SIMULATION-BASED SCHEDULING FOR A HOT PRESS FORGING FACTORY USING DATA-DRIVEN MODELS

Seyoung Kim, Jeongmi Lee, Hyeongrok Heo and Kwang Ryel Ryu

*Department of Electrical and Computer Engineering
Pusan National University, Busan, Republic of Korea*

ABSTRACT

We use a genetic algorithm (GA) to search for an optimal production schedule for a hot press forging factory. Our GA evaluates each candidate schedule by simulating its execution using cost models of all the equipment involved in the forging process. The cost models are learned from data collected from IoT infrastructure installed at our target factory. Experimental results show that our proposed method gives schedules of higher productivity with lower energy cost compared to the heuristic method that is similar to the real practices at our target hot press forging factory.

KEYWORDS

Scheduling Optimization, Predictive Model, Simulation, Rolling Horizon, Genetic Algorithm, Hot Press Forging Factory

1. INTRODUCTION

Hot press forging refers to the process of shaping metals to desired configurations through heating to high temperatures and then applying pressures. The equipment of a typical factory for hot press forging include heating furnaces, press machines, cutting machines, and heat-treatment furnaces. A heating furnace usually accommodates several ingots (chunks of metal) at a time and heats them to a temperature high enough (mostly around 1,200 °C) for subsequent pressing. The energy and time costs for a heating depend on the weights and materials of the accommodated ingot combination. The ingots, after being completely heated, often remain in the furnace with the temperature maintained until a press machine becomes ready after its previous job and then requests one for processing. The ingots are fetched out of the furnace one by one following the requests from the press machines. The longer the ingots wait within a furnace, the more extra energy the furnace consumes. Good heating furnace schedules with good ingot combinations together with well-synchronized press machine schedules enable energy saving as well as productivity enhancement. Sometimes the ingots need to be cut into a few workpieces before or after pressing. Since the press and cutting machines are run by electricity and not so energy consuming, it is just their processing times that matter for scheduling. The processing times for pressing and cutting depend on the size, weight, and shape of the workpiece. After cutting and pressing are all over, all the workpieces must go through the process of heat treatment for the purpose of improving mechanical properties of the final product. The heat treatment is also a highly energy consuming process. The energy and time costs for heat treatment depend on the material types of the workpiece combination being treated together in a heat-treatment furnace.

Previous works on using genetic algorithms (GA) for optimizing the production schedule of a press forging factory deal only with scheduling the heating furnace jobs (Fei et al., 2017; Serdobintsev et al., 2014). What we propose in this paper is a method based on a GA that searches for an optimal production schedule covering an entire factory, where the quality of each candidate schedule is evaluated by a simulation of the overall forging processes using the cost models of all the equipment involved. The models of time and energy costs used for the simulation are built by learning from the process data collected via an IoT infrastructure together with the operation data revealing the corresponding workpieces processed. Using these models, we can predict how much time and energy would be spent by a machine or a furnace to process a workpiece or a set of workpieces, which is essential for simulating a given schedule execution. To cope with not only the uncertainty of the job progresses in the factory environment but also the prediction errors by the models, we adopt the so-called rolling horizon scheduling method (Jian and Yuseng, 1997), according to which rescheduling is done

at a regular interval that is much shorter than the length of the scheduling horizon. Experimental results show that our proposed method gives schedules of higher productivity with lower energy cost compared to the heuristic method that is similar to the real practices at our target hot press forging factory. The next section describes the proposed method in more detail. Section 3 reports the results of experiments, and finally section 4 gives summary and the direction of our future works.

2. PROPOSED METHOD

The solution representation of our GA includes only a job schedule for all the heating furnaces to be run during the upcoming horizon. When a candidate solution (i.e., a candidate schedule) is evaluated, however, the job schedules for the other equipment are all determined by applying the respective dispatching rules and then the overall schedules are executed through a simulation. The job dispatching for press machines, cutting machines, and heat-treatment furnaces is done on an urgency basis. Whenever an equipment becomes ready after finishing its previously assigned job (or jobs), it is assigned the most urgent job (or a set of jobs in the case of heat-treatment furnaces) among the jobs that are waiting after finishing all the preceding processes. The objective function used by our GA is

$$\min (w_E \cdot E + w_T \cdot T)$$

where E is the gas consumption per unit weight (m^3/ton) for heating by the furnaces, T is the total makespan per unit weight (h/ton), and w_E and w_T are the respective weights. The schedule thus obtained for a horizon of length h is executed only for a short duration r with $r \ll h$. The reason for this is twofold. First, the schedule can hardly be executed exactly as planned because of the inherent uncertainty of the processes involved in hot press forging. Second, the schedule is built through simulations based on data-driven models that are not really accurate. Before the duration r is over, we run GA again to obtain a new schedule of the same horizon length h to be executed next. Notice that r becomes the rescheduling interval for GA.

Various cost models are learned from IoT sensor data to predict the following quantities: time taken for heating ingot combinations, gas consumption required for each heating, time taken for pressing a workpiece, time taken for cutting, time taken for heat treatment, and gas consumption for each treatment. These models learned from real data are actually used to build an emulator that virtually realizes our target factory, because we cannot experimentally execute schedules and measure performances at a real factory as desired. For the simulations by GA during the search, we derive the same type of models through learning from data that are generated by running the emulator. The performance of our rolling-horizon scheduling is then measured by applying the schedules and observing the results using the emulator.

3. EXPERIMENTAL RESULTS

Our target factory is equipped with thirteen heating furnaces each with the capacity of 300 tons, two gigantic press machines, three cutting machines, and five heat-treatment furnaces each again with the capacity of 300 tons. The length of scheduling horizon is approximately two weeks during which about 3,000 tons of workpieces (or about 100 workpieces) are processed. The rescheduling interval is one day, which implies that each scheduling by GA allows for one day of factory operation. To validate our scheduling method, we run the factory on our emulator for seven days using the schedules produced by GA and observe the key performance indicators (KPI) that are the average workload of heating furnaces (the higher the better utilization), the average gas consumption (the lower the better), and the yield or productivity (the higher the better). Table 1 compares KPIs achieved by different methods obtained from averaging the results of four runs, which shows that the proposed method performs much better than the heuristic method used at our target factory.

Table 1. Comparison of KPIs by different methods, which are obtained from averaging the results of four runs

Workload of heating furnaces (ton/h)			Gas consumption (m ³ /ton)			Yield (ton/h)		
Proposed method	Without rescheduling	Heuristic	Proposed method	Without rescheduling	Heuristic	Proposed method	Without rescheduling	Heuristic
5.42	5.05	3.38	299.5	312.3	336.3	10.2	9.7	9.3

4. SUMMARY AND FUTURE WORKS

In this paper, we have proposed a simulation-based scheduling method that is targeted to a hot press forging factory. The cost models of various equipment used in the simulations are learned from real data collected via the IoT infrastructure installed at our target factory. Experiments by using the factory emulator reveals that the proposed method significantly outperforms the heuristic method used at the target factory. Currently, we are doing more experiments trying more runs (Table 1 shows the average of only four runs) for a more convincing comparisons. One important question in this study would be how robust our simulation-based scheduling is against the prediction errors of the cost models used in the simulations. If the model errors are too high, we may not be able to find a good schedule using such models. The next step, therefore, is an empirical investigation on the sensitivity of our scheduling method to the model error. Since we can easily amplify the errors by deliberately adding noise to the model output, we should be able to see, for example, how much model error would eventually downgrade the performance to the same level as the heuristic method.

ACKNOWLEDGEMENT

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ICT Consilience Creative program (IITP-2019-2016-0-00318) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation)

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