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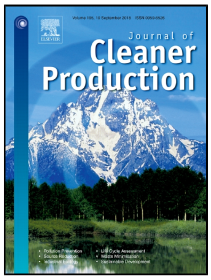

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Modeling, analysis, and improvement of integrated productivity and energy consumption in a serial manufacturing system

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Abstract

The performance of a manufacturing system is measured by factors such as its productivity and energy efficiency. Current systems lack the required indices to measure its efficiency and highlight the areas of inefficiency in the system. The paper is aimed at improving the overall performance of manufacturing system by suggesting methods for integrated improvement in above two factors. This paper establishes performance indices for measuring energy efficiency and productivity of the system, which uses easily available sensor data from the production line. The energy structure and effects of downtime events on the production line has been analyzed to develop energy and productivity performance indicators. The indices are utilized to identify the machines which is most power inefficient and results in maximum production loss of the system. These indicators are utilized to illustrate our method for improving productivity and concepts of downtime-bottleneck and power-bottleneck. The methods proposed are verified by simulation studies.

Keywords: performance indicators, downtime, downtime-bottleneck, power-bottleneck, sustainable manufacturing

1. Introduction

The primary aim of any manufacturing system is reducing per unit production cost. This can be achieved by improving energy efficiency and productivity. Reducing energy waste has gained importance as sustainability and green methods became more prevalent. Recent studies show that the energy consumption in the manufacturing sector has almost tripled in past 60 years to almost approximately 30 quadrillions BTU in the United States (U.S. EIA, 2012). In the manufacturing system, the largest fraction of energy is consumed by production line, which accounts for almost 75% of total energy consumption by manufacturing system (U.S. EIA, 2012).

Manufacturing facilities lack the required performance indices to evaluate the energy efficiency of the system. Most facilities utilize energy consumed per part to evaluate machine performance, which when utilized alone reflects wrong results for energy efficiency of the machine(Boyd, 2011). The reason behind this is non-linearity of the manufacturing system. In this paper, the dynamic energy structure has been analyzed for developing performance indicators to better illustrate energy efficiencies. Understanding the dynamic energy leads to accurate identification of downtime-bottleneck and power-bottleneck. These bottlenecks can be used to accurately identify the source of energy inefficiencies in the manufacturing system and subsequently improve same.

To improve productivity, an integrated modeling method is required that captures dynamic nature of manufacturing system and evaluates its performance using real-time sensor data. Efforts have been made for productivity improvement, performance evaluation but they were based on the steady state of the system which can predict long-term steady state behaviors. These methods are not applicable to transient production lines. In our model, the performance of all working stations in a serial manufacturing system is assessed by utilizing real-time sensor data. A unified severity index has been defined, which ranks each station in terms of net production loss and help managers to properly allocate limited resources. In this paper, productivity and energy efficiency of the system has been integrated and a measure has been provided for improving its overall performance both in terms of productivity, and energy efficiency.

The rest of the paper is presented as follows. We have provided literature review in section 2. In section 3, we have covered notations and assumptions followed in the paper. Section 4 presents the mathematical modeling of the paper. In Section 5, we have defined and elaborated downtime bottleneck and power bottleneck. Section 6 represents the simulation experiments. Finally, we summarize and plan future work in section 7.

2. Literature review

Researchers have been ignoring energy management for a long time. Most of the previous studies were made on quality control and productivity gain without focusing on energy efficiency (Guerrero et al., 2011; Fang et al., 2011). In most of these research and studies, energy efficiency or consumption is treated as a by-product of the manufacturing process rather than one of the main parameters for decision-making process. Energy consumption is just another cost term in the objective function of the optimization problem. General Electric developed a method named energy treasure hunt method to determine energy inefficiency in their plant by arranging daily and weekend plans (U.S. EPA, 2009). This method is based on manual, recursive trial and error method which is dependent on the expertise of the inspector on finding ways to minimize energy waste in the plant.

Another method for evaluating energy consumption is trend decomposition (Tol and Weyant, 2006). This is a practical method used to determine decrease in energy efficiency. However, there is not any general or standard system for which this method is accepted to be best suited. Generally, there are four diverse ways which can be used on basis of different situations and constraints (Liu and Ang, 2007). For accurate results, while using this method it is essential to have knowledge about constraints to be employed for analysis. Limitation of this method is it cannot be used in real time to solve various problems that arise on a regular basis in the production line.

Research has been done in the field of lean manufacturing (Sahoo et al., 2008; Verrier et al., 2015) which reduced production cost and increases productivity of system but have a negligible effect on energy efficiency of manufacturing system. Other ways of reducing production cost include optimizing the lot size (Naeem et al., 2013), minimizing loss (Batson and Shishoo, 2004), product recovery (Meng et al., 2017) but neither of them energy efficiency of the manufacturing system.

In Brundage et al., 2016, Brundage and Chang developed sustainable manufacturing performance indicator to evaluate the energy efficiency of system but they did not consider productivity of system while in Li et al., 2014, the focus is on event-based modeling without taking energy efficiency into account. An analytic hierarchy process scoring methodology is used in Harik et al., 2015 to measure sustainability of manufacturing systems but doesn't specifically focus on improving productivity and energy efficiency of the system. In Brundage et al., 2014b and Dababneh et al., 2016, HVAC system and production are coupled to maximize cost savings but system output is sacrificed. Researchers have developed various ways like material, energy, waste process flow modelling (Smith and Ball, 2012), energy and utility management maturity model (Ngai et al., 2013) etc. to promote sustainable manufacturing but requires extensive guidance to implement them.

Extensive research has been done on modelling and analysis of manufacturing system (Hopp and Spearman, 1996; Shi and Zhou, 2009; Jaber and Khan, 2010), scheduling and material and maintenance requirement planning (Shi, 2006; Xu et al., 2018; Sun et al., 2018), and material handling systems (Poon et al., 2011; Heragu et al., 2011; Shahbazi et al., 2016), lean manufacturing (Green et al., 2010; Sartal et al., 2018). Much of the previous works focus on performance metrics of isolated manufacturing system which is based on the nature of the methods used in the respective manufacturing processes. None of them integrates energy efficiency and productivity, and are only concerned with physical system without closely connecting with overall manufacturing system.

It is clear from above illustrations that present literature fails to deliver enough insight into a system where both productivity and energy efficiency of the production line is integrated and improvised by use of real-time sensor data. Such a system can respond quickly to day-to-day problems in the plant and enables quick and accurate evaluation of productivity and energy efficiency. Our paper focuses on the above area. To the best of our knowledge, there hasn't been any work in the field mentioned above.

3. Notations and assumptions

In this paper, a continuous flow model has been adopted. In a continuous flow model, number of jobs in the buffer vary continuously opposed to integer steps from zero to capacity of the buffer. It was adopted to make mathematical calculations and analysis easier, as dynamics of the system can be easily be expressed in integral or differential forms. This assumption in the model does not affect the actual system dynamics (Tan and Gershwin, 2011; Gershwin, 1994). Fig. 1 describes a serial manufacturing system with N stations and N-1 buffers.

Fig. 1. A serial manufacturing system.

Following notations are used throughout the paper:

Table 1 Notations

B_n	Capacity of nth buffer where, $1 \le n \le N-1$
$b_n(t)$	Buffer level of B_n , n = 1,…,N-1, at time t
α_j	Ratio of power consumption of machine j in idle and working state
$\vec{e}_i$	(S_m, S_n, t_i, d_i), failure of S_m leads to S_n being non-operational for d_i duration, at time t_i
e_j	Efficiency of machine j
$\vec{E}$	[$\vec{e}_1$,…, $\vec{e}_N$] denotes the order of disruption events for the system
$EI_j(t)$	Instantaneous energy consumption of machine j at time t
EP	Energy consumption per unit part of manufacturing system during time period [0,T)
EP_d	Energy consumption per unit part of manufacturing system during time period [0,T) as a result of disruption events
EP_e	Energy consumption per unit part of manufacturing system during time period [0,T) without disruption events
EP(t)	Instantaneous energy consumption per unit part of production line at time t
$\vec{f}_j$	[$\vec{e}_{i,1}$,…, $\vec{e}_{i,Nj}$], , i = 1,…,N, represents the order of disruption events for machine j
L_n	Production loss due to S_n , $1 \le n \le N$
N^*	Slowest station on the line
$O_j(t)$	j = 1,…,N-1, represents opportunity window of machine j at time t
$P_{id,j}$	Rated power consumption of machine j while machine is idle
$P_{p,j}$	Rated power consumption of machine j while machine produces parts
$T_{id,j}$	Time during which machine j is idle
T_n	Cycle time of station (machine) S_n , $1 \le n \le N$

$T_{p,j}$	Time during which machine j produces parts
$TL(\vec{e}_i)$	Manufacturing time loss as a result of downtime event $\vec{e}_i$
Y(T)	Number of parts produced by system during time period [0,T)
$Y_n(T)$	Output of station S_n, $1 \leq n \leq N$, during time period of [0,T)
DBN	Downtime bottleneck
MTBF	Mean time between failures
MTTR	Mean time to repair
PBN	Power Bottleneck
PI	Performance indicator

Following assumptions have been made in the paper:

1. A machine is starved if it is operational and its upstream buffer is empty and vice versa.
2. Last machine is never blocked and first machine is never starved.
3. Each buffer has a finite capacity.

4. Mathematical modeling and system dynamics

First, the effect of downtime events on throughput of the production line needs to be understood. For the same, a system having more than one slowest stations is considered. Overall effect of downtime events on the stations needs to be evaluated, thus the last slowest station S_{N^*} in the line is chosen as the reference station. It is required to understand that any downtime event may or may not result in permanent production loss depending on the duration of downtime event. There would not be a permanent production loss till the slowest machine is starved or blocked. For example, let's suppose a machine m such that m < N^*, slowest machine N^* would not be starved till all the buffer between m and N^* is depleted, resulting in production loss which can be recovered in the future.

We are interested in finding out exact time for which slowest machine S_{N^*} is blocked or starved due to an interruption event $\vec{e}_i$. O_i denotes the time after which station S_{N^*} starts to stave or block due to downtime event $\vec{e}_i$. The case where downtime, $d_i > O_i$ is discussed, otherwise, production time loss would be zero.

Let's consider an arbitrary downtime event $\vec{e}_i$ = (S_m, S_n, t_i, d_i). In case of m < N^*, by principle of conservation of flow to the machines between S_m and S_N^* during $[t_i, t_i + d_i]$, the following equation is obtained.

$$\Delta Y_m(t_i + d_i, E) - \Delta Y_{N^*}(t_i + d_i, E) = \sum_{k=m+1}^{N^*} b_k(t_i + d_i, E) - b_k(t_i, E) \qquad (1)$$

Where $\Delta Y_k(t_i + d_i, E) = Y_k(t_i + d_i, E) - Y_k(t_i, E)$ represents the output of any station k during $[t_i, t_i + d_i]$. Since station S_m is down during $[t_i, t_i + d_i]$, the term $\Delta Y_m(t_i + d_i, E)$ is zero. Thus,

$$\Delta Y_{N^*}(t_i + d_i, E) = \sum_{k=m+1}^{N^*} -b_k(t_i + d_i, E) + b_k(t_i, E) \qquad (2)$$

$\forall d_i \geq O_i$, all the buffers $B_{m+1}, ..., B_{N^*}$ between stations S_m and S_{N^*} are empty at $t_i + d_i$, that is $\sum_{k=m+1}^{N^*} b_k(t_i + d_i, E) = 0$. Thus,

$$\Delta Y_{N^*}(t_i + d_i, E) = \sum_{k=m+1}^{N^*} b_k(t_i, E) \qquad (3)$$

Above equations imply $\mathrm{O}_i = \inf\{d \geq 0 : s.t.\Delta Y_{N^*}(t_i + d_i, E) = \sum_{k=m+1}^{N^*} b_k(t_i, E)\}$. Buffers between S_m and S_{N^*} are empty, thus it takes $\sum_{k=m}^{N^*-1} T_K$ for a job to go from S_m to S_{N^*}. Thus,

$$\mathrm{TL}(\vec{e}_j) = d_i - O_i + \sum_{k=m+1}^{N^*} T_K \tag{4}$$

Similarly, above parameters for the case n > N* could be found by using the principle of conservation of flow to the machines between S_n and S_{N^*} during [$t_i, t_i + d_i$]. In this scenario, all the buffers between S_n and S_{N^*} would become full to their respective capacities. Station S_n will resume production after time $t_i + d_i$. All the stations between S_n and S_{N^*} including them would receive jobs immediately from their respective upstream buffer. O_i and $\mathrm{TL}(\vec{e}_j)$ are therefore given by:

$$\mathrm{O}_i = \inf\{d \geq 0 : s.t.\Delta Y_{N^*}(t_i + d_i, E) = \sum_{k=N^*+1}^{n} B_k - b_k(t_i, E)\}$$

$$\mathrm{TL}(\vec{e}_j) = d_i - O_i \tag{5}$$

In the scenario where n = m = N* i.e. slowest is down, it would directly contribute to permanent production loss. Thus,

$$\mathrm{TL}(\vec{e}_j) = d_i \tag{6}$$

The value of O_i can be easily determined by performing simple calculations on the data obtained from sensor information. The above analysis allows us to study the effect of each disruption event on overall production output of system quantitatively in terms of production time loss. Our model consists of multiple slowest stations which include special case consisting of single slowest station.

4.1 Unified Severity Index

In this section, the total production loss is quantified using production time loss calculated in above section. A unified index which can be used to direct the flow of resources in an efficient and optimized way in the system would also be determined in this section.

Let's consider an arbitrary downtime event $\vec{e}_i = (S_m, S_n, t_i, d_i)$. Let $d_i^* = \inf\{d > 0 : s.t., \mathrm{TL}(\vec{e}_j) > 0\}$. If d > d_i^*, S_{N^*} is down, starved or blocked depending on location of downtime event between $t_i + d_i^*$ and $t_i + d_i^* + \mathrm{TL}(\vec{e}_j)$. Whereas, if d < d_i^*, downtime event would not result in stoppage of S_{N^*}. Thus a set, F_{N^*}, is defined, consisting of intervals of time for which the station S_{N^*} seize its operations as a consequence of downtime events $\vec{E}$; as follows**:**

$$F_{N^*} = \{[t_i + d_i^*, t_i + d_i^* + \mathrm{TL}(\vec{e}_j)), i = 1, \ldots, n \; s.t., \mathrm{TL}(\vec{e}_j) > 0\} \tag{7}$$

S_{N^*} can only stop as a result of downtime event $\vec{E}$, thus the last slowest station or reference station is allowed to seize its operations only during time intervals which are present in the set F_{N^*}. Thus total stoppage time D of the slowest station S_{N^*} during time interval [0, T) can be defined as

$$D = \left| \bigcup_{i \in \eta^s} [t_i + d_i^*, t_i + d_i^* + \mathrm{TL}(\vec{e}_j)) \right| \tag{8}$$

Where, $\eta^s = \{i = 1, \ldots, n, s.t., \mathrm{TL}(\vec{e}_j) > 0\}$ and $d_i^* = \inf\{d > 0 : s.t., \mathrm{TL}(\vec{e}_j) > 0\}$

Thus net production loss is equal to

$$\begin{gathered} \mathbf{L}\,(t) = D / T_{N*} \\ \Rightarrow \mathbf{L}\,(t) = D / T_{N*} = \left| \bigcup_{i \in \eta^s} [t_i + d_i^*, t_i + d_i^* + \mathrm{TL}(\vec{e}_j) \right| / T_{N*} \end{gathered} \tag{9}$$

Let $\mathrm{L}(\vec{e}_i)$ denote the production loss caused due to the event $\vec{e}_i$. If a downtime event $\vec{e}_i$ doesn't overlap with any other downtime events, then $\mathrm{L}(\vec{e}_i) = |\, [t_i + d_i^*, t_i + d_i^* + \mathrm{TL}(\vec{e}_j))\, | / T_{N^*}$. If $\vec{e}_i$ overlaps with other events then output loss is equally shared among the events. Let $\vec{e}_{n,1},...,\vec{e}_{n,n_m}$ be the sequence of downtime events caused due to the station S_n. Then the permanent production loss, L_n, caused due to S_n is

$$L_n = \sum_{i=1}^{n_n} \mathrm{L}(\vec{e}_{n,i}) \tag{10}$$

The impact of each station on the overall production output can be determined by utilizing permanent production loss as a unified ranking index. It provides real-time analysis and a natural severity ranking of each station which is extremely useful in prioritizing the limited resources.

4.2 Energy structure and performance index

The effects of downtime events on the system has been analyzed in previous sections. In this section, the impacts of downtime events on energy efficiency of the manufacturing system will be analyzed. The structure of energy can be analyzed using the data obtained from production line like power, throughput, buffer etc. For ease of mathematical calculation, a serial production line similar to that in previous section with N machines and a single slowest machine is considered.

First let's understand various components of operation for a machine during time period [0, T)

$$T = T_{p,j} + T_{id,j} + T_{off,j} + T_{warm,j} \tag{11}$$

Where $T_{off,j}$ represents the time during which machine is not operating hence power consumed is zero. $T_{warm,j}$ represents the warm up time for machine j. Warm up period is assumed to be zero for ease of calculations. Power consumed during idling as a percentage of power consumed during production of parts can be represented as

$$P_{id,j} = \alpha_j P_{p,j} \ , \qquad \alpha_j \in (0,1] \tag{12}$$

The energy consumed per unit part of the manufacturing system is dynamic in nature, where energy efficiency and productivity or production count are coupled into a single dynamic system. This energy dynamics can be represented by mathematical function consisting of individual machine's parameters such as duration of down time, buffer levels, and rated power of machine etc. In our model, the interactions among production processes are equivalently compared to "internal forces," while the downtime events are equivalently compared to "external forces" to analyze the dynamic energy structure. Thus, the energy dynamics can be represented by following space-time equation(Brundage et al., 2014a):

$$\frac{d[EP]}{dt} = f(t, EP(t), Z(t)) \tag{13}$$

Where Z(t) = $\vec{E}$ = [$\vec{e}_1$,…, $\vec{e}_N$] denotes the sequence of downtime events during [0, T). To solve above equation, the following homogeneous and non-homogenous equations have been considered:

$$\frac{d[EP]}{dt} = f(t, EP(t)) \tag{14}$$

$$\frac{d[EP]}{dt} = f(t, EP(t), Z(t)) \tag{15}$$

First equation represents the virtual scenario with no downtime events on the production line. Since there are no downtime events each machine will operate at all time during [0, T). Thus solution of homogenous equation can be represented by

$$EP_e = \frac{\sum_{j=1}^{N} P_{p,j} T}{T / T_{N^*}} = T_{N^*} \sum_{j=1}^{N} P_{p,j} \tag{16}$$

The non-homogenous equation represents the scenario with downtime events and can be represented as

$$EP_d = EP - EP_e \tag{17}$$

Production count(C) during the time period [0, T) is

$$C = (T - \bigcup_{i \in \eta^s} [t_i + d_i^*, t_i + d_i^* + \mathrm{TL}(\overrightarrow{e_i}))\,|) / T_{N^*}$$

$$\Rightarrow C = (T - \bigcup_{i \in \eta^s} [t_i + d_i^*, t_i + d_i) |) / T_{N^*} \tag{18}$$

Where $d_i^* = \inf\{d > 0 : s.t., \mathrm{TL}(\vec{e}_j) > 0\}$

In order to find out total energy consumed by of production line, energy consumed during the period [0, T) is required to be analyzed

$$E = \sum_{j=1}^{N} P_{p,j} T_{p,j} + P_{id,j} T_{id,j}$$

$$= \sum_{j=1}^{N} P_{p,j} (T_{p,j} + \alpha_j T_{id,j}) \tag{20}$$

Where, $T_{id,j} = T - T_{p,j} - T_{off,j}$ (21)

$$T_{p,j} = T_j \int_0^T Y_j(t'; E) dt' \tag{22}$$

$$T_{off,j} = \sum_{k=1}^{\eta_j} d_k \tag{23}$$

$$\Rightarrow T_{id,j} = T - T_j \int_0^T Y_j(t'; E) dt' - \sum_{k=1}^{\eta_j} d_k \tag{24}$$

Where η_j is total number of downtime events for machine j and η_j^e is number of effective downtime events which leads to permanent production loss.

By using above equations, the general solutions for EP and EP_d are:

$$EP = \frac{\sum_{j=1}^{N} [P_{p,j} (T - \sum_{k=1}^{\eta_j} d_k - (1 - \alpha_j) T_{id,j})]}{C} \tag{25}$$

$$EP_d = \frac{\sum_{j=1}^{N}[P_{p,j}(\bigcup_{i\in\eta^s}[t_i + d_i^*, t_i + d_i)| - \sum_{k=1}^{\eta_j} d_k - (1-\alpha_j)T_{id,j})]}{C} \tag{26}$$

Performance indicator cab be defined as:

$$\frac{\textit{Energy consumption per unit part with no disruption events}}{\textit{Net energy consumption per unit part}}$$

$$PI = \frac{EP_e}{EP}$$

$$= \frac{\sum_{j=1}^{N}[P_{p,j}(T - \bigcup_{i\in\eta^s}[t_i + d_i^*, t_i + d_i)|]}{\sum_{j=1}^{N}[P_{p,j}(T - \sum_{k=1}^{\eta_j} d_k - (1-\alpha_j)T_{id,j})]} \tag{27}$$

Where, $\eta^s = \{i = 1, ..., n, s.t., \mathrm{TL}(\vec{e}_j) > 0\}$

The PI accurately illustrates the performance of manufacturing system in contrast with portion of the energy consumption per part which is static with no disruption events. It illustrates the energy wastage due to downtime events. There are three cases which are given as follows:

1. Case 1: PI < 1 – This is the case when energy consumption per unit part for the manufacturing system is more than that in the scenario with no disruption events. It occurs due to permanent production loss due to effective downtime events.
2. Case 2: PI = 1 – This represents the situation when energy consumption per unit part for the manufacturing system is equal to the scenario with no disruption events. However, there could be more energy savings by turning off certain machines at certain intervals without affecting net production.
3. Case 3: PI > 1 – This represents the situation when manufacturing system is consuming less energy than the scenario without disruption events.

5. Performance bottlenecks

Two bottlenecks are introduced in this section, downtime bottleneck (DBN) and power bottleneck (PBN). The DBN provides information for directing limited resources to the machine which would result in maximum increase in energy efficiency of the manufacturing system. The PBN delivers information for replacing an individual machine with a more power efficient machine which would lead to largest increase in energy efficiency of the production line. Both bottlenecks utilize sensor data.

Downtime bottleneck

A machine j is DBN if an infinitesimal reduction in its downtime results in largest increase in energy efficiency of the entire production line.

$$\frac{\partial EP}{\partial d_j} > \frac{\partial EP}{\partial d_i}, \forall i \neq j \tag{28}$$

In order to find above partial derivative, quotient rule for partial differential equations is used

$$\frac{\partial EP}{\partial d_j} = \frac{\partial(\frac{E}{C})}{\partial d_j} = \frac{(C)(\frac{\partial E}{\partial d_j}) - (E)((\frac{\partial C}{\partial d_j}))}{C^2} \tag{29}$$

Here E represents total energy consumption of production line and other symbols have their usual meanings.

$$E = \sum_{j=1}^{N} [P_{p,j}(T - \sum_{k=1}^{\eta_j} d_k - (1-\alpha_j)T_{id,j})] \tag{30}$$

$$\frac{\partial E}{\partial d_j} = \lim_{\partial d_j \to 0} \frac{E(d_j + \partial d_j) - E(d_j)}{\partial d_j} \tag{40}$$

Where η_j is total number of downtime events for machine j

$$E(d_j+\partial d_j)=\sum_{j=1}^{N}[P_{p,j}(T-\sum_{k=1}^{\eta_j}d_k-(1-\alpha_j)T_{id,j})]-(\partial d_j)(\eta_j P_{p,j}) \tag{41}$$

It should be noted that a small change in ∂d_j doesn't affect $T_{id,j}$, due to the fact that it is impossible for machine to break when it is idle.

$$\frac{\partial E}{\partial d_j}=-\eta_j P_{p,j} \tag{42}$$

$$\frac{\partial C}{\partial d_j}=-\frac{\partial PL}{\partial d_j}=\lim_{\partial d_j\to 0}\frac{PL(d_j+\partial d_j)-PL(d_j)}{\partial d_j} \tag{43}$$

Where PL is the loss in production which cannot be recovered.

It is fair to assume that there would be no conversion of non-effective downtime events (downtime events which do not cause permanent production loss) into effective downtime events (downtime events which cause permanent production loss), due to infinitesimal change in MTTR, since change is very small. It is known that production due to machine j when subjected to sequence of downtime events $\vec{f}_i = [\vec{e}_{i,1}, \ldots, \vec{e}_{i,Nj}]$ is equivalent to summation of stoppage interval caused by machine j

$$PL(\partial d_j)=\frac{\sum_{j=1}^{\eta_j^e}d_i-d_i^*}{T_{N^*}} \tag{44}$$

Where $d_i^*=\inf\{d>0: s.t., \mathrm{TL}(\vec{e}_j)>0\}$

PL is simply summation of stoppage interval since there can't be any overlapping of downtime events on a single machine and η_j^e is number of effective downtime events which leads to permanent production loss.

$$PL(d_j+\partial d_j)=\frac{\sum_{j=1}^{\eta_j^e}d_i+\partial d_j-d_i^*}{T_{N^*}} \tag{45}$$

$$\frac{\partial C}{\partial d_j} = -\frac{\sum_{j=1}^{\eta_j^e} 1}{T_{N^*}} = -\frac{\eta_j^e}{T_{N^*}} \tag{46}$$

$$\frac{\partial EP}{\partial d_j} = \frac{\frac{\partial E}{\partial d_j}}{E} - \frac{\frac{\partial C}{\partial d_j}}{C} \tag{47}$$

Thus a machine j is bottleneck if it satisfies the following

$$H_j + I_j > H_i + I_i, \forall i \neq j \tag{48}$$

$$H_k = \frac{-\eta_k P_{p,k}}{\sum_{i=1}^{N} [P_{p,i}(T - \sum_{i=1}^{\eta_i} d_k - (1-\alpha_i) T_{id,i})]} \tag{49}$$

$$I_k = \frac{\eta_k^e}{T - \bigcup_{k \in \eta^s} [t_k + d_k^*, t_k + d_k) |} \tag{50}$$

Power Bottleneck

The PBN provides a tool to replace a machine with a new machine in an optimal way. PBN represents the machine, which once swapped with a machine having greater power efficiency, results in maximum increase in energy efficiency. Thus a machine j is PBN if

$$\frac{\partial EP}{\partial P_j} > \frac{\partial EP}{\partial P_i}, \forall i \neq j \tag{51}$$

The above equation can be evaluated as follows

$$\frac{\partial(\frac{E}{C})}{\partial P_j} = \frac{\frac{\partial E}{\partial P_j}}{C} \tag{52}$$

$$E(P_j + \partial P_j) = \sum_{j=1}^{N} [P_{p,j}(T - \sum_{k=1}^{\eta_j} d_k - (1-\alpha_j)T_{id,j})] + \partial P_j (T - \sum_{k=1}^{\eta_j} d_k - (1-\alpha_j)T_{id,j}) \tag{53}$$

$$\Rightarrow \frac{\partial E}{\partial P_j} = (T - \sum_{k=1}^{\eta_j} d_k - (1-\alpha_j)T_{id,j}) \tag{54}$$

Putting the values found in above equations in $\frac{\partial EP}{\partial P_j} > \frac{\partial EP}{\partial P_i}, \forall i \neq j$ and simplifying it, the following inequality to identify PBN is obtained.

$$\alpha_j (T - \sum_{k=1}^{\eta_j} d_k) + (1-\alpha_j)T_{p,j} > \alpha_i (T - \sum_{k=1}^{\eta_i} d_k) + (1-\alpha_i)T_{p,i}, \forall i \neq j \tag{55}$$

In the next section, the results from simulation studies would be discussed.

6. Simulation studies

A simulation model built using Arena software is used to replicate data of a production line, which would be obtained using the dispersed sensor network of the respective manufacturing system in the practical scenario. The model is run for a time horizon of [0, T) with T = 8 hours which represents each shift. The values of various parameters used in simulation such as buffer capacity, MTTR etc. are shown in table 2. MTTR and MTBF follow an exponential distribution with means shown in table 2. Simulation was ran for 50 replications and obtained permanent production loss due to each station as shown in table 2.

Table 2 Station parameters

Station	**Cycle time (min)**	**MTBF (min)**	**MTTR (min)**	**Buffer Capacity (parts)**	**Permanent Production Loss (units)**

1	2.5	40.00	13	-	8
2	1.5	56.67	13	35	7
3	1.0	190.00	13	40	0
4	2.0	90.00	13	37	4
5	3.0	56.67	13	45	5
6	2.5	40.00	13	41	14
7	2.0	990.00	13	40	0

Simulation provides severity ranking for stations in terms of permanent production loss due to each station, that is $S_6 > S_1 > S_2 > S_5 > S_4$. Elaborated information for decision making involving budget allocation and resource planning is provided by this analysis and integrated model. For example, the maintenance work can be prioritized based on station or event severity ranking.

An alternative method to increase productivity of system is discussed and experimentally proven. According to the method mentioned above, stations resulting in maximum permanent production loss of production line are selected and these stations are made to produce extra parts before production shifts. The number of extra parts produced should be equal to respective accumulated production loss. Two experiments have been performed to illustrate this method.

In first experiment, it is illustrated that stations with highest production loss per shift should be selected. Three policies are compared on the basis of increase in system productivity. In first policy, stations with highest production loss i.e. stations 1 and 6 are chosen. In second policy, station with minimum standalone output i.e. stations 5 and 6 are chosen. In third policy, stations with most accumulated downtime i.e. stations 1 and 4 are chosen. In each policy selected stations are made to produce 10 extra parts each. The simulations are run for 50 replications and results are tabulated in table 3. Results prove that policy based on our method i.e. policy 1 leads to largest increase in system productivity.

The second experiment illustrates that the number of extra units produced should be equal to permanent production loss of each station. Eight experiments are conducted, in experiment i, station 1 produces 2+i extra units while station 6 produces 2+2i extra units. The results of this experiment are depicted in figure 2. The results show that highest improvement in system output is in the sixth experiment where number of extra parts is equal to respective production loss, hence proving our method.

Table 3 Comparison of policy 1, 2 and 3

Policy/Improvement	Minimum Improvement (units)	Maximum Improvement (units)	Mean Improvement (units)
Policy1	10	15	13.20
Policy2	5	11	8.25
Policy3	4	8	6.5

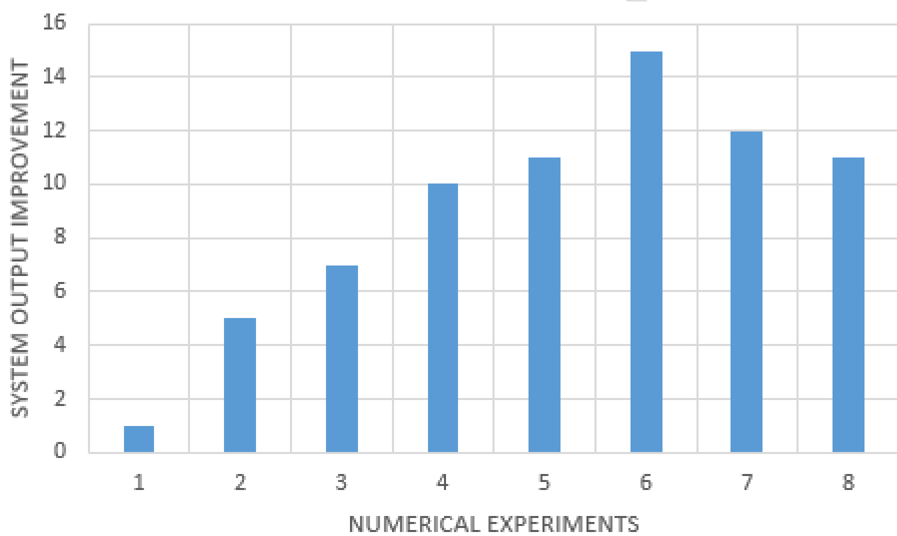

Fig. 2. System output improvement of each numerical experiment

Comparison of DBN and PBN with general industry indicators

In this section, the results of simulation studies conducted to confirm the results of section 5 are illustrated. Our simulation study utilizes 100 dissimilar line combinations to examine the efficiency of DBN and PBN. These combinations represent the different possible layouts possible in the industry thus ensuring robustness of proposed concepts. To create different scenarios MTBF (min) is selected randomly from set

{40, 56.67, 90, 190, 990} and value of $P_{p,j}$ (kWh) is selected randomly from the set {80, 100, 120} and similarly cycle time (min) is randomly selected from the set {1, 1.5, 2, 2.5, 3}, while α_j is kept constant. Data used for simulation like cycle time, power consumption rate etc. are selected to represent the general industrial scenario for experimental testing. DBN helps in determining the direction of investment for reducing downtime or repair time of a particular machine. Reducing downtime does not require major resources and is done frequently in the industry. Therefore, to test performance of DBN, MTTR of respective machine determined by respective indicator, is reduced by 10% and the change in value of performance indicator (PI) is noted. PBN helps in determining direction of investment for replacement of an old machine with power efficient machine. Replacing machine is a resource intensive activity and cannot be done on a regular basis thus results of PBN are reported on a yearly scale. $P_{p,j}$ of the respective machine is reduced by 30kW and change in PI is noted. Each combination is ran for a time duration of 8 hours and tested against baseline case. The parameters for baseline is shown in table 4 and the results of DBN and PBN comparisons are shown in table 5 and table 6 respectively.

Table 4 Baseline Parameters

Station	**Cycle time (min)**	**MTBF (min)**	**MTTR (min)**	**Buffer Capacity (parts)**	$P_{p,j}$ **(kW)**	$P_{id,j}$ **(kW)**
1	2.5	40.00	10	-	120	90
2	1.5	56.67	10	328	100	75
3	1.0	190.00	10	328	100	75
4	2.0	90.00	10	352	120	90
5	3.0	56.67	10	377	80	60
6	2.5	40.00	10	423	80	60
7	2.0	990.00	10	425	100	75

Table 5 DBN vs general industrial indicators

Indicator	Total Energy Consumed(kWh)	Total parts produced(kWh)	Average energy consumed	Average parts produced	% Change PI
Baseline	486695	10233	4866	102	-
Max EP_j	528097	11227	5281	112	1.42%
Min MTBF	505676	10638	5057	106	0.36%
Max $P_{p,j}$	497887	10447	4979	104	0.10%
Max EI_j	519111	10987	5191	109	0.97%
DBN	550344	11888	5503	118	**3.05%**

Table 6 PBN vs general industrial indicators

Indicator	Average yearly energy consumption(kWh)	% Change PI
Baseline	1776091	-
Max EP_j	1739859	2.04%
Min MTBF	1741457	1.95%
Max $P_{p,j}$	1742345	1.90%
Max EI_j	1738260	2.13%
PBN	1735063	**2.31%**

The results depict that DBN leads to more than double percentage increase in PI with respect to second best performer. Moreover, number of units produced in case of DBN are large compared to second best indicator. The performance of PBN is also better than rest of the indicators. Use of PBN leads to average savings of 41028 kWh and approximately 3000 kWh with respect to second best performer. Both PBN and DBN are ranked 1 in all the 100 scenarios. Both of these indicators are easy to use and results in better performance. While it is important to decrease the energy waste, it is also important to increase the throughput of the system. In case of DBN, it is observed that it results in increased throughput with minimal rise in energy consumption. To understand more about the benefits of DBN and PBN, monetary analysis is performed to estimate the monetary savings of the organization by decision making via DBN and PBN.

$$savings = productivity\ gain - energy\ consumption$$

For experimental purposes, it is assumed that profit per unit part is 1000 INR. Based on the official government data (Open Government Data, 2018) electricity cost is 4.82 INR per kWh in India. Replacing a machine is a big investment thus PBN savings are calculated on a yearly scale. DBN involves reduction in repair time of the machine which is done more frequently in production line, thus DBN savings are calculated on a monthly scale. Table 7 shows the results of DBN, PBN savings versus monetary savings from other general industrial indicators.

Table 7 Monetary savings from DBN and PBN

Indicator	PI(DBN)	PI(PBN)	Monthly Savings (DBN) (INR)	Yearly Savings (PBN) (INR)
Baseline	0.69	0.69	-	-
Max EP_j	0.70	0.70	238332.6	350591.8
Min MTBF	0.69	0.70	94052.37	171580.4
Max $P_{p,j}$	0.69	0.70	48015.72	112996.3
Max EI_j	0.69	0.70	179326.1	280903.2
DBN or PBN	0.71	0.71	404463.1	555826.1

It is clear from the above results that DBN and PBN performs significantly better than general industrial indicators in every aspects. Performance Indicator value for both DBN and PBN are the best and both results in almost double monetary savings compared to the second best performer. An interesting point to note about DBN is though it results in more energy consumption but it also increases the productivity of the system with minimal increase in energy consumption thus making it more efficient in terms of energy and monetary savings. On the other hand, PBN results in most energy savings and monetary savings compared to rest of the indicators.

The indicators PI, DBN, PBN, and Unified Severity Index can be utilized in monitoring performance of the manufacturing system. A dashboard can be developed which uses real-time sensor data from the production line to calculate and display the values of above indicators. These indicators can be utilized by managers for decision making process for diverting the limited resources for maximum improvement. For example, if throughput of the line is less than expected, unified severity index can be used to identify the machine or station which is resulting in maximum production and resources can be diverted to that specific machine to improve productivity. Similarly PI can be utilized to monitor energy efficiency of the production line and DBN or PBN can be utilized to identify power inefficient machine. DBN can be utilized to identify the machine which requires most repairing resources while PBN can be used for decision-making process of machine replacement and which machine to be replaced, if replacing a machine.

7. Conclusion

In this paper, first production system's dynamics with multiple slowest stations is studied. It is proven that only downtime events which cause blockage or starvation of slowest station, results in permanent production loss. Then a unified severity index is developed in terms of production loss. In the next section, dynamic structure of energy for serial production line is analyzed and the effect of downtime events on energy consumption in terms of energy consumed per part is studied. Performance indicators are developed to evaluate energy efficiency of the system. DBN and PBN are defined in section 5 and proven mathematically. The proposed indices, Unified Severity Index, PI, DBN, and PBN can be calculated using real-time sensor data obtained from the production line. These indices can be used by manager to take crucial decisions about limited resources. For example, unified severity index can be used to modify the buffer space arrangement of production line or PBN can be used to replace a power-hungry machine.

Future research will integrate opportunity windows and these bottleneck indicators (DBN, PBN) to further reduce the energy consumption. Furthermore, the relationship between two components will be explored in greater detail to improve responsiveness and overall efficiency. A user-friendly dashboard will be developed to help plant manager to take decisions using indices proposed in the paper.

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- Performance indices for measuring energy efficiency and productivity of a serial manufacturing system are developed
- Unified severity index is developed to quantify total production loss from each station
- Energy dynamics of the serial manufacturing system is studied and performance indicator is developed to measure energy efficiency of the system
- Performance bottlenecks (downtime bottleneck, power bottleneck) are established to optimize the distribution of the resources to machines
- Simulation studies were performed to verify the proposed methods