Sustainable energy aware industrial production scheduling

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Abstract. This paper describes a software component that was developed to solve the energy aware production scheduling problem. Firstly, day-ahead energy prices and energy production mix are forecast using publicly available data. Secondly, a Constraint Programming (CP) scheduling model was developed in order to minimize production cost and CO_2 emissions. The paper presents a hybrid methodology to forecast day ahead energy prices, a simplified CP model and preliminary results from the application of energy aware scheduling algorithms to a 3D additive printing industrial production use case.

Keywords: production scheduling · Constraint Programming · energy price forecasting

1 Introduction

Emerging industrial sustainability domain dictate new production efficiency interventions since manufacturing plants are facing increasing pressure to reduce their carbon footprint, driven by concerns related to energy costs and climate changes. To create an energy sustainable environment in the industrial production ecosystem multiple aspects should be taken into account and a hierarchical decision-making process should be implemented. Supply chain, production planning and scheduling and maintenance planning inter-wind with floor-shop energy monitoring, gas emissions tariffs tracking and energy market prices to create a sustainable manufacturing system. In this paper we focus on the production planning and scheduling aspect where day-ahead energy prices are forecast and used.

2 Related work

Customer Environmental Awareness (CEA) urge energy-intensive manufacturers into creating an energy saving strategy. In [13], several mathematical models have been developed to support enterprises that are facing choices of self-saving, shared savings and guaranteed savings to determine the optimal strategies of improving energy efficiency when CEA is considered. At production level, production scheduling is critical in decision making process while been computationally demanding and sensitive on data availability and credibility. Many decision support approaches has been proposed. During the FP7 ARTISAN project an energy-aware hierarchical optimization DSS that used an Iterated Local Search with application to the textile industry was implemented [14]. A rescheduling method is proposed to tackle the problem of reducing energy consumption when resolving dynamic flexible job-shop scheduling problem under machine breakdowns [11]. In [4], a hybrid mathematical model and an NGSA-II multi-objective genetic algorithm is used to address integrated production scheduling, maintenance planning and energy controlling for sustainable manufacturing systems. A recent trend is the collaboration between manufacturing enterprises and energy providers. In [12], a multi-agent architecture aimed at elaborating predictive and reactive energy-efficient scheduling through collaboration between cyber physical production and energy systems is proposed. A framework of data-driven sustainable intelligent/smart manufacturing based on demand response for energy-intensive industries is proposed in [8] where a framework is implemented to support multi-level demand response models that address machine, shop-floor and factory levels. A framework to allow collaboration between energy providers and manufacturing companies is proposed in [10]. Energy price forecasts are signaled to the manufacturers and an adaptive production scheduling approach considering the power usage of manufacturers in response to time-varying energy prices is presented.

3 Day Ahead Energy Price Forecasting

Electricity energy prices and source mix varies based on the time of the day and the period of the year. Synchronizing energy hungry production tasks with "green" energy availability is of outmost importance for sustainable production. To achieve sustainability, the variability of the energy production should be incorporated in the production scheduling process. Fig. 1 presents a typical intraday electricity production and demand variability [15].

To implement a forecast on the day ahead energy cost data from multiple sources have to be acquired. In addition, for every supported energy market, a different forecast model should be created as prices per market usually follow different patterns. The implemented algorithms use as input the following data:

1. Electric energy production data
   (a) Day ahead historical predictions
   (b) Realized historical production

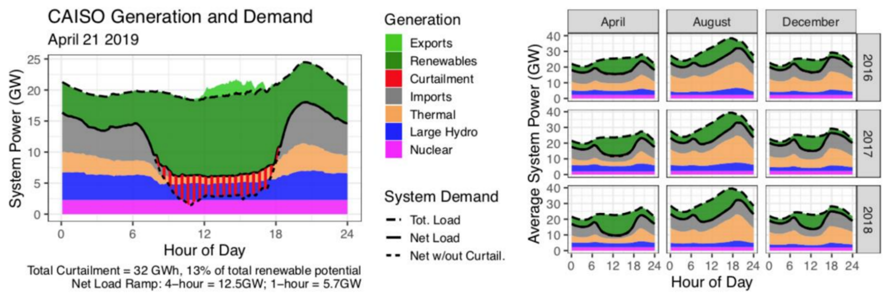

Fig. 1. Typical Electricity Production variability [15]

   (c) Connected energy markets predictions if available
   (d) Published energy production estimations
2. Electric energy demand data
   (a) Day ahead historical demand predictions
   (b) Realized historical consumption
   (c) Up and Down Reserves
   (d) Connected energy markets predictions if available
   (e) Published energy demand by energy market operator
3. System Marginal Prices per energy market supported
   (a) Day ahead historical predictions
   (b) Realized historical SMP
   (c) Connected energy markets SMP if available
4. Weather data
   (a) Temperature, wind speed, solar radiation etc.
   (b) Outside temperature, relative humidity, etc.
5. Miscellaneous data
   (a) Holidays, working days, weekdays, year period

All input was sourced from publicly available data sources. We performed a feature selection analysis [3] to determine the most important features from the available data sets. Fig. 2 present the features importance for the prediction of the energy prices. It can be observed that due to the intense variability in the behaviour of the energy market players the most important feature component is the mean price of the last 7 days, which was not the most significant component if the same analysis was performed some years ago when the energy market was more stable . Multiple forecasting algorithms were used to create a hybrid ensemble prediction model that exhibits a more robust performance compared to individual forecasting algorithms. The individual forecasting algorithms that were used are regression methods (OLS, Ridge, Lasso) [2], Tree based methods (Random Forest) [9] and RNN(LSTM) [7]. Fig. 3 shows a visual representation of the predicted System Marginal Price (SMP) for the day-ahead Greek Energy Market versus the actual realized values for the Greek energy market.

4 Energy-aware production scheduling problem

The Production Scheduling Component is part of the ENERMAN Intelligent Decision Support System and implements a number of energy aware production mapping and scheduling algorithms. The component provides as output the assignment and scheduling of jobs to machines, machine operational mode per task and produces the estimated total energy consumption, energy cost and the estimated total CO_2 emissions for the produced solution.

The Production Scheduling Component expects in the final version the following inputs:

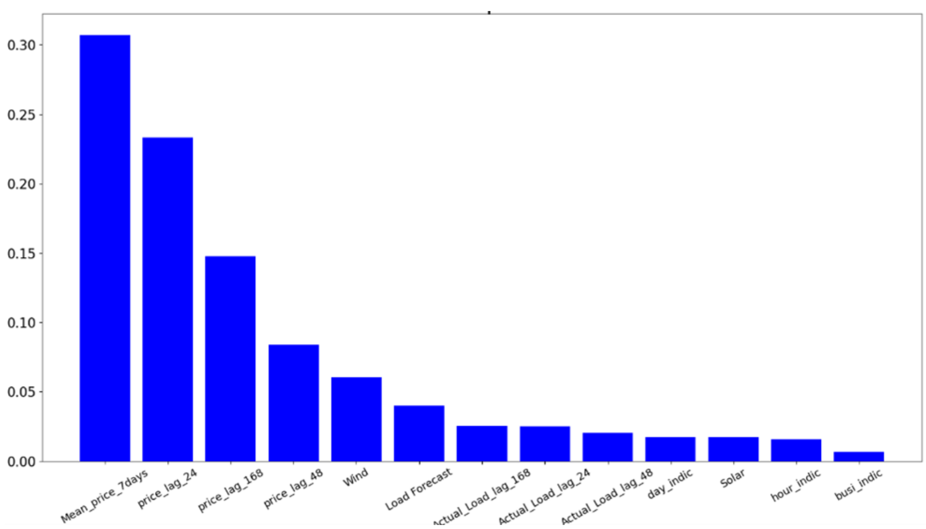

Fig. 2. Features Importance Analysis

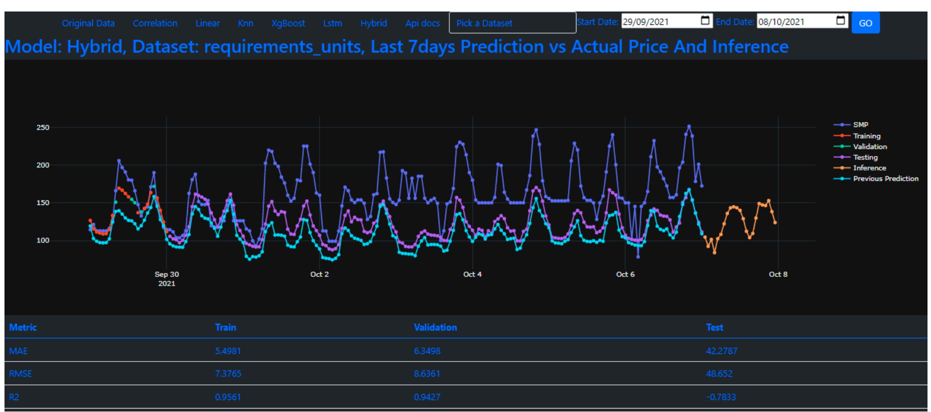

Fig. 3. Hybrid Energy Market Price Forecasting

1. Task related data
   (a) Energy consumption per task for each compatible machine
   (b) Execution time for each compatible machine and operation mode
   (c) If it is an obligatory or optional job
   (d) Job execution flexibility (availability, deadline, time windows)
2. Machine related data
   (a) Energy consumption function at different operational states
   (b) Machine availability (planned maintenance, operating personnel etc)
   (c) Machine pre-allocated capacity
3. Production description data
   (a) Feasibility of schedulable time periods (Available working days & hours)
   (b) Time horizon and related penalties if not a schedule meets makespan requirements
   (c) Dependencies between tasks
   (d) Intermediate products storage availability and feasible time windows
   (e) Transfer time and energy cost to move intermediate products between machines / sites
4. Energy prices per hour for the relative energy markets
5. Energy production mix per hour for the relative energy markets

Some of the implemented heuristics and ILP algorithms are based on ideas presented in [6], [1] and [5] but are outside the scope of the current paper. In the current paper, a reduced version of a Constraint Programming model to solve the problem is presented. The CP model only supports one operational mode per machine and 2b, 3b-3e inputs are ignored. The model will be extended in the future to support the full problem definition.

Let $T = \{1, 2, \ldots, t\}$ be a number of independent non-preemptive tasks and $M = \{1, 2, \ldots, m\}$ be a set of heterogeneous machines. The goal is to allocate and schedule all tasks to the machines while minimizing the total cost and/or the CO_2 emissions. Each task can only be executed on a subset $M_t \subseteq M$ of the available machines and due to the heterogeneity of the machines, the execution time D_{ij} and consumed energy C_{ij} of task t_i on machine m_j are not the same. Let $T_m \subseteq T$ be the tasks that can be executed on machine m. Let the variables s_i and e_i denote the start and end time of task t_i, while the variable x_{ij} is a binary decision variable that equals to 1 when task t_i is assigned to machine m_j, otherwise $x_{ij} = 0$. Using s_i, e_i, D_{ij} and x_{ij} an optional fixed size interval variable I_{ij} is introduced for each $t_i \in T_m$ and $m_j \in M_t$. In addition, each task $ti \in T$ is associated with a resource envelope type $r_l \in R$ and for each type pair $(r_l, r_n) \in R$ different energy consumption H_{ln} and execution time G_{ln} is defined to represent the setup process between tasks. Finally, for each machine $m \in M$ and for every pair $(t_i, t_k) \in T_m$ a pair of Boolean variables p_{mik}, q_{mik} is introduced that help us to identify that task t_i precedes t_k. The above problem can be formulated as a CP model and optimal solution for realistic problems can be achieved in minutes. A simplified version of the scheduling problem model is as follows:

$$\forall\ t_i \in\ T, \sum_{m \in M_t} x_{im} = 1 \tag{1}$$

$$\forall\ m \in\ M, \forall\ t_i, t_k \in\ T_m, i \neq\ k,\ p_{mik} = 1\ \leftrightarrow\ x_{im} + x_{km} = 2 \tag{2}$$

$$\forall\ m \in\ M, \forall\ t_i, t_k \in\ T_m, i \neq\ k,\ p_{mik} = 0\ \leftrightarrow\ x_{im} + x_{km} < 2 \tag{3}$$

$$\forall\ m \in\ M, \forall\ t_i, t_k \in\ T_m, i \neq\ k,\ q_{mik} = 1\ \leftrightarrow\ s_i \leq\ s_k \tag{4}$$

$$\forall\ m \in\ M, \forall\ t_i, t_k \in\ T_m, i \neq\ k,\ q_{mik} = 0\ \leftrightarrow\ s_i \geq\ s_k \tag{5}$$

$$\forall\ m \in\ M, \forall\ t_i, t_k \in\ T, i \neq\ k, p_{mik} = 1,\ q_{mik} = 1 \leftrightarrow\ s_i + D_{im} + G_{r_i r_k} \leq\ s_k \tag{6}$$

$$\forall\ m \in\ M, \forall\ t_i, t_k \in\ T, i \neq\ k,\ p_{mik} = 1,\ q_{mik} = 0 \leftrightarrow\ s_k + D_{km} + G_{r_k r_i} \leq\ s_i \tag{7}$$

Equation (1) ensures that each task is assigned to exactly one machine. A non-overlapped in time execution sequence between two tasks t_i, t_k is imposed by (6) and (7), when they are assigned to the same machine. The full version of the model includes additional interval variables that act like pre-scheduled tasks in the model and prohibit the real tasks to be scheduled during a machine unavailability periods, adaptation to constraints (6) and (7) are required to take into account these pre-scheduled tasks.

Multiple objectives are supported. For example, if we want to minimize the total energy consumption the objective is set to

$$min \sum_{i \in T, j \in M} x_{ij} * C_{ij} \tag{8}$$

If we want to minimize total CO_2 emissions or the total energy cost, an extension to the above model is required. Given a time horizon L where for each time period $[l_a, l_b]$ we have forecast the cost of energy S_{ab} and the renewable energy percentage P_{ab} in the available energy, for each machine $m_j \in M$ and for every task $t_i \in T_m$ an extra array of variables E_{ij} is introduced that for each point in time in the time horizon calculates the cost or the CO_2 emissions. For example, if we want to minimize the total energy cost the objective function can be written

$$min \sum_{i \in T, j \in M_t} x_{ij} * E_{ij}[s_i] \tag{9}$$

Given the solution of the optimization model is part of a decision process multiple objectives can be combined using weights introduced by the user and alternative solutions can be generated.

Figure 4 presents optimal solutions for the two aforementioned objectives for a small example, where grey areas are prohibited scheduling periods for each machine, blue tasks have $A0$ resource envelope while orange tasks have $A1$ resource envelope. To demonstrate the effect of energy prices we used a linear decreasing cost per minute. It can be observed in the right Gantt chart that the tasks are scheduled as right as possible while still satisfying where lower energy prices are realized.

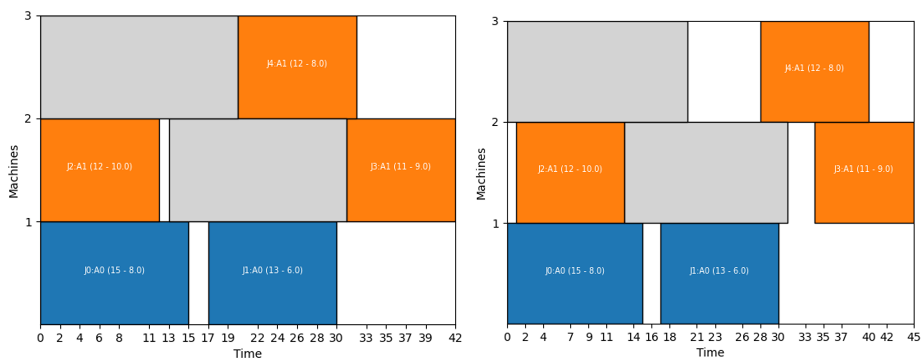

Fig. 4. Solutions using different objective functions example.

5 Use case description and preliminary results and conclusions

The Enerman project has multiple use cases that must be supported by the production scheduling algorithms. Problem data originate from industrial partners that have energy demanding production processes like automotive manufacturing, semiconductor production, steel and aluminum production, food processing and 3D additive components manufacturing. Preliminary results originate from a 3D metallic component printing process were machines with different laser technologies and variable performance capabilities are present in the production environment. Each task is independent but the setup time between tasks on the same machine depends on the powdered material used to manufacture the previous component. If the same material is used the setup time can be reduced but the setup time never reaches 0 as some cleaning between jobs is required. In addition, each machine has different operational points for the laser that allow more energy efficient production to be realized by prolonging the production time. Preliminary results that use historic production schedules and forecast energy prices for the specific energy market that the company is operating show that if the tasks have used the introduced optimization model to produce an alternative production schedule that aligned the more energy demanding tasks with low cost energy periods, a significant cost reduction could be achieved. To assess the effect of the forecast quality, we performed a lower bound optimal scheduling were the realized SMP values were used instead of using the forecast values. It was observed that using the forecast energy prices a reduction of about 7% in the production cost was achieved compared to a reduction of about 9% that was achieved if we have predicted exactly the realized SMP prices, while in both case a model optimal solution has been found.

6 Conclusions and future work

This short paper presents preliminary work over the problem of minimizing the cost of production scheduling in an industry setting. Industries that are heavily depended on the energy cost for their operation need an automated way of avoiding suboptimal schedules. Future prices are difficult to predict. Thus, it is very important to generate high quality forecasts to be used as input to the scheduling algorithm. In this context, we propose a CP model that is able to produce good schedules taking into account the forecast electricity prices. The CP optimization model will be extended to support dependencies between tasks, intermediate product storage capacity constraints, time windows for intermediate product storage and time and energy cost for the transfer of the intermediate product between machines.

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