JOB SHOP SCHEDULING WITH FLEXIBLE ENERGY PRICES

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***Abstract*—The rising energy prices – particularly over the last decade – pose a new challenge for the manufacturing industry. Reactions to climate change, such as the advancement of renewable energies, raise the expectation of further price increases and variations. Regarding the manufacturing industry, production planning and controlling can have a significant influence on the in-plant energy consumption. In this paper, we develop a scheduling method as a linear optimization model with the objective to minimize energy costs in a job shop production system.**

INTRODUCTION

Since the industrial revolution, the worldwide economic prosperity depends on the reliable provision of electric energy. Yet the generation of this energy by means of fossil fuels is, as measured by the associated CO_2-emissions, the main contributor to climate change (Finkbeiner et al. 2010). According to the Federal Association for Energy and Water Management, the electricity costs for private customers rose by 85% between the years 2000 and 2010. Within the same period, an increase of 130% was noted for the industrial sector (Bauernhansl et al. 2013). One of the driving factors in this distinct rise are increases in taxes and other charges, such as the EEG reallocation charge (EEG = Erneuerbare-Energien-Gesetz; Renewable Energies Act of Germany). The most of the remunerated electricity under the EEG is traded at spot-markets like the European Energy Exchange (EEX) or the European Power Exchange (EPEX). As supply and demand determine the price, energy tariffs are highly variable over the day. In line with this, methodologies for price predictions for competitive energy markets have been published by Lei and Feng 2012 and others. The spot-markets are trading electricity for the following day (Day-Ahead). Figure 1 shows exemplary the hourly electricity price for the following day - in this case for the 21st of January 2016, with a standard deviation of 20.75 (39.8%). The hourly electricity prices are used in this research to minimize the energy consumption costs by means of intelligent scheduling.

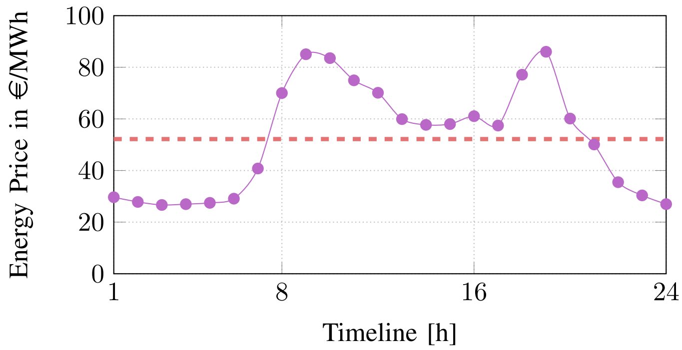

Fig. 1. Hourly electricity price and average (dashed line, for information purposes) for the following day, in this case 21th of January 2016 (Own representation of data from www.epexspot.com)

RELATED LITERATURE

Energy-efficient scheduling and the reduction of energy consumption has been a very important issue over the recent years. In this area of research, Weinert et al. 2011 introduced a so-called energy blocks methodology, which allows for the accurate prediction of energy consumption and integrates energy efficiency criteria into production system planning and scheduling. Dai et al. 2013 proposing an improved genetic simulated annealing algorithm for energy efficient flexible flow shop scheduling, focusing on the two objectives makespan and energy consumption. Furthermore, Liu et al. 2014 developed a multi-objective scheduling method in which the reduction of the energy consumption was one of the primary objectives.

The three papers mentioned above consider only two operational machine states with respect to the energy consumption: Idle (or standby) and processing. In 2014, Shrouf et al. 2014 extended these works by making also decisions on a machine level, which allowed them to consider more operational-modes of a machine. Developing a model for optimizing the total energy consumption costs when scheduling jobs on a single machine, they consider the operating states *Idle*, *Processing*, *Turning Up* and *Turning Down*.

The extension of this approach to more than one machine

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complicates matters substantially. Dependencies between all machines are unavoidable and need to be modeled when assuming a job shop production system. Already the basic job shop problem is known to be NP-complete and to be computationally extremely difficult.

Concerning exact solution methods for job shop problems, rather few methods have been published. Until 2005, the most effective approaches have been branch-and-bound algorithms that branch on the job orders on the machines in the so-called disjunctive graph model. In the traditional job shop problem, the optimal starting times of the jobs can be easily computed once the decisions concerning the order of the jobs are made. Aiming to avoid unnecessary branchings, these algorithms typically also employ constraint programming techniques in order to tighten the bounds for the job starting times and infer job orders during the branch-and-bound process.

Motivated by the success of time-indexed models and solution approaches for other scheduling problems (Sousa and Wolsey 1992; Akker 1994), Martin and Shmoys 2005 eventually proposed to use time-indexed integer programming formulations also for the job shop problem. Using such a formulation together with effective bound tightening techniques and specialized branching, they have been able to computationally derive lower bounds that were stronger than those obtained with disjunctive graph models and job order based formulations.

In a time-indexed formulation, the planning horizon is discretized and binary variables are used to indicate if a job starts at a specific time. Formulations of this type are widely used to tackle project scheduling and dynamic planning problems that involve complex resource, precedence, or state constraints, as these additional constraints often can be formulated much easier in a time-index model than in a continuous time model. Already Ford and Fulkerson 1962 observed that dynamic flow problems in a network with transit times on the arcs can be modeled equivalently as static flow problems in time-expanded networks, which is equivalent to a time-indexed formulation of the problem.

Successful applications of time-indexed and time-expanded problem formulations include the optimization of supply chains (Küçükyavuz 2011; Pochet and Wolsey 2006), production planning in mining, energy production, and other industries (Louis and Hill 2003; Chicoisne et al. 2012; Epstein et al. 2012; Lambert et al. 2014), timetabling in transportation (Schöbel 2007; Serafini and Ukovich 1989), and many more. In many of these cases, the time-indexed integer programming formulations also lead to mathematically stronger linear relaxation than their continuous time counterparts, which is beneficial in branch-and-bound algorithms. This benefit typically comes at the cost of a much larger problem formulation. However, exploiting the special structure of the time-indexed formulations in specialized solution algorithms, the size of the formulation that actually has to be solved often can be reduced substantially. A discussion of the main features, strengths, and limitations of alternative modeling and optimization techniques, with a special focus on short-term scheduling of chemical batch processing, can be found in the survey of Méndez et al. 2006.

A computational evaluation of different mixed-integer programming formulations for parallel machine scheduling problems for job-related objective functions such as weighted completion time, weighted tardiness, maximum lateness, and number of tardy jobs has been published in Unlu and Mason 2010. The results of this study, as mentioned also in Berghman et al. 2014, suggest that time-indexed formulations perform reliably well for such problems and should be explored further for the solution of scheduling problems with multiple machines. Time-indexed formulations are widely used to model variable operational-modes of devices and plants in various applications (for example in unit commitment planning for electricity networks or in dynamic spectrum assignment in telecommunication networks) or to model time-dependent job-related objective functions in scheduling problems. To the best of our knowledge, however, the use of time-indexed formulations to model the job-independent ramping and switching dynamics of the machines' operational states in a multi-machine scheduling problem has not yet been investigated, yet.

Problem Definition

When considering a common job shop production system, each machine usually has a varying energy demand depending on its operational state. Production systems that consist of chipping (e.g. milling machines) or transforming tool machines (e.g. presses or benders) typically have a vast demand of energy (Neugebauer 2008). Further examples of high energy consumers are industrial laser welding or laser cutting systems (Ahn et al. 2016). Note that a considerable share of the electricity consumption of these machines in practice is actually associated with the standby-mode, when the machines are active but not working (Neugebauer 2008; Ahn et al. 2016). Furthermore, peripheral systems, such as cooling and ventilation, loading and unloading mechanisms, or hydraulic systems require a significant amount of electricity even in standby-mode. Shutting down these modules is generally refused in industrial practice on account of the necessary process stability. Operational states would have to be predictable and reliable in order to initiate a safe ramp down without risking process stability.

If one did assume that machines ramp down entirely when not in use, an initial evaluation would exhibit short idle times and, thus, a high level of machine capacity utilization, which in turn saves energy. This would reduce the energy demand during standby-mode and the machine in question could ramp down after each processing operation. However, long idle times are also possible, which would allow for a complete ramp down of the machine. The feasibility of this option depends on planning a timely and safe restart and the subsequent flawless resumption of production.

Our research specifically addresses these questions. We aim to develop models where the operating-modes of all machines are planned together with the scheduling of the jobs in a period-specific manner such that longer ramp up, ramp down, and standby-processes are adequately considered. Thus, periods with lower energy costs could be utilized to schedule production processes with high energy demands and remaining in standby-mode or even ramping down production facilities in more expensive periods can save energy costs.

Referring to the above mentioned use case (chipping or transforming tool machines as well as laser welding and cutting), we have identified five crucial operational states that should be considered: *off*, *ramp up*, *setup*, *processing*, *standby* and *ramp down*. ramp up and ramp down can be seen as transitional states with a fixed duration depending on the machine. The transition time between standby and processing or standby and setup and vice versa is assumed to be negligible. In industrial practice, this transition only lasts a matter of seconds and is typically too short to affect a solution that ranges from minutes to hours. The essential decisions related to the machines are to decide whether a machine is switched off and on or whether it is left in standby in a production break. Both choices require energy and cause costs, and the first one is only possible if the break is long enough for ramping down and up.

To determine the processing periods for all operations and the operational states for each machine, our proposed model provides:

1) start period of processing each operation on the machines,
2) start period for setting up a machine for the upcoming operation (implicitly), and
3) all operational status transitions for each machine.

Formulation of the Model

All jobs and machine states are planned within a specific time period. The planning horizon is discretized into $T \in \mathbb{N}$ equally long intervals, called periods, and denoted by $[T] := \{0, \dots, T-1\}$. If ℓ represents the duration of a period, $t \in [T]$ denotes the period from time $t\ell$ to time $(t+1)\ell$. In accordance with Shrouf et al. 2014, every time period is associated with its individual energy price described by $C_t \in \mathbb{R}^+$. Note that all durations and times are given and modeled as integers, so only integer multiples of the period length ℓ can be represented exactly in this model.

The given set of v machines is denoted by $M = \{M_j\}_{j=1}^{v}$ (using an arbitrary predefined order on the machines). The considered operational machine states are described by the set $S := \{off,\ standby,\ processing,\ setup,\ rampup,\ rampdown\}$. For each operational state $s \in S$ and each machine $j \in M$, a specific energy demand $P_{j,s} \in \mathbb{R}$ is given. For the two transition states ramp up and ramp down, we are also given the transition times $d_j^{rampup} \in \mathbb{N}$ and $d_j^{rampdown} \in \mathbb{N}$ for ramping up machine j from operational state off and for ramping it down to off, respectively.

In accordance with Özgüven et al. 2010, we let $J = \{J_i\}_{i=1}^{n}$ denote the given set of n jobs.

Each job $i \in J$ consists of $O_i \in \mathbb{N}$ individual operations (sub-tasks). The k-th operation of job i is denoted operation (i,k). The overall set of all operations of all jobs is denoted by $O := \{(i,k) \mid i \in J,\ k \in \{1,\dots,O_i\}\}$. For each operation $(i,k) \in O$ we are given

- the machine setup time $d_{i,k}^{setup} \in \mathbb{N}_0$,
- the operation processing time $d_{i,k}^{op} \in \mathbb{N}$, and
- the associated machine $m_{i,k} \in M$.

Furthermore, for each job $i \in J$ we have

- a release time a_i
- a due time f_i
  Note: Release date a_i means job i can start from period a_i (at time $a_i\ell$). Due date f_i means job i must be completed within period $f_i - 1$ (not later than $f_i\ell$).

Assumptions

1) Every machine can only process or setup for one operation at a time.
2) Once an operation has started to process, interruptions are not allowed. The same applies for setup processes.
3) Every job contains operations in a linear sequence. Consequential operation (i,k) must be completed before operation $(i,k+1)$ begins.
4) No time is required for changes between operating-modes from standby to processing and vice versa.
5) Changes between operating-modes (ramp up and ramp down) cannot be interrupted after they have been initiated.
6) A machine can be setup for operation (i,k) even if the preceding operation of the same job $(i,k-1)$ is still being processed on another machine.
7) The setup of operations $(i,1)$ can be initiated prior to the release time a_i of job i.
8) Processing operations have to start immediately after the related setup process.
9) Two artificial periods are added at the beginning and at the end of the planning horizon (-1 and T), which are free of any machine activity (processing, setup, ramp up or ramp down). These only serve to describe the initial and final states of the machines. In this paper, we assume that all machine must be in state off in these periods.

Preprocessing

Initially, bounds $a_{i,k}$ and $f_{i,k}$ for the earliest and the latest starting times for the individual operations (i,k), respectively, are determined on the basis of the given parameters. This approach reduces the solution space significantly and increases the speed and efficiency of the model.

1) For all operations $(i,k) \in O$ determine:

$$a_{i,k} := \max\left(a_i + \sum_{q=1}^{k-1} d_{i,q}^{op},\ d_{m_{i,k}}^{rampup} + d_{i,k}^{setup}\right)$$

$$f_{i,k} := f_i - 1 - \sum_{q=k}^{O_i} d_{i,q}^{op}$$

2) Determine $A := \{(i,k,t) \in O \times [T] \mid a_{i,k} \le t \le f_{i,k}\}$ of possible operations-startperiod-pairs. Thus, operation (i,k) can only start between the periods $a_{i,k}, \dots, f_{i,k}$.

Decision Variables

We introduce two types of binary decision variables: α-variables model the start periods of the operations and β-variables represents the operational states for all machines in all periods.

For each operation (i,k) and each start-period t with $(i,k,t) \in A$ (i.e., t is a permissible start time for (i,k)), we have a binary variable $\alpha_{i,k,t} \in \{0,1\}$, which is interpreted as

$$\alpha_{i,k,t} = \begin{cases} 1 & \text{Processing of operation } (i,k) \\ & \text{starts in period } t. \\ 0 & \text{Else.} \end{cases}$$

For each machine $j \in M$, each state $s \in S$, and each period $t \in [T] \cup \{-1,\ T\}$, we have a binary variable $\beta_{j,s,t} \in \{0,1\}$, which means

$$\beta_{j,s,t} = \begin{cases} 1 & \text{In period } t \text{ machines } j \\ & \text{is in operational state } s. \\ 0 & \text{Else.} \end{cases}$$

Objective Function

The objective function needs to determine and minimize the energy consumption costs. The operational state of each machine is set by the decision variable β. Parameter $P_{j,s}$ represents the associated power demand. With C_t the energy price per period is provided. Thus Equation 1 minimizes the total energy costs.

$$\min\left(Z = \sum_{j \in M} \sum_{t=0}^{T-1} \sum_{s \in S} \beta_{j,s,t} \cdot P_{j,s} \cdot C_t\right) \tag{1}$$

Constraints

Equalities (2) ensure that every machine has exactly one operational state in each period.

Equalities (3) fix the specific operational state off at the beginning (period -1) and in the end (period T) of the planning horizon for each machine.

Equalities (4) ensure that every operation will start exactly once in its permissible horizon (depending on the release and due date).

Inequalities (5) ensure that machine j is in operational state processing in period t if some operation of duration d started between $t-d+1$ and t and, thus, is still running in period t on this machine. Similarly, inequalities (6) ensure that machine j is in operational state setup in period t if some operation with setup time d starts between $t+1$ and $t+d$ and, thus, requires machine setup in period t on this machine. Moreover, together with (2) these constraints guarantee that machine j can be in setup-mode for or actually executing at most one single operation at a time. Thus, operations and setups do not overlap on any machine, the so-called parallel constraints hold.

Inequalities (7) imply the so-called sequential constraints. Enforcing for all times t that operation (i,k) starts no later than $t - d_{i,k}^{processing}$ if operation $(i,k+1)$ starts in period t (or earlier), these inequalities imply that operation (i,k) indeed completes running before operation $(i,k+1)$ starts.

Inequalities (8) and (9) finally model the technical constraints that are related to the machine states and the duration of ramp up and ramp down phases. The required minimum duration of the ramp down phases is enforced via constraints (8). These ensures that, if machine j is active (i.e. processing, in setup, or in standby) in period t, then it cannot be off (or even already in ramp up-mode again) in period $t + d_j^{rampdown}$ (or earlier): It must either remain active in processing, setup, or standby-mode after the operation it was executing (or setting up for) in period t or, if it decides to ramp down after this operation, the ramp down phase cannot have ended by period $t + d_j^{rampdown}$ or earlier. Similarly, constraints (9) ensure that the ramp up phases are at least as long as required. If the energy consumption in the ramp up and ramp down states is not lower than that in the off state and, similarly, that energy consumption in the processing and setup state is not lower than that in the standby state, these constraints suffice to ensure that the machine state schedules in an optimal solution of the model satisfy the given constraints. Otherwise, one may add further constraints similar to (8) and (9) to ensure that ramping phases have exactly the required lengths and that machines actually switch to off or standby whenever possible.

$$\sum_{s \in S} \beta_{j,s,t} = 1 \qquad \forall\ j \in M,\ t \in [T] \cup \{-1,\ T\} \tag{2}$$

$$\beta_{m,off,t} = 1 \qquad \forall\ m \in M,\ t \in \{-1,\ T\} \tag{3}$$

$$\sum_{t \in [T]:(i,k,t) \in A} \alpha_{i,k,t} = 1 \qquad \forall\ (i,k) \in O \tag{4}$$

$$\sum_{\substack{(i,k) \in O: \\ m_{i,k}=j}} \sum_{q=t-d_{i,k}^{processing}+1}^{t} \alpha_{i,k,q} \leq \beta_{j,processing,t} \qquad \forall\ j \in M,\ t \in [T] \tag{5}$$

$$\sum_{\substack{(i,k) \in O: \\ m_{i,k}=j}} \sum_{q=t+1}^{t+d_{i,k}^{setup}} \alpha_{i,k,q} \leq \beta_{j,setup,t} \qquad \forall\ j \in M,\ t \in [T] \tag{6}$$

$$\sum_{q=0}^{t-d_{i,k}^{processing}} \alpha_{i,k,q} \geq \sum_{q=0}^{t} \alpha_{i,k+1,q} \qquad \forall\ i \in J,\ k \in \{1,\ldots,O_i-1\},\ t \in [T] \tag{7}$$

$$\beta_{j,off,q} + \beta_{j,rampup,q} \leq 1 - \beta_{j,processing,t} - \beta_{j,setup,t} - \beta_{j,standby,t} \qquad \forall\ j \in M,\ t \in [T],\ q \in \{t+1,\ldots,t+d_j^{rampdown}\} \tag{8}$$

$$\beta_{j,off,q} + \beta_{j,rampdown,q} \leq 1 - \beta_{j,processing,t} - \beta_{j,setup,t} - \beta_{j,standby,t} \qquad \forall\ j \in M,\ t \in [T],\ q \in \{t-d_j^{rampup},\ldots,t-1\} \tag{9}$$

Computational Results

This section presents an exemplary case study of a 5×5 job shop problem to demonstrate how scheduling affects the total energy consumption and total energy costs. The study scrutinizes five jobs processed on the same number of machines. The planning horizon spans three consecutive days. It was decided to plan by hours and every period lasts one hour with a total of 72 periods. The proposed plans rely on the energy price model given in Figure 1 for each day. Consequential energy is most expensive between 8 a.m. and 8 p.m.. Our proposed planning horizon begins and ends at midnight. All jobs and their respective release and due dates are given in Table I. These dates are to be strictly adhered to, as delayed jobs are not allowed. The associated operations with all related parameters are given in Table II.

TABLE I. Jobs

i	a_i	f_i
1	0	72
2	8	72
3	16	72
4	24	72
5	48	72

TABLE II. Operations

(i,k)	$m_{i,k}$	$d_{i,k}^{setup}$	$d_{i,k}^{processing}$
1, 1	1	3	4
1, 2	2	3	4
1, 3	4	1	6
1, 4	5	1	6
1, 5	2	4	4
2, 1	3	3	4
2, 2	2	3	4
2, 3	5	1	5
2, 4	4	1	5
2, 5	1	3	4
3, 1	1	4	5
3, 2	2	4	5
3, 3	3	4	8
3, 4	5	3	4
4, 1	3	2	5
4, 2	2	2	5
4, 3	4	1	4
4, 4	5	1	4
5, 1	1	2	3
5, 2	2	2	3
5, 3	3	2	3

TABLE III. Machines

j	1	2	3	4	5
d_j^{rampup}	3	3	3	2	1
$d_j^{rampdown}$	2	2	2	1	1
$P_{j,off}$	0	0	0	0	0
$P_{j,rampup}$	18	10	5	4	2
$P_{j,setup}$	8	8	8	3	3
$P_{j,processing}$	20	20	20	6	6
$P_{j,standby}$	7	1	0.5	0.5	0.5
$P_{j,rampdown}$	5	5	5	2	2

As presented by Table III, the duration for ramping up and down as well as the demand for energy in the different operational states varies between machines. Machine M_1, for example, has the highest energy consumption in standby-mode. Ramping up is also quite expensive in comparison to the other machines of the production system. Machines M_3–M_5 require less energy and are comparatively cheap in standby-mode. The highest consumption of energy for processing and setup-mode is linked with Machines M_1–M_3. It is expected that our model will schedule jobs to these machines only in periods with cheap energy prices, if possible.

Figure 3 visualizes a schedule plan without taking either energy consumption or energy prices into consideration. All jobs are planned by minimizing their makespan to complete them as soon as possible. Along with the planned operational periods, all further machine-specific operating-modes are visualized. The key can be found in Figure 5.

Figure 4 presents the energy-efficient solution of our new model. Several things are particularly noticeable. The first salient findings are the scheduled operational states. The machines are not switched on continuously. In addition to the setup and processing states, ramping up and down is planned as well as the standby-mode. The analysis of the schedule of M_1–M_3 was the first step. As shown in Table III, these machines have a vast demand for energy in all operational states. M_1 has the highest energy consumption in standby-mode. This is reflected by the schedule plan: M_2 and M_3 ramp up hours before they start to process operations. This can be explained by the energy prices. As energy is cheap between 0 a.m. and 8 a.m., the model plans expensive processes in such periods. Obviously the cost for the subsequent standby-mode over many hours is lower than ramping up the machines just prior to the job. This was also observed for the ramping down of M_3. M_1 ramps up just in time due to its high energy consumption during standby-mode. Consequently the standby-mode for M_1 is used very rarely. M_3 is in standby-mode during the more expensive periods. In contrast, M_1 and M_2 are processing during these expensive periods as specific due dates need to be met. M_5 does not use the standby-mode. Although energy consumption in standby-mode is very low, it is cheaper to turn the machine off completely during the non-productive time.

The key performance indicators for both solutions are compared in Figure 2. It is interesting to note that, with exception of M_1, the energy consumption of the optimized solution remains the same or is indeed higher than its makespan counterpart. Yet the resulting energy costs are lower owing to the well-conceived scheduling strategy. Merely M_4 causes slightly higher costs in our model compared to the minimizing makespan model.

Table IV aggregates the energy consumption and the resulting costs for all machines of scenario 1 (optimized makespan) and scenario 2 (optimized energy consumption costs). The provided significant savings are given in the last two columns.

TABLE IV. Results

	Scenario 1	Scenario 2	Savings	
energy consumption	2,194 kWh	2,052 kWh	142 kWh	6.5%
energy costs	€120	€93	€27	22.3%

Conclusions and Future Work

This work proposed a model for minimizing the total energy consumption costs when scheduling a job shop production system. Considering the continuous changes of energy prices, our model can help to organize a more efficient production schedule, especially for high-energy production systems. Furthermore we evaluated the significant energy price savings that could be obtained by using this model instead of the commonly used lead time minimization.

For further benchmark experiments, we propose to use the model for a continuous rolling and overlapping planning long-term study by means of simulation. Finally, our study

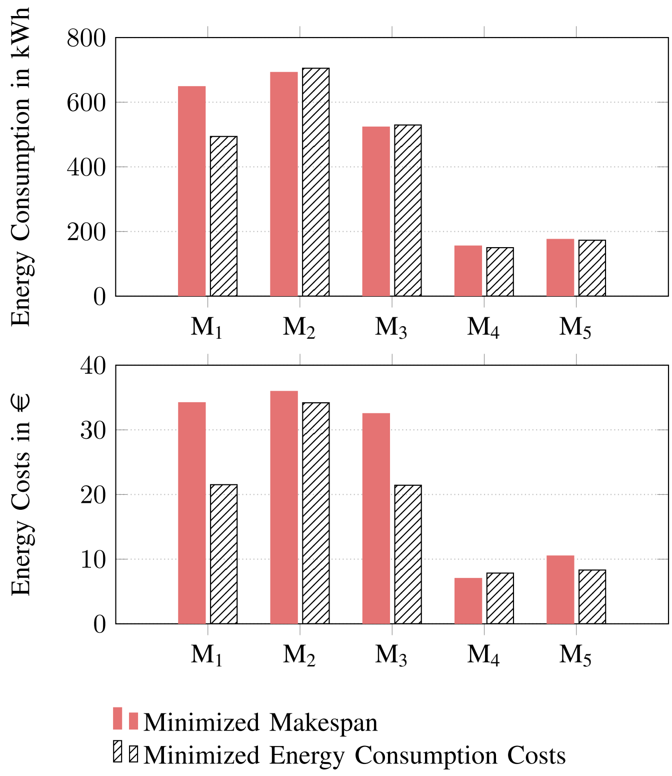

Fig. 2. Comparison of Schedule Plans in Terms of Energy Consumption and Costs

is planned to be integrated as an ecological component of a sustainable production planning concept. The hierarchical production planning as proposed by Hax and Meal 1973 might contribute to creating an ecological and also social environment for sustainable production planning (Trost et al. 2016).

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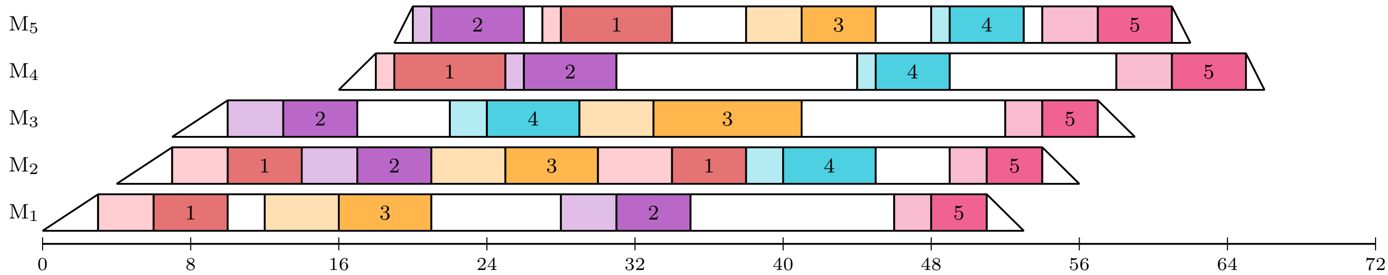

Fig. 3. Schedule plan for minimized makespan

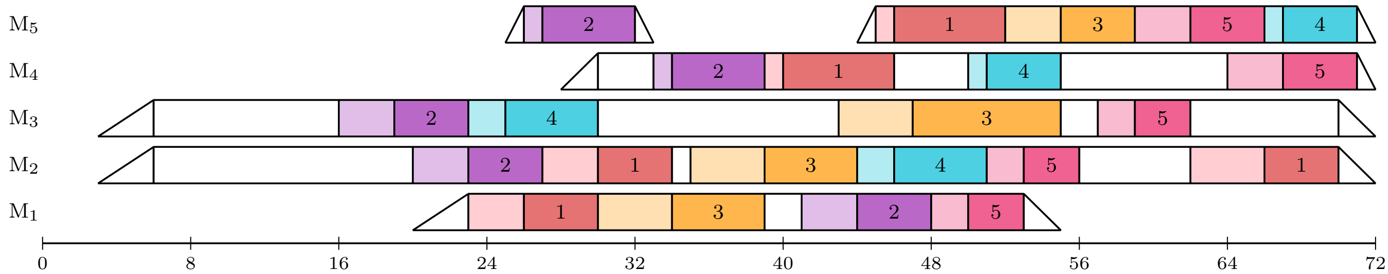

Fig. 4. Schedule plan for minimized energy consumption costs

Fig. 5. Key for Figures 3 and 4

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