in the original test feeder. Consequently, results from different papers cannot be directly compared. Existing benchmark systems [31] such as SimBench [98,99] and IEEE test feeders [100] may be evaluated and refined towards a unified multi-microgrid scheduling test bed. In addition to common typologies, a wide variety of assets, unified input profiles, and detailed DER parameters may reduce the need for custom modifications.
- *Common Metrics*: To be able to compare results from different studies, common metrics are required. While most papers provide operating costs, resilience-based metrics such as energy not supplied, are less common. Future work may profit from an increased focus on unified resilience metrics [48] and may intensify the discussion on their significance.
- *Independent Validation*: Rising from the need for comparable results, a fine-grained assessment of multiple algorithms may be conducted. In addition to common benchmark systems that are used by multiple authors, more detailed insights may be gained. A common execution platform may, for instance, enable detailed assessments on the computational performance. Some publications including [56,64] already compare their methods to a reference, but future implementations may profit from a more extensive study.

- *Readiness and Practical Implementation*: Although the first multi-microgrid test sites are already implemented [9], only one key contribution demonstrated the practical implementation of resilient scheduling [59] and no one went beyond laboratory experiments. Hence, considerable effort is needed until the approaches can demonstrate practical use in real-world situations [101]. Future testing and validation work may highly profit from previous experiences [9,31,102] and structured testing methodologies such as holistic testing [101,103].
- *Resilience Assessment in the Field*: One particular challenge towards a safe deployment is the resilience assessment in productive operation. Unlike in laboratory-based setups, testing the resilience may impact the overall performance of the grid. However, undiscovered failures in the control strategies may have fatal consequences as well [30]. Future work may include save strategies to verify resilience against low probability, high impact events in operation.

6. Conclusions

Resilient, proactive scheduling in the context of multi-microgrids is currently at a development stage that bears a manifold variety of optimization-based approaches but lacks practical experiences in implementing these methods beyond simulation-based test beds. However, practical experiences in related fields such as first insights into the operation of multi-microgrids in general, show a considerable potential in enhancing both security and cost of conventional electricity supply. The study systematically identifies the main contributions in proactive, resilient multi-microgrid scheduling and provides an in-depth analysis of selected literature. The typical scheduling approach uses an optimization-based framework that minimizes the running costs while meeting several resilience and operation constraints. However, the wide variety in modeling, solving, and validation of these scheduling problems raises the need for the presented detailed discussion. Several design decisions and the current spectrum of approaches are identified to aid future refinements and to back first practical implementations alike.

Corresponding to the current stage of development, several open issues and future perspectives were identified. Considerable work needs to be done in validating existing approaches and assessing the performance in practical implementations. Research work that compares various scheduling algorithms on a common ground is needed to establish a common view on the scheduling performance and to guide towards field tests. Similarly, engineering aspects should be emphasized to ease a future, widespread application. Also, a considerable potential of methodological improvements was identified. For instance, the quality of asset models may be raised by studying the robustness, limits, and practical applicability of common modeling assumptions. Solution approaches such as distributed optimization that show benefits in related fields may be increasingly applied for resilient multi-microgrid scheduling as well. Other potential improvements include systematic studies on extended failure models and novel fault mitigation measures that may strengthen the resilience of the scheduling outcome even further. Finally, a broad discussion on opportune applications of multi-microgrid scheduling in comparison to various other approaches such as purely economic scheduling in web of cells, needs to be held. This paper contributes to the discussion on finding the sweet spot of multi-microgrid systems by highlighting the SotA in resilient proactive scheduling.

Supplementary Materials: The following are available at http://www.mdpi.com/1996-1073/13/17/4543/s1. Several search terms were used to identify the key contributions. The list contains the search terms, the date of the search operation, as well as the resulting matches. For each search operation, Google Scholar was used as a search engine. Since subsequent entries were found to be less relevant, the number of considered matches was limited to the first 80 publications. The first three search terms were repeatedly applied to update the list of publications and to identify temporal changes in the search results. To avoid missing out relevant publications, all terms were selected such that a broad spectrum of publications is covered.

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Abbreviations

The following abbreviations are used in this manuscript:

AC	Alternating Current
CHP	Combined Heat and Power
CSA	Clonal Selection Algorithm
DC	Direct Current
DER	Distributed Energy Resource
DR	Demand Response
EES	Electrical Energy Storage
EMA	Exchange Market Algorithm
PaCcET	Pareto Concavity Elimination Transformation
EV	Electric Vehicle
FA	Firefly Algorithm
ICA	Imperialist Competitive Algorithm
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MT	Micro Turbine
OLTC	On-Load Tap Changer
PCC	Point of Common Coupling
PV	Photovoltaics
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
RES	Renewable Energy Sources
SoC	State of Charge
SotA	State-of-the-Art
SRQ	Sub-Research Question
V2G	Vehicle to Grid
WT	Wind Turbine

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Supplementary Materials: The Spectrum of Proactive, Resilient Multi-Microgrid Scheduling: A Systematic Literature Review

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1. Literature Identification

Several search terms were used to identify the key contributions. The list contains the search terms, the date of the serach operation, as well as the resulting matches. For each search operation, Google Scholar was used as a search engine. Since subsequent entries were found to be less relevant, the number of considered matches was limited to the first 80 publications. The first three search terms were repeatedly applied to update the list of publications and to identify temporal changes in the search results. To avoid missing out relevant publications, all terms were selected such that a broad spectrum of publications is covered.

1. *Date*: 2018-11-28, *Terms*: "microgrid scheduling resiliency": 80 publications, [1–80]
2. *Date*: 2018-12-03, *Terms*: "microgrid scheduling reliability": 80 publications, [1,3,5,6,10–12,14,16,18,25,27,40,81–147]
3. *Date*: 2018-12-06, *Terms*: "microgrid energy management resiliency": 80 publications, [1,3–5,7,8,12–15,17,19–22,26,31,37,40,43,46,51,52,58,64,66,71,114,124,148–198]
4. *Date*: 2019-11-07, *Terms*: "microgrid scheduling resiliency": 80 publications, [1–32,34,35,37,38,40–43,46,47,49,51,53,59–63,67,68,72,77,78,80,124,199–221]
5. *Date*: 2020-03-10, *Terms*: "microgrid scheduling reliability": 80 publications, [1,3,5,6,11,12,14,16,18,24,25,27,35,44,73,81–87,89,92,94,97–99,101,104–108,117–120,123,125–127,129,134,138,139,141,142,144,145,222–251]
6. *Date*: 2020-03-11, *Terms*: "microgrid energy management resiliency": 80 publications, [1,4,7,8,13–15,19–22,26,30,31,38,40,42,43,45,48,56,58,64,68,148,149,151,155,159–162,166,170,182,187,190,199,206,207,209,218,219,225,252–287]
7. *Date*: 2020-03-17, *Terms*: "networked microgrid optimization resiliency": 80 publications, [4,8,12,13,38,40,45,47,57,62,71,124,182,187,201,206,207,210,213,216,220,253,256,257,262,275,288–341]
8. *Date*: 2020-03-19, *Terms*: "multi-microgrid optimization resiliency": 80 publications, [1,10,40,56,59,66,152,167,186,200,201,206,213,220,257,265,286,312,332,342–402]
9. External sources (e.g. recommendation) that are not covered by other terms: 2 publications, [403,404]

2. Screening and Eligibility Test Results

The following classification was recorded in the literature selection step. Please note that according to the review methodology, a contribution may be classified without screening the entire publication, in case enough evidence is collected. Hence, a contribution may not be assigned to all categories that indicate limited eligibility for the purpose of this research. For a detailed description on the selection criteria, please refer to the main publication.

- *Key Contributions*: 20 publications, [2,18,30,41,57,107,138,217,220,222,229,230,232,252,275,280,307,310,357,371]
- *Limited Topological Considerations*:
  - *No power transmission constraints*: 31 publications, [6,80,81,94,99,102,112,144,202,219,224,225,228,233,236,238,240,246,249,253,257,261,284,292,380,385,393–395,400,403]
  - *Single-bus microgrid only*: 15 publications, [1,5,11,43,86,87,95,97,211,214,223,237,241,243,263]
  - *AC/DC interlinking constraints only*: 4 publications, [13,207,212,216]
- *Limited Technological Coverage*:

- *Limited Asset Types*: 46 publications, [19,27,61,63,109,161,199,205,215,221,236,250,254,256,262,264,265,274,281,296,305,306,308,309,316,324,326,329,331,341,344–347,352,354,370,375–377,379,384,385,387,390,398]
- *Limited stochastic considerations*: 41 publications, [8,13,21,35,42,124,164,167,199,208,240,242,243,245,246,255,260,262,265,269,286,292,296,300,305,317,326,328,332,342,346,354,360,373,377,379,385,390,394,399,400]

- *Limited Resilience Aspect Coverage*: 98 publications, [4,12,16,17,23–25,29,32,33,36,39,50,53,58,65,66,70,71,73,75,76,79,82,83,88,91,92,100,101,103,104,106,108,113,115–118,121,126,128–134,136,139–142,147–149,152,166,171,174,184,185,202,204,210,219,224,226,233,240,243,245,249,251,253,260,261,263,265,284,285,316,319,328,361,364,365,375,377,379–382,387,399,400,403,404]
- *Limited Focus on Normal Operation*: 75 publications, [3,14,15,20,34,37,38,40,44,67,74,89,90,93,98,110,119,123,151,168,170,187,199,200,203,213,227,234,238,246,248,264,267,273,274,282,283,288,290,293,295,299,300,304–306,317,324,329,332,335,339,340,344,345,347,348,350,351,353,355,359,369,370,372,373,384,388–390,392,393,395,397,398]
- *No Scheduling Algorithm Available*: 140 publications, [7,9,10,22,26,28,31,45–49,51,52,54,56,59,60,62,64,68,69,72,77,84,85,96,105,111,114,120,122,125,127,135,137,145,146,150,153–160,163,165,169,172,173,175–183,186,188–198,201,206,209,218,231,235,239,242,244,247,258,259,266,268,270–272,276–279,283,286,287,289,291,294,297,298,301–304,309,311–315,318,320–323,325,327,330,333,334,336–338,343,349,356,358,362,363,366–368,374,386,391,396,401,402]
- *Limited Full-Text Availability*: 6 publications, [55,78,143,162,378,383]

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2.2 Publication B

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Own contribution

The presented methodology, model formulations, the algorithmic refinements and the novel scheduling algorithm were developed by the applicant. The software implementation of the algorithms and the assessment platform, investigation, analysis, validation, visualization, as well as draft-writing were also performed by the applicant. Both authors contributed to the conceptualization and the second author undertook the review, editing, administration, and supervision of this work.

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Hybrid Optimization Toward Proactive Resilient Microgrid Scheduling

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ABSTRACT Microgrids are one important lever to increase power system resilience and to tightly integrate renewable energies at the same time. Commonly, an optimization-based proactive scheduling controls assets in advance in a cost-effective way and ensures that contingencies may be successfully mitigated. However, often strong simplifications are introduced to manage the high computational complexity of scheduling, which can adversely impact fault mitigation. To consider essential phenomena such as power flow limitations and low-level control capabilities in detail, a novel hybrid scheduling approach is presented that integrates mathematical programming and arbitrary nonlinear constraint models via decision trees. A detailed case study compares the new method to an extended hybrid scheduling approach from literature. It is demonstrated that hybrid optimization can efficiently solve proactive resilient scheduling problems and that the tree-based algorithm provides a feasible solution, even in case the reference algorithm fails. Details on the convergence of both algorithms give further insights into the working principles and show that the novel method quickly finds a feasible solution that is successively improved afterwards. By the novel combination of highly-developed solvers for both mathematical programming and detailed asset models it is expected that this study further supports the operation of power systems and reduces costly reserve requirements.

INDEX TERMS Energy management system, heuristic optimization, hybrid optimization, microgrid scheduling, power system resilience, proactive resilient scheduling.

NOMENCLATURE

DEDICATED INDICES AND SETS

$\mathbb{DG}$	Set of controllable Distributed Generators (DGs).
$\mathbb{LD}$	Set of volatile loads and energy sources.
$\mathbb{ST}$, $\mathbb{IG}$	Set of storage and inverter-based plants.
$\mathbb{LI}$, $\mathbb{BS}$	Set of all lines and buses .
$\mathbb{T}$, t	Set and Index of time instants.
l, a, b	Index of loads, DG, and storage units, respectively.
$\mathbb{SC}$, s	Set and index of scenarios.
$\mathbb{V}$	Set of violated constraints.

VARIABLES

$\vec{x}$	Generic vector of all model variables.
$\vec{x}^{\mathrm{C}}$	Candidate solution of the scheduling problem.
$p_{a,t}^{\mathrm{DG}}$	Active power scheduled for DG a at time t .
$o_{a,t}^{\mathrm{DG}}$	Operational status of DG a at time t .
p_t^{NDG}	Nominal power of all scheduled DGs at time t.
$p_{b,t}^{\mathrm{CHG}}$	Charged active power of storage b at time t.
$p_{b,t}^{\mathrm{DCH}}$	Discharged active power of storage b at time t.
$e_{b,t}^{\mathrm{ST}}$	Energy stored in b after time step t.
$o_{b,t}^{\mathrm{CHG}}$	Charging mode of storage b at time t.
p_t^{BUY}	Active power bought from the main grid at time t.
p_t^{SELL}	Active power sold to the main grid at time t.
o_t^{SELL}	Main grid transfer direction at time t.
c_t^{TOT}	Total operating costs at time t.
$o_{i,t}^{\mathrm{STA}}$	Startup indicator of asset i at time t.
p_t^{UP}	Scheduled up-spinning reserve at time t.
p^{MinUP}	Minimal up-spinning reserve.
o_t^{MinUP}	Minimal up-spinning reserve indicator at time t.

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o_i^{TR}	i-th auxiliary variable to encode tree constraints.
$P_{i,t,s}^v$, $Q_{i,t,s}^v$	Total active/reactive power of asset i at time t and in scenario s, having type $v \in \{\mathrm{DG}, \mathrm{ST}, \mathrm{PV}, \mathrm{WT}\}$.
$S_{i,t,s}$	Total apparent power of asset i at t in s.
$U_{i,t,s}$	Voltage at bus i at time t and scenario s .
$I_{i,t,s}$	Current in line i at time t and scenario s .
$\tilde{v}$	Normalized counterpart of variable or parameter v.

FUNCTIONS

$c(\vec{x})$	Costs of a schedule $\vec{x}$.
$\vec{g}^{\,\mathrm{l}}(\vec{x})$	Set of linear constraint functions.
$\vec{g}^{\,\mathrm{n}}(\vec{x})$	Set of nonlinear constraint functions.
$\vec{g}_h^{z,\mathbb{H}}$	Heuristically defined partition of $\vec{g}^z$.
$G^z(\vec{x})$	Constraint violation level of $\vec{g}^z$.
$P(e)$	Probability of event e.
$\mathrm{dec}(\mathcal{T})$	Root decision of subtree $\mathcal{T}$.
$\mathrm{left}(\mathcal{T})$	Active subtree of tree $\mathcal{T}$, iff $\mathrm{dec}(\mathcal{T})(\vec{x}) \leq 0$.
$\mathrm{right}(\mathcal{T})$	Active subtree of tree $\mathcal{T}$, iff $\mathrm{dec}(\mathcal{T})(\vec{x}) \gtrsim 0$.

PARAMETERS AND CONSTANTS

$\bar{v}$, $\underline{v}$	Upper and lower limit of variable v.
ΔT	Duration of a single scheduling interval.
$p_{l,t}^{\mathrm{LD}}$	Expected active power demand of generalized load l at time t.
$o_{b,-1}^{\mathrm{CHG}}$	Initial charging mode of storage b.
μ_b^{ST}	Average round-trip efficiency of storage b.
$e_{b,-1}^{\mathrm{ST}}$	Initial energy in storage b.
$e_{b,\lvert\mathbb{T}\rvert}^{\mathrm{ST}}$	Energy in storage b at the end of the time horizon.
$o_{a,-1}^{\mathrm{DG}}$	Initial operational status of DG a.
c_a^{DG}	Cost of producing one unit of energy in DG a.
c_t^{BUY}	Cost of buying one unit of energy at time t.
c_t^{SELL}	Cost of selling one unit of energy at time t.
$p_{a,t}^{\mathrm{OP}}$	Forced operating point of asset i at time t.
n_i^{STA}	Number of permitted starts on asset i.
K_a^v	Droop gain or function of asset a and type v.
M	A suffcently large big-M constant.
ϵ	A small but strictly positive constant.

I. INTRODUCTION

Microgrids are considered as one solution to increase power system resilience, to tightly integrate volatile Renewable Energy Sources (RES) and to fully leverage the economic potential of Distributed Energy Resources (DERs) [1]. Although there are other definitions as well, this work follows [2] and considers microgrids as tightly controlled electrical networks that can be operated in both grid-connected and islanded mode. Due to the great flexibility that is provided by many microgrids, considerable potential is given for a scheduling algorithm to optimize the operation [3]. Resilient scheduling in emergency mode, for instance, often reduces the impact of a contingency without primarily targeting operating costs. In contrast, proactive resilient scheduling algorithms minimize the normal operation cost while no failure is observed, but at the same time, they prepare the network to gracefully degrade in case of contingencies. According to related work, resilience is considered as the ability to reduce the impact of potentially harmful events and includes both a fully robust but also a gracefully degraded operation [4].

A detailed review of proactive scheduling approaches is published in [4] noting that, although every algorithm follows an optimization-based methodology, a broad variety of solution approaches is observed. Common scheduling techniques include mathematical methods (like Mixed Integer Linear Programming (MILP) formulations) that can be solved by generic software components and heuristic approaches such as genetic algorithms [5]. As demonstrated in this work, the broad variety of approaches directly relates to the high computational complexity of microgrid scheduling that leaves room for various specialized methods including heuristics.

Since control and scheduling decisions can have a considerable impact on the safe operation of a microgrid [6], some authors included physical constraints such as voltage limits in their scheduling formulations. Due to the inherently nonconvex nature of physical power flows, mostly linearization is used to fit the MILP or heuristic optimization techniques to solve the nonlinear mixed-integer problem [4]. The former technique can suffer from linearization errors causing overapproximation or reduced confidence in the eligibility of results while the latter approach cannot fully utilize the potential of highly-developed solvers for mathematical programming problems. However, literature sparsely indicates under which circumstances one merit outweighs the other.

Most work formulates the proactive scheduling problem as one monolithic set of equations without discussing external implementations of asset models in detail [4], [7]. For instance, in [8], a linearized version of the power flow equations is directly integrated into the scheduling model. Several studies including [9] using Benders decomposition, are partitioning the models into subproblems to efficiently solve them. Although the monolithic formulation and its decomposition gives full access to details such as derivatives, engineering efforts of formulating system constraints can be considerably eased by relying on well-proven and accepted external simulation models [10], [11].

In [10], a security-constrained optimal dispatch approach is presented that uses a heuristic multi-objective optimization technique. An external power system simulator and normalized constraint violation levels are used to filter infeasible candidate solutions. In addition to static voltage and current margins, which are also reflected in related works, [10] includes transient voltage and frequency stability constraints.

However, the problem formulation is restricted to unit commitment without considering the operational status of DER.

A manual decomposition into an outer multi-objective problem that manages storage schedules and inner optimizations scheduling the other resources, both in normal and emergency operation, is presented in [12]. The nested MILP problems consider power flows by iteratively updating a power loss constant, in case the power flow does not indicate any physical constraint violation. In case a violation is encountered, the whole subproblem including its linear equations is solved by an optimal power flow solver. Despite using the external power flow optimization, less emphasis is put on the complexity of handling nonlinear constraints as most schedules are assumed to be feasible.

Also [11] described the integration of an external power system simulator to enforce voltage and current constraints in resilient scheduling. In contrast to [10], a quadratic-programming formulation with linear constraints is extended by constraints derived from a sensitivity analysis on the grid model. Both, the iterative scheme as well as the structure of added constraints can also be found in Benders decomposition as applied in [9]. However, [9] uses (integer) linear programs that cannot handle the nonlinear power flows in [11], and both approaches differ in their constraint generation.

Given the interaction of mathematical programming and the constraint enforcement heuristic, [11] successfully demonstrates the application of a hybrid optimization approach, i.e., a combination of diverse algorithmic components [13], in resilient microgrid scheduling. Still, the external constraints were only applied in a single time interval of the multi-period optimization problem. Questions regarding applicability in multi-period constraints and approximation errors remain open. Despite the detailed power system models, the effects of low-level controls such as voltage and frequency droop on the feasibility of a particular candidate schedule are hardly covered [10], [11].

A. CONTRIBUTIONS TO MICROGRID SCHEDULING

This work studies the application of external constraint models in proactive, resilient microgrid scheduling and proposes a novel hybrid optimization method to solve MILP models with external, nonlinear constraints. A common MILP basis formulation for microgrid scheduling in conjunction with external nonlinear constraints is developed. Based on the common formulation, two scheduling approaches are presented. The first one addresses the state-of-the-art by extending the sensitivity-based constraint learning technique of [11] to multi-period resilience constraints. The second one explores novel paths in hybrid scheduling by utilizing machine learning techniques to approximate the constraint surface within the MILP. To the best of our knowledge, an adapted version of the constraint synthesis technique in [14] for the first time iteratively links a stochastic local search and the global MILP scheduling problem.

A case-study is used to thoughtfully evaluate and compare both approaches on common ground. In contrast to related work, the case study demonstrates both the application of external grid models to formulate constraints and the influence of low-level controls on the feasibility of schedules. Further insights into the effects of problem formulation and decomposition are presented. Following the unavailability of a universal optimization strategy [15], several cases in which the sensitivity-based approach fails to deliver good or even any feasible solutions could be identified. At the same time it is demonstrated that due to the more powerful approximation model, the novel scheduling approach can deliver excellent results, even if the sensitivity-based one fails.

B. ORGANIZATION

This work is organized as follows. In Section II, the problem of proactive, resilient microgrid scheduling is described and the formulation of the subsequent study is developed. Section III utilizes the problem definition to define two methods of solving the scheduling task including external resilience constraints. A case study in Section IV compares the approaches and studies their performance under several problem variations. In Section V, results are discussed and finally, Section VI concludes the findings.

II. RESILIENT SCHEDULING PROBLEM FORMULATION

In this study, it is assumed that a proactive, resilient scheduling algorithm centrally computes the set points of all controllable assets based on the current operational status and the most recent forecasts. In contrast to the related work that presents a broad variety of different assets including Electric Vehicles (EVs), micro turbines, and controllable loads [9], [16], [17], this work focuses on the most generic assets in order to facilitate performance analysis and comparability. It is assumed that the microgrid hosts exactly two types of schedulable assets. The first one groups generic DERs that can be independently scheduled for each time interval. The second one comprises Electrical Energy Storages (EESs) that do have an internal state of charges that depends on previous scheduling decisions. Furthermore, it is assumed that the microgrid includes volatile RES, which are providing basic voltage control capabilities. However, the active power output and demand of volatile RES and loads, respectively, are assumed to show a stochastic behavior. For each stochastic quantity, it is assumed that appropriate deterministic forecasts are available, but that the realizations are unknown at scheduling time.

Each scheduling run optimizes the asset set points over a finite time horizon. Although some authors presented an iterative scheme that repeats a scheduling operation and only applies the most recent set points [11], this performance analysis avoids any bias due to erroneously correlated updates. Hence, it focuses on one single scheduling run without taking update mechanisms into account, but it does not prevent the application in an updating scheme. The proactive algorithm itself is executed before any contingency is encountered [18]. However, in the presence of general security policies or early warning signs, the microgrid is actively prepared to sustain

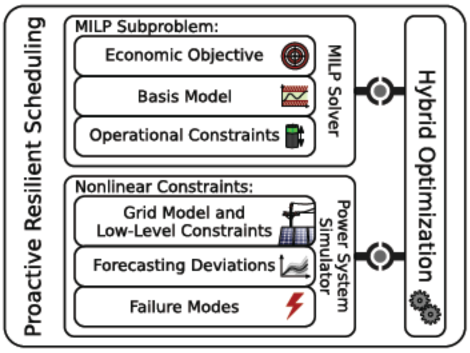

FIGURE 1. **Decomposition of the proactive resilient scheduling problem into individual linear and nonlinear models.**

catastrophic events and to increase power system resilience. In contrast to robustness, resilience permits a degraded operation, for instance by shedding noncritical loads, in case of contingencies. Following the definition of [18], power system resilience may even be addressed in case the scheduling algorithm manages to avoid any degraded state at all. Since scheduling is executed in the preparation phase, it is assumed that the microgrid is connected to a healthy main grid and that any countermeasures such as islanding the microgrids or parts thereof are conducted by separate emergency mechanisms. Yet, the scheduling algorithm can influence the performance of countermeasures for instance, by reserve commitment and relocation [17].

Fig. 1 gives an overview of the scheduling problem including the individual models and highlights the role of hybrid optimization techniques to solve them. To generalize the optimization procedures, the whole problem is firstly generically modeled in Section II-A and later refined by the detailed model in Sections II-B to II-D. Economic aspects are covered by a single-node MILP formulation and first resilience aspects are included by the deterministic reserve constraints in Section II-C. In more detail, a resilient operation is covered by the grid simulation scenarios in Section II-D that include detailed effects of failure modes (e.g., line outages) and mitigation techniques such as partial islanding.

A. GENERALIZED PROACTIVE SCHEDULING

In order to efficiently solve the problem of finding an optimal schedule $\vec{x}$, a decomposition into an objective function $c(\vec{x})$, as well as a set of linear constraints $\vec{g}^{\,\mathrm{l}}(\vec{x})$ and one of nonlinear constraints $\vec{g}^{\,\mathrm{n}}(\vec{x})$ is applied. The entire scheduling problem is defined as finding a schedule $\vec{x}$ that minimizes $c(\vec{x})$ such that both (1) and (2) are satisfied.

$$g_i^{\mathrm{l}}(\vec{x}) \le 0 \quad \forall i = 1, \ldots, |\vec{g}^{\,\mathrm{l}}| \tag{1}$$

$$g_i^{\mathrm{n}}(\vec{x}) \le 0 \quad \forall i = 1, \ldots, |\vec{g}^{\,\mathrm{n}}| \tag{2}$$

A shorthand notation $\vec{g}^{\,\mathrm{ln}}$ is used to address all constraints $\vec{g}^{\,\mathrm{ln}} = \vec{g}^{\,\mathrm{l}} \cup \vec{g}^{\,\mathrm{n}}$ at once. Note that, according to common practice, equality constraints are transformed into inequality constraints, without loss of generality [19]. The objective function $c(\vec{x})$ must be in a form such that the subproblem of minimizing $c(\vec{x})$ considering constraints (1) can be efficiently solved by mathematical programming. In particular, the study focuses on MILP subproblems.

All constraints that should be included in full detail are subsumed by the nonlinear functions $\vec{g}^{\,\mathrm{n}}(\vec{x})$. Typical representatives include voltage and current constraints considering the effects of low-level controls on the actual asset set points. Due to the decomposition, $\vec{g}^{\,\mathrm{n}}(\vec{x})$ can be computed via external power system simulations and does not have to be present in closed form. In practice, evaluating the nonlinear constraint can even involve external solvers, e.g., to compute power flows. Consequently, it is assumed that the function evaluation $\vec{g}^{\,\mathrm{n}}(\vec{x})$ is computationally intensive and should not be excessively triggered by a heuristic algorithm. Decomposition of a scheduling problem, as it is implicitly presented in related work such as [11], involves decisions on either using a simplified version or including the full complexity of the physical model. Due to the effort of evaluating and coupling $\vec{g}^{\,\mathrm{n}}(\vec{x})$, the coexistence of simplified versions in $\vec{g}^{\,\mathrm{l}}(\vec{x})$ as well as detailed counterparts in $\vec{g}^{\,\mathrm{n}}(\vec{x})$ can further improve the scheduling performance.

B. MILP BASIS FORMULATION

To facilitate a detailed analysis of the scheduling algorithm, a simple MILP formulation based on a deterministic power-balance model and insights listed in review [20] is developed. In practice, stochastic or robust formulations such as [12] and [8] may be included to account for the inherent uncertainties in microgrid scheduling. However, a detailed analysis of such models is well beyond the scope of this work. The state of each Distributed Generator (DG) unit $a \in \mathbb{D}\mathrm{G}$ at time $t \in \mathbb{T}$ is modeled by two variables, the operation status $o_{a,t}^{\mathrm{DG}} \in \mathbb{B}$ and the scheduled power output $p_{a,t}^{\mathrm{DG}} \in \mathbb{R}$. The operating range of each machine is directly constrained by (3).

$$\underline{p}_a^{\mathrm{DG}} \cdot o_{a,t}^{\mathrm{DG}} \le p_{a,t}^{\mathrm{DG}} \le \bar{p}_a^{\mathrm{DG}} \cdot o_{a,t}^{\mathrm{DG}} \quad \forall a \in \mathbb{D}\mathrm{G}, t \in \mathbb{T} \tag{3}$$

Similarly, each EES unit $b \in \mathbb{S}\mathrm{T}$ is modeled by an operating mode $o_{b,t}^{\mathrm{CHG}} \in \mathbb{B}$ indicating whether b is allowed to charge, as well as the charging and discharging power $p_{b,t}^{\mathrm{CHG}}, p_{b,t}^{\mathrm{DCH}} \in \mathbb{R}$, respectively. Additionally, the usable energy that is stored in b after the scheduling interval t, i.e., right before $t+1$, is modeled by $e_{b,t}^{\mathrm{ST}}$. A constant round-trip efficiency μ_b^{ST} is applied while charging and models all internal losses. Equations (4) to (6) model the corresponding constraints.

$$0 \le p_{b,t}^{\mathrm{CHG}} \le \bar{p}_b^{\mathrm{CHG}} \cdot o_{b,t}^{\mathrm{CHG}} \quad \forall b \in \mathbb{S}\mathrm{T}, t \in \mathbb{T} \tag{4}$$

$$0 \le p_{b,t}^{\mathrm{DCH}} \le \bar{p}_b^{\mathrm{DCH}} \cdot \left(1 - o_{b,t}^{\mathrm{CHG}}\right) \quad \forall b \in \mathbb{S}\mathrm{T}, t \in \mathbb{T} \tag{5}$$

$$e_{b,t}^{\mathrm{ST}} = e_{b,t-1}^{\mathrm{ST}} + \left(p_{b,t}^{\mathrm{CHG}} \cdot \mu_b^{\mathrm{ST}} - p_{b,t}^{\mathrm{DCH}}\right) \cdot \Delta T \quad \forall b \in \mathbb{S}\mathrm{T}, t \in \mathbb{T} \tag{6}$$

Although the approach does not exclude multiple Points of Common Coupling (PCCs), it is assumed that all PCCs access a single market and that power flows in the simplified MILP formulation are bound by total transfer capabilities. To model different prices for buying and selling energy, the power transfer from or to the main grid is split into two variables, $p_t^{\mathrm{BUY}} \in \mathbb{R}$ and $p_t^{\mathrm{SELL}} \in \mathbb{R}$, respectively. The directional indicator variable $o_t^{\mathrm{SELL}} \in \mathbb{B}$, as well as constraints (7) and (8) ensure mutual exclusiveness.

$$0 \leq p_t^{\mathrm{BUY}} \leq \bar{p}^{\,\mathrm{BUY}} \cdot \left(1 - o_t^{\mathrm{SELL}}\right) \quad \forall t \in \mathbb{T} \tag{7}$$

$$0 \leq p_t^{\mathrm{SELL}} \leq \bar{p}^{\,\mathrm{SELL}} \cdot o_t^{\mathrm{SELL}} \quad \forall t \in \mathbb{T} \tag{8}$$

The economic evaluation of a schedule follows a deterministic single-node power balance (9) scheme without considering losses.

$$\sum_{a \in \mathbb{D}\mathrm{G}} p_{a,t}^{\mathrm{DG}} - \sum_{l \in \mathbb{L}\mathrm{D}} p_{l,t}^{\mathrm{LD}} + p_t^{\mathrm{BUY}} - p_t^{\mathrm{SELL}} + \sum_{b \in \mathbb{S}\mathrm{T}} \left(p_{b,t}^{\mathrm{DCH}} - p_{b,t}^{\mathrm{CHG}}\right) = 0 \quad \forall t \in \mathbb{T} \tag{9}$$

Variable day-ahead market prices c_t^{BUY} and c_t^{SELL} that are known at scheduling time, as well as the average production costs c_a^{DG} of each DG a determine the operation expenses c_t^{TOT} at each time instant t. Equations (10) and (11) define the cost function $c(\vec{x})$ of a schedule $\vec{x}$. Constraints (3) to (9) describe the base set of linear constraints $\vec{g}^{\,1}(\vec{x})$.

$$c_t^{\mathrm{TOT}} = c_t^{\mathrm{BUY}} \cdot p_t^{\mathrm{BUY}} - c_t^{\mathrm{SELL}} \cdot p_t^{\mathrm{SELL}} + \sum_{a \in \mathbb{D}\mathrm{G}} c_a^{\mathrm{DG}} \cdot p_{a,t}^{\mathrm{DG}} \quad \forall t \in \mathbb{T} \tag{10}$$

$$c(\vec{x}) = \sum_{t \in \mathbb{T}} c_t^{\mathrm{TOT}} \tag{11}$$

C. EXTENDED MILP FORMULATION

Starting from the scheduling basis formulation that focuses on the most basic model, a set of optional constraints is developed to study the impact of model complexity on the performance of heuristic approaches. The first set of constraints limits the operating region of specific assets to incorporate needs that do not directly follow from technical asset limits. Practical applications of these additional operating limits $\bar{p}_{a,t}^{\mathrm{OP}}$ and $\underline{p}_{a,t}^{\mathrm{OP}}$ include thermal demand of a Combined Heat and Power (CHP) plant and local reserve policies. Although the operation constraints are defined on a subset $\mathbb{X}$ of assets and time, $\mathbb{X} \subseteq \mathbb{D}\mathrm{G} \times \mathbb{T}$, (12) does not model any interdependence between assets a and time instants t.

$$\underline{p}_{a,t}^{\mathrm{OP}} \leq p_{a,t}^{\mathrm{DG}} \leq \bar{p}_{a,t}^{\mathrm{OP}} \quad \forall a, t \in \mathbb{X} \subseteq \mathbb{D}\mathrm{G} \times \mathbb{T} \tag{12}$$

A set of dynamic constraints that link variables among instants of time is introduced by restricting the number of startup and charging operations to avoid excessive wear out. Similarly, a minimum number of startups may force an asset into operation. For both, DG and storage units, the auxiliary variable $o_{i,t}^{\mathrm{STA}} \in \mathbb{B}$ indicates whether asset i activated its operation mode at time instant t. Given the indicator constraints (13) and (14), the number of startup operations can be restricted by (15).

$$o_{a,t}^{\mathrm{DG}} - o_{a,t-1}^{\mathrm{DG}} \leq o_{a,t}^{\mathrm{STA}} \leq \frac{1}{2}\left(1 + o_{a,t}^{\mathrm{DG}} - o_{a,t-1}^{\mathrm{DG}}\right) \quad \forall a \in \mathbb{D}\mathrm{G}, t \in \mathbb{T} \tag{13}$$

$$o_{b,t}^{\mathrm{CHG}} - o_{b,t-1}^{\mathrm{CHG}} \leq o_{b,t}^{\mathrm{STA}} \leq \frac{1}{2}\left(1 + o_{b,t}^{\mathrm{CHG}} - o_{b,t-1}^{\mathrm{CHG}}\right) \quad \forall b \in \mathbb{S}\mathrm{T}, t \in \mathbb{T} \tag{14}$$

$$\underline{n}_i^{\mathrm{STA}} \leq \sum_{t \in \mathbb{T}} o_{i,t}^{\mathrm{STA}} \leq \bar{n}_i^{\mathrm{STA}} \quad \forall i \in \mathbb{D}\mathrm{G} \cup \mathbb{S}\mathrm{T} \tag{15}$$

A linear reserve model is introduced to ensure that critical loads $\mathbb{L} \subset \mathbb{L}\mathrm{D}$ can be supplied in case of main grid failures. To simplify the discussion, it is assumed that storage units are grid following devices that are only used for energy arbitrage. The reserve model itself consists of three metrics, the nominal power of all DGs in the primary reserve, $p_t^{\mathrm{NDG}} \in \mathbb{R}$, the up-spinning reserve $p_t^{\mathrm{UP}} \in \mathbb{R}$ at time t, and the minimum up-spinning reserve in the entire scheduling horizon $p^{\mathrm{MinUP}} \in \mathbb{R}$. The modeled metrics can be used to manually enforce sufficiency or to link external models as shown in Section III. To study the latter use-case, a verbose formulation that does not use a relaxed lower-bound of p^{MinUP} was chosen. Constraints (16) to (18) consequently model the basic primary reserve requirements.

$$p_t^{\mathrm{NDG}} = \sum_{a \in \mathbb{D}\mathrm{G}} \bar{p}_a^{\,\mathrm{DG}} \cdot o_{a,t}^{\mathrm{DG}} \quad \forall t \in \mathbb{T} \tag{16}$$

$$p_t^{\mathrm{UP}} = p_t^{\mathrm{NDG}} - \sum_{l \in \mathbb{L}\mathrm{D}} p_{l,t}^{\mathrm{LD}} + \sum_{b \in \mathbb{S}\mathrm{T}} \left(p_{b,t}^{\mathrm{DCH}} - p_{b,t}^{\mathrm{CHG}}\right) \quad \forall t \in \mathbb{T} \tag{17}$$

$$\underline{p}_t^{\mathrm{UP}} \leq p_t^{\mathrm{UP}} \leq \bar{p}_t^{\mathrm{UP}} \quad \forall t \in \mathbb{T} \tag{18}$$

To model the minimum spinning reserve on the scheduling horizon, a set of binary auxiliary variables $o_t^{\mathrm{MinUP}} \in \mathbb{B}$ are indicating whether the minimum reserve is reached at time t and constraints (19) to (21) are introduced.

$$p^{\mathrm{MinUP}} \leq p_t^{\mathrm{UP}} \quad \forall t \in \mathbb{T} \tag{19}$$

$$p_t^{\mathrm{UP}} - p^{\mathrm{MinUP}} \leq M \cdot \left(1 - o_t^{\mathrm{MinUP}}\right) \quad \forall t \in \mathbb{T} \tag{20}$$

$$\sum_{t \in \mathbb{T}} o_t^{\mathrm{MinUP}} = 1 \tag{21}$$

Constant M needs to be chosen such that it exceeds any left-hand-side value of (20). Note that the nonlinear constraints may imply the MILP reserve formulation and therefore (13) to (21) are also used to study the effects of redundancies.

D. GRID MODEL AND LOW-LEVEL CONTROLS

In contrast to other publications such as [8] that presented a linearized form of the static power flow equations, it is assumed that the grid model is covered by the nonlinear constraint set $\vec{g}^{\,n}$ in detail. As long as the constraint function is computable, the algorithms do not require any specific model structure and may include balanced and unbalanced steady-state models to assess asset loading and voltage limits, as well as transient models to ensure a stable operation in case of failures [10]. However, to support a detailed performance analysis, grid constraints based on a series of static power flows are derived. Due to inherent uncertainties, it is assumed that the grid constraints extend the deterministic formulation of the linear subproblem by considering forecasting deviations and failure conditions via a set of scenarios $\mathbb{S}\mathrm{c}$. Methods to find a few representative scenarios such as [21], are, however, beyond the scope of this work and manually selected boundary-cases are added.

For each scenario $s \in \mathbb{S}\mathrm{c}$ and each time step t, the balanced AC power flow equations are solved by a Newton-Raphson algorithm as described in [22]. In addition to the scheduled active power $p^{\mathrm{DG}}_{a,t}$ of each asset a, it is assumed that each active unit a on island c participates in frequency control and provides steady-state balancing power according to its droop gain K^{f}_a and the frequency deviation $\Delta f_{c,t,s}$. Note that $\Delta f_{c,t,s}$ is set such that the active power on each island c is balanced [22]. The reactive power $Q^{\mathrm{DG}}_{a,t,s}$ of each generator is determined based on a piece-wise linear droop curve $K^{\mathrm{u}}_a(U_{a,t,s})$, where $U_{a,t,s}$ is the voltage at the bus connecting asset a [23]. Equations (22) and (23) summarize the injected power for each DG.

$$P^{\mathrm{DG}}_{a,t,s} = p^{\mathrm{DG}}_{a,t} + o^{\mathrm{DG}}_{a,t} \cdot K^{\mathrm{f}}_a \cdot \Delta f_{c,t,s} \quad \forall a \in \mathbb{D}\mathrm{G} \tag{22}$$

$$Q^{\mathrm{DG}}_{a,t,s} = o^{\mathrm{DG}}_{a,t} \cdot K^{\mathrm{u}}_a(U_{a,t,s}) \quad \forall a \in \mathbb{D}\mathrm{G} \tag{23}$$

In contrast to DGs that participate in both primary frequency and voltage control, it is assumed that all inverter-based DERs $\mathbb{I}\mathrm{G}$ as given in (24) limit voltage control if the nominal apparent power $\bar{S}^{\mathrm{IG}}_l$ is exceeded.

$$Q^{\mathrm{IG}}_{l,t,s} = \begin{cases} K^{\mathrm{u}}_l(U_{l,t,s}) & S_{l,t,s} \leq \bar{S}^{\mathrm{IG}}_l \\ \bar{Q}^{\mathrm{IG}}_{l,t,s} & \text{otherwise} \end{cases} \quad \forall l \in \mathbb{I}\mathrm{G} \tag{24}$$

Given the results of the AC power flow, including the currents in each line i, $I_{i,t,s}$, the apparent power $S_{a,t,s}$ of all assets a, and the voltage magnitude $U_{j,t,s}$ of all buses j, the set of constraints $\vec{g}^{\,\mathrm{n}}$ can be summarized as (25).

$$\vec{g}^{\,\mathrm{n}} = \begin{pmatrix} I_{i,t,s} - \bar{I}_i & i \in \mathbb{L}\mathrm{I},\, t \in \mathbb{T},\, s \in \mathbb{S}\mathrm{c} \\ S_{a,t,s} - \bar{S}_a & a \in \mathbb{I}\mathrm{G} \cup \mathbb{D}\mathrm{G},\, t \in \mathbb{T},\, s \in \mathbb{S}\mathrm{c} \\ U_{j,t,s} - \bar{U}_j & j \in \mathbb{B}\mathrm{s},\, t \in \mathbb{T},\, s \in \mathbb{S}\mathrm{c} \\ \underline{U}_j - U_{j,t,s} & j \in \mathbb{B}\mathrm{s},\, t \in \mathbb{T},\, s \in \mathbb{S}\mathrm{c} \end{pmatrix} \tag{25}$$

To increase the expressiveness of the constraint model and to guide a heuristic procedure, the constraints z can be divided into several partitions, $\vec{g}^{\,z,\mathbb{H}}_h$, $h \in \mathbb{H} \cup \{\emptyset\}$, $z \in \{\mathrm{l}, \mathrm{n}, \mathrm{ln}\}$ of $\vec{g}^{\,z}$, to express the heuristic dependence on values of $\mathbb{H}$. For instance, $\vec{g}^{\,\mathrm{n},\mathbb{T}}_t$ groups all nonlinear constraints that strongly depend on the state at time instant t or do not show any such heuristically defined dependency ($t = \emptyset$). Without loss of generality, the external constraints do not expose internal model variables such as voltage levels and phase angles, that need to be solved by the optimization procedure. Instead, nested solvers can be used to efficiently determine the solution of the constraint model.

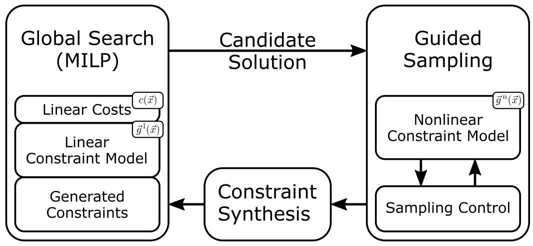

FIGURE 2. Component interaction of the hybrid optimization scheme.

III. SCHEDULING SOLVING METHODS

A first intuition on the complexity of solving microgrid scheduling is given in Appendix A, showing that the problem is at least weakly NP-hard, by providing a polonomial time reduction from the Knapsack problem to scheduling. Although several algorithms are available that solve practical instances of Knapsack [24], the reduction demonstrates that in particular the integer states of DG units raise the computational complexity. Additionally, the nonlinear constraints $\vec{g}^{\,\mathrm{n}}(\vec{x})$ may encode arbitrary decision problems that further rise the computational complexity. Hence, complexity must be considered to keep practical instances computationally tractable, for example by using heuristics that approximate an exact solution and by efficiently using highly-developed tools such as MILP and power-flow solvers.

The main idea of the problem decomposition presented in Section II-A is to separate those models that can be efficiently handled by existing MILP solvers, i.e., $c(\vec{x})$ and $\vec{g}^{\,\mathrm{l}}(\vec{x})$, from those that need to be linearized first. Instead of requiring a differentiable closed form representation of $\vec{g}^{\,\mathrm{n}}$, the heuristic approach samples the nonlinear constraint function near the linear optimum and iteratively extends $\vec{g}^{\,\mathrm{l}}$ by a local approximation. Due to the complexity of evaluating $\vec{g}^{\,\mathrm{n}}$, samples must be drawn efficiently to generate the MILP constraints. Fig. 2 illustrates the heuristic optimization scheme.

One may note that the MILP scheduling formulation contains several variables such as $p^{\mathrm{CHG}}_{b,t}$, $p^{\mathrm{DCH}}_{b,t}$, and $o^{\mathrm{CHG}}_{b,t}$ that show a strong interdependence. To reduce the number of variables when sampling, a normalized representation is introduced. Each schedule is thereby represented by the DG status $o^{\mathrm{DG}}_{a,t}$, as well as the normalized power output $\tilde{p}^{\mathrm{DG}}_{a,t}$, and storage level $\tilde{e}^{\mathrm{ST}}_{b,t}$ as defined by (26) and (27), respectively.

$$\tilde{p}^{\mathrm{DG}}_{a,t} = \frac{p^{\mathrm{DG}}_{a,t} - \underline{p}^{\mathrm{DG}}_a}{\bar{p}^{\mathrm{DG}}_a - \underline{p}^{\mathrm{DG}}_a} \quad \forall a \in \mathbb{D}\mathrm{G},\, t \in \mathbb{T} \tag{26}$$

$$\tilde{e}^{\mathrm{ST}}_{b,t} = \frac{e^{\mathrm{ST}}_{b,t} - \underline{e}^{\mathrm{ST}}_b}{\bar{e}^{\mathrm{ST}}_b - \underline{e}^{\mathrm{ST}}_a} \quad \forall b \in \mathbb{S}\mathrm{T},\, t \in \mathbb{T} \tag{27}$$

To simulate a schedule and to synthesize constraints, the original MILP variables are obtained by clipping invalid values (e.g., $\tilde{p}^{\mathrm{DG}}_{a,t} \gneq 0$ in case $o^{\mathrm{DG}}_{a,t} = 0$) to the operation ranges implied by (3), (4), and (5). Note that the repair heuristic and the normalization step eliminate some, but not all infeasible configurations, for instance in case the extended reserve requirements (16) to (18) are enabled.

A. SENSITIVITY CONSTRAINT SYNTHESIS

The sensitivity-based method repeatedly extends the MILP model by local approximations of the nonlinear constraints until either the candidate solution of the MILP model does not show constraint violations anymore or the MILP model becomes infeasible. If the latter applies, no schedule can be generated. Since the constraint synthesis approach presented in [11] addresses a single time interval only, nonlinear constraints $\vec{g}^{\,\mathrm{n}}(\vec{x})$ that cover multiple intervals cannot be directly integrated into the online optimization of the multi-stage scheduling method. Therefore, the input vector is extended to the entire scheduling horizon and the sensitivity-based synthesis is directly integrated into the scheduling problem at once. Furthermore, the approach in [11] is limited to voltage and current limits. This work generalizes the methodology to arbitrary constraints.

In case the candidate solution $\vec{x}^{\,\mathrm{C}}$ of the linear subproblem turns out to be infeasible and $\mathbb{V}$ is the set of violated nonlinear constraints, the set of MILP constraints (28) is added.

$$g_i^{\mathrm{n}}(\vec{x}^{\,\mathrm{C}}) + \frac{\partial g_i^{\mathrm{n}}}{\partial \vec{x}}(\vec{x}^{\,\mathrm{C}}) \cdot (\vec{x} - \vec{x}^{\,\mathrm{C}}) + \epsilon \leq 0 \quad \forall i \in \mathbb{V} \qquad (28)$$

To feature convergence even if $\vec{g}^{\,\mathrm{n}}(\vec{x})$ or its partial derivatives are affected by numerical inaccuracies, a strictly positive constant ϵ is introduced that strengthens the permitted region. According to [11], $\frac{\partial \vec{g}^{\,\mathrm{n}}}{\partial \vec{x}}$ is numerically approximated in case the Jacobean is not directly available. For each scheduling variable $\tilde{x}_i$, the sampling control block introduces a small perturbation ρ on that variable and samples $\vec{g}^{\,\mathrm{n}}(\tilde{x}_1, \ldots, \tilde{x}_{i-1}, \tilde{x}_i + \rho, \tilde{x}_{i+1}, \ldots, \tilde{x}_{|\vec{g}^{\,\mathrm{n}}|})$ anew. For discrete variables, a state change is enforced.

To contain the number of samples and to reduce numerical errors, two sampling heuristics are introduced. The first one skips the perturbation of $\tilde{p}_{a,t}^{\mathrm{DG}}$ in case the DG is not operational, i.e., $o_{b,t}^{\mathrm{CHG}} = 0$ and no effect is expected. The second heuristic uses the partitioning $\vec{g}_t^{\,\mathrm{n},\mathbb{T}}$ with respect to scheduling time t to skip those variables that most likely do not influence the outcome of failing constraints. Scheduling variables at a time instant t are considered if and only if $\vec{g}_t^{\,\mathrm{n},\mathbb{T}} \cap \left\{ g_i^{\mathrm{n}} | i \in \mathbb{V} \right\} \neq \emptyset$ or $\vec{g}_{\emptyset}^{\,\mathrm{n},\mathbb{T}} \cap \left\{ g_i^{\mathrm{n}} | i \in \mathbb{V} \right\} \neq \emptyset$.

After sampling the neighborhood of $\vec{x}^{\,\mathrm{C}}$, the constraint synthesis routine approximates (28) via the observed changes in the output metric. Note that following [11], constraints from previous iterations are never revoked and that the local approximation of $\vec{g}^{\,\mathrm{n}}(\vec{x})$ is not restricted to any particular neighborhood. Hence, considerable overapproximation may be observed, in case the adjusted schedule largely deviates from the candidate solution.

B. TREE-BASED CONSTRAINT APPROXIMATION

An alternative model to approximate $\vec{g}^{\,\mathrm{n}}(\vec{x})$ as MILP problem is to encode the decisions implied by (2) as decision trees. Instead of enforcing local approximations (28) globally, a divide-and-conquer approach is implemented that recursively splits the set of schedules [25]. The tree structure which can model even nonconvex sets is then transformed into a MILP representation by adding new binary variables [14]. The tree-based method uses two mechanisms to find feasible solutions of the scheduling problem. First, a global MILP search that includes an approximation of $\vec{g}^{\,\mathrm{n}}(\vec{x})$ is used to find initial solutions. Secondly, a stochastic local search is used to sample $\vec{g}^{\,\mathrm{n}}(\vec{x})$ near the candidate solution and improve it even further. Considering all known samples, a new approximation of the nonlinear constraint function is generated in each global iteration and replaces previous approximations in the MILP. Due to the replacement, subsequent global iterations can further improve the operating costs. In the following evaluations, two global termination criteria, a static number of maximum iterations and a threshold on the improvement rate are applied.

A single decision tree $\mathcal{T}_i$ consists of a series of splits that recursively divide the solution space into feasible and infeasible regions [14]. Each binary split on the subtree $\mathcal{T}_j$ is based on a decision $\mathrm{dec}(\mathcal{T}_j)$ that involves a subset of the scheduling variables $\vec{x}$. In order to transform the tree into MILP form, each split must follow the linear form $\mathrm{dec}(\mathcal{T}_j)(\vec{x}) = \vec{w}^{\mathrm{T}} \cdot \vec{x} + w_0 \leq 0$, where $\vec{w}$ and w_0 are constant weights. To simplify the training procedure that generates $\mathcal{T}_i$, the linear form can be further restricted to decisions that only involve a single scheduling variable at once.

Each individual nonlinear objective g_i^{n} may be directly approximated by a single decision tree $\mathcal{T}_i$. Similar to each constraint that is added in (28), each tree introduces an overhead in terms of additional constraints and possibly some auxiliary variables. To reduce the size of the MILP problem and the amount of redundant constraints, the heuristic partitioning scheme $\mathbb{H}$ is used to consolidate nonlinear constraints that are likely to share dependencies. For each partition $\vec{g}_h^{\,\mathrm{n},\mathbb{H}}$, $h \in \mathbb{H}$, a decision tree $\mathcal{T}_h$ is grown that approximates the conjunction of each constraint in $\vec{g}_h^{\,\mathrm{n},\mathbb{H}}$. Clearly, the conjunction of all classification results in the forest $\mathcal{T}_h, h \in \mathbb{H}$ approximates the entire set of nonlinear constraints (2).

Similar to approximation of $\frac{\partial \vec{g}^{\,\mathrm{n}}}{\partial \vec{x}}$, a sampling-based approach is proposed to grow the decision trees $\mathcal{T}_i$ without requiring insights into $\vec{g}^{\,\mathrm{n}}(\vec{x})$. The sampling control logic now directly addresses the decision boundary of $\vec{g}^{\,\mathrm{n}}(\vec{x})$ near the candidate solution $\vec{x}^{\,\mathrm{C}}$ instead of approximating the Jacobean at $\vec{x}^{\,\mathrm{C}}$ and deducing the decision boundary in a subsequent step. Given all samples, a classification tree algorithm such as C4.5 and CART is deployed to fit the corresponding trees [25]. Note that in case the hybrid optimization algorithm includes linear, multivariate splits, the corresponding learning method must support that model as well. To ease analysis and reduce the complexity of generated splits, this work uses a CART-based algorithm as implemented in [26] that does not include multivariate splits. The training algorithm itself recursively divides the set of samples into two partitions such that the impurity considering feasible and infeasible members is minimized according to the Gini index [25].

The accuracy, size and complexity of generated trees largely depends on the input features they are trained on. For instance, a constraint on the total up-spinning reserve, p_t^{UP} may either directly access that variable or approximate it via all status variables $o_{a,t}^{\mathrm{DG}}$, in case p_t^{UP} is not exposed to the decision tree. To boost the expressiveness and interpretability of generated trees, additional heuristics beyond the basic state variables $o_{a,t}^{\mathrm{DG}}$, $p_{a,t}^{\mathrm{DG}}$, and $e_{b,t}^{\mathrm{ST}}$ can be included in the feature set. For each sample $\tilde{x}$, all features that are exposed to the decision tree algorithm need to be calculated. Likewise, the MILP problem must model corresponding variables in order to automatically transform the decision tree. In this study, the linking variables $o_{a,t}^{\mathrm{DG}}$, $p_{a,t}^{\mathrm{DG}}$, $e_{b,t}^{\mathrm{ST}}$, $p_{b,t}^{\mathrm{CHG}}$, $p_{b,t}^{\mathrm{DCH}}$, p_t^{NDG}, and p^{MinUP} have been manually selected. An automated feature selection process that can improve the approximation even further is considered to be out of scope.

Several classification tree algorithms include pruning steps that reduce the number of nodes in favor of a less complex and more general decision tree [25]. While for classical machine-learning use cases, robustness against outliers and overapproximation plays an important role, hybrid optimization requires a constraint model that reliably excludes infeasible regions. Since it is assumed that the function $\vec{g}^{\,\mathrm{n}}(\vec{x})$ itself, except for some small numeric errors, is deterministic, no outliers are expected in the training set. Moreover, misclassification can prolong convergence in case an infeasible candidate solution is not excluded. Hence, the algorithm traits accuracy for simplified trees by excluding any pruning step that would introduce misclassified training samples.

C. SAMPLING STRATEGY

Arising from the need of drawing samples from $\vec{g}^{\,\mathrm{n}}(\vec{x})$ efficiently while determining the feasible region near the linear candidate solution $\vec{x}^{\,\mathrm{C}}$, a randomized local search strategy is introduced. Starting from $\vec{x}^{\,\mathrm{C}}$, samples are generated towards the next local optimum. In case $\vec{x}^{\,\mathrm{C}}$ is already feasible, the local search may further refine the optimum and the local approximation of $\vec{g}^{\,\mathrm{n}}(\vec{x})$. Otherwise, the search procedure first needs to find samples in the feasible region in order to subsequently approximate the boundary. Although it is, in principle, sufficient to approximate the feasibility of all nonlinear constraints well, without considering the linear ones, the region of interest largely depends on the linear subproblem. Hence, the full problem (1) and (2) is considered for local search and all linear constraints that are not already implied by the normalized representation $\tilde{x}$ are added to the constraint set for local search as well.

According to the separation technique described in [19], the total constraint violation level $G^{\mathrm{ln}}(\vec{x})$ as defined by (29) is given priority on comparing candidate solutions.

$$G^z(\vec{x}) = \sum_{i=1}^{|\vec{g}^{\,z}|} \min(g_i^z(\vec{x}), 0), \quad z \in \{\mathrm{n}, \mathrm{l}, \mathrm{ln}\} \tag{29}$$

In case no precedence on the violation level is observed, the objective value is taken into account. Local search iteratively samples from a neighborhood that contains all schedules deviating by at most n variables from the currently best local schedule $\tilde{x}^{\mathrm{L}}$. In case a better solution is sampled, $\tilde{x}^{\mathrm{L}}$ is updated accordingly. To further guide local search, the probability $P(\text{alter}\,\tilde{x}_{i,t})$ of altering a single variable $\tilde{x}_{i,t}$ at time instant t is chosen as (30) proportionally to the total violation level, or the operating cost at that time.

$$P(\text{alter } \tilde{x}_{i,t}) \propto \begin{cases} c_t^{\mathrm{TOT}}(\tilde{x}) & G^{\mathrm{ln}}(\tilde{x}) = 0 \\ G_t^{\mathrm{ln},\mathbb{T}}(\tilde{x}) + G_{\emptyset}^{\mathrm{ln},\mathbb{T}}(\tilde{x}) & \text{otherwise} \end{cases} \tag{30}$$

The deviation of each selected continuous variable will be sampled from a centered normal distribution $\mathcal{N}(0, \sigma)$ and clipped to the boundaries [0, 1] of each normalized variable. Starting from a large neighborhood, both, the number of altered variables n and the standard deviation σ are systematically decreased to support convergence. As soon as the moving average number of improvements drops below a given threshold, the next set of neighborhood parameters is applied or sampling is stopped.

D. TREE CONSTRAINT SYNTHESIS

Given the decision tree $\mathcal{T}$, the algorithm [14] is extended to generate a set of, up to an arbitrarily small tolerance ϵ, equivalent MILP constraints. A subtree $\mathcal{T}_j$ is considered feasible in case it contains a path to a feasible leaf node. For each decision $\mathrm{dec}(\mathcal{T}_j)$ that leads to both feasible subtrees, an unbounded binary variable o_k^{TR} is introduced that encodes the outcome in subsequent decisions. Specifically, $o_k^{\mathrm{TR}} = 1$, if $\mathcal{T}_j$ is active, $\mathrm{dec}(\mathcal{T}_j)(\vec{x}) \leq 0$, and the left branch is taken. Given a single tree, the set of previously added auxiliary variables encodes the active path within that tree and determines whether a constraint is considered. In case only one subtree is feasible, given the path to that constraint is active, it must always be satisfied and no auxiliary variable is added. Inactive constraints are masked by introducing a large constant M that exceeds any feasible value of $|\mathrm{dec}(\mathcal{T}_j)(\vec{x})|$.

Algorithm 1 defines the tree constraint synthesis in detail. Initially, the procedure is called on the entire tree given an empty masking term $v = 0$. It recursively adds linear constraints until all feasible subtrees are enumerated. In order to generate MILP constraints, [14] relaxes the strict inequality $\mathrm{dec}(\mathcal{T})(\vec{x}) \gtrsim 0$ to a soft one. However, such a transformation can include values that the decision tree $\mathcal{T}$ classifies as infeasible and convergence of the hybrid optimization algorithm can be adversely affected. To support convergence, this work introduces an ϵ offset to model strict inequalities instead of relaxing the decision. In addition, the application of Algorithm 1 in a closed-loop optimization setup instead of an open-loop constraint learning task is demonstrated.

IV. CASE STUDY ON SCHEDULING ALGORITHMS

From a design point of view, both methods for solving the nonlinear scheduling problem have their own merits.

Algorithm 1 Synthesis Procedure Transforming Tree $\mathcal{T}$ Into the Set of Constraints $\vec{g}^{\,t}$ (based on [14])

```
function Syn(feasible tree 𝒯, masking term ν)
    g⃗ᵗ ← ∅
    if left(𝒯) and right(𝒯) are feasible then
        Introduce new variable o_k^TR ∈ 𝔹
        g⃗ᵗ ← g⃗ᵗ ∪ {dec(𝒯) ≤ M · (1 − o_k^TR) + ν}
        g⃗ᵗ ← g⃗ᵗ ∪ {dec(𝒯) ≥ ε−M · o_k^TR−ν}
        g⃗ᵗ ← g⃗ᵗ ∪ Syn(left(𝒯), ν + M · (1 − o_k^TR))
        g⃗ᵗ ← g⃗ᵗ ∪ Syn(right(𝒯), ν + M · o_k^TR)
    else if left(𝒯) is feasible then
        g⃗ᵗ ← g⃗ᵗ ∪ {dec(𝒯) ≤ ν}
        g⃗ᵗ ← g⃗ᵗ ∪ Syn(left(𝒯), ν)
    else if right(𝒯) is feasible then
        g⃗ᵗ ← g⃗ᵗ ∪ {dec(𝒯) ≥ ε−ν}
        g⃗ᵗ ← g⃗ᵗ ∪ Syn(right(𝒯), ν)
    end if
    return g⃗ᵗ
end function
```

Sensitivity-based optimization features a simple implementation and tree-constraint synthesis, in theory, overcomes the limitations of a global plane approximation. A case study was designed to analyze the performance of both algorithms on a common ground, to verify the theoretical expectations and to give insights into preferred use-cases.

A. TEST SYSTEM AND CONTROLS

Due to the widespread application in scheduling [4], [27], [28] and the challenging network design that leads to frequent voltage violations, the whole study is based on a modified version of the well-established Baran testfeeder [29]. Since the original network does not include any generation, the feeder was extended by DG, Photovoltaics (PV), Wind Turbine (WT), and storage plants following the configuration in [27]. However, maximum and minimum power of all DGs were scaled by one half to avoid generator tripping in islanded low-load scenarios. The power limits of $\pm 1\,MW$, the location, and the constant average efficiency of $\mu_b^{\mathrm{ST}} = 0.9$ of all storage units b were kept, but to study charging cycle limitations in more detail, the storage size was reduced to 0.9 MWh usable capacity. In contrast to [27] that does not include details on volatile RES, this study considers the voltage control capabilities of all generation units and therefore additionally assumes that PV and WT plants are limited to an apparent power $\bar{S}_l^{\mathrm{DER}}$ of 0.1 MVA and 0.2 MVA, respectively. Table 1 and Fig. 3 summarize the system configuration of all DGs and the network topology, respectively.

To demonstrate the integration of low-level controls in proactive scheduling, the model of [27] and [29] was amended by voltage and frequency droop control. Based on [30], for each volatile DER and storage unit, Q-of-U droop control was enabled scaling the maximal and minimal reactive power between bus voltages of 0.92 p.u. and 1.08 p.u.

TABLE 1. Location and rating of controllable DGs.

DER a	Bus	$\bar{p}_a^{\mathrm{DG}}$ (MW)	$\underline{p}_a^{\mathrm{DG}}$ (MW)	$\bar{Q}_a^{\mathrm{DG}}$ (Mvar)
DG1	8	2.1	0.5	2.1
DG2	13	1.69	0.5	1.69
DG3	16	1.69	0.5	1.69
DG4	25	2.36	0.5	2.36

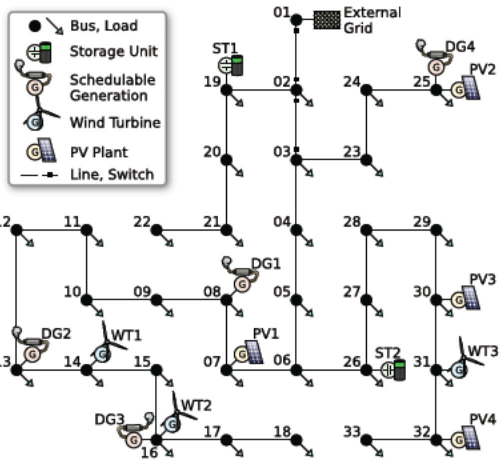

FIGURE 3. Network topology used to assess the algorithms.

considering a dead band of 0.96 p.u. and 1.05 p.u. For the static reactive power limits used to define the droop curve, it is assumed that no active power is generated or drawn from the grid, but total apparent power limitations $\bar{S}_l^{\mathrm{DER}}$ are considered as well.

All scheduled DG units also participate in voltage control via a droop curve that scales the reactive power between 0.92 p.u. and 1.08 p.u. bus voltage as well. In any islanded subgrid, all scheduled DG units also participate in grid forming and active power control via a primary frequency bias that is scaled according to the operating range $\bar{p}_a^{\mathrm{DG}} - \underline{p}_a^{\mathrm{DG}}$. The whole nonlinear network model, including the low-level controls is solved by a series of load flow calculations as implemented by the quasi-dynamic simulation of DIgSILENT PowerFactory. The feasibility of each candidate solution is rated by any equipment overload and any violation of the target voltage band of 0.95 to 1.05 p.u. For each single constraint, the level of constraint violation is calculated based on the distance to the feasible region normalized by a nominal operating condition of 100% loading and 1 p.u. bus voltage.

B. INPUT PROFILES AND FAILURE MODES

Both scheduling algorithms operate on forecasts of volatile loads and generation. Fig. 4 plots the hourly load and RES forecasts. Shading in the graphics illustrates the share of individual assets on the total power profiles. To challenge the algorithms under test by increasing grid imbalance, a day with

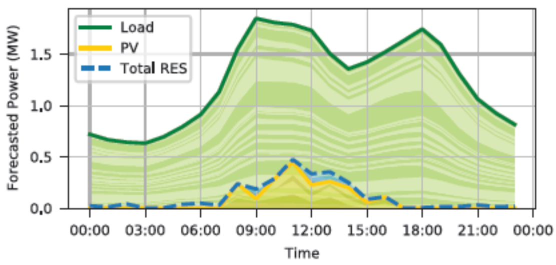

FIGURE 4. Forecasted power of all loads as well as PV, and WT generation.

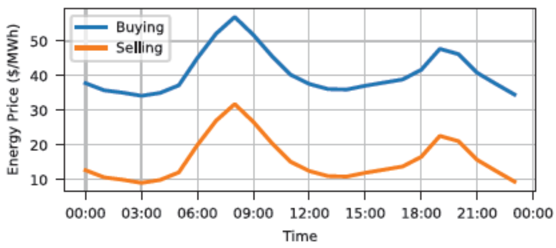

FIGURE 5. Dynamic electricity prices including grid transfer fees.

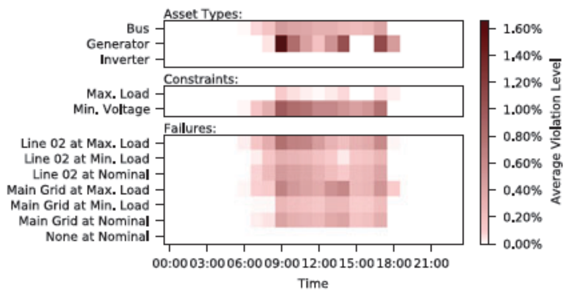

FIGURE 6. Average normalized violation levels according to different partitioning schemes.

low RES generation was modeled. The load profiles were selected from [31] and scaled according to the nominal load. Dynamic prices of buying and selling electricity that are given in Fig. 5 are based on data from [32] and the assumption of constant grid transfer fees. For each DG unit, a price of \$90 $\frac{1}{\mathrm{MWh}}$ is assumed that is considerably above the grid tariffs. To reduce the chance of over fitting each algorithm, parameter tuning was conducted on input profiles different from the presented validation data.

The linear partition $\vec{g}^{\,\mathrm{l}}(\vec{x})$ of the scheduling model directly operates on the deterministic forecasts, but for the nonlinear constraints $\vec{g}^{\,\mathrm{n}}(\vec{x})$, a set of deviation and failure scenarios must be available. To support further analysis, two worst-case deviations were manually defined. The first one models a power shortage and increases each load by 10% while decreasing the DER generation by the same amount. Similarly, the second scenario includes a power surplus by increasing and decreasing DER generation and loads, respectively, by 10% as well. In addition to islanding from the main grid as demonstrated in [27], this study assumes that the line connecting buses 02 and 03 is highly exposed and that the grid can be partly islanded in case that line trips. For each of the deviation cases and each of the islanding options one worst-case scenario of a complete loss of connection is added to the uninterrupted scenarios.

To assess varying complexities of the scheduling problem, some study cases impose some linear operation constraints (12) to (21) that set the minimum operating power of DG3, $\underline{p}^{\mathrm{OP}}_{\mathrm{DG3},t}$ to $\underline{p}^{\mathrm{OP}}_{\mathrm{DG3},t} = 0.5\mathrm{MW}$ for $t \in [8{:}00 - 17{:}00]$. Additionally, the maximum number of charging cycles, $\bar{n}_b^{\mathrm{STA}}$ for each storage $b \in \mathbb{ST}$ is set to $\bar{n}_b^{\mathrm{STA}} = 1$ per day and the minimum spinning reserve $\underline{p}^{\mathrm{UP}}_t$ was set to $\underline{p}^{\mathrm{UP}}_t = 0, t \in \mathbb{T}$.

C. SIMPLIFIED ECONOMIC SCHEDULING

The first case studies the performance of purely linear scheduling that includes both, the basic reserve constraints (16) to (18) and the operational constraints (12) to (15). In the experiment, the second storage unit, ST2, was removed to further simplify the problem and to ease the comparison with other simplified cases. Without considering the nonlinear constraints $\vec{g}^{\,\mathrm{n}}(\vec{x})$, the model returns a lower bound for the resilient operation costs of \$1716.28. Clearly, economic scheduling, despite the reserve constraints, fails to deliver a feasible solution w.r.t. the nonlinear constraints $\vec{g}^{\,\mathrm{n}}$. Fig. 6 shows the average violation level according to several partitioning schemes of the nonlinear constraints. Partitions that do not show any violation, are excluded from the graphics.

One may note that although most violations occur in the presence of some failures, also nominal operation as considered by linear scheduling shows some violations that can impact the operation. For both failure modes, a considerable amount of violations is observed. Even for main grid outages that are covered by the minimum spinning reserve constraint of the linear model, considerable DG overload due to the impact of voltage regulation and frequent undervoltage situations are encountered. Induced by the limited infeed in the study period, no scenario shows any overvoltage conditions. Most violations are detected at buses (undervoltage) and DG units (overload). The few violations of inverter-based generation units (WT and PV) are directly caused by saturation of voltage control. DG units show overload due to both, voltage and frequency control demands.

D. HYBRID SCHEDULING OF A SIMPLIFIED MICROGRID

In the most reduced study case of hybrid scheduling, all optional constraints are disabled and the second storage unit, ST2, is removed from the microgrid. As a consequence, a solution returned by the MILP solver does not necessarily imply the basic resilience constraints (16) to (21). Any spinning reserve requirement has to be learned from the grid model. However, since the grid model includes asset loading, every feasible solution with respect to the nonlinear constraints $\vec{g}^{\,\mathrm{n}}$ is also feasible regarding $\vec{g}^{\,\mathrm{l}}(\vec{x})$, the linear ones. As for all study cases, a fixed number of 20 global

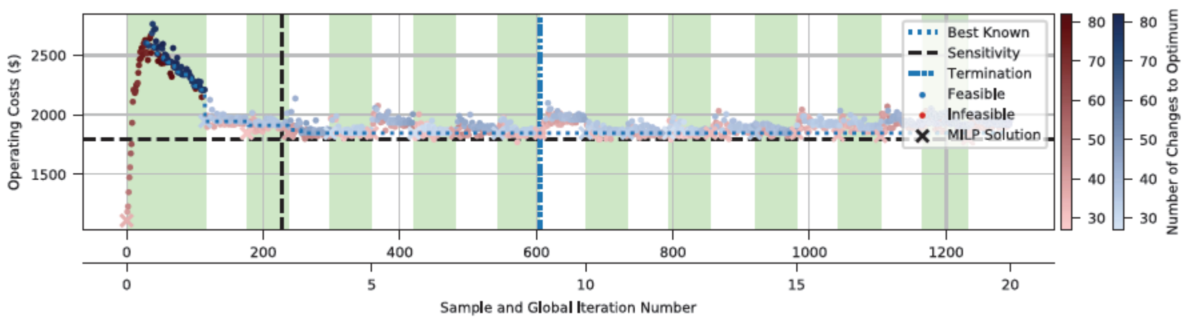

FIGURE 7. Convergence of the tree-based algorithm on the simplified test system without operational constraints.

TABLE 2. Local neighborhood configurations i including the number of altered variables n_i and the standard deviation σ_i.

Nr.	n_i	σ_i	Nr.	n_i	σ_i
0	8	0.3	1	4	0.2
2	3	0.2	3	2	0.1
4	1	0.075	5	1	0.05

iterations to demonstrate long-term minima and a dynamic termination criterion that ends global search if the last five iterations do not yield any improvement were installed. Furthermore, a neighborhood scheme of six configurations with descending sizes was chosen. The manually tuned number of changed variables n_i and the standard deviation σ_i of each neighborhood i are listed in Table 2. As soon as the improvement rate of the last ten samples drops below 20%, the next configuration is chosen or local search is ended.

The convergence of one tree-based optimization run as well as the scheduling run of the deterministic sensitivity-based approximation are illustrated in Fig. 7. Within the first iteration, local search finds several feasible solutions, but the local optimum having costs of \$2210.31 shows a considerable distance to the best known solution of 76 changes in the vector of normalized scheduling variables $\tilde{x}$ and 23% higher costs. Subsequent runs of the extended linear model reduce the gap to the optimum and due to approximation of $\vec{g}^{\,n}(\vec{x})$ show both feasible and infeasible results. Although the tree-based method delivers the first feasible solution within fewer samples, even the long-term operation showed slightly higher operation costs of 2.9% compared to the optimal sensitivity-based results on that particular run.

In contrast to the deterministic sensitivity-based approach, the tree-based method includes a stochastic local search. To account for stochastic effects both in the execution time and the local search, for each case, the optimization runs are executed 32 times and the results of all experiments are listed in Table 3. For tree-based scheduling, the final result as well as the processing time highly depend on the termination criterion and an adequate tradeoff needs to be found. Both, a constant number of 20 global iterations as illustrated in Fig. 7 as well as the dynamic termination criterion that may terminate earlier are used for the tree-based configurations. Timing and accuracy of the sensitivity-based approach, likewise, can be influenced by the ϵ offset heuristically set to $\epsilon = 0.01\%$. Similar to the exemplary run illustrated in Fig. 7, the tree-based approach shows average long-term minimal costs of \$1841.04 or an increase of 2.5% compared to the sensitivity-based solution of \$1795.62. However, all optimization runs of the tree-based method find a first feasible solution below 41 samples and therefore before the 223 samples required by the reference.

To estimate the computational effort of executing the algorithms, the timing of all experiments was recorded and the detailed results using the rate-based termination criterion are listed in Table 4. All experiments were conducted on a virtual Windows 10 (build 18363) machine having four assigned Intel Xeon CPU E5-2690 v4 cores clocked at 2.60 GHz and 32 GB memory. The algorithms themselves were implemented in Python 3.7 accessing PowerFactory 2021 SP2. The MILP model was solved by the open source solver CBC 2.10 accessed via the Pyomo library version 6.0 [33]. To reduce mutual influence, no more than two experiments were executed in parallel.

One can see that the average sensitivity run of 22.05 minutes wall clock time is considerably faster than the average tree-based run taking 85.83 minutes. Given that most of the time is consumed by the grid simulation, the observations from Fig. 7 that the sensitivity-based scheduling converges considerably faster can be further supported. In contrast to the grid simulation that accounts for 92% and 90%, respectively of the total wall clock time, MILP constraint synthesis including and solving the MILP models in total only takes 6% of the time for tree-based and 5% for sensitivity-based scheduling, respectively. Likewise, neither the simulation setup nor the remaining actions of both algorithms have a significant effect on the computational effort. Similar effects can also be seen from the process time statistics that also accounts for parallel actions as conducted by the grid simulation.

E. SCHEDULING WITH OPERATIONAL CONSTRAINTS

To demonstrate the behavior of both algorithms in case of rising model complexity, as in Section IV-C, storage unit ST2 is

TABLE 3. Optimization results of all cases covering the tree-based and the sensitivity-based method.

	Variable:	Costs - Const. Rounds ($)				Costs - Termination ($)				Samples to First Feasible			
	Metric:	Avg.	Std.	Min.	Max.	Avg.	Std.	Min.	Max.	Avg.	Std.	Min.	Max.
Case	Algorithm												
Most Simplified	Tree-Based	1841.04	14.52	1795.37	1850.96	1854.23	16.20	1821.09	1894.73	25.0	4.9	17	41
	Sensitivity-Based	1795.62	0.00	1795.62	1795.62	1795.62	0.00	1795.62	1795.62	223.0	0.0	223	223
Operational Constraints	Tree-Based	1981.28	0.00	1981.28	1981.28	1983.23	7.73	1981.28	2016.92	44.0	29.6	13	111
	Sensitivity-Based	2128.95	0.00	2128.95	2128.95	2128.95	0.00	2128.95	2128.95	114.0	0.0	114	114
Complete	Tree-Based	1973.48	6.74	1950.09	1994.85	1984.61	17.12	1972.52	2029.84	37.1	23.0	15	132
	Sensitivity-Based	-	-	-	-	-	-	-	-	-	-	-	-

TABLE 4. Computation time until the termination criterion is met.

	Timer:	Wall Clock Time (min)				Process Time (CPU min)			
	Algorithm:	Tree-Based		Sensitivity-Based		Tree-Based		Sensitivity-Based	
	Metric:	Avg.	Std.	Avg.	Std.	Avg.	Std.	Avg.	Std.
Case	Operation								
Most Simplified	Setup	0.75	0.08	0.56	0.04	0.75	0.02	0.47	0.02
	Grid Simulation	80.37	22.75	18.76	0.79	137.21	38.85	29.08	2.36
	MILP Solution	0.47	0.43	1.01	0.04	0.43	0.42	0.99	0.03
	MILP Synthesis	3.06	1.51	0.94	0.06	3.06	1.52	1.54	0.11
	Residual Steps	1.19	0.37	0.77	0.02	1.22	0.35	0.90	0.02
	Total	85.83	24.94	22.05	0.91	142.68	41.03	32.98	2.46
Operational Constraints	Setup	0.75	0.06	0.46	0.02	0.75	0.02	0.38	0.01
	Grid Simulation	59.73	10.64	10.02	0.06	101.54	18.23	16.71	0.12
	MILP Solution	1.11	1.94	1.38	0.01	1.07	1.94	1.36	0.01
	MILP Synthesis	1.78	0.56	0.26	0.01	1.79	0.57	0.43	0.02
	Residual Steps	0.88	0.18	0.33	0.00	0.91	0.16	0.46	0.00
	Total	64.24	11.89	12.44	0.07	106.05	19.42	19.35	0.12
Complete	Setup	1.21	0.84	0.36	0.05	0.80	0.02	0.35	0.01
	Grid Simulation	72.23	23.23	7.49	0.03	120.61	39.43	12.59	0.11
	MILP Solution	1.96	2.04	0.16	0.00	1.92	2.04	0.15	0.00
	MILP Synthesis	2.69	1.61	0.23	0.01	2.69	1.61	0.40	0.02
	Residual Steps	0.67	0.90	0.11	0.00	1.11	0.36	0.16	0.00
	Total	78.76	26.31	8.35	0.07	127.13	42.48	13.65	0.12

still excluded, but all operational constraints are enabled. Due to the cycle restrictions, considerable interdependence among scheduling variables is added and the nonlinear constraints do not imply the linear ones anymore. Additionally, the minimum generation requirements of DG3 directly affect the sampling procedures and further increase the chance of selecting a linearly infeasible solution.

Fig. 8 illustrates the convergence of one scheduling run using tree-approximation and adds the bounds achieved by the sensitivity-based method. One can note that tree-constraint approximation outperforms the sensitivity-based method both in terms of final operating costs and the number of samples until a first feasible solution is found. As listed in Table 3, sensitivity-based scheduling returns a solution that shows 7.5% higher costs than the average (and simultaneously best known) tree-based solution after 20 iterations of \$1981.28. Similarly, all tree-based optimization runs delivered an initial solution within the first 111 samples, having an average of 44.0 samples while the sensitivity-based approach required 114 samples to obtain the first feasible schedule and 120 samples to finish its computation.

Compared to sensitivity-based scheduling that terminates within 12.44 minutes wall clock time, the average tree-based run requires a larger number of 644 samples until the convergence criterion is met and therefore shows an increased computational effort of 64.24 minutes. However, using the same number of samples that are needed to finalize the sensitivity-based algorithm, the average cost of \$2126.27 for the tree-based method only marginally differs from the final sensitivity-based result. The increased effort could therefore be used to improve the final solution. Giving the distance to the optimum and the operating costs drawn in Fig. 8, it can be seen that due to the intended overapproximation of the decision tree and the randomization of local search, new regions of the solution space are explored, even after a feasible MILP solution was found. Although that first feasible and best known solution was found in the fourth MILP run, subsequent search shows distances of up to 27 changed variables to the optimum.

F. SCHEDULING OF THE COMPLETE MICROGRID

The last study case includes the full set of assets and operational constraints as described in Section IV-A and IV-B. Despite the moderate size of the problem covering six controllable assets, the state-of-the-art reference algorithm, sensitivity-based constraint approximation, failed to deliver any feasible solution at all. After adding the constraint plane approximation at the initial solution, the solver reported the

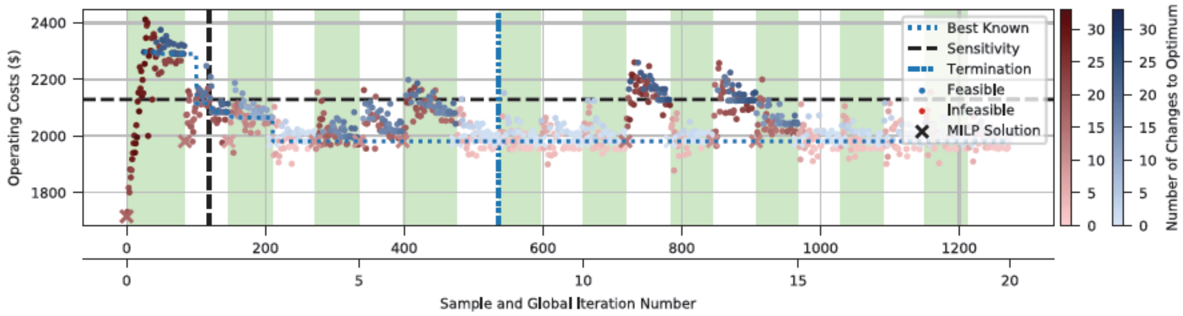

FIGURE 8. Convergence of the tree-based algorithm on the simplified test system with operational constraints.

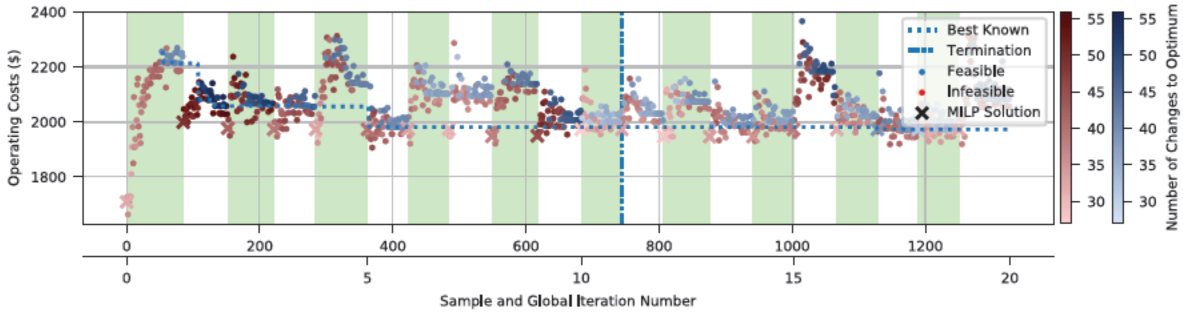

FIGURE 9. Convergence of the tree-based algorithm on the complete test system.

entire problem to be infeasible and no feasible solution could be scheduled. Even without the sample reduction heuristic that was introduced to render several problem instances computationally tractable, no feasible solution was found.

In contrast to the sensitivity constraint synthesis, the tree-constraint method finds a feasible solution within the first local search and 37.1 samples in average. The execution time of 8.35 minutes on average that is needed to determine the infeasibility of the sensitivity-based model, is considerable lower than the execution times in the other sensitivity-based cases requiring 22.05 and 12.44 minutes, respectively. For the tree-based method, an average execution time of 78.76 minutes is observed. Fig. 9 illustrates convergence of the latter method. Although the majority of 18 MILP solutions are infeasible, the approximation model was also able to successfully restrict the MILP model towards a feasible solution. In the entire scheduling run, every MILP problem could be solved to optimum. Similarly, all 32 repetitions successfully returned a feasible solution and an average operating cost of $1975.12 was achieved.

V. DISCUSSION OF CASE STUDY RESULTS

By implementing and testing two hybrid scheduling approaches, an improved sensitivity-based approach from literature and a novel tree-based method, this work successfully demonstrates the feasibility of hybrid optimization that couples nonlinear constraints and MILP. Table 5 summarizes the main features of both algorithms. In contrast to several state-of-the-art approaches, no manual linearization is needed [4], [8] and both, the MILP subproblem and the grid model could be solved by off-the-shelf solvers.

TABLE 5. Comparison of tree-based and sensitivity-based hybrid scheduling.

Aspect	Hybrid Method Tree	Sensitivity
Integration of off-the-shelve solvers	✓	✓
Efficient use of grid simulation runs	✓	✓
Consideration of low-level controls	✓	✓
Suitable problem complexities	High	Low
Implementation effort	Medium	Low
Feasible intermediate solutions	✓	–

The study on hybrid optimization shows a good performance of the sensitivity-based approximation of inherently nonlinear grid constraints for some simplified cases. However, it also demonstrates that in other cases, it completely fails to generate feasible schedules. In contrast, the novel tree-constraint method that uses a more complex approximation structure in the MILP problem, quickly provides feasible solutions in all experiments and outperforms the sensitivity-based approach in all but the most simplified configurations.

The original sensitivity-based algorithm as presented in [11] is integrated into one stage of a multi-stage energy management system and originally does not include any scheduling decisions that involve multiple instants of time. In particular, no multi-period operational constraints such as the startup restrictions (15) are involved in the presented MILP model. Despite significant differences in the experimental setup, this study supports the reported effectiveness of sensitivity-based constraint approximation [11] for some cases and in addition to the original work, clearly demonstrates the limits in case of more complex setups.

In contrast to the sensitivity-based method that samples the nonlinear constraints for the sake of approximation only, the tree-based method features a sampling strategy that both quickly finds a feasible local optimum and provides the training data to extend the linear model. As a result, all experiments show that tree-based scheduling requires fewer samples to provide an initial feasible solution. Early solutions specifically enable use cases that quickly require a feasible schedule but tolerate later updates towards better solutions.

Over all sensitivity and tree-based experiments, 88% and 96%, respectively, of the process time is spent on the grid simulation performed once per sample. With the share being that high, the number of samples has a substantial impact on the total processing time. In the tree-based algorithm, the number of samples that need to be drawn strongly depends on the targeted accuracy that can be balanced by the termination criterion. However, the study case in Section IV-E demonstrates that tree-based scheduling only draws a few hundreds samples more to get significantly improved results and performs equally well, on the same number of samples. Still, the additional samples considerably prolong the execution time and need to be weighted in the accuracy tradeoff.

Due to the local search procedure, the tree-based method does not require the MILP subproblem to generate a feasible solution at all, as long as the local search finds suitable solutions and the generated tree properly restarts the heuristic search procedure. However, all cases showed that at least some valid solutions are generated by the extended MILP model and several times including iteration number 17 in Fig. 9, the MILP solution even improved the global optimum. In average over all tree-based experiments having a constant number of 20 global iterations, 7.4% of the MILP runs improved the global optimum.

It was demonstrated that several proactive scheduling problems can also be solved by purely heuristic approaches that do not include mathematical programming [4], [7]. Although the experimental setup shows significant differences (a smaller test system without considering discrete DG states but dynamic grid constraints are used), comparison to [10] indicates a considerably reduced number of evaluated samples by using hybrid optimization techniques. In contrast to purely heuristic approaches, the presented hybrid optimization techniques show a reduction in the number of samples by one order of magnitude. However, a detailed comparison on common ground is beyond the scope of this work.

Although the test system was specifically designed to challenge the algorithms under test and to trigger physical constraints, all study cases demonstrate that scheduling decisions can have adverse effect on the grid, if the assets are operated close to their limits. Given the modeled conditions, no algorithm delivered an initial MILP solution that satisfied all grid constraints which aligns well with results from related studies that highlight the need of detailed grid constraints [6], [34]. The first case on purely economic scheduling provided an in-depth analysis of the encountered constraint violations and showed that even without considering any contingencies, low-level controls can induce some overload conditions that are not predicted by the simplified scheduling formulation. However, the large majority of grid constraint violations is related to the feasibility of fault mitigation techniques.

VI. CONCLUSION AND OUTLOOK

Motivated by the high computational complexity of proactive scheduling as well as the need of efficiently considering low-level controls and nonlinear grid constraints, this work presents two hybrid approaches that successfully combine mathematical programming and heuristic optimization. A case study demonstrates that the novel optimization method based on decision trees can solve the scheduling problem, even in case a sensitivity-based method extended from literature fails to deliver results at all. However, the study also identifies a simplified case in which the sensitivity-based approach returns slightly better results and therefore gives indication which method may be best suited for a problem at hand. Detailed insights into the convergence of both algorithms show that the tree-based approach quickly delivers first feasible solutions and that the sensitivity-based method can suffer from considerable overapproximation of infeasible states.

The hybrid optimization techniques enable the usage of external grid models that cannot be included in classical mathematical programming and a first comparison to purely heuristic approaches indicates a considerably improved performance of hybrid scheduling. Similar to most related work [4], the study gives qualitative answers concerning the performance of presented algorithms. However, large-scale evaluation that covers a broad variety of grid configurations and operating conditions is needed to quantify the performance on a common ground and give final precedence over the studied algorithms. To ease analysis, the study deploys only manually defined worst-case heuristics and few fault mitigation techniques. Future work includes a refined stochastic or robust model to better quantify reserve requirements, the assessment of transient phenomena and additional fault mitigation techniques such as rerouting or load shedding to reduce local reserve needs.

In the presented experiments, decision trees are restricted to axis-parallel splits, i.e., each decision involves a single coupling variable only. Future work may also assess the effect of arbitrary linear splits [14], study the parametrization of local search in more detail and may include more advanced termination criteria that further reduce the number of samples. Other techniques such as generalized Benders decomposition [35] may also be used in proactive scheduling. Despite the focus on microgrids future work includes the application of hybrid scheduling in other contexts such as active distribution systems. By presenting the algorithms and studying various details on solving scheduling tasks with nonlinear constraints, this work also contributes to a broader discussion on hybrid optimization methods.

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APPENDIX A COMPLEXITY OF SCHEDULING

To give a first intuition on the computational complexity of microgrid scheduling, a polynomial-time reduction from the Knapsack problem, a weakly NP-hard problem [24], to scheduling is provided. The Knapsack problem $\mathcal{P}^{\mathrm{KN}}$ is defined as (31), given the positive integers v_i, w_i, and W.

$$\max_{\vec{x}\in\mathbb{B}^n} \sum_{i=0}^{n} v_i x_i$$
$$\text{s.t.} \sum_{i=0}^{n} w_i x_i \le W \tag{31}$$

The scheduling problem $\mathcal{P}^{\mathrm{SCH}}$ is now defined as finding $o_{a,t}^{\mathrm{DG}}, o_{b,t}^{\mathrm{CHG}}, o_t^{\mathrm{SELL}} \in \mathbb{B}$ and $p_{a,t}^{\mathrm{DG}}, p_{b,t}^{\mathrm{CHG}}, p_{b,t}^{\mathrm{DCH}}, p_t^{\mathrm{BUY}}, p_t^{\mathrm{SELL}} \in \mathbb{R}$ that minimize $c(\cdot)$ s.t. (3) to (11) are satisfied. Hence, a relaxed version with an empty set of nonlinear constraints is studied. Let $\mathcal{I}^{\mathrm{KN}} = (\vec{v}, \vec{w}, W)$ be an arbitrary instance of $\mathcal{P}^{\mathrm{KP}}$, then the mapping to $\mathcal{P}^{\mathrm{SCH}}$ is defined as (32) to (40).

$$\mathbb{T} = \{0\} \tag{32}$$
$$\mathbb{D}\mathrm{G} = \{1, \ldots n\} \tag{33}$$
$$\mathbb{L}\mathrm{D} = \mathbb{S}\mathrm{T} = \emptyset \tag{34}$$
$$\underline{p}_i^{\mathrm{DG}} = w_i \quad \forall i \in \mathbb{D}\mathrm{G} \tag{35}$$
$$\bar{p}_i^{\mathrm{DG}} = w_i \quad \forall i \in \mathbb{D}\mathrm{G} \tag{36}$$
$$\bar{p}^{\,\mathrm{SELL}} = W \tag{37}$$
$$\bar{p}^{\,\mathrm{BUY}} = 0 \tag{38}$$
$$c_0^{\mathrm{SELL}} = \max_{i\in\mathbb{D}\mathrm{G}} \frac{v_i}{w_i} + \epsilon \tag{39}$$
$$c_i^{\mathrm{DG}} = c^{\mathrm{SELL}} - \frac{v_i}{w_i} \quad \forall i \in \mathbb{D}\mathrm{G} \tag{40}$$

Clearly, (32) to (40) can be computed in polynomial time. From (3), (35), and (36), it follows that

$$p_{i,0}^{\mathrm{DG}} = w_i \cdot o_{i,0}^{\mathrm{DG}} \quad \forall i \in \mathbb{D}\mathrm{G}. \tag{41}$$

From the original power balance (9), as well as the mapping (32) to (34), and (38), the balance simplifies to

$$\sum_{i\in\mathbb{D}\mathrm{G}} p_{i,0}^{\mathrm{DG}} = p_0^{\mathrm{SELL}}. \tag{42}$$

Consequently, the power transfer constraint (8) transforms to constraint (43) with the first inequality trivially fulfilled.

$$0 \le \sum_{i\in\mathbb{D}\mathrm{G}} w_i \cdot o_{i,0}^{\mathrm{DG}} \le W \tag{43}$$

Similarly, it can be concluded from (7) and (38), that the only valid solution of $p_0^{\mathrm{BUY}} = 0$. Note that the transfer mode o_t^{SELL} can therefore be freely set to $o_t^{\mathrm{SELL}} = 1$, without loss of generality.

Given the cost definition of $\mathcal{P}^{SCH}$, (11), the defined mapping, as well as (41) and (42), the objective function simplifies to (44).

$$\begin{aligned} c(\vec{x}) &= c_0^{\mathrm{TOT}} \\ &= -c_0^{\mathrm{SELL}} \cdot p_0^{\mathrm{SELL}} + \sum_{i\in\mathbb{D}\mathrm{G}} c_i^{\mathrm{DG}} \cdot p_{i,0}^{\mathrm{DG}} \\ &= \sum_{i\in\mathbb{D}\mathrm{G}} \left(c_i^{\mathrm{DG}} - c_0^{\mathrm{SELL}}\right) \cdot p_{i,0}^{\mathrm{DG}} \\ &= \sum_{i\in\mathbb{D}\mathrm{G}} -v_i \cdot o_{i,0}^{\mathrm{DG}} \end{aligned} \tag{44}$$

One can see that for any valid solution of $\mathcal{P}^{\mathrm{KN}}$, x_i, a schedule $o_{i,0}^{\mathrm{DG}} = x_i$, $o_0^{\mathrm{SELL}} = 1$, $p_0^{\mathrm{BUY}} = 0$, and $p_0^{\mathrm{SELL}}, p_{i,0}^{\mathrm{DG}}$ according to (42) and (41), respectively, that satisfies, constraints (3) to (9) can be found. At the same time, (43) ensures that each valid schedule of the mapped scheduling instance is mapped to a valid instance of Knapsack in polynomial time. On using the relation (44), it can be seen that any solution that maximizes the Knapsack gains minimizes the scheduling costs and vice versa.

From the polynomial time reduction from $\mathcal{P}^{\mathrm{KN}}$ to $\mathcal{P}^{\mathrm{SCH}}$ and the fact that $\mathcal{P}^{\mathrm{KN}}$ is weakly NP-hard [24], it can be concluded that $\mathcal{P}^{\mathrm{SCH}}$ is at least weakly NP-hard, as well.

ABBREVIATIONS

CHP	Combined Heat and Power
DER	Distributed Energy Resource
DG	Distributed Generator
EES	Electrical Energy Storage
EV	Electric Vehicle
MILP	Mixed Integer Linear Programming
PCC	Point of Common Coupling
PV	Photovoltaics
RES	Renewable Energy Sources
WT	Wind Turbine

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2.3 Publication C

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The presented assessment methodology, model formulations, the improved power flow, and the implementation thereof were developed by the applicant. Additionally, the investigation, analysis of results, validation, visualization, and draft-writing were also undertaken by the applicant. As for Section 2.2, both authors contributed to the conceptualization and the second author undertook the review, editing, administration, and supervision of this work.

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Assessing the Value of Proactive Microgrid Scheduling

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ABSTRACT Microgrids and multi-microgrids are commonly installed to fulfill rising flexibility needs and to boost the system resilience by advanced fault mitigation capabilities. On top of a complex control architecture, proactive resilient scheduling optimizes the operation of such grids in advance. Although several scheduling algorithms include measures to limit the effects of faults, the impact of proactive scheduling on the system resilience is not widely assessed. This work presents an advanced simulation-based assessment method that includes an extended power flow formulation to consider low-level control and device capabilities even in islanded mode. A case study assesses resilience gains and costs of proactive scheduling based on multiple algorithms and an extensive set of operating conditions. It turned out that even on a suitable test grid that is specifically designed to challenge scheduling algorithms, a large share of the faults can already be handled by low-level controls without the need of considering them in scheduling. However, the remaining share of unhandled faults can be well influenced by advanced proactive scheduling algorithms and an appropriate resilience constraint formulation. Given the evaluation results, it can be supported that in less critical applications, scheduling focuses on economic aspects only without considering fault mitigation. Nevertheless, a detailed assessment is needed to justify the algorithmic choice and to improve the quality of resilient algorithms. The presented method adds a tool that can efficiently assess the value of proactive scheduling based on extensive simulations.

INDEX TERMS Energy management, power flow, microgrids, microgrid scheduling, power system resilience, proactive resilient scheduling.

NOMENCLATURE

SETS AND DEDICATED INDICES

$\mathbb{D}\mathrm{G}$, a	Set and index of controllable generators.
$\mathbb{S}\mathrm{T}$, b	Set and index of storage units.
$\mathbb{P}\mathrm{V}$, c	Set and index of Photovoltaic (PV) plants.
$\mathbb{W}\mathrm{T}$, w	Set and index of Wind Turbines (WTs).
$\mathbb{L}\mathrm{D}$, l	Set and index of volatile loads.
$\mathbb{S}\mathrm{C}$, s	Set and index of scenarios.
$\mathbb{T}$, t	Set and Index of time instants.
$\mathbb{L}\mathrm{I}$, $\mathbb{B}\mathrm{S}$	Set of all lines and buses.

REAL-TIME VARIABLES

$U_{i,t}$, $\varphi_{i,t}$	Voltage magnitude and angle at bus i at time t.
$P^{v}_{i,t}$, $Q^{v}_{i,t}$	Total active/reactive power of asset i at time t, having type $v \in$ {DG, ST, PV, WT, LD, EX, EM}.
$P^{\mathrm{BS}}_{i,t}$, $Q^{\mathrm{BS}}_{i,t}$	Net active/reactive power injected at bus i at t.
$O^{\mathrm{DG}}_{a,t}$	Operational status of generator a at time t.
$O^{\mathrm{LI}}_{l,t}$	Operational status of line l at time t.
$E^{\mathrm{ST}}_{b,t}$	Energy stored in b at time t.
$I_{i,t}$	Current magnitude in line i at time t.
$S_{i,t}$	Total apparent power of asset i at time t.
C^{TOT}_{t}	Total operating costs at time t.
$f_{i,t}$	Frequency in island i at time t.
$k^{\mathrm{f,ST}}_{b,t}$	Dynamic frequency droop of storage b at t.
$P^{\mathrm{R},v}_{i,t}$	Reserve power request of asset i typed v at t.
E^{NS}	Unsupplied energy.
$v^{\bullet}$	Primary control setpoint of variable v.
v°	Secondary control setpoint of variable v.

The associate editor coordinating the review of this manuscript and approving it for publication was Jethro Browell.

SCHEDULING VARIABLES

$p^{v}_{a,t}$	Active power of asset a at time t, having type $v \in \{\text{DG, ST, PV, WT, LD}\}$.
$o^{\text{DG}}_{a,t}$	Operational status of generators a at time t.
$p^{\text{CHG}}_{b,t}$	Active charging power of storage b at time t.
$p^{\text{DCH}}_{b,t}$	Active discharging power of storage b at time t.
$e^{\text{ST}}_{b,t}$	Energy in b stored after time step t.
$o^{\text{CHG}}_{b,t}$	Charging indicator of storage b at time t.
p^{BUY}_{t}	Bought active power at time t.
p^{SELL}_{t}	Sold active power at time t.
o^{SELL}_{t}	Selling mode of the upstream grid at time t.
c^{TOT}	Overall operating costs.
$p^{E,DCH}_{b,t}$	Emergence power, storage b can provide at t.
$p^{E,CHG}_{b,t}$	Emergence power, storage b can absorb at t.
p^{NetLD}_{t}	Volatile net load at time t.
$u_{i,t}$	Predicted voltage at bus i and time t.
$\iota_{i,t}$	Current magnitude in line i at time t.
v^{s}	Assignment of variable v in scenario s.

PARAMETERS AND EXTERNAL INPUTS

$\bar{v}$, $\underline{v}$	Upper and lower limits of variable v.
v^{*}	Nominal value of variable v.
$v^{\diamond}_{t}$	Volatile maximum of variable v at time t.
$\bar{v^{*}}$, $\underline{v^{*}}$	Nominal range (min, max) of variable v.
$\lvert Y\rvert_{i,j}$, $\theta_{i,j}$	Admittance matrix entry (magnitude and angle) between bus i and j.
T^{St}	Duration of a single time step.
T^{Sta}	Maximum generator startup time.
T^{Sto}	Maximum generator stopping time.
$v_{w,t}$, $V_{w,t}$	Wind speed forecast and measurement at WT w and time t.
$g_{c,t}$, $G_{c,t}$	Irradiance forecast and measurement in plane of the PV array c at time t.
$\tau^{\text{PV}}_{c,t}$, $\mathcal{T}^{\text{PV}}_{c,t}$	Temperature forecast and measurement of PV array c at t.
k^{PV}_{c}	Temperature coefficient of PV array c.
$k^{\text{f},v}_{a}$, $k^{\text{u},v}_{a}$	Frequency and voltage droop of asset a, type v.
$k^{\text{f,EM}}_{\text{IB}}$, $k^{\text{f,EM}}_{\text{OB}}$	Emergency frequency droop constants.
$k^{s,\text{RE}}_{a}$	Reserve coefficient for asset a in scenario s.
c^{BUY}_{t}, c^{SELL}_{t}	Cost of buying and benefits from selling electricity from the upstream grid at time t.
c^{DG}_{a}	Operating cost of generation unit a.
Γ^{v}_{i}	Bus, asset i of type v is connected to.
Γ^{IL}_{i}	Island, asset i is connected to.

FUNCTIONS

$\mu^{\text{CHG}}_{b}(P)$	Charging efficiency curve of storage b.
$\mu^{\text{DCH}}_{b}(P)$	Discharging efficiency curve of storage b.
$\rho^{\text{WT}}_{w}(v)$	Turbine curve of WT w.
$S(\cdot)$	Scheduling function under test.
$\bar{P}^{\text{E}}_{b}(E, T)$	Maximum power of storage b at (E, T).
$\underline{P}^{\text{E}}_{b}(E, T)$	Minimum power of storage b at (E, T).
$\mathbb{E}(e)$	Observed share of event e.

I. INTRODUCTION

Most power systems are faced with fundamental transitions that will drastically alter the way electricity grids are planned and operated. Microgrids and multi-microgrids provide one solution to facilitate an increasing number of volatile Renewable Energy Sources (RES), to rigorously exploit the economic potential of Distributed Energy Resources (DERs), and simultaneously to strengthen the system resilience [1]. In favor of other competing definitions, this work defines microgrids as tightly integrated electrical networks that can be both operated as islanded and grid-connected systems [2], [3]. Multi-microgrids extend the concept of individual microgrids by jointly operating them within a distribution system. Despite the high potential in integrating renewables, several microgrid designs still heavily rely on the presence of fossil-fueled generation [4]. Due to policies towards a net-zero CO_2 economy, the integration of large shares of RES in microgrids and further reduction of CO_2 emission became a priority in research [5]. In literature, a multitude of control approaches are presented to preserve or even increase system resilience while incorporating significant amounts of stochastic generation. Several proactive scheduling approaches, for instance, are presented which balance increasing reserve needs and strengthen the microgrid operation before faults are encountered [3], [6].

Although most of the proactive algorithms follow an optimization-based framework, a broad diversity of problem formulations and solution methods are found. Common differences between algorithms include the level of detail, i.e. the number and abstraction of phenomena that are considered at scheduling time. For instance, [7] focused on provisional microgrids that depend on the grid-forming capabilities of adjacent microgrids, but did not include physical power flow restrictions beyond static bounds. On the contrary, [8] considered detailed voltage and current constraints based on the highly nonlinear AC power flow equations. Commonly, scheduling algorithms are deployed on top of a complex control architecture that manages short-term disturbances, coordinates transitions from and to the islanded mode, and ensures a stable operation of the system [9]. It was shown that scheduling and control decisions can have a significant impact on the stable and safe operation of microgrids [10]. Therefore, several algorithms included physical constraints in their scheduling decisions [11]. However, only very few of them considered the low-level control such as primary frequency regulation or fault reconfiguration algorithms. One of these approaches is introduced by [12] that includes primary frequency control constraints to ensure successful islanding, but did not consider reactive power and voltage control requirements. More recently, [3] proposed a hybrid scheduling mechanism that considers both frequency and voltage control requirements in day-ahead scheduling. Yet, storage units are excluded from primary control and saturation effects due to power limits are not covered in detail.

To evaluate such algorithms, several testbeds are implemented that enable the assessment of critical aspects such as islanding, synchronization, and stability [9], [13]. A broad range of assessment methods including purely simulation-based approaches, hardware-in-the-loop solutions, and field trials can be found. For instance, [14] implements a purely simulation-based testbed to study transient phenomena in exclusively inverter-based microgrids, but does not focus on long-term operation and scheduling. A laboratory-scale testbed that specifically focuses on scheduling is described in [15]. The authors compare the performance of an energy management heuristic to an optimal scheduling formulation and provide first insights into the economic benefits of the optimization-based approach. Yet, only 15 operating scenarios originating from five independent measurement days were used in the economic assessment. Due to the focus on a small, single-bus microgrid, grid reconfiguration actions and the impact of scheduling on physical grid constraints are beyond the scope of [15].

In general, very few approaches specifically target the evaluation of scheduling algorithms in long-term operation. Commonly, the approaches are evaluated on a very limited set of environmental conditions without taking the impact of failure scenarios, detailed forecasting models, and low-level controls on the physical grid operation into account [11], [15]. Due to the limited evaluation, little quantitative evidence on the long-term benefits of proactive and resilient scheduling is collected. Specifically, in the presence of low-level controls such as primary frequency control and heuristic grid reconfiguration schemes, it is not well understood as to how much intelligence regarding modeling details and solution methodologies is needed on scheduling level to resiliently operate microgrid and multi-microgrid systems. Still, previous studies give a first indication on possible resilience improvements but also increased operation costs and considerable computational burden [3], [4], [11], [16].

Dynamic, transient simulations are well suited to assess the performance of low-level controls in detail [9], [14], but high modeling efforts and the considerable computational costs hinder their application in long-term assessment. Steady-state power flow computations are a common method to reduce the computational burden, but classical formulations are not well suited for islanded microgrids [17], [18]. Several methods that allow modeling of distributed frequency and voltage control without dedicated slack nodes are already developed. For instance, [17] presents a balanced power flow formulation. Similarly, [18] introduces droop-based voltage and frequency control for both balanced and unbalanced grids. To improve convergence of the unbalanced network equations, an extended Newton Raphson algorithm is developed. Despite considerable effort, device constraints, RES curtailment, dynamic droop coefficients, and outage conditions are rarely considered in islanded power flows. However, detailed assessment methods covering these aspects are needed to guide future implementation and research efforts in proactive multi-microgrid scheduling.

A. CONTRIBUTIONS TO POWER SYSTEM RESILIENCE

This work investigates the operation performance of various scheduling algorithms on a comprehensive simulation-based testbed and specifically addresses the proactive consideration of network failures, low-level controls and physical constraints. To the best of our knowledge, for the first time, the impact of day-ahead scheduling formulations on system resilience is quantified based on a large-scale assessment that handles a broad range of operating conditions. A dedicated focus is put on phenomena such as voltage constraints and low-level controls that can, but may not be considered at scheduling time. Due to the large-scale evaluation covering hundred-thousands of scenarios, detailed quantitative insights into the impacts of proactive scheduling are provided. Such impacts include the system performance in case of asset failures and the costs in normal operation. All performance metrics are based on an independent set of simulation runs and do not rely on indicators that are directly returned by the scheduling algorithms.

To efficiently cover a broad range of operating conditions traditional power flow computations are significantly extended to consider dynamic droop controls, RES curtailment, detailed device capabilities, and outage conditions in an islanded grid. In contrast to dynamic simulations, the presented steady-state formulations do not require modeling of dynamic aspects such as time constants and were successfully applied in long-term assessments. Additional real-time controls that are hardly considered in the related scheduling literature include heuristic secondary control and fault rerouting. Hence, this work provides a first indication whether such facilities can reduce the need for resilience considerations at scheduling time and the resulting computational burden.

In contrast to the state-of-the-art that commonly considers only simple statistical models to characterize forecasting deviations, separate measurement and forecasting data sources are used. Required scheduling inputs are based on numerical weather prediction, while independent measurement data are taken to assess the real-time performance. Due to the clean separation, systematic and correlated forecasting deviations can be considered and common simplifications such as temporally independent errors are avoided. A rich set of failure scenarios that far exceeds the conditions reflected in the scheduling algorithms is induced. Such failures include single line outages that can be tackled by real-time control but may result in unexpected topologies and

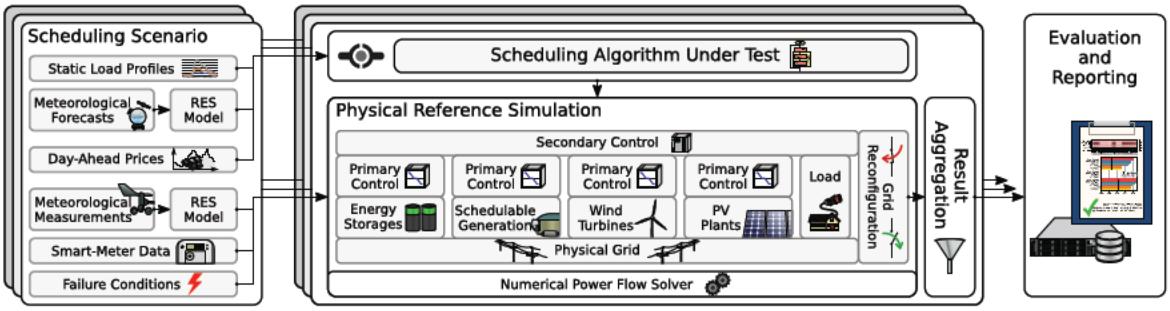

FIGURE 1. Overview on the problem decomposition and the simulation-based microgrid testbed.

multiasset outages that split the grid into independent subgrids. Hence, the assessment specifically includes conditions that are originally not foreseen by the scheduling algorithms.

B. ORGANIZATION

The remaining part of the work is organized as follows: Section II gives a detailed, formal description of the microgrid operation problem including physical asset models and considered control impacts. In section III, the simulation-based assessment methods are thoughtfully described and in section IV, the method is applied in a case study to evaluate the value of proactive scheduling. Section V discusses the study results and section VI concludes this work.

II. MICROGRID OPERATION PROBLEM FORMULATION

Micrograds are typically composed of an interlinked control architecture that keeps parameters such as the system frequency and bus voltages stable, mitigates faults, and ensures economic operation. A brief overview on the control architecture as well as the testbed that assesses the control approaches of this work is provides in Fig. 1. Within the control architecture, scheduling algorithms commonly optimize the microgrid operation with respect to the current state and predicted conditions in advance [11]. At the end of the scheduling horizon or as soon as updates are available, computations are repeated and new setpoints are applied. To ensure a maximum compatibility with existing approaches and to account for daily updated forecasting data [19], this work assumes that scheduling decisions are computed once and are not updated afterwards.

Due to the high computational complexity of the scheduling problem [3], low-level controls that quickly balance out disturbances are needed. This study assumes that the system frequency is controlled by P-of-f droop (i.e., $P(f)$) and that nodal voltages are influenced by Q-of-U droop (i.e., $Q(U)$) of participating generators. It is also assumed that storages are elected as grid forming devices in the islanded mode and that a transition into that mode is feasible. Since these grid forming devices require reserve capacity to balance out short-term fluctuations [15], a dynamic droop scheme is used that alters the active power share each storage is providing, according to the current State of Charge (SoC). On top of the droop-based primary control, a heuristic secondary control is established that modifies the high-level scheduling decisions in case insufficient reserve capacity is detected. Additionally, a reconfiguration algorithm modifies tie-line switch states to mitigate the impact of tripping power lines and to reduce the amount of unsupplied load. Since in a practical implementation, all low-level controls need to be operated in real-time, only polynomial-time heuristics are applied.

It is assumed that all low-level controls stably operate the microgrid. Hence, the assessment focuses on the steady-state impact. Transient studies that are needed to ensure a stable operation, islanding, and reconnection of the microgrid are well beyond the scope of this work. In contrast to scheduling that operates on forecasts only, it is also assumed that all low-level controls have access to real-time measurements and the previously calculated setpoints. In addition, it is assumed that topological information including fault locations is available in real-time. As illustrated in Fig. 1, the performance of the microgrid is assessed by a series of power flow calculations that incorporate the steady-state impact of low-level control approaches and detailed device constraints. After each power flow calculation, the storage states and secondary control actions are updated and the subsequent calculation is started.

Although related work introduces, several specific asset types such as controllable loads, Electric Vehicles (EVs) and micro turbines [7], [20], [21], this study focuses on the most common assets [11] to simplify the interpretation of results. Two generic, schedulable asset types, Distributed Generators (DGs) that can be freely controlled within their limits and storage units that depend on the current SoC are modeled. Additionally, two volatile RES (PV and WTs) as well as uncontrollable loads are included. All asset types are reflected in the scheduling formulations and in the independent evaluation. However, the level of detail between input data sources and considered failure modes differ significantly in the scheduling and evaluation formulation.

A. VOLATILE RENEWABLES AND LOADS

Volatile RES and loads are modeled by two different sets of input variables. One, $\tilde{p}^{\diamond,v}_{i,t}$, $v \in \{\text{PV, WT, LD}\}$ describes the PV, WT, and load forecasts that are available at scheduling time. On the contrary, $\bar{P}^{\diamond,v}_{i,t}$ describes the measurements that are available in real-time only. It is assumed that load forecasts and measurements are directly available, e.g. in terms of standard load profiles and smart meter measurements, whereas the amount of PV and wind power is computed based on meteorological forecasts and observations. Due to the broad availability of meteorological measurements, this study calculates both forecast and measurement based on asset models. Nevertheless, the real-time RES models can be substituted by direct power measurements, in case sufficient on-site data is available.

The available output power of WT w, is calculated by the turbine curve ρ_w^{WT} that translates the wind speed into the turbines output power. Given the wind speed forecasts and measurements at time t, $v_{w,t}$ and $V_{w,t}$, respectively, the available power is given by $p_{w,t}^{\diamond,\mathrm{WT}} = \rho_w^{\mathrm{WT}}(v_{w,t})$ and $P_{w,t}^{\diamond,\mathrm{WT}} = \rho_w^{\mathrm{WT}}(V_{w,t})$. Following related work [21], the PV output of plant c is modeled proportionally to the in-plane irradiance forecast $g_{c,t}$ and measurement $G_{c,t}$. Furthermore, outputs are corrected by an optional temperature coefficient k_c^{PV} utilizing the deviation of the array temperatures $\tau_{c,t}^{\mathrm{PV}}$ and $\mathcal{T}_{c,t}^{\mathrm{PV}}$, respectively from the nominal temperature $\mathcal{T}_c^{*,\mathrm{PV}}$. Equations (1) and (2) show the PV generation model.

$$p_{c,t}^{\diamond,\mathrm{PV}} = P_c^{*,\mathrm{PV}} \cdot \frac{g_{c,t}}{G^*} \cdot \left(1 + k_c^{\mathrm{PV}} \cdot \left(\tau_{c,t}^{\mathrm{PV}} - \mathcal{T}_c^{*,\mathrm{PV}}\right)\right) \quad (1)$$

$$P_{c,t}^{\diamond,\mathrm{PV}} = P_c^{*,\mathrm{PV}} \cdot \frac{G_{c,t}}{G^*} \cdot \left(1 + k_c^{\mathrm{PV}} \cdot \left(\mathcal{T}_{c,t}^{\mathrm{PV}} - \mathcal{T}_c^{*,\mathrm{PV}}\right)\right) \quad (2)$$

B. SCHEDULING MODEL

Based on the forecasts $p_{w,t}^{\diamond,\mathrm{WT}}$, $p_{c,t}^{\diamond,\mathrm{PV}}$, and $p_{l,t}^{\diamond,\mathrm{LD}}$ as well as the initial storage conditions $e_{b,-1}^{\mathrm{ST}}$, the scheduling algorithm $S(\cdot)$ calculates the control setpoints $p_{a,t}^{\mathrm{DG}}$, $o_{a,t}^{\mathrm{DG}}$, and $p_{b,t}^{\mathrm{ST}}$. To model the level of details that are considered by an algorithm $S(\cdot)$ and to assess the impact on the microgrid operation, different formulations based on prior work [3] are considered. A detailed formulation of the algorithms can be found in the original publication that assesses the computational performance but does not focus on operational aspects.

1) ECONOMIC SCHEDULING $S^{\mathrm{EC}}(\cdot)$

The least level of detail is modeled by a purely economic Mixed Integer Linear Programming (MILP) formulation of the scheduling problem that neither includes grid constraints nor considers reserves that are needed for a successful islanding transition. Storage units $b \in \mathbb{B}$s modeled in (3) to (7) are constrained by their charging mode $o_{b,t}^{\mathrm{CHG}} \in \mathbb{B}$, the stored energy $e_{b,t}^{\mathrm{ST}}$ and its bounds, as well as the device limits $\bar{p}_b^{\mathrm{CHG}}$ and $\bar{p}_b^{\mathrm{DCH}}$. Storage losses are included in a constant round-trip efficiency μ_b^{ST}.

$$0 \le p_{b,t}^{\mathrm{CHG}} \le \bar{p}_b^{\mathrm{CHG}} \cdot o_{b,t}^{\mathrm{CHG}} \quad (3)$$

$$0 \le p_{b,t}^{\mathrm{DCH}} \le \bar{p}_b^{\mathrm{DCH}} \cdot \left(1 - o_{b,t}^{\mathrm{CHG}}\right) \quad (4)$$

$$\underline{e}_b^{\mathrm{ST}} \le e_{b,t}^{\mathrm{ST}} \le \bar{e}_b^{\mathrm{ST}} \quad (5)$$

$$e_{b,t}^{\mathrm{ST}} = e_{b,t-1}^{\mathrm{ST}} + \left(p_{b,t}^{\mathrm{CHG}} \cdot \mu_b^{\mathrm{ST}} - p_{b,t}^{\mathrm{DCH}}\right) \cdot T^{\mathrm{St}} \quad (6)$$

$$p_{b,t}^{\mathrm{ST}} = p_{b,t}^{\mathrm{DCH}} - p_{b,t}^{\mathrm{CHG}} \quad (7)$$

DG units $a \in \mathbb{D}$G are constrained by the minimal and maximal active power, $\underline{p}_a^{\mathrm{DG}}$ and $\underline{p}_a^{\mathrm{DG}}$ as given in (8).

$$\underline{p}_a^{\mathrm{DG}} \cdot o_{a,t}^{\mathrm{DG}} \le p_{a,t}^{\mathrm{DG}} \le \bar{p}_a^{\mathrm{DG}} \cdot o_{a,t}^{\mathrm{DG}} \quad (8)$$

Loads and RES are included by their expected power demand and output without considering any emergency measures. Main grid transfers are considered by directional variables p^{BUY}, and p_t^{SELL} as well as a directional indicator $o_t^{\mathrm{SELL}} \in \mathbb{B}$ as shown in (9) and (10).

$$0 \le p_t^{\mathrm{BUY}} \le \bar{p}^{\,\mathrm{BUY}} \cdot \left(1 - o_t^{\mathrm{SELL}}\right) \quad (9)$$

$$0 \le p_t^{\mathrm{SELL}} \le \bar{p}^{\,\mathrm{SELL}} \cdot o_t^{\mathrm{SELL}} \quad (10)$$

For each time step, a simple active power balance (11) reduces the topology to one single bus without including topological information of physical effects such as losses.

$$\sum_{a \in \mathbb{DG}} p_{a,t}^{\mathrm{DG}} + \sum_{b \in \mathbb{ST}} p_{b,t}^{\mathrm{ST}} + \left(p_t^{\mathrm{BUY}} - p_t^{\mathrm{SELL}}\right) + \sum_{c \in \mathbb{PV}} p_{c,t}^{\diamond\mathrm{PV}} + \sum_{w \in \mathbb{WT}} p_{w,t}^{\diamond\mathrm{WT}} - \sum_{l \in \mathbb{LD}} p_{l,t}^{\diamond\mathrm{LD}} = 0 \quad (11)$$

The overall objective is to minimize the operating costs c^{TOT} determined by the power setpoints and the DG operating costs c_a^{DG} as well as main grid transfer costs c_t^{BUY} and benefits c_t^{SELL} within the scheduling horizon.

$$c^{\mathrm{TOT}} = \sum_{t \in \mathbb{T}} \left(c_t^{\mathrm{BUY}} \cdot p_t^{\mathrm{BUY}} - c_t^{\mathrm{SELL}} \cdot p_t^{\mathrm{SELL}} + \sum_{a \in \mathbb{DG}} c_a^{\mathrm{DG}} \cdot p_{a,t}^{\mathrm{DG}}\right) \cdot T^{\mathrm{St}} \quad (12)$$

All computations are based on deterministic forecasts without considering stochastic fluctuations and associated risks.

2) RESERVE-AWARE SCHEDULING $S^{\mathrm{RE}}(\cdot)$

In addition to economic scheduling, $S^{\mathrm{RE}}(\cdot)$ includes further constraints which ensure that enough storage capacity and spinning reserve is available to sustain a main grid outage until further DG can be started. The reserve constraints in [3] are slightly extended by a scenario-based formulation that introduces safety coefficients and accounts for secondary-control delays. For each time step $t \in \mathbb{T}$ and storage $b \in \mathbb{S}$T, the emergency power $p_{b,t}^{E,DCH}$ that can be provided until additional generation is started and the power that can be maximally absorbed $p_{b,t}^{E,CHG}$ until excess generation is stopped is modeled. Both variables are constrained by the storage state and its power ratings as shown in (13) to (16).

$$0 \le p_{b,t}^{E,DCH} \le \frac{e_{b,t-1}^{\mathrm{ST}} - \underline{e}_b^{\mathrm{ST}}}{T^{\mathrm{Sta}}} \quad (13)$$

$$p_{b,t}^{E,DCH} \le \bar{p}_b^{\mathrm{DCH}} \quad (14)$$

$$0 \le p_{b,t}^{E,CHG} \le \frac{\bar{e}_b^{\mathrm{ST}} - e_{b,t-1}^{\mathrm{ST}}}{T^{\mathrm{Sto}} \mu_b^{\mathrm{ST}}} \quad (15)$$

$$p_{b,t}^{E,CHG} \le \bar{p}_b^{\mathrm{CHG}} \quad (16)$$

Given the reserve coefficients $k_a^{v,\text{RE}}$ of asset a and scenario v, the net load including RES $p_t^{v,\text{NetLD}}$ is first defined by (17).

$$p_t^{v,\text{NetLD}} = \sum_{l\in\mathbb{LD}} k_l^{v,\text{RE}} \cdot p_{l,t}^{\diamond,\text{LD}} - \sum_{c\in\mathbb{PV}} k_c^{v,\text{RE}} \cdot p_{c,t}^{\diamond,\text{PV}} - \sum_{w\in\mathbb{WT}} k_w^{v,\text{RE}} \cdot p_{w,t}^{\diamond,\text{WT}} \tag{17}$$

The reserve requirements are then modeled as (18) and (19).

$$\sum_{a\in\mathbb{DG}} \bar{p}_{a,t}^{\text{DG}} \cdot o_{a,t}^{\text{DG}} + \sum_{b\in\mathbb{ST}} p_{b,t}^{E,DCH} \geq p_t^{v,\text{NetLD}} \tag{18}$$

$$\sum_{a\in\mathbb{DG}} \underline{p}_{a,t}^{\text{DG}} \cdot o_{a,t}^{\text{DG}} - \sum_{b\in\mathbb{ST}} p_{b,t}^{E,CHG} \leq p_t^{v,\text{NetLD}} \tag{19}$$

3) PHYSICS CONSTRAINED SCHEDULING $S^{\text{PH}}(\cdot)$

In addition to the economic and reserve-constrained formulation, the physics-constrained algorithm asserts that the power flow must converge for the given setpoints and that voltage, frequency, and loading limits are met. In contrast to [3] that uses a commercial power system simulator to execute the embedded power flow calculations, this work includes the extended formulation as given in Sections II-C to II-G. Nevertheless, all volatile inputs $p_{c,t}^{s,\text{PV}}$, $p_{w,t}^{s,\text{WT}}$, $p_{l,t}^{s,\text{LD}}$ are based on a static set of worst-case scenarios s that is generated from the available forecasts only. For each scenario, the AC power flow is solved. The resulting bus voltage levels $u_{i,t}^s$, $i \in \mathbb{B}\text{s}$ and line current magnitudes $\iota_{i,t}^s$, $i \in \mathbb{L}\text{I}$ are constrained as $\underline{u} \leq u_{i,t}^s \leq \bar{u}$ and $\iota_{i,t}^s \leq \bar{\iota}_i$, respectively. In addition, the frequency $f_{i,t}^s$ on each island i and scenario s needs to be within its permissible limits $\underline{f} \leq f_{i,t}^s \leq \bar{f}$.

C. SECONDARY CONTROL

To assess the impact of day-ahead scheduling decisions on the emergency operation, the steady-state impact of the most essential low-level controls is modeled. Primary control alters the active power generation setpoints to balance out short-term fluctuations. Secondary control provides a reserve heuristic that schedules new generation or shuts down running DGs in case existing generation units are operated close to their limits. For each DG a, the requested reserve is defined by the power that exceeds the nominal operating range $\underline{P}_a^{*,\text{DG}}$ to $\bar{P}_a^{*,\text{DG}}$. The upwards reserve $P_{a,t}^{\text{R,UP}}$ calculates as $P_{a,t}^{\text{R,UP}} = P_{a,t}^{\text{DG}} - \bar{P}_a^{*,\text{DG}}$ and the downwards reserve as $P_{a,t}^{\text{R,DO}} = \underline{P}_a^{*,\text{DG}} - P_{a,t}^{\text{DG}}$. For storage units b, additionally, the maximum power that can be supplied or absorbed until secondary control actions take effect, is considered.

To estimate the maximum power that can be provided or absorbed for a period of T, (20) and (21) define the power limit heuristics, $\bar{P}_b^{\text{E}}(E,T)$ and $\underline{P}_b^{\text{E}}(E,T)$, at a storage state E and the efficiency curves $\mu_b^{\text{CHG}}(P)$ and $\mu_b^{\text{DCH}}(P)$.

$$\bar{P}_b^{\text{E}}(E,T) = \frac{\left(E - \underline{E}_b^{\text{ST}}\right) \cdot \min_P \left(\mu_b^{\text{DCH}}(P)\right)}{T} \tag{20}$$

$$\underline{P}_b^{\text{E}}(E,T) = \frac{\left(E - \bar{E}_b^{\text{ST}}\right)}{T \cdot \max_P \left(\mu_b^{\text{CHG}}(P)\right)} \tag{21}$$

Algorithm 1 Secondary Control Heuristic Matching the Reserve Requests of a Single Island

```
function Sec(Status O_i^IN, nominal P_i^* and reserve P^R)
    O^OUT ← O^IN
    repeat
        M ← {i, ¬O_i^OUT ∧ P_i^* ≤ P^R}
        if M ≠ ∅ then
            n ← argmax_{i∈M}(P_i^*)
            O_n^OUT ← 1
            P^R ← P^R − P_n^*
        end if
    until M = ∅
    return O^OUT
end function
```

Since the storage efficiency depends on the output power itself, a worst-case efficiency is assumed to limit convergence issues while solving the equations. Given the dynamic power limits based on the storage state, the reserve requests (22) and (23) are calculated by the nominal output power range and the power that cannot be provided due to energy limits.

$$P_{b,t}^{\text{R,UP}} = \max\left(\bar{P}_b^{\text{ST}} - \bar{P}_b^{\text{E}}(E_{b,t}^{\text{ST}}, T^{\text{Sta}}), P_{b,t}^{\text{ST}} - \bar{P}_b^{*,\text{ST}}\right) \tag{22}$$

$$P_{b,t}^{\text{R,DO}} = \max\left(\underline{P}_b^{\text{E}}(E_{b,t}^{\text{ST}}, T^{\text{Sto}}) - \underline{P}_b^{\text{ST}}, \underline{P}_b^{*,\text{ST}} - P_{b,t}^{\text{ST}}\right) \tag{23}$$

To compute the secondary control actions, first, the reserve power requests for each island i, $P_{i,t}^{\text{R},v}$ are computed by (24).

$$P_{i,t}^{\text{R},v} = \sum_{j,\Gamma_j^{\text{IL}}=i} \max(P_{j,t}^{\text{R},v}, 0) \quad v \in \{\text{UP}, \text{DO}\} \tag{24}$$

The secondary control algorithm SEC implements a greedy heuristic that changes the DG status setpoints $o_{a,t}^{\text{DG}}$ to closely meet the reserve request. In each iteration, one DG status is altered that shifts the remaining reserve requirement closest to zero. Algorithm 1 defines the procedure for a single island and one reserve request direction in more detail. Since the set of candidate machines $\mathbb{M}$ decreases monotonically, it can be seen that the computations terminate within polynomial time.

In case an island i shows a power surplus, i.e. $f_i > f^*$, SEC is applied to the inverted operating status $\neg o_{i,t}^{\text{DG}}$ of all DG units on that island to compute the assets that need to be shut down. Equation (25) models the secondary control outputs of the operating status $O_{i,t}^{\circ,\text{DG}}$.

$$O_{i,t}^{\circ,\text{DG}} = \begin{cases} \text{SEC}\left(o_{i,t}^{\text{DG}}, P_i^{*,\text{DG}}, P_{i,t-T^{\text{Sta}}}^{\text{R,UP}}\right) & f_{i,t} < f^* \\ \neg\text{SEC}\left(\neg o_{i,t}^{\text{DG}}, P_i^{*,\text{DG}}, P_{i,t-T^{\text{Sto}}}^{\text{R,DO}}\right) & f_{i,t} > f^* \\ o_{i,t}^{\text{DG}} & f_{i,t} = f^* \end{cases} \tag{25}$$

In case a DG unit a is newly scheduled, (26) will apply the nominal output value as power set point $P_{a,t}^{\circ,\text{DG}}$.

$$P_{a,t}^{\circ,\text{DG}} = \begin{cases} P_a^{*,\text{DG}} & \text{if } O_{a,t}^{\circ,\text{DG}} \wedge \neg o_{a,t}^{\text{DG}} \\ p_{a,t}^{\text{DG}} \cdot O_{a,t}^{\circ,\text{DG}} & \text{otherwise} \end{cases} \tag{26}$$

D. PRIMARY CONTROL

In islanded operation, short-term fluctuations are commonly balanced by droop-based real-time control [17], [18]. As illustrated in Fig. 1, the steady-state impacts of primary control are considered in the extended load flow. Each operational DG a adjusts its active power setpoint $P_{a,t}^{\bullet,\mathrm{DG}}$ according to the locally measured frequency $f_{i,t}$. Since the model focuses on the steady state, for each electrically connected island in the microgrid, a single frequency variable is introduced. Given the topology function Γ_j^{IL} that returns the island of asset j as well as the droop coefficient $k_a^{\mathrm{f,DG}}$ the primary frequency control is modeled as (27).

$$P_{a,t}^{\bullet,\mathrm{DG}} = P_{a,t}^{\circ,\mathrm{DG}} - k_a^{\mathrm{f,DG}} \cdot (f_{\Gamma_a^{\mathrm{IL}},t} - f^*) \tag{27}$$

In addition to DG, also storage units b directly contribute to primary frequency control. However, the units implement a dynamic scheme that gradually reduces the droop $k_{b,t}^{\mathrm{f,ST}}$ in case the nominal SoC limits $\underline{E}_b^{*,\mathrm{ST}}$ and $\bar{E}_b^{*,\mathrm{ST}}$ are exceeded. To quickly enter the nominal operating range again, the reduction further depends on the sign of the frequency deviation as given in (28) and (29).

$$k_{b,t}^{\mathrm{f,ST}} = \begin{cases} k_b^{*,\mathrm{f,ST}} \cdot \dfrac{E_{b,t-1}^{\mathrm{ST}} - \underline{E}_b^{\mathrm{ST}}}{\underline{E}_b^{*,\mathrm{ST}} - \underline{E}_b^{\mathrm{ST}}} & \text{if } f_{\Gamma_b^{\mathrm{IL}},t} \le f^* \wedge \\ E_{b,t-1}^{\mathrm{ST}} \le \underline{E}_b^{*,\mathrm{ST}} k_b^{*,\mathrm{f,ST}} \cdot \dfrac{\bar{E}_b^{\mathrm{ST}} - E_{b,t-1}^{\mathrm{ST}}}{\bar{E}_b^{\mathrm{ST}} - \bar{E}_b^{*,\mathrm{ST}}} & \text{if } f_{\Gamma_b^{\mathrm{IL}},t} \ge f^* \wedge \\ E_{b,t-1}^{\mathrm{ST}} \ge \bar{E}_b^{*,\mathrm{ST}} k_b^{*,\mathrm{f,ST}} & \text{otherwise} \end{cases} \tag{28}$$

$$P_{b,t}^{\bullet,\mathrm{ST}} = P_{b,t}^{\circ,\mathrm{ST}} - k_{b,t}^{\mathrm{f,ST}} \cdot (f_{\Gamma_b^{\mathrm{IL}},t} - f^*) \tag{29}$$

In contrast to DG and storage units, it is assumed that volatile RES do not participate in regular frequency control. However, a limited frequency sensitive mode for over-frequency events following [22] is implemented to reduce the infeed in case of severe over-frequency events. Considering the nominal operating boundary $\bar{f}^*$, the output power of asset i type $v \in \{\mathrm{PV, WT}\}$ is calculated as (30).

$$P_{i,t}^{\bullet,v} = \begin{cases} P_{i,t}^{\diamond,v}\left(1 - k_i^{\mathrm{f},v}(f_{\Gamma_i^{\mathrm{IL}},t} - \bar{f}^*)\right) & f_{\Gamma_i^{\mathrm{IL}},t} > \bar{f}^* \\ P_{i,t}^{\diamond,v} & \text{otherwise} \end{cases} \tag{30}$$

For each asset j having type v, the topology function Γ_j^v specifies the bus j is connected to. The reactive power setpoint $Q_{i,t}^{\bullet,v}$ of all generation units i typed $v \in \{\mathrm{DG, ST, PV, WT}\}$ is controlled by a static Q-of-u droop $k_i^{\mathrm{u},v}$ and the locally measured voltage magnitudes $U_{\Gamma_i^v,t}$ as modeled by (31).

$$Q_{i,t}^{\bullet,v} = k_i^{\mathrm{u},v} \cdot \left(U_{\Gamma_i^v}^* - U_{\Gamma_i^v,t}\right) \tag{31}$$

E. DEVICE CONSTRAINTS

For each generation unit i of type v a set of active and apparent power limits is introduced to model saturation effects in the power flow computations. In general, the active power setpoints from the primary control, $P_{i,t}^{\bullet,v}$ are directly limited by the minimal and maximal supported active power $\underline{P}_i^v$ and $\bar{P}_i^v$, respectively. The active power takes precedence over reactive power outputs that are curtailed to limit the total apparent power $\bar{S}_i^v$, given $|\underline{P}_i^v|, |\bar{P}_i^v| \le \bar{S}_i^v$. The active power output of volatile RES is specifically defined by (32) that considers optional inverter constraints by an additional limit $\bar{P}_i^v$.

$$P_{i,t}^v = \min\left(\bar{P}_i^v, \max(0, P_{i,t}^{\bullet,v})\right), \quad v \in \{\mathrm{PV, WT}\} \tag{32}$$

The DG model (33) additionally considers the operating status $O_{i,t}^{\circ,\mathrm{DG}}$ returned by secondary control to enforce zero output power, in case the unit is switched off.

$$P_{a,t}^{\mathrm{DG}} = \min\left(\bar{P}_a^{\mathrm{DG}} O_{a,t}^{\circ,\mathrm{DG}}, \max(\underline{P}_a^{\mathrm{DG}} O_{a,t}^{\circ,\mathrm{DG}}, P_{a,t}^{\bullet,\mathrm{DG}})\right) \tag{33}$$

The state of each storage plant b is modeled by the energy $E_{b,t}^{\mathrm{ST}}$ that is stored at time t. Given the charging and discharging efficiency curves $\mu_b^{\mathrm{CHG}}(P)$ and $\mu_b^{\mathrm{DCH}}(P)$ the storage state is advanced by (34).

$$E_{b,t}^{\mathrm{ST}} = \begin{cases} E_{b,t-1}^{\mathrm{ST}} - \dfrac{P_{b,t}^{\mathrm{ST}} T^{\mathrm{St}}}{\mu_b^{\mathrm{DCH}}(P_{b,t}^{\mathrm{ST}})} & \text{if } P_{b,t}^{\mathrm{ST}} \ge 0 \\ E_{b,t-1}^{\mathrm{ST}} - P_{b,t}^{\mathrm{ST}} T^{\mathrm{St}} \mu_b^{\mathrm{CHG}}(P_{b,t}^{\mathrm{ST}}) & \text{otherwise} \end{cases} \tag{34}$$

Limited storage capacity is accounted for by the energy-dependent power boundaries $\underline{P}_b^{\mathrm{E}}(E,T)$ and $\bar{P}_b^{\mathrm{E}}(E,T)$ as modeled in (21) and (20), respectively. Hence, the active output power is modeled as (35).

$$\begin{aligned} P_{b,t}^{\mathrm{ST}} = \min\Big(&\bar{P}_b^{\mathrm{ST}}, \bar{P}_b^{\mathrm{E}}(E_{b,t}^{\mathrm{ST}}, T^{\mathrm{St}}), \\ &\max(\underline{P}_b^{\mathrm{ST}}, \underline{P}_b^{\mathrm{E}}(E_{b,t}^{\mathrm{ST}}, T^{\mathrm{St}}), P_{b,t}^{\bullet,\mathrm{ST}})\Big) \end{aligned} \tag{35}$$

Given the active output power of asset i, the reactive power limit $\bar{Q}_{i,t}^v$ of all asset types v is calculated as (36) and the reactive output power $Q_{i,t}^v$ as (37).

$$\bar{Q}_{i,t}^v = \sqrt{(\bar{S}_i^v)^2 - (P_{i,t}^v)^2} \tag{36}$$

$$Q_{i,t}^v = \min\left(\bar{Q}_{i,t}^v, \max(-\bar{Q}_{i,t}^v, Q_{i,t}^{\bullet,v})\right) \tag{37}$$

F. PHYSICAL GRID MODEL

In case an electrically connected part of the grid i is itself connected to the main grid, a Point of Common Coupling (PCC) is modeled by two slack variables $P_{i,t}^{\mathrm{EX}}$, $Q_{i,t}^{\mathrm{EX}}$ and a constant voltage $U_{\Gamma_i^{\mathrm{EX}},t}$ on the connected bus. Simultaneously, the frequency is fixed to $f_i = f^*$ in order to model inactive primary and secondary controls. In case the electrically connected island i is not itself connected to any external grid, f_i is kept as a free variable that models a distributed slack. To reduce non-converging power flows due to the detailed saturation model, for each island, an emergency model is introduced. As soon as the system frequency exceeds the permitted range, the virtual emergency power $P_{i,t}^{\mathrm{EM}}$ models the power that would be needed to stabilize the system. To support the convergence of the entire power flow, (38) introduces an emergency droop $k_{\mathrm{OB}}^{\mathrm{f,EM}}$ that determines the power in case the frequency exceeds the permitted band and a small but positive droop heuristic $k_{\mathrm{IB}}^{\mathrm{f,EM}}$, $k_{\mathrm{IB}}^{\mathrm{f,EM}} \ll k_{\mathrm{OB}}^{\mathrm{f,EM}}$, that additionally supports convergence.

$$P_{i,t}^{\mathrm{EM}} = \left(\begin{cases} k_{\mathrm{OB}}^{\mathrm{f,EM}}(\bar{f} - f_{i,t}) & \text{if } f_{i,t} > \bar{f} \\ k_{\mathrm{OB}}^{\mathrm{f,EM}}(\underline{f} - f_{i,t}) & \text{if } f_{i,t} < \underline{f} \end{cases} \right) + k_{\mathrm{IB}}^{\mathrm{f,EM}}(f^* - f_{i,t}) \tag{38}$$

The injected active and reactive net power of each bus, $P_{i,t}^{\mathrm{BS}}$ and $Q_{i,t}^{\mathrm{BS}}$, respectively is calculated as (39) and (40). Note that $\mathbb{V}$ is defined as the set of all generation units $\mathbb{V} = \{\mathrm{DG}, \mathrm{ST}, \mathrm{PV}, \mathrm{WT}, \mathrm{EX}, \mathrm{EM}\}$ including any external grid connections and the virtual emergency power source.

$$P_{i,t}^{\mathrm{BS}} = \sum_{v \in \mathbb{V}} \sum_{j, \Gamma_j^v = i} P_{j,t}^{v} - \sum_{l, \Gamma_l^{\mathrm{LD}} = i} P_{l,t}^{\mathrm{LD}} \tag{39}$$

$$Q_{i,t}^{\mathrm{BS}} = \sum_{v \in \mathbb{V}} \sum_{j, \Gamma_j^v = i} Q_{j,t}^{v} - \sum_{l, \Gamma_l^{\mathrm{LD}} = i} Q_{l,t}^{\mathrm{LD}} \tag{40}$$

The basis of the microgrid model is then given by the well-known AC power flow equations. To strengthen the comparability to related work [3], [11], [21], the balanced power flow model is used. For each bus $i \in \mathbb{B}\mathrm{s}$, a voltage magnitude $U_{i,t}$ and angle $\varphi_{i,t}$ is introduced. Given $P_{i,t}^{\mathrm{BS}}$ and $Q_{i,t}^{\mathrm{BS}}$ as well as the admittance matrix entries for the buses $i, j \in \mathbb{B}\mathrm{s}$, $|Y|_{i,j} \angle \theta_{i,j}$, the power flow equations can be given by (41) and (42) [17], [18].

$$P_{i,t}^{\mathrm{BS}} = U_{i,t} \sum_{j \in \mathbb{B}\mathrm{s}} |Y|_{i,j} \, U_{j,t} \cos(\varphi_{i,t} - \varphi_{j,t} - \theta_{i,j}) \tag{41}$$

$$Q_{i,t}^{\mathrm{BS}} = U_{i,t} \sum_{j \in \mathbb{B}\mathrm{s}} |Y|_{i,j} \, U_{j,t} \sin(\varphi_{i,t} - \varphi_{j,t} - \theta_{i,j}) \tag{42}$$

G. EMERGENCY GRID RECONFIGURATION

A grid reconfiguration scheme models the effect of real-time topology reconfiguration actions that isolate faults and reconnect the remaining sections, if possible. It is assumed that all tie-line switches can be remotely controlled well below the simulation step size T^{St}. Furthermore, it is assumed that all faults can be located and isolated such that no healthy section of the network is directly affected. At the beginning of each scenario and after each topological change (i.e., faults or repair actions), the reconfiguration heuristic is executed. The main goal is to establish a maximally connected, healthy, and radial network. Hence, islanding will be avoided, in case an external grid connection is feasible and each island will be as large as possible to share available power reserves. Since the study focuses on the steady-state effects only, it is assumed that all configurations can be stably operated and that grid forming and black-start is adequately addressed within each island having at least one operational DG or storage unit.

The grid reconfiguration task is mapped to a minimal spanning forest problem that is solved in polynomial time using Prim's algorithm [23]. Each line l is mapped to an edge of the graph and the edge weight $c_{l,t}^{\mathrm{LI}}$ is guided by the line admittance after clearing the fault $Y_{l,t}$. To limit the number of switching operations and to account for lines that cannot be isolated by remotely operated switches, the initial operating status of line l connecting bus j and i, $O_{l,0}^{\mathrm{LI}}$ is considered in the weight heuristic (43) as well.

$$c_{l,t}^{\mathrm{LI}} = \begin{cases} \left| \dfrac{1}{Y_{l,t}} \right| & \text{if } \neg O_{l,0}^{\mathrm{LI}} \\ 0 & \text{otherwise} \end{cases} \tag{43}$$

III. BENCHMARKING METHODS

One of the research goals is to quantify the impact of scheduling algorithms on the complex operation of a multi-microgrid and the resulting system resilience. To study the long-term effects, a simulation-based study that focuses on steady-state phenomena is chosen. Fig. 1 shows the main components of the assessment method including the dedicated grid simulation. For all algorithms under test, a common set of input conditions (e.g., forecasts and the corresponding measurements) is generated and the impacts of the scheduling decisions are independently evaluated. Due to the identical inputs, the results can be directly compared without considering stochastic fluctuations among test runs. In contrast to the preliminary work [24] that describes the concepts of a microgrid testbed, this work significantly refines the models, drastically increases the number of considered conditions, and presents detailed results on several algorithms.

Since fault mitigation options and consequently the impact on the system resilience largely depend on the considered grid and included assets, the scheduling algorithm needs to be chosen according to local requirements. For instance, a network that is designed to accept all scheduling states needs less consideration than a grid that is operated close to its limits. The presented method targets the efficient case-specific evaluation by a generalized assessment framework that solves the system model given in Section II.

A. SCENARIO GENERATION

The assessment requires an extensive set of inputs including dynamic grid prices, environmental conditions and load profiles. Since several inputs such as solar irradiation and wind speed [25], [26] show a considerable temporal correlation, first, a subset of scheduling time frames is selected from the available days in the long-term measurement and forecast series. According to each of the absolute time frames, the input measurements and forecasts will be selected without the need of reducing the long-term time series to a consecutive period. Since the inputs are based on common time frames, the correlations among different data sources such as seasonal effects on energy consumption are modeled as well.

In contrast to the RES generation forecasts that are based on numerical weather predictions targeting the particular measurement time and location, generation forecasts are based on generic profiles. Hence, possibly sensitive information that is needed to model user behavior and load forecasts can be kept at a minimum. Such information on loads includes the type of load (e.g., households and agricultural load) and the yearly energy consumption, only.

The environment conditions are amended by a detailed set of failure scenarios that are exposed to the real-time models only. Each failure scenario temporarily alters the operating status of selected assets such as lines and the external grid connection and may trigger real-time actions such as grid reconfiguration. All failure scenarios are considered as rare events that cannot be well quantified in a limited Monte Carlo simulation. To specifically focus on the system resilience in such rare events, for each set of environmental input conditions, all failure scenarios as well as a reference scenario without any fault are applied.

B. SIMULATION-BASED ASSESSMENT

For each previously defined input scenario, the RES generation is predicted and a dedicated scheduling run using the algorithm under test is conducted. All algorithms under test follow an optimization based approach and therefore the cost minimization problems defined in Section II-B are solved. All MILP formulations are directly solved by exact mathematical programming techniques. In case a problem turns out to be infeasible (e.g., due to its reserve requirements), a default output that does not schedule any generation at all is returned and the microgrid is operated by its real-time controls, only. The highly nonlinear physical constraint formulation cannot be solved by a MILP solver and therefore the hybrid heuristic optimization technique defined in [3] is applied. In case no feasible solution that satisfies all constraints is found by the heuristic method, the best known schedule that may still result in some constraint violations is used in the assessment.

Given the results of the scheduling run, the failure scenarios are applied and for each set of real-time conditions, the independent evaluation of the real-time operation is conducted. At the beginning of each scenario and after status changes, the fault reconfiguration algorithm is executed and the topological information including the admittance matrix Y and connected assets are computed. Afterwards, the system model including primary and secondary control is solved in a series of power flow computations. For each time step, a dedicated computation is triggered and the internal states such as the secondary control setpoints as well as the storage states are updated. The set of equations that describe the system state as defined in Section II are numerically solved by the hybrid root-finding algorithm of [27].

C. PERFORMANCE METRICS

The quality of all scheduling algorithms is quantified by the impacts on real-time operation of the network and whether the most important grid constraints can be met. As such, it is evaluated whether the bus voltages are within the permitted voltage range and whether overloading of assets such as lines is observed. The occurrence of such constraint violation events is addressed by the rate $\mathbb{E}(e)$ that counts the share of events e on the total number of time instants in the set of interest. For instance, $\mathbb{E}(U^s_{i,t} < \underline{U}_i)$ gives the ratio of undervoltage events to the total number of time steps at bus i. Similar aggregations are conducted for overload events $\mathbb{E}(I^s_{i,t} > \bar{I}_i)$ of line i as well.

Additionally, the fault mitigation rate $\mathbb{E}(\text{mtg})$, i.e., the share of time steps in the fault duration that can fully avoid any voltage, frequency, and loading violation is defined as (44).

$$\mathbb{E}(\text{mtg}) = \mathbb{E}(\forall i \in \mathbb{B}\text{s}, \underline{U} \leq U^s_{i,t} \leq \bar{U} \wedge \underline{f} \leq f^s_{i,t} \leq \bar{f} \wedge \forall j \in \mathbb{L}\text{I}, I^s_{j,t} \leq \bar{I}_j) \quad (44)$$

The mitigation rate indicates performance improvements compared to statically operated distribution systems that cannot automatically mitigate any fault. In contrast to the other event rates, $\mathbb{E}(\text{mtg})$ specifically focuses on the system performance in times of induced failure conditions without considering other outages due to improper operation and scheduling decisions.

Although the event rates $\mathbb{E}(e)$ well quantify the number of constraint violations, the impact of such events is not well covered. One common metric to describe the impact of any violation on the supplied loads is the (expected) energy not served $E^{\text{NS},s}$ that describes the amount of energy that cannot be supplied due to outage conditions in scenario s [11], [28]. Since this work does not rely on probabilistic failure models, the unsupplied energy $E^{\text{NS},s}$ is always aggregated given a certain failure mode such as main-grid outages. Following the definition of $\mathbb{E}(\text{mtg})$, outage conditions include severe voltage and frequency band violations beyond a given threshold as well as overload events that are assumed to trigger an immediate shutdown of electrically connected subgrids. Note that a detailed model of the protection system that includes cascading faults exceeds the scope of this work by far. Therefore, it is assumed that the status of all assets is tightly monitored and that any constraint violation immediately triggers a complete loss of load on the subgrid without considering further degraded states.

To assess the economic performance of any scheduling algorithm, the total operating costs as encountered in the independent grid simulation, $C^{\text{TOT},s}$ of scenario s are taken. Hence, $C^{\text{TOT},s}$ incorporates forecasting deviations and does not rely on the cost estimate committed at scheduling time.

IV. CASE STUDY

The case study aims at demonstrating the large-scale assessment method and giving first detailed insights into the performance of several scheduling algorithms. Three base algorithms are selected that represent different levels of detail and complexity. The first one implements simple economic scheduling without considering resilience or forecasting deviations, the second one includes linear sufficiency constraints that target a successful islanding, and the most complex algorithm adds nonlinear grid constraints. In addition, several algorithmic variants that study the impact of worst-case formulations and forecasting deviations are considered.

All algorithms were evaluated on a common test system that is specifically designed to challenge the algorithm under test and to trigger extreme cases that may not be found in other

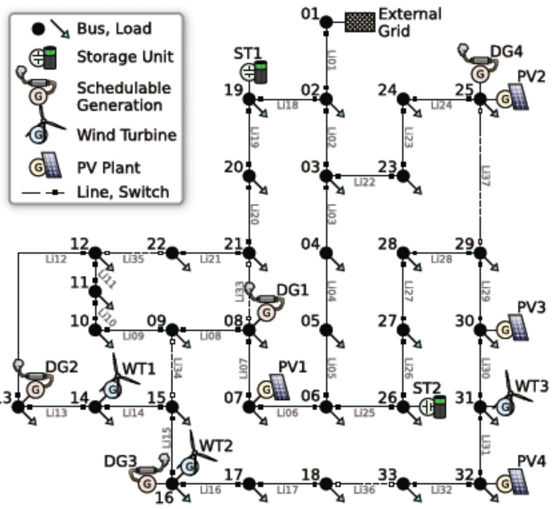

FIGURE 2. Network topology of the benchmark system extended from [3].

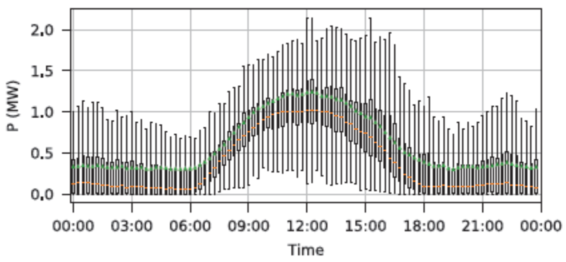

FIGURE 3. Distribution of the total real-time RES generation in the input scenarios.

distribution systems. In contrast to related work, the case study covers a rich set of operating conditions and performs a large-scale assessment of manifold failure scenarios. In the following, a detailed description of the test system as well as the evaluation results of all algorithms are given.

A. BENCHMARK SYSTEM

The topology of the benchmark system is based on a commonly used test grid called Baran test feeder that was specifically designed to challenge algorithms under test [3], [11], [29]–[31]. Although the test system is widely used in scheduling, several authors include extensions to fully support the assessment of multi-microgrids. This work follows the extensions of [3] but increases the share of volatile RES and available storage capacity to specifically focus on highly loaded, low-emission power systems. In addition, tie-lines and switches that are present in the original Baran test feeder [29] are modeled in this work as well. Fig. 2 shows the network topology including loads, generation units, tie-lines, and switches. It is assumed that every switch in the diagram can be remotely operated by the reconfiguration algorithm. The detailed parameters of all schedulable generation units can be directly found in [3]. PV and WTs are increased to a maximum apparent power of $\bar{S}_i^{\mathrm{PV}} = 0.25$ MVA and $\bar{S}_i^{\mathrm{WT}} = 1.0$ MVA, respectively. Both storage units were extended to $\bar{P}_b^{\mathrm{ST}} = 1.5$ MW with a usable capacity of $\bar{E}_b^{\mathrm{ST}} = 1.5$ MWh and $\underline{E}_b^{\mathrm{ST}} = 0$ MWh, each. To avoid frequent deep discharge and provide additional operation reserves, the upper and lower capacity limits for scheduling are set to 95% and 5% of the total capacity, respectively. In addition to a constant storage efficiency for scheduling as described in [3], a detailed efficiency curve according to [32] and [33] is included in the physical grid model.

Following [3] and [34], Q-of-U control scales (i.e., $Q(U)$) the maximal reactive power between 0.92 p.u. and 1.08 p.u. for all active generation units. Likewise, the P-of-f droop (i.e., $P(f)$) is chosen s.t. the whole operating range of all active DG and storage units is covered within a ±200 mHz deviation range. A nominal storage range $\bar{E}_b^{*,\mathrm{ST}}$ to $\underline{E}_b^{*,\mathrm{ST}}$ of 0.8 p.u. to 0.2 p.u is configured for all storage units. The permissible voltage and frequency limits that trigger loss of load and generation are set to 0.9 p.u., 1.1 p.u. and ±400 mHz, respectively.

The reforecasting dataset [19] that covers several decades of state-of-the-art forecasting outputs with historic data represents the scheduling-time predictions. The forecasts are spatially and temporally aligned with the measurements from [35]–[39] which are taken to model the full dynamics of meteorological phenomena in high temporal resolution. WT curves are taken from [40] and the nominal inplane irradiance G^* is set to 1 $\frac{\mathrm{kW}}{\mathrm{m}^2}$. Fig. 3 illustrates the statistical distribution of the accumulated volatile generation calculated from the measurement series. For each daytime, the boxplot shows the total generation quartiles excluding outliers as calculated by [41] and the average generation over all scenarios as green triangle. Clearly, the daytime pattern induced by the PV generation is visible. Load forecasts are modeled by the static load profiles [42] that match the measurement profiles taken from [43]. For all scenarios, the total real-time load is illustrated in the boxplot of Fig. 4. Day-ahead prices are available at [44] and illustrated in Fig. 5. The operating costs of DGs are directly taken from [3]. Table 1 shows the forecasting error for all asset types relative to the maximum output power. For convenience and to ease comparison to other datasets, the evaluation includes the standard error deviation and the Root-Mean-Square Error (RMSE) in addition to mean absolute error. For PV outputs, both the daytime and whole-day error including trivial night-time predictions are given.

To assess the performance in case of contingencies, several main grid, single line, and branch faults are modeled. However, to keep the assessment computationally tractable, no exhaustive failure definition is applied. Instead, Table 2 shows the faulty assets in each category. Note that all whole-branch faults isolate a section of the grid that needs to be operated in islanded mode. On the contrary, the studied single

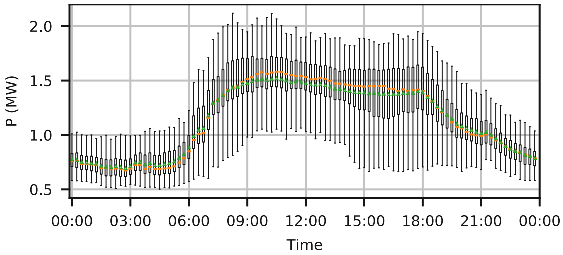

FIGURE 4. Distribution of the total real-time load in the input scenarios.

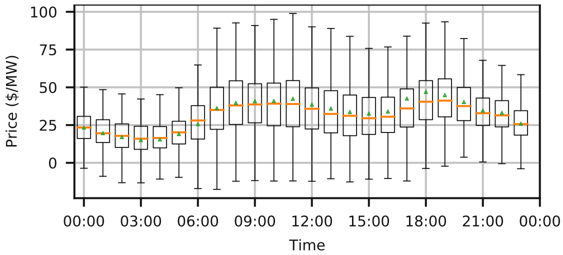

FIGURE 5. Distribution of the main grid transfer price for selling electricity in the input scenarios.

TABLE 1. Forecasting error statistics relative to the nominal power.

	Mean Err. (%)	Err. Std. (%)	RMSE (%)
PV	2.90	25.71	25.87
PV (Daytime)	6.59	37.31	37.88
WT	2.08	20.44	20.55
Load	-0.09	11.52	11.52

line fault can always be compensated by grid reconfiguration. According to related work, a fault clearance time of three hours was modeled [21], [30]. For each faulty asset, eight different incident times covering the entire scheduling period result in 144 failure cases and one normal operating case. Given the sample size of 365 environmental scenarios, a total number of 52,925 scenarios per algorithm is covered. Similar to the related work on complex power flow computations in islanded systems [17], [18], a total share of 0.016% of all power flows does not converge. Consequently, scenarios with non-converging power flows were removed from the evaluation and are not considered in the metrics.

B. ECONOMIC SCHEDULING

A purely economic scheduling algorithm $S^{\mathrm{EC}}(\cdot)$ that does not include any resilience constraints at all establishes the baseline for resilient multi-microgrid scheduling. Fig. 6 to 8 show the constraint violation rates for overvoltage $\mathbb{E}(U_{i,t}^s > \bar{U}^*)$, undervoltage $\mathbb{E}(U_{i,t}^s < \underline{U}^*)$, and overload events $\mathbb{E}(I_{i,t}^s > \bar{I}_i)$, respectively. Note that the voltage-related events consider the tighter scheduling-time bounds of $\bar{U}^* = 0.95$ p.u. and $\underline{U}^* = 1.05$ p.u. aligning to the same safety margins as physics-constraint scheduling. Nevertheless, average unserved energy

TABLE 2. Faulty assets per contingency.

Main Grid	Single Line	Whole Branch
External Grid	Li02	Li02, Li06, Li36
	Li07	Li06, Li18, Li36
	Li13	Li22, Li25, Li36
	Li18	Li03, Li20, Li37
	Li23	Li02, Li19
	Li28	Li02, Li07, Li15
		Li07, Li15, Li18
		Li25, Li36, Li37
		Li15, Li25, Li37
		Li06, Li15, Li18
		Li02, Li06, Li15

E^{NS} shown in Fig. 9 considers the wider protection-related limits to compute the amount of lost load. In case an algorithm avoids all constraint violations of a particular type, no statistics are shown in the graphics.

One can observe that the purely economic algorithm does not adhere to the tight voltage band used for scheduling and consequently shows a considerable number of overvoltage events near WT2 for all failure types and normal operation. Given the wider safety-related voltage limits, no violation in normal operation mode and only a marginal maximum rate event of 0.029% per asset in case of single-line faults are seen. Similarly, only a few undervoltage events that mostly occur on islanding faults are observed for both bounds. Since the network is designed to host nominal loads without overload events, all failures that do not involve grid reconfiguration actions can be tolerated without overload events. However, for single-line faults, a considerable overload rate of up to 0.11% is observed. Fig. 8 indicates that due to the reconfiguration actions and the nature of the test grid in challenging algorithms under test, small sized lines such as line 18 as well as tie lines 35 and 36 are mostly affected. Similar overload events can be observed on whole-branch failures that include grid reconfiguration actions as well.

Fig. 9 shows the average unserved energy E^{NS} per day and failure type. No unserved load is observed in normal operating scenarios and single-line faults do not trigger as much loss of load as incidents that result in islanding actions. To relate the observed loss E^{NS} to the best known solutions, a lower bound given all assessed algorithms is calculated. For each input scenario, the best known solution having the least unserved energy is taken. The lower bound itself also includes reference runs that cannot be practically implemented and therefore only serves as a theoretical guidance metric that describes the best known system performance.

The fault mitigation rates of the economic scheduling algorithm and all failure types are listed in Table 3. It can be seen that a large share of single line faults are handled by the grid reconfiguration algorithm without any indicated voltage, frequency band, and loading violation but that some failure conditions cannot be avoided. Specifically, for main-grid and whole-branch failures that operate parts of the grid in islanded mode, slightly reduced mitigation rates are observed.

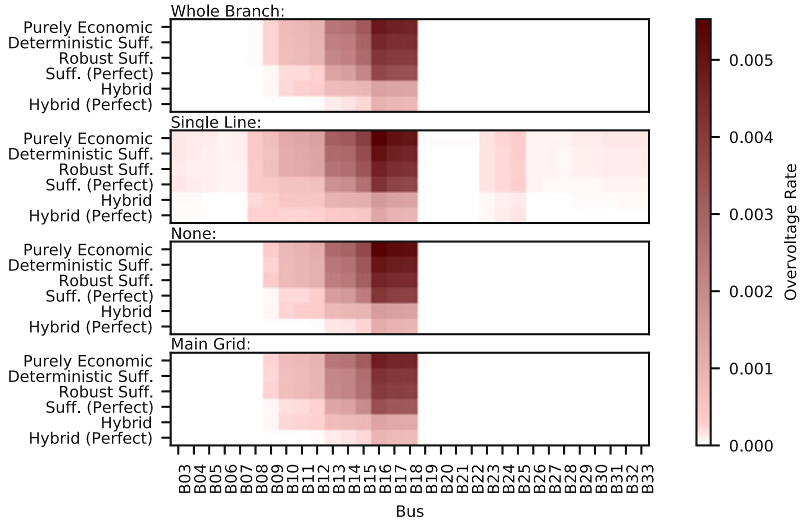

FIGURE 6. Share of overvoltage events on all time steps considering the tight scheduling-time limits.

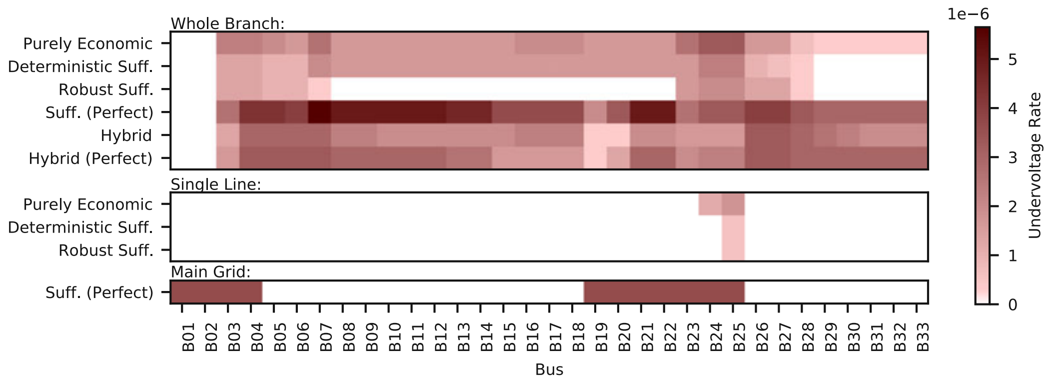

FIGURE 7. Share of undervoltage events on all time steps considering the tight scheduling-time limits.

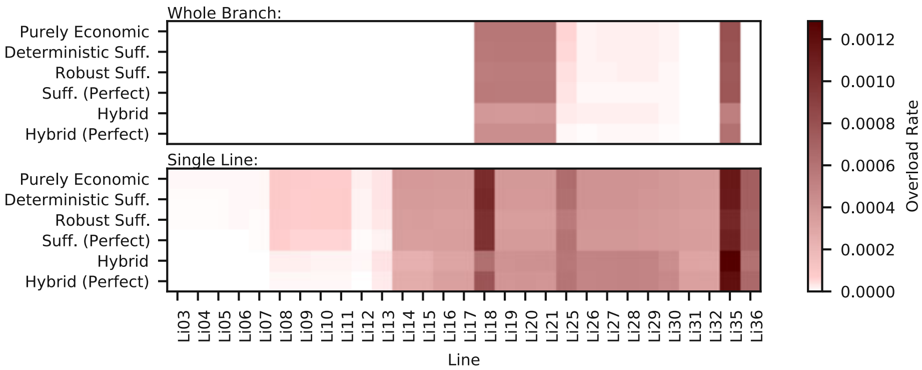

FIGURE 8. Share of overload events on all time steps.

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TABLE 3. Fault mitigation rates of the assessed algorithms and failures.

Failure Class Algorithm	Main Grid	Single Line	Whole Branch
Purely Economic	0.942	0.986	0.870
Deterministic Suff.	0.946	0.986	0.871
Robust Suff.	0.951	0.987	0.877
Suff. (Perfect)	0.952	0.987	0.882
Hybrid	0.965	0.990	0.891
Hybrid (Perfect)	0.965	0.988	0.893

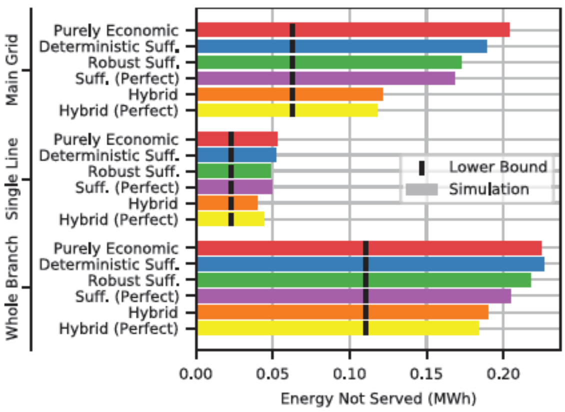

FIGURE 9. Average ENS of all scenarios.

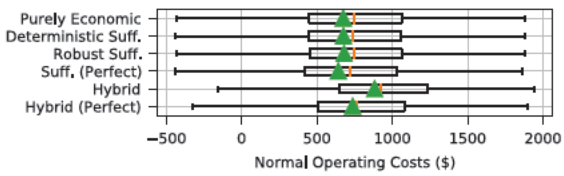

FIGURE 10. Operating costs in normal operation.

Given the purely economic scheduling results, it can be seen that already a large share of faults is compensated by the low-level controls without the need of considering them in scheduling.

Due to the economic scheduling formulation, no infeasible scenario is detected and hence, no fallback schedule is used. Fig. 10 shows a boxplot of the operating cost distribution achieved in purely economic scheduling in normal operation. One can see that due to the high share of RES, several days have negative operating costs. In average, a financial baseline of $674.89 per day is established.

C. RESERVE CONSTRAINT SCHEDULING

The reserve-aware scheduling formulation $S^{\mathrm{RE}}(\cdot)$ adds linear sufficiency constraints that manage available storage and spinning DG reserves until secondary control can take further actions. Three variations of the sufficiency-based formulation are assessed. The first one, deterministic sufficiency-based scheduling, solely applies the constraints to the nominal operation scenario as predicted without taking any deviations into account. The second one, the robust sufficiency-based algorithm defines two worst-case scenarios that both need to be covered by scheduled reserves. Following related work [3], a maximum load case assumes 20% reduction of volatile RES generation and 20% increase of all loads. Similarly, a maximum generation case alters all loads and RES power outputs by a factor of 0.8 and 1.2, respectively. To specifically study the impact of forecasting deviations on the results, a third sufficiency-based scheduling run with perfect predictions is added. Naturally, the perfect run only serves as a best-case reference that cannot be reached with realistic forecasts.

Fig. 6 to 10 and Table 3 include the results of all reserve-constraint scheduling runs. Similar to purely economic scheduling, no overload event in normal operation is seen. However, for deterministic, robust, and perfect scheduling, maximum overload rates of 0.11%, 0.1%, 0.11%, respectively are observed with single-line faults. Again, the narrow scheduling-related voltage band does not hold and all algorithms show overvoltage events. However, in the safety-related wider band, only at single-line faults, overvoltage events are encountered with a maximum event rate of 0.029%, and 0.026% per asset for the deterministic and robust case, respectively. Most undervoltage-related events are observed at whole-branch faults that are not targeted by the formulation itself. Nevertheless, even with the 0.9 p.u. limit, undervoltage events at whole-branch faults are encountered for the deterministic and perfect variations having maximum rates per asset of 0.0017% and 0.0037%, respectively. Still, few undervoltage events regarding the narrow scheduling-related voltage band are seen at single-line faults (deterministic and robust) and even at main grid faults (perfect forecasts), but none of them are visible in the safety-related statistics.

Although the sufficiency-based variations consider main grid outages, a considerable amount of lost load is encountered for all three variations. However, only a marginal amount of 0.00%, 4.03% and 0.00% of all violations at the deterministic, robust and perfect scheduling algorithm, respectively can be traced back to infeasible problems. In total, 100.00%, 96.99%, 100.00%, respectively of the scheduling runs are feasible. Given the observation that even perfect forecasting without any infeasible schedules shows a significant amount of unserved energy, it is demonstrated that the linear approximation does not fully prevent outages. As illustrated in Fig. 10, the deterministic, robust and perfect sufficiency-based scheduling show the average operating costs of $675.64, $679.93, and $642.02, respectively.

D. PHYSICS CONSTRAINT SCHEDULING

Physics-aware hybrid scheduling $S^{\mathrm{PH}}(\cdot)$ follows the same worst-case assumption as the reserve-constraint formulation $S^{\mathrm{RE}}(\cdot)$, but additionally considers voltage, frequency and loading constraints of the detailed power flow model. Again, the impact of forecasting deviations on the scheduling performance is studied by a reference run that assumes a perfect forecast instead of the detailed prediction data. Due to the comprehensive constraints, in total, 74.25% and 82.19% of all hybrid and perfect hybrid runs, respectively, converge to a feasible solution. For all other cases, the best known solution instead of a generic default schedule is taken as a basis for further evaluations.

Both hybrid variations show few violations of the scheduling-related tight overvoltage bound, but none of the algorithms manages to avoid constraint violations at all. On the contrary, both configurations avoid undervoltage constraint violations except for whole-branch failures. Given the wider voltage bounds, only a few overvoltage events (with a maximum event rate of 0.011% per asset) in case of single-line failures and even less undervoltage events (with a maximum rate of 0.0020% per asset) in whole-branch failures actually lead to loss of load. Again, one can observe a considerable number of overload events in case fault reconfiguration actions are taken. In particular, the hybrid and perfect hybrid algorithms show overload rates of up to 0.13%, 0.12%, respectively in case of single line faults that are not covered by the worst-case assumptions.

Fig. 9 still shows a considerable amount of lost load for both algorithms in case of main-grid and whole-branch faults. Nevertheless, only 40.18% and 34.80% of the main-grid fault scenarios that show lost load for hybrid and perfect hybrid scheduling can be accounted for by infeasible and nonconvergent cases. In particular the hybrid optimization run which uses perfect forecasts demonstrates the impact of worst-case assumptions on the scheduling performance. Although the real-time measurements in the reference run are known, hybrid scheduling assumes a full-time outage as worst case while the validation step asserts three hour fault duration. Hence, the system state in the validation runs can differ from the tolerable worst-case assumption and may lead to loss of load.

As illustrated in Fig. 10, the hybrid and perfect hybrid evaluation show the average operating costs of \$883.01 and \$737.11, respectively. Despite the tight resilience constraints, both variants still show several scenarios in which earnings from selling excess energy or consuming electricity in case of negative grid prices outweigh the cost of generating and buying electricity.

V. DISCUSSION

In contrast to related work, this assessment covers a large variety of operating conditions and failure modes. The method includes an independent evaluation step cleanly separating the information that is available at scheduling and real-time. Hence, this work shows several detailed effects on the system resilience, such as the impact of failures that are not directly covered by the scheduling algorithms. The large-scale assessment is driven by an extended power flow formulation considering a high level of detail such as individual device constraints and low-level controls in partially islanded power systems. Since the method is based on steady-state power flows, an efficient replication without the need for dynamic models is expected.

Due to a common set of input scenarios and system configurations, the outcomes of each algorithm can be directly compared without considering stochastic fluctuations among single validation runs. Although the highly loaded benchmark system that is specifically designed to challenge algorithms under test does not show any safety-relevant events under normal operating conditions, the implemented fault mitigation measures call for active grid capacity management in abnormal cases. For instance, severe line overloading events of up to 380% are observed after grid reconfiguration measures. Since the grid is operated beyond static worst-case boundaries, either the scheduling algorithm or a dedicated dynamic grid capacity management needs to assign save operating limits for all relevant assets to avoid such violations.

Given the high fault mitigation rates of economic scheduling ranging from 87.0% at whole-branch faults that include partially islanded grids to 98.6% at single-line faults that can be rerouted, it can be seen that even in the challenging test grid a large share of events can already be handled by appropriate low-level controls. Nevertheless, a considerable influence of scheduling-time algorithms on the remaining events that cannot be fully handled by low-level control alone is found. For instance, the algorithmic choice shows significant impact on the unserved energy E^{NS} that incorporates severe voltage and frequency violations leading to loss of load. Hybrid scheduling reduces the average lost load in case of main-grid outages by 40.5% with respect to the purely economic baseline. Similarly, robust sufficiency-based scheduling already achieves an E^{NS} reduction of 15.5% and a slight decrease of 7.0% can still be seen in the deterministic sufficiency-constrained case.

Note that all algorithms, except the purely economic base case directly consider main grid outages but introduce different levels of abstraction to formulate the corresponding constraints. As such, the least level of abstraction including the highest level of detail (i.e., the hybrid scheduling formulation) achieves the least unserved load. Nevertheless, even in case of hybrid scheduling, necessary simplifications such as whole-day grid outages lead to a significant lost load of in average 66 kWh on all feasible hybrid scheduling runs. The increasing share of nonconverging or infeasible scheduling runs of up to 25.75% in hybrid scheduling and corresponding lost load further indicates a considerable amount of unserved energy, that cannot be avoided by studied measures. The same observation can be made by the lower bound shown in Fig. 9 indicating a significant amount of lost load scenarios that cannot be avoided by any of the scheduling algorithms.

In contrast to failures that are directly considered by the scheduling formulations, only a reduced impact of the algorithms on the system performance in case of unconsidered incidents is observed. Still, hybrid scheduling can reduce the amount of lost load by 24.3% and 15.5% for single-line and whole-branch faults, respectively. Nevertheless, other algorithms show even less performance improvement and some variations such as deterministic sufficiency-based scheduling with whole branch faults even show a reduced performance.

From a resilience point of view, all robust formulations can well handle forecasting deviations and only show marginal degradation to the idealistic counterparts that assume a perfect forecast. For instance, on main-grid faults, only a reduction in lost load of 2.5% and 2.4% for sufficiency-based and hybrid scheduling is observed when eliminating forecasting errors. In the overvoltage chart of Fig. 6, an average overvoltage rate reduction of 27.9% and 56.0% was observed for sufficiency-based and hybrid algorithms when assuming perfect forecasts, but due to safety margins needed to account for fluctuations such as those induced by the upstream grid, no major reduction in the loss of load is observed.

A more severe impact of forecasting deviations can be observed on the operating costs drawn in Fig. 10. Specifically the hybrid scheduling algorithm shows a considerable increase in the average operating costs of 19.8% for the robust variant compared to the perfect forecast. Hence, advanced forecasting techniques that reduce corresponding errors can have an impact on the economic performance of hybrid scheduling. In case of the linear formulation, only a cost increase of 5.9% of the robust variant compared to the perfect reference is seen. In general, the observed resilience gains come with an additional cost for robust sufficiency-based and hybrid scheduling of 0.7% and 30.8%, respectively. The presented large-scale evaluation method allows balancing additional costs and benefits on a detailed per-case basis.

VI. CONCLUSION AND OUTLOOK

Driven by the need of assessing the performance of resilient (multi-)microgrid scheduling algorithms, this work presents an extensive assessment method that specifically focuses on resilience aspects and the impact of scheduling decisions on real-time operation. It is successfully demonstrated that despite the complex power system model that includes primary and secondary control as well as emergency response measures, a large variety of input conditions such as failure scenarios and RES generation can be practically covered. Hence, the need for strong simplifications including limited operating scenarios is drastically reduced in practice. Although the method focuses on the individual assessment of microgrid installations, a detailed case study already provides several insights into the resilient operation of (multi-)microgrids, the impact of scheduling algorithms on the system performance, and promising research perspectives.

Even on the test system that is specifically designed to challenge scheduling algorithms under test, a large majority of the assessed failures including 94.2% of all main grid and 98.6% of all single-line faults can already be mitigated by low-level control and real-time mitigation techniques alone without considering resilience aspects in scheduling. Several practical applications that tolerate the remaining chance of lost load therefore justify to focus on purely economic scheduling without considering resilience aspects.

Nevertheless, the choice of the scheduling algorithm shows a considerable influence on the remaining outages that cannot be avoided by low-level controls alone. Specifically, an influence of the scheduling formulation including the representation of physical phenomena and failure modes on the remaining lost load is found. The advanced hybrid optimization algorithm that considers physical grid constraints and low-level control at scheduling time shows the greatest potential in reducing the impact of failures. Hence, it can be concluded that both future work on and evaluation of resilient scheduling algorithms needs to put a strong focus on the representation of physical aspects and on accurately modeling failure modes in scheduling. The independent validation step of the presented assessment method allows to address such modeling aspects without the need of directly relying on scheduling-time metrics.

Given the results from references using perfect forecasts, it can be seen that the forecasting quality has little impact on the system resilience and that the stochastic phenomena such as forecasting deviations can be well handled by a few worst-case scenarios and static safety margins. However, a considerable influence of forecasts on the economic performance is found. To further reduce operating costs, future work can put a lever on improving the accuracy of forecasts and on an improved stochastic representation. Even under perfect forecasting conditions, the strict scheduling constraints that target a full avoidance of any impacts lead to a considerable number of infeasible problems. Further research on the assessment of soft constraints permitting a certain level of degradation and additional flexibility such as load shifting needs to be undertaken to quantify the impact of such measures.

Future work on the assessment method itself includes an advanced model of the protection system that allows to consider cascading faults, more detailed models of the upstream grid affecting the (multi-)microgrid, as well as the implementation of additional real-time fault mitigation and control techniques that can integrate further flexibility. To include more detailed control and component models, further improvements on the convergence of islanded power flow computations are needed. Additionally, work on the large-scale integration of dynamic simulations can further raise the confidence in a stable operation in case stability cannot be assured otherwise. Finally, the presented evidence on the value of resilient scheduling is limited to a single thoughtfully evaluated test grid. Further research is needed to study the proactive scheduling on a large variety of networks including related benchmarks and real-world systems. This work in presenting the large-scale assessment framework lays the foundation of such investigations and provides a tool for an efficient case-specific analysis.

ABBREVIATIONS

DER Distributed Energy Resource
DG Distributed Generator
ENS Energy Not Supplied

EV	Electric Vehicle
MILP	Mixed Integer Linear Programming
PCC	Point of Common Coupling
PV	Photovoltaic
RES	Renewable Energy Sources
RMSE	Root-Mean-Square Error
SoC	State of Charge
WT	Wind Turbine

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M.H. Spiegel
Towards Advanced Resiliency-Oriented Multi-Microgrid Scheduling
Abstracts from the 8th DACH+ Conference on Energy Informatics, Energy Informatics, SpringerOpen, vol. 2, sup. 2, 2019.

M.H. Spiegel, E.M.S.P. Veith, and T.I. Strasser
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M.H. Spiegel and T.I. Strasser
Hybrid Optimization Toward Proactive Resilient Microgrid Scheduling
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M.H. Spiegel and T.I. Strasser
Assessing the Value of Proactive Microgrid Scheduling
IEEE Access, vol. 10, pp. 51062 51078, 2022.

Peer-reviewed International Conference Papers

M.H. Spiegel and T.I. Strasser
Experiences with Meteorological Models for Asset Scheduling in Local Energy Communities and Microgrids
CIGRE South East European Regional Council Colloquium 2021, November 30, Austria, Online Conference, 2021.

M.H. Spiegel and T.I. Strasser
A Testbed-based Approach for the Resilience Assessment of Multi-Microgrids
CIGRE Session 2022, August 28 - September 02, Paris, 2022.

Presentations at International Conferences

M.H. Spiegel
Resiliency Assessment of Multi-Microgrid Scheduling Approaches
CIGRE e-Session 2020, August 24 - September 2, Paris, Online Conference, 2020.

List of Abbreviations

AC	Alternating Current
CDF	Cumulative Density Function
CHP	Combined Heat and Power
CI	Continuous Integration
CSA	Clonal Selection Algorithm
DC	Direct Current
DER	Distributed Energy Resource
DG	Distributed Generator
DR	Demand Response
EES	Electrical Energy Storage
EMA	Exchange Market Algorithm
ENS	Energy Not Supplied
EV	Electric Vehicle
FA	Firefly Algorithm
ICA	Imperialist Competitive Algorithm
KPI	Key Performance Indicator
MILP	Mixed Integer Linear Programming
MIP	Mixed Integer Programming
MT	Micro Turbine
OLTC	On-Load Tap Changer
OPF	Optimal Power Flow
PaCcET	Pareto Concavity Elimination Transformation
PCC	Point of Common Coupling

PV	Photovoltaics
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
RES	Renewable Energy Sources
RMSE	Root-Mean-Square Error
SoC	State of Charge
SotA	State-of-the-Art
V2G	Vehicle to Grid
WT	Wind Turbine

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Curriculum Vitae

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Education and Training

Since 2019 **Doctoral programme**

Engineering Sciences Mechanical Engineering, TU Wien, Vienna, Austria

Advanced resilience-oriented control of multi-microgrids

2015 – 2018 **Dipl.-Ing.** (Master of Science), Passed with Distinction

2011 – 2015 **Bachelor of Science**, Passed with Distinction

Computer Engineering, TU Wien

- Scientific foundations of computer science, mathematics, physics, and electrical engineering
- Elaborated skills and knowledge in digital design, hardware-software codesign, microcontroller- and operating system programming, software architecture and modelling, signal processing, parallel and real-time computing, fault tolerance, formal verification, as well as automation
- Construction of networked embedded systems

2005 – 2010 **School Leaving Certificate and Diploma Certificate of the Higher Federal Technical College of Information Technology**, Passed with Distinction

Network Engineering, HTL Wien 3R Rennweg, Vienna, Austria

Excerpt of Work Experience

Since 2018 **Doctoral Fellow**, *AIT Austrian Institute of Technology GmbH,*

- Research on the efficient and resilient control of (multi-)microgrids
- Successful contribution to project proposals and implementations
- Contribution to and coordination of joint software development work

2017 – 2018 **Research Fellow**

2014 – 2015 **Research Fellow**, *Austrian Institute of Technology GmbH*

Research on the interaction of generic simulated components (FMI) and automation infrastructure (IEC 61499) in real-time setups.

2013 – 2017 **Various Tutorships**, *TU Wien, Faculty of Informatics*, (six terms)

2012 – 2016 **Various Internships**, *AIT Austrian Institute of Technology GmbH*, (over five months in total)