Energy Savings Opportunities and Energy Efficiency Performance Indicators for a Serial Production Line

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Abstract. *Modern manufacturing facilities waste various energy savings opportunities (ESO) and lack proper performance indicators to measure energy efficiency on the production line. This work develops new energy savings opportunity strategies to maximize energy savings for the entire manufacturing facility. The ESO is an opportunity window calculated from on-line production data, such as production count, machine downtime records, buffer levels, and machine idle status, allowing certain machines to be turned off for energy savings without negatively affecting throughput. New energy efficiency performance indicators are presented that use real time production data to identify the least energy efficiency machine on the line. To achieve this goal, a baseline for energy consumption is established for the production line based on a scenario with no downtime events in the system. The energy savings opportunity strategy utilizes the Energy Efficiency Performance Indicators (EEPI) to take the opportunity window for the least energy efficient machine at opportune times, allowing for improvements to be made to the machine, increasing the overall energy efficiency of the line. This strategy takes energy saving opportunities at set increments allowing enough time for the system to recover between each opportunity window. Case studies on a serial production line are performed to validate the conclusions from the paper.*

Keywords: Energy Savings Opportunities, Energy Efficiency Performance Indicators

1 Introduction

With escalating fuel prices and increasing global competition, manufacturing companies are seeking methods to cut costs in any way possible. There are many opportunities to reduce costs in the energy consumption of the facility. These companies are searching for a way to reduce energy cost without sacrificing quality or affecting the yield of their products. The energy consumption in the industrial sector has almost doubled in the past 60 years and accounts for about one-half of the world's total energy consumption [1,2]. In the US alone, the industrial sector spent over $100 billion in energy costs [3] and was responsible for approximately 34% of all energy consumed in 2006. In a typical manufacturing plant, the largest source of energy consumption is the production system where 67% of the total energy cost is attributed to the production process [4]. Being the center of a manufacturing system, production operation directly impacts energy distribution within the manufacturing environment as a whole. The dynamics of the energy demand, largely determines the total energy cost, since the cost of energy (e.g., electricity) actually varies minute-by-minute depending on demand and peak power.

According to *Assessment Study on Sensors and Automation in the Industries of the Future* from the US Department of Energy Industrial Technologies Program,"integrated plant-wide control" is projected to achieve about 317 Trillion Btu/yr energy savings, while "real-time control of energy usage" has a projected savings of 280 Trillion Btu/yr [5]. However, most previous research efforts have not focused on the entire production line, instead looking at the individual machine level [6]. At the machine level there can be an 80% reduction in energy consumption if instead of leaving non-bottleneck machines idle, these machines are turned off until needed [7,8]. It has also been discovered that 85% of energy in a manufacturing environment is utilized for functions not related to the production of parts [9].

There are few studies that address factory floor planning while considering energy saving opportunities [10-13]. Previous work into this topic has been severely limited with most work focusing on maintaining the quality of the product and the desired productivity while neglecting the energy saving potential. These methods treat the energy consumption as an additional cost term for an optimization problem or the consumption is analyzed as a result of high level decision making and scheduling. The energy consumption is considered a byproduct of the production system and not a main driver in the decision process on the factory floor or the control scheme of the overall system.

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Some existing methods, such as the energy treasure hunt developed at GE [14] focused on developing weekend and daily shutdown plans, and managing the leak tag program. Such program is mainly based on non-operation obvious waste, requires expert knowledge on the part of the inspector, and is a "trial and error" manual procedure. There is still a lack of integrated systematic control methodology to drive overall effective energy savings.

One main obstacle in providing an integrated systematic control scheme is the lack of appropriate performance indicators for the facility. While many companies are able to provide key performance indicators (KPI) for a plant, these indicators do not properly address the problem areas on the floor [15-16]. These indicators normally single out the machine with the most energy usage, however this machine may not necessarily be the key issue in terms of energy inefficiency. This is due to the nonlinearity of the production system, which makes it difficult to quantify the impact of individual downtime incidents on the entire operation. The machine center with the most energy usage may not be the least energy efficient machine because of the effects of downtime effects from other machines.

This paper develops and implements new Energy Efficient Performance Indicators (EEPI) that incorporate energy usage from all facets of the manufacturing floor and the facility, and provide energy saving opportunity in real-time production. The EEPI takes into account random downtime events on the manufacturing floor and will allocate the energy usage into two separate categories based on permanent production loss and the lack of synchronization on the floor. This allows the identification of the process that is the most energy inefficient. In addition, the ESO will be applied to save energy and reduce the peak energy consumption so as to reduce overall cost.

The rest of the paper is structured as follows. In section 2 we present the energy savings opportunities for the serial production line. We discuss the energy efficiency performance indicators in Section 3. Section 4 provides simulation studies of the energy opportunities on a serial production line. We dissect the results and provide conclusions and future work in Section 5.

2 Energy Dynamic Analysis for the Production System

2.1 Nomenclature

Some nomenclature utilized for this paper is as follows:

- $s_m(t), m = 1,2,...M$ denotes the actual processing speed of machine S_m at time t.
- $\int_0^T s_m(t')dt', m= 1,2,...M$ denotes the production volume of station S_m during time interval [0,T).
- $M^* = argmin_{m=1,...M} \frac{1}{T_m}$ denotes the slowest machine in the line.
- $b_m(t), m = 2,3,...,M$ denotes the buffer level of B_m at time t.
- $\boldsymbol{e}_i = (m_j, t_i, d_i)$, $i = 1,...,n$, $j = 1,2,...,M$ denotes a downtime event for station m_j at time t_i for a duration of d_i time units.
- $E = \{\boldsymbol{e}_1,\boldsymbol{e}_2,...,\boldsymbol{e}_n\}$ denotes a sequence of downtime events for the line.

2.2 Assumptions and Background

This papers utilizes continuous flow models as seen in Figure (1) [17-19]. The continuous flow model will treat

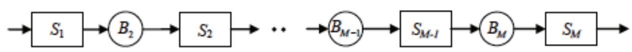

Fig. 1: A Serial Production Line with M Machines and M-1 Buffers

the quantity of jobs in the buffer as varying continuously from zero to the capacity of the buffer as opposed to integer steps. This is done for ease of analysis. The actual system dynamics are not affected by this assumption regardless if the system is continuous or discrete [20,21]. For the serial production line as seen above, we can make the following assumptions:

1. Each station S_i has a constant rated speed equal to $\frac{1}{T_m}$, where T_m is the cycle time of the station. A station will run at its rated speed if it is operational and is neither starved nor blocked.
2. A machine is starved if it is operational and its upstream buffer is empty.
3. A machine is blocked if it is operational and its downstream buffer is full.
4. The first machine, S_1, is never starved and the last machine, S_M, is never blocked.
5. Each Buffer $B_2, B_3, ..., B_M$ have a finite capacity. $B_2, B_3, ..., B_M$ denotes the maximum capacity of the buffer.
6. $S_{M^*} = argmin_{m=1,...M} \frac{1}{T_m}$ is unique.
7. W is the actual energy consumption for the production system.
8. The total rated power consumption of the line is $P = P_1 + P_2 +, ..., P_M$.

2.3 Energy Savings Opportunities

In this section we introduce the concept of the opportunity window. This opportunity window W_m is the longest amount of time machine m can be down without resulting in a permanent production loss for the system[22-24]. The definition for the opportunity window can be seen below in equation (1):

$$W_m(T_d) = sup\{d \geq 0 : s.t.\exists T^*(d), \int_0^T s_m(t)\,\mathrm{d}t = \int_0^T \check{s_m}(t, \boldsymbol{e})\,\mathrm{d}t, \forall T \geq T^*(d)\} \tag{1}$$

where $\int_0^T s_m(t)\,\mathrm{d}t$ and $\int_0^T \check{s_m}(t, \boldsymbol{e})\,\mathrm{d}t$ are the production counts of the end of line station, S_M at time T with and without the inserted downtime event $\boldsymbol{e}_i = (m_j, t_i, d_i)$ respectively. Utilizing this energy saving opportunity, certain machines can be turned to energy savings mode for an amount of time less than or equal to their respective opportunity window without negatively impacting the normal production.

When there are random downtime events in the system, not every event contributes to a permanent production loss for the production line. It is proven in [22-24] that given a realization of the production process subject to a sequence of downtime events $E = \{\boldsymbol{e}_1, \boldsymbol{e}_2, ..., \boldsymbol{e}_n\}$ and supposing that $max_{i=1,...,n}\{t_i + d_i\} < T$, if the slowest machine M^* stops for D time units during [0,T), then for any station m in the production line there exists a $T^* \geq T$, such that,

$$\int_0^{T'} s_m(t')\,\mathrm{d}t' - \int_0^{T'} s_m(t', E)\,\mathrm{d}t' = \frac{D}{T_{M^*}}, \forall T' > T^* \tag{2}$$

where $\int_0^{T'} s_m(t')\,\mathrm{d}t'$ and $\int_0^{T'} s_m(t', E)\,\mathrm{d}t'$ are the production volume without and with a sequence of downtime events E respectively. Thus the smallest possible downtime duration d_i^* for the i^{th} failure event $\boldsymbol{e}_i$ $=(m_j, t_i, d_i)$ is found in equation (2):

$$d_i^* = inf\{d \geq 0 : s.t. T_{M^*} \int_{t_i}^{t_i+d} s_{M^*}\mathrm{d}t' = W(m_i, \boldsymbol{b}(t_i; E))\} \tag{3}$$

where d_i^* is the time it takes the buffers between station m and M^* to become empty if $(m < M^*)$ or full if $(m > M^*)$. If the actual downtime duration $d_i > d_i^*$ then there is permanent production loss on the line equal to $d_i - d_i^*$. If the downtime duration $d_i < d_i^*$ is less then the above value than there is no permanent production loss.

3 Energy Efficiency Performance Indicators

For the development of the Energy Efficiency Performance Indicators, we must first introduce an energy baseline for the factory. The first step in this process if to define the overall production time of the manufacturing line. The entire production line is dictated by the slowest machine in the system, $S_m^* = 1/T_m^*$, where T_m^* is the cycle time of the slowest machine. If the production count of the line is M, then we can define the overall production time as:

$$t_p = \frac{M}{S_{m^*}} = M \times T_{m^*}. \tag{4}$$

This is the baseline: the shorts possible time that the manufacturing line can produce M products. Knowing that this is the baseline, this means that the actual time it takes to produce M parts will always be:

$$t_r \geq t_p, \tag{5}$$

where t_r is the actual production time to produce M parts. We can now quantify the energy consumption to a dynamic and static portion in the manufacturing process, and categorize the energy consumption in detail (production related and unrelated). The dynamic part is attributed to random disruptions on the line, while the static part is related to synchronization operation. The static part of the energy consumption can be defined as W_1, which can be seen in equation (6):

$$W_1 = W \times \frac{t_p}{t_r}. \tag{6}$$

The dynamic portion of the energy consumption due to random downtime events on the line is W_2 and can be defined as:

$$W_2 = W \times \frac{t_r - t_p}{t_r}. \tag{7}$$

As one can see the total energy consumption $W_1 + W_2 = W$. The next step in the process is to distribute the energy consumption at the machine level to aid in developing the Energy Performance Indicator (EPI) for the entire line. The portion of the energy consumption that is due to normal machine operation can be estimated using the power rating of the individual machines. It is defined as $W_{i,1}$:

$$W_{i,1} = W_1 \times \frac{P_i}{P}, \tag{8}$$

where P_i is the power consumption of machine i and P is the rated power consumption of the entire line. Next, we develop the portion of energy that is wasted during permanent production loss, which is $W_{i,2}$. Permanent production loss occurs when there is a downtime event at machine i d_i that is longer than the opportunity window d_i^*. This will cause the slowest machine to become blocked or starved depending on the location of the down machine. Using this knowledge, the formula for $W_{i,2}$ becomes:

$$W_{i,2} = W_2 \times \frac{(d_i - d_i^*)}{\Sigma(d_i - d_i^*)}. \tag{9}$$

We can then use $W_{i,1}$ and $W_{i,2}$ to find the energy consumption per part at each machine, $ECPP$:

$$ECPP = \frac{W_{i,1} + W_{i,2}}{M_i}, \tag{10}$$

where M_i is the production count of machine i. If we sum the $ECPP$ for every machine, this will give us the performance indicator for the production line, which we will delineate as energy performance indicator (EPI_{Actual}).

$$EPI_{Actual} = \sum_{i=1}^{M} \frac{W_{i,1} + W_{i,2}}{M_i}. \tag{11}$$

When there is no energy waste the $W_{i,2}$ term goes to zero, which gives the energy baseline, defined as $EPI_{Baseline}$:

$$EPI_{Baseline} = \sum_{i=1}^{M} \frac{W_{i,1}}{M_i}. \tag{12}$$

As one can see as the production becomes very inefficient and M_i becomes small, while $W_{i,1}$ and $W_{i,2}$ grow larger the EPI_{Actual} will grow larger than the baseline. The larger the gap between the baseline and the EPI_{Actual}, and the higher the EPI_{Actual} the less efficient the production line is performing.

However, the EPI_{Actual} cannot completely describe the energy efficiency of individual machines. For example, certain machines may have to consume larger energy than other machines, so it cannot be concluded that this machine is energy inefficient. The key is the proportion of the energy consumed in effectively producing products. Therefore, an additional performance indicator is defined as the Energy Efficiency Performance Indicator ($EEPI$). This performance indicator for an individual machine is equal to:

$$EEPI_i = \frac{W_{i,1}}{W_{i,1} + W_{i,2}}. \tag{13}$$

When there is no energy waste (i.e. no random downtime events) then the $W_{i,2}$ term will go to 0 making the $EEPI_i = 1.0$. This is the energy baseline. When downtime events cause much permanent production loss with all of the energy consumption being wasted during interruption events, which causes $W_{i,2}$ to increase making the $EEPI_i = 0.0$.

4 Case Studies

The production system for the case study is a 5 Machine 4 Buffer system (5M4B) with maximum buffer contents of 18 parts for each buffer. The parameters of the line can be seen in Table 1. The simulation time for this study is 168 hours with the buffers starting at half their maximum capacity. This case study uses a case where the slowest machine is the most efficient with the least energy consumption to illustrate how the $EEPI$ can identify the least energy efficient machine in a situation when it is not the slowest machine.

4.1 Case 1: $d = 0$

The line is first run without any inserted opportunity windows. This will provide us with production data for a line that has no inserted downtime events. This will serve as our base scenario without any energy efficiency control strategy. The EPI_{Actual} for the entire line is calculated using the formula in equation (11) and can be seen in Figure (2).

Table 1: Production Line Parameters

Parameter	m_1	m_2	m_3	m_4	m_5
CT (mins/part)	3	3	5	3	3
MTTR (mins)	37.5	37.5	0	37.5	37.5
MTBF (mins)	150	150	150	150	150
Efficiency (%)	80%	80%	100%	80%	80%
Power (kW)	500	500	100	500	500

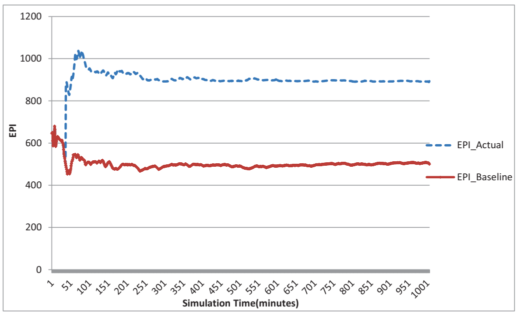

Fig. 2: EPI for the Entire Line with $d = 0$

The solid line indicates the $EPI_{Baseline}$, which is the energy consumption without any permanent production loss, calculated from equation (12). The dashed line represents the actual EPI for the entire manufacturing line. This case will allow us to compare the following cases when we insert downtime events into the production line. If the EPI_{Actual} is greater than this case then the production line is less energy efficient than without any energy opportunity windows. If the gap between the two is smaller than Case 1 then the line is more energy efficient.

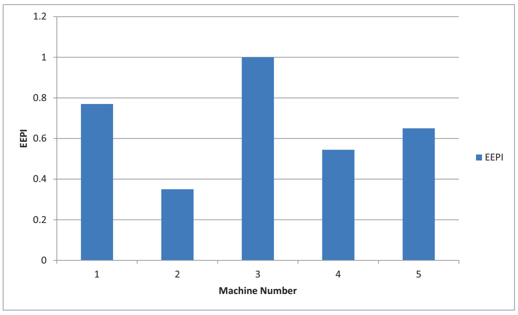

Fig. 3: EEPI for the Each Machine with $d = 0$

To find the least energy efficient machine in the line, we utilize equation (13), and plot the results in Figure (3). This indicates the energy efficiency for individual machines since it takes into account the permanent production loss at each machine due to random downtime events. In this case, machine 2 is the least energy efficient machine as indicated by $EEPI$ since downtime events at machine 2 cause the slowest machine, machine 3, to become starved, therefore causing permanent production loss. Machine 3 has an $EEPI$ equal to 1.0 because it has no random downtime events, any time not producing parts is due to the other machines causing it to be blocked or starved.

4.2 Case 2: $d = d_i^*$

The next case that is run takes into account inserted opportunity windows that are calculated according to equation (3). Using the opportunity window each machine is turned off at various times, allowing sufficient time for the machine to recover before taking the energy savings opportunity again. There is permanent production loss for this case because the random downtime events due to machine inefficiencies cause the buffer levels to not reach their full capacity, therefore decreasing the opportunity window . The permanent production loss is 12.3% compared to case 1.

The production count of machine 3 and machine 5 can be seen in Figure (4). Only two machines are shown since each machine except the slowest has the same parameters and would make it difficult to see the inserted opportunity windows in the production count graph if all were shown at once. Therefore, only the slowest machine and the last machine are shown since the production count of the last machine will equal the production count of the entire line. Only a portion of the simulation is shown as well to better illustrate the production count of each machine.

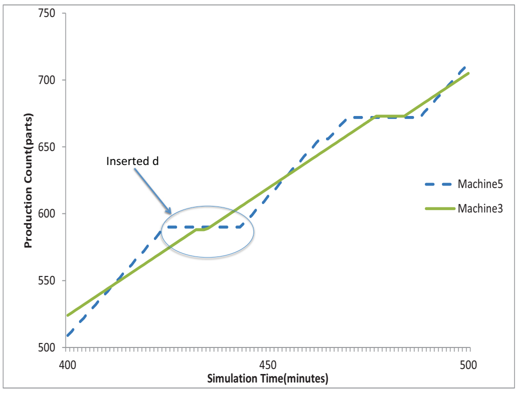

Fig. 4: Production Count of Machine 3 & 5 for $d = d_i^*$

The inserted opportunity window for machine 5 can be seen from approximately 425 mins - 450 mins where the machine has zero change in production count. The EPI_{Actual} and the $EPI_{Baseline}$ of the entire line with the inserted opportunity windows can be seen in Figure (5).

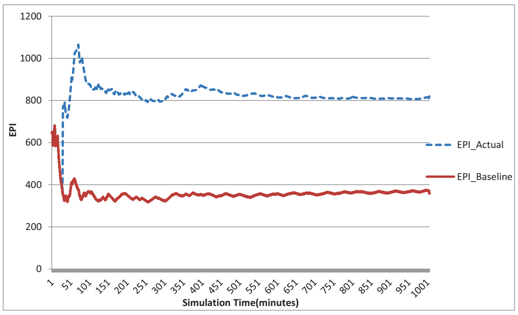

Fig. 5: EPI for the Entire Line with $d = d_i^*$

As one can see the EPI_{Actual} and the $EPI_{Baseline}$ decreases for the entire line with the insertion of energy savings opportunities, which is due to the small production loss.

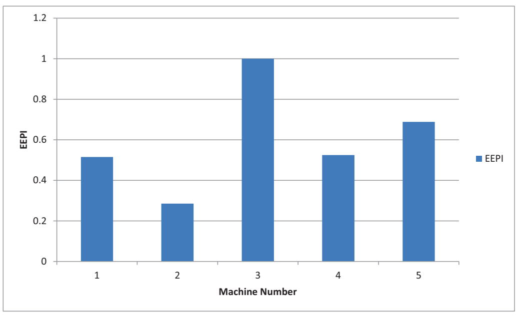

Fig. 6: EEPI for the Each Machine with $d = d_i^*$

The $EEPI$ for each machine can be seen in Figure (6). The $EEPI$ once again illustrates that machine 2 is the least energy efficient. The $EEPI$ cannot be compared to other scenarios, as it is only an indicator of the machine efficiency for each given case. It enables us to identify the least energy efficient machine on the line.

4.3 Case 3: $d < d_i^*$

The last case that is simulated is a more conservative energy saving opportunity strategy. This case has inserted downtime events at each machine that are shorter than the maximum calculated energy opportunity windows for that machine by considering stochastic random downtimes so that less permanent production loss will be observed from case 2. The production count of machine 3 and machine 5 from this case can be seen in Figure (7).

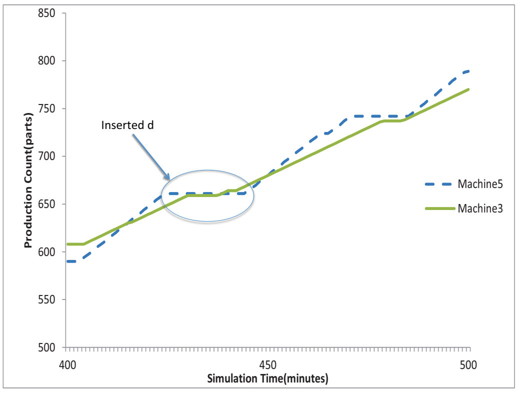

Fig. 7: Production Count of Machine 3 & 5 for $d < d_i^*$

The production count is higher from the previous case during the time interval shown. This is due to the more conservative energy saving opportunity strategy.

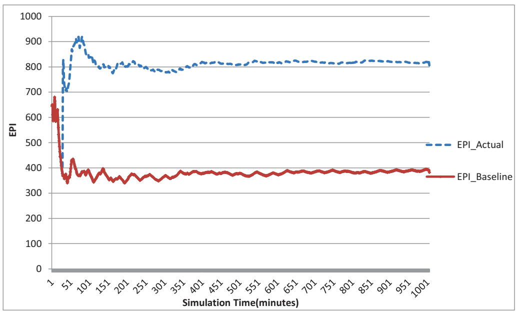

Fig. 8: EPI for the Entire Line with $d < d_i^*$

The EPI_{Actual} and the $EPI_{Baseline}$ are close to those in case 2. This makes sense since the energy consumption is slightly more than in case 2, but there is less of a throughput impact. Since there is less of a production impact in this case, we can conclude that this is the best of the three cases.

Lastly, the $EEPI$ is calculated and shown in Figure (9). Once again machine 2 is still the least energy efficient machine, which is to be expected since we have not performed any control actions to fix this machine.

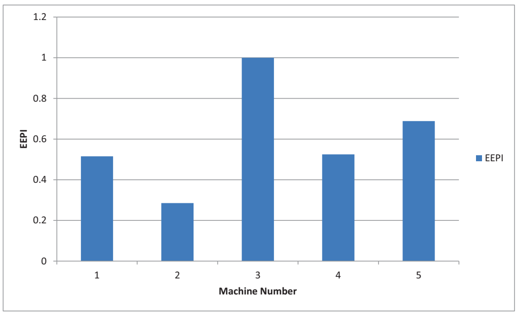

Fig. 9: EEPI for the Each Machine $d < d_i^*$

Theses results demonstrate that EPI_{Actual} and $EPI_{Baseline}$ decreases with inserted ESO. This is due to the fact that although the inserted downtime saves the overall energy consumption per part, too much ESO may have the risk to cause more energy consumed by the idling of the bottleneck machine. $EEPI$ captured the portion of the energy used on actually producing parts for each machine rather than downtime and idling, therefore it is used to identify the least energy efficient machine of the production line and help to find the root cause of energy inefficiency.

5 Conclusions and Future Work

This paper investigates energy saving opportunities for a serial production line while developing new energy performance indicators for the production line and at the machine level. The performance indicators are tested using simulation studies using three different cases. These studies use different downtime events to prove the concept of the energy opportunity window as well as the energy performance indicators. The indicators are able to correctly identify the machine with the least energy efficiency for each case.

The next step in this research is to develop a control methodology to help alleviate the problem of the least energy efficient machine by utilizing the energy opportunity window or by performing preventative maintenance. Also, a dynamic energy saving opportunity strategy will be developed to optimize cost savings.

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