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ORIGINAL PAPER

Towards the concept of gas-to-power demand response

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Abstract

Due to the war in Ukraine, the European Commission has released its "Save Gas for a Safe Winter" plan, communicating the goal of reducing gas consumption in the electricity sector, among others. In this paper, the gas consumption in the electricity sector is picked up and the well-established concept of demand response is brought into alignment with the consumption of gas in the electricity sector, leading to the concept of gas-to-power demand response. Two proposed programs based on this concept are then applied in a production planning approach that shows how companies could proactively contribute to easing the tense situation in Europe, particularly in Germany, especially using methods such as scheduling and/or lot-sizing. This article is intended to serve as a basis for further discussions in the political and economic sectors.

Keywords Demand response · Operations research · War · Gas-fired electricity generation · Gas-to-power

JEL Classification C61 · M11 · Q4

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1 Motivation

In July 2022, as a result of the war in Ukraine, the European Commission (EU-COM) announced its plan to reduce gas demand: "Save Gas for a Safe Winter". According to this plan, member states are to reduce gas consumption by 15% by the spring of 2023 and, in particular, create incentives for energy savings in industry; cf. EU-COM (2022a). In addition to this plan, the proposed regulation on coordinated gas reduction states that: First, measures taken on national level shall, for example, financially incentivise industry to reduce energy consumption; second, the measures shall be market-based; third, measures shall be considered that reduces gas in the electricity sector; cf. EU-COM (2022b). The last point in particular aims to reduce the use of gas-fired power plants, which currently lead to significantly higher electricity prices, also due to the merit order; cf. Dellnitz et al. (2020).

Especially with regard to the third point of the European Commission's regulation, demand response in the electricity sector is a well-established concept that turns passive electricity consumers into active market participants; cf. Eid et al. (2016). Aligning such a concept to gas-fired electricity instead of electricity in general might be a promising instrument helping to ease the situation in Europe. However, even apart from the current tense situation—for example, beyond winter 2022/2023—the concepts presented here can be applied to make gas-based electricity consumption more flexible and responsive. As a consequence, the concept of gas-to-power demand response is proposed in this paper. In addition, companies can apply planning approaches such as scheduling and/or lot-sizing, in particular, to leverage flexibility potentials by using the gas-to-power demand response concept. The main purpose of this article is therefore to conceptualize gas-to-power demand response concepts and to demonstrate how such concepts can help alleviate the current tight situation, especially in Germany. This could serve as a basis for further research and discussion.

The remainder of this article is organized as follows: In Sect. 2, we will present a short primer on demand response in general and propose the new concept of gas-to-power demand response. Two possible programs for this are presented. These programs are examplified in a production planning approach. Therefore, Sect. 3 is devoted to a brief literature overview of related studies, model development and problem description. Section 4 presents the results of the computational study and discusses the necessity of incentivation when using gas-to-power demand response programs. Section 5 concludes this work.

2 Demand response and the concept of gas response

2.1 Gas-to-power demand response

Demand response (DR) is a well-established concept in Europe for enhancing system coordination and system reliability via market-based mechanisms; cf. EU-COM (2013) and (Albadi and El-Saadany 2008). In the context of electricity systems, the employment of smart meters—in conjunction with information and communication technology—is turning end users of electricity, such as companies, into active market players. In this context, DR can be understood as electricity demand that is responsive to economic signals. Different DR programs can be differentiated [cf. Eid et al. (2016) for a detailed overview]:

- *Price-based DR*: The economic signals are electricity prices, and special electricity tariffs, such as real-time pricing (RTP), where the electricity price is adjusted hourly (or at shorter intervals), allowing end-users to adjust their electricity consumption to these dynamic prices.
- *Incentive-based programs*: Customers are motivated to provide load flexibility via incentives or penalties. Under emergency DR, for example, grid operators instruct participants to reduce electricity consumption at very short notice during periods when the grid is jeopardized. Customers receive appropriate incentives—of a financial nature, for example—or penalties if they do not comply.

To take account to the previously stated goals of the EU-COM (see Sect. 1), an alignment of DR to the consumption of gas (instead of electricity in general) could be a promising approach. In the literature, the concept of "natural gas demand response" is very slowly emerging, but is aimed more at programs for direct gas consumption by industry, etc., and is less related to electricity generation. For example, economic signals are gas prices in price-based programs; e.g., Ruhnau et al. (2022). To account for the consumption of gas-fired electricity and shift or reduce end-use electricity consumption at times when gas-fired power plants are increasingly used to generate electricity, we propose the concept of "gas-to-power DR (G2P-DR)" to mitigate such a situation. In G2P-DR, the economic signals are not the gas prices but the gas factors inherent in the electricity mix. This concept is also motivated by the fact that, for example, in June and July of 2022 large quantities of gas-fired power [in mWh] were generated (and needed) in Germany; see www.smard.de. Figure 1 shows the gas-fired power generation in Germany for one working week (Mon–Fri)

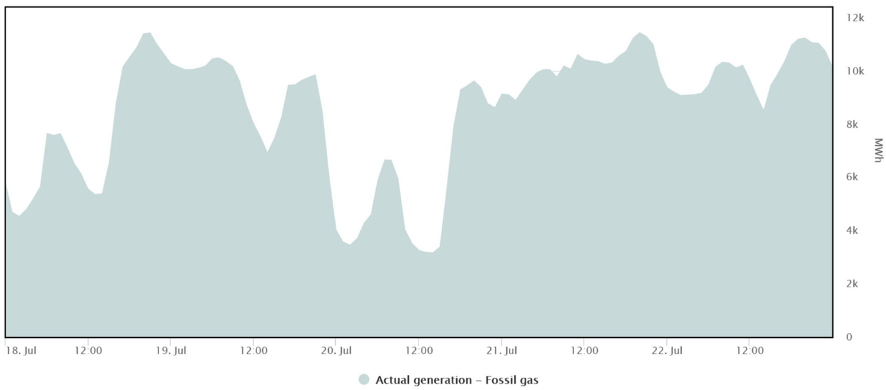

Fig. 1 Gas-fired power generation in Germany, 07/18/22–07/22/22

in July 2022 (Fig. 1 is obtained from www.smard.de). However, the gas factors are obtained by dividing the amount of gas-fired power generated during a given period by the maximal amount of gas-fired power generated in a period over all periods of the time horizon considered. Instead of the maximum value, a specified reference value can also be used. Based on these factors, different programs are conceivable, see Subsect. 2.2.

2.2 Two gas-to-power demand response programs

We will now present two possible G2P-DR programs: the first related to RTP adapted to G2P-DR, and the second related to emergency DR. Possibilities to incentivize end users such as companies to participate in one of these programs are discussed in Sect. 4.

- *Factor-based G2P-DR: Real-time-factorization (RTF)* This program follows the idea of RTP, but uses hourly (or more frequent) gas factors instead of electricity prices as economic signals. Figure 2 shows a corresponding gas factor trajectory for the gas-fired power generation shown in Fig. 1. Along real-time gas factors, companies, for example, can shift electricity-intensive processes to times when these factors are low. Such an approach is usually followed in the context of production planning under RTP when electricity costs are to be reduced; cf. Bänsch et al. (2021).
- *Incentive-based G2P-DR: Emergency G2P-DR (EDR)* The idea is that participants will receive an external signal to reduce electricity consumption at very short notice during periods when more electricity is being generated from gas-fired power plants and fed into the power grid. A prespecified critical gas factor can be defined and a breaching of such critical value triggers a notice. In Fig. 3, a critical factor of 0.9 is selected, which results in 6 different time frames of different length. For example, a company can reduce its electricity consumption

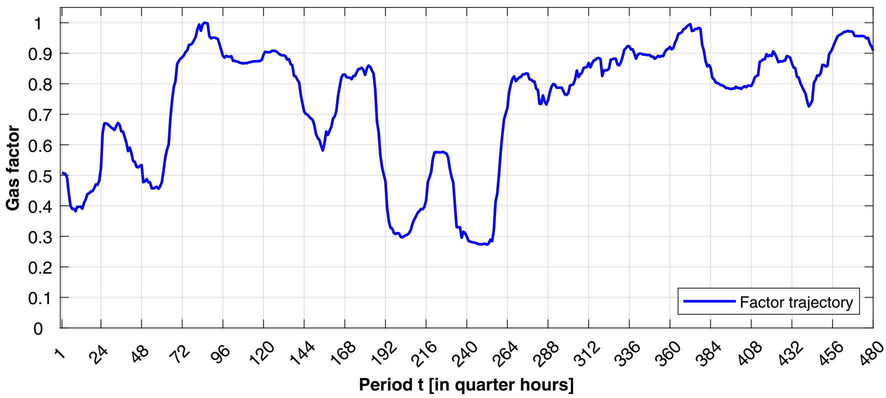

Fig. 2 Gas factor trajectory, 07/18/2022–07/22/2022

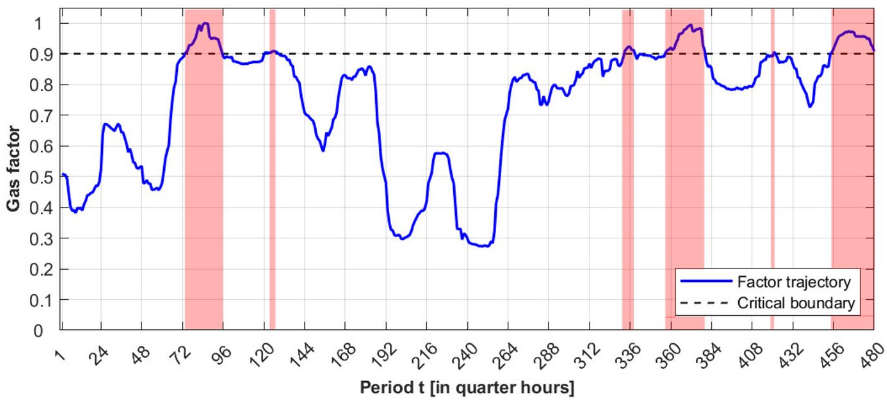

Fig. 3 Exemplary emergency boundary

for production processes in response to such a notice. A justification for external signaling in production planning can be found in Scholz and Meisel (2022).

3 Application of G2P-DR in bicriteria production planning

3.1 Brief literature overview

In this paper, two topics—namely factorization of electrictiy consumption and event-driven (re-)planning—are combined and applied in production planning to address the current gas crisis in Europe. Since the first topic is closely related to the energy-efficient production planning (EEPP) research strand, we first provide a brief overview of related articles; for a general overview regarding energy-aware production planning, however, see e.g. (Biel and Glock 2016; Gao et al. 2020) and (Bänsch et al. 2021), or (Neufeld et al. 2022) for multicriteria production planning considering, for example, parallel machines (hybrid flowshops in particular). Cf. (Dong and Ye 2022; Oukil et al. 2022) or (Wang and Wang 2022) for current work in the research area of energy efficient production planning.

In energy-efficient production planning, electricity consumption (EC)—as a green measure—is often combined with classical criteria, such as makespan or total tardiness. In more recent developments of EEPP, time-dependent electricity costs are taken into account to evaluate energy consumption with respect to time—leading to a price-based factorization of electricity consumption; cf. e.g. (Mansouri et al. 2016; Jia et al. 2017; Wichmann et al. 2019; Ding et al. 2021) and (Ho et al. 2021). In some contributions, a carbon emission-based factorization of electricity consumption is considered to further focus the green perspective; cf. (Lei and Guo 2015; Ding et al. 2016; Dellnitz et al. 2020; Schulz and Linß 2020) and (Gu et al. 2021). Here, the flexibility of production systems usually is captured by variable machine states (e.g. “on”, “off”, etc.) and/or different (discrete) production speed levels and/or the embedding of parallel machines with different power requirements; cf. e.g. (Ding et al. 2016; Giglio et al. 2017; Schulz et al. 2019, 2020; Dellnitz et al. 2020) and (Wang et al. 2022). In particular, these multicriteria-based studies have shown that minimizing (factorized) electricity consumption generally does not simultaneously minimize the makespan of a production; see also (Mansouri et al. 2016) and (Jia et al. 2017). However, none of these works considered time-dependent gas factorization to address the current European gas crisis.

The second topic—event-driven (re-)planning—is also part of the EEPP literature. In this strand of research, companies’ planning tools are aligned with external signals, such as excessive power availability or insufficient power on the grid. Companies then respond by accelerating or shutting down production, eventually, in order to obtain a reward. Here, the studies of (Zhang et al. 2018; Weitzel and Glock 2019) and (Scholz and Meisel 2022) are worth noting. In Scholz and Meisel (2022), for example, the authors considered, among other things, production scheduling when companies receive a short-term external signal about the availability of excess renewable energy. To deal with such signals, the authors applied a multicriteria approach, combining total tardiness, peak load, and consumption

Table 1 Classification of selected articles in the context of EEPP

Articles	C_{max}	EC	$Price-/CO_2-factorizedEC$	Gas-factorized EC
Anghinolfi et al. (2021)	✓	✓	✗	✗
Zhang et al. (2019)	✓	✓	✗	✗
Zhou et al. (2021)	✓	✓	✗	✗
Li et al. (2018)	✓	✓	✗	✗
Mansouri et al. (2016)	✓	✓	✗	✗
Dai et al. (2013)	✓	✓	✗	✗
Chen et al. (2020)	✓	✓	✗	✗
May et al. (2015)	✓	✓	✗	✗
Lu et al. (2018)	✓	✓	✗	✗
Dai et al. (2019)	✓	✓	✗	✗
Wei et al. (2022)	✓	✓	✗	✗
Cao et al. (2021)	✓	✗	✓	✗
Schulz et al. (2019)	✓	✗	✓	✗
Moon et al. (2013)	✓	✗	✓	✗
Schulz et al. (2020)	✓	✗	✓	✗
Heydar et al. (2022)	✓	✗	✓	✗
Ho et al. (2021)	✓	✗	✓	✗
Ding et al. (2016)	✓	✗	✓	✗

of excess renewable energy. However, handling gas-related events is also an open issue in this research strand.

Table 1 summarizes our observations.

To the best of our knowledge and as a consequence of the above Table 1, the G2P-DR programs proposed in this paper have not yet been studied in the EEPP literature.

3.2 Problem description

We now study a single-stage parallel machine production planning problem in order to exemplify and demonstrate the applicability and the impacts of the two proposed G2P-DR programs in Sect. 2.2. The practical relevance of such problems has been justified by, for example, Moon et al. (2013). We perform short-term integrated scheduling and lot-sizing over one working week, i.e. from 12 p.m. on Sunday to 12 p.m. on Friday, under the following assumptions [(e.g., Giglio et al. (2017)]:

- The planning horizon (18/07/2022–22/07/2022) is divided into 480 periods of one quarter hour each.
- The two conflicting criteria, makespan and gas-fired electricity consumption, are minimized simultaneously.
- The single-stage parallel machine environment consists of several machines whith non-identical electricity coefficients.
- Different machine states and discrete production speed levels that allow for integer output in a period are taken into account to leverage gas-fired electricity consumption (five different speed levels in total).
- Electricity coefficients (in kW) are randomly generated for each state of each machine: *Off* (0 kW); *Ramp-up* (drawn from $\mathcal{U}_{\{20,21,\ldots,60\}}$); *Standby* (drawn from $\mathcal{U}_{\{4,5,\ldots,8\}}$); *Production* (drawn from $\mathcal{U}_{\{145,146,\ldots,210\}}$).
- The change in electricity consumption with variation of the production speed is calculated using the conversion formula in Schulz et al. (2020).
- All jobs are known at the beginning of the working week and the due dates are at the end of the working week. The quantities demanded for each job are randomly generated.
- Preemption and lot-splitting are possible.
- A machine can process at most one job in one period, and the selected production speed cannot change in one period. The latter also applies to a selected machine state.
- For simplicity, warehousing, backlog and machine setups are neglected.
- For RTF, the gas factors shown in Fig. 2 are used. For EDR, the highlighted emergency time frames shown in Fig. 3 are used.

According to this problem description, a bicriteria mixed-integer minimization problem (MIP) is formulated by (1)–(14) in the case of RTF. Regarding EDR, (2) is simply replaced by (2*) in (1)–(14):

Table 2 Indices, parameters and variables

Indices	
m	Machine $m \in \mathcal{M} = \{1, ..., M\}$
j	Job $j \in \mathcal{J} = \{1, ..., J\}$
i, h	Machine states $i, h \in \mathcal{I} = \{0, ..., I\}$ with the following states: *off* ($i = 0$), *ramp-up* ($i = 1$), *standby* ($i = 2$) and *production* ($i = 3$)
t	Period (a quarter hour) $t \in \mathcal{T} = \{1, ..., T\}$
v	Production speed level $v \in \mathcal{N} = \{1, ..., N\}$
Parameters	
c_t^{RTF}	Gas factor in period t of the electricity mix considered
c_t^{EDR}	$c_t^{EDR} = \rho$ if a critical event occurs in period t, 0 otherwise. $\rho > 0$ is a prespecified penalization factor
a_{vj}^{prod}	Quarter hourly production rate of job j on each machine at speed level v
d_j	Demanded quantities of job j
γ_{ih}^{tran}	Transition parameter from machine state i to state h (1 if possible, 0 otherwise)
a_{im}^{elec}	Quarter hourly electricity consumption of machine m in state $i \in \mathcal{I} \setminus \{I\}$
$\hat{a}_{vm}^{elec\_I}$	Quarter hourly electricity consumption of machine m in production state I at speed level v
Decision variables	
x_{jmtv}	Equals 1 if job j will be processed on machine m in t at speed level v, otherwise 0
δ_{imt}^{state}	Equals 1 if machine m has state i in period t, otherwise 0
$\hat{\delta}_{mtv}^{state\_I}$	Equals 1 if machine m is in production state I at speed level v in period t, otherwise 0
s_t^{buy}	Amount of electricity [in kWh] to be purchased in period t
α_t	Equals 1 if a job is produced in period t and 0 otherwise
β	Nonnegative auxiliary variable used for linearization
C_{max}	Equals the makespan
G_{RTF}	Equals the gas-factorized electricity consumption to be minimized
G_{EDR}	Equals the penalization from electricity consumption in critical periods to be minimized

$$\textbf{min} \qquad \mathrm{G}_{EDR} = \sum_{t=1}^{T} c_t^{EDR} \cdot s_t^{buy} \tag{2*}$$

Table 2 contains the corresponding symbols.

$$\textbf{min} \qquad \mathrm{C}_{max} = \beta \tag{1}$$

$$\textbf{min} \qquad \mathrm{G}_{RTF} = \sum_{t=1}^{T} c_t^{RTF} \cdot s_t^{buy} \tag{2}$$

s.t.

$$\alpha_t \cdot M \geq \sum_{j=1}^{J} \sum_{m=1}^{M} \sum_{v=1}^{N} x_{jmtv} \quad \forall\, t \in \mathcal{T} \tag{3}$$

$$\beta \geq t \cdot \alpha_t \quad \forall\, t \in \mathcal{T} \tag{4}$$

$$\sum_{v=1}^{N} \sum_{t=1}^{T} \sum_{m=1}^{M} a_{vj}^{prod} \cdot x_{jmtv} = d_j \quad \forall\, j \in \mathcal{J} \tag{5}$$

$$\sum_{i=0}^{I} \delta_{imt}^{state} = 1 \quad \forall\, m \in \mathcal{M},\ t \in \mathcal{T} \tag{6}$$

$$\widehat{\delta}_{mtv}^{state\_I} - \sum_{j=1}^{J} x_{jmtv} = 0 \quad \forall\, t \in \mathcal{T},\ m \in \mathcal{M},\ v \in \mathcal{N} \tag{7}$$

$$\delta_{Imt}^{state} - \sum_{v=1}^{N} \widehat{\delta}_{mtv}^{state\_I} = 0 \quad \forall\, t \in \mathcal{T},\ m \in \mathcal{M} \tag{8}$$

$$\delta_{imt}^{state} + \delta_{hm,t+1}^{state} \leq 1 + \gamma_{ih}^{tran} \quad \forall\, i, h \in \mathcal{I},\ m \in \mathcal{M},\ t \in \mathcal{T} \backslash \{T\} \tag{9}$$

$$\sum_{m=1}^{M} \left(\sum_{v=1}^{N} \widehat{a}_{vm}^{elec\_I} \cdot \widehat{\delta}_{mtv}^{state\_I} + \sum_{i=0}^{I-1} a_{im}^{elec} \cdot \delta_{imt}^{state} \right) = s_t^{buy} \quad \forall\, t \in \mathcal{T} \tag{10}$$

$$\delta_{0m1}^{state} + \delta_{1m1}^{state} = 1 \quad \forall\, m \in \mathcal{M} \tag{11}$$

$$x_{jmtv},\ \alpha_t \in \{0, 1\} \quad \forall\, t \in \mathcal{T},\ j \in \mathcal{J},\ m \in \mathcal{M},\ v \in \mathcal{N} \tag{12}$$

$$\delta_{imt}^{state},\ \widehat{\delta}_{mtv}^{state\_I} \in \{0, 1\} \quad \forall\, t \in \mathcal{T},\ i \in \mathcal{I},\ m \in \mathcal{M},\ v \in \mathcal{N} \tag{13}$$

$$s_t^{buy},\ \beta \geq 0 \quad \forall\, t \in \mathcal{T} \tag{14}$$

With (1) and (2) or (2*), we simultaneously minimize the makespan C_{max} and the gas-factorized electricity consumption G_{RTF} under RTF or makespan and the penalization of electricity consumption G_{EDR} when EDR is applied, respectively. Constraints (3)–(4) control the makespan. More precisely, α_t equals 1 if a job is processed in a period t on any machine. Note here that M equals the total number of machines and serves as a correction factor if the right hand side is greater than 1. Furthermore, $t \cdot \alpha_t$ gives the total number of periods if any job is still to be processed in period t. With (5), we have modelled equality conditions for meeting the demanded quantities d_j for each job j. The due dates of the jobs are therefore at the end of the planning horizon and are thus implicitly considered by (5). Equation (6) ensure that a machine has only one state and never becomes stateless. Equation (7) in combination with (8) control the production state in tandem with the speed level, i.e. $\delta_{mtv}^{state\_I}$ equals 1 if any x_{jmtv} equals 1 in (7). The latter is only the case when one job j is assigned to machine m at speed level v in period t. Equation (8) couple the production mode $i = I$ of a machine with one speed level exclusively. Constraints (9) control the state transitions of a machine. Here, a machine can either retain a state $\delta_{imt}^{state} + \delta_{hm,t+1}^{state} = 2$, with $h = i$ and $1 + \gamma_{ih}^{tran} = 2$, or can change it, choosing $h \neq i$, if the transition from state i to state h is feasible. Equation (10) balance the electricity consumption and equation (11) are used for initialization, i.e., a machine m is either in the off state ($i = 0$) or the ramp-up state ($i = 1$) in the period $t = 1$. (12)–(14) are binary and non-negativity conditions.

The presented model is solved applying the modified weighted Tchebycheff method (MWTM) in the case of RTF, and both the MWTM and the method of the global criterion using the Tchebycheff metric with lexicographic reoptimization (MGC) in the case of EDR. The weighted Tchebycheff method is a commonly used scalarization method in multi-objective optimization for computing (weak) Pareto optimal solutions. Applying this method with a modified augmented Tchebycheff metric (instead of the classical Tchebycheff metric) leads to strictly Pareto optimal solutions by systematically varying the weights of the objective functions; cf. Liu (2016) and Miettinen (1998). In the case of EDR, we are additionally interested in a single Pareto-optimal solution. Since no preference information of a decision-maker is considered, we apply the method of the global criterion using the Tchebycheff metric and lexicographic reoptimization. The method of the global criterion using the Tchebycheff metric produces a single (weak) Pareto optimal solution that minimizes the distance between a reference point (e.g., the ideal point) and the feasible objective region. Since this can lead to a weak Pareto optimal solution, lexicographic reoptimization is used to address this shortcoming. Further details can be found in Miettinen (1998).

All calculations are conducted via GAMS 41 using CPLEX with 12 threads and a relative optimality criterion of 0.001 on a 64 bit Windows 10 PC with 3500 MHz, 16 cores and 32 logical processors. For example, the computation of corresponding Pareto front representations for the presented instance demonstrated in the next section required in total approximately 5500 s in the case of RTF and approximately 2528 s in the case of EDR. In the latter case, the computation of Pareto-optimal points using the MGC took in total approximately 47 s.

4 Results and discussion

For an instance of the presented MIP, we show representations of the Pareto fronts both under RTF and under EDR [using (2*) instead of (2)] in this section. The data used for the numerical example shown can be found in Appendix 1. The scenario consists of 4 machines ($M = 4$) with randomly generated coefficients and 5 jobs ($J = 5$). The quantities d_j are also generated randomly and the total demand of all jobs corresponds to approx. 88.73% of machine utilization at the highest production speed. The implications drawn are also valid for other calculated scenarios.

4.1 Results in the case of RTF

On the left-hand side of Fig. 4, we see a Pareto front representation visualizing the trade-off between makespan and gas-factorized electricity consumption. Consequently, the schedule which results in a minimal makespan does not result in the minimal gas-factorized electricity consumption. The corresponding electricity consumption of those two schedules are depicted in the diagram on the right in Fig. 4. Ultimately, this means that a company can choose whether it executes the schedule minimizing the makespan of 421 periods or the schedule which minimizes gas-factorized electricity consumption but with a makespan of 480 periods, or any Pareto optimal schedule inbetween. This freedom of choice is only possible if flexibility potentials exist (e.g. in production processes and/or a time buffer to meet the demand) enabling the exploitation of trade-offs between makespan and gas-factorized electricity consumption.

But why would a company execute a schedule that reduces gas-factorized electricity consumption if it comes at the expense of the makespan? Therefore, appropriate incentives must exist. An initial guess could be that market-based electricity prices already reflect gas factors so that production scheduling can follow the classic RTP. However, such a one-to-one relationship between electricity prices and gas factors is not generally valid. This means that, under RTP, minimizing electricity costs does not minimize gas-factorized electricity consumption as shown in Fig. 5. In Fig. 5, electricity prices and corresponding gas factors (again, the 29th CW of 2022, Mon–Fri) do have a positive correlation of ≈ 0.68. This still results in trade-offs between electricity costs and gas-factorized electricity consumption. We also checked this for each workweek (Mon–Fri) in August 2022 in Germany, and while we see partially higher correlations of $\approx 70 - 78\%$, this one-to-one relationship still does not hold.

For a country's energy supply, it is reliable to manage energy consumption according to classical concepts, e.g., via (local) balancing groups. In times of crisis, however, the scarcity of individual energy resources may force a switch to a different pricing scheme which particularly protects the source in question.

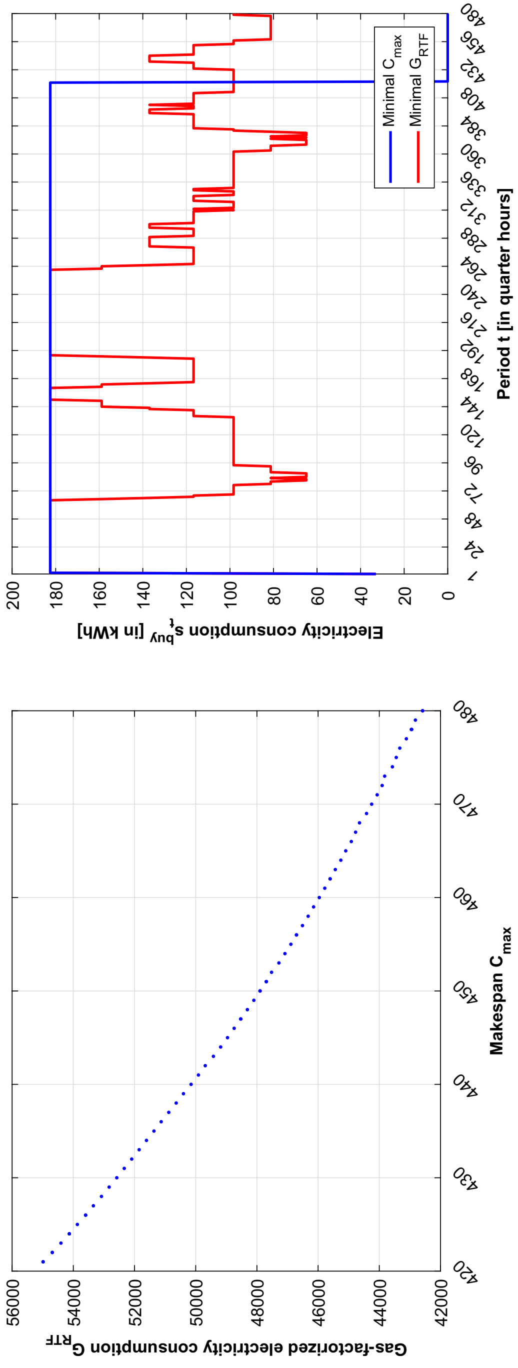

Fig. 4 Pareto front and electricity consumption of selected schedules

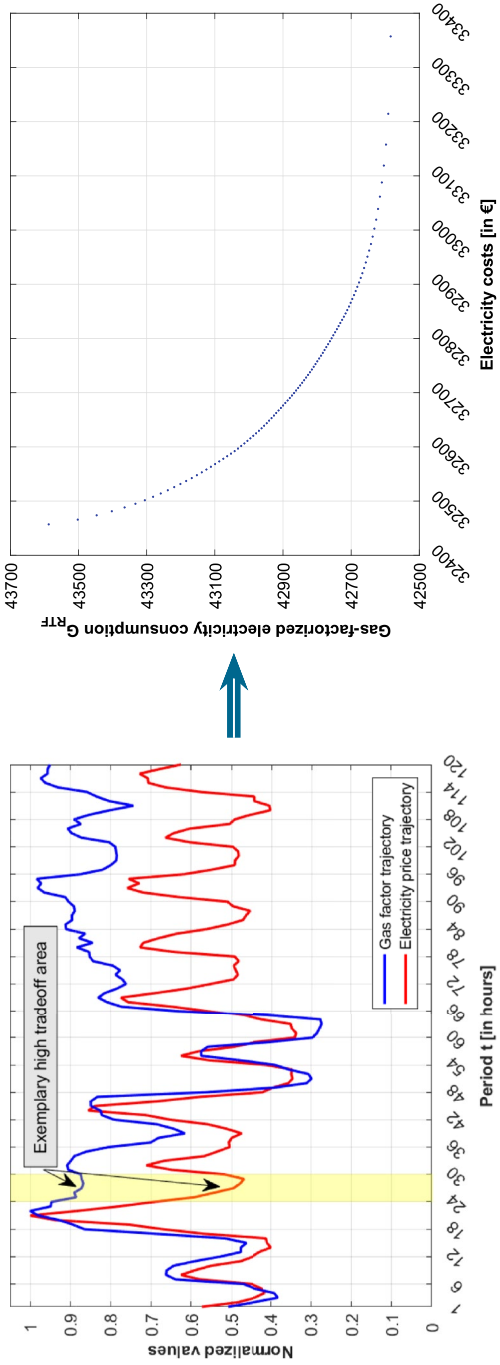

Fig. 5 Trade-offs between electricity prices and gas factors

Therefore, we show a simple scheme that does not affect the optimality of our planning problems. To incentivize companies aiming at this goal, an electric utility can choose, for example, a price $p \cdot c_t^{RTF}$ per kWh, with $p > 0$. The company's objective (2) then adjusts as follows:

$$\mathbf{min} \qquad \mathrm{G}_{RTF}^{(p)} = \sum_{t=1}^{T} p \cdot c_t^{RTF} \cdot s_t^{buy} = p \cdot \sum_{t=1}^{T} c_t^{RTF} \cdot s_t^{buy} = p \cdot \mathrm{G}_{RTF}. \qquad (2')$$

To put it clearly, an optimal solution regarding (2) is also optimal for (2′). Such a one-to-one correspondence between prices and gas factors can therefore be a reliable tool in crisis situations such as the winter of 2022/2023.

4.2 Results in the case of EDR

As our second example, we conduct production planning under EDR as shown in Fig. 3. A value of 0.9 has been chosen as the critical gas factor; exceeding such a value triggers an emergency scenario on very short notice, in which electricity consumption during the emergency time window is penalized. In total, there are six time frames in which the critical value is exceeded. Since the companies will be notified to reduce their electricity consumption very shortly before such an emergency period occurs, we propose a rolling-planning approach. This is a somewhat different approach than the one taken in the case of the RTF, where historical data have been used for the calculations, which is often the case in the corresponding literature; cf. e.g. Zhang et al. (2018) or (Scholz and Meisel 2022). However, the rolling planning is conducted using the following procedure:

- *Step 1:* We solve the MIP (1), (2*)–(14) minimizing the makespan for the considered time horizon, neglecting any event, i.e. $c_t^{EDR} = 0 \; \forall \, t$. This initial solution is saved.
- *Step 2.1:* When an event is triggered, we fix the decision variables related to the previous periods of the event to the corresponding values of the previously gen-

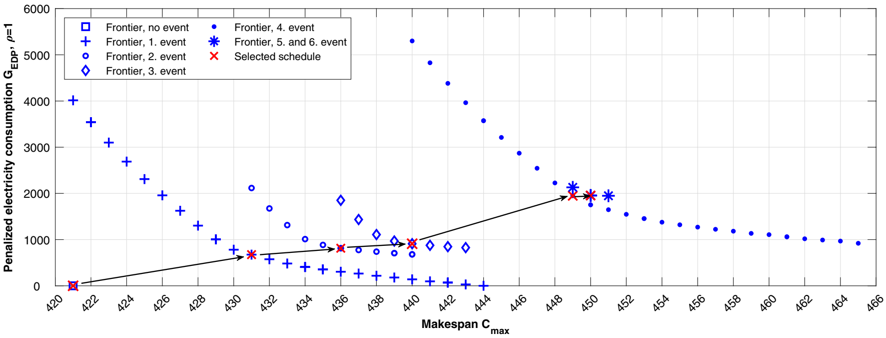

Fig. 6 Visualization of the described rolling planning

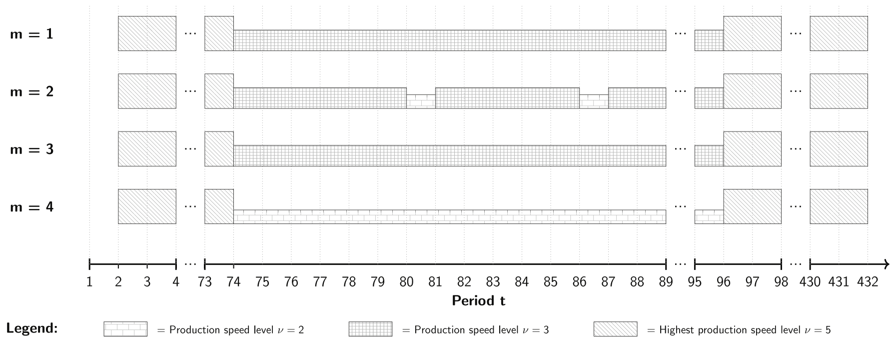

Fig. 7 Gantt chart, obtained schedule in the 1st event

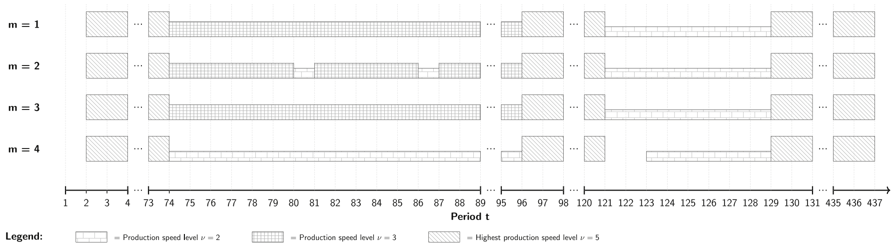

Fig. 8 Gantt chart, obtained schedule in the 2nd event

erated solution. We solve the MIP again, computing a Pareto front representation via the MWTM, but considering the penalization of the electricity consumption in the emergency time frame.

- *Step 2.2:* Since a Pareto front representation is calculated in step 2.1, a single solution has to be selected by a decision-maker. This solution is saved. However, if a single solution is to be directly calculated, a no-preference method such as MGC can be applied instead.
- *Step 3:* Step 2.1 and 2.2 are repeated until no further event occurs in the considered time horizon. The last saved solution is then the final schedule.

By applying the described rolling planning, we obtain Fig. 6. Of course, if an initial generated solution is feasible, the subsequent solutions are also feasible. The blue symbols are respective Pareto fronts and the red crosses are the solutions obtained by MGC. In the southwest corner, we see the initial schedule with a makespan of 421 and no penalized electricity consumption (since no event has been triggered so far). By going forward through time and adjusting the schedule if an emergency event is triggered, we obtain a final solution with a makespan of 450 and a penalized electricity consumption of about 2000 kWh. Note here that the 6th event has no effect because the makespan of 450 periods of the final schedule takes place before the corresponding emergency period begins. However, if all events were neglected, the penalized electricity consumption in this example would be 11,227

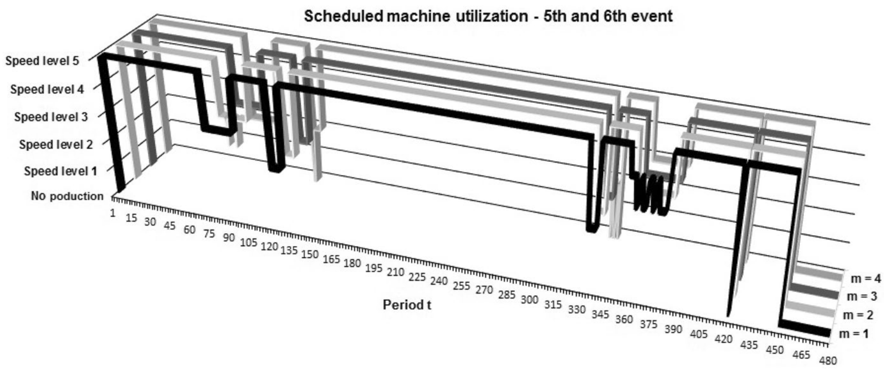

Fig. 9 Rescheduling of machine utilization, 5th event

kWh, which is 9227 kWh higher than the penalized electricity consumption determined by the described procedure.

Figure 7 depicts the schedule obtained by the MGC in the first event, which takes place from period $t = 74$ to $t = 95$, inclusively. It can be seen that when the first event occurs, the speed levels of the machines decrease to consume less power during the specific emergency time window. However, this throttling of the production speed of the machines comes at the expense of the makespan. The result of the rescheduling process due to the second event is illustrated in Fig. 8. The second event takes place in the period $t = 121$ to $t = 128$ inclusive. Again, the speeds of the machines decrease during the duration of the second event, which in turn increases the makespan compared to Fig. 7.

Overall, the rescheduling is mainly reflected in the machine speeds. This behavior is vizualized for the fith and sixth event in Fig. 9. Note that the sixth event has no impact on the schedule because it occurs in the period $t = 455$ to $t = 480$, but the jobs have already been fulfilled. See Appendix 1 for corresponding figures of the other rescheduling processes of the machine utilization.

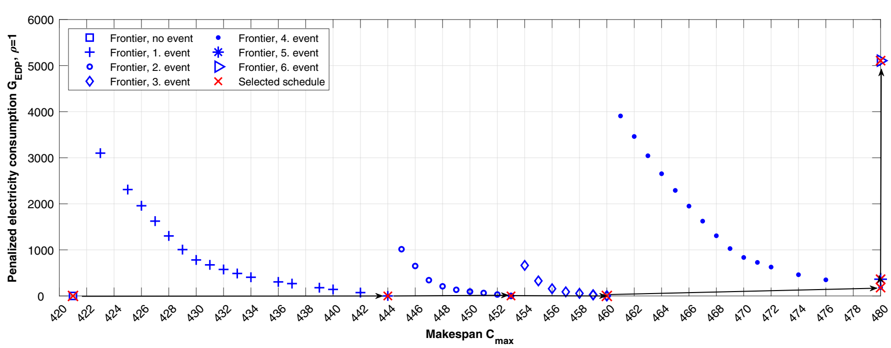

Fig. 10 Cold penalization

As in the case of RTF, there have to be flexibility potentials to optimize for penalized electricity consumption. In Fig. 6, points—and thus schedules—are selected that are located between the extreme points of the Pareto front. Of course, other schedules could be selected as well to proceed with such solutions.

In Fig. 10, only those solutions are selected which minimize the penalized electricity consumption when an event occurs. However, care has to be taken when choosing appropriate schedules because this could also lead to a "cold penalization". This means that a company may lose its flexibility in optimizing electricity consumption if another event occurs because the production makespan has already reached a maximum value that cannot be exceeded without violating the due dates of orders. Note here that period $t = 480$ is the due date for all jobs. In Fig. 10, such a cold penalization leads to a final schedule with a makespan of 480 periods and a penalized electricity consumption of 5108.3 kWh, which is higher than the 2000 kWh under application of MGC. However, this is still lower than the 11,227 kWh in the case where all events are neglected and only the makespan is minimized.

As in the case of RTF, incentives must be provided for companies to participate in such a program. One possibility could be to grant a financial credit. This would be reduced depending on the penalized electricity consumed. The credit surplus would be paid out; in the event of a credit deficit, the company would have to make up the difference.

5 Conclusion

In this paper, we have discussed the concept of gas-to-power demand response (G2P-DR) and proposed two possible programs for it: Real-time-factorization (RTF) as a factor-based program and emergency G2P-DR (EDR) as an incentive based program. The proposal for such an approach was driven primarily by the European Commission's "Save Gas for a Safe Winter" plan, which seeks, among other things, to reduce gas consumption in the power sector. Therefore, demand-side mechanisms such as demand response were adopted and adjusted to create incentives for participants (e.g., companies) to respond to increasing gas-fired power generation and corresponding power feed into the grid. The application of the proposed programs was exemplified in a production planning approach studying trade-offs between makespan and gas-fired electricity consumption. Both programs, RTF and EDR, show a significant reduction potential of consumed gas-fired electricity. In any case, both proposed programs have certain advantages. EDR is incentive-based and could ease a tight energy situation in times of need. RTF, on the other hand, penalizes and financially rewards companies for paying attention to their gas-fired power consumption in general. Depending on the design of the two programs, a combination of these would also be conceivable. Of course, other ecological criteria (e.g. indirect emissions) or regulatory measures (e.g. a cap on gas prices) could also be added to the production planning concept described. In addition, as a subject of further research, the potential of the concept of G2P-DR as well as the complexity of the planning concept at hand can be studied in a larger computational study. Apart from this, the gas-factors determined in this article are based on the overall electricity generation in Germany. This aspect can be further refined by focusing, for example, on individual balancing groups since in practice, companies usually procure their electricity locally. Thus, a consideration of gas factors at the local level could also be a subject of further study.

However, the main purpose of this paper was to show general ways in which quantitative planning methods such as scheduling and/or lot-sizing can help to ease or counteract the tense situation related to gas consumption in Europe due to the war in Ukraine. The ideas presented here could serve as a discussion point for further research or for the design of control-relevant micro- or macroeconomic instruments.

Appendix A Input data used for the numerical example

See Fig. 11 and Tables 3, 4 and 5.

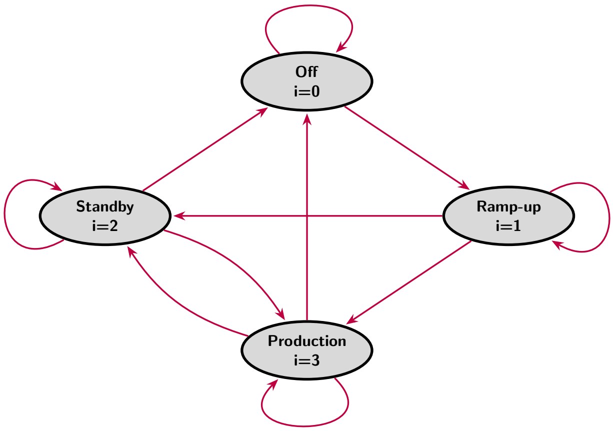

Fig. 11 Feasible machine state transitions

Table 3 Power levels of the machines [in kW]

	m = 1	m = 2	m = 3	m = 4
Off	0	0	0	0
Ramp-up	28	40	44	20
Standby	5	7	8	2
Production	145	195	180	210

Table 4 Output of an arbitrary machine on a quarter-hourly basis

Speed level v	$v = 1$	$v = 2$	$v = 3$	$v = 4$	$v = 5$
Output a_{vj}^{prod}	1	2	3	4	5

Table 5 Quantities demanded for the demonstrated example

	j = 1	j = 2	j = 3	j = 4	j = 5
Quantities d_j	1600	1700	1600	1800	1700

$$\hat{a}_{vm}^{elec\_I} = \left[1 + 0.6 \cdot \left(\frac{a_{5j}^{prod}}{a_{vj}^{prod}} - 1\right)^2 - 1.4 \cdot \left(\frac{a_{5j}^{prod}}{a_{vj}^{prod}} - 1\right)\right] \cdot a_{3m}^{elec} \cdot \frac{a_{vj}^{prod}}{a_{1j}^{prod}}$$

Equation A1: Conversion formula used for calculating $\hat{a}_{vm}^{elec\_I}$

Appendix B Supplementary material

See Figs. 12, 13, 14, 15 and 16.

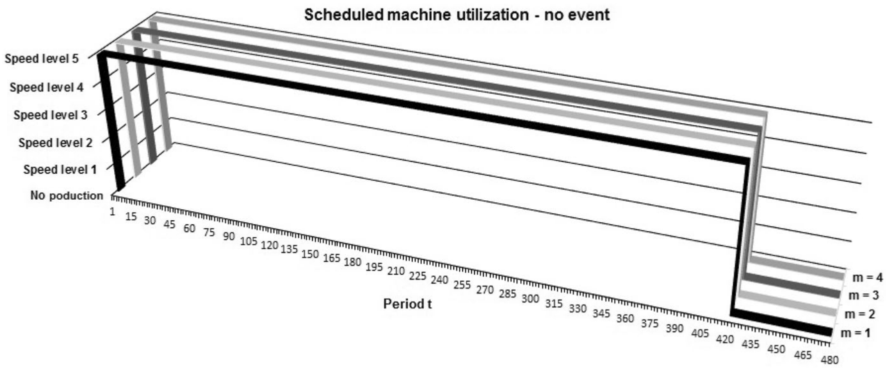

Fig. 12 Rescheduling of machine utilization, no event occurs

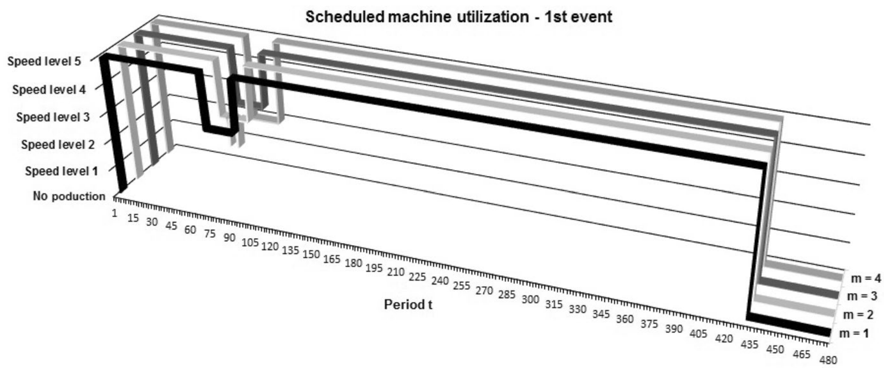

Fig. 13 Rescheduling of machine utilization, 1st event

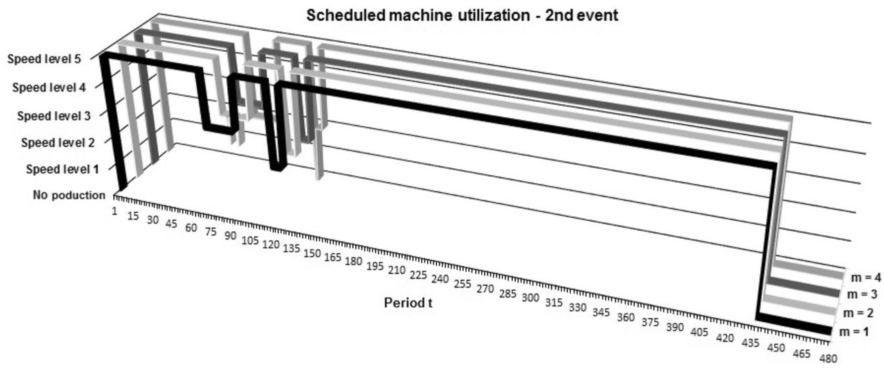

Fig. 14 Rescheduling of machine utilization, 2nd event

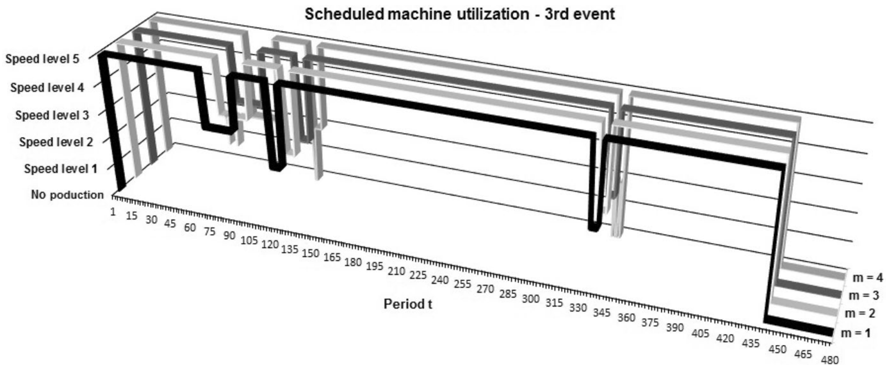

Fig. 15 Rescheduling of machine utilization, 3rd event

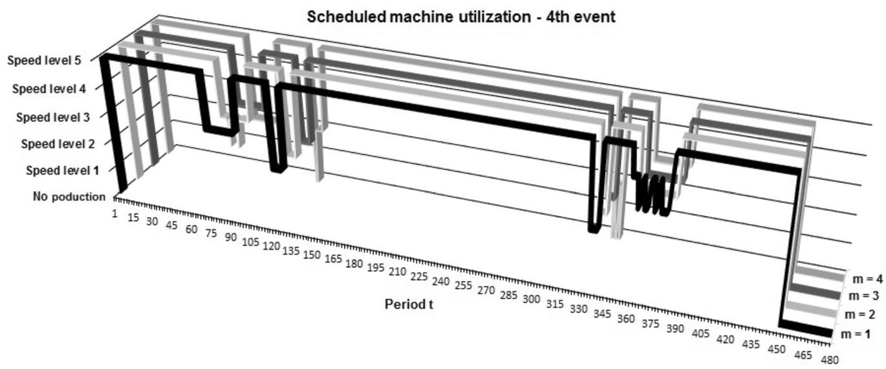

Fig. 16 Rescheduling of machine utilization, 4th event

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Data availability The datasets generated during and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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