

43rd IAEE INTERNATIONAL CONFERENCE

Mapping the Energy Future -Voyage in Uncharted Territory-

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TOKYO

To all participants
at the venue

The conference has been closed.

Closing Plenary 

A STOCHASTIC APPROACH TO DYNAMIC PARTICIPATION IN ENERGY COMMUNITIES

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Motivation and Scope

- Photovoltaic (PV) systems: Decentralized electricity production and *prosumers*
- From individual self-consumption to collective self-consumption to active participation
- Trading and sharing of PV generation within a certain framework: Energy communities and peer-to-peer trading
- When energy communities are more established in the future
- Search for optimal technology vs. optimal participants
- How to design or assign contracts in energy communities
- Previous work within my thesis:
 - Peer-to-peer trading under consideration of the prosumers' willingness-to-pay [1] → LP
 - Dynamic participation in local energy communities [2] → Bi-level

[1] T. Perger et al., PV sharing in local communities: Peer-to-peer trading under consideration of the prosumers' willingness-to-pay, Sustainable Cities and Society, Volume 66, 2021, <https://doi.org/10.1016/j.scs.2020.102634>.

[2] Perger T and Auer H. Dynamic participation in local energy communities with peer-to-peer trading [version 1; peer review: 1 approved]. Open Research Europe 2022, 2:5 (<https://doi.org/10.12688/openreseurope.14332.1>)

Research question and framework

- Research Question:

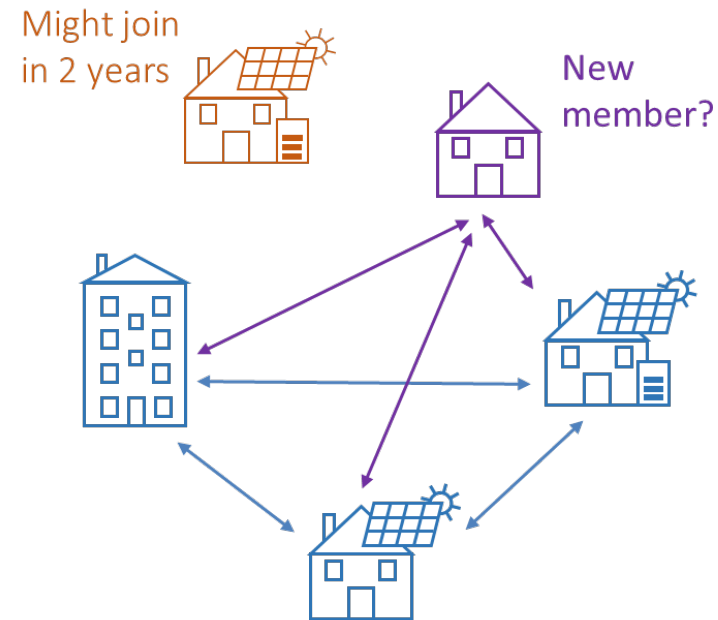
We want to find out if having knowledge about the future development of prosumers in energy communities can help a community manager to make better decisions selecting new participants.

- Framework:

- Voluntary participation
- Low entry barriers: Prosumer can join or leave easily
- PV sharing beyond the meter

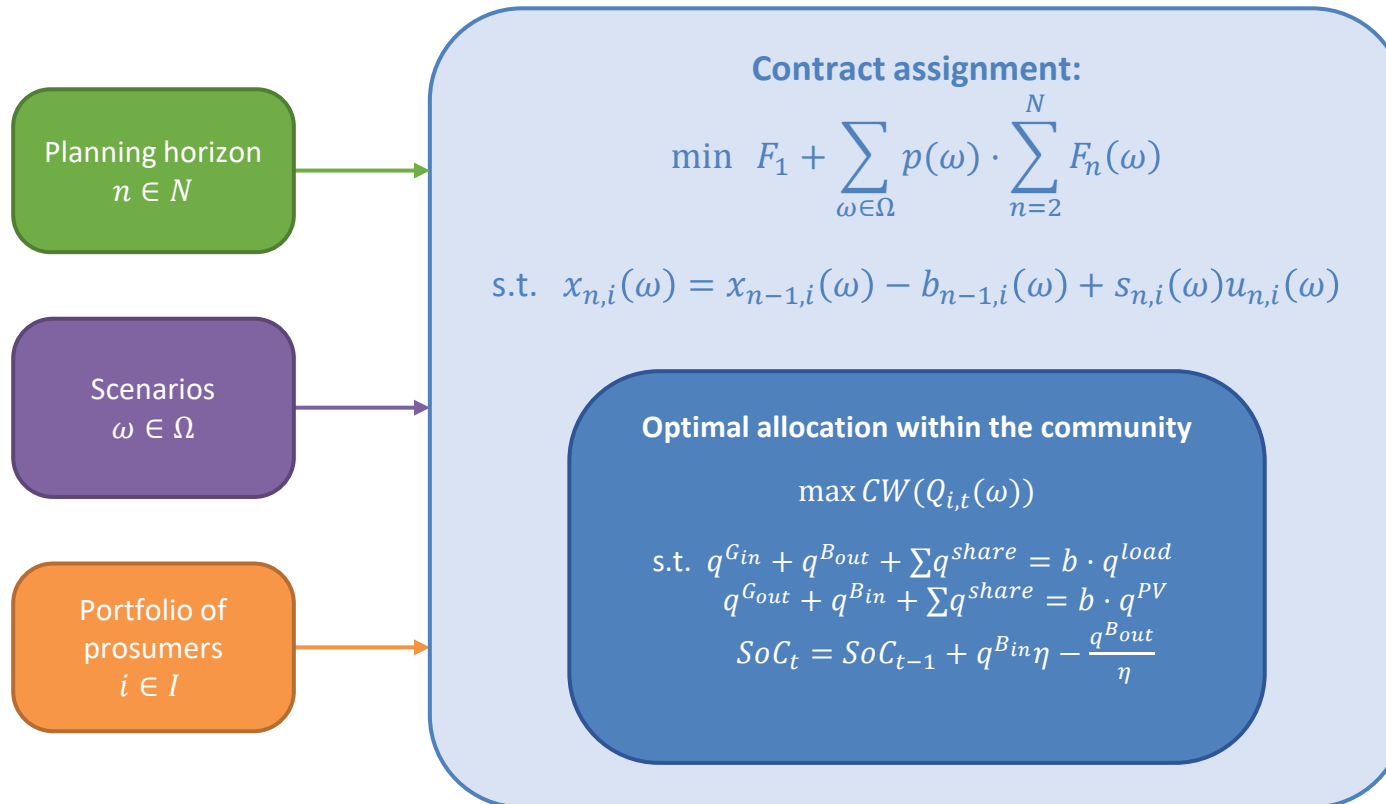
- Method:

A stochastic dynamic program is developed to select participants with a look-ahead policy (planning over a certain time horizon).



Stochastic dynamic programming in general

- Dynamic programming is a mathematical method to solve sequential (multi-level) decision processes.
- The quality of a decision is not only measured by its current impact, but by its influence on the whole process.
 - Example: Chess game
- Components:
 - Control (decision) variables
 - State variables
 - Transition function (system dynamic)
 - Objective function
- Deterministic vs. stochastic dynamic programming
- Policy: function to determine decisions given available information in a state (*mapping* from state to action)
- How to choose a policy class?



Method

Upper-level problem ("leader"):

- Transition function: $x_{n,i}(\omega) = x_{n-1,i}(\omega) - b_{n-1,i}(\omega) + s_{n,i}(\omega)u_{n,i}(\omega)$
- Exogenous information:
 - Deterministic for $n=1$: $s_{1,i}$
 - Stochastic for $n>1$: $s_{n,i}(\omega)$
 - Note that $x_{n,i}(\omega) = 0$ if $s_{n,i}(\omega) = 0$
- Emissions of prosumer i per year n and scenario ω : $emissions_{n,i}(\omega) = \sum_{t \in T} e_t q_{i,t,n}^{G_{in}}(\omega)$

- As part of the objective function:

$$F_n(\omega) = \sum_{i \in I} (emissions_{n,i}(\omega) - b_{n,i}(\omega) emissions_{out,i}) \cdot s_{n,i}(\omega) \cdot b_{0,i}$$

- Including the planning horizon and scenarios:

$$\min_{x_{n,i}(\omega), u_{n,i}(\omega), b_{n,i}(\omega), Q_{i,t,n}(\omega)} F_1 + \sum_{\omega \in \Omega} \sum_{n=2}^N p(\omega) F_n(\omega)$$

Method

- Lower-level problem ("follower"):
 - Maximizing the community welfare, given the parameters selected in the upper problem
- Two parts in community welfare CW:
 - Maximizes the overall self-consumption of the community and
 - Optimally distributes PV generation between the prosumers (peer-to-peer trading)
- Constraints:
 - Covering electricity demand and PV generation
 - Battery storage operation

$$\max_{Q_{i,t,n}(\omega)} \sum_{n \in \mathcal{N}, \omega \in \Omega} \sum_{t \in \mathcal{T}, i \in \mathcal{I}} \left(p_{t,n}^{G_{out}} q_{i,t,n}^{G_{out}}(\omega) - p_{t,n}^{G_{in}} q_{i,t,n}^{G_{in}}(\omega) + \sum_{j \in \mathcal{I}} wtp_{i,j,t} q_{i,j,t,n}^{share}(\omega) \right) \quad (13a)$$

subject to: (13b)

$$q_{i,t,n}^{G_{in}}(\omega) + q_{i,t,n}^{B_{out}}(\omega) + \sum_{j \in \mathcal{I}} q_{j,i,t,n}^{share}(\omega) - b_{n,i}(\omega) q_{i,t}^{load} = 0 \quad (\lambda_{i,t,n}^{load}(\omega)) \quad \forall i, t, n \quad (13c)$$

$$q_{i,t,n}^{G_{out}}(\omega) + q_{i,t,n}^{B_{in}}(\omega) + \sum_{j \in \mathcal{I}} q_{i,j,t,n}^{share}(\omega) - b_{n,i}(\omega) q_{i,t}^{PV} = 0 \quad (\lambda_{i,t,n}^{PV}(\omega)) \quad \forall i, t, n \quad (13d)$$

$$SoC_{i,t-1,n}(\omega) + q_{i,t,n}^{B_{in}}(\omega) \cdot \eta^B - q_{i,t,n}^{B_{out}}(\omega) / \eta^B - SoC_{i,t,n}(\omega) = 0 \quad (\lambda_{i,t,n}^{SoC}(\omega)) \quad \forall i, t > t_0, n \quad (13e)$$

$$SoC_{i,t=t_{end},n}(\omega) + q_{i,t_0,n}^{B_{in}}(\omega) \cdot \eta^B - q_{i,t_0,n}^{B_{out}}(\omega) / \eta^B - SoC_{i,t_0,n}(\omega) = 0 \quad (\lambda_{i,t_0,n}^{SoC}(\omega)) \quad \forall i, t = t_0, n \quad (13f)$$

$$SoC_{i,t=t_{end},n}(\omega) - SoC_{init} = 0 \quad (\lambda_{i,t_{end},n}^{SoC_{init}}(\omega)) \quad \forall i, t = t_{end}, n \quad (13g)$$

$$SoC_{i,t,n}(\omega) - b_{n,i} SoC_i^{max} \leq 0 \quad (\mu_{i,t,n}^{SoC^{max}}(\omega)) \quad \forall i, t, n \quad (13h)$$

$$q_{i,t,n}^{B_{in}}(\omega) - b_{n,i} q_i^{B_{in}^{max}} \leq 0 \quad (\mu_{i,t,n}^{B_{in}^{max}}(\omega)) \quad \forall i, t, n \quad (13i)$$

$$q_{i,t,n}^{B_{out}}(\omega) - b_{n,i} q_i^{B_{out}^{max}} \leq 0 \quad (\mu_{i,t,n}^{B_{out}^{max}}(\omega)) \quad \forall i, t, n \quad (13j)$$

How is the bi-level problem solved?

- Transformation of the lower-level problem with its corresponding KKT conditions (“Karush-Kuhn-Tucker”):
- Mathematical program with equilibrium constraints (MPEC)
- The equilibrium problem of the follower is parametrized by the leader’s decisions variables
- Formulation of a set of complementarity conditions
- Big-M transformation

Data and assumptions

- Model implemented in *Python* using *Pyomo* [1] and *Gurobi* as solver
- Portfolio of 20 prosumers consisting of ten single houses (SH), eight small apartment buildings (SAB), and two small businesses (SME)
 - SH: PV systems with up to 5 kW_{peak} installed
 - SAB and SME: PV systems with up to 8 kW_{peak} installed
 - Some prosumer have BESS included
- Initial set-up: 5 SH, 4 SAB, 1 SME
- Electricity demand data and PV production data from open-source tools ([2] and [3])
- Annual hourly data is clustered into 3 representative days using a Python module [4]

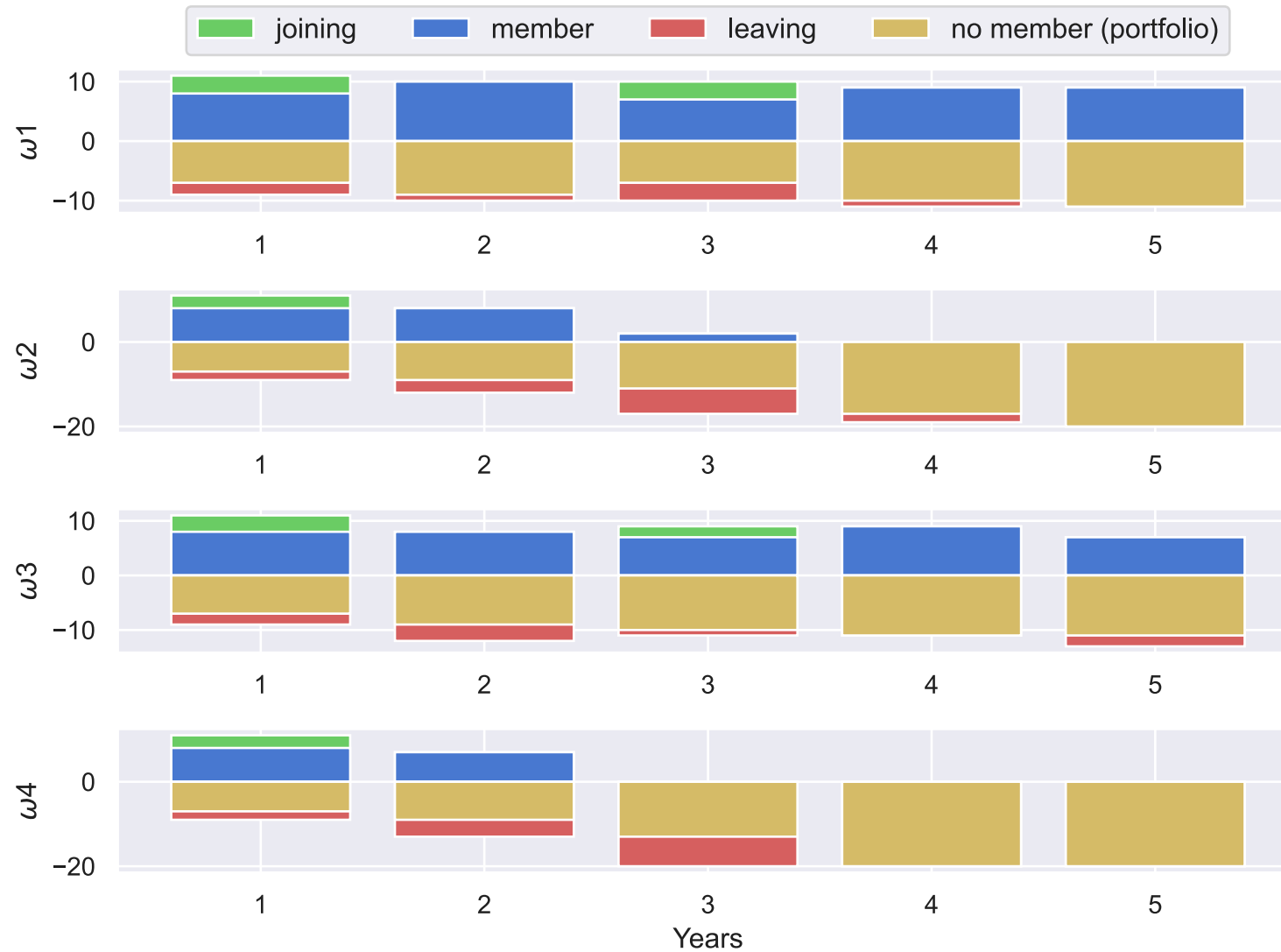
[1] <https://pyomo.readthedocs.io/en/stable/>; [2] <https://www.loadprofilegenerator.de/>

[3] <https://www.renewables.ninja/>; [4] <https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html>

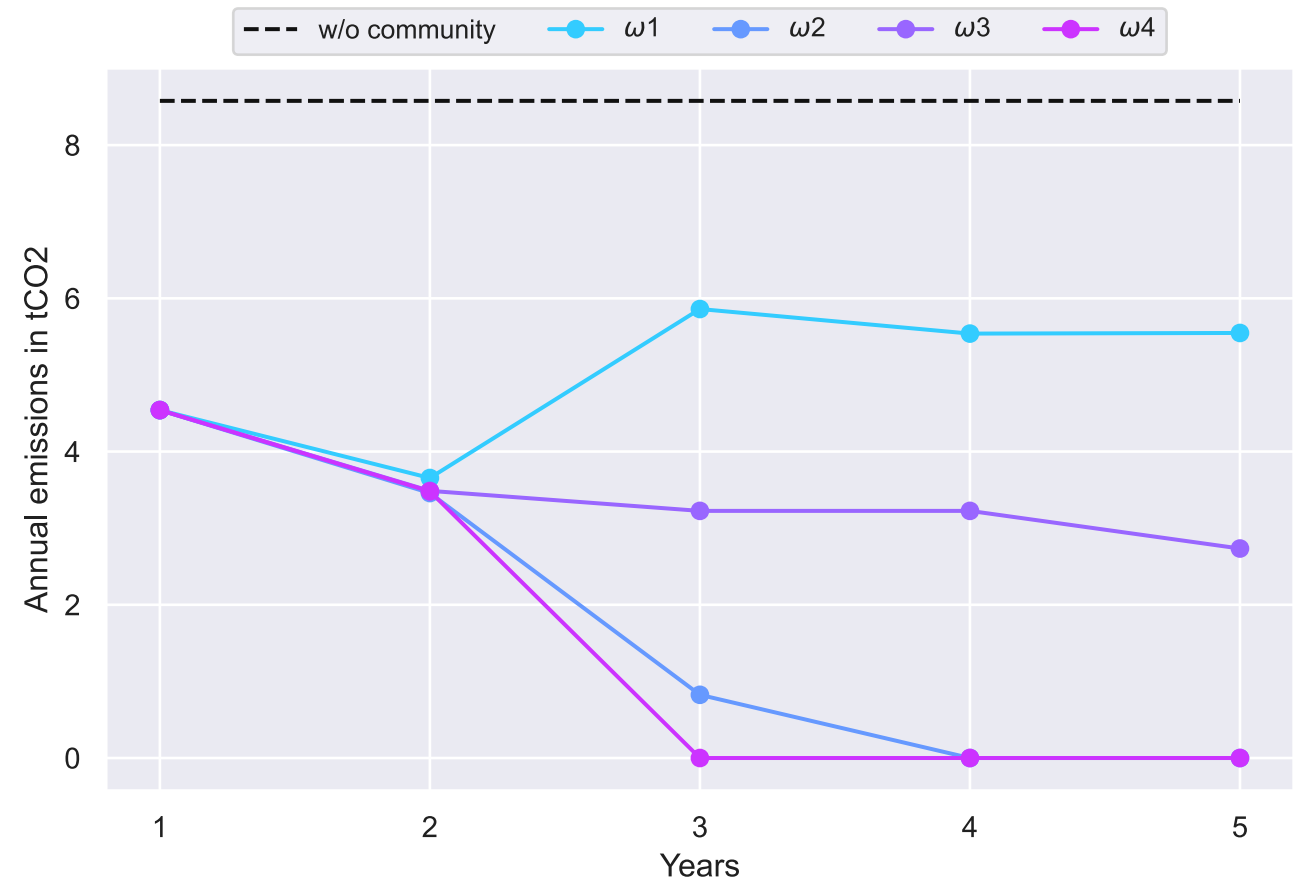
Scenarios

- Finite set of scenarios to represent possible developments within energy communities.
- Considering a high number of possible prosumers and their decisions as well as a time horizon of a few years, in general one would end up with a very large scenario tree.
- Due to the high computational efforts of stochastic programming, we do not aim at using the full scenario tree for our research. Instead, a relatively small set of completely different scenarios is developed to represent the wide spectrum of possibilities.
- The use case that will be shown in the results section considers three prosumer types: single houses (SH), apartment buildings (SAB), and small businesses (SME). At the beginning, 5 SHs, 4 SABs, and 1 SME are present in the community.
- From there, four different scenarios are considered:
 - ω_1 : additional SABs might want to join in the upcoming years
 - ω_2 : the SABs might want to phase-out in the upcoming years
 - ω_3 : additional SHs might want to join in the upcoming years
 - ω_4 : the SHs might want to phase-out in the upcoming years

Results: Acceptance/dropping out per scenario



Results: Emissions per scenario



Findings and limitations of this work:

- Objective function minimizes individual emission balances instead of costs
 - Peer-to-peer trading includes preference to save emissions
 - Environmental incentives play a particularly important role for participants of energy communities
 - This analysis focuses entirely on environmental interests
- Rejection of potential participants
 - Energy community should be a small, socially tangible entity of manageable size
 - Boundaries are consciously drawn
- Scenario selection can be crucial if wrong assumptions are made
- How to implement in practice?
 - Forecast of electricity demand of future participants difficult



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Thank you for your attention!

GitHub

<https://github.com/tperger/PARTICIPATE>

<https://github.com/tperger/FRESH-COM>

Energy community model FRESH:COM

About the (open-source) model:



- Linear optimization model FRESH:COM [4] maximizing the community welfare of a local energy community by peer-to-peer trading

- Community welfare:

$$CW = \underbrace{\sum_{t \in T, i \in I} p_t^{G_{out}} q_{i,t}^{G_{out}} - \sum_{t \in T, i \in I} p_t^{G_{in}} q_{i,t}^{G_{in}}}_I + \underbrace{\sum_{t \in T, i, j \in I} wtp_{i,j,t}^{share}}_{II}.$$

- Allocation mechanism: Peer-to-peer trading under the consideration of each prosumer's *individual willingness-to-pay*:

$$wtp_{i,j,t} = p_t^{G_{in}} + w_j(1 - d_{i,j}) \cdot e_t.$$

- Members: Private households and SMEs
 - Photovoltaic (PV) and Battery Energy Storage Systems(BESS)

[4] T. Perger, FRESH:COM, <https://github.com/tperger/FRESH-COM>