Evaluation of Energy Efficiency and Productivity in Scheduling by Using Physical Simulator

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Green manufacturing has been becoming more critical in response to changing a demand for manufacturing sustainability from lower carbonization to strict decarbonization. This paper extends our previous work on energy awareness in scheduling and investigates the relation between energy efficiency and productivity based on the physically measured data including power consumption and uncertainties that can be observed through the developed manufacturing physical simulator. It is also demonstrated, through physical scheduling simulations in a brute-force way, that our manufacturing simulator is capable of evaluating energy-efficient operations of manufacturing systems.

1. Introduction

Manufacturing industries account for more than 30% of total energy consumption in Japan[1]. Green manufacturing has been recognized as one of critical activities along with plant-wide optimization, the development of demand-driven supply chain management in smart manufacturing. Here green manufacturing refers to manufacturing activities and processes directing reductions in CO₂ emissions and energy and resource savings. The first step to enhance green manufacturing is, as seen in factory energy management systems[2], to visualize associated manufacturing information. Those systems have been gradually applied into practice[3] to foster energy awareness on the shop floors and workers, leading to the improvement of energy efficiency and productivity in manufacturing processes.

The next step that should be taken after the visualization of energy use[4] is to implement a decision-making system that can minimize the total energy consumption or maximize the energy efficiency in production volumes per joules of the system without deteriorating the productivity performance such as production speed and manufacturing lead time. The collection of energy-consumption data are fed back to the planning division to provide or replan a capacity and energy load plan for forthcoming production[5].

The effective energy optimization techniques, however, have not yet been applied into practice.

This paper extends our previous work[6] on green manufacturing and investigates the relation between energy efficiency and productivity under a real circumstance based on the physically measured data including power consumption and uncertainties that can be observed in a specific physical system. Yonemoto et al.[6] have developed a manufacturing simulator based on the what we call measurement and control platform[7], and demonstrated its embedded job sequence generator. A miniature factory model is utilized as a physical system to be connected to the developed simulator. It is expected that the manufacturing simulator with scheduling can evaluate the in-process manufacturing energy efficiency and productivity through real time measuring of power consumption and physical material flow. It is also demonstrated through physical scheduling simulation in a brute-force way that our manufacturing simulator is capable of evaluating energy-efficient operations of manufacturing systems.

2. Related Work

Mansouri et al. introduced a new concept of green scheduling and proposed a multi-objective mathematical model involving energy consumption under variable processing times[8]. They applied their optimization framework to a sequence-dependent two machine flowshop scheduling problem. Buzzone et al.[9] developed the integrated energy-aware scheduling module in advanced planning and scheduling systems. A model to control peak power on a shop-floor is incorporated into the module. The applicability of their approach was demonstrated by applying it to a test case. He et al.[10] proposed an energy-saving optimization methodology under the flexible job shop
configuration by selecting an appropriate machine tool and sequencing the operations at the planning phase. They provided a mathematical model for such energy optimization problem and then clarified the trade-off between makespan and energy consumption. Fang et al. considered a shop-floor scheduling problem with maximizing the productivity and minimizing the carbon footprint and peak load[11]. They clarified some potential trade-offs among those criteria by applying their proposed methods to a two-machine job shop problem. Other varieties of models and methods for energy-efficient scheduling have been proposed. Some of them can be found in[2,12,13]. Most studies, however, have not considered physical phenomena associated with energy consumption in a manufacturing process, but only focus on building a scheduling-decision model under an ideal manufacturing environment without considering uncertainties.

In the real manufacturing industries, energy conservation activities have been pursued by implementing factory energy management systems[3,14] that can collect the real energy consumption and point of production information. Energy awareness has been also taking into account in some manufacturing system simulations. Hibino et al.[15] proposed a computational simulation system to evaluate the energy consumption and productivity. They demonstrated the efficiency of their evaluation system by applying it to semiconductor manufacturing systems. The energy consumption model, however, tends to be oversimplified since both of theoretical and practical models of energy consumption for manufacturing subsystems such as machine tools do not necessarily exist. Therefore, the dynamics of energy consumption may not be always reflected properly in the computational simulation.

Unlike the above approach, we consider to utilize a physical simulator combined with a scheduling unit to evaluate the productivity and energy efficiency in manufacturing based on the real electric power consumption and the material flow in the manufacturing system.

3. Developed Physical Simulator

3.1 Framework of Simulator

Fig. 1 shows the framework of the manufacturing simulator based on the measurement/control platform developed[5,6]. The characteristic point of the simulator lies on a direct connection with physical systems such as machine tools, industrial robots and also miniature factory simulation as a testbed. This indicates that, at this point, we do not consider to build a manufacturing system model on the cyber space; any computational factory simulations are not utilized. The framework shown in Fig. 1 does not also require simulation or mathematical models to describe energy consumption and also uncertainties occurring in the system.

The measurement and control platform collects power consumption data and its associated physical data such as a cutting resistance in real time from the physical system. The platform consists of data acquisition modules to measure current and voltage and embedded real-time controller for the apparatus control via EtherCAT, USB and PLC. Under the premise that drivers and libraries for the target hardware components of the physical system are available, the specific physical properties of the component can be assimilated into the platform, and therefore it is expected that green manufacturing simulators evaluating the energy efficiency and productivity could be efficiently developed without any dedicated virtual model of consumed electric energy. In this study, a simple scheduler that can provides a job sequence is implemented into the platform with a view to investigating and evaluating how job sequences influence on the energy efficiency of the physical system.

3.2 Miniature System as Testbed

A miniature flexible transfer line (FTL) by Fischertechnik is employed as a physical testbed. It is composed of two simulated machine tools, milling and drilling machines (machine 1 and 2, respectively), four different loading belt conveyors to the system, between machines 1 and 2, one unloading belt conveyor, and also two pushers. The stepping motor driving the main spindles of milling and drilling machines and belt conveyors can be controlled directly from the digital I/O module equipped on the measurement and control platform, or by using the Robot TX controller equipped on the miniature FTL. In this study, Robot TX was used for the simplicity of the controlling. The electric power profile of a real machine tool can be given to the simulator by controlling a motor speed of the machine station on the miniature FTL. The miniature FTL has two switching sensors to activate the pushers, which change the direction of workpiece’s movement and keep a tact time (timing of workpiece release), and five approximate sensors to detect workpieces existing in the miniature FTL as depicted in Fig. 2. Workpieces enters the system from the left bottom of Fig. 2, which is detected by the sensor on the loading conveyor 3. Any congestion due
the pushers 7 and 8.

resolved by controlling the timing of the movement of
to a processing delay caused by an uncertainty can be

Fig. 3 Monitoring interface of power consumption and
material flow
to a processing delay caused by an uncertainty can be
resolved by controlling the timing of the movement of
the pushers 7 and 8.

Fig. 3 shows the monitoring interface, through
which real-time changes in power consumption of each
component and the whole system can be perceived. The waves expressing the consumed power are up-
dated every one second. Information associated with
productivity performance such as manufacturing lead
time ad cycle time can be also monitored in real time
by calculating them based on the sensor information.

4. Scheduling Model

4.1 Scheduling in FTL

The objective FTL system introduced in 3.2 has
two machining stations, independently-controlled con-
veyors. The scheduling model on the system can be
described based on a two-machine permutation flow
shop scheduling model with intermediate buffers and
transportation times. Consider N workpieces are pro-
cessed over the planning horizon T, and that work-
pieces are released into the system at regular intervals
according to the pre-specified cycle time, \( \bar{C} = T/N \).
The following notations are used:

\( r_i = \text{Release time of the } i\text{-th workpiece (equivalent}
to workpiece } i \text{). (} i = 1, \ldots, N \text{)} \)

\( p_{ik} = \text{Processing time of } i\text{-th workpiece on machine}
tool } k \text{ (} k = 1, 2 \). \)

\( s_1 = \text{Transportation time on belt conveyor 3 to ma}-
\text{chine tool 1 via conveyor 4. (See Fig. 2) } \)

\( s_{12} = \text{Transportation time on belt conveyor 5 be-
tween machine tools 1 and 2. } \)

\( s_2 = \text{Transportation time on belt conveyor 6 after the}
process on machine tool 2. } \)

\( c_{ik} = \text{Completion time of workpiece } i \text{ on machine tool}
k \text{. } \)

\( c_i = \text{Completion time of workpiece } i \text{. } \)

The release time of workpiece is fixed according to
the cycle time, and we here consider \( r_i = (i-1)C \)
(\( i = 1, \ldots, N \)). The predictive starting time of pro-
cessing workpiece is \( r_i + s_1 \). The completion time \( c_{ik} \)
of workpiece \( i \) at machine tool \( k \) can be expressed by
using its immediate predecessor \( i - 1 \),

\[
c_{i1} = \max(r_i + s_1, c_{i-1,1}) + p_{i1},
\]

\[
c_{i2} = \max(c_{i-1,2}, c_{i1} + s_{12}) + p_{i2},
\]

where \( c_{01} = c_{02} = 0 \). The \( i\)-th workpiece is supposed
to go out from the system at \( c_i = c_{i2} + s_2 \).

4.2 Performance Measures

We first define in-process (dynamic) performance
measures that can be obtained over the planning hori-
zon. Let \( N(t) \) and \( V(t) \) (\( t > 0 \)) respectively denote
the number of processed workpieces (pcs) and consumed
electric energy measured by the platform at \( t \). The energy efficiency of the target manufacturing system,
denoted by \( E(t) \) at \( t \), is given by

\[
E(t) = \frac{N(t)}{V(t)}.
\]

The production speed \( P(t) \) and the cycle time per
workpiece \( C(t) \) at \( t \) are also defined by using \( N(t) \):

\[
P(t) = \frac{N(t)}{t},
\]

\[
C(t) = \frac{1}{N(t)} \sum_{i=1}^{N(t)} (c_{i+1} - c_i).
\]

The following static performance measures realized
at the end of production are considered:

- Total energy consumption \( V \),
- Total energy efficiency:

\[
E = \frac{N}{V},
\]
- Cycle time:

\[
C = \frac{1}{N-1} \sum_{i=1}^{N} (c_{i+1} - c_i),
\]
- Manufacturing lead time per workpiece:
\[ L = \frac{1}{N} \sum_{i=1}^{N} (c_i - r_i), \]  

where \( V \), \( c_i \) and \( r_i \) are supposed be measured by the platform on the simulator.

5. Physical Scheduling Simulation

This section investigates how a workpiece sequence will affect on the energy efficiency by using the developed simulator. It should be noted that a brute-force way for scheduling (sequencing) is employed in the experiments to observe every possible pattern, and therefore we do not consider here optimization of any of the performance measures.

5.1 Schemes

The following situations are considered in this study:

- 60 workpieces (\( N = 60 \)) are processed in the FTL to produce four different machine parts A, B, C and D, over the planning horizon, \( T = 360 \) sec.
- The quantity of each part was equally set to 15.
- The processing time \( p_k \) on machine \( k \) of the part:
  \[ (p_{1A}^A, p_{1B}^A) = (3, 6), \quad (p_{2A}^B, p_{2B}^B) = (4, 3), \quad (p_{1C}^C, p_{1D}^C) = (6, 3), \quad (p_{2C}^D, p_{2D}^D) = (3, 4). \]
- The transportation times \( s_1 = 5, s_{12} = 3, s_2 = 5 \), which were determined based on the measurement and their average.
- The traveling time of pusher 7 in Fig. 2 was set to 6 sec: It pushes a workpiece waiting to conveyer 4 with 3 sec and then comes back to the original position with 3 sec.
- The moving time of pusher 8 in Fig. 2 was also set to 6 sec.
- The predicted cycle time \( \hat{C} = T/N = 6 \) sec.

To investigate the effect of sequence of the parts, all possible sequences, 24 patterns in total were considered. Once a sequence is determined, the workpieces were released with a cyclic fashion, that is, \( \text{ABCD} \) \( \text{ABCD} \) \( \text{...} \), indicating that 15 simulations were conducted for each sequence. Fig. 4 depicts an example of the schedule generated by sequence ABCD.

By using the sequence, the processing times of each workpiece at the machine tools are changed, i.e., their respective motor speeds are changed.

5.2 Results and Discussions

Simulations by using the physical simulator were carried out for each of 24 sequences, and then the performance measures introduced in 4.2 were calculated according to the measured power consumption and starting, transportation, processing and finishing times of each workpiece. The obtained values of the dynamic performances, i.e., energy consumption \( E(t) \), production speed \( P(t) \), cycle time \( C(t) \) and also \( V(t) \), for all 24 sequences are summarized in Fig. 5. During the simulation runs, random conveyer congestions and unexpected conveyer stoppage often occurred as often seen in real automated manufacturing lines. These troubles naturally cause a delay in completion of processing workpieces, leading deterioration of the productivity. The actual cycle time of each simulation run is significantly larger than the ideal one (\( \hat{C} \)) and tends to converges to 7 sec to 8 sec. The production speed also tends to converges to a certain value. The energy-related performance \( E(t) \) and \( V(t) \) relatively varies according to the sequences. Holistically, the productivity and energy efficiency considered to be much influenced by the early stage of simulations, in what follows the results of the first two simulation runs (i.e., the processing of the first eight workpieces) are not taken into account as the warm-up period of the simulations.

Table 1 summarizes the results of physical simulations followed by the mean, standard deviations (SD), coefficient of variation (CV), and root square mean errors (RMSE). Note that, under the conditions investigated here, the measured electric energy per workpiece in average was 0.34 J, which can also be calculated by the reciprocal of the total energy efficiency in averages. The total energy consumption \( V \) and en-
ergy efficiency $E$ vary in accordance with a sequence of parts, and the results of $CV$ delivers the fluctuations in $V$ and $E$ are almost the same as that on manufacturing lead time, $L$. According to the RMS error, the actual cycle time was delayed 1.48 sec and that of actual manufacturing lead time was 7.10 sec longer than expected.

The $SD$ and $CV$ of total energy consumption on all predictive schedules without any uncertainties causing schedule delays were also calculated based on the average energy consumptions of machines 1 and 2, conveyors and pushers derived from the simulations runs, resulting in $SD = 0.049$ and $CV = 0.0025$. They are significantly smaller than those of the actual total energy consumption shown in Table 1. These results indicate the uncertainties naturally influence the energy consumption, and likewise the energy efficiency.

In Table 1, there seems to be some sequences yield better energy efficiency, while others provide better productivity. This tendency can be examined by the Pareto optimality. Fig. 6 depicts the manufacturing lead time against the energy related performance measures. The black squares in Fig. 6 express the Pareto optimal sequences among 24 sequences, the underlined, which is relatively near optimal sequence, is also shown in Fig. 6 as a reference. Four sequences starting from partial sequence $AB$ or $AC$ are effective in regard to manufacturing lead time. This is understandable because three of them provide the best predictive lead time. While the sequences beginning with part $D$ or $C$ effect on energy consumption as shown in Fig. 6(a). The sequence beginning with part $B$ seems to be intermediate. As for the partial sequences $AB$ and $AC$, the same tendency is observed in Fig. 6(b). The results in Fig. 6 deliver that the sequence beginning with $AB$ or $AC$ is considered as a productivity-first schedule, while $CDAB$, $CDBA$ and $DACB$ will be energy-aware schedule in the circumstances investigated here.

The above observations indicate that, if optimization of scheduling is applied to the manufacturing operations (without taking into account inferior sequences), it becomes a trade-off between the manufacturing lead time and energy-related performance measure in accordance with a sequence selected.

6. Concluding Remarks

This paper has investigated the relation between the productivity and energy efficiency in production scheduling by utilizing the physical simulator developed. The following conclusions can be drawn:

- There exists a trade-off between the manufacturing lead time and total energy consumption, and also between the lead time and energy efficiency when optimization of scheduling is considered.
- The developed physical simulator is capable of evaluating the energy efficiency and productivity in scheduling under the conditions considered in this study.
- It is fair to say that the reasonable results were obtained by the physical simulator, indicating that simulations of manufacturing systems can be carried out based on physical data from the physical system.

In this study, however, the optimization issues in scheduling was not taken into account nor discussed as mentioned in 5, and therefore it is needed to implement or connect with a high performance scheduling optimizer that can control releasing a preferable schedule, e.g., an energy-aware schedule or a high productivity schedule and so forth. Future work also includes the connection of the developed simulator with real manufacturing testbed to investigate its applicability and effectiveness as a practical simulator.

Acknowledgements

This paper is partly supported by the Grants-in-Aid for Scientific Research of the Japan Society for the Promotion of Science, No.18K11740.
(a) Lead Time ($L$) vs Total Energy Consumption ($V$)

(b) Lead Time ($L$) vs Total Energy Efficiency ($E$)

Fig. 6 Results of production and energy efficiency

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