Industrial Production Scheduling in the Energy Deregulation Era

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Abstract. This paper extends a preliminary model to address the very important problem of aligning industrial production with time periods where more renewable energy is available. Modern industries may use multiple energy sources, each having different temporal and quantitative availability. Our model uses forecasted day-ahead energy prices and energy production mix to generate an optimized production schedule. A toolset approach is applied where multiple solvers that share a common data model is implemented. The paper presents a production level Constraint Programming (CP) model and results from applying the toolset to a number of real world instances.

Keywords: Sustainability, Industrial Production Scheduling, Flexible Job Shop Scheduling

1 Introduction and related work

Emerging industrial sustainability domain dictate new production efficiency interventions driven by concerns related to energy costs and climate changes. Local energy production, renewable energy sources that introduce stochasticity in the availability and auxiliary energy markets effect the energy mix and prices creating a new deregulated era. Production scheduling is critical in the sustainability decision making process. Integrated production scheduling, maintenance planning and energy controlling for sustainable manufacturing systems using a hybrid of a Non-dominated Sorting Genetic Algorithm (NGSA-II) based multi-objective genetic algorithm and a mathematical model is used in [1]. A framework to allow collaboration between energy providers and manufacturing companies is proposed in [2]. 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. In [3] a Mixed Integer Linear Programming (MILP) stochastic programming model is proposed that simultaneously optimize production scheduling and electricity procurement. An energy aware scheduling model to optimize steel industry operations when multiple energy sources are available using a minimum-cost network flow for cost optimization is proposed in [4]. Recently, a flowshop scheduling problem to simultaneously minimize makespan and total energy cost using critical-path based local search methods is proposed in [5].

2 The EnerMan EAPS toolbox

The EnerMan Energy Aware Production Scheduling (EAPS) Toolbox supports the combined requirements collected from diverse problems from energy demanding production processes like automotive manufacturing and testing, semiconductor production, steel and aluminum production, food processing and 3D additive components manufacturing. A generic software component allows potential users to introduce new features in their production planning and scheduling. The toolbox implements a number of constructive heuristics, meta-heuristics and a Constraint Programming (CP) based solver. In the current paper, a version of the CP solver is presented.

3 Constraint Programming Solver

The current CP model extends a preliminary CP model[6]. Special constructs like interval variables, specialized global constraints (e.g., noOverlap, circuit, element) among others are employed. The current implementation uses the most performant open source solver (OR-Tools CP-SAT) and a commercial one (ILOG CP). Python is used for implementation as it was easier to manipulate the amount of data required. The toolbox is provided to the other services of the EnerMan platform as a OpenAPI RESTFul services, exchanging data model information as JSON based messages.

Let J/T_j represent the set of jobs/tasks that must be scheduled, A the set of task attributes and $a_{j,t}$ the attribute associated with each task. The set of factories and set of machines in a f factory are represented by F and M_f respectively. O_m and c_m represent the operation model and capacity of machine m. The setup time that will be needed if tasks $t1$, $t2$ will be scheduled at machine m, with task $t2$ processed as the next task after task $t1$ is represented by $S_{m,t1,t2}$. For each task t of job j and for all possible start times the task can be scheduled at factory f, machine m and operation mode o, vectors $C_{j,t,o,m,f}$ and $EC_{j,t,o,m,f}$ hold the energy consumption and cost that task t incurs. These values are calculated in advance by considering the machine characteristics and the energy cost components.

The main variables of the model $xvar_{j,t,o,m,f}$ are optional interval variables that represent if a task t of job j instance is performed on a machine m of factory f using operational mode o and have a start time $s_{j,t}$, an end time $e_{j,t}$ and a Boolean variable $is\_p_{j,t,o,m,f}$ that represent if they exist. $evar_{j,t,o,m,f}$ is an integer variable for the energy cost of a task. Additionally, auxiliary variables s_j , e_j are the start and end time of a job, $assigned\_to_{j,t}$ holds the machine it is processes on, $b_{t1,t2,m,f}$ are Boolean variables that assumes value 1 if both tasks $t1$, $t2$ are processed at the same machine and task $t1$ is processed immediately before task $t2$ on machine m of factory f.

The global constraint *noOverlap* is used to avoid simultaneous processing of multiple tasks at the same machine when the capacity of a machine equals to 1. When $c_m \geq 1$, the global constraint *Cumulative* is been used instead. For each $f \in F, m \in M_f, j \in J, t \in T_j, o \in O_m$

$$noOverlap(allxvar_{j,t,o,m,f}), c_m = 1 \tag{1}$$

$$Cumulative(allxvar_{j,t,o,m,f}, c_m), c_m \geq 1 \tag{2}$$

If a machine is not available for specific time periods across the horizon of the schedule, a set of dummy interval variables are defined with fixed starting times and durations corresponding to the time periods that this machine is not available. This set of dummy interval variables are used in the previous constraint, disallowing processing of tasks to this machine.

Each $t \in T_j$ of $j \in J$ must be scheduled exactly at one available machine.

$$\sum_{f \in F, m \in M_f, o \in O_m} is\_p_{j,t,o,m,f} = 1 \tag{3}$$

To impose a setup time, when a pair of incompatible tasks are scheduled in sequence at the same machine, the global constraint Circuit is used that defines a Hamiltonian path in a sequencing graph that visits each node exactly once. To determine the task sequence, a graph is defined for each machine and the nodes of this graph are all the tasks that can be executed at it. For each $f \in F, m \in M_f$,

$$Circuit(arcs_{m,f}) \tag{4}$$

$$EndOf(xvar_{j,t1,o,m,f}) + S_{m,t1,t2} <= StartOf(xvar_{j,t2,o,m,f}) \tag{5}$$

The energy cost of a task depends on the starting time of the corresponding interval variable. The global constraint Element determines the energy cost of a task t.

$$Element(StartOf(xvar_{j,t,o,m,f}), EC_{j,t,o,m,f}, evar_{j,t,o,m,f}) \tag{6}$$

The objective function coefficients c1, c2 determine the relative weights between energy consumption and energy cost.

$$\min \sum_{j \in J,\ t \in T_j,\ f \in F,\ m \in Mf,\ o \in Om} \left(c1 * C_{j,t,o,m,f} * is\_p_{j,t,o,m,f}\ c2 * evar_{j,t,o,m,f} \right) \tag{7}$$

4 Evaluation, Conclusions and future work

Fig. 1 represents a weekly solution from a semiconductor manufacturing industry, with colours representing different task types, the red line the variability of energy cost and the green line the cumulative energy cost. In the specific instance more than 9K tasks are scheduled. It was observed that it is possible to reduce the production cost by 6% while in parallel we reduced the generated CO_2 by 15% without sacrificing throughput. We intend to release the solvers along with the data model and problem data to the public when we manage to anonymize the related data and appropriate approvals are given by the problem owners.

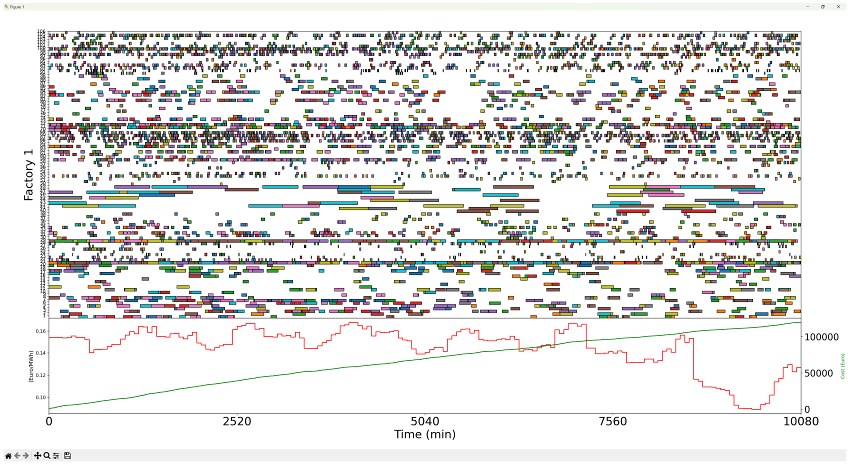

Fig. 1. Weekly schedule from a single factory of a semiconductor manufacturing industry.

We intend to extend the toolbox with the ability to automatically generate what-if scenarios based on the forecasted prediction variability to calculate alternative solutions transitions that will allow the factory to during the implementation of a scenario if a demand response signal is observed the factory to participate in the demand response energy market without significantly sacrificing production performance.

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