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19.2 Stochastic optimization method to schedule production steps according to volatile energy price

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Abstract
Manufacturing systems are one of the main consumers of electrical energy worldwide. Inaccurate demand side prediction and time dependent renewable power generation can cause volatile energy prices in short term energy trading. Future manufacturing systems can benefit from volatile energy prices by managing their demand. This affects the profitability and also has a positive effect on CO_2-emissions. Leveraging this potential requires scheduling of production steps based on order situation, electrical energy demand of each machine, and day-ahead electricity market prices. A stochastic optimization method for the scheduling of production machines with specific processing times and energy consumption has been developed and implemented as a software prototype. The optimization method is validated for eight production machines as a part of a production line to shift load to off-peak hours when electricity prices are lower.

Keywords:
Manufacturing Systems, Energy Markets, Demand-Side Management, Optimization, Product-Service Systems

1 INTRODUCTION

Volatile and increasing prices of energy resources become a key factor in global competition. Companies are forced to use the progressive flexibility offered by manufacturing systems and integrate sustainable strategies through rescheduling production steps to resource- and energy-economical time.

In the last decade, the European manufacturing industry has witnessed an increase in electricity costs of 43% and the German industry an increase of 120% [1]. According to the prognosis of the European Commission, these costs will increase by another 23% by 2020 [2]. In Europe, electrical energy is still predominantly produced from non-renewable resources. The costs for these non-resources resources increased even more during that period. For example, the nominal European non-renewable primary energy resources costs increased in the last decade by oil 240% for petroleum, 207% for natural gas, and 185% for coal [3]. At the same time, the world manufacturing energy consumption is projected to increase by 44% from 2006 to 2030 [4].

Inaccurate demand side prediction and the higher percentage of renewable energy increases the uncertainty of energy supply because of fluctuating in-feeds and prediction errors. For more resource efficiency and effectiveness, consumption and generation of electrical energy need to take place at the same time. This leads to short-term trading of electrical energy. Time-dependent demand and generation of energy causes rapidly changing prices. However, a reliable forecasting and cost model for factory-wide electrical energy consumption hardly exists. Taking into account the degrees of freedom coming from the adaptation of electrical energy demand to volatile prices, time-flexible operations in production lines can become more profitable and can help to better integrate renewable resources to the power grid and reduce the CO_2-footprint.

In this paper, different scheduling strategies based on a model for cylinder head production line in the automotive industry are developed. The model relies on power measurement data of a typical production line. It is shown by simulation, how the production line can be scheduled by considering the order situations and automatically aggregated electrical energy demand of each machine. Thereby, the scheduling strategies are investigated with regard to the costs. Taking into account the electrical energy prices of the European Energy Exchange (EEX) spot market, an optimization based on the cost target function is implemented. The economic benefit is illustrated and the potential ecological benefit is discussed.

2 MOTIVATION

Limited resources, striving for economic and socio-political independence of the European Union inevitably lead to sustainable manufacturing. Sustainability Engineering is about exploiting the dynamics of fair competition by processes of knowledge creation and innovation in order to achieve sustainable global living conditions. One way to achieve this goal consists of substituting non-renewable resources with renewable resources. The economical challenge hereby is a resource-saving product-service design creating competitive products [5].

As presented in Figure 1, 89% of the primary energy consumption in Germany in 2011 still originates from non-renewable primary energy resources. Only 11% of the primary energy is from renewable resources helping to reduce the CO_2 emissions. After energy conversion and processing of raw materials, only 65% of the primary energy remains for final consumption. A percentage of 22% of the energy converted is directly available as electrical energy, which is 14% of the primary energy consumption. From the final electrical energy consumption 22% is generated by renewables. About 870PJ, approximately 46% of the electrical energy, was traded on the market as day-ahead and intra-day electrical energy to the consumer´s demand in 2011 [6].

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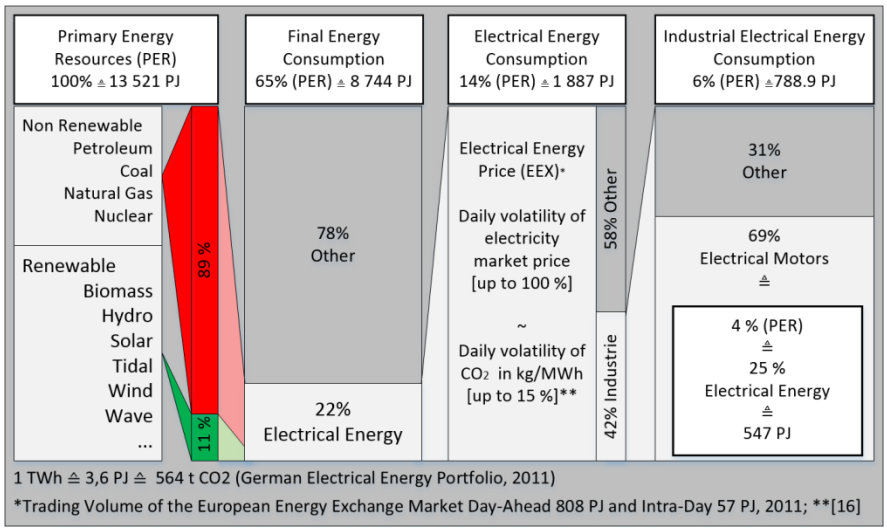

Figure 1: Quantitative assessment for German energy conversion in primary resources shares with loses in transformation.

Depending on the electrical energy generation portfolio, the CO_2 emissions per MWh generated change. Thereby, a part of 58% is consumed by commerce, public institutions, private households, and others, whereas 42% of the electrical energy is consumed by industry. It also means that 6% of the primary energy is consumed by industry for electrical energy needs. Most of the electrical energy consumed by industry is converted into mechanical energy by electrical motors. This is one fourth of the overall generated electrical energy in Germany. Chiotellis and Grismajer show an approach for real-time analysis of electrical power, based on data stream analysis [7]. Taking this approach into account, it is theoretically possible to identify value adding processes and calculation of production planning relevant indicators out of power measurements in real time.

An application for this approach could be grid stability and short term trading of electrical energy. Since the electrical energy is more and more generated by fluctuating renewable energy sources, an increasing importance for power grid stability accrues for the loads. The benefits of managing this significant percentage of energy consumed by industrial electrical motors are twofold: more efficient grid integration for renewable energies can be reached, the company's energy costs can be reduced and the consumed electrical energy could be theoretically scheduled to a CO_2 neutral time.

2.1 Problem Description

In this paper, a result-oriented service is developed aligning the production schedule and order situation to the spot market prices for electrical energy.

The electrical energy demand of a production machine, line, and factory or across multiple factories in a neighbourhood is flexible within the production constraints. If the production line does not operate at full capacity, then there is an opportunity to shift production steps over a day. Smart meters can provide real-time electricity prices from the market to the factory. If this information is utilized effectively by customers via in-process monitoring of electrical power in relation to operation steps of the production machine, then the electrical energy costs can be reduced. This can be done by scheduling the load to off-peak hours when the prices are low. Thus, the CO_2-footprint can be reduced. While it is relatively easy to consider the day-ahead prices in the scheduling process of a single machine, the complexity increases dramatically when considering the production line. A production line consisting of only a few machines presents much more constraints and production necessary data from different sources. In addition, the scheduling strategy needs to be flexible to react on changing constraints. It is also important to develop a generic model which can be easily adapted to other production lines and multiple objective functions.

To achieve this goal a generic discrete-time mixed integer linear programming (MILP) model is developed and implemented in the Advanced Interactive Multidimensional Modeling System (AIMMS). The input data is given by the power measurements of the production line and the EEX spot market prices.

2.2 State of the Art

In the United States minimum energy efficiency standards can trace their origins to the mid-1970s. At that time, the first programs implemented aimed to change both the level and the time of electricity demand among the customers [8]. This method is defined as demand-side management (DSM), also known as energy demand management, referring to the management of time-flexible loads. On the one side, it can be applied for shifting peak loads to reduce the demand if there is little energy generated by renewable sources. On the other side, DSM can also be useful for valley filling, for example to increase the electrical load at night consuming the energy produced by renewable sources.

In order to realize DSM, advanced metering infrastructure (AMI) has to be installed on the consumer side. These smart meters measure the electricity consumption, condition and convert the data signals as well as have computational tasks and communicate with the superior hierarchy data management unit. Besides DSM, the AMI additionally offers the energy suppliers the possibility to generate a better load forecast for day-ahead planning by changing load information. This is of high interest, since it helps to improve the system's efficiency by also reducing the need for ancillary services such as frequency regulation services. With regard to

industrial consumers, all time-flexible production processes can take part in DSM. Implementing DSM, incentives for adapting the demand according to the renewable energy generation are to be given to the consumers. This can be done by linking the electricity price to the amount of energy generated by renewable sources such that the consumers benefit from reduced prices in times with high generation. To that aim, different pricing models can be found in literature [9]. One simple pricing model for example can be realized by offering an on-peak and an off-peak price. Another approach, which is implemented in this work, is to connect the demand to the real-time electrical energy market prices. This approach assumes that the electrical energy for the production line is fully obtained at the EEX spot market.

The economic potential for DSM of industrial processes in developed countries has been recognized by numerous institutions and authors as Mitra [10], Paulus [11], Graus [12]. These publications deal with various processes, mainly from the chemical industry, where the consumption of electricity depends on different unit operations: grinding (cement, paper pulp production), compression (air separation), electrolysis (chloralkali, aluminum) and drying (paper production).

The energy profiles of all manufacturing equipment can be combined in cumulative load profiles for different factory levels e.g., energy demand for a machine, a process chain, or the whole plant. Moreover Dornfeld and Vijayaraghavan show in 2010 that the analysis of the energy profile with a different sample rate allows choosing a best energy usage strategy for a particular manufacturing tool or a whole process [13]. Vijayaragavan and Dornfeld proposed a software-based approach, which allows automated energy reasoning and support decision making based on the complex event processing (CEP) and rules engines (RE) techniques in order to automate monitoring and analysis of energy consumption in manufacturing systems [13]. This approach was further developed by Chiotellis and Grismajer for real-time analysis of electrical power, based on data stream analysis and event-driven system and implemented as a software application [7]. The approach allows aggregating all scheduling relevant productions data out of measured power streams. This reduces the number of needed information sources for the proposed model into measured power data and daily energy price from the EEX market. The following method uses the real-time analysis of electrical power as input adapter, which is described by Chiotellis and Grismajer for state detection, to indicate the electrical energy consumption and the process duration for each machine in the production line.

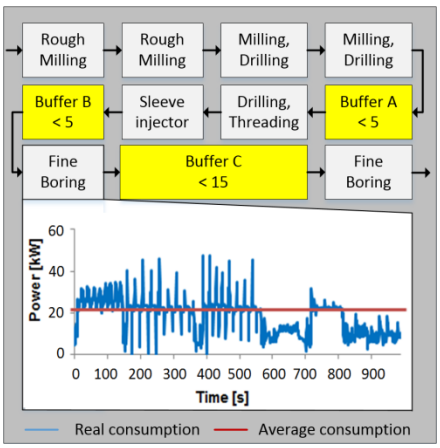

Figure 2: Production line model and power stream.

3 PRODUCTION LINE MODEL

This section describes the production line model. Information is given on the required production line data and the necessary simplifications of the real data. The prototype developed is evaluated by scheduling an existing production line in an automotive industry.

The layout of the production line as well as one example for the power consumption of the included production machines is shown in Figure 2. Every production machine consumes a different amount of electrical energy over time and process. The diagram demonstrates the power consumption over the processing duration as well as the average energy consumption.

3.1 Machine States

Each type of electrically driven production equipment has various operating states that can be characterised by energy consumption and duration. The energy consumption of production machine is the sum of the energy consumption of their components. In order to execute production tasks, a sub-set of the components is activated and depends on the predefined process. The needed mechanical energy will convert directly from the electrical energy and thus consumes energy according to its operating profile. Weinert provides illustrative examples and modelling framework for operating states [14]. The production machine operation states can be identified from the metered power profile [7]. Considering the electrical energy consumption three relevant machine states for energy based scheduling can be identified:

- **Idle:** lowest energy consumption ~ 0,1% - 1% constant base power - no value creation
- **Waiting:** higher energy consumption ~ 10% - 40%, machine is waiting to produce - no value creation
- **Processing:** highest energy consumption ~100%, product, process specific energy profile - value creation

3.2 Scheduling Horizon

The prototype shall calculate the optimal production schedule for the next day. Therefore the scheduling horizon is 1 day ≙ 24 hours. The electrical power consumption data is streamed with 1 Hz frequency from each production machine and is given as kW/s. This data is logged on the embedded industrial PC. Each processing step and duration of machines is automatically extracted from the meter [15]. The extracted process duration is given in seconds. A time slot length of one second would lead to 86400 time slots per day. So the prototype would have 86400 time slots in which every machine could be in “Processing”, “Waiting” or “Idle” state. Additionally the constraints have to be fulfilled for every time slot. This would result in an extensive computational time.

To avoid an extensive computational time the time slot lengths should be as long as possible. This leads to set the greatest common divisor (gcd) as time slot length determined from scheduling horizon of 24 hours, the electrical energy price interval of 1 hour and all time durations of the “Processing” state. The time slot in this case is set of 300 seconds ≙ 5 minutes. This leads to process durations between one and three time slots and a scheduling horizon of 288 time slots (≙ 24 hours).

4 IMPLEMENTATION

In this model a MIP formulation is chosen. The reason is that the prototype will be more generic and will be able adjust more quickly to scheduling problems with different target function, constraints, number of machines, machine configurations and electrical energy consumption.

Sets:	
M (index m)	Set of production machines
T (index t)	24 hour time horizon divided in 5 minute timeslots denoted by *t*
J (index j)	Set of jobs/orders
Binary matrix (variables):	
P_{jmt}	1 when job *j* on machine *m* at timeslot *t* is processing
W_{jmt}	1 when job *j* on machine *m* at timeslot *t* is in waiting state
I_{jmt}	1 when job *j* on machine *m* at timeslot *t* is in Idle state
X_{jmt}	1 when job *j* on machine *m* at timeslot *t* is starting
Parameters:	
pi_m	Consumption of the "Idle" state
pw_m	Consumption of the "Waiting" state
pp_m	Consumption of the "Producing" state
pu	Capacity limit - sum of all machines is limited to this value
d_m.	timeslots - each machine *m* has constant predefined process duration
ts	Earliest start time – no process can start before this timeslot
te	Latest end time – every process has to be finished before this timeslot
tc	Current timeslot ($ts < tc < te$)
b_m	Buffer opportunities after each production unit
c_t	Cost per kWh from the EEX market "€/kW per timeslot"
c_e	Total cost for the electrical energy over 24 hours
c_s	Simplified total cost for the electrical energy over 24 hours
c_c	Considered energy cost for the electrical energy of one day
o_m	Necessary time period for switch from waiting to idle

Table 1 : Relevant definitions.

4.1 Mathematical Model

The mathematical model includes the machine model and the constraints of operation of the machines as well as the overall production line. Special attention is given to a computational time-reduced model in the planning horizon.

Each machine *m* has to be in one of three consumption states: pi_m (consumption of the "Idle" state), pw_m (consumption of the "Waiting" state), pp_m (consumption of the "Producing" state). The energy consumption of the sum of all machines is limited to a value denoted by *pu* (capacity). Each machine *m* has a constant predefined process duration d_m. The scheduling intervals are set to 5 minutes slots. Thus, parameter d_m contains the required number of timeslots for processing. Each timeslot is specified by *t*, whereas *tc* is the current time. The planning horizon is bounded by two special settable timeslots: the earliest start time *ts* and the latest end time *te*. Outside these timeslots, the consumption state is set idle. The number of parts ordered is called jobs and denoted by *j*. The buffer opportunities following each machine in the production process are defined by b_m. The cost per kWh is extracted from the EEX spot market and converted to "€/kW per timeslot" which is saved in vector c_t. The time to switch to idle state for every machine is given in vector o_m.

The Costs Target Function: The total cost for the electrical energy over 24 hours results from the different machine states *(P, W, I)* multiplied by their power consumption *(pp, pw, pi)* and the electrical energy costs (*c*) at every time slot:

$$\sum_{\forall\, j,m,t} \begin{pmatrix} P_{j\,m\,t} * pp_m * c_t + W_{j\,m\,t} * pw_m * c_t \\ + I_{j\,m\,t} * pi_m * c_t \end{pmatrix} = c_e \qquad (1)$$

To reduce the computing time, the model considers only two machine states in the planning horizon: "Producing" and "Waiting". Outside of it, each machine is in "Idle" state. Since avoiding the relatively high energy consuming "Waiting" state is mandatory, the optimization result is analysed by a second procedure. This procedure changes the "Waiting" state to "Idle" state whenever "Waiting" is active for o_m (default is 15 minutes) number of timeslots or longer. This limitation ensures that no damage is induced by switching the production equipment off and on too often. The simplified total cost function is:

$$\sum_{\forall\, j,m,t} (P_{j\,m\,t} * pp_m * c_t + W_{j\,m\,t} * pw_m * c_t) = c_s \qquad (2)$$

The planning horizon includes two states from which one has to be applied to every timeslot. So $W_{j\,m\,t}$ can be defined by $P_{j\,m\,t}$ as $W_{j\,m\,t}$= 1 - $P_{j\,m\,t}$ follows. This lead to the equation for the simplified total energy costs:

$$\sum_{\forall\, j,m,t} (P_{j\,m\,t} * pp_m * c_t + (1 - P_{j\,m\,t}) * pw_m * c_t) = c_s \qquad (3)$$

The last simplification is that instead of optimizing the producing time, it is much faster to schedule the start times of every job. The effect on the results will be minimal because the average process duration is 11 minutes and the price changes every 60 minutes. The considered energy cost is the target function:

$$\sum_{\forall\, j,m,t} (X_{j\,m\,t} * pp_m * c_t) = c_c \qquad (4)$$

The aim is to find the values of $X_{j\,m\,t}$, $P_{j\,m\,t}$, $W_{j\,m\,t}$, $I_{j\,m\,t}$ minimizing the considered energy cost while fulfilling the following constraints.

Constraints: Constraints are equations and inequalities which reduce the set of possible results for the target function and the variables. In this prototype constraints are mathematically equivalent to the physical constraints given by the production line model. Every job *j* on a production unit *m* needs to be fulfilled before the end time. Fulfilment constraint:

$$\sum_{t=ts}^{te} X_{j\,m\,t} = 1\,. \quad \forall\,(j,m) \qquad (5)$$

At every timeslot *t* the sum of energy consumption must not exceed the mandated capacity *pu*. Capacity constraint:

$$\sum_{\forall\, j,m} (W_{j\,m\,t} * pw_m + P_{j\,m\,ts} * pp_m) \le pu \quad \forall\, t \qquad (6)$$

To start a new job on a production unit the previous job on this unit need to be finished. Ordering constraint:

$$\sum_{t=ts}^{tc} t * X_{j\,m\,t} + d_m \geq \sum_{t=ts}^{tc} t * X_{j+1\,m\,t} \quad \forall\,(j,m,tc) \tag{7}$$

Starting a new job on a production unit, the same job on the previous unit needs to be finished. Example: processing step 5 of job 10 can only start if the processing step 4 of job 10 is finished. Dependency constraint:

$$\sum_{t=ts}^{tc} t * X_{j\,m\,t} + d_m \geq \sum_{t=ts}^{tc} t * X_{j\,m+1\,t} \quad \forall\,(j,m,tc) \tag{8}$$

The storage opportunities of the processed parts after each production unit are limited. Consequently the number of jobs done by the previous machine minus the buffer b_m must not exceed the number of processed jobs on the next machine. Buffer constraint:

$$\sum_{t=ts}^{tc} X_{j\,m\,t} - b_m \leq \sum_{t=ts}^{tc-d_m} X_{j\,m+1\,t} \quad \forall\,(j,m,tc) \tag{9}$$

4.2 Program Architecture

The architecture of the prototype includes three parts, presented in figure 3. The necessary inputs are:

- **INPUT ADAPTER:** State detection out of measured power stream and calculation of energy per job [7].
- **Electrical cost per hour:** Daily electricity market price €/MWh for 24 hours.
- **Manual Input:** Number of orders, earliest/latest starting time and chosen strategy.

In the second part "program" the LP file is processed by the mathematical solver CPLEX to determine the ideal start time of each job on every production machine. Thus, the binary matrix X_{jmt} will be calculated. The ideal start time is given, if the first derivative of the target function (4) is equal to zero and second derivative greater than zero.

Next a procedure calculates the binary matrix. Followed by the optimization of the schedule through changing the "Waiting" states to "Idle" whenever is possible. The optimised production schedule is used to calculate the electrical energy costs for the production line. This cost in combination with exported version of the production schedule is categorised as the output part of the prototype.

4.3 Scheduling Strategies

The scheduling of the production steps according to the volatile energy prices is done through shifting the jobs in different manners. Shifting offers the possibility to start processes when the electrical energy price is low. Each strategy stands for a different way to generate the production schedule and requires further degrees of flexibility. The constraints limit the degree of freedom. Three main scheduling approaches are the basis of our investigations:

- **Without Shift:** Every job is fulfilled one after the other. Start time of the first job is fixed.
- **Block Shift:** Every job is fulfilled one after the other. The start time of the first job is flexible. First job need to be started within a variable timeframe.
- **Window Shift:** Every job can start at every time in the defined planning horizon.

Out of these scheduling approaches five scheduling strategies (S) were derived:

- **S0:** Equates the current state of the production scheduling plan. The electrical energy price is kept constant. (Without Shift)
- **S1:** Take into account volatile electrical energy prices from the EEX market. (Without Shift)
- **S2:** The start time of production blocks is flexible. Start time with the lowest energy costs is chosen. (Block Shift)
- **S3:** Every job is fulfilled one after other. (Window Shift)
- **S4:** The "Window Shift" gets shifted over the predefined flexible start time. The start time with the lowest energy costs is chosen. (Block Shift; Window Shift)
- **S5:** Every production machine starts with one unprocessed part from the day before in it. As a result every machine can start at the same time. (Block Shift, Window Shift)

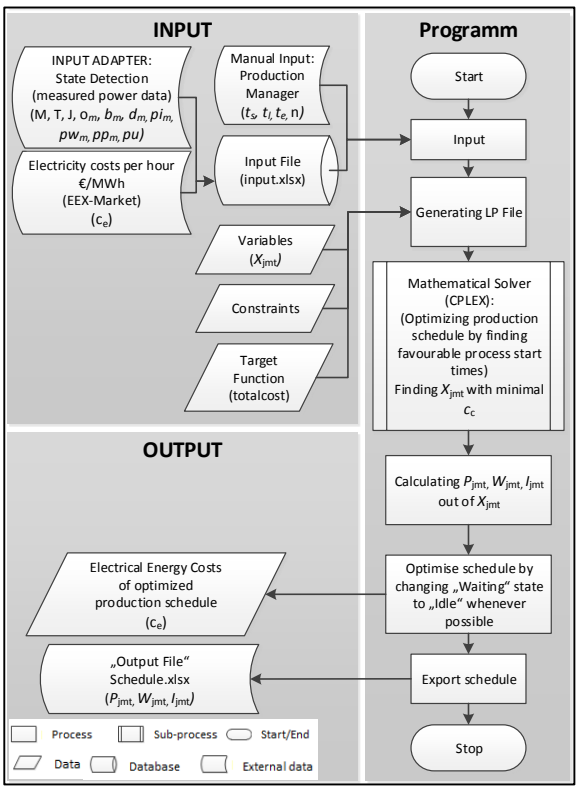

Figure 3: Program flowchart.

5 RESULTS

To demonstrate the potential of this method, 20 orders consisting of 8 production machines as a part of a production line are scheduled. The orders are equivalent to a typical day with a low workload or high maintenance activities. The strategies are tested for three different days. The daily base price for one MWh on the EEX market oscillates round 42€/MWh. The first day, 2nd May 2013 represents a low European Electricity Index (ELIX) Day Base (EDB) for a working day with 32,48€/MWh. The second day is the 25th Sep. 2012 with an EDB of 42.9 €/MWh and represents an average working day. The third day is 13th Feb. 2012 is a high EDB of 109 €/MWh.

The result is shown in figure 4. As mentioned before the first strategy S0 represents the electrical energy costs based on constant energy price of 0,12 €/kWh. Other strategies S1 – S5 schedule the production line according to the EEX Market. The savings for the first two days (low and average EDB) for all strategies are between 58% and 78.6% of the electrical energy costs compared to the current electrical energy costs. The third day (high EDB) strategies S2 - S5 provide savings between 3.2% and 32.3%. The strategies S1 would result in higher electrical energy costs between 19.4%. These outcome need to point out even if the EDB is 256% above the average all strategies which include shifting of processes lead to electrical energy costs savings. The results show that the flexibility of the production line is directly proportional to the cost and CO_2 savings. The most important saving factors are:

- **Flexibility:** Jobs with low shifting range have a low optimization potential. The flexibility is affected by the constraints and the capacity of the production line.
- **Consumption margin:** The main factor in reducing electricity costs is avoiding the non-value-adding machine states. If their electricity consumption is very low the benefit of avoiding them is also low.

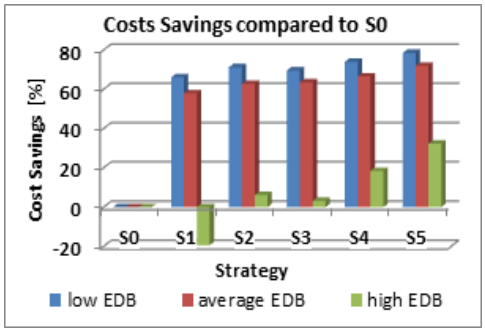

Figure 4: Normalize electricity cost savings.

6 SUMMARY AND OUTLOOK

A method for saving electrical energy costs by scheduling a production line according to the electricity market price has been developed and implemented. The input data for the model is mainly acquired from electrical power data and an interlinking to the EEX spot market. It was shown that depending on the scheduling strategy and the volatile electrical energy prices that the savings are up to 78.6% of the electrical energy costs. These savings correspond to 64.50€ and 34kg CO_2.

Future work includes a multi-criteria based optimization which will allow the minimization of the CO_2 emissions and the electrical energy costs. Additionally, the idle optimization should be included in the LP formulation. This has to be done by adding an additional variable.

7 ACKNOWLEDGMENTS

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