Load Profile Optimization Using Electricity Wholesale Market Price Data for Discrete Manufacturing

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Abstract. Several strategies for reducing energy costs can be derived from the energy procurement cost function for Austrian end users of electrical energy. Based on short-term energy procurement on the *day-ahead* trading floor an optimization problem for cost-optimal scheduling of the load curve of a single plant has been formulated. A preliminary study for an annealing furnace is presented and it is found that the approach can lead to significant savings during periods of volatile prices. Furthermore, the strategy is applicable to any production process that provides sufficient flexibility, and therefore, if the trade-off between peak energy costs is included, can be applied to entire production systems.

Keywords: energy flexibility · demand side management · demand response · energy price volatility · day-ahead · energy-cost-optimization

1 Introduction

For end-use customers of electrical energy, price volatility is expected to persist beyond a phase of fluctuating and generally high prices since the end of 2021. This will be caused by different factors, notably one of them being the rising share of variable renewable energy (VRE) on the supply side [3]. The associated uncertainty of energy-costs will and already is affecting more and more industrial subsectors that are dependant on energy to perform value-adding. The energy-intensive sector (EIS) is already working on mitigating energy costs and lowering the environmental impact of the inherent processes for quite some time, driven by a high share of energy-related costs of unit costs as well as policy measures.

Industry is generally dependent on the availability of energy at reasonable prices, but when energy prices were sufficiently low, end-use customers outside the EIS, whose demand for energy is on a lower level, were not significantly affected by the cost. These intermediate energy consumers have not yet intensively addressed the issue of cost containment in energy procurement and must now respond. This set of industrial enterprises can be denominated as the energy-dependant sector (EDS) and encircles a rather specific set of production

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processes [3]. The difference in how energy is consumed by companies within the EIS and the EDS is significant thus, strategies specifically tailored to the production systems within the EDS, that largely coincide with discrete mechanical manufacturing (DMM) must be found.

2 State of the Art

In order to incentivize sustainability measures in the industrial sector one has to look at energy-related costs. Considering DMM the most significant energy carrier in Austria is electric energy [2,3]. The total procurement costs EPC for electric energy can be described with a procurement cost function, including all taxes, tariffs, grid and energy costs [3]:

$$EPC = C_f + c_p P_p + W(c_{W,f} + \bar{c}_W) \tag{1}$$

Therein C_f are fixed costs and c_p is the cost factor for peak power demand P_p, i.e. the maximum power uptake within the billing period. The three variables in Eq. 1 are the peak power demand P_p, the amount of electric energy consumed W and the wholesale market price, represented as the mean costs per billing period $\bar{c}_W$. Because of high utilization and a low share of downtime or operational readiness of plants, lowering W through energy efficiency is the way to go in the EIS. In the EDS however energy efficiency, i.e. the lowering of energy input whilst maintaining the same level of product output, is not that easily scalable [3]. Lowering the overall energy uptake is of the essence within the EDS too, but unclaimed flexibilities on the demand side considering production systems of DMM are more easily accessible. Rather than lowering the energy uptake per se these may be utilized in order to react to the growing share of VRE on the supply side and thus, to mitigate costs [3,4]. This is in opposition to most processes within the EIS, where continuous processes cannot be interrupted. In contrast to discrete production, there is also little or no leeway for postponing or prioritizing process cycles regarding batch processes.

Schwaiger et al. deduced two basic ways for flexibilizing the demand side with regards to energy costs, either by *pro-* or *reactive flexibilization* [3]. This is based on the two market floors end-use customers will trade on in order to procure electric energy short-time. We decidedly neglected long-term trading because of the increasing short-term volatility of energy prices through VRE and the as of yet unknown long-term developments caused by the transformation of the energy system and focused on *proactive flexibilization*.

2.1 Proactive Flexibilization

Equations defining the incurrence of costs by directly or indirectly trading electric energy on the short-term wholesale trading floors, be it near real time (*intraday*), or on the day preceding delivery (*day-ahead*) have been stated by Schwaiger et al. [3]. The according costs for *day-ahead* trading are stated in Eq. 2. In the following the denotations (left superscript) d for the day of delivery, $d-1$ for

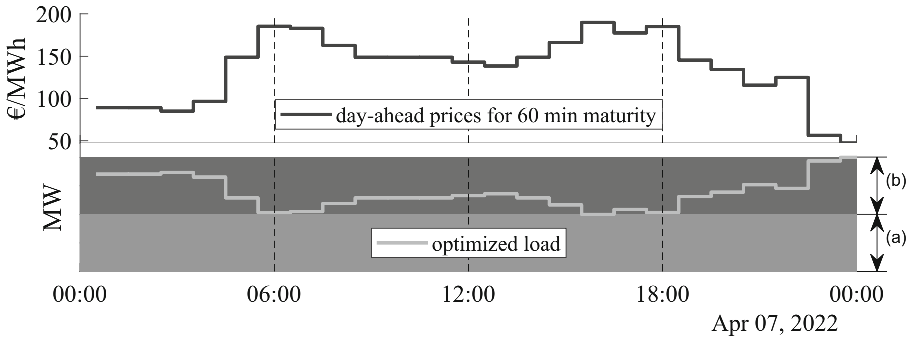

Fig. 1. A qualitative example for *proactive flexibilization*; (a) baseload; (b) potential bandwith for flexibilization [1]

the day before delivery and $\bar{d}$ for a reference workday are used as well as the indices (right subscript) $i = 1, ..., 24$ for hourly and $j = 1, ..., 4$ for quarter hourly products.

$$^{d-1}C = \sum_{i=1}^{24} {}^{\bar{d}}W_i \; {}^{d-1}c_i \tag{2}$$

Minimizing ^{d-1}C is the basic goal for *proactive flexibilization*, i.e. optimizing the load curve for the next day by planning accordingly. Basically the load curve should resemble the vertical reflection of the graph representing hourly price. More so, optimally the load curve has maxima where prices are lowest and vice versa. A qualitative example for *proactive flexibilization* is given in Fig. 1 where a load curve with a given base load (a) and a flexible bandwidth (b) is fitted accordingly. In this simple example the discrete prices have been mirrored to the abscissa, normalized on the interval [0,1] and multiplied with the power flexibility potential in order to produce the optimized load curve.

3 Energy-Cost Optimization for DMM through Proactive Flexibilization

Given the aforementioned situation on the supply side from the viewpoint of an end-use consumer corresponding to DMM the following problem arises: The usually rather volatile load profile has to be matched with different blocks of energy procured on the wholesale market at least a day in advance.

Schwaiger et al. introduced proactive flexibilization as a price-driven strategy to procure electric energy on the day-ahead trading floor [3]. It is formulated as an optimization problem for the convolution of the two functions $^{d-1}c(t)$ for the day-ahead prices and $P_{plant}(t)$ for the power uptake of a single plant:

$$({}^{d-1}c * P_{plant})(t) = \int_{\tau_1}^{\tau_2} {}^{d-1}c(\tau) P_{plant}(t-\tau)\, d\tau \tag{3}$$

The result of Eq. 3 is the time-dependant cost function for a single cycle of the plant where ${}^{d-1}c(t)$ and $P_{plant}(t)$ are functions continuous in time. The power uptake of the plant may in fact be represented by a time-continuous function, e.g. when it's load curve can be defined analytically depending on the process parameters, or empirically by learning from past cycles. In an early stage of implementing *proactive flexibilization* P_{plant} will rather be represented by the measurement of the plants power uptake during a typical production cycle, thus being discrete in time. *Day-ahead* prices will be set for products with a maturity of 60 min and thus also are discrete in time, i.e. $c_i = c_1, c_2, c_3, ..., c_{24}$. Either way the problem stated in Eq. 3 has to be solved numerically. If the plant's power uptake is continuous in time it has to be discretizised to $P_i = P_1, P_2, P_3, ..., P_{24}$. The numerical convolution is defined as

$$(c_i * P_{plant,i})(n) = \mathbf{P}_{plant} \overrightarrow{c} \tag{4}$$

where $\overrightarrow{c}$ is the vector of hourly day-ahead prices and $\mathbf{P}_{plant}$ is the convolution matrix.

$$\overrightarrow{c} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{24} \end{bmatrix}, \ \mathbf{P}_{plant} = \begin{bmatrix} \overrightarrow{P}_{plant} & 0 & 0 & \dots & 0 \\ 0 & \overrightarrow{P}_{plant} & 0 & \dots & 0 \\ \vdots & 0 & \overrightarrow{P}_{plant} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & \overrightarrow{P}_{plant} \end{bmatrix} \tag{5}$$

The minimum of the convolution will yield the most energy-cost effective point in time to start the process cycle:

$$min(\mathbf{P}\vec{p}) \rightarrow t_{start} \tag{6}$$

4 Prestudy of Proactive Flexibilization

A practical implementation of proactive flexibilization has been evaluated for the annealing of machine parts. The corresponding plant is an air convection oven equipped with electrical heating. Thus, the plants power consumption mainly stems from the operation of the heating resistors with a small portion of the overall uptake caused by the electric motors driving fans. The technical specifications of the plant are stated in Table 1.

Cycle duration and power uptake over time are mainly influenced by the mass of steel to be treated, the dimension of the parts and the holding temperature. The plant will always be loaded up to the maximum and processes other than annealing with a far lower energy demand may be conducted, but are the exception. Thus, a representative annealing process cycle, i.e. the plants power uptake over time, has been monitored, see Fig. 2. This process-specific load curve was averaged to 60 min intervals and used as input $\overrightarrow{P}_{plant}$ for the optimization problem stated in Eq. 6. For proactive flexibilization the goal is to best match

Table 1. Technical data of the annealing convection oven

		Unit
Nominal power of the heating resistors	450	kW
Maximum load of steel parts	30	t
Annealing target temperature	600	°C

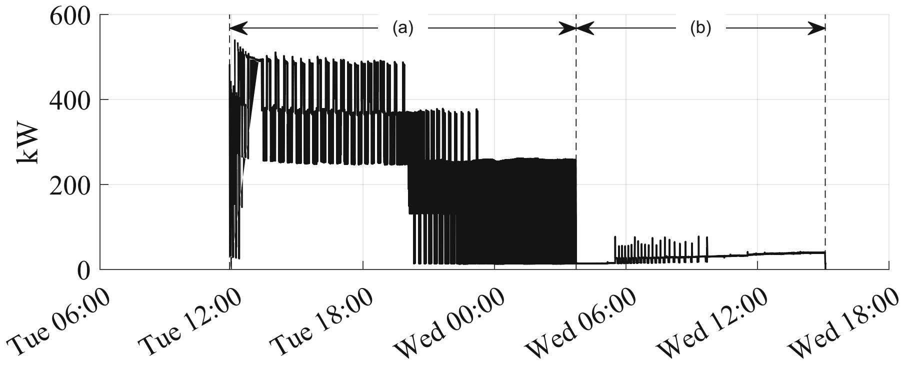

Fig. 2. Uptake of electrical power; annealing oven; (a) phase with active heating resistors (heating up, maintaining temperature and controlled cooling down); (b) cooldown phase where only fans are active

load to the *day-ahead* prices, where only maturities of 60 min can be traded at the moment. Therefore the characteristics of the load curve during the hour are not of interest. Only the cumulative electric energy consumed during the period is of importance.

The other input of Eq. 6, i.e. the hourly prices on the *day-ahead* trading floor $\overrightarrow{c}$, has been derived from historic wholesale price data from EPEX Spot [1]. Week long time frames ranging from the first quarter of 2021 to the second quarter of 2022 have been selected for evaluation. The length of the time frame stems from the fact that the annealing process' duration is well over 24 h. Therefore it can not be scheduled on a daily basis but weekly. Thus, the energy-cost optimal starting point within a week for the given reference cycle has been calculated.

Figure 3 shows an exemplary result for calendar week 8 in 2021. In the upper graph the hourly prices on the *day-ahead* trading floor are shown on the primary axis, as well as the energy-cost-optimized annealing cycle starting at t_{start} and its counterpart resulting in the cost maximum indicated by the power uptake over time on the secondary axis. As the cycle duration is around 27 h it must be started on Saturday at the latest. The lower graph represents the overall costs for electrical energy per annealing cycle, i.e. the solution of the numerical convolution as stated in Eq. 4. By being able to freely shift the cycle in time over a whole week a maximum difference in costs ΔC of €72 could be achieved

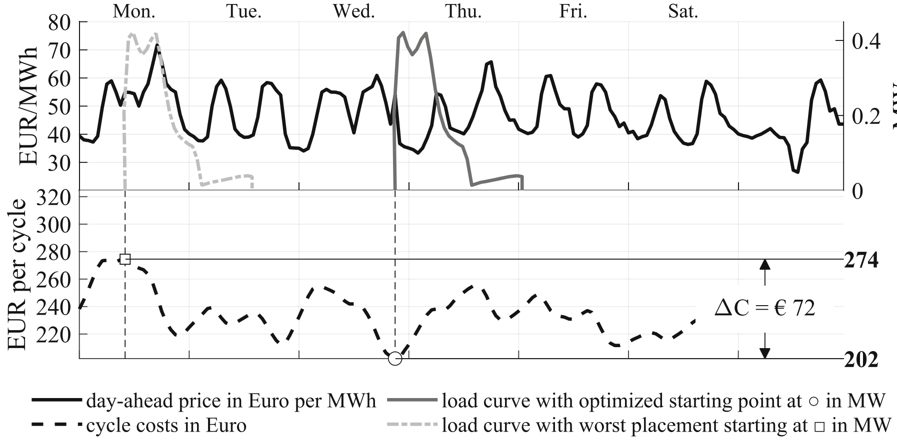

Fig. 3. Weekly *proactive flexibilization* of an annealing cycle for calendar week 8 in 2021

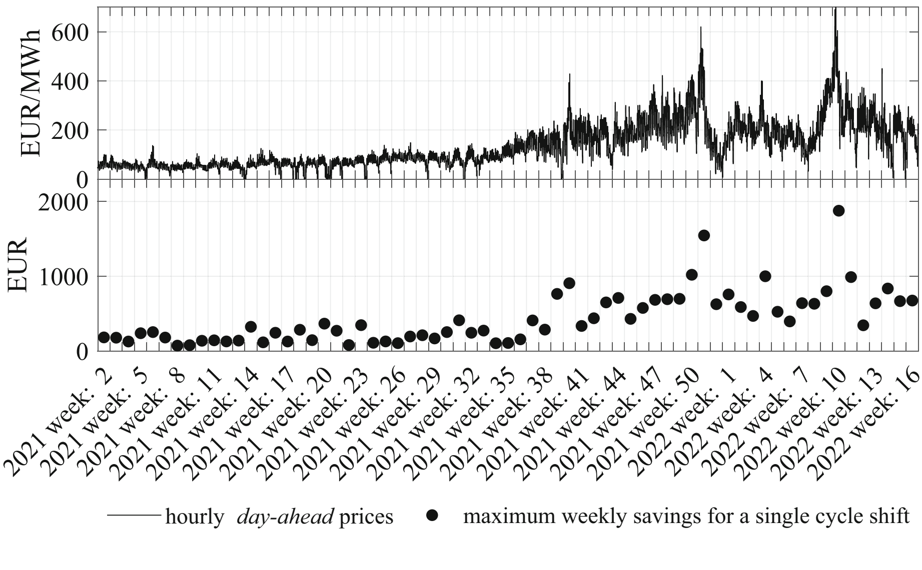

Fig. 4. Maximum weekly potential savings by shifting the annealing cycle in time [1]

between the best and worst timed cycles. This result has been generated within a time frame with stable wholesale energy market prices, represented by a typical daily pattern of high prices during mid day and low prices during the night, as well as differences over the span of the week where prices on weekends are generally moderate.

Results of weekly energy-cost optimization of the annealing cycle are stated in Fig. 4 and have been generated from calendar week 2 in 2021 to calendar week 16 in 2022. Looking at the top graph the rise of energy prices to the end of 2021 can be seen. Furthermore, the aforementioned familiar pattern in price fluctuation over the week has been more and more disrupted by the end of 2021, resulting in the uncertainty of even short-term predictions. A typical outcome of energy-cost-optimization for the ca. 27 h long annealing cycle in times of stable and thus, predictable market prices, is that it will be shifted to the weekend. On extending the time frame for optimization to two weeks, the phases of high power demand (i.e. the phase of heating up) thus, would be shifted to the night from Saturday to Sunday.

In calendar week 10 of 2022 the energy-cost-optimal cycle costs differ as much as €1.877 from the worst placed cycle, representing the maximum theoretical savings over the whole period analyzed. In conclusion the shifting in time of the presented annealing cycle only results in significant savings when the usual price pattern during a week does not hold up and especially when the spread of high and low prices during a week is high.

5 Conclusion and Outlook

Two strategies for energy-cost optimization have been deduced from the energy procurement cost function, being *pro-* and *reactive flexibilization*. It has been emphasized on the latter, which focuses on load scheduling typically at least a day ahead and has been formulated as a numerical convolution of hourly prices on the *day-ahead* trading floor and the time-discrete load curve of a single plant. The minimum of the function resulting from the convolution gives the cost-optimal starting point of the process cycle in time.

A prestudy of *proactive flexibilization* has been conducted, using historical *day-ahead* market data and the time series of a representative process cycle of an air convection annealing oven. It could be shown that in weeks where prices are following a usual pattern, even if they are relatively high, potential savings are moderate. In times of high volatility and a high price level, savings for this particular application range from several hundred to several thousand Euros. The typical outcome is to shift the cycle to the weekend because of the 27 h duration and long time slots of lower prices then. The prestudy was performed ignoring further limitations caused by production planning that may not allow for the energy-cost-optimized process cycle placement and thus, practicable savings may be much lower. The duration of the process cycles, the times in between needed for loading and unloading and the two shift rotation restrict flexibilization greatly. In practice operation of the given plant also needs to adhere to a given schedule because of a high workload.

The following conclusions can be derived, which lead to steps for expanding the approach of *proactive flexibilization* and increase practicability:

- As a basic assessment unclaimed flexibility of production processes within a factory has to be assessed to choose the right production processes for *flexibilization*. An indicator for quantifying the potential regarding flexibility is lacking.

- Given high enough energy costs it may even be practical to increase flexibility by changing given procedures, but costs due to the increased effort in production planning must be weighed against the savings in energy costs.
- Limits given by production planning have to be introduced to *proactive flexibilization*, i.e. the time frame available for energy-cost optimization has to be adjusted accordingly.
- Given additional restrictions $min(\mathbf{P}\vec{p})$ will have to be solved repeatedly, whilst after each iteration the time frame has to be trimmed.
- Since *proactive flexibilization* is plant or process specific, multiple computations must be performed in parallel to cover an entire facility and the procedure must be extended to calculate the expected trade-off due to peak power costs.
- The numerical convolution is easily scalable which is beneficial for practical implementation, especially given the necessity of multiple parallel calculations with potentially many iterations each, when applied to a production system or even a factory.

Assuming that current developments within the (electrical) energy system will lead to persistent volatility and given the fact that investment costs for implementing *proactive flexibilization* are low, it can provide enough of a monetary incentive in order to be applicable in practice. In addition, the application is not process-specific in terms of production technology and can therefore be used on a larger scale, provided sufficient flexibility is offered. We assume that a high potential of unclaimed flexibilities exists in DMM in general, as well as a high potential for actively expanding flexibilities for the purpose of energy-cost optimization.

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References

1. Epex Spot. Market data (2022)
2. Eurostat. Energy balance flow for Austria 2019 (2022)
3. Schwaiger, C., Trautner, T., Bleicher, F.: Energy-cost-optimized strategies for discrete mechanical manufacturing. Procedia CIRP (2022)
4. Serale, G., Gnoli, L., Giraudo, E., Fabrizio, E.: A supervisory control strategy for improving energy efficiency of artificial lighting systems in greenhouses. Energies **14**(1), 202 (2021)