Operational methods for minimization of energy consumption of manufacturing equipment

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Abstract This paper develops operational methods for minimization of energy consumption of manufacturing equipment. It is observed that there can be a significant amount of energy savings when non-bottleneck (i.e., underutilized) machines/equipment are turned off when they will be idle for a certain amount of time. Using this fact, several dispatching rules are proposed. A detailed performance analysis indicates that the proposed dispatching rules are effective in decreasing the energy consumption of especially underutilized manufacturing equipment. In addition, a multi-objective mathematical programming model is proposed to minimize the energy consumption and total completion time. Using this approach, a production manager will have a set of nondominated solutions (i.e., the set of efficient solutions) which he/she can use to determine the most efficient production sequence which will minimize the total energy consumption while optimizing the total completion time.

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Keywords: Energy Efficient production Planning, Sustainable Manufacturing, Green Manufacturing, Single Machine Scheduling

1 Introduction

In the last 50 years, the consumption of energy by the industrial sector has more than doubled and industry currently consumes about half of the world's energy [20]. In the U.S.A., the industrial sector consumes approximately 34% of all energy, 3.4% of which is electricity [6]. In 2006, energy costs for U.S. manufacturers were $100 billion annually [25], which today is even higher as a result of the increase in fuel costs. This concern over energy consumption is heightened by the fact that the majority of sources are non-renewable [28] (e.g., petroleum, coal, etc). Beyond the increasing cost of energy, there are also significant environmental effects. As energy is produced from non-renewable sources, CO_2 is emitted into the atmosphere adding to the effect of global warming. As one kilowatt-hour of electricity is produced, 900 grams of carbon dioxide are released into the atmosphere [3]. The increase in price and demand for petroleum and other fossil fuels, together with the reduction in reserves of energy commodities, and the growing concern over global warming, have resulted in greater efforts toward the minimization of energy consumption. Many solutions for a reduction of energy usage have been proposed, but such reduction is difficult to achieve since consumption does not appear to be managed in a structured way. Fallek [7] notes that understanding the facilities' history of energy use can impact the bottom line. The research presented in this paper takes an operational approach to minimizing energy consumption within a manufacturing facility.

The goal of many modern manufacturers is to decrease the cost of production by any means possible while satisfying the environmental regulations and ensuring quality, and customer satisfaction [8]. Gutowski et al. [9] notes that in the Toyota Motor Corporation (a mass production environment), 85.2% of the energy is used in non-machining operations which are not directly related to the production of parts. Kordonowy [12] characterizes the power consumption of a mill, lathe, and injection molding machine by analyzing the background runtime operations of machining (i.e., spindle, jog, coolant pump, computers and fans, etc.). It is observed that over 30% of the energy input into the system during machining is consumed by these background processes. Dahmus and Gutowski [4] and Drake et al. [5] observe that the total energy requirement for the active removal of material can be quite small compared to the background process needed for operating a machine. Furthermore, Drake et al. [5]) show that whenever a machine or a component is turned on, there is a significant amount of start up energy consumption and confirm that when a machine is idle a significant amount of energy consumed.

Minimization of energy consumption has been an area of interest especially in computer and embedded electronic systems. For example, Swaminathan and Chakrabarty [27] propose a control system to reduce energy consumption and extend battery life. By simply changing the state of the devices (e.g., on/off, etc.), they shows that there can be a significant reduction in energy consumption. Simunic et al. [21, 22] provide similar results for specific portable devices with the same goal to lower energy usage. Using similar algorithms the authors observed energy savings up to 42% for the hard disk, 50% for the SmartBadge and 67% for the WLAN card when compared to the usual controls. Tiwari et al. [29] show that when proper software power minimization is utilized, a 40% energy savings can be achieved in microprocessor power consumption.

A scheduling problem which is largely discussed in the literature is the minimization of total completion time. Completion time is the point in time where a machine has finished processing a part. When all of the release dates are zero (all the jobs are available at the beginning, $t = 0$), the shortest processing time rule minimizes the total completion time problem [18]. Very simply stated, process all jobs in order of increasing processing time in a single batch. When this assumption is omitted (i.e., all of the jobs are not available at the beginning), the total completion time problem is NP-hard [1, 16], i.e., no known algorithm can solve this problem in polynomial time.

In many facilities, it is common to see that some of the non-bottleneck machines are left running idle. For example, in a Wichita, Kansas, USA aircraft supplier of small parts, manufacturing equipment energy and time data was collected at a machine shop of four CNC machines. The results of that study are presented in Table 1; where Idle + Break Time represents for each machine the % time in an 8-hour shift that the machine is idle but running plus % time the machine is left running during break time. Note idle time does not include activity considered as set up, part removal, or maintenance. Idle + Energy Break Savings represents for each machine the % total energy consumed in an 8-hour shift during idle time plus break time. It is referred to as "savings" because this is the % energy that can be saved by turning the machine OFF. Although this machine shop is considered as the bottleneck by the production planning department, it was observed that in a 8-hour shift, on average a machine stays idle 16% of the time. If the machines were turned off during these breaks and idle times, it was calculated that at least 13% energy savings could be achieved. Note that percent energy savings is lower than percent time because of the energy consumed during actual cutting. It is observed that leaving the non-bottleneck machines Idle is considered as a normal operating practice.

*************Insert Table 1 around here *************

In environmental conscious manufacturing, methods like life cycle analysis [2] and reverse logistics and end of life decisions [11, 13] are utilized to minimize impacts on environment. The objective of this paper is to develop operational methods for machine scheduling to reduce energy consumption and from that to design a machine controller which will optimize energy usage. The controller will basically have two types of decisions: either leave the machine idle, or turn-off the machine for a pre-determined amount of time. The controller will make decisions to minimize energy usage while meeting other scheduling criteria. The decision to leave the machine idle or shut it down, will utilize dispatching rules and multi-objective optimization. This control problem studied in this paper is difficult because all jobs are not available at the beginning, i.e., job release dates are unknown. Instead, some information about job arrivals such as the distribution of the inter-arrival times and its parameters, etc. may be available. The issue is how to best use this information to predict the next arrival in order to facilitate the decision of the controller and make the most efficient use of energy. Statistical methods may be readily applied to identify the inter-arrival time distribution to predict the next arrival. When the inter-arrival times do not follow a known distribution, a neural network model to forecast the arrival process replaces statistical models. Once the next arrival is known (or can be estimated), the controller will make a decision using the proposed dispatching rules or utilizing multi-objective optimization.

The organization of this paper is as follows. In the next section several dispatching rules to minimize energy consumption are presented and their performance is evaluated under different operating conditions. In section 4, a neural network model is proposed for the case when the arrival process of incoming jobs does not follow a probability distribution. Section 5 is on multi-objectives optimization which enables the controller to reduce energy consumption while optimizing additional scheduling objectives.

2 Dispatching rules to minimize energy

In this section, several dispatching rules for a machine controller which minimizes energy usage are presented. When a machine is turned on, it takes warm-up time before the machine is ready to process a part. A warm-up consumes Start up (turn on) energy, i.e., the energy required to start up the machine. To process a part the machine consumes Make Part Power per unit time. Idle power is the power required per unit time by the machine when staying idle. The machine requires Stop Time to be turned off which consumes stop (turn off) energy.

The ability to predict the next arrival of a job (i.e., the inter-arrival time between jobs) is a critical issue that needs to be considered in deciding if the machine should be turned off or not. When the only objective is minimizing the total energy usage while not postponing processing of jobs (i.e., if possible, start processing a job as soon as the job becomes available), predicting the next arrival time becomes critical. Based on the ratio of shut down/start up energy and idle energy, one can come up with a dispatching rule which will tell the operator/machine controller if the machine should be turned off for a certain amount of time (i.e., before the next arrival happens).

Let S be the breakeven duration for which Turn OFF+Turn ON is economically justifiable instead of running the machine at idle, i.e.,

$$S = \frac{\text{Turn OFF +Turn ON Energy}}{\text{Idle Power Consumption per unit time}}.$$

Let γ be the interarrival time between jobs and t_{OFF} be the time required to turn off and then turn on the machine. If $\gamma \geq \max(S, t_{OFF})$, then the machine can be turned off for a particular length of time and then turned on to process some other jobs. This logic is used to design several dispatching rules and compare the performance of these dispatching rules to a production plan where the energy savings are not considered (i.e., the no controller (i.e., unintelligent) case where the machine simply starts, then is either idle or processing a part and finally shuts down).

A ten job example is used through this section to illustrate and compare energy consumption and maximum completion time for the proposed dispatching rules. The interarrival time and service time are exponentially distributed with a mean of 20 and 6 seconds, respectively. The initial condition of the machine is assumed to be off. The warm up takes 10 seconds and consumes three hp.sec (the initial spike in Figure 1). The Make Part Power and idle power are 6 hp and 0.3hp, respectively. Turning off takes 2 seconds consuming 1 hp.sec of energy. As a result, a turn off-turn on sequence (setup) consumes 4 hp.sec in 12 seconds. Matlab 7 [17] is used to test the effectiveness of the dispatching rules on a Hewlett Packard Personal Computer with 1.66MGhz processor and 512MB of memory.

In Table 3, the energy consumption and maximum completion time of several dispatching rules are given and Figure 1 represents the power consumption of the machine over time when there is no controller. The area of the first spike which starts at $t = 0$ represents the turn on energy. The area of the very last spike at 209.64 seconds is the turn off energy. Finallay, the machine is in idle power at $t = 50$. When there is no controller, the total energy consumption (TEC) is 503.9hp.sec and the maximum completion time (C_{max}) of 209.64 seconds is achieved. Note that the energy consumption when there is no controller is an upper bound, while the maximum completion time is a lower bound.

*************Insert Figure 1 around here *************

In Section 2.1, the developed dispatching rules for minimizing energy consumption are described. Next, in Section 2.2, the effect of batching on energy consumption is analyzed.

2.1 Dispatching Rules to Minimize Energy Consumption when there is no batching

Assuming that a job should be processed as soon as the machine becomes available (i.e., no scheduled idle time is allowed) the machine is shut down if three conditions hold:

- there is no part waiting in the queue
- there is enough time for a turn off - turn on operation before the next job arrives
- the total idle energy consumption is greater than the energy to shut down and restart the machine

If the jobs need not be processed as soon as they are available, the second condition can be relaxed. Note that the dispatching rule presented above (DRMEC1) provides a lower bound on energy consumption and maximum completion time when there is no batching consideration (since this problem is deterministic). Figure 2 shows that when DRMEC1 is utilized, the total completion time does not change. The number of setups (turn off/turn on) increases to five and TEC reduces to 489.02hp.sec.

*************Insert Figure 2 around here *************

Now, let's assume that release dates of the incoming jobs are unknown. However, inter-arrival time distribution and parameters related to this distribution are given. The second dispatching rule (DRMEC2a) turns off the machine for at least the next arrival or average interarrival time (λ) only if

- there is no part waiting in the queue
- the average inter-arrival time (λ) is less than time needed to turn off-turn on operation,
- the idle energy of waiting λ minutes is greater than the energy of a turn off-turn on Operation.

The objective is to achieve the lower bound with a lack of information on the jobs. DRMEC2a consumes energy at least as much as DRMEC1, i.e., the energy consumption is between the lower and upper bound as described before.

*************Insert Figure 3 around here *************

Assuming that the interarrival time is exponential, instead of turning the machine on when there is no part waiting, we can just wait for another λ minutes (this is as a result of the memoryless property of the exponential distribution [**?**]). Note that the exponential distribution is the only distribution having this property. For example, when the interarrival time is uniformly distributed between a

and b, The probability that the next arrival will be in more than t time units, is $P(x > t) = \frac{b-t}{b-a}$ and the probability that the next arrival will be in more than $s+t$ time units given that the next arrival will be in more than t time units is $P(x > s+t|x > t) = \frac{P(x>s+t)}{P(x>t)} = \frac{b-s-t}{b-t} \neq \frac{b-s}{b-a}$. In the case where the interarrival time is not exponential, therefore after each waiting interval, a new waiting time has to be computed depending on the preceding one if no part has arrived. Eventually, this dispatching rule (DRMEC2b) results in turning off the machine until the next job is available. One can also try to turn off the machine for an amount of time in which there will be no arrival for a certain confidence level. This rule (DRMEC2c) is very similar to DRMEC2a: but, instead of using the mean of the distribution in the decision process, an α% confidence interval on non-arrival of parts is utilized.

Figure 3 and Table 3 show that when DRMEC2a, DRMEC2b and DRMEC2c (using a 60% confidence interval) are utilized, the total completion time increases in only DRMEC2b to 219.64. The number of setups (i.e., the number of the turn off/turn on operations) for DRMEC2a and DRMEC2c is seven while for DRMEC2b, the total number of setups is six.

Assuming that the distribution of arrivals is known but the distribution parameters has to be estimated, similar dispatching rules can be proposed. A smart controller would then learn the parameter of the distribution. As a result, initially, the average inter-arrival time is considered to be zero. If there is no job available job for processing and the estimated interarrival time ($\hat{\lambda}$) is longer than the breakeven duration (S), the machine is turned off for $\hat{\lambda}$ ((DRMEC3a). A variant of DRMEC2b can be implemented for the case where the distribution parameter has to be estimated (DRMEC3b). Finally, the last dispatching rule (DRMEC3c) uses confidence interval instead of the average inter-arrival time as in DRMEC2c.

*************Insert Figure 4 around here *************

Figure 4 shows that when DRMEC3a, DRMEC3b and DRMEC3c are utilized, the total completion time increases in only DRMEC3b to 219.64. DRMEC3b behaves exactly as DRMEC2b. The energy consumption increases in all other cases. The number of setups (turn off/turn on) for DRMEC3a and DRMEC3c is six while for DRMEC3b, the total number of setups is five.

2.2 Dispatching Rules to Minimize Energy Consumption when there is batching

One of the lean manufacturing principles is on reducing the number of setups (in this case turn on/off machines) and the waste (energy consumption). One might achieve a lean system by batching the jobs to be processed. The proposed approach on reduction of energy consumption in a manufacturing environment can be implemented using a variety of ways. For example, consider the "k in a batch dispatching rule" where jobs have to join a queue before they are processed. In this rule, there should be at least k jobs (batch size) in the queue before processing can start (i.e., the machine is turned on). The machine processes jobs until the queue is empty. If there is sufficient time until the arrival of the next k jobs, then the machine is turned off to realize more energy savings. Using this algorithm, the total energy consumption is smaller than when the schedule is known (DRMEC1a dispatching rule). However, as expected, the maximum completion time is greater as a result of postponing processing of jobs. In Table 3 and Figure 5, we can find the results for a batch of $k = 2$ (DRMEC4a) and $k = 3$ (DRMEC4b). When $k = 2$, the number of setups decreases to four. However, the completion time increases to 228.64 seconds. For $k = 3$, there are two setups and the overall completion time is 224.51 seconds.

*************Insert Figure 5 around here *************

Figures 6 demonstrates the effect of processing jobs in groups (batches) on total energy consumption. For an experimental setting with 20 jobs and random arrival times. When k varies from 1 to 10 the following observations are made. a) The longest completion time is observed when the batch size is 10 and the lowest one is at $k = 6$. b) there is no monotonic relation between the completion time and the batch size. c) When the batch size increases, the number of setups decreases, and thus the total energy consumption decreases. In other words, the effect of batch size on completion time is not very predictable. The effect of batch size on energy consumption is predictable and intuitive.

*************Insert Figure 6 around here *************

2.3 A summary of comparison of the proposed dispatching rules

*************Insert Tables 2 and 3 around here *************

*************Insert Figure 7 around here *************

Table 2 displays a summary of the properties of the proposed dispatching rules described in Sections 2.1 and 2.2. In Table 3, the maximum completion time (C_{max}), total energy consumption (TEC), total idle, start up and shut down energy consumption (TISSEC), i.e., TEC-total processing energy and the number of setups needed for all of the dispatching rules are given. The lower bound on energy consumption when there is no batching is when the problem is deterministic, i.e., the interarrival, release and processing times are known. In this case, DRMEC1 provides a lower bound on energy consumption. The upper bound (DRMEC1) is reached when no controller is used. We can see that the best dispatching rule concerning completion time as well as energy consumption is DRMEC2b where the machine is turned off until the next arrival if the expected interarrival time is longer than the breakeven time S and information about the distribution of the jobs inter-arrival time and the parameter of the distribution is known. When less information is known, the algorithms give results between the two bounds. Furthermore, for all dispatching rules, TISSEC (which can be seen as a waste, non-productive machine time) is lower than the no-controller case (see Figure 7). Although DRMEC2b and DRMEC3b consume less TISSEC than DRMEC1b, this is in the expense of longer completion time. Similarly, when there is batching, the more parts the batch consists off, the more energy is saved but generally the more time it takes.

3 Experimental analysis of the dispatching rules

*******Insert Table 4, 5, 6 and 7 around here *******

In the experimental design, n is varied over 100, 200 and 300 jobs. λ can take values of 6.25, 12.5 and 18.75 while the levels that p can take are 5, 10 and 15, i.e., $\lambda = 1.25p$. The idle power is 1hp and setup energy which includes turn on and turn off energy is 5hp.sec. The average number of setups can be found by dividing the total setup energy by the turn off/turn on energy. For each setting, 10 runs are conducted and the results for the experimentation are presented in Table 4, 5 and 6. The overall average performance of the dispatching rules is presented in Table 7. In these tables, n is the number of jobs. C_{max} is the completion time of the last job, T_{idle} is the total idle time and T_{OFF} is the total time that the machine is off. TSE is the total setup energy and TISSEC is total idle and setup energy. The distribution of interarrival time and processing time are assumed to be exponential with mean of λ and p, respectively. Although C_{max}, T_{idle}, T_{OFF}, TSE and TISSEC are reported in the Tables 4, 5 and 6, other relevant data can be calculated using these values. For example, the total processing time (TPT) can be calculated as $TPT = C_{max} - T_{idle} - T_{OFF}$. We define performance improvement for any criteria as percentage improvement by a dispatching rule on a criterion when compared to the no controller case.

When $\lambda > p$, there is significant potential savings in the total energy waste (i.e.,TISSEC). For example, when $n = 100$, $\lambda = 6.25$ and $p = 5$, DRMEC1 (which provides an upper bound in energy saving when there is no batching) provides 43.8% savings in TISSEC compared to the no controller case (Table 4). For the same settings, when $n = 200$, the saving is 44.9% and when $n = 300$, this is 41.8%. Similarly when $\lambda = 18.75$ and $p = 5$ (Table 6), the savings in total waste are 75.7%, 76.9% and 76.7% for $n = 100$, 200 and 300 jobs, respectively. The case where $\lambda > p$ might indicate that the machine is not a bottleneck machine, i.e., the machine utilization rate is not high and the machine is not always processing a job. In this case, the proposed algorithm has a significant potential to decrease energy consumption.

When $\lambda < p$, arriving jobs cannot be serviced before jobs join a queue. It is observed that the machine rarely stands idle, thus although the controller decreases the total waste, i.e., TISSEC, the saving is not that significant. For example, when $n = 100$, $\lambda = 6.25$ and $p = 10$, although DRMEC1 provides 43.1% savings in TISSEC, this is less than 2 % of the total processing energy (Table 4).

On the average, the upper bound on potential savings is 72.5% (i.e., comparison of DRMEC1 vs No controller) in the case where available jobs should be processed immediately (Table 7). Overall the most effective dispatching rule is DRMEC2b. When jobs can be postponed, on the average, DRMEC2b provides 80% energy savings compared to 72.5% in DRMEC1b. However, this is at the expense of a 0.15%

increase in the maximum completion time. When production is postponed, the energy consumption decreases. The proposed dispatching rules decreases the idle time significantly at the expense of increasing the total number of setups. However, the total idle and setup energy consumption is significantly lower than the no controller case when the machine is not a bottleneck.

When batching is allowed, DRMEC5a and DRMEC5b are utilized as dispatching rules, The total completion time increases. For example, when $\lambda = 12.5$ and $p = 5$, DRMEC5a (batch of two) decreases the TISSEC by 82.1%, 83.7% and 83.2% for $n = 100$, 200 and 300, respectively (Table 5). DRMEC5b (batch of three) on average saves 88.1% in TISSEC for the same parameters. When batching is considered for these dispatching rules, the maximum completion time increases only by 0.7%. When overall simulation results are considered, DRMEC5a increases the completion time 0.3% and decreases the TISSEC by 88.6% (Table 7). Similarly, DRMEC5b decrease the energy consumption by 91.9% at the expense of a 0.6% increase in maximum completion time.

To summarize, the proposed dispatching rule provide an effective mean to minimize the total energy consumption the savings in energy consumption depend on the interarrival time, processing time of jobs and the breakeven time of the machine. If the warm up time is longer than the inter-arrival time, or if turn on/turn off energy is high, the controller using the proposed dispatching rules will provide similar results with the no controller case, i.e., it is better to never turn the machine off until the last job is processed. The lower the warm up time, stop time, turn on/turn off energy, and machine utilization rate, the larger the potential savings in energy consumption is. This is also true when the idle energy is relatively high. There are some cases where the controller will be inefficient (i.e., will not provide significant savings in TISSEC). For example machine with large warm up time and warm up energy (such as an industrial oven) will not take advantage of a controller. Thus to decide whether the proposed dispatching rules would be useful or not, is to determine the characteristics of the machine (e.g. using the energy data collection framework proposed in [5]).

4 Predicting job arrivals using neural networks

The dispatching rules proposed in Section 3 rely on the accuracy of interarrival time estimation. Suppose that the inter-arrival times follow a non-stationary Poisson process, i.e., a Poisson process where the inter-arrival rate $\lambda(t)$ is a function of time. In a manufacturing environment, this simply implies that the rate of arrival at a specific station depends on the time. For example, the rate of arrival can be higher in the morning and in the afternoon, and less around the lunch break, i.e., at noon. In this case, the interarrival times cannot be modelled using a probability distribution or a direct forecasting method, instead an artificial neural network (ANN) based forecasting model is constructed to predict the next arrival given the relevant inputs. ANNs have shown to be very effective in time series predictions and forecasting. Examples of success can be seen in economics, physical phenomena like forecasts of the weather, and physiological phenomena as in predicting a rise in temperature. ANN approaches are particularly good at short term predictions [23].

The ANN is constructed to predict the next arrival based on the preceding arrivals. The ANN forecast and the dispatching rule will be combined to make decisions.

The ANN paradigm used in this application is the feedforeward fully connected multi-layered perceptron trained by the plain vanilla version of the backpropagation algorithm [14, 23, 30]. Training and test data consisted of the time series of interarrivals using five prior consequitive arrivals (i.e., $a_t, , a_{t+4}$) inputs to predict the next interarrival (a_{t+5}, i.e.,

$$f\left(a_t, a_{t+1}, a_{t+2}, a_{t+3}, a_{t+4}\right) \Rightarrow a_{t+5}.$$

The data for simulating interarrivals was generated using an algorithm described previously [15]. Then, this data is used for constructing the ANN forecasting model. The data follows a non-stationary Poisson process (Figure 8). The interarrival rate follows an exponential distribution with a non constant rate where the arrival rate is larger at noon. The network architecture 5:4:4:1 was chosen by experimentation. The network was trained using data from fifty different problems and then validated using another 50 problem sets. Training and validation root mean square errors were 0.28 and 0.85 and a correlation coefficient of 0.99 is obtained. These values indicate that the ANN can forecast arrivals very accurately.

Variations of the dispatching rules presented in Section 3 and and the trained ANN are combined. Each time the machine finishes processing a part, the controller decides to shut down the machine or leave it running at idle based on the ANN forecast. The data use for validating the ANN was used in assessing the combined ANN and dispatching algorithm. Table 8 provides the result for the processing of the fifty parts. A variation of DRMEC2a algorithm in which the predicted interarrival time is compared with the breakeven time, S, and the decision to turn off/turn on the machine is given, and the no controller algorithm is compared. The results indicate a decrease in the energy consumption with the proposed methodology when compared to a machine with no controller (74.2 vs. 63.9 hp.sec.s, i.e., more than 10% savings).

*************Insert Figure 8 around here *************

*************Insert Table 8 around here *************

To summarize, using the dispatching rule significant energy savings can be achieved especially in a non-bottleneck machine environment. It is also observed that if jobs can be postponed and grouped together, the resulting energy savings might be higher. In the next section, our goal is to provide a multiobjective optimization approach to minimize both energy consumption and the total completion time to obtain the best compromise between two objectives.

5 Multi-objective optimization

In a manufacturing company, the energy consumption may not be the only objective when the controller makes a decision; one or more criteria such as completion time, lateness (the discrepancy between the due date of a job and completion time), tardiness (lateness of a job if it fails to meet its due date), and throughput may also be important. When more than one criterion is considered, usually, a multi-objective scheduling approach should be utilized [10]. In this section, it is assumed that the decision maker's goal is to minimize the energy consumption and the total completion time at the same time.

Assume that n jobs have to be processed in the order of their arrivals (i.e., first in first out basis). Suppose the decision maker would like to minimize two objectives at the same time. Given the arrival time (r_j), processing time (P_j) of job j is known, one can optimize to find an optimal schedule to determine the total completion time (C_j) of all jobs while considering the energy required to process all orders using the following mathematical program:

$$
\begin{aligned}
&\min_{C,y} \quad f_1 = \textstyle\sum_{j=1}^{n-1} ((C_{j+1} - P_{j+1}) - C_j)\,\mathrm{IP} + \sum_{j=1}^{n-1} y_j + \mathrm{PP} \sum_{j=1}^{n} P_j \\
&\min_{C,y} \quad f_2 = \textstyle\sum_{j=1}^{n} C_j \\
&\qquad C_j - P_j \geq r_j && \forall j = 1...n \\
&\qquad If\ ((C_{j+1} - P_{j+1}) - C_j) > S \\
&\qquad\quad \text{then } y_j = \mathrm{SE} - ((C_{j+1} - P_{j+1}) - C_j)\mathrm{IP},\ \text{else } y_j = 0, && \forall j = 1...n-1 \\
&\qquad C_{j+1} - P_{j+1} \geq C_j, && \forall j = 1...n-1 \\
&\qquad C_j, y_j \geq 0
\end{aligned}
$$

In this formulation, IP is the idle power per unit time, SE is the setup energy (i.e., turn off/turn on energy), PP is the power to process a job per unit time and S is the breakeven duration for which turn OFF/ON is economically favorable. The two objectives are minimization of the total completion time $f_1 = \sum_{j=1}^{n} C_j$ and minimization of the Total Energy Consumption

$$f_2 = TEC = \sum_{j=1}^{n-1} \left((C_{j+1} - P_{j+1}) - C_j \right) \mathrm{IP} + \sum_{j=1}^{n-1} y_j + \mathrm{PP} \sum_{j=1}^{n} P_j.$$

This is equal to

$$TEC = \left(C_n - C_1 - \sum_{j=2}^{n} P_j \right) \mathrm{IP} + \sum_{j=1}^{n} y_j + \mathrm{PP} \sum_{j=1}^{n} P_j$$

which is the sum of the total idle energy without considering any turn on/offs and the total setup energy which excludes the idle energy included in the first term. The total energy equation excludes start energy before the first operation and stop energy after the last operation and the total processing energy which is a constant. The first set of constraints simply states that a job cannot be processed before it is actually available. The second set of constraints represents the decision whether to leave the machine idle or to perform a setup. The third set of constraints determines the completion time of a job and ensures that a job can not be processed before the preceding job is completed.

In the above multiobjective formulation, the objective functions are linear but the second set of constraints have to be linearized in order to obtain a mixed integer linear program. By transforming the second set of constraints, we obtain the following linear mixed integer multiobjective program to minimize total completion time and energy consumption (LMIP-MTCTEC):

$$
\begin{aligned}
&\min_{C,y,b} && \textstyle\sum_{j=1}^{n-1}((C_{j+1}-P_{j+1})-C_j)\mathrm{IP}+\sum_{j=1}^{n-1}y_j && \\
&\min_{C,y,b} && \textstyle\sum_{j=1}^{n}C_j && \\
& && C_j-P_j \geq r_j, && \forall j=1...n \\
& && ((C_{j+1}-P_{j+1})-C_j)-S \leq Lb_{1j}, && \forall j=1...n-1 \\
& && y_j-(\mathrm{SE}-((C_{j+1}-P_{j+1})-C_j)\mathrm{IP} \leq L(1-b_{1j}), && \forall j=1...n-1 \\
& && -y_j+(\mathrm{SE}-((C_{j+1}-P_{j+1})-C_j)\mathrm{IP} \leq L(1-b_{1j}), && \forall j=1...n-1 \\
& && -(((C_{j+1}-P_{j+1})-C_j)-S) \leq Lb_{2j}, && \forall j=1...n-1 \\
& && y_j \leq L(1-b_{2j}), && \forall j=1...n-1 \\
& && -y_j \leq L(1-b_{2j}), && \forall j=1...n-1 \\
& && C_{j+1}-P_{j+1} \geq C_j, && \forall j=1...n-1 \\
& && C_j, y_j \geq 0 && \\
& && b_{1j}, b_{2j} \in \{0,1\} &&
\end{aligned}
$$

In this formulation, L is a large constant and b_{1j} and b_{2j} are the binary variables utilized in linearizing the "Ifthen" constraint in the original formulation. When $((C_{j+1}-P_{j+1})-C_j) > S$, $b_{1j}=1$ and $b_{2j}=0$ and

$$y_j = \mathrm{SE}-((C_{j+1}-P_{j+1})-C_j)\mathrm{IP}$$

(third and fourth set of constraints in LMIP-MTCTEC). If $((C_{j+1}-P_{j+1})-C_j) \leq S$, then $b_{1j}=0$ and $b_{2j}=1$, thus, $y_j=0$ (fifth and sixth constraints in LMIP-MTCTEC. Note that since $\mathrm{PP}\sum_{j=1}^{n}P_j$ is a constant, this term has been dropped from LMIP-MTCTEC.

The above multi-objective problem can be solved by combining the two objectives into a single objective by adding weighted sum of both objectives, i.e. the objective function for the weighted problem (LMIP-MTCTEC-W) is

$$f(w_1, w_2) = w_1 f_1 + w_2 f_2 = w_1 \sum_{j=1}^{n} C_j + w_2 \left(\sum_{j=1}^{n-1} ((C_{j+1} - P_{j+1}) - C_j)\mathrm{IP} + \sum_{j=1}^{n-1} y_j \right)$$

This mathematical program is a mixed integer problem. For any pair of weight combinations, (w_1, w_2), a non-dominated solution can be obtained [26]. Note that in a multiobjective optimization problem, an improvement of one objective of a non-dominated solution requires a decrease in one or more of the other objectives. To obtain a set of non-dominated solutions, the following procedure can be utilized:

Step 1: Generate random values for w_1 and w_2 where $w_1 + w_2 = 1$.

Step 2: Solve LMIP-MTCTEC-W.

Step 3: Add the solution to the set of non-dominated solutions.

Step 4: If stopping criterion is not satisfied, go to Step 1.

The stopping criterion can be having a predetermined number of non-dominated solutions solutions, which usually depends on the available computational power and time. After the set of non-dominated solutions is obtained, the decision maker can determine the "best solution/scheduling plan" to be implemented using his/her preferences such as having the maximum completion time or cycle time being less than a specific duration, etc. The decision maker can choose any of those non-dominated solutions based on his/her secondary objectives, i.e., the decision maker can analyze the trade-off between total completion time and total energy consumption to make the final production planning decisions. The decision maker's preferences might help to eliminate several non-dominated solutions. Methods like the Analytical Hierarchy Process [24] can be utilized to obtain the most preferred solution.

Following is an example of a set of non-dominated solutions for the problem given in Table 9. Figure 9 presents the set of non-dominated solutions obtained using the procedure described above for the 9 job example. The least TISSEC (total idle and setup energy) occurs when the total completion time is the highest. Similarly, the highest TISSEC corresponds to the lowest total completion time. Among the non-dominated solutions, for example, if a constraint on total completion time of being less than 210 seconds is added, four solutions could be eliminated. Among the remaining solutions, we may select the solution that consumes the least energy.

*************Insert Table 9 around here *************

*************Insert Figure 9 around here *************

Note that LMIP-MTCTEC-W assumes that jobs should be processed in the order of arrivals. Some might argue that LMIP-MTCTEC-W might not be very relevant to practical situations. The next step in this research is to propose a mutiobjective mathematical program with minimum total completion time and energy consumption while allowing processing of jobs in any order. Since $1|r_j|\sum_{j=1}^{N} C_j$ is an NP-Hard problem [1, 19], this multiobjective program is NP-hard as well. In solving this multiobjective program, LMIP-MTCTEC-W appears as a sub-problem if decomposition or metaheuristic approaches are utilized.

6 Conclusion

This paper addresses the energy consumption of a production facility by minimizing the expended energy of manufacturing equipment through operational methods. The methodology is based upon the realization that large quantities of energy are consumed by non-bottleneck machines as they lay idle. The developed methadology may help to reduce the total energy consumption while optimizing some other production scheduling objective.

In the first step, several algorithms are developed for a machine controller using the given information about the schedule. The controller, along with its dispatching rules, has proven to efficiently decrease energy consumption. The following results were observed:

- Batching increases the total completion time and decreases the number of setups and idle time thus the total setup energy and the idle energy
- When production is postponed, the energy consumption may decrease.
- When the machine is not a bottleneck, i.e., the machine utilization rate is not high and the machine is not always processing a job, the proposed dispatching rules have a potential to decrease energy usage significantly. The dispatching rules decreases the idle time significantly at the expense of increasing the total number of setups. However, the total idle and setup energy is decreased significantly when the machine is not bottleneck.

- If the interarrival time until the next job is longer than the breakeven duration, turning off the machine until the arrival of next job (i.e., DRMEC2b dispatching rule) provides significant savings in energy consumption.

In the second step, an ANN was constructed to forecast interarrivals (non-stationary arrivals with unknown distributions) and combine with dispatching rules. This combination has resulted in an efficient controller for ”unusual” schedules. Finally, multi-objectives optimization models were used to to minimize energy consumption and total completion time. The solutions are non-dominated solutions and assist the controller in choosing the best schedule.

Further research will be conducted to determine the trade off between machine wear due to repeated on/off cycles and energy savings. Other research will concentrate on developing machines with multiple sleep mode states and a specific controller for those machines. These lower power modes will have different warm up time and warm up energy and may reduce the negative effects of turning on and off the machine.

Acknowledgement: The authors acknowledge the National Science Foundation for support of the research reported in the article: DMI-NSF 0537839

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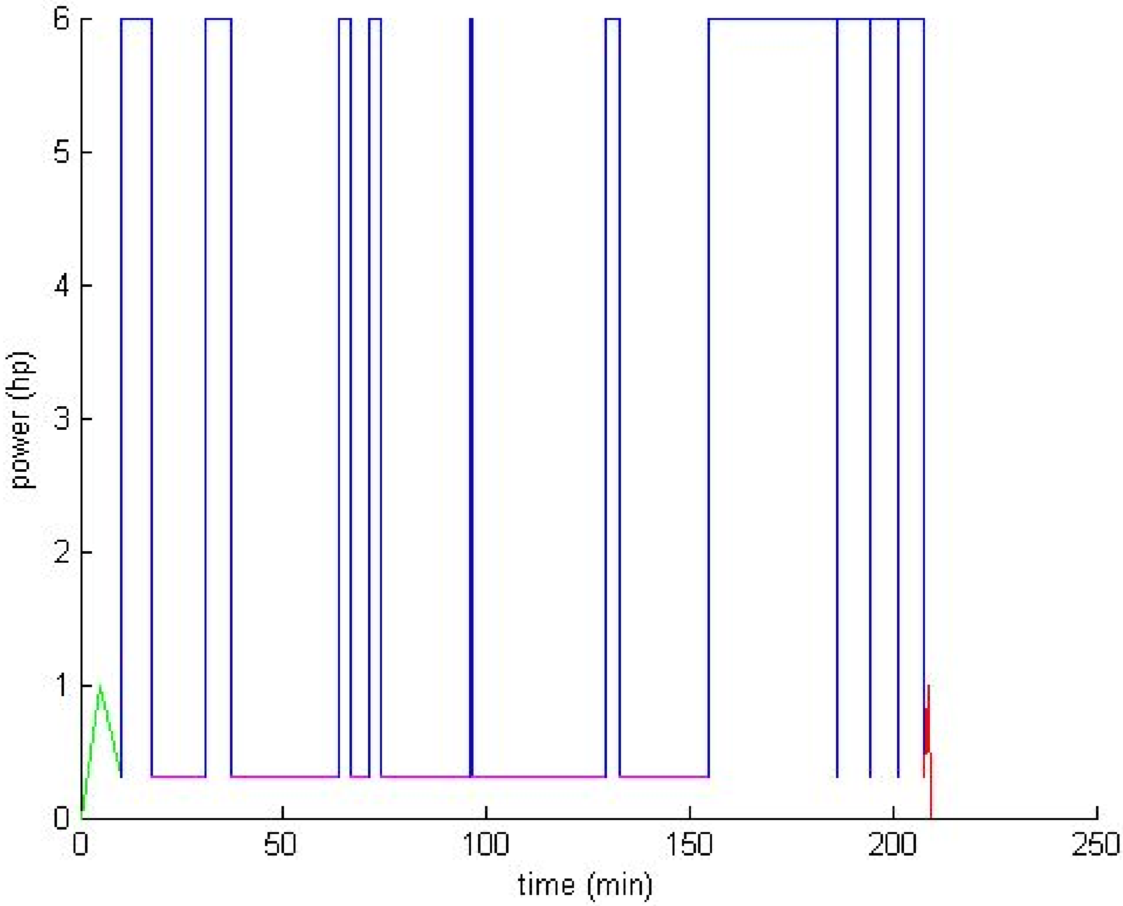


Figure 1: Power requirement vs time- No Controller case

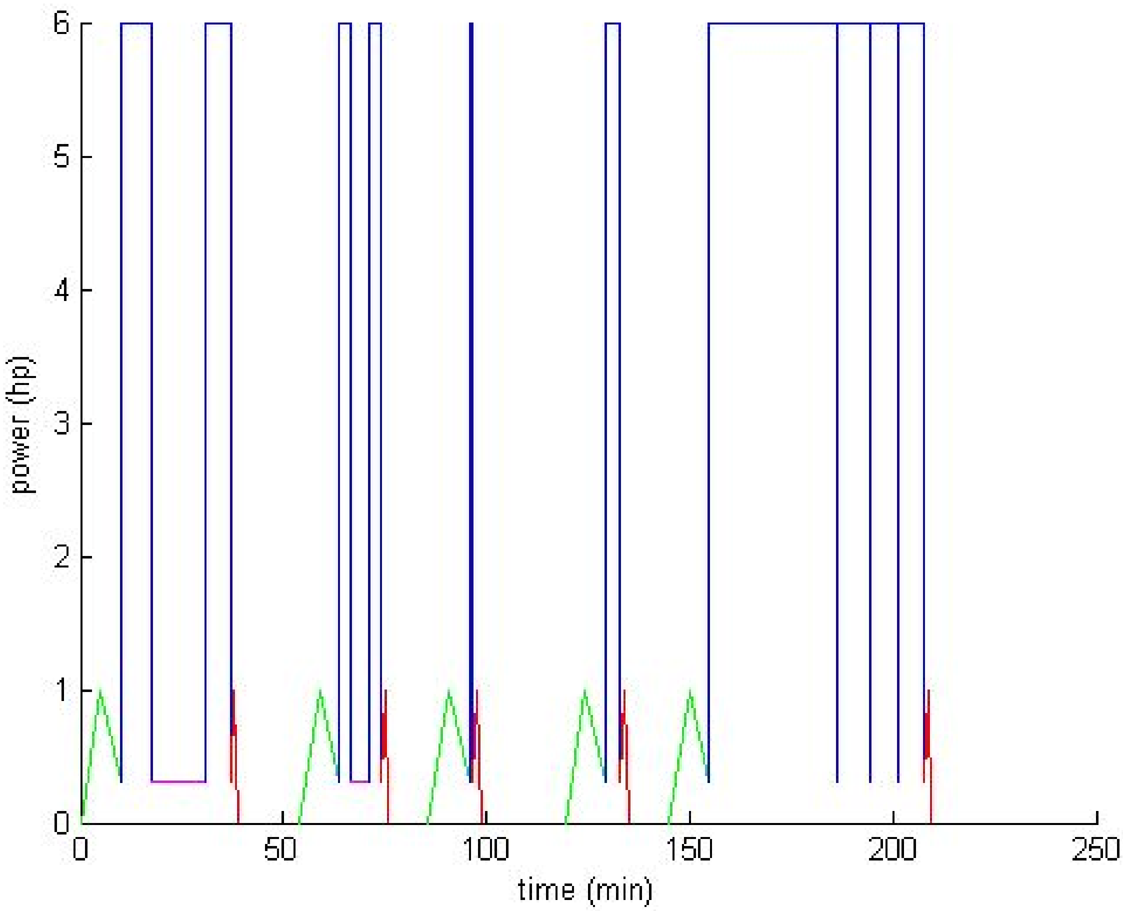
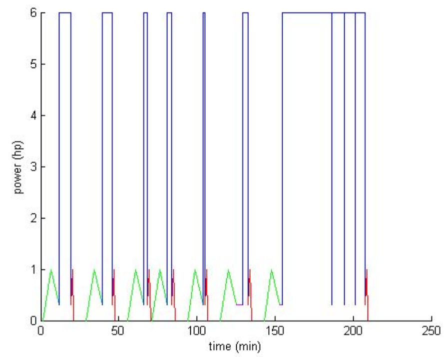
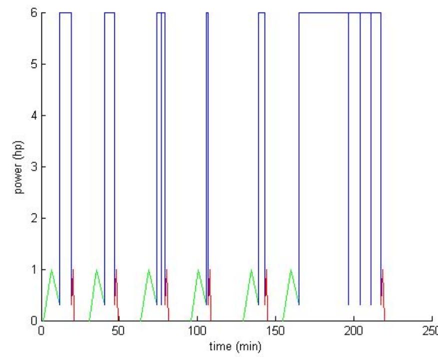


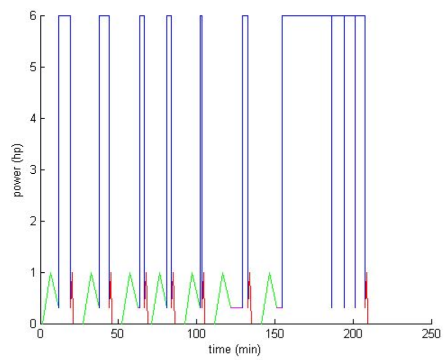
Figure 2: Power requirement vs time for DRMEC1 dispatching rule



a) DRMEC2a

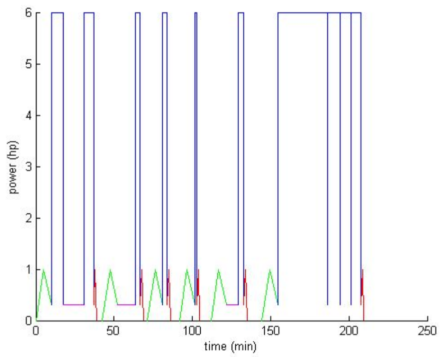


b) DRMEC2b

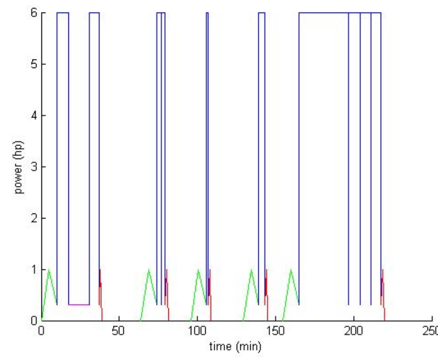


c) DRMEC2c

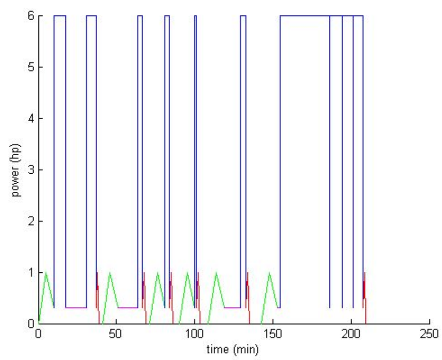
Figure 3: Power Requirement vs Time for DRMEC2a, DRMEC2b and DRMEC2c dispatching rules



a) DRMEC3a

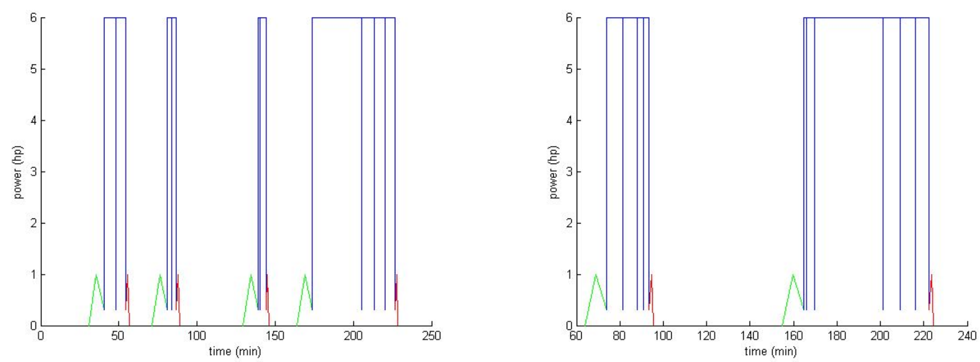


b) DRMEC3b



DRMEC3c

Figure 4: DRMEC3a, DRMEC3b and DRMEC3c dispatching rules



a) DRMEC4a b) DRMEC4b

Figure 5: Power Requirement vs Time when there is batching

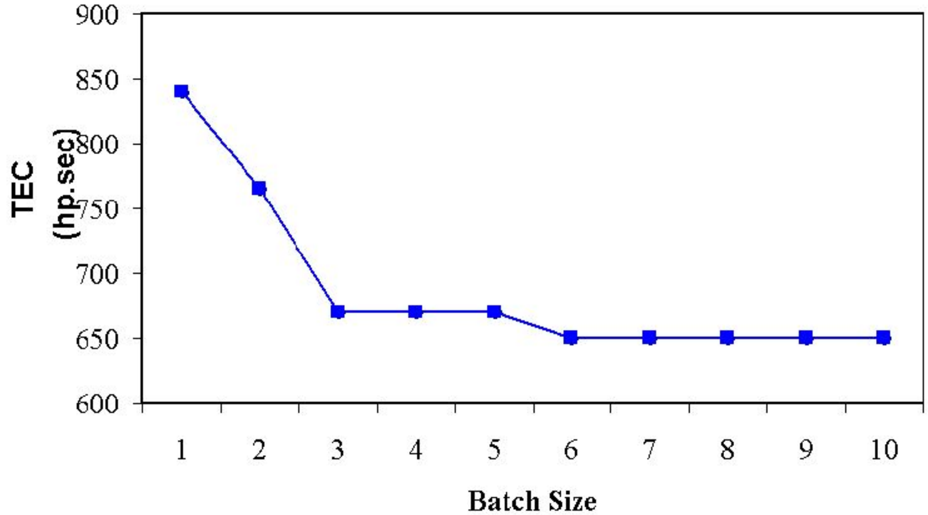


Figure 6: Effect of processing jobs in groups on the total energy consumption

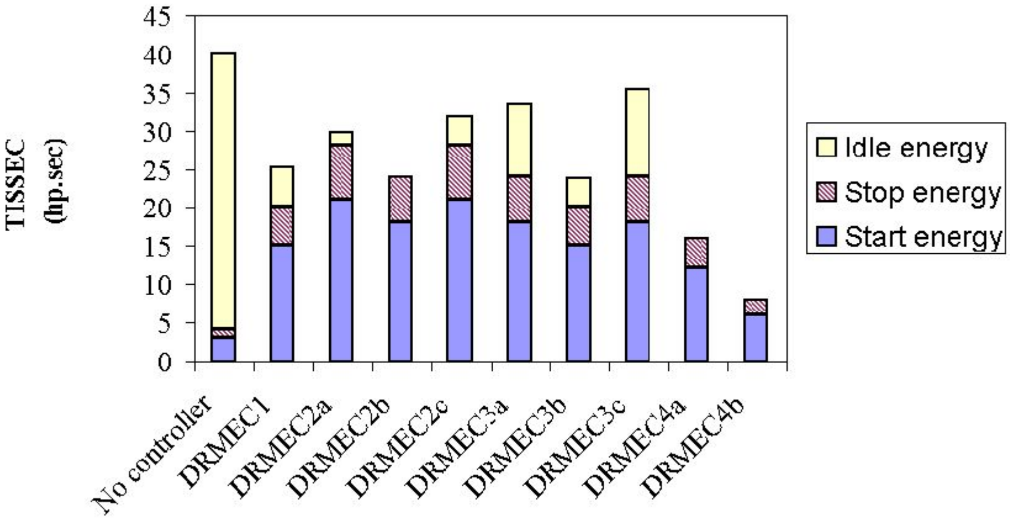


Figure 7: Energy consumption when different dispatching rules are utilized

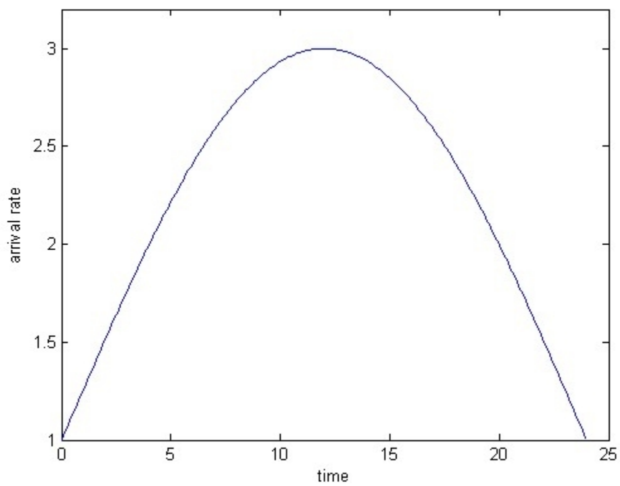


Figure 8: Arrival rate depending on time and data for training and testing

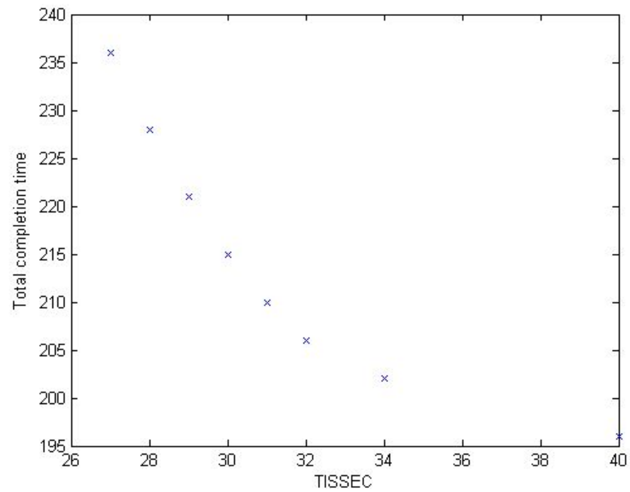


Figure 9: Representation of the non-dominated solution for the instance of the problem

	Machine 1	Machine 2	Machine 3	Machine 4
Idle + Break Time	23%	16%	28%	28%
Idle + Break Energy Savings	23%	9%	14%	6%

Table 1: Data on machine utilizations in a small sized industry: The given data is a lower bound on % of 8 hour shift for potential energy savings over all machines

Dispatching Rule	Schedule idle time	Batch size	Distribution		Confidence level
			Arrivals	Parameters	
No controller	-	-	-	-	-
DRMEC1	-	-	Deterministic	-	-
DRMEC2a	x$\bullet$	-	Exponential	Known	-
DRMEC2b	x$*$	-	Exponential	Known	-
DRMEC2c	x$\bullet$	-	Exponential	Known	x
DRMEC3a	x$*$	-	Exponential	Estimated	-
DRMEC3b	x	-	Exponential	Estimated	-
DRMEC3c	x	-	Exponential	Estimated	x
DRMEC4a	x	2	Exponential	-	-
DRMEC4b	x	3	Exponential	-	-

Table 2: Description of the different dispatching rules($\bullet$ = stop for a certain amount of time, $*$ = wait until next arrival)

Dispatching Rule	C_{max} (sec)	TEC (hp.sec)	TISSEC (hp.sec)	Number of Setups
No controller	209.64	503.90	40.10	1
DRMEC1	209.64	489.02	25.22	5
DRMEC2a	209.64	493.63	29.83	7
DRMEC2b	219.64	487.80	24.00	6
DRMEC2c	209.64	495.58	31.78	7
DRMEC3a	209.64	497.43	33.63	6
DRMEC3b	219.64	487.67	23.87	5
DRMEC3c	209.64	499.28	35.48	6
DRMEC4a	228.64	479.80	16.00	4
DRMEC4b	224.51	471.80	8.00	2

Table 3: Summary of the results of different algorithms (Total processing energy=463.8 hp.sec)

Table 4: Performance of dispatching rules when the interarrival time, $\lambda = 6.25$

		$n = 100$					$n = 200$					$n = 300$				
	Heuristic	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC
$p = 5$	No contr	665.2	159.0	6.0	5.0	164.0	1264.4	235.8	6.0	5.0	240.7	1896.7	414.0	414.0	5.0	419.0
	DRMEC1	665.2	39.2	125.8	53.0	92.2	1264.4	59.1	182.7	73.5	132.5	1896.7	106.3	106.3	137.5	243.8
	DRMEC2a	668.3	42.5	125.7	100.5	143.0	1267.9	65.1	180.1	144.5	209.6	1899.1	104.1	104.1	255.5	359.5
	DRMEC2b	669.0	0.0	168.9	77.0	77.0	1268.1	0.0	245.5	109.0	109.0	1901.0	0.0	0.0	198.5	198.5
	DRMEC2c	665.2	158.3	6.7	5.0	163.3	1264.4	235.1	6.6	5.0	240.1	1896.7	413.4	413.4	5.0	418.4
	DRMEC3a	667.7	60.7	106.8	79.0	139.7	1267.3	127.3	117.4	89.0	216.3	1899.1	143.4	143.4	211.0	354.4
	DRMEC3b	667.8	31.2	136.4	62.5	93.7	1267.7	83.0	162.0	70.5	153.5	1901.0	68.7	68.7	167.0	235.7
	DRMEC3c	666.7	83.3	83.1	57.0	140.3	1265.0	191.0	51.4	32.0	223.0	1897.0	295.6	295.6	90.0	385.5
	DRMEC4a	672.2	0.0	172.1	46.0	46.0	1269.7	0.0	247.1	73.0	73.0	1903.9	0.0	0.0	128.0	128.0
	DRMEC4b	673.5	0.0	173.3	37.5	37.5	1272.0	0.0	249.4	52.5	52.5	1905.9	0.0	0.0	91.0	91.0
$p = 10$	No contr	1034.6	10.2	6.0	5.0	15.2	2021.3	26.4	6.0	5.0	31.4	2938.0	13.1	13.1	5.0	18.1
	DRMEC1	1034.6	2.2	14.0	7.5	9.7	2021.3	3.6	28.8	11.5	15.1	2938.0	2.6	2.6	8.0	10.6
	DRMEC2a	1035.8	3.4	13.9	10.5	13.9	2023.6	11.4	23.3	18.0	29.4	2940.1	2.9	2.9	14.0	16.9
	DRMEC2b	1036.3	0.0	17.9	9.5	9.5	2024.8	0.0	35.9	15.0	15.0	2941.4	0.0	0.0	12.0	12.0
	DRMEC2c	1034.8	9.7	6.7	5.0	14.7	2021.4	25.8	6.7	5.0	30.9	2938.2	12.5	12.5	5.0	17.5
	DRMEC3a	1036.1	5.9	11.8	9.0	14.9	2022.9	13.0	21.0	13.0	26.0	2939.2	7.2	7.2	9.5	16.7
	DRMEC3b	1035.6	4.5	12.7	8.0	12.4	2024.4	9.7	25.7	13.0	22.8	2939.9	7.1	7.1	9.5	16.6
	DRMEC3c	1037.3	2.7	16.2	8.5	11.2	2022.8	9.6	24.3	11.0	20.6	2941.4	3.6	3.6	9.0	12.5
	DRMEC4a	1041.2	0.0	22.8	7.0	7.0	2029.2	0.0	40.3	8.5	8.5	2943.5	0.0	0.0	6.0	6.0
	DRMEC4b	1045.6	0.0	27.2	6.0	6.0	2033.1	0.0	44.2	7.0	7.0	2949.6	0.0	0.0	5.5	5.5
$p = 15$	No contr	1531.1	15.3	6.0	5.0	20.3	3037.7	7.0	6.0	5.0	12.0	4433.3	2.0	2.0	5.0	7.0
	DRMEC1	1531.1	1.5	19.7	8.5	10.0	3037.7	0.2	12.8	6.5	6.7	4433.3	0.9	0.9	5.5	6.4
	DRMEC2a	1532.9	5.9	17.2	13.0	18.9	3038.2	1.4	12.1	9.0	10.4	4435.4	0.1	0.1	7.5	7.5
	DRMEC2b	1534.7	0.0	24.9	11.5	11.5	3040.4	0.0	15.8	9.0	9.0	4435.4	0.0	0.0	7.0	7.0
	DRMEC2c	1531.2	14.7	6.7	5.0	19.6	3038.0	6.6	6.7	5.0	11.6	4433.7	1.8	1.8	5.0	6.8
	DRMEC3a	1532.4	11.4	11.2	8.0	19.4	3038.2	3.8	9.7	7.0	10.8	4433.8	1.8	1.8	5.5	7.2
	DRMEC3b	1532.7	11.3	11.6	7.5	18.8	3039.2	3.3	11.2	7.0	10.3	4433.8	1.8	1.8	5.5	7.2
	DRMEC3c	1533.3	4.9	18.6	7.5	12.4	3040.6	0.6	15.4	6.5	7.0	4435.4	1.4	1.4	5.0	6.4
	DRMEC4a	1538.7	0.0	28.9	5.5	5.5	3044.1	0.0	19.4	5.5	5.5	4441.7	0.0	0.0	5.5	5.5
	DRMEC4b	1543.9	0.0	34.1	5.5	5.5	3049.3	0.0	24.6	5.0	5.0	4448.7	0.0	0.0	5.5	5.5

Table 5: Performance of dispatching rules when the interarrival time, $\lambda = 12.5$

		$n = 100$					$n = 200$					$n = 300$				
	Heuristic	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC
$p = 5$	No contr	1242.6	699.8	6.0	5.0	704.8	2541.4	1525.1	6.0	5.0	1530.2	3741.8	2269.2	2269.2	5.0	2274.2
	DRMEC1	1242.6	53.2	652.6	185.0	238.2	2541.4	129.5	1401.7	366.0	495.5	3741.8	197.4	197.4	552.0	749.4
	DRMEC2a	1246.0	194.3	514.9	240.0	434.3	2543.1	468.4	1064.4	495.5	964.0	3744.2	704.8	704.8	744.0	1448.7
	DRMEC2b	1247.0	0.0	710.2	212.0	212.0	2545.6	0.0	1535.3	427.5	427.5	3745.6	0.0	0.0	642.0	642.0
	DRMEC2c	1245.5	218.2	490.5	241.5	459.7	2543.0	518.3	1014.4	499.5	1017.8	3744.0	768.7	768.7	755.0	1523.6
	DRMEC3a	1245.7	223.2	485.7	233.0	456.2	2543.1	486.2	1046.7	493.5	979.7	3743.7	727.8	727.8	739.5	1467.3
	DRMEC3b	1247.0	17.0	693.1	207.5	224.5	2545.6	9.2	1526.2	426.0	435.2	3745.6	26.4	26.4	638.0	664.3
	DRMEC3c	1245.3	230.2	478.2	235.0	465.2	2543.0	524.9	1007.8	497.5	1022.4	3744.0	789.1	789.1	749.0	1538.1
	DRMEC4a	1249.2	0.0	712.3	126.0	126.0	2547.5	0.0	1537.3	249.0	249.0	3749.0	0.0	0.0	381.0	381.0
	DRMEC4b	1250.8	0.0	714.0	87.0	87.0	2550.0	0.0	1539.7	174.0	174.0	3752.1	0.0	0.0	270.0	270.0
$p = 10$	No contr	1332.2	331.1	6.0	5.0	336.1	2501.1	502.1	6.0	5.0	507.1	3866.7	860.8	860.8	5.0	865.8
	DRMEC1	1332.2	27.8	309.3	88.0	115.8	2501.1	45.8	462.3	127.0	172.8	3866.7	68.7	68.7	212.5	281.2
	DRMEC2a	1334.3	93.0	246.2	115.0	208.0	2504.3	146.0	365.3	172.0	318.0	3868.5	271.0	271.0	275.5	546.5
	DRMEC2b	1336.2	0.0	341.1	102.5	102.5	2505.4	0.0	512.4	148.0	148.0	3870.9	0.0	0.0	240.5	240.5
	DRMEC2c	1334.3	103.3	236.0	116.5	219.7	2503.7	159.8	350.8	174.0	333.8	3868.3	299.3	299.3	277.5	576.9
	DRMEC3a	1334.4	98.8	240.5	111.0	209.8	2504.4	153.2	358.1	167.5	320.7	3868.7	275.4	275.4	273.0	548.5
	DRMEC3b	1336.2	20.1	321.0	99.5	119.6	2505.4	17.1	495.3	144.5	161.6	3870.9	11.1	11.1	238.5	249.6
	DRMEC3c	1334.3	101.5	237.7	110.5	211.9	2504.0	158.3	352.6	168.0	326.3	3868.4	294.2	294.2	274.5	568.7
	DRMEC4a	1338.6	0.0	343.5	58.0	58.0	2510.8	0.0	517.7	85.5	85.5	3874.4	0.0	0.0	143.5	143.5
	DRMEC4b	1342.4	0.0	347.3	40.5	40.5	2514.2	0.0	521.2	63.5	63.5	3877.5	0.0	0.0	107.0	107.0
$p = 15$	No contr	1587.7	84.7	6.0	5.0	89.7	3287.4	88.4	6.0	5.0	93.4	4617.6	118.3	118.3	5.0	123.3
	DRMEC1	1587.7	7.3	83.4	22.5	29.8	3287.4	7.1	87.3	23.0	30.1	4617.6	5.7	5.7	31.0	36.7
	DRMEC2a	1589.8	24.8	68.0	32.0	56.8	3290.3	28.3	68.9	31.5	59.8	4618.9	37.9	37.9	40.5	78.4
	DRMEC2b	1591.6	0.0	94.6	28.5	28.5	3292.3	0.0	99.3	30.5	30.5	4622.3	0.0	0.0	36.0	36.0
	DRMEC2c	1589.5	27.4	65.2	32.0	59.4	3290.6	30.5	67.1	32.5	63.0	4619.0	41.4	41.4	41.5	82.8
	DRMEC3a	1589.7	30.4	62.4	30.5	60.9	3290.5	34.7	62.8	29.0	63.7	4619.1	47.0	47.0	35.5	82.4
	DRMEC3b	1590.5	8.4	85.1	27.0	35.5	3292.0	14.1	84.8	28.0	42.2	4621.5	11.9	11.9	34.0	45.8
	DRMEC3c	1590.4	22.9	70.5	28.5	51.5	3291.1	23.4	74.8	27.0	50.4	4619.2	39.7	39.7	34.5	74.2
	DRMEC4a	1598.3	0.0	101.4	17.0	17.0	3297.9	0.0	104.9	15.5	15.5	4627.2	0.0	0.0	21.0	21.0
	DRMEC4b	1601.5	0.0	104.5	13.0	13.0	3301.8	0.0	108.8	12.0	12.0	4635.6	0.0	0.0	15.5	15.5

Table 6: Performance of dispatching rules when the interarrival time, $\lambda = 18.75$

		n = 100					n = 200					n = 300				
	Heuristic	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC
$p = 5$	No contr	1829.7	1335.8	6.0	5.0	1340.8	3849.1	2840.1	6.0	5.0	2845.1	5737.1	4224.4	4224.4	5.0	4229.4
	DRMEC1	1829.7	60.7	1281.1	264.5	325.2	3849.1	109.1	2737.0	546.5	655.6	5737.1	165.9	165.9	812.5	978.4
	DRMEC2a	1833.4	415.7	929.8	320.0	735.7	3851.9	937.1	1911.8	647.5	1584.6	5740.4	1368.1	1368.1	967.0	2335.1
	DRMEC2b	1834.7	0.0	1346.8	291.0	291.0	3853.3	0.0	2850.3	596.0	596.0	5741.8	0.0	0.0	877.5	877.5
	DRMEC2c	1833.1	454.6	890.6	321.5	776.0	3851.9	1026.4	1822.6	651.0	1677.4	5740.0	1501.6	1501.6	974.0	2475.6
	DRMEC3a	1833.1	445.8	899.4	317.5	763.3	3851.9	958.1	1890.8	643.0	1601.1	5740.3	1343.7	1343.7	961.5	2305.2
	DRMEC3b	1834.7	17.7	1329.0	287.5	305.2	3853.3	19.7	2830.6	594.0	613.7	5741.8	27.4	27.4	874.0	901.4
	DRMEC3c	1832.7	473.6	871.3	319.0	792.6	3851.9	1030.7	1818.3	647.5	1678.2	5740.1	1456.7	1456.7	966.0	2422.7
	DRMEC4a	1836.8	0.0	1348.9	165.0	165.0	3857.9	0.0	2854.9	327.5	327.5	5744.5	0.0	0.0	493.5	493.5
	DRMEC4b	1839.8	0.0	1351.9	113.5	113.5	3860.5	0.0	2857.5	223.0	223.0	5746.9	0.0	0.0	342.0	342.0
$p = 10$	No contr	1926.7	887.8	6.0	5.0	892.8	3676.3	1677.2	6.0	5.0	1682.3	5675.2	2740.3	2740.3	5.0	2745.3
	DRMEC1	1926.7	35.6	858.2	170.0	205.6	3676.3	67.4	1615.9	341.5	408.9	5675.2	113.4	113.4	539.5	652.9
	DRMEC2a	1929.2	310.8	585.6	199.5	510.3	3678.4	501.1	1184.3	398.0	899.2	5679.2	848.5	848.5	645.0	1493.5
	DRMEC2b	1931.5	0.0	898.6	189.0	189.0	3680.4	0.0	1687.4	369.5	369.5	5679.5	0.0	0.0	590.0	590.0
	DRMEC2c	1928.8	336.1	559.8	200.5	536.6	3678.4	552.9	1132.5	400.0	952.9	5678.9	934.0	934.0	650.5	1584.5
	DRMEC3a	1929.3	324.5	572.0	195.0	519.5	3678.4	537.3	1148.1	397.0	934.3	5679.3	841.8	841.8	638.5	1480.3
	DRMEC3b	1931.5	19.5	879.2	185.5	205.0	3680.4	11.9	1675.5	369.0	380.9	5679.5	26.2	26.2	588.5	614.7
	DRMEC3c	1928.9	337.8	558.3	195.0	532.8	3678.4	575.4	1110.0	399.0	974.4	5678.6	904.0	904.0	643.0	1547.0
	DRMEC4a	1935.4	0.0	902.5	101.5	101.5	3683.1	0.0	1690.0	207.5	207.5	5685.5	0.0	0.0	322.5	322.5
	DRMEC4b	1938.8	0.0	906.0	70.5	70.5	3686.1	0.0	1693.0	144.0	144.0	5693.4	0.0	0.0	233.0	233.0
$p = 15$	No contr	1962.3	445.4	6.0	5.0	450.4	3808.8	853.3	6.0	5.0	858.3	5863.6	1317.9	1317.9	5.0	1322.9
	DRMEC1	1962.3	16.4	435.1	87.5	103.9	3808.8	38.4	820.9	174.0	212.4	5863.6	40.5	40.5	249.5	290.0
	DRMEC2a	1965.3	149.3	305.2	102.5	251.8	3813.6	249.4	614.7	206.5	455.9	5867.1	441.0	441.0	293.0	733.9
	DRMEC2b	1965.8	0.0	455.0	93.5	93.5	3813.5	0.0	864.0	190.5	190.5	5868.2	0.0	0.0	266.5	266.5
	DRMEC2c	1965.8	163.2	291.7	104.0	267.2	3813.5	276.6	587.3	209.5	486.1	5866.6	485.0	485.0	294.5	779.5
	DRMEC3a	1965.5	145.1	309.6	102.0	247.1	3813.8	262.8	601.6	203.5	466.3	5867.5	447.4	447.4	292.0	739.4
	DRMEC3b	1965.8	14.3	440.7	92.5	106.8	3813.5	18.9	845.1	187.5	206.4	5868.2	23.6	23.6	266.0	289.6
	DRMEC3c	1965.8	144.4	310.6	102.5	246.9	3813.5	267.9	596.1	205.0	472.9	5867.2	466.4	466.4	289.0	755.4
	DRMEC4a	1972.6	0.0	461.8	50.0	50.0	3819.1	0.0	869.6	101.5	101.5	5875.9	0.0	0.0	149.5	149.5
	DRMEC4b	1981.3	0.0	470.4	35.0	35.0	3823.2	0.0	873.7	72.5	72.5	5883.5	0.0	0.0	107.5	107.5

Table 7: Average Performance of dispatching rules

	$n = 100$					$n = 200$					$n = 300$				
Heuristic	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC	C_{max}	T_{idle}	T_{OFF}	TSE	TISSEC
No contr	1456.9	441.0	6.0	5.0	446.0	2887.5	861.7	6.0	5.0	866.7	4307.8	1328.9	1328.9	5.0	1333.9
DRMEC1	1456.9	27.1	419.9	98.5	125.6	2887.5	51.1	816.6	185.5	236.6	4307.8	77.9	77.9	283.1	361.0
DRMEC2a	1459.4	137.7	311.8	125.9	263.6	2890.2	267.6	602.8	235.8	503.4	4310.3	419.8	419.8	360.2	780.0
DRMEC2b	1460.7	0.0	450.9	112.7	112.7	2891.5	0.0	871.8	210.6	210.6	4311.8	0.0	0.0	318.9	318.9
DRMEC2c	1458.7	165.0	283.8	114.5	279.6	2889.4	314.7	555.0	220.2	534.8	4309.5	495.3	495.3	334.2	829.5
DRMEC3a	1459.3	149.5	299.9	120.6	270.1	2890.1	286.3	584.0	226.9	513.2	4310.1	426.2	426.2	351.8	777.9
DRMEC3b	1460.2	16.0	434.3	108.6	124.6	2891.3	20.8	850.7	204.4	225.2	4311.4	22.7	22.7	313.4	336.1
DRMEC3c	1459.4	155.7	293.8	118.2	273.9	2890.0	309.1	561.2	221.5	530.6	4310.1	472.3	472.3	340.0	812.3
DRMEC4a	1464.8	0.0	454.9	64.0	64.0	2895.5	0.0	875.7	119.3	119.3	4316.2	0.0	0.0	183.4	183.4
DRMEC4b	1468.6	0.0	458.7	45.4	45.4	2898.9	0.0	879.1	83.7	83.7	4321.5	0.0	0.0	130.8	130.8

Algorithm	Energy consumption (hp sec)	C_{max} (sec)
No controller	74.3	27.6
Neural Network and algorithm	63.9	27.6

Table 8: Comparison between neural network controller and no controller

job	1	2	3	4	5	6	7	8	9
release date	1	3	13	14	18	21	25	30	36
processing time	3	6	4	2	2	1	5	4	3

Table 9: Experimental setting for multiple-objectives problem