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A Linear Programming Model For Renewable Energy Aware Discrete Production Planning And Control

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Abstract

Industrial production in the EU, like other sectors of the economy, is obliged to stop producing greenhouse gas emissions by 2050. With its Green Deal, the European Union has already set the corresponding framework in 2019. To achieve Net Zero in the remaining time, while not endangering one's own competitiveness on a globalized market, a transformation of industrial value creation has to be started already today. In terms of energy supply, this means a comprehensive electrification of processes and a switch to fully renewable power generation. However, due to a growing share of renewable energy sources, increasing volatility can be observed in the European electricity market already. For companies, there are mainly two ways to deal with the accompanying increase in average electricity prices. The first is to reduce consumption by increasing efficiency, which naturally has its physical limits. Secondly, an increasing volatile electricity price makes it possible to take advantage of periods of relatively low prices. To do this, companies must identify their energy-intensive processes and design them in such a way as to enable these activities to be shifted in time. This article explains the necessary differentiation between labor-intensive and energy-intensive processes. A general mathematical model for the holistic optimization of discrete industrial production is presented. With the help of this MILP model, it is simulated that a flexibilization of energy-intensive processes with volatile energy prices can help to reduce costs and thus secure competitiveness while getting it in line with European climate goals. On the basis of real electricity market data, different production scenarios are compared, and it is investigated under which conditions the flexibilization of specific processes is worthwhile.

Keywords

Renewable energy; Production planning and control; Scheduling; Optimization; Simulation; Modelling; Mixed-integer linear programming

1. Introduction

In 2019 the European Union has declared its Green Deal as the framework for all member states to become climate neutral by 2050. While this already has great impact on everyday activities for European companies and individuals, likewise, especially the production and manufacturing sector is affected. [1] In terms of energy supply, lesser carbon certificates are leading to a higher share of renewables. Increasing energy prices are probably to be expected, but certainly the interconnected European energy markets are about to become more volatile [2]. Both, increasing energy prices and higher volatility, are traditionally said to interfere with economic growth. Companies and individuals similarly will reduce their economic activities once prices render them deficient. More energy intensive products will be discontinued first. For manufacturing companies, reducing production activity ultimately leads to individual economic decline. [3] Companies of

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the same sector often apply similar production techniques and processes, for which reason the decline likely affects the whole sector. Since the transition away from fossil fuels is not yet driven by shortages in fossil supply, companies from other countries, not bound to the European carbon certificate system, could be replacing local manufacturing capacity due to lower prices [4].

While these effects do not convey a bright look-out for the European manufacturing sector, there are chances of recovery even besides political measures. To remain competitive in a globalized market, manufacturing companies individually have to reduce the impact of increasing prices and greater volatility. Without doubt, the most important countermeasures for many industries are innovation and efficiency. No thoughts have to be made around energy, which is no longer needed for a certain output. [5] Besides innovation and efficiency, higher volatility also implies chances for those being able to freely distribute manufacturing operations in time. Today, energy tariffs often harness time independent pricing. Energy consumers pay suppliers an insurance like premium for time independency. Traditionally, industrial energy consumers do not incorporate variable energy prices in their planning of manufacturing activities. [6] The premium paid for time independence can be saved, once the ability to allocate energy intensive activities to periods of lower energy prices is achieved. In that way, utilizing periods of lower prices can contribute to keeping manufacturing cost low and to secure competitiveness in situations of global competition.

This article presents a holistic approach to modelling manufacturing revenue under variable energy prices. An overview of related literature and preceding work is given in chapter 2. Chapter 3 is dedicated to the differentiation of energy-intensive and labor-intensive manufacturing tasks and processes. The mixed-integer linear model depicting a generic manufacturing setting is presented in chapter 4. Experiments have been carried out to demonstrate the benefits of applying energy cost optimized production planning. The respective experiment design is described in chapter 5 and the corresponding results are given in chapter 6. Chapter 7 concludes with a discussion of the presented findings and their generalizability.

2. Related Works

Production planning and control in discrete manufacturing scenarios essentially results in a multiplicity of mathematical optimization problems. Discrete manufacturing, in contrast to process manufacturing, hereby creates products manufactured in such a way that they are turned into units. One of the common representatives of discrete manufacturing includes mechanical engineering. Particularly in the manufacturing industry, the manufacturing of products in discrete units is found, which arise from parts-related manufacturing and assembly processes. Discrete and process manufacturing both have their very own constraints and objectives, leading to two distinct areas of research. The mathematical modelling and optimization of both has yet attracted researchers´ attention for some decades. Already in 1979 [7] gave an extensive overview on the “rapidly expanding area of deterministic scheduling theory” and dating its origins back to the 1950th. For the theory of optimally distributing manufacturing jobs to machining equipment, [7] and [8] have categorized the discipline’s problems according to their manufacturing context. Problems in which one single machine is required for every job are classified as “Single machine problems” and “Parallel machine problems”, depending on the number of machines taken into account. In scenarios where one single job needs execution on multiple machines, scheduling problems are called “Open shop, flow shop, and job shop problems.” For an open shop scheduling, the machine order is expected to be immaterial, whereas it is fixed in flow shop scenarios and of varying order in job shop problems. Ever since the foundation of this field of study, researchers are trying to improve existing algorithms and heuristics for known problems and to develop new ones for yet untreated problems.

In more recent years, concerns of manufacturing’s environmental impact have received growing attention by scholars. Known problems in the sequencing and scheduling sphere have been adapted to incorporate perspectives of energy efficiency and sustainability. [9] For the most fundamental problems of single machine scheduling, [10] and [11] worked on the minimization of total energy consumption, tardiness, completion time and total energy usage. More complex optimization problems arise if two machines are put in line, which is the flow shop's simplest form. [12] and [13] discuss the minimization of total energy consumption and makespan for such manufacturing scenarios by means of mixed integer linear programming. [14] employed the same objectives to the parallel machine scheduling problem, considering identical machines running at the same speed. In the identical parallel machine context [15] proposed a model for the minimization of total weighted tardiness, total completion time and peak power consumption. For unrelated parallel machine setups with differing machine speeds [16] optimized for total tardiness and total energy consumption. [17] used mixed integer linear programming total energy consumption and makespan minimization. The same is applied by [18] for energy saving by scheduling machines on and off states. Many scholars focused on the practice-oriented flow shop problem modelling. For classical flow shop problems, [19] minimized peak power requirements together with inventory cost. [20] minimized total energy consumption under the perspective of product quality. [21] and [22] considered tardiness and delivery penalties together with total energy consumption. Scheduling of machine shutdowns in the flow shop scope is discussed by [23]. For the permutation flow shop with equal job orders among all machines [24]–[27] minimized total energy consumption together with the total makespan. [24] and [28] worked on the same objectives in the context of distributed non-idle permutation flow shops. [29] replaced the permutation flow shop makespan objective by total tardiness. [30] added complexity by also taking transportation and setup times into account. For flexible flow shop scheduling problem [31] considered peak power consumption. [32] minimized completion time and total energy consumption in the same context. [33] included labor cost and worker flexibility in their optimization. Peak power, makespan and tardiness are considered by [34], whereas [35] changed peak power for total power consumption and tardiness for overall production cost objectives. [36] and [37] cover optimization in the light of just makespan and total energy consumption, and [38] and [39] replace the makespan objective by total weighted tardiness.

For classical job shop scheduling problems, [40] took varying power requirements for manufacturing's initial and processing phase into account, under the objective of makespan optimization. [41], [42] and [43] optimized both makespan and total energy consumption in the job shop sphere, while [44] aimed for total energy consumed only. [45] proposed a two-stage approach, minimizing makespan first and optimizing total energy consumption be altering cutting speeds afterwards. [46] chose a two-stage approach as well, minimizing tardiness and makespan, while incorporating total energy consumed via a constraint. [47] minimized weighted tardiness and total energy consumption through variable machining speeds. [48] minimized total energy consumption by dismantling energy consumption to its direct and indirect portions. Distributed multi-factory job shops have been dealt with by [49], optimizing makespan and total energy consumption as well. For the flexible job shop problem with grouped identical parallel machines [50] minimized overall production cost through a mixed integer programming model. [51] used a linear approach to minimize total energy consumption in flexible job shop settings. [52] optimized for total energy consumption and [53] added a makespan objective. [54] focused on transportation induced flexible job shop energy consumption. [55] applied scheduling of machine on/off cycles under the goal of total energy consumption and makespan minimization. In contrast to flow shop and job shop problems, open shop optimization under the perspective of energy efficiency has not yet received considerable attention by scholars. Besides typical machine scheduling problems, some have worked on cellular and reconfigurable manufacturing systems. [56] minimized flow time, energy consumption and makespan for cellular manufacturing systems. In the context of reconfigurable manufacturing systems, [57] maximized throughput while minimizing energy consumption. While most contributions are aiming for the optimization of peak or total energy consumption, makespan and tardiness in their respective fields, some authors also include more extensive sustainability criteria. [58] optimized for waste reduction and greenhouse gas emissions in cellular manufacturing systems. [59] considered material waste in the scope of flexible flow shop systems.

While energy consumption and efficiency often are at the core of sustainability efforts, energy is mostly referred to as electrical power usage. As shown by the collection of publications mentioned above, many authors target peak power reduction or total power consumption, often combined with further objectives. Eventually, all energy related dimensions of optimization are aspects of a broader economical perspective of business, quantified in units of money. Since energy prices are largely dependent on the time of energy consumption in liberalized energy markets [60], researchers have already identified the potential of machine scheduling optimization under time of use energy tariffs.

Even though sustainability issues have already received some attention in the context of scheduling manufacturing activities, only few scholars have yet incorporated time of use tariffs in their scheduling modelling. For single machine scheduling, [61] and [62] incorporate variable energy prices in their optimization. [63] and [64] adapt the approach to scheduling of two machines in line. For identical parallel machine scheduling, [65] have optimized for variable energy tariffs, [66] did this for hybrid parallel machine scheduling and [67]–[69] for unrelated parallel machines. [70] presented classical flow shop optimization under variable energy prices, while [71] and [72] optimized the flexible flow shop problem. More scholars have focused on energy prices in various machine scheduling problems, without considering variable market prices [9].

This contribution aims at integrating the aforementioned perspectives of optimization under the goal of highest attainable revenue. The analysis of the existing literature on the integration of variable energy prices into operational planning and control shows that there is still a lack of realistic problem formulations. The above-mentioned works predominantly present general. The corresponding extension to be able to use energy price optimized production planning in specific manufacturing contexts is still pending. In addition to the usual restrictions of established operational planning, such as capacities, deadlines and personnel availability, additional constraints must be taken into account in the context of energy price-optimized planning. These include, in particular, electricity prices and, due to the growing share of renewable energy sources, also weather data. Here it is tried to integrate all planning aspects of production in workshop settings and for manufacturing of customized industrial goods. The perspectives of demand, availability and cost are acknowledged for the planning dimensions of employees, machinery/equipment and energy. Peak energy demand is incorporated, while not minimized, but rather limited via a constraint. In terms of business and overall cost, the total energy consumption of production activities is of comparatively lower interest in contrast to the associated cost.

3. Labor-intensive vs. energy-intensive processes

When trying to optimize industrial production along demand, supply, and cost with the goal of maximizing overall manufacturing revenue, cost of energy must not be neglected. Time variable energy tariffs offer an additional perspective of optimization, since energy intensive operations can be planned for execution in periods of comparatively lower prices. In practice, to obtain the possibility of such optimization, all activities planned to be executed have to be assessed for their energy demand. Commonly, planners know much about which machinery and equipment and how many personnel of which qualification is required for every operation's successful completion. Knowledge on how much energy is consumed over the course of operational execution, however, is typically more scarce.

A first step to remedy this circumstance is a detailed assessment of the equipment being used for every recurring operation. By measuring the true energy consumption and its course over time per machine, the most vital part for differencing energy-intensive processes from labor-intensive ones is completed. Additionally, dismantling the already existent data used for production planning is required to calculate the operation related demand of employees. Depending on the operational complexity, the assessment of workforce required has a quantitative and qualitative perspective. It is essential to denote the number of employees needed for every operation, but also the necessary qualifications employees need to hold available. Once assessing energy and workforce demand is accomplished, all operations or tasks, jobs or processes can be classified in terms of flexibilization requirements. Flexibilization hereby means the ability to shift operations in time with limited impacted on cost and tardiness risk. Not all operations are required to be highly flexible in time. Those of low energy demand can be scheduled with preference for other cost factors than energy prices. At the same time, operations of high energy demand and low workforce involvement are of high importance for time-dependent flexibilization. A trade-off has to be made for high energy operations with high workforce dependencies. While higher flexibility is generally preferable, changes to those operations to increase flexibility have to be made under the consideration of a possible associated increase in labor cost.

4. Optimization model

To tackle the challenges of an integrative and energy cost aware discrete production planning, the following mathematical model has been developed to represent all cost factors typically being relevant to scheduling in industrial manufacturing. This mixed-integer linear model is set up to optimize scheduling of a set of unlinked manufacturing operations $o \in O$. All operations require the availability of certain machinery $m \in M$ for their completion. Besides the essential machinery, also workforce demand is considered. Vital competencies $c \in C$ are defined for every operation. Employee availability is realistically modelled in dependence to the course of time, which in turn is sampled in periods $t \in T$. Table 1 depicts all sets used for modelling manufacturing scenarios. Table 2 lists all the parameters and a short respective description. Table 3 contains the decision variable formulation, and table 4 shows the actual model. The model is optimized by a single maximizing objective function and contains a total of six constraints, including the decision variable binary constraint. For the experiments carried out and presented in chapter 5, the model has been implemented using the PuLP linear programming API for Python [73]. Calculations have are done using the COIN-OR open source branch-and-cut solver Cbc [74].

Table 1: Model sets

Set	Notation	Description
Machines	$m \in M$	Every individual machine m is element of the set of machines M.
Operations	$o \in O$	Every individual operation o is element of the set of all operations O.
Periods	$t \in T$	Every individual period t is element of the set of all periods T.
Competencies	$c \in C$	Every individual competence c is element of the set of all competencies C.

Table 2: Model parameters

Parameter	Notation	Description
Energy demand	b_{om}	Average number of energy units needed per period by machine type m for operation o
Energy cost	k_t	Cost per energy unit in period t
Energy capacity	h_t	Maximum number of energy units available per period t
Employee demand	d_{oc}	Number of employees of competence c needed for operation o
Employee cost	w_c	Cost per employee of competence c per period
Employee capacity	f_{ct}	Available number of employees of competence c in period t
Machine cost	p_m	Cost per machine of type m per period
Machine capacity	g_m	Available number of machines of type m
Revenue	e_o	Revenue of operation o, if accepted

Table 3: Model decision variable

Decision variable	Notation	Description
Acceptance of Job	$X_{omt} \in \{0; 1\}$	Binary decision variable; One if operation o is executed on machine m and running in period t, zero otherwise

Table 4: Model formulation

Objective function		
1.	$\max \sum_{o \in O} \sum_{m \in M} \sum_{t \in T} \sum_{c \in C} (e_o - b_{om} * k_t - d_{oc} * w_c - p_m) * X_{omt}$	
Constraints		
2.	$\sum_{m \in M} \sum_{t \in T} X_{omt} \leq 1$	$\forall\, o \in O$
3.	$\sum_{o \in O} X_{omt} \leq 1$	$\forall\, m \in M \wedge t \in T$
4.	$\sum_{o \in O} X_{omt} \leq g_m$	$\forall\, m \in M \wedge t \in T$
5.	$\sum_{o \in O} \sum_{m \in M} X_{omt} * d_{oc} \leq f_{ct}$	$\forall\, t \in T \wedge c \in C$
6.	$\sum_{o \in O} \sum_{m \in M} X_{omt} * b_{om} \leq h_t$	$\forall\, t \in T$
7.	$X_{omt} = \{0; 1\}$	$\forall\, o \in O \wedge m \in M \wedge t \in T$

The energy demand is represented by parameter b_{om} and dependent on operation o and machine m. Energy cost denotes as k_t and peak energy consumption is limited by the parameter h_t, both are subject to period t. Employee demand, cost and availability are modelled alike by the parameters d_{oc}, w_c and f_{ct}. All are dependent on competence c, demand additionally dependents on operation o and availability on period t. For machines, cost and capacity formalize as parameters p_m and g_m and are naturally dependent on the machine m, but independent of their time of use. Since the model aims at maximizing overall revenue from production activities, besides all relevant cost factors, revenue obtained from operations has to be taken into account. Revenue is depicted as a parameter e_o, with dependence on operation o.

To determine the highest obtainable revenue, the optimization must decide on which operations are to be chosen for manufacturing and during which period every single chosen operation must take place. This is done via a single binary decision variable X_{omt}. If an operation o is scheduled for manufacturing on machine m in period t, the decision variable X_{omt} becomes one, while being zero otherwise.

The model's objective function (formula 1) sums up all cost relevant parameters and deducts them from the respective revenue obtainable. Energy cost is multiplied by energy demand and employee demand is multiplied by the respective cost. Together with the machine cost parameter, everything is deducted from the revenue. This sum is then multiplied by the decision variable X_{omt}, which decides on revenue and cost realization. The objective function is sensing for maximization of the sum of all revenues and cost. Formula 2 represents the model's first constraint, which ensures every operation is being planned for execution not more than once by setting the sum over all X_{omt} for each operation to be less or equal to one. The second constraint (formula 3) ensures no machine is scheduled more than in each period. For that, the sum over all X_{omt} for each machine and period is set to be smaller or equal to one. Constraint three (formula 4) keeps the machine allocation below the capacity available by setting the sum over all X_{omt} for each machine and period to be smaller or equal to the machine capacity g_m. The exceedance of the limits set for employee and energy capacity are guaranteed by the constraints four and five (formulas 5 and 6). Constraint four sums up the product of the decision variable X_{omt} times the employee demand for every period and competence. The sum is set not to be greater than the employee capacity per period and competence. Constraint 5 multiplies the decision variable X_{omt} by the energy demand and sums up all products for every period. This is set to be smaller or equal to the energy capacity per period. The last constraint 6 (formula 7) is a binary constraint, realistically limiting the solution space by setting the decision variable X_{omt} to either zero or one.

5. Experiment design

Following the optimization model's contrivance, its viability is tested by executing numeric experiments using the aforementioned Python implementation. Multiple data sets of varying sizes are used to answer two questions: Is a mixed-integer linear programming model of this vein solvable for scenarios of realistic sizes, and therefore relevant to industry applications? If the model turns out to have executions times low enough for business adoption, the second question is whether manufacturing companies can actually benefit from including time varying energy prices in their production planning? Eventually, the possibility of calculating price optimality does not convince decision makers of its adoption, but the proof of revenue increase might do.

A total of six data sets are optimized. For each, the objective function value or maximized revenue is calculated, and a production schedule is created. Since no consistent real manufacturing data has been available during the experiments, all manufacturing related numbers are randomized and drawn from ranges of estimates, in which the authors confide to be common industry values. However, data on energy prices is taken from the German Bundesnetzagentur's electricity market information platform 'SMARD' [75] and depict the actual course for the first week of 2022. All in all, the experiments optimize randomized average production scenarios under real market conditions. The data sets do contain three manufacturing scenarios (small, medium, large) of which each is optimized under varying and average energy prices. The course of energy prices and their average are shown in figure 1.

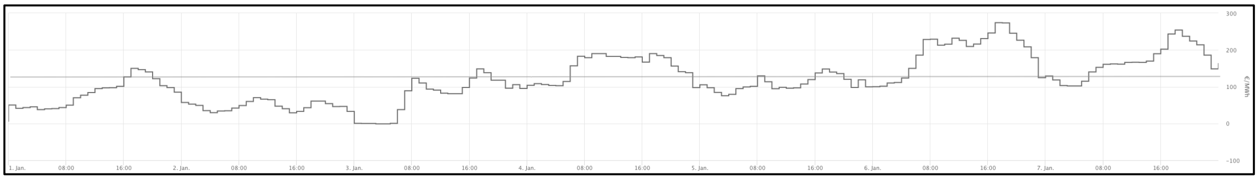

Figure 1: German wholesale electricity prices from [75], first week of January 2022, sampled hourly, in €/MWh

Since problem complexity rises disproportionately with larger data sets, variations in data mainly concern the number of machines, employees and operations taken into account. All calculations are reproducible using the code published under the associated GitHub repository[1]. Besides all Python code, the data set description and pre-generated data set files are available in structured JSON format. Solutions and scheduling tables are provided as well. All code and data are published under the CC BY 4.0 license.

6. Results

First and foremost, the experiments described above are showing, that optimizing scheduling in industrial manufacturing using freely available open source solver software [74] is possible not only for laboratory sized problems, but also for those keeping industrial practitioners busy today. While for mixed-integer linear optimization solution times grow exponentially with additional parameters or increased set sizes, readily

[1] Repository URL: https://github.com/vincentadomat/CPSL23

available hardware[2] is capable of deterministically computing optimal results for common problem sizes in a matter of seconds or minutes. For the smallest data sets, optimality has been found after only 0.14 seconds for average prices and 0.11 seconds variable prices. The largest data sets took 164.41 and 291.6 seconds to compute. Therefore, it can assuredly be said that executions times are low enough for business adoption.

From a business perspective, though, it is more important if optimization actually leads to improved revenue from manufacturing activities. Every optimization forecasts the total revenue from the operations scheduled. An example scheduling table depicting which operation is to be executed on which machine during which period is given by figure 2.

period	57	58	59	60	61	62	63	64	65
date	03.01.2022	03.01.2022	03.01.2022	03.01.2022	03.01.2022	03.01.2022	03.01.2022	03.01.2022	03.01.2022
time	08:00	09:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00
energy cost	122.93	110.17	93.38	90.73	82.37	80.9	80.99	98.05	123.51
machine 1			operation 35	operation 77				operation 81	
machine 2			operation 96					operation 5	
machine 3			operation 16			operation 67	operation 66		
machine 4						operation 4		operation 97	
machine 5		operation 37	operation 27				operation 71		
machine 6			operation 93		operation 62		operation 43	operation 65	
machine 7		operation 47							
machine 8		operation 8	operation 100					operation 2	
machine 9		operation 89		operation 98	operation 14			operation 12	
machine 10					operation 83			operation 61	
machine 11					operation 69	operation 21		operation 31	
machine 12						operation 78		operation 86	
machine 13			operation 91					operation 82	
machine 14					operation 18				
machine 15	operation 32		operation 39		operation 28	operation 17	operation 87	operation 40	
machine 16						operation 45			
machine 17			operation 36			operation 80	operation 72	operation 84	
machine 18									
machine 19		operation 51			operation 90				
machine 20					operation 11	operation 33	operation 13		
machine 21		operation 42					operation 30	operation 24	
machine 22			operation 25		operation 94				
machine 23						operation 63	operation 76	operation 74	
machine 24	operation 68					operation 53			
machine 25			operation 3		operation 41			operation 44	
machine 26			operation 19	operation 99	operation 34			operation 22	
machine 27								operation 1	
machine 28								operation 88	
machine 29							operation 7	operation 20	
machine 30				operation 23					

Figure 2: Example scheduling table as output by the Python model implementation, giving the optimal acceptance and scheduling of 100 operations over 30 machines for variable prices on 3rd January 2022 from 8 am till 4 pm.

Only if all operations are performed as scheduled, the revenue forecasted can be realized. Optimizing the experiment data sets based on average and varying prices with otherwise identical values has shown only little difference in overall revenue obtained. For the medium-sized data set total revenue under average prices is forecasted with €177,892.16 and with €178,724.86 for varying prices. Even though the increase of only 4.66‰ might not lead any decision maker to comprehensively reorganize manufacturing scheduling. At the same time, comparing not only total revenue but the scheduling tables also reveals great difference in which operations are chosen for manufacturing and for which periods their execution is planned. It can be seen, that under varying prices operations involving energy-intensive processes are scheduled towards periods of lower prices, while operations with labor-intensive processes are to be executed in periods of higher prices and higher workforce availability. Stronger evidence for revenue improvement from energy optimized scheduling is expected to be obtained under the use of less uniform and homogeneously distributed values in the manufacturing data sets.

7. Discussion

Performing industrial-sized manufacturing scheduling by mixed-integer linear programming optimization is shown to be viable and can increase overall revenue obtain from such activities. The experiments carried out to furnish proof to the initial assumptions have undoubtedly displayed the model's applicability, even though from a retrospective viewpoint the data on which the experiments are founded is believed to be unfit for generating persuasive results. On the other hand, the calculations presented for non-varying average prices

[2] 2020 M1 Apple MacBook Air with 16 GB RAM

are based on the arithmetic means and do not include common surpluses charged by energy suppliers. Nevertheless, the experiments demonstrate the model's ability to perform manufacturing scheduling under varying electricity prices. In terms of improving industrial manufacturing for adaption to renewable energy sources and increasing price volatility, the model presented in chapter 4 is giving an important prospect of how scheduling can be adapted. Besides an increase in revenue, the ability to shift manufacturing operations opens the opportunity to foster the switch to renewable energy sources even before required by European legislation. Flexibilization thereby is the key to enabling more variable schedule configurations. At first, the assessment of existing manufacturing processes for their energy-intensity and labor-intensity must be fulfilled. The prioritization of highest impact processes when increasing flexibility by removing scheduling constraints must follow.

To put the model presented to beneficial use in real manufacturing scenarios, some essentials are still missing. Currently, no technique for forecasting energy prices is discussed or integrated. Hence, an optimization can currently only be done retrospectively. According to [76] scholars already have identified the need for renewable energy forecasting, but this growing field of research is purposefully excluded from the work at hand. In the future, the model will be extended to especially incorporate operational dependencies. For many real manufacturing settings, the scheduling of unrelated operations among unrelated machines does not describe reality comprehensively and sufficiently. To solve this issue, additional constraints and an additional decision variable will be needed, which will render the model to be non-linear and thereby more difficult to solve optimally.

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