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**Energy performance evaluation and energy savings opportunities
for Manufacturing systems**

A Thesis Presented

by

Shiyao Wang

to

The Graduate School

in Partial Fulfillment of the

Requirements

for the Degree of

Master of Science

in

Mechanical Engineering

Stony Brook University

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Abstract of the Thesis
**Energy performance evaluation and energy savings opportunities
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Presently, with the development of modern manufacturing system, the usage of energy is growing rapidly. Since most of fuel we use are non-renewable resources, fuel becomes a very big part of cost. How to use the energy more efficiently is the main concern now. This thesis provides a systematic method to evaluate the energy efficiency of a production system and decompose the unnecessary energy waste of a manufacturing facility from the measured data with stochastic frontier analysis model. A new energy efficiency indicator is developed for the energy consumption level and efficiency of machines and production lines. Energy savings opportunity widows are applied to maximize energy consumption efficiency and enable the rearranging of the scheduled maintenance without permanent production loss.

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List of Abbreviations

KPI -----Key Performance Indicator

EIA----Energy Information Administration

HVAC-----Heating, Ventilation, Air Conditioning

SFA-----Stochastic Frontier Analysis

OLS----Ordinary Least Squares

MLE-----Maximum Likelihood Estimation

OECD-----The Organization for Economic Co-operation and Development

HDD----Hot Degree Days

CDD-----Cold Degree Days

EEPI-----Energy Efficiency Performance Indicator

EDD----Energy Dynamic Distribution

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1 Introduction

Productivity and quality of manufacturing systems have been analyzed extensively for more than 60 years [1-7]. On the contrary, very few researches are focused on the utilization of energy. With the rapidly increasing energy costs and environment pollution, more and more concerns are paid on reducing energy consumption and green-house gas emission. According to the investigation by U.S. EIA, the manufacturing industry in the U.S has spent \$96 billion on the fuel and electricity consumption [8]. The energy consumption cost in transportation alone in the manufacturing industry is over \$4 billion, in which \$791 million are attributed to motor vehicle assembly plants [8].

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 [9]. However, the research has mostly been on the individual machine level [10], like how to improve the performance of a machine, not about the control of the entire production line. 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 [11,12]. It has also been discovered that 85% of energy in a manufacturing environment is utilized for functions not related to the production of parts [13].

During a production operation the energy consumption in industry plants can be divided into two fundamental parts, caused by production operations and caused by facilities. The facility section is mainly impacted by the HVAC and lightning use. Production operations are formed by normal production and waste. The efficiency of energy consumption comes from the normal production operations. On the other hand, the waste brings the inefficiencies of the line, which consists of two different parts, the unsynchronized part and unscheduled downtime. The unsynchronized part can be described as the technical limitation of the production line, the unscheduled downtime represent the random failure factor in operations. The construction is showed as figure-1 below:

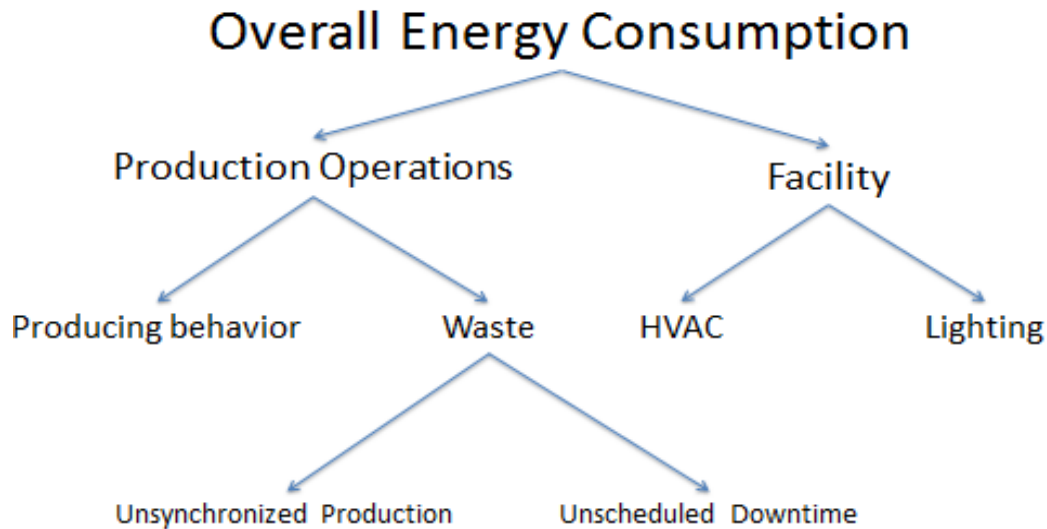


Figure- 1 Constitution of energy consumption

There are few studies that address factory floor planning while considering energy saving opportunities [14-16]. Previous work in this area has been focused on control of the quality of products and the expected throughput without considering the energy saving potential. These methods treat the energy consumption 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.

Some existing methods, such as the energy treasure hunt developed at GE [17] focus on developing weekend and daily shut down 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 facilities, the most common way is using energy consumed per part. This key performance indicator (KPI) can express the relationship between

throughput and energy consumption directly. Many energy dashboard companies use this KIP as the main factor on their interfaces. However, two parameters in their KPI are final production account and total energy consumption, which are very unscientific for ignoring the uncompleted jobs. If only counting final completed parts, it is impossible to determine the energy hog in a specified production line and energy efficiency level is inaccurate.

The structure of the thesis is as follows. In Section 2 we will provide the methods that have been developed by other scholars. Section 3 will discuss the SFA model for the purpose of detecting the energy consumption performance of plant view. In the following Section 4 we will discuss the energy savings opportunity windows and optimization. We will provide the conclusion and future work in Section 5.

2 Literature Review

A lot of studies have been made in the past few years on the evaluation of energy consumption and energy savings opportunity for the manufacturing industry [18].

2.1 Industry-specific micro-economic analyses

Anton Dietmair and Alexander Verl have published a paper about energy consumption modeling and optimization for production machines [19]. The efficiency in general is commonly agreed to be expressed by the equation: $efficiency = \frac{benefit}{total\ effort}$ [20]. So for each production process the efficiency can be calculated by the benefit and effort. For example, in the cutting processes, the object of operation is remove material on the working parts. The more material has been cut, the higher benefit there will be, and the effort is the energy consumption to operate the machine. e_{proc} and $P_{proc}(t)$ are the energy and power consumption for specific process. E_{proc} and $P_{proc}(t)$ are the integral of energy and power consumption. V_{rem} and $V_{rem}(t)$ are the volume and remove rate of removed material. The expressions are as follows: $e_{proc} = \frac{E_{proc}}{V_{rem}}$, $p_{proc}(t) = \frac{P_{proc}(t)}{V_{rem}(t)}$. This method allows managers to compare energy efficiency between different processes alternatives, and can be extended to other production alternatives. However there are some processes which have no accurate model for the benefit, such as surface quality. Therefore, the efficiency of processing can be seen as the ratio between the absolute minimum of the energy that is required, $E_{min,abs}$ and the actual energy consumption of the machine, E_{real} :

$$efficiency = \frac{E_{min,abs}}{E_{real}}. \text{ However in the real situation, it is every hard to get the minimum}$$

theoretical energy consumption for manufacturing applications. Thus, instantaneous power consumption can take replace to represent the instantaneous efficiency of the machine which is

completing a process: $\eta_{Machine}(t) = \frac{P_{proc}(t)}{P_{Machine}(t)}$. The machine energy consumption efficiency for

the whole time can be expressed as the integral by time step as $\eta_{Machine} = \frac{\int P_{proc}(t)dt}{\int P_{Machine}(t)dt}$ [19].

2.2 Energy trend decomposition methods

Trend decomposition is one of the most common ways to analyze the energy or green-house emissions trends [21]. Particularly, when facing the energy consumption in industrial operation in which area the energy consumption can be sorted by various uses. Trend decomposition has been proven to be a very practical method to detect the cause of industrial structure or the output index from factors during the production operation that may change the energy consumption. This method also provides guidance for the decrease in energy efficiency, and a number of other factors. In recent studies, it has been extended to the decomposition of carbon emissions trends.

The trend decomposition is widely used in various researches. However, there is no standard or generally agreed upon method for energy trend decomposition. Thus, it is very important to employ the proper method to ensure an accurate analysis. There are four methods which have been used most in different condition: 1) theoretical foundation, 2) adaptability or transferability, 3) ease of implementation, 4) ease of interpretation of results [22]. In 2007, in order to establish carbon reduction policies in 14 EU countries, Diakoulaki and Mandaraka determine provide the analytical result of whether the decoupling of CO₂ emission increases with the industry development by index decomposition of emission trends [23].

2.3 Econometric methods

These studies proved that econometric method can be applied to illustrate a large number of problems. The econometric method does not have the limitation from data, such as problems about instantaneous, spatial and sectorial detail. Analysis methods are varied with the object. For example, single-equation models, large numbers of methods can be applied from very simple, such as OLS, to a sophisticated one. On the other hand, there are some limitations for the econometric methods. After all, it is solving industrial problem with the economic models. The obstacle exists that it can only provide guidance in a more macroscopic view instead the engineering detail, like neglect of productivity. A paper [24] written by Adeyemi and Hunt in 2007, with the principle by GH, GS, and Huntington, explores the issue of energy saving technical change and the asymmetric price responses. With the panel data from 15 OECD countries from 1962 to 2003, they tentatively prove that the increase of energy demand by

corporations are more related to asymmetric price responses instead of energy saving technical change.

2.4 'Bottom-up' method

Different studies refer to the 'Bottom-up' method. This model can be implemented in wide ranges from macroscopic view to microscopic view, and the model can be varied from complex to simple. It needs more detail of the processes or even a specific technology to be utilized. Three methods are widely used in the 'Bottom-up method:' 1) 'hybrid' models 2) optimization, and 3) simulation [18]. The advantage of 'Bottom-up' method is that users are able to detect whether the emerging technologies can reduce the energy consumption or not with the model, and changes in demand and fuel prices can be considered explicitly. However, it is hard to find the linear relationships between each identified process and technology, which means there is difficulty to apply the linear optimization [25], so the economic scale cannot be represented. The paper [26] by Murphy et al., does not use constant elasticity of substitution function as the basis from which to depart, these researchers have taken a 'Bottom-up' approach and inserted 'behavior realism' and equilibrium feedbacks and employed the 'hybrid' modeling framework as the simulation algorithm for solution. This framework makes use of econometrically estimated parameters to describe the key micro-economic behaviors. It allows users to draw the trajectories of potential functionality of new technologies, while comparing different specific processes.

3 Stochastic Frontier Modeling

For the purpose of deciding and locating the problems of operation over all the possible factors that might impact the energy consumption efficiency, we choose stochastic frontier modeling as the method of regression. This method is very accurate to analyze the technical inefficiency of specified factors from cross section data.

3.1 The methodology

This section utilizes a stochastic frontier model from a manufacturing energy efficiency level optimization problem. Since stochastic frontier analysis (SFA) was proposed in 1977 as an economic mathematical model by Aigner and Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977), many researches and applications have been made. The concept is used to evaluate the production inefficiency and decomposed inefficiency into its technical and allocated components [27].

The SFA model can be expressed as $y = f(x; \beta) \times \exp\{v - u\}$, where y is the observed outcome (goal attainment), x is vector variable input, and β is vector technical parameter related to each variable. The error component v which follows the distribution $(0, \sigma_v^2)$ is defined to capture the stochastic disturbance to the output. The other error component u is a non-negative number which is used to indicate the impact of technical inefficiency. Therefore most producers set the stochastic frontier above or below $y = f(x; \beta) \times \exp\{v\}$ for $u = 0$ or $u \geq 0$. Further research by Battes and Corra assigned a half normal distribution to u , thus β , σ_v^2 and σ_u^2 associate with u , are parameters that need to be estimated. Either distributional assumption on u implies that the composed error $(v - u)$ is negatively skewed, and statistical efficiency requires that the model be estimated by maximum likelihood (which we abbreviated MLE). After estimation, an estimate of mean technical inefficiency in the sample was provided by $E(-u) = E(v - u) = -\sigma_u$ in the half normal-exponential case.

Previous research by Lovell and Schmidt announced that it is not feasible to estimate technical inefficiency by observation since it is not possible to separate individual residuals into their two components (v and u). Then Jondrow et al. (1982) quickly proposed in his paper (JLMS) that

$[u_i|v_i - u_i]$ can represent technical inefficiency for each individual variable in both mean and mode of conditional distribution.

Unlike other most of other study in this area, the estimation of model parameter β is the first concern. The goal of this research is estimate and analysis the technical inefficiency in samples or aggregated samples. SFA is only a tool for estimation, therefore it is impossible to find a model which is suitable for every field. Production and cost analysis model is based on Cobb-Douglas, or other forms of logarithmic models. The Cobb-Douglas model can be express in general as:

$$Y = AL^\beta K^\alpha \quad (\text{Eq.1})$$

Where

A = Represents the total factor productivity;

L = Labor input (the total number of person-hours worked in the data collecting period);

K = Capital input (the monetary worth of all machinery, equipment, and buildings);

Y = Total production.

3.2 The model

The concept of using SFA to evaluate energy efficiency level can be easily expressed in terms of a liner regression model [28]. To evaluate energy consumption efficiency the most direct indicator can be described in form of kWh/unit. Thus a simple linear equation for this can be written as:

$$E_i = \alpha + \beta Y_i \quad (\text{Eq.2})$$

Where

E = Energy usage, either electricity, non-electricity energy;

Y = Production, measured by physical production;

With measured data from plant, a regression can be made to fit the parameters α and β . However, there is a difference between the actual output and estimated output for the data may not be measured perfectly and it is only a simple expression of the relationship between input

and output, the estimated parameters rely on that any departures in the plant data from Eq.2 are “random” [29]. So the actual relationship between output and inputs are as Eq.3:

$$E_i = \alpha + \beta Y_i + \varepsilon_i \quad (\text{Eq.3})$$

$$\varepsilon_i \sim N[0, \sigma^2]$$

Where

ε_i = Random error term.

In order to get the best case that leads to the least summation of departures from average level, ordinary least square regression (OLS) is one way to reach the goal. However, the data above average means the inefficiency which is the most interest. This departure of energy use per production may be caused by HVAC system or capacity utilization. Maximum likelihood estimation provides solution to establish a frontier based on Eq.3, and we will obtain the best-case frontier that has the lowest energy use per production.

Even though the frontier has been made to indicate the efficiency between actual energy use and the best case, this is still not a perfect model. There still is some error during data collecting or analysis that has not been considered, and in equations every inputs represents the factor that contributes to the manufacturing energy use, so it is necessary to include the stochastic error, in term of v_i , which may have positive or negative affect into consideration. At the same time, there will be another form of error u_i refers to technical inefficiency. Unlike the random error term, technical inefficiency can only be positive which follows the half-normal distribution in our case. So the general form of SFA model for energy consumption per production will be:

$$E_i/Y_i = f(X_i, \beta) + (u_i - v_i) \quad (\text{Eq.4})$$

$$v \sim N[0, \sigma_v^2]$$

Where

E = Energy usage, either electricity, non-electricity energy;

Y = Production, measured by physical production;

X = Systematic decision variables (i.e., plant capacity, or utilization rates);

β = Parameters to be estimated.

Here the assumption has been made that energy inefficiency u is distributed according to half-normal distribution. Then it is possible to estimate parameters of Eq. 3, along with the distribution parameters of u . This kind of approach has its advantages. The estimated parameters can normalize systematic impact and indicate the distribution of efficiency. The standard linear regression can only provide guidance of average performance but frontier regression captures the behavior of best performer which is the baseline in our case.

Thus with given data for the target, with Eq.3, it is possible to compute the difference between actual energy consumption and estimated baseline:

$$\frac{E_i}{Y_i} - f(X_i, \beta) + v_i = u_i \quad (\text{Eq.5})$$

Since we have the technical inefficiency u_i and probability distribution of it, it is easy to calculate the probability that technical inefficiency is bigger than the estimation. Here we define $\Phi(x)$ as the cumulative probability density function for a half-normal distribution:

$$\phi(u; \sigma_u) = \frac{\sqrt{2}}{\sigma\sqrt{\pi}} \exp\left(-\frac{x^2}{2\sigma_u^2}\right) \quad u > 0 \quad (\text{Eq.6})$$

And

$$\Phi(x; \sigma_u) = \int_0^x \phi(u) du \quad (\text{Eq.7})$$

Here we can use two different ε_i from two SFA models where one of them contains all the independent variables and the other does not have the variable. From the difference of them we can have a score, which is our final technical inefficiency (TI).

$$\text{EPI} = \varepsilon'_i - \varepsilon_i \quad (\text{Eq.8})$$

This score reflects the impact from random components that has not been considered in function $f(X_i, Z_i, \beta)$. So the TI give manager guidance of energy inefficiency of a plant by computing distribution of technical inefficiency, and specific standardized system factors will be eliminated. This model will provide hypothetical and practical view of plant operation. EXCEL data tool solver provides simulation of maximum likelihood solution to estimate half-normal distribution frontier after the standard regression.

The final equation for energy consumption is:

$$\frac{E_i}{Y_i} = \beta_0 + \beta_1 HDD_i + \beta_2 CDD_i + \beta_3 Utilization_i + \beta_4 Lightening_i + u_i - v_i \quad (\text{Eq.9})$$

Where

E=Total energy use (in kWh)

Y=Total number of completed jobs

HDD= Heating degree days (in °F) for the plant

CDD= Cold degree days (in °F) for the plant

Utilization= Utilization percentage for the plant, defined as actual output/potential output under fully used capacity.

β = Vector parameters to be estimated

The variable v is distributed as $N(0, \sigma_v^2)$.

3.3 Procedure

- 1) According to the mathematic model we have, use OLS to get all the parameters that will be used to describe the frontier.
- 2) Assumptions that have been made above, $v_i \sim N[0, \sigma_v^2]$ and $u_i \sim N^+[0, \sigma_u^2]$ are both independently distributed, non-related with independent variable. So we have mean of u_i as $E(u_i) = \sqrt{2\pi}\sigma_u$, variance of u_i as $V(u_i) = (\pi - 2)\sigma_u^2/\pi$. The same reason, for the stochastic error we can also have mean of v_i as $E(v_i) = 0$, variance of v_i as $V(v_i) = \sigma_v^2$ So according to the relationship $\varepsilon_i = v_i - u_i$ we can have the variance of ε_i as the summation of $V(u_i)$ and $V(v_i)$, which is $V(\varepsilon_i) = \sigma_v^2 + (\pi - 2)\sigma_u^2/\pi$
- 3) According to the assumption of distribution on v_i and u_i , probability density function can be written as:

$$f(u_i) = 2(\sqrt{2\pi}\sigma_u)^{-1} \exp(-u_i^2/2\sigma_u^2) \quad (\text{Eq.10})$$

$$f(v_i) = (\sqrt{2\pi}\sigma_v)^{-1} \exp(v_i^2/2\sigma_v^2) \quad (\text{Eq.11})$$

Based on the independency assumption, joint probability density function of u_i and v_i is the product of their probability density functions:

$$f(u_i, v_i) = (\pi\sigma_u\sigma_v)^{-1} \exp(-u_i^2/2\sigma_u^2 - v_i^2/2\sigma_v^2) \quad (\text{Eq.12})$$

For the relationship that $\varepsilon_i = v_i - u_i$, joint probability density function can be expressed as:

$$f(u_i, \varepsilon_i) = (\pi\sigma_u\sigma_v)^{-1} \exp(-u_i^2/2\sigma_u^2 - (\varepsilon_i + u_i)^2/2\sigma_v^2) \quad (\text{Eq.13})$$

Integrate function above by u_i , we can have ε_i 's marginal probability function:

$$\begin{aligned} f(\varepsilon_i) &= \int_0^\infty f(u_i, \varepsilon_i) du_i = 2(\sqrt{2\pi}\sigma)^{-1} [1 - \Phi(\varepsilon_i\lambda/\sigma)] \exp(-\varepsilon_i^2/2\sigma^2) \quad (\text{Eq.14}) \\ &= 2\sigma^{-1} \phi(\varepsilon_i/\sigma) \Phi(-\varepsilon_i\lambda/\sigma) \end{aligned}$$

Where

$\Phi(x)$ = Cumulative distribution function of x

$\phi(x)$ = Probability density function of x

$\lambda = \sigma_u/\sigma_v$

$\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$

From the result above, we can have $E(\varepsilon_i) = -E(u_i) = -\sqrt{2\pi}\sigma_u$, $V(\varepsilon_i) = (\pi - 2)\sigma_u^2/\pi + \sigma_v^2$

4) We can describe the logarithm likelihood function for i^{th} sample in formula below:

$$\ln L = I \ln \sqrt{2/\pi} - I \ln \sigma + \sum_i \ln \Phi(-\varepsilon_i\lambda/\sigma) - (2\sigma^2)^{-1} \sum_i \varepsilon_i^2 \quad (\text{Eq.15})$$

Where

I = Maximum likelihood coefficient

Use first order condition to apply the maximum optimization, we can have formulas as follows:

$$\frac{\partial^2 \ln L}{\partial^2 \sigma^2} = -\frac{1}{2\sigma^2} I + \frac{1}{2\sigma^4} I \sum_{i=1}^I \varepsilon_i^2 + \frac{1}{2\sigma^3} \lambda \sum_{i=1}^I \frac{\phi(\varepsilon_i\lambda/\sigma)\varepsilon_i}{\Phi(-\varepsilon_i\lambda/\sigma)} = 0 \quad (\text{Eq.16})$$

$$\frac{\partial \ln L}{\partial \lambda} = -\frac{1}{\sigma} \sum_{i=1}^I \frac{\phi(\varepsilon_i\lambda/\sigma)\varepsilon_i}{\Phi(-\varepsilon_i\lambda/\sigma)} = 0 \quad (\text{Eq.17})$$

$$\frac{\partial \ln L}{\partial \beta_0} = \frac{1}{\sigma^2} \sum_{i=1}^I \varepsilon_i^2 + \frac{\lambda}{\sigma} \sum_{i=1}^I \frac{\phi(\varepsilon_i \lambda / \sigma) \varepsilon_i}{\Phi(-\varepsilon_i \lambda / \sigma)} = 0 \quad (\text{Eq.18})$$

$$\frac{\partial \ln L}{\partial \beta_i} = \frac{1}{\sigma^2} \sum_{i=1}^I \varepsilon_i^2 \ln x_i + \frac{\lambda}{\sigma} \sum_{i=1}^I \frac{\phi(\varepsilon_i \lambda / \sigma) \varepsilon_i}{\Phi(-\varepsilon_i \lambda / \sigma)} = 0 \quad (\text{Eq.19})$$

With data analysis and data solver in EXCEL we can program and solve these functions and determine all the parameters we need from OLS, β_0 , β_i , ε_i .

5) Repeat the process, eliminating the variable we are interested in. This provides ε_i' and the final TI_i for this variable will be:

$$TI_i = \varepsilon_i' - \varepsilon_i \quad (\text{Eq.20})$$

After all these procedures, we can detect the operation inefficiency of specified facility. The difference of the research with exist method is my research is based on self-benchmark comparison. It is a time-based analyze, the data are all collected from the same plant, instead of from different plants or different area. This is a more practical guidance for manager to observe the problem and make improvement by collected data.

3.4 Case study

Here we use data collected from a plant of GM during 2011. The table below listed all the factors that might impact the energy inefficiency which we concern.

Date	Y (KWH/Unit)	HDD	CDD	Utilization	Lighting	β_0	Production Count	Total Energy (KWH)
2011/1/18	154.54	31	0	119%	13.82	1	3745	578752.3
2011/1/19	166.41	42	0	122%	15.96	1	3851	640844.91
2011/1/20	177.6	43	0	124%	18.84	1	3893	691396.8
2011/1/21	171.41	51	0	124%	10.14	1	3891	666956.31
2011/1/24	171.79	44	0	123%	18.63	1	3886	667575.94
2011/1/25	158.36	37	0	132%	12.45	1	4139	655452.04
2011/1/26	168.63	36	0	125%	10.32	1	3921	661198.23
2011/1/27	161.64	39	0	130%	12.19	1	4092	661430.88
2011/1/28	168.51	37	0	126%	12.85	1	3961	667468.11
2011/1/31	191.33	51	0	113%	15.53	1	3555	680178.15
2011/2/1	189.46	46	0	116%	13.71	1	3643	690202.78
2011/2/2	497.28	44	0	40%	19.10	1	1252	622594.56
2011/2/3	171.89	50	0	130%	14.26	1	4085	702170.65

2011/2/4	165.72	44	0	129%	19.75	1	4056	672160.32
...

Table- 1 Historical data from plant in 2011

For the convenience of display, here we only select the data from January. As shown above during the whole month the plant worked only 9 days. And the data named as HDD, means the degrees that have been changed by heating operation. The same, CDD means the degrees that have been changed by cooling operation. The 0 shows that there is no operation of such operation, which makes sense, since during the January there is no need to turn on the cooling system. The Utilization shows the percentile usage compared with full capacity. Lighting is the running time of lighting system. Y which is calculated by $Y = \frac{\text{total energy}}{\text{Production count}}$ is the depended variable.

After modeling and analyzing by EXCEL, we can get result as followed (here we just use utilization and lighting as the research object):

Variables	Coefficients	Standard Error	t Stat
Intercept	194.76	74.13	2.63
HDD	1.02	0.39	2.57
CDD	0	0	65535
Utilization	-61.20	50.77	-1.20
Lighting	0.57	0.83	0.69
MLE (l(β, λ, σ)): -27.06 λ : 5.17E-02 σ^2 : 23.98			

Table- 2 estimation result calculated with overall operation factors

The table above shows the parameter of each variable when we consider every factor after modeling and estimation.

Variables	Coefficients	Standard Error	t Stat
Intercept	215.06	66.62	3.23
HDD	1.05	0.388	2.70
CDD	0	0	65535
Utilization	-71.69	47.35	-1.51
MLE (l(β, λ, σ)): -27.54 λ : 2.17E-02 σ^2 : 26.64			

Table- 3 estimation result calculated without lighting system

The table above shows the parameter of each variable when we consider all factors except lighting after modeling and estimation.

Variables	Coefficients	Standard Error	t Stat
Intercept	106.39	17.00	6.35
HDD	1.087	0.37	3.23
CDD	0	0	65535
Lighting	0.94	0.78	1.11
MLE (l(β, λ, σ)): -24.99		λ : 4.47E+03	σ^2 : 24.99

Table- 4 estimation result calculated without utilization system

The table above shows the parameter of each variable when we consider all factors except utilization after modeling and estimation.

Overall	Lighting	Utilization	TI-Lighting	TI-utilization
-7.3091	-7.7657	1.4242	0.4566	-8.7333
3.5472	6.2759	6.7019	-2.7286	-3.1547
-5.8401	-8.3162	0.0061	2.4761	-5.8461
-3.7806	-1.3013	0.0056	-2.4793	-3.7862
-0.9159	-0.9273	0.0093	0.0113	-0.9252
7.3304	5.3746	13.3693	1.9559	-6.0388
-0.7718	-1.1816	1.3538	0.4098	-2.1256
5.3300	4.9212	9.7826	0.4088	-4.4526
4.2253	3.7177	14.8491	0.5076	-10.6238

Table- 5 results comparison

Since we have the standard error for each case, it is easy for us to get the TI of each factor. The overall standard errors indicate the effect from all the probable factors and stochastic impacts. And lighting and utilization represent the standard errors that do not take them into consideration. So by the difference of overall and lighting, overall and utilization we can have the technical inefficiency of those two factors which eliminate the stochastic factor.

We can show the result in charts which can be observed more clearly:

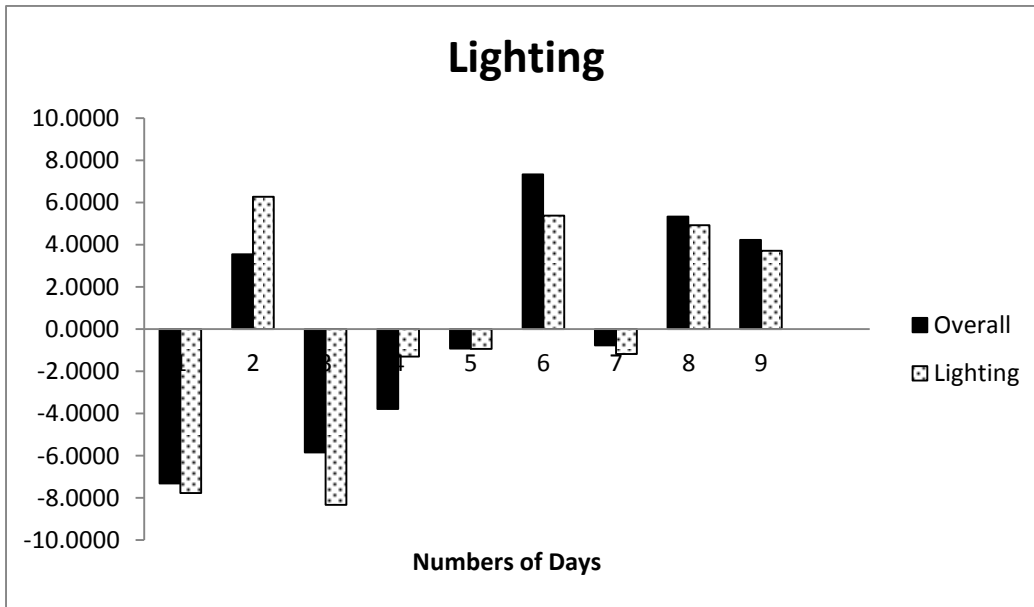


Figure- 2 SFA estimation result for lighting system

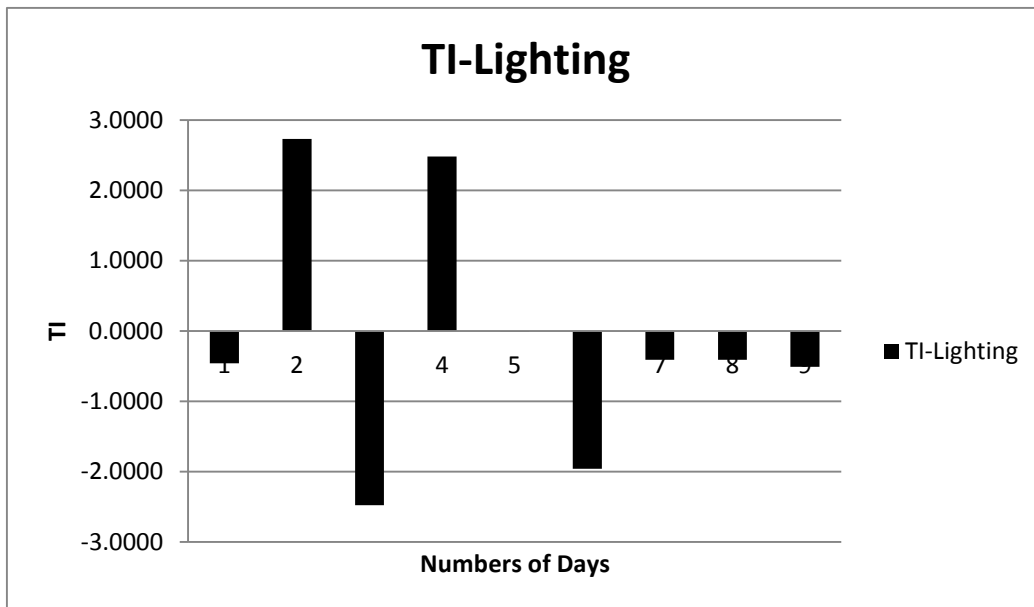


Figure- 3 Technical inefficiency for lighting system

As far as we can see in the first chart above, the black bar represents the standard error of overall factors, and the dashed bar represents the standard error of factors except lighting system. The differences between two sorts of standard errors will be the technical inefficiency for operation on lighting system, as the second chart show. The result suggests that the 2nd, 4th, 5th day in the whole month have the positive value of technical efficiency, in other words they have

a negative effect on the energy efficiency. The rest of days in this month perform well. The bigger the value is, the less efficiently the lighting system performs.

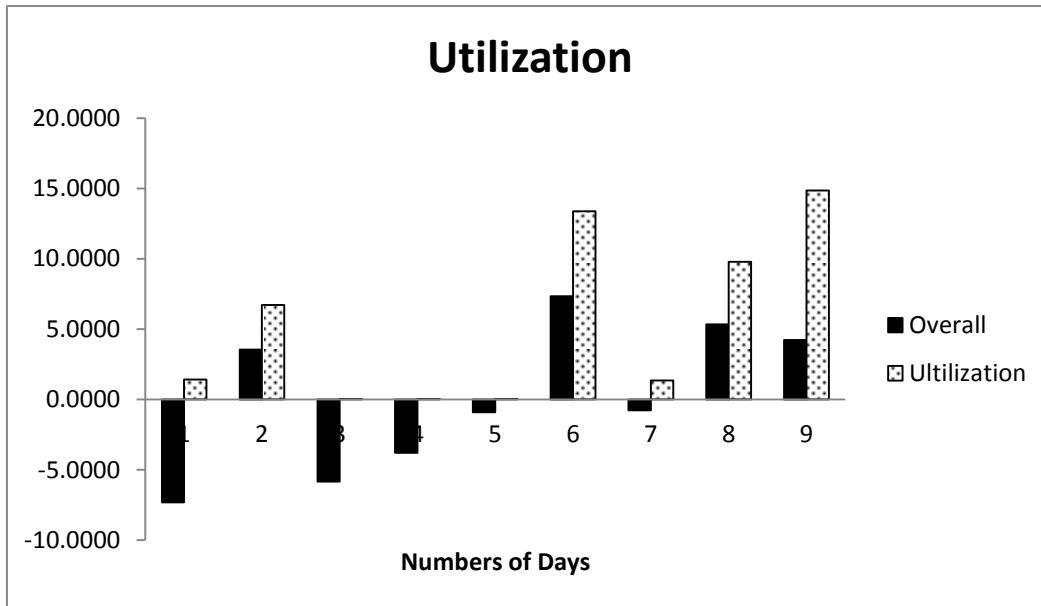


Figure- 4 SFA estimation result for utilization system

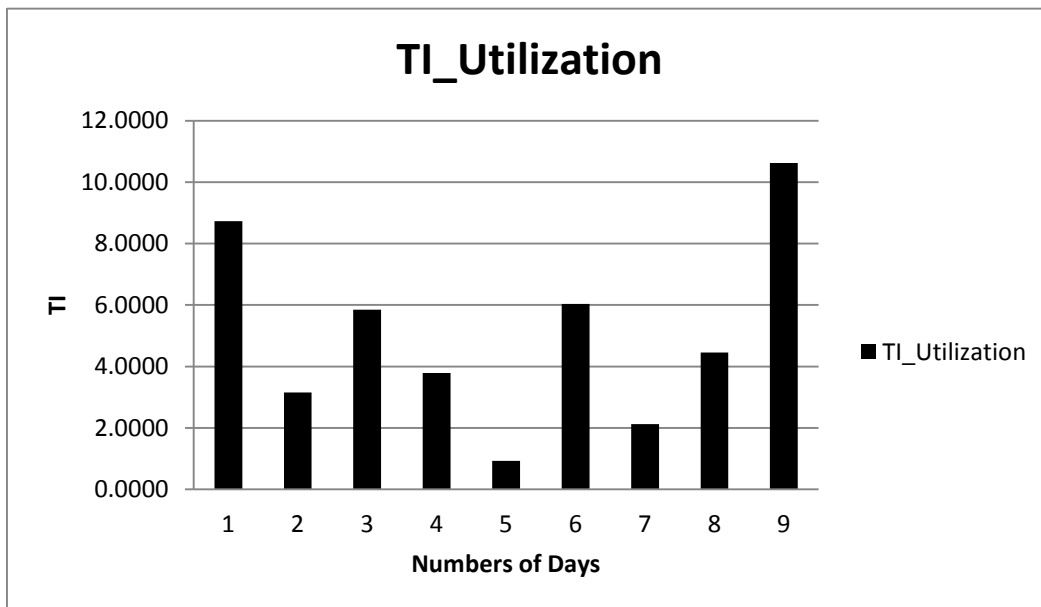


Figure- 5 Technical inefficiency for utilization system

For the same reason, on the aspect of utilization, all the days operation of production behavior have led to negative impact on the energy efficient. The 9th day has the highest technical

inefficiency on utilization. From the original data we can observe that on 2011/1/31, it has the highest energy per part, and a small utilization. However it cannot be proven that there is a direct relationship between those two factors, but it reflects the problem of the system and the accuracy of the SFA model.

4 Energy Dynamic Distribution and Energy Efficiency Performance Indicator

From the SFA modeling above, it is possible to detect the energy inefficiency problem in the plant level. However, when the result shows that utilization has the negative impact on energy consumption efficiency, SFA modeling will not be able to provide more detailed information and locate the problem. Therefore, we invent an energy efficiency performance indicator (EEPI) and energy dynamic distribution (EDD) to show in detail which specified machine causes the inefficiencies.

4.1 Baseline setup

We use the EEPI to signify energy consumption efficiency more dynamically and accurately, so it is important to set up the baseline energy consumption. In this report, series line has been set as the target.

For the purpose, the baseline has to be a case without any random breakdown events. This eliminates the impact of random failure which is leads to the inefficiency. The process for defining the baseline is as follows:

- 1) The slowest machine with a rated-speed:

$$S_{m^*} = 1/T_{m^*} \quad (\text{Eq.21})$$

Where T_{m^*} is the cycle time of the slowest machine.

- 2) The production count of the line is M.

There for the overall production time, t_p should be:

$$t_p = \frac{M}{S_{m^*}} = M \times T_{m^*} \quad (\text{Eq.22})$$

This is the best case scenario: the shortest possible time that the production line can produce M products. We set this case as our base line.

4.2 Real Scenario Study

In real production operations, there always exist random breakdown events, which will likely lead to permanent loss for the production system. This means the actual operation time t_r must be equal (if there is not any random breakdown event happens during the operation) or larger than t_p in the same situation by producing M jobs.

$$t_r \geq t_p \quad (\text{Eq.23})$$

This will help sort energy consumption into two parts. The baseline energy consumption, which is represented by W_1 and random downtime waste energy which is represented by W_2 . However, in order to standardize and quantize the energy, we assume, the machines consume the same amount of energy in one time unit when it is running. So it is easy to get the expression of W_1 and W_2 :

$$W_1 = W \times \left(\frac{t_p}{t_r}\right) \quad (\text{Eq.24})$$

$$W_2 = W \times \left(1 - \frac{t_p}{t_r}\right) \quad (\text{Eq.25})$$

Where

W = Total energy consumption of the whole production system.

W_1 = Baseline energy consumption.

W_2 = Wasted energy caused by stochastic downtime events.

It can be further categorized into another two forms. The unsynchronized part comes from the technical constrain which determined by rated-speed of each work station and structure of the system. Expression will be given:

$$W'_{1i} = W_{1i} \times \left(\frac{t_{pi}}{t_p}\right) \quad (\text{Eq.26})$$

$$W'_{3i} = W_{1i} \times \left(1 - \frac{t_{pi}}{t_p}\right) \quad (\text{Eq.27})$$

$$t_{pi} = M/S_i \quad (\text{Eq.28})$$

Where

t_{pi} = Time of machine i uses to produce M jobs.

S_i = Rate-speed of machine i .

W'_{1i} = Baseline energy consumption for machine i .

W'_{3i} = Unsynchronized energy waste on machine i .

W_1 and W_2 should be distributed to each machine by different principles. W_1 is the proportion of the rated power level of the machine to the total rated energy consumption of every machine. W_1 represents the energy consumption when machine is running normally. On the other hand, W_2 should follow the proportion of permanent loss for W_2 indicates the waste energy caused by the random breakdown events. The expression is as follows:

$$W_{1i} = W_1 \times \left(\frac{P_i}{\sum_{i=1}^m P_i} \right) \quad (\text{Eq.29})$$

$$W_{2i} = W_2 \times \left(\frac{L_i}{\sum_{i=1}^m L_i} \right) \quad (\text{Eq.30})$$

Where

P_i = Rated power level of machine i 's.

L_i = Permanent loss caused by machine i .

W_{1i} and W_{2i} = Distributed categorized energy for each machine i .

The permanent loss will generate when the slowest machine is blocked or starved, so in the program we will count the number of time steps that slowest machine are starved or blocked, and then multiply the speed of slowest machine to get the permanent loss on production counts.

The EEPI has to indicate the efficiency of machines, must reflect the energy consumption in term of per unit job. Therefore, production count need to be integrated with each distributed energy, W_{1i} , W_{2i} :

$$EDD_{Actuali} = (W_{1i} + W_{2i})/M_i \quad (\text{Eq.31})$$

$$EDD_{Baselinei} = W_{1i}/M_i \quad (\text{Eq.32})$$

$$EDD_{Actual} = \sum_{i=1}^m EPI_i \quad (\text{Eq.33})$$

$$EDD_{Baseline} = \sum_{i=1}^m EPI_i = \sum_{i=1}^m \frac{W_{1i}}{M_i} \quad (\text{Eq.34})$$

Where

M_i = the production count of machine i .

$EDD_{Actuali}$ =Actual energy dynamic distribution of machine i .

EDD_{Actual} = Actual energy dynamic distribution of the whole production system.

$EDD_{Actuali}$ =Baseline energy dynamic distribution of machine i .

EDD_{Actual} = Baseline energy dynamic distribution of the whole production system.

So far, EDD only shows the energy consumption level, it is not enough to indicate the efficiency, the EDD provide here gives the energy using level, for there exists probability that machines who have high EDD are just purely huge energy consumer. Therefore, it is necessary to check the relationship between W_{1i} and W_{2i} :

$$EEPI_i = W_{1i}/(W_{1i} + W_{2i}) \quad (\text{Eq.35})$$

Where

$EEPI_i$ = Energy efficiency performance indicator of machine i .

The advantage of this method is by using KPI, not only can evaluate the energy efficiency level of the whole production system, but also can give guidance of situation of each machine in a dynamic and scientific way with respect of each step's energy consumption.

4.3 Case study

Here we just use simulation with reasonable parameters to prove the practicability.



Figure- 6 Line structure for simulation

4.3.1 Case1: Slowest machine is the energy bottleneck

First, aim on a production line which has the very simple structure. This is a five machine and four buffer (5M4B) line. They all have the same efficiency and power consumption. Machine 3 is the slowest machine. Simulation time is set as 10080 minutes, with 500 minutes warm up time.

The parameters are given as follows:

Station	MTTF (min)	MTTR (min)	Rated Speed (min/part)	Power (kw)	Buffer	Buffer capacity	Initial buffer level	Efficiency
Machine1	150	37.5	3	100	Queue2	18	9	80%
Machine2	150	37.5	3	100	Queue3	18	9	80%
Machine3	150	37.5	5	100	Queue4	18	9	80%
Machine4	150	37.5	3	100	Queue5	18	9	80%
Machine5	150	37.5	3	100				80%

Table- 6 Parameters of simulation for case 1

Figure-7 gives us the energy consumption level of the production line. The dashed line above gives the actual energy consumption level of manufacturing each part for the whole production line. And the solid line below represents the theoretical energy consumption level of manufacturing each part for the whole production line. The higher the value is means the bigger the energy consumption level of this production line. As we can see, at the beginning there is a very intense fluctuation. This is because the machine efficiency is distributed exponentially for the whole simulation time, any downtime at the very beginning will make machine very inefficient leading to the energy consumption level to be very high at that time point. After 2000 minutes the EDD level comes to a steady state. This will reflect the energy consumption level of production line.

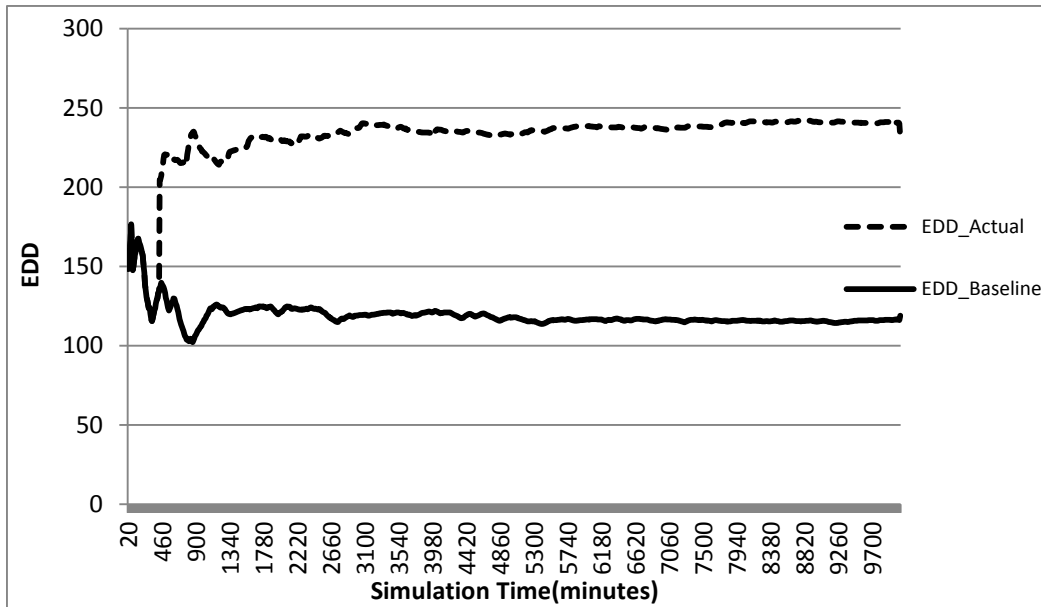


Figure- 7 EDD on production line level for case 1

The bar graphs below gives us the individule EDD of each machine and EEPI of each machine at moment of 5000. In Figure-8, the dashed region represent the theoretical proprotion of energy consumption for an operation machine. And the region filled with solid behind dashed region shows the actual energy consumption for an operation machine. The difference between those two indicators means the energy waste caused by permanent loss on the production counts. The higher value of two indicators, the more energy consumption level machine will be. Figure-9 shows the rate of actual part and baseline part of energy consumption, which is treated as energy efficiency of the operation machine. The higher the value is, the more energy efficiency the operation machine is. The charts suggest that Machine 3 has the highest energy consumption level, and lowest energy efficiency. Thus, Machine 3 can be determined as the energy bottleneck of production line. In this case the slowest machine is the energy bottleneck.

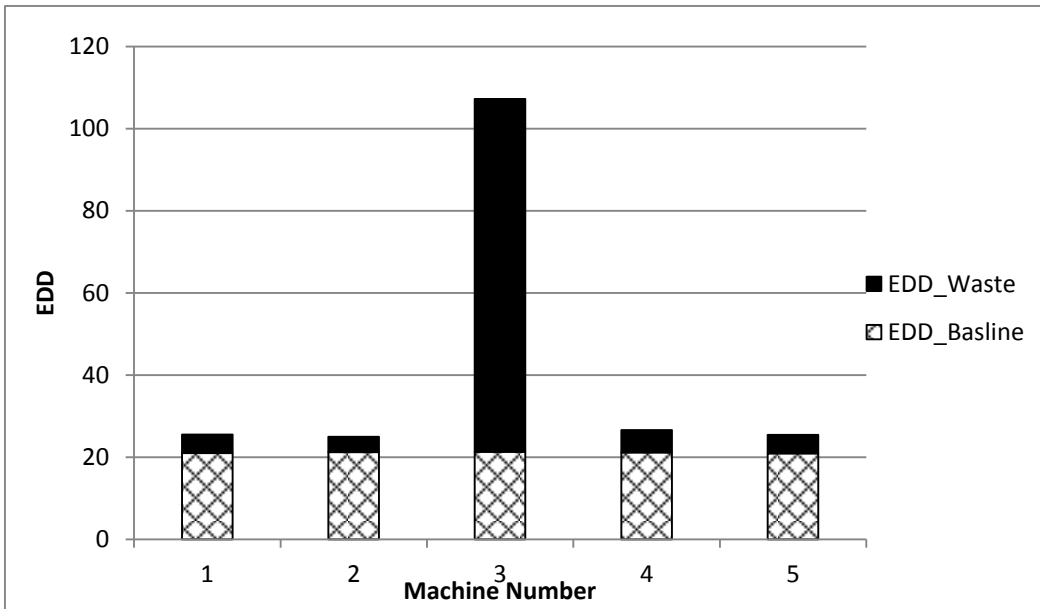


Figure- 8 EDD on individual machine level at 500 time step for case 1

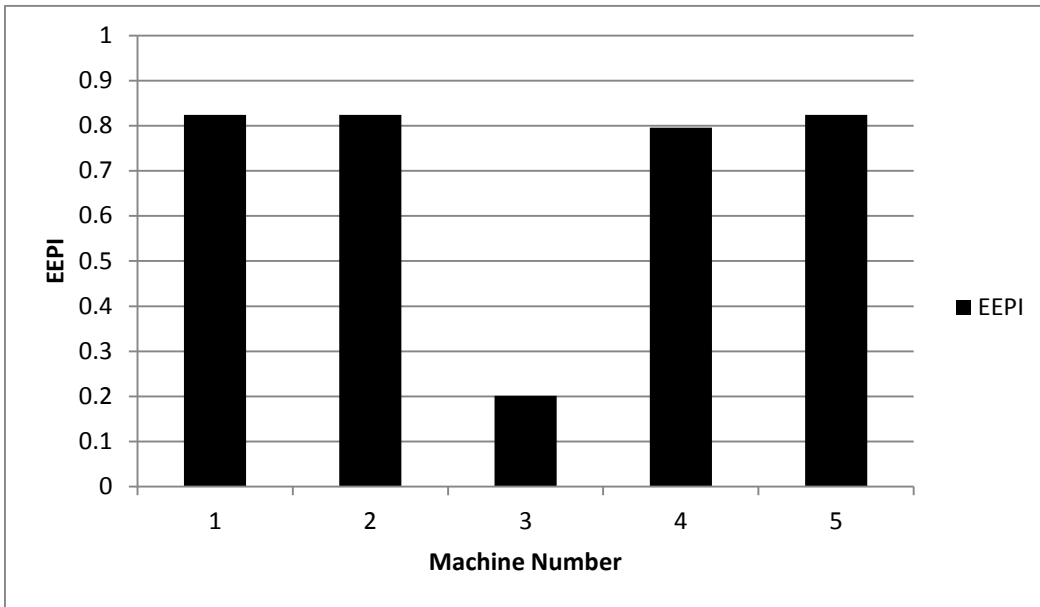


Figure- 9 EEPI on individual machine level at 500 time step for case 1

4.3.2 Case 2: The slowest machine is not the energy bottleneck

The slowest machine will not always be the energy bottleneck. The parameters listed below illustrate that Machine 3 is still the slowest machine, while Machine 2 has the smallest efficiency.

Station	MTTF (min)	MTTR (min)	Rated Speed (min/part)	Power (kw)	Buffer	Buffer capacity	Initial buffer level	Efficiency
Activity1	150	37.5	3	100	Queue2	18	9	80%
Activity2	150	100	3	100	Queue3	18	9	60%
Activity3	150	16.66667	5	100	Queue4	18	9	90%
Activity4	150	37.5	3	100	Queue5	18	9	80%
Activity5	150	37.5	3	100				80%

Table- 7 Parameters of simulation for case 2

According to the result at simulation time 5000, it is obviously that Machine 2 has the highest energy consumption and lowest energy efficiency. This proves that the slowest machine does not have to be the energy bottleneck.

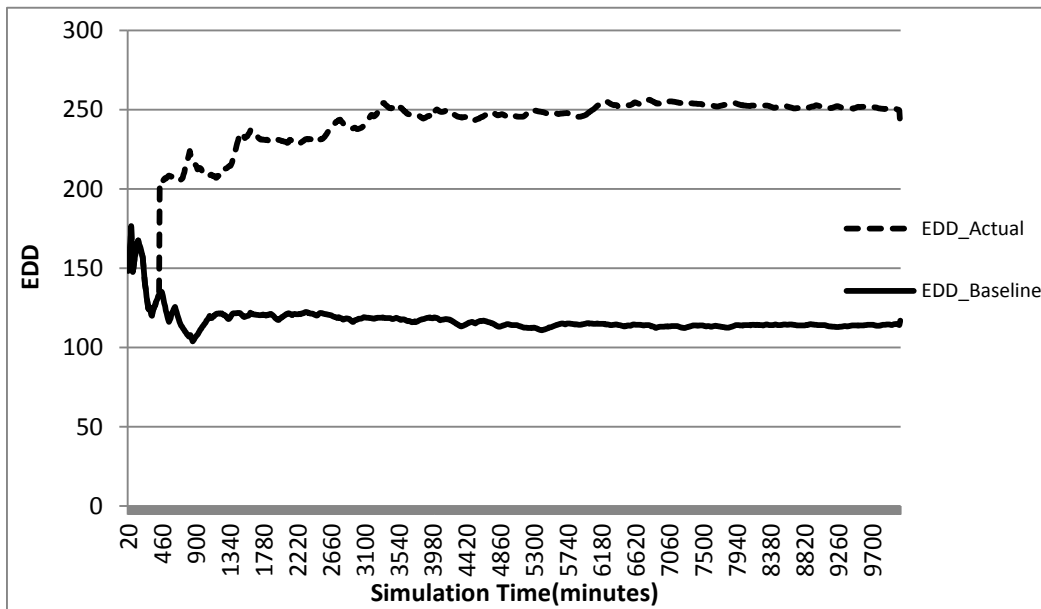


Figure- 10 EDD on production line level for case 2

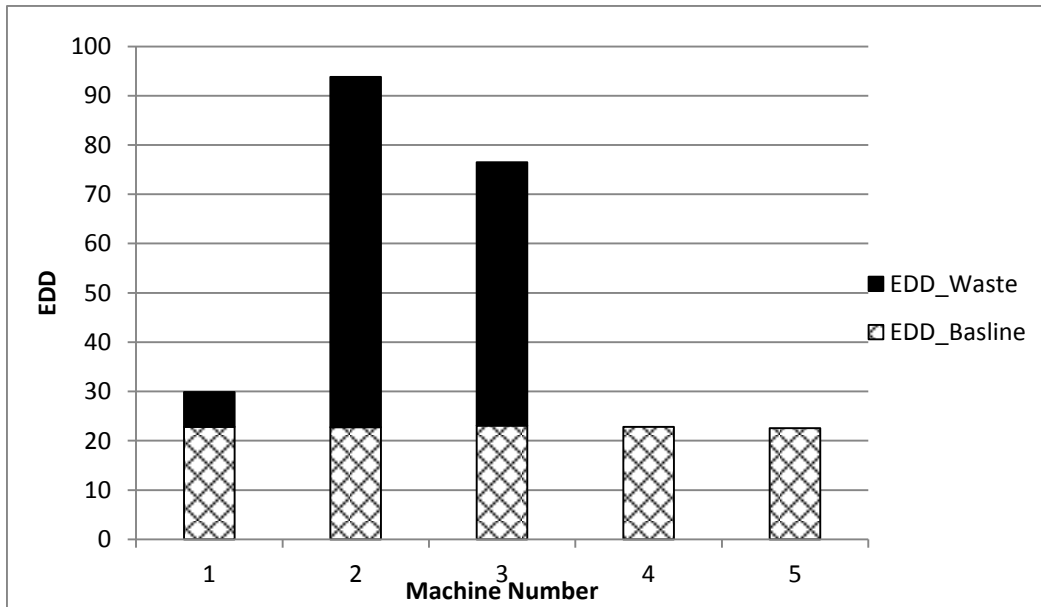


Figure- 11 EDD on individual machine level at 500 time step for case 2

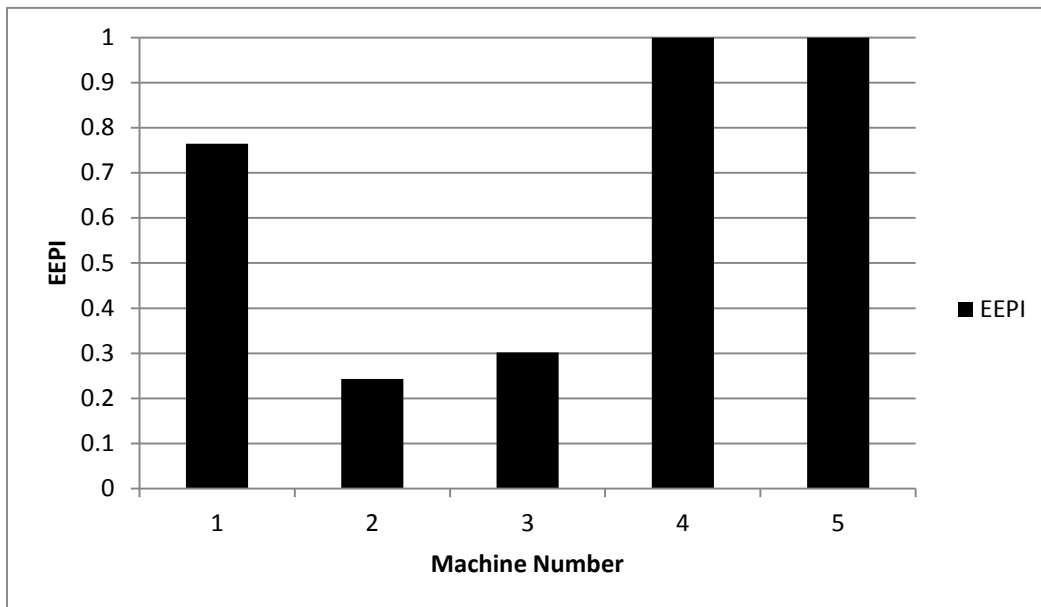


Figure- 12 EEPI on individual machine level at time step for case 2

By simulation we find the machine which has the highest energy consumption level not always be the most inefficient machine. There is probability that some machine has the higher power consumption to produce a part, but it has the most efficiency on utilizing the energy. So it is a smart method to evaluate the production energy consumption with EDD in the whole line level. In order to locate the energy bottleneck, the user needs to combine EEPI and EDD together.

5 Energy savings Opportunities Window and Optimization

Since we can evaluate the energy performance from both plant and production line view, the next step is to improve the energy efficiency of the manufacturing system.

5.1 Opportunity window

In order to saving energy in machine perspective, we brought a concept called opportunity window [28-30]. This is a time period when the downtime duration exceeds this threshold would have permanent impact on system performance; usually reflect on the production count. Permanent loss is the difference between production line throughput with and without taking scheduled downtime events. The definition for opportunity window can be seen below:

$$W_m(T_d) = \sup\{d \geq 0: s. t \exists T^*(d), \int_0^T s_m(t) dt = \int_0^T \check{s}_m(t, e) dt, \forall T \geq T^*(d)\} \quad (\text{Eq.36})$$

Where

$$\int_0^T s_m(t) dt \text{ and } \int_0^T \check{s}_m(t) dt = \text{the production counts of the end of line machine.}$$

S_M at time T with and without the inserted downtime event $e_i = (m_j, t_i, d_i)$ respectively. Utilizing this opportunity, certain machine 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.

Not every random downtime event contributes to a permanent production loss for the production line. It is proven in [29-31] that given a realization of the production process subject to a sequence of downtime events $E = \{e_1, e_2, e_3, \dots, e_n\}$ and supposing that $\max_{i=1,2,\dots,n} \{t_i + d_i\} < T$, if the slowest machine M^* stops for D time units during $[0, T]$, then for any machine m in the production line there exists a $T^* \geq T$, such that,

$$\int_0^{T'} s_m(t') dt' - \int_0^{T'} s_m(t', E) dt' = \frac{D}{T_{M^*}}, \forall T' > T^* \quad (\text{Eq.37})$$

Where

$\int_0^{T'} s_m(t') dt'$ and $\int_0^{T'} s_m(t', E) dt' =$ the production counts of the end of line machine without and with a sequence of downtime events E respectively.

Thus the smallest possible downtime duration d_i^* for i^{th} failure event $e_i = (m_j, t_i, d_i)$ is found:

$$d_i^* = \inf\{d \geq 0: s. t. T_{M^*} \int_{t_i}^{t_i+d} s_{M^*} dt' = W(m_i, b(t_i; E))\} \quad (\text{Eq.38})$$

Where

d_i^* = the time it takes to make buffers between machine m and M^* to become empty if

$m < M^*$ or become full if $m > M^*$.

If the actual downtime event $d_i > d_i^*$ then the permanent loss of production counts will be $d_i^* - d_i$.
If the downtime event $d_i < d_i^*$ then there will not be any permanent loss on the production line.

5.2 Expected energy opportunity window

If all machines operate without any downtime, energy savings opportunity window of any station m at time t in the serial production line is:

$$d_m^*(t) = \begin{cases} T_{M^*} \sum_{k=m+1}^{M^*} b_k(T_d), & m < M^* \\ 0, & m = M^* \\ T_{M^*} \sum_{k=M^*+1}^m (B_k - b_k(T_d)), & m < M^* \end{cases} \quad (\text{Eq.39})$$

Where

M^* = The slowest machine

b_k = The buffer level of buffer k at moment T_d

B_k = The buffer capacity of buffer k

$d_m^*(t)$ = The opportunity window for machine m at time t

Since there would not be any permanent loss on production counts while inserting the opportunity window, after a certain period of time the system should recover to its original status. The maximum energy opportunity window is then the amount of time that it takes upstream buffers ($m > M^*$) to fill completely and for downstream buffers ($m < M^*$) to empty completely. This can be seen below:

$$d_m^*\{max\}(t) = \begin{cases} T_{M^*} \sum_{k=m+1}^{M^*} B_k, & m < M^* \\ 0, & m = M^* \\ T_{M^*} \sum_{k=M^*+1}^m B_k, & m < M^* \end{cases} \quad (\text{Eq.40})$$

5.3 Case Study

The production system for the case study is a production line with 5 machines and 4 buffers (5M4B). Buffer capacity is set as 18 and initial buffer level is 9. The parameters of the line can be seen in the table below. The simulation time is 10080 minutes, with 500 minutes warm up time.

Station	MTTF (min)	MTTR (min)	Rated Speed (min/part)	Power (kw)	Buffer	Buffer capacity	Initial buffer level	Efficiency
Machine1	150	37.5	3	100	Queue2	18	9	80%
Machine2	150	37.5	3	100	Queue3	18	9	80%
Machine3	150	37.5	5	100	Queue4	18	9	80%
Machine4	150	37.5	3	100	Queue5	18	9	80%
Machine5	150	37.5	3	100				80%

Table- 8 Parameters for simulation on ESO

5.3.1 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 us as a control case for this numerical simulation. The EDD of the entire line can be calculated by Eq.32. The maximum opportunity window for each machine can be calculated by Eq.31:

Machine	W_{max}
Machine1	180
Machine2	90
Machine3	0
Machine4	90
Machine5	180

Table- 9 Maximum opportunity window for each machine

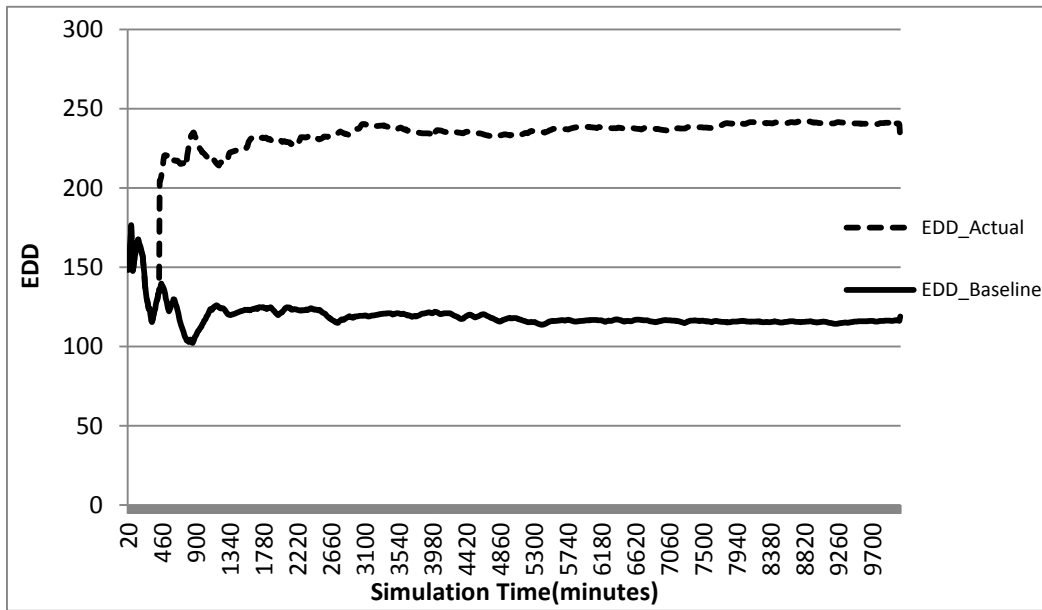


Figure- 13 EDD of production line level without inserted ESO

The solid line gives us the baseline energy consumption, which is the energy consumption without any permanent production loss. The dashed line represents the actual EDD for the entire manufacturing line. The EDD and EEPI for each machine can also be calculated, and show as followed figures:

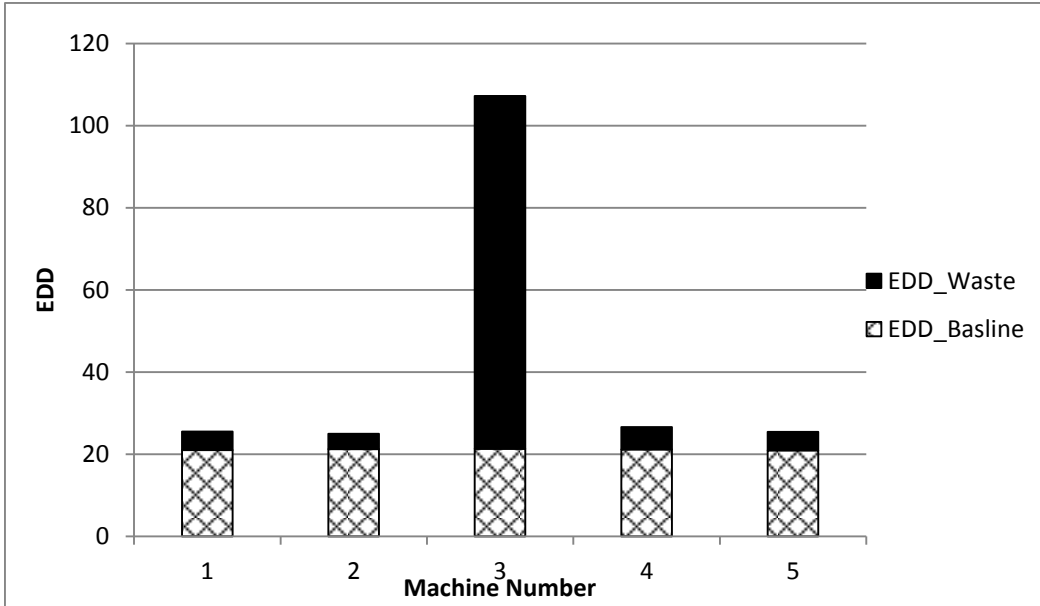


Figure- 14 EDD on individual machine level at 500 time step without inserted ESO

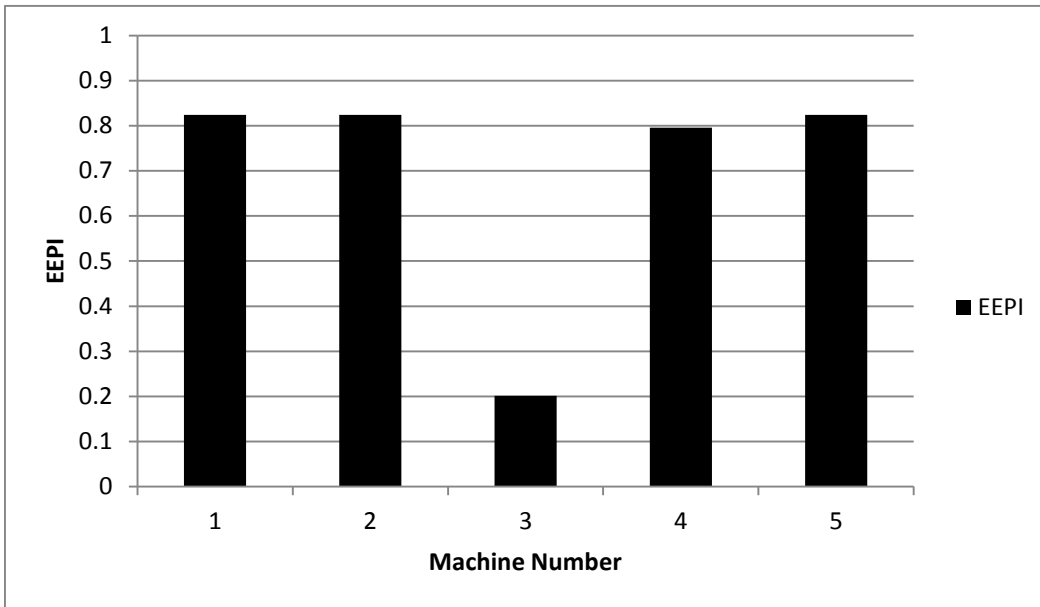


Figure- 15 EEPI on individual machine level at 500 time step without inserted ESO

The Machine3 is the energy bottleneck, for it is the slowest machine. It has no opportunity window to prevent the permanent loss, every downtime events will impact the system.

5.3.2 Case 2 : $d \leq d_i^*$

For the second case, we insert certain sequence downtime events $E = \{e_1, e_2, e_3, \dots, e_n\}$ to manufacturing line during the operation listed in the follow table.

e	m_j	d_i	$d_i^*(t)$	t_i
e_1	1,2,4,5	100,50,50,100	180,70,75,175	140
e_2	1,2,4,5	100,50,50,100	160,60,90,170	880
e_3	1,2,4,5	100,50,50,100	155,90,90,180	2590
e_4	1,2,4,5	100,50,50,100	180,90,90,180	2990
e_5	1,2,4,5	100,50,50,100	175,75,80,175	3850
e_6	1,2,4,5	100,50,50,100	140,70,85,180	4530
e_7	1,2,4,5	100,50,50,100	180,90,90,180	4780
e_8	1,2,4,5	100,50,50,100	170,80,80,175	5470
e_9	1,2,4,5	100,50,50,100	170,50,80,180	5830
e_{10}	1,2,4,5	100,50,50,100	105,90,60,150	6290
e_{11}	1,2,4,5	100,50,50,100	180,90,90,180	6960
e_{12}	1,2,4,5	100,50,50,100	180,90,90,180	7190
e_{13}	1,2,4,5	100,50,50,100	145,75,75,160	7640
e_{14}	1,2,4,5	100,50,50,100	160,90,75,160	8140
e_{15}	1,2,4,5	100,50,50,100	180,90,90,180	8580
e_{16}	1,2,4,5	100,50,50,100	150,90,75,150	8910
e_{17}	1,2,4,5	100,50,50,100	180,90,90,180	9640

Table- 10 Inserted ESO without permanent production loss

Obviously, duration of each downtime event is within the current opportunity window. The time points of downtime event are selected under the condition that with inserted downtime event there will not be any permanent loss after the whole simulation time.

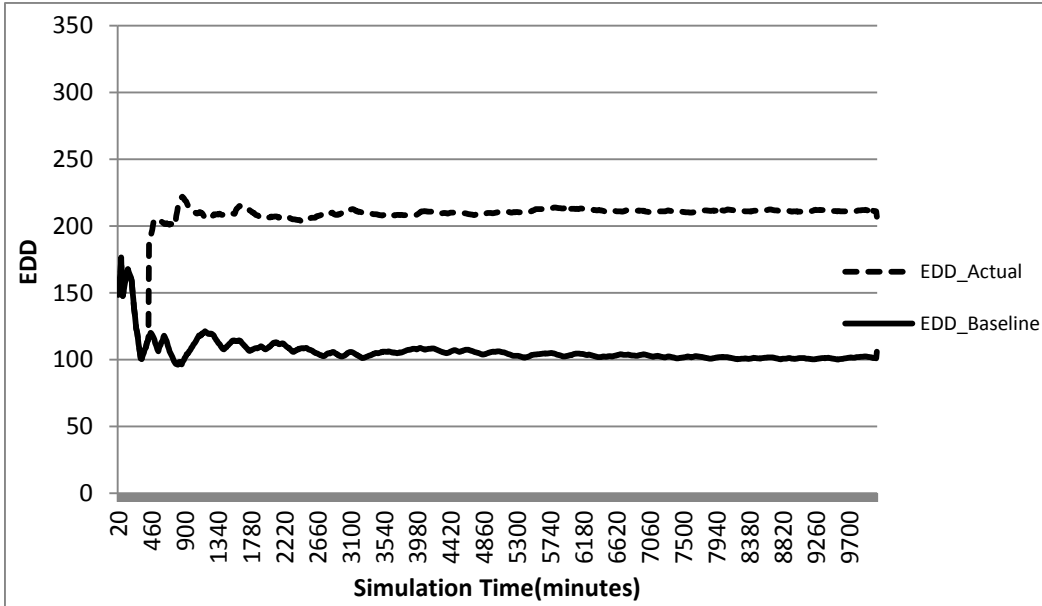


Figure- 16 EDD of production line level with inserted ESO

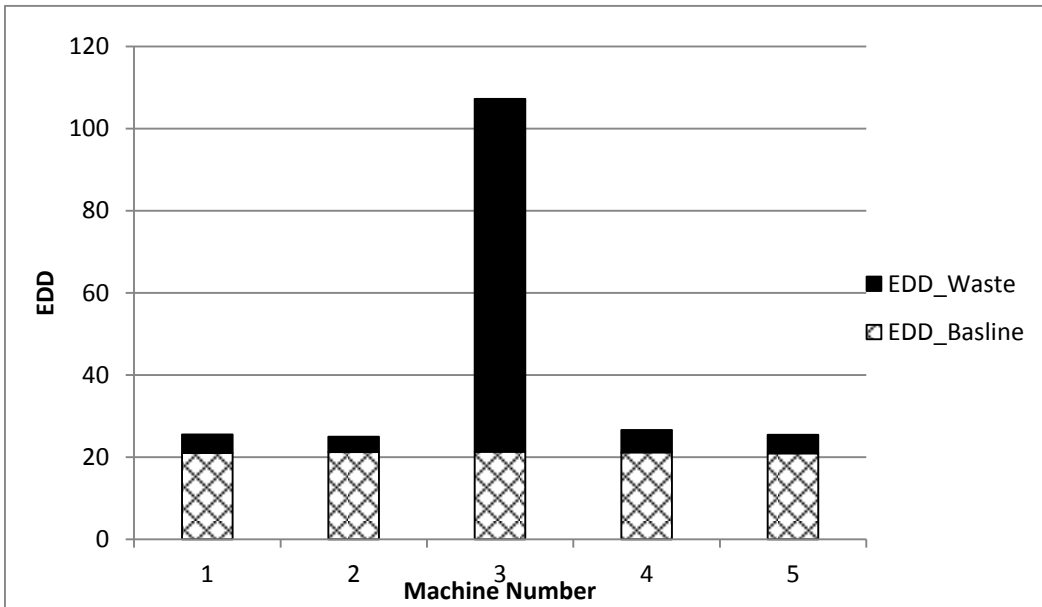


Figure- 17 EDD on individual machine level at 500 time step with inserted ESO

Figure-1

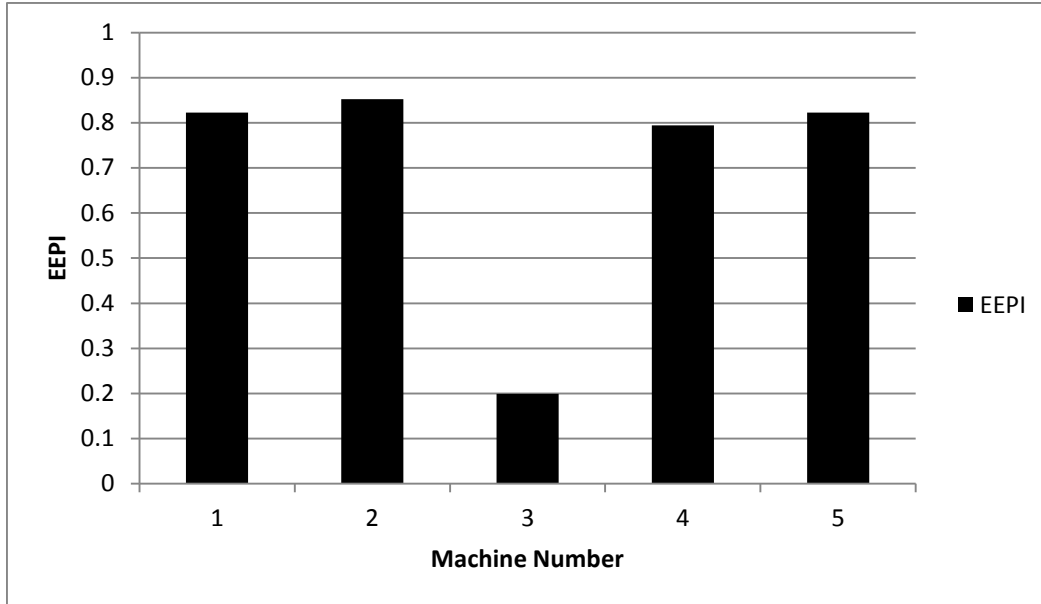


Figure- 18 EEPI on individual machine level at 500 time step with inserted ESO

Since there is no permanent loss for the production line, it is very obvious that EDD_{Actual} for the whole production line has decreased significantly, and $EDD_{Baseline}$ also slightly decreased. The EEPI and EDD for individual machine have not changed, that can be proved by the Eq.31 and Eq.32. For the only parameter changed in the situation is total energy consumption W , there is no impact on the production count. So the ratio between W_1 and W_2 is still the same, which results in the remaining of individual EEPI. Actually, it is easy to understand that the energy saving is coming from the decrease on W'_{3i} , the unsynchronized part of energy. The inserted downtime events makes the other machines more synchronized to the slowest machine.

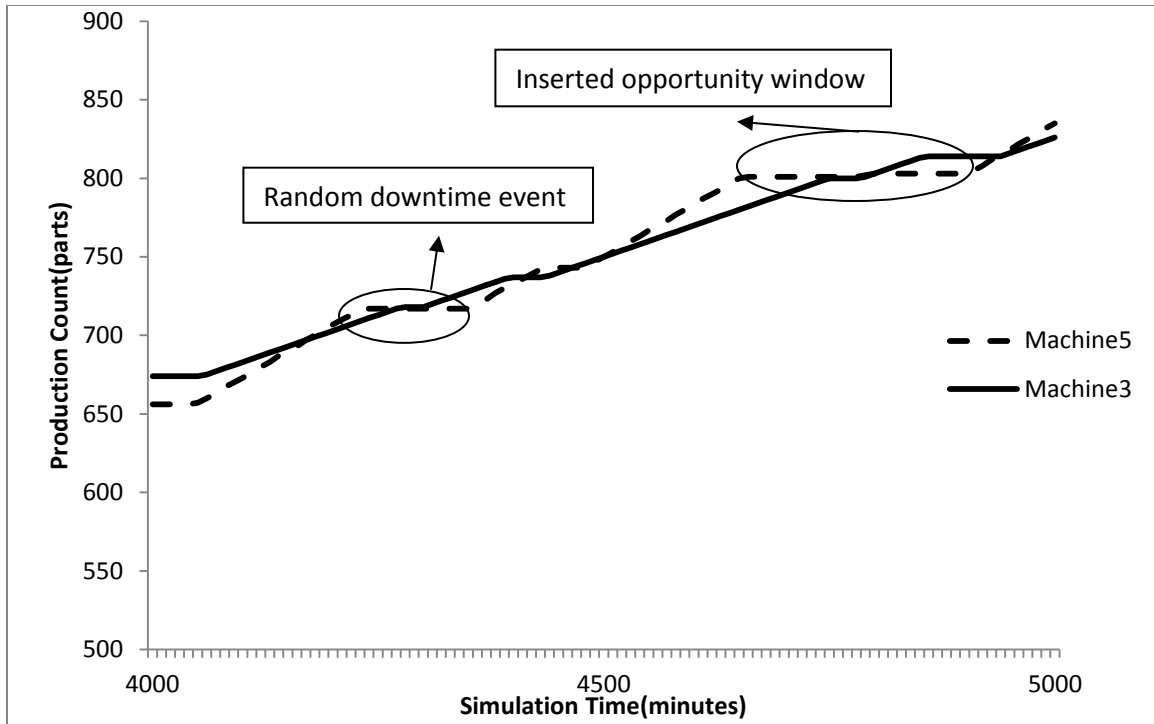


Figure- 19 Production counts of machine5 and machine 3 between 4000 to 5000 time step

The production counts for Machine 5 and Machine 3 can be seen from the figures above. Only two machines are shown since each machine expect 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 last machine will equal to the production count of the entire line. Only a portion of simulation is shown as well to better illustrate the production count of each time.

5.4 Optimization control

Since the opportunity window can only be calculated with the real-time data, we cannot predict the opportunity window. Even after we calculated the opportunity window by the real-time data, we cannot promise in the next time step after taking the opportunity window the machine will 100% be on for the machine has its stochastic downtime events. If not, the next time step will cause the permanent loss to the production line. Although, taking the opportunity window by real-time online data can lead to the least permanent loss to the manufacturing line which ideally no permanent loss. However, it is very complicated and unpredictable. In this situation managers

have the limited resources, it is may generate more cost than the loss for production count. Therefore our goal is how to take the energy opportunity window more strategically.

We brought some advanced conditions based on the condition of least permanent loss. First of all, never take the full opportunity window in order to leave some space for the coming unpredictable downtime events. Second, it is more practicably for managers if there is a schedule to take energy saving opportunity windows.

We have made the simulation of inserting downtime events in the operation within the present opportunity window. From the result we can notice some phenomenon that might help us on the strategy making: 1) all the downtime events are fixed for each machine. 2) there is likely a regular time period between each time of taking energy opportunity window.

With these phenomena, we can make a linear regression about the time point of inserting downtime event based on the case in the case 2 in previous section. We can have:

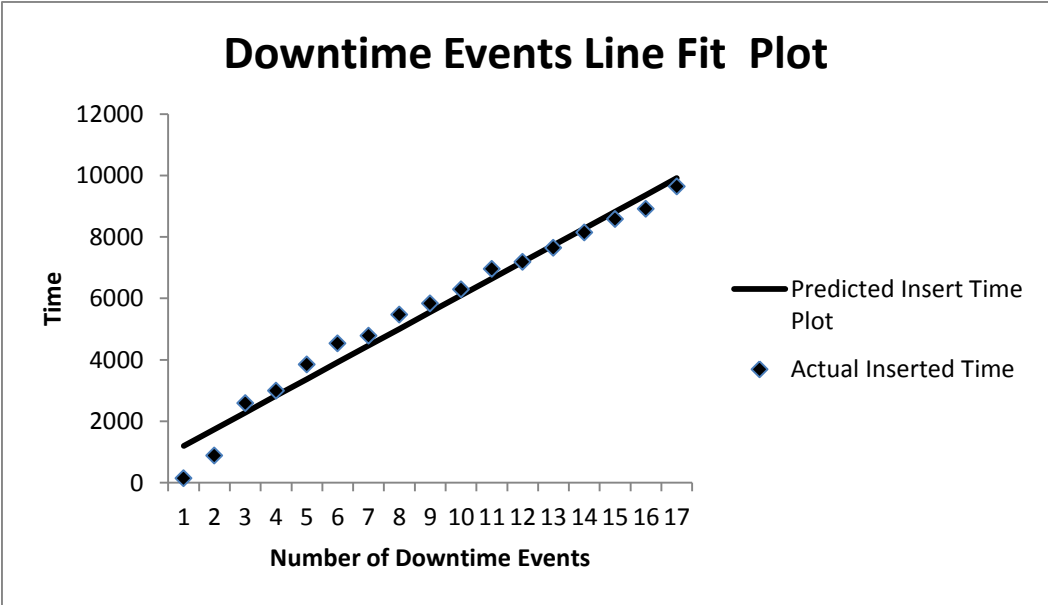


Figure- 20 Downtime events line fit plot with inserted fixed ESO 1

	Coefficients	Standard Error
Intercept	651.62	243.87
ESO Interval	544.66	23.80

Table- 11 OLS regression result 1

From the result we can treat the intercept as the first time of taking opportunity window, and regression result of downtime events coefficients can be treated as the distance between taking each opportunity window. However, this is only one case of study, we need to do more cases with different parameters changing to get the result of what exactly has impact on the distance of two breakdown events, here we call it opportunity window control cycle.

5.4.1 Case1: change the d_i ($d_i < d_i^*$)

Few cases have been done when we change the period length of downtime events. We want to know the relationship between the frequency of control and the length of ESO.

As take opportunity window each time as follows:

Machine	ESO
Machine1	60
Machine2	30
Machine3	0
Machine4	30
Machine5	60

Table- 12 ESO parameters 2

The downtime column represents the length of opportunity window that we inserted each time point. And dots on the downtime events line fit plot shows the time points we inserted opportunity window in orders, with such data we can provide regression and get the predicted time period between two different opportunity window, in this case which is 452 minutes.

The regression result would be as follows:

	Coefficients	Standard Error
Intercept	481.68	170.45
ESO Interval	412.74	14.23

Table- 13 OLS regression result 2

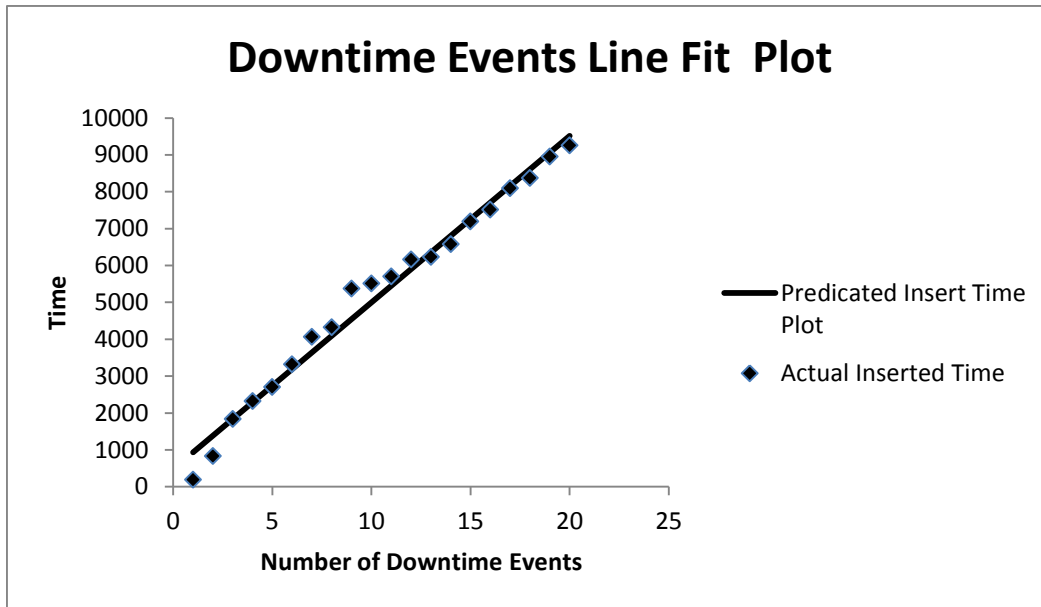


Figure- 21 Downtime events line fit plot with inserted fixed ESO 2

Then we prolong the duration of downtime events the parameters are shown in following table:

As take opportunity window each time as follows:

Machine	ESO
Machine1	80
Machine2	40
Machine3	0
Machine4	40
Machine5	80

Table- 14 ESO parameters 3

The regression result would be as follows:

	Coefficients	Standard Error
Intercept	526.68	60.96
ESO Interval	432.74	4.45

Table- 15 OLS regression result 3

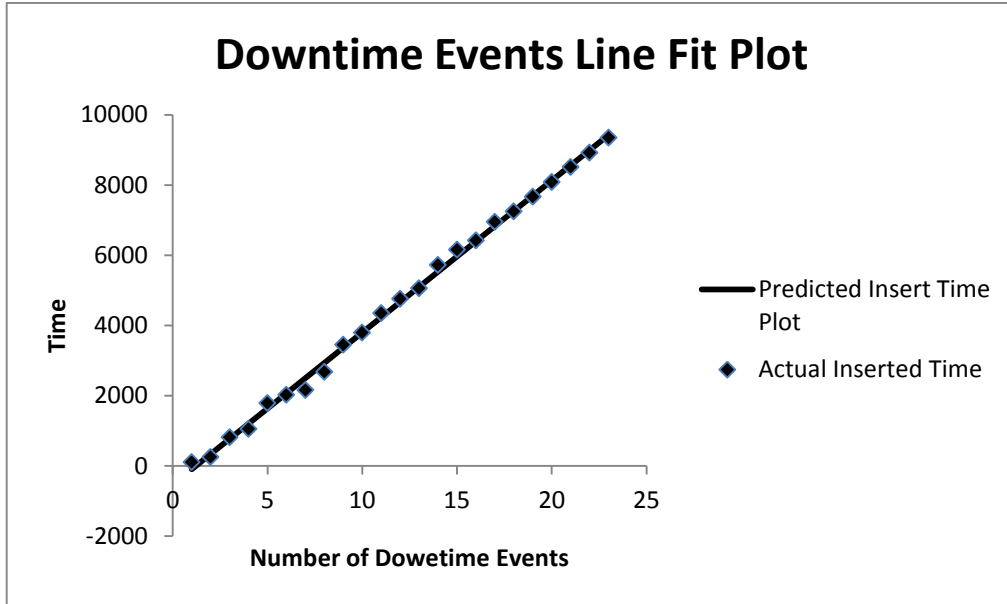


Figure- 22 Downtime events line fit plot with inserted fixed ESO 3

Here we continue increase the duration of downtime events, as it is still within the maximum opportunity window.

As take opportunity window each time as follows:

Machine	ESO
Machine1	120
Machine2	60
Machine3	0
Machine4	60
Machine5	120

Table- 16 ESO parameters 4

The regression result would be as follows:

	Coefficients	Standard Error
Intercept	151.54	227.21
ESO Interval	684.75	26.68

Table- 17 OLS regression result 4

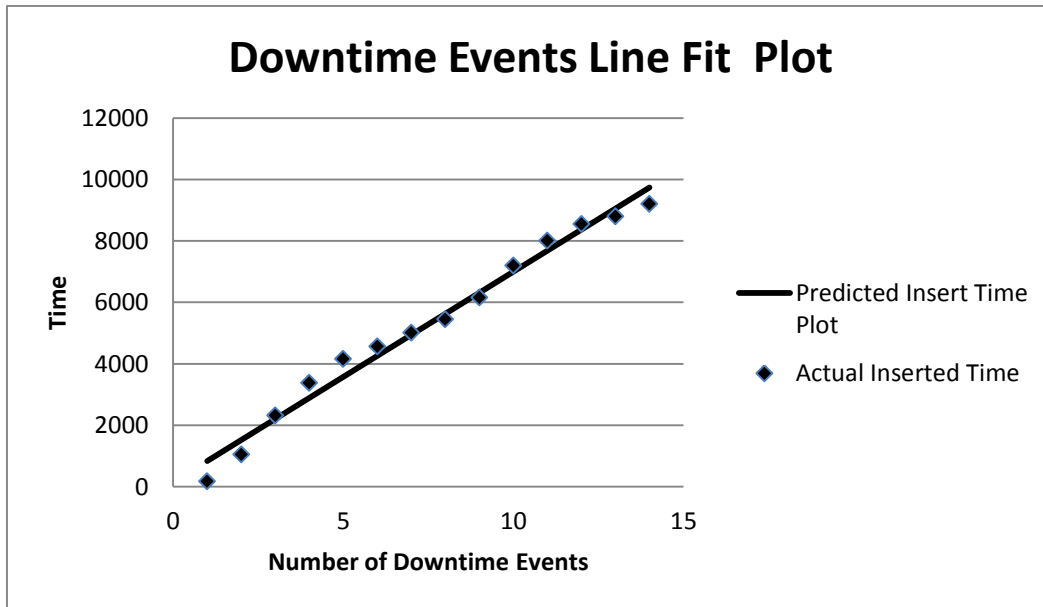


Figure- 23 Downtime events line fit plot with inserted fixed ESO 4

The result shows that the longer the opportunity has been taken, the longer distance between each breakdown event will be. This implies that when we taking longer opportunity window, the recovery time will be longer too. The recovery time is the opposite process of taking opportunity window, it takes upstream buffers ($m > M^*$) to empty completely and for downstream buffers ($m < M^*$) to fill completely.

5.4.2 Case 2: ESO optimization control

The cases we have done are all based on the result from one run, but not from a trial which contains more than one run to make it big enough to provide statics and general meaning. We want to prove that the scheduled inserting of energy saving opportunity window will not or little bit impact on the production count.

Here we use a case in this section, the downtime event are as follows:

Machine	ESO
Machine1	120
Machine2	60
Machine3	0
Machine4	60
Machine5	120

Table- 18 ESO parameters for optimization control

The difference is here we use a trial instead of a single run. The trial consists of 20 individual runs, which are all follow the exponential distribution, the 20 runs are generated from 20 different seeds by the simulation software. With the same method above we can have 20 different regression results which will not be shown here, then calculate the average of two coefficients. There we can have:

Coefficients	
Intercept	270.14
ESO Interval	646.07

Table- 19 Average estimation result for trial

Then we take the opportunity window with the calculated coefficients, first time at 270 and every 646 minutes we insert a downtime event, and after simulating the 20 runs, we can have the average production counts and the 95% interval of it. Compare it with the production counts without taking any opportunity window, as follows:

	Low 95% Rang	Average	High 95% Range
Without ESO	1408.50	1561.33	1714.16
With ESO	1447.67	1479.15	1510.63

Table- 20 95% confidence interval for with and without inserted ESO

It is obviously that there is overlapping between the production counts interval. In stochastic analysis, this means there is possibility that with inserting the scheduled downtime event there will not be any permanent loss in the whole production operation. The result illustrated that it is practicably that we take the energy savings opportunity window with a schedule. It is more enforceable for managers to apply opportunity window in the real production operation, and it is more convenient to control the manufacturing system. With this manner, energy has been saved without impact the throughput which is the main goal of the manufacturing industry. It maximizes the energy consumption efficiency, reduces the cost, and decreases the emission of greenhouse gases.

On the other hand, during the production action, there always need scheduled maintenance to keep the machines in a good condition. In other word, the as the operation time increase for a machine the probability of failure on this machine will increase. The maintenance on machines

can maintain the probability or even decrease the number for the machine to let machines have better performance. But this maintenance always come with the price that managers have to shut down machines event they have not meet the failure, the loss on the throughput will appear. The energy savings opportunity windows provide a solution to the managers to rearrange the scheduled maintenance without permanent loss.

6 Conclusions and Future Work

Energy efficiency is a key issue for future factories. Since the technology of energy consumption efficiency constrained by machine itself cannot be improved because of the energy source and method of utilizing power, what we can do now is find solution of investigate the unnecessary waste on energy during the processing operation and give solution to improve it. In the thesis, we applied SFA model into the industry operation. By estimation with measured data from real operation, we can detect during the processing which operation has the least technical inefficiency in a plant view. The result shows us that within January the lighting system has been energy efficient for most of the working days. For utilization, which can be treated as machines operation, are all inefficient during the whole month. And the unprocessed data sort of can shows the same phenomena which mean our estimation make sense and are accurate.

We have brought a new energy consumption efficiency evaluation method. With two indicators EEPI and EDD users are able to know the energy consumption level of a production line, and locate the energy consumption bottleneck which is the most energy inefficiency machine. Comparing with other familiar method, this method has taken consider into the energy use in each time step, instead of only use the overall production count and overall energy use. Also, with limited measured data, this method use the most accurate way to decompose energy consumption into two different parts, W_1 which is the minimum theoretical energy consumption for the line, and W_2 which is the dynamic distributed wasted energy.

Inserting energy savings opportunity windows is the solutions that we proposed to improve energy consumption efficiency. The case study illustrates that there is significant decrease on the energy consumption level while we insert opportunity window. One advantage of ESO is that users do not have to worry about decline on the throughput. However, the calculation of ESO is hard to predict it can only be calculate by the real-time data. Thus, after considering the convenience and practicability of application on real manufacturing system, we use OLS to estimate the optimized schedule for taking ESO. And the result shows that with the increasing on downtime period of each insert, the distance between two downtime events will increase. And the exponential distributed trial tells us the scheduled ESO inserting will statistically not cause any permanent loss for the production system.

In the future, we want to apply the EDD and EEPI to a more complex line structure, such as parallel line, assembly line, and closed loop line, for in real manufacturing industry most of study objects all have very complex line structures. How to evaluate their energy consumption level is one of our research targets in the future. Also, now the taking of ESO can only decrease the energy consumption level not also increase the energy efficiency at the same time. We want to develop a more practical solution that can increase the energy efficiency of the production line.

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Appendix

Appendix A: The EXCEL Visual Basic code to realize SFA:

- 1) Analysis: this program is used for calculate the decision variables by SFA model

```
Sub analysis()  
    Application.ScreenUpdating = False  
    Sheet2.Range("A8:R230").Select  
    Sheet2.Range("A8:I230").ClearContents  
    Sheet2.Range("J8:Q230").ClearContents  
    Selection.Borders(xlDiagonalDown).LineStyle = xlNone  
    Selection.Borders(xlDiagonalUp).LineStyle = xlNone  
    Selection.Borders(xlEdgeLeft).LineStyle = xlNone  
    Selection.Borders(xlEdgeTop).LineStyle = xlNone  
    Selection.Borders(xlEdgeBottom).LineStyle = xlNone  
    Selection.Borders(xlEdgeRight).LineStyle = xlNone  
    Selection.Borders(xlInsideVertical).LineStyle = xlNone  
    Selection.Borders(xlInsideHorizontal).LineStyle = xlNone  
    Selection.Font.Italic = False  
    With Selection  
        .HorizontalAlignment = xlRight  
        .VerticalAlignment = xlBottom  
        .WrapText = False  
        .Orientation = 0  
        .AddIndent = False  
        .IndentLevel = 0  
        .ShrinkToFit = False  
        .ReadingOrder = xlContext  
        .MergeCells = False  
    End With  
    Sheet2.Range("A5:A230").Select  
    Sheet2.Range("A8").Activate  
    Selection.NumberFormat = "m/d/yyyy"  
  
    Dim xR As Range  
    Dim D1, D2 As Date  
    D1 = Sheet2.Cells(5, 1)  
    D2 = Sheet2.Cells(5, 2)  
  
    If D1 > D2 Then  
        MsgBox ("Input Error")  
    Exit Sub  
    End If  
  
    Set xR = Range("sheet1!A2").CurrentRegion  
    With xR  
        .AutoFilter  
        .AutoFilter Field:=1, Criteria1:=">=" & D1, Operator:=xlAnd, Criteria2:="<=" & D2  
        Range("sheet1!A2").CurrentRegion.Copy  
        Range("sheet2!A7").PasteSpecial xlValues
```

```

.AutoFilter
End With

Dim df As Integer, i As Integer
i = 8
df = 0

Do While IsEmpty(Sheet2.Cells(i, 1)) = False
    i = i + 1
    df = df + 1
Loop

For i = 0 To df - 1
    Range("J8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=SUMPRODUCT(R6C3:R6C7,RC[-7]:RC[-3])"
Next

For i = 0 To df - 1
    Range("K8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=RC[-9]-RC[-1]"
Next

For i = 0 To df - 1
    Range("L8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=RC[-1]*RC[-1]"
Next

For i = 0 To df - 1
    Range("M8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=RC[-2]*R2C1/SQRT(R2C2)"
Next

For i = 0 To df - 1
    Range("N8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=NORM.S.DIST(RC[-1],TRUE)"
Next

For i = 0 To df - 1
    Range("O8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=LN(RC[-1])"
Next

For i = 0 To df - 1
    Range("P8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=RC[-6]"
Next

For i = 0 To df - 1
    Range("Q8").Offset(i, 0).Select
    ActiveCell.FormulaR1C1 = "=RC[-15]-RC[-1]"
Next

```

```

Range("I2").Value = df
Application.Run "ATPVBAEN.XLAM!Regress", ActiveSheet.Range(Cells(8, 2), Cells(7
+ df, 2)), _
ActiveSheet.Range(Cells(8, 3), Cells(7 + df, 6)), False, False, , ActiveSheet.Cells(9 + df,
1) _
, False, False, False, False, , False

Cells(6, 3) = Cells(26 + df, 2).Value
Cells(6, 4) = Cells(27 + df, 2).Value
Cells(6, 5) = Cells(28 + df, 2).Value
Cells(6, 6) = Cells(29 + df, 2).Value
Cells(6, 7) = Cells(25 + df, 2).Value

Range(Cells(7, 1), Cells(7 + df, 18)).Borders(xlEdgeLeft).LineStyle = xlContinuous
Range(Cells(7, 1), Cells(7 + df, 18)).Borders(xlEdgeTop).LineStyle = xlContinuous
Range(Cells(7, 1), Cells(7 + df, 18)).Borders(xlEdgeBottom).LineStyle =
xlContinuous
Range(Cells(7, 1), Cells(7 + df, 18)).Borders(xlEdgeRight).LineStyle = xlContinuous
Range(Cells(7, 1), Cells(7 + df, 18)).Borders(xlInsideVertical).LineStyle =
xlContinuous
Range(Cells(7, 1), Cells(7 + df, 18)).Borders(xlInsideHorizontal).LineStyle =
xlContinuous
Range("A2").Select
ActiveCell.FormulaR1C1 = "1"

SolverOk      SetCell:="$C$2",      MaxMinVal:=1,      ValueOf:=0,
ByChange:="$C$6:$G$6,$A$2" _
, Engine:=1, EngineDesc:="GRG Nonlinear"
SolverOptions MaxTime:=0, Iterations:=0, Precision:=0.000001, Convergence:= _
0.0001, StepThru:=False, Scaling:=True, AssumeNonNeg:=False, Derivatives:=1

SolverOk      SetCell:="$C$2",      MaxMinVal:=1,      ValueOf:=0,
ByChange:="$C$6:$G$6,$A$2" _
, Engine:=1, EngineDesc:="GRG Nonlinear"
SolverSolve
End Sub

```

And the operation interface are as shown in below:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	λ	σ^2	(β, λ, σ)	σ^2	σ^2	OLS	MLE	LR=2(OLS-MLE)	df											
2	5.17E-02	23.98	-27.06	0.06	23.92	-26.74	-27.06	-0.64	9.00				log($\Phi(\sigma/\sigma)$)							
3							σ^2 (OLS)						-6.230688254							
4							21.3048													
5	2011/1/1	2011/1/31	β HDD	CDD(β, λ)	Util(β, λ)	Lightening	β_D	analysis												
6			1.0295	0.0000	-61.2067	0.5791	194.7691													
7	Date	Y (KWH/Unit)	HDD	CDD	Utilization	Lightening	β_D	Production Count	Total Energy (KWH)	β_{HDD}	β_{CDD}	σ	σ^2	$\sigma/\text{root}(\sigma^2)$	$\Phi(\sigma/\sigma)$	log($\Phi(\sigma/\sigma)$)	Best practice	μ	ERI	
8	2011/1/18	154.54	51	0	1.19	13.820	1	3745	578752.3	161.8491	-7.3091	53.4232	-0.0771	0.47	-0.76	161.8491	-7.3091	1.2521		
9	2011/1/20	177.6	43	0	1.24	18.846	1	3895	691396.5	174.0628	3.5472	12.5829	0.0374	0.51	-0.66	174.0628	3.5472	17.7185		
10	2011/1/21	171.41	51	0	1.24	10.145	1	3891	666956.31	177.2501	-5.8401	34.1065	-0.0616	0.48	-0.74	177.2501	-5.8401	14.2421		
11	2011/1/24	171.78	44	0	1.23	18.631	1	3886	667575.94	175.5706	-3.7806	14.2929	-0.0399	0.48	-0.73	175.5706	-3.7806	9.1391		
12	2011/1/25	158.36	37	0	1.32	12.450	1	4139	655452.04	159.2759	-0.6159	0.8389	-0.0097	0.50	-0.70	159.2759	-0.6159	9.1506		
13	2011/1/26	168.65	36	0	1.25	10.514	1	3921	661198.23	161.2996	7.3304	53.7553	0.0774	0.53	-0.63	161.2996	7.3304	8.4359		
14	2011/1/27	161.64	39	0	1.3	12.195	1	4092	661490.38	162.4118	-0.7718	0.5957	-0.0061	0.50	-0.70	162.4118	-0.7718	8.7406		
15	2011/1/28	168.51	37	0	1.26	12.850	1	3961	667468.13	163.1800	5.3300	28.4088	0.0262	0.52	-0.65	163.1800	5.3300	41.8291		
16	2011/1/31	191.33	51	0	1.19	15.536	1	3555	680178.15	187.1047	4.2253	17.8530	0.0446	0.52	-0.66	187.1047	4.2253	4.5391		
17																				
18	SUMMARY OUTPUT																			
19	Regression Statistics																			
20	Multiple R	0.889584482																		
21	R Square	0.791360551																		
22	Adjusted R Square	0.582721103																		
23	Standard Error	7.084186088																		
24	Observations	9																		
25	ANOVA																			
26		df	SS	MS	F	Significance F														
27	Regression	4	761.4087854	190.3521964	3.79295745	0.112426993														
28	Residual	4	200.7427701	50.18569253																
29	Total	8	962.1515556																	
30																				
31																				
32																				
33		Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%													
34	Intercept	195.0905407	74.13097182	2.63169814	0.058082811	-10.7302332	400.9109145													
35	X Variable 1	1.02909078	0.399077474	2.578674182	0.061413334	-0.07892592	2.13710748													
36	X Variable 2	0	0	0	#N/A!	0	0													
37	X Variable 3	-61.28396315	50.77048651	-1.20707828	#N/A!	-202.245459	79.67755282													
38	X Variable 4	0.578454548	0.833276818	0.694192656	0.525770214	-1.73509269	2.892001989													
39																				
40																				
41																				

Figure-1

Appendix B: Calculation: this program is made for the last result of SFA

Sub Calculation()

Application.ScreenUpdating = False

Sheets("sheet2").Activate

analysis

Sheets("sheet3").Activate

analysis2

Sheets("sheet4").Activate

analysis4

Sheets("sheet1").Activate

Range("P8:S230").ClearContents

Dim a As Integer

a = Cells(1, 15)

For x = 1 To a

Sheets("Sheet1").Cells(7 + x, 16) = Sheets("Sheet2").Cells(7 + x, 17)

Sheets("Sheet1").Cells(7 + x, 17) = Sheets("Sheet3").Cells(7 + x, 17)

Sheets("Sheet1").Cells(7 + x, 18) = Sheets("Sheet4").Cells(7 + x, 17)

Next

For n = 8 To 7 + a

16) Sheets("Sheet1").Cells(n, 19) = Sheets("Sheet1").Cells(n, 17) - Sheets("Sheet1").Cells(n,

16) Sheets("Sheet1").Cells(n, 20) = Sheets("Sheet1").Cells(n, 18) - Sheets("Sheet1").Cells(n,

If Cells(n, 19) = 0 Then

Cells(n, 19) = ""

```

End If

If Cells(n, 20) = 0 Then
    Cells(n, 20) = ""
End If
Next

ActiveSheet.ChartObjects("Chart 7").Activate
ActiveChart.PlotArea.Select
ActiveChart.SeriesCollection(1).Values = Range(Sheets("Sheet1").Cells(8, 16),
Sheets("Sheet1").Cells(a + 7, 16))

ActiveSheet.ChartObjects("Chart 7").Activate
ActiveChart.PlotArea.Select
ActiveChart.SeriesCollection(2).Values = Range(Sheets("Sheet1").Cells(8, 17),
Sheets("Sheet1").Cells(a + 7, 17))

ActiveSheet.ChartObjects("Chart 7").Activate
ActiveChart.PlotArea.Select
ActiveChart.SeriesCollection(3).Values = Range(Sheets("Sheet1").Cells(8, 18),
Sheets("Sheet1").Cells(a + 7, 18))

ActiveSheet.ChartObjects("Chart 1").Activate
ActiveChart.PlotArea.Select
ActiveChart.SeriesCollection(1).Values = Range(Sheets("Sheet1").Cells(8, 19),
Sheets("Sheet1").Cells(a + 7, 19))

ActiveSheet.ChartObjects("Chart 1").Activate
ActiveChart.PlotArea.Select
ActiveChart.SeriesCollection(2).Values = Range(Sheets("Sheet1").Cells(8, 20),
Sheets("Sheet1").Cells(a + 7, 20))

ActiveSheet.Shapes.Range(Array("Button 5")).Select
ActiveSheet.Shapes("Button 5").ScaleWidth 0.8444444444, msoFalse, _
    msoScaleFromTopLeft
ActiveSheet.Shapes("Button 5").ScaleHeight 0.6746983837, msoFalse, _
    msoScaleFromTopLeft
Range("A1").Select
End Sub

```

And the operation interface is as shown below:

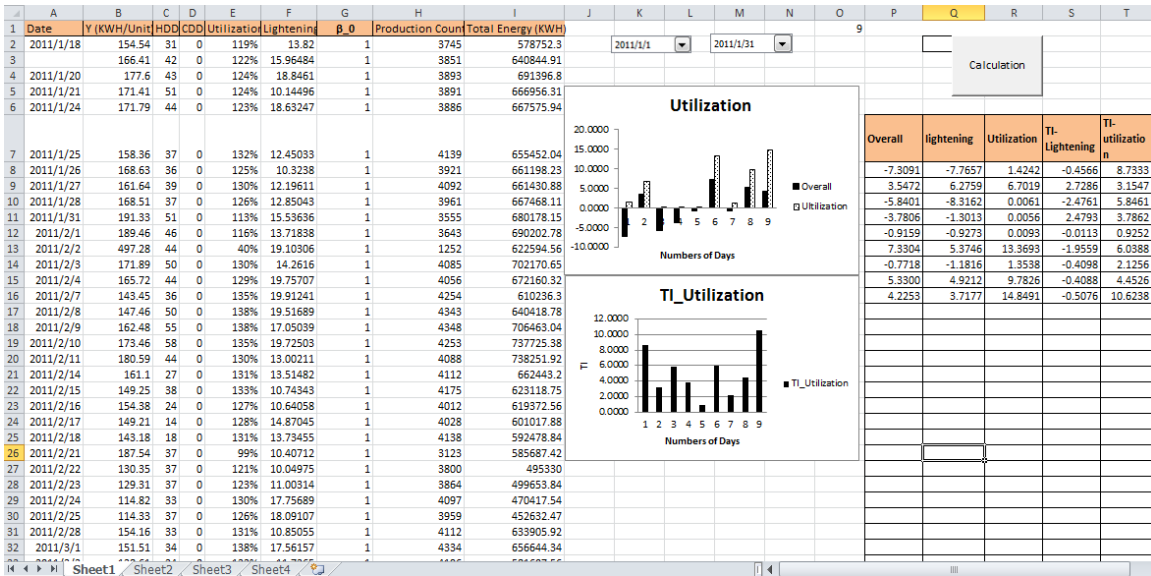


Figure-2

Appendix C: The code to realize energy consumption evaluation

1) the SIMUL8 interface:

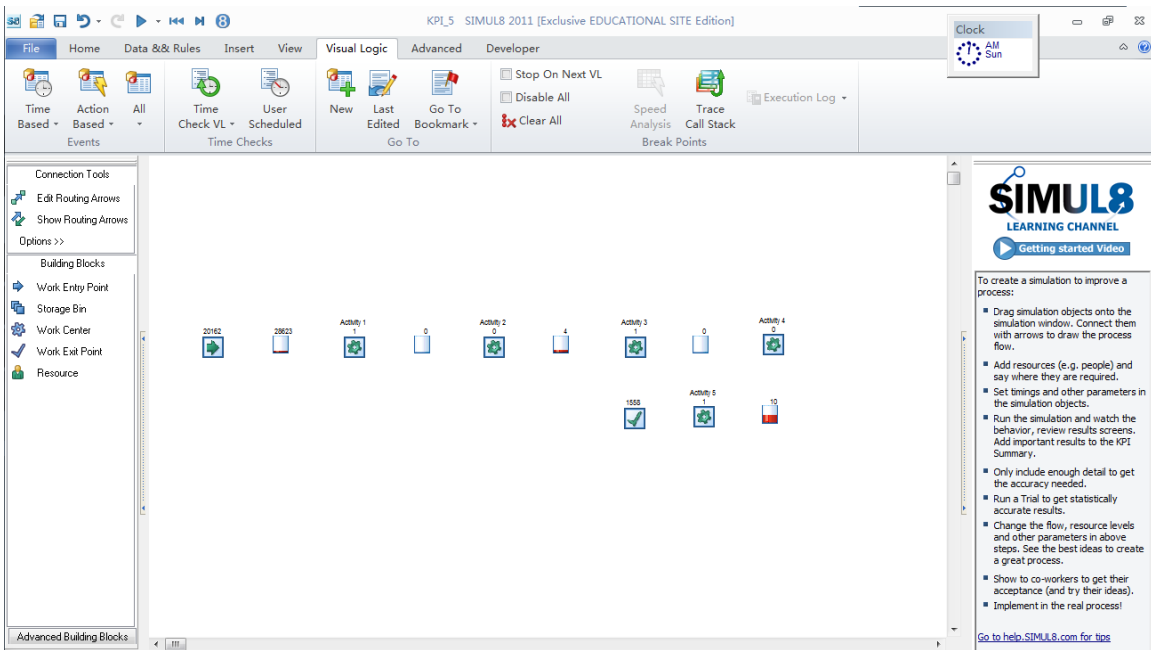


Figure-3

2) The EXCEL Visual Basic code to realize EEPI and EDD:

Sub calculation()

```

Application.ScreenUpdating = False
Sheets("OW").Select
Range("H2:M1008").Select
Selection.clearcontents
Dim m As Integer, n As Integer, t As Double, j As Integer, i As Integer, k As Integer, x As Integer, y As Integer, b As Integer, a As Integer
Dim PC_m() As Double, buffer() As Integer, D() As Double, t_total() As Double, OW() As Double, speed() As Double, BC() As Integer, mtbf() As Double, mttr() As Double
Dim index_down() As Integer, index_up() As Integer, index As Double, PL() As Double, PL_total As Double, power_total As Double
Dim S_star As Integer, BTC As Integer, tp As Double, W1 As Double, W2 As Double, E_total As Double, Em1() As Double, Em2() As Double, power() As Double
Dim KPI_total As Double, KPI_m() As Double, t_step As Integer
Dim BL() As Double, ST() As Double, SUM() As Double, r As Integer, indicator() As Integer, BN As Integer, BNE As Integer, KPI_indicator As Double
Dim power_step() As Integer
Dim KPI_ideal() As Double, KPI_total_ideal As Double, status() As Integer, energy_consumption() As Double, energy_total As Double
Dim warm_up As Double, KPI_SCORE() As Double, energy_status() As Double, RC() As Double
i = 2
j = 2
k = 2
m = 0
n = 0
b = 0
t_step = 1
warm_up = 1
t = 0
S_star = 0
index = 0
PL_total = 0
power_total = 0
Sheets("Downtime").Activate
Do While IsEmpty(Cells(1, i)) = False
    m = m + 1
    i = i + 1
Loop
Do While IsEmpty(Cells(j, 1)) = False
    n = n + 1
    j = j + 1
Loop
Do While IsEmpty(Sheets("BufferLevel").Cells(1, k)) = False
    b = b + 1
    k = k + 1
Loop

```

```

ReDim buffer(1 To b, 1 To n) As Integer, BC(1 To b) As Integer, KPI_m(1 To m) As Double,
Em1(1 To m) As Double, Em2(1 To m) As Double
ReDim D(1 To m, 1 To n) As Double, t_total(1 To j) As Double, PC_m(1 To m, 1 To n) As
Double, OW(1 To m) As Double, mtbf(1 To m) As Double, mtrr(1 To m) As Double
ReDim index_down(1 To m) As Integer, index_up(1 To m) As Integer, speed(1 To m) As Double,
PL(1 To m) As Double, power(1 To m) As Double
ReDim BL(1 To m, 1 To n) As Double, ST(1 To m, 1 To n) As Double, SUM(1 To m, 1 To n) As
Double, indicator(1 To m) As Integer
ReDim KPI_ideal(1 To m) As Double, status(1 To m, 1 To n) As Integer, energy_consumption(1
To m) As Double, KPI_SCORE(1 To m) As Double
ReDim energy_status(1 To m, 1 To n) As Double, RC(1 To m) As Double, power_step(1 To m)
As Integer
For x = 1 To m
    mtbf(x) = Sheets("Inputs").Cells(x + 1, 2)
    mtrr(x) = Sheets("Inputs").Cells(x + 1, 3)
    speed(x) = Sheets("Inputs").Cells(x + 1, 4)
Next
'Sheets("Inputs").Cells(25, 4) = speed(8)
For x = 1 To m
    If speed(x) > index Then
        index = speed(x)
        S_star = x
    End If
Next x
For y = 1 To n
    t_total(y) = Cells(y + 1, 1) - warm_up
Next
For x = 1 To m
    power(x) = Sheets("Inputs").Cells(x + 1, 5)
Next
For x = 1 To m
    power_total = power_total + power(x)
Next
For x = 1 To m
    For y = 1 To n
        D(x, y) = Sheets("Downtime").Cells(y + 1, x + 1) * t_total(y) / 100
    Next
Next
For x = 1 To m
    For y = 1 To n
        PC_m(x, y) = Sheets("PC").Cells(y + 1, x + 1)
    Next
Next
For x = 1 To m

```

```

For y = 1 To n
    BL(x, y) = Sheets("BL").Cells(y + 1, x + 1)
Next
Next

For x = 1 To m
    For y = 1 To n
        ST(x, y) = Sheets("ST").Cells(y + 1, x + 1)
    Next
Next

For x = 1 To m
    For y = 1 To n
        SUM(x, y) = BL(x, y) + ST(x, y)
    Next
Next

For x = 1 To b
    BC(x) = Sheets("Inputs").Cells(x + 1, 7)
Next

For x = 1 To b
    For y = 1 To n
        buffer(x, y) = Sheets("BufferLevel").Cells(y + 1, x + 1)
    Next
Next

Sheets("Status").Cells(2, 2) = n
For x = 1 To n
    Sheets("Status").Cells(x + 1, 1) = t_total(x)
Next

For y = 1 To n
    For x = 1 To m
        Sheets("summation").Cells(y + 1, x + 1) = SUM(x, y)
    Next
Next

For x = 1 To m
    For y = 1 To n
        If y < n Then
            Sheets("Status").Cells(y + 1, x + 1) = D(x, y + 1) - D(x, y)
            If Sheets("Status").Cells(y + 1, x + 1) < 0.9 Then
                Sheets("Status").Cells(y + 1, x + 1) = t_step
            Else
                Sheets("Status").Cells(y + 1, x + 1) = 0
            End If
            Sheets("summation").Cells(y + 1, x + 1) = SUM(x, y)
        End If
    Next
Next

```

```

For y = 1 To n
  For x = 1 To m
    status(x, y) = Sheets("Status").Cells(y + 1, x + 1)
  Next
Next

For x = 1 To m
  power_step(x) = Sheets("Inputs").Cells(x + 1, 5)
Next

Sheets("Status").Activate
For y = 2 To n
  r = 0
  BNE = 1
  KPI_total = 0
  KPI_total_ideal = 0
  KPI_indicator = 0
  PL_total = 0
  energy_total = 0
  tp = PC_m(m, y) * speed(m)

  For x = 1 To m
    energy_status(x, y) = status(x, y) * power(x)

    energy_consumption(x) = energy_consumption(x) + energy_status(x, y)
  Next

  For x = 1 To m
    energy_total = energy_total + energy_consumption(x)
  Next

  W1 = energy_total * tp / t_total(y)
  W2 = energy_total * (t_total(y) - tp) / t_total(y)
  For x = 1 To m
' this part of logic determine the bottleneck by the starve block method
    If BL(x, y) > ST(x, y) Then
      indicator(x) = 1
    Else
      indicator(x) = 0
    End If

    r = r + indicator(x)

    BTC = 0
    a = 0
    If x < S_star Then
      For k = x To (S_star - 1)
        BTC = BTC + buffer(k, y)
      Next
      OW(x) = BTC * speed(S_star)

```

```

End If

If x = S_star Then
    OW(x) = 0
End If

If x > S_star Then
    For k = S_star To (x - 1)
        BTC = BTC + buffer(k, y)
        a = a + BC(k)
    Next
    OW(x) = (a - BTC) * speed(S_star)
End If

' this part of logic determine the KPI
If status(x, y) = 0 Then
    BTC = 0
    a = 0
    If x < S_star Then
        For k = x To (S_star - 1)
            BTC = BTC + buffer(k, y)
            a = a + BC(k)
        Next
        RC(x) = (a - BTC) * 1 / (1 / speed(x) - 1 / speed(S_star))
        If BTC = 0 Then
            PL(x) = PL(x) + t_step / speed(S_star)
        End If
    End If
End If

If x = S_star Then
    PL(x) = PL(x) + t_step / speed(S_star)
    RC(x) = 0
End If

If x > S_star Then
    For k = S_star To (x - 1)
        BTC = BTC + buffer(k, y)
        a = a + BC(k)
    Next
    RC(x) = BTC * 1 / (1 / speed(x) - 1 / speed(S_star))
    If BTC = a Then
        PL(x) = PL(x) + t_step / speed(S_star)
    End If
End If
Sheets("OW").Cells(y - 1, x + 7) = RC(x)
End If
Sheets("PL").Cells(y - 1, x + 1) = PL(x)
Next

For x = 1 To m - 1
    If r = m Then
        BN = m
    End If
End For

```

```

Else
  If r = 0 Then
    BN = 1
  Else
    If indicator(x) = indicator(x + 1) Then
      Else
        If SUM(x, y) > SUM(x + 1, y) Then
          BN = x + 1
        Else
          If SUM(x, y) < SUM(x + 1, y) Then
            BN = x
          End If
        End If
      End If
    End If
  End If
End If
Next
For x = 1 To m
  PL_total = PL_total + PL(x)
Next
For x = 1 To m
  If PL_total > 0 Then
    Em2(x) = W2 * PL(x) / PL_total
  End If
  Em1(x) = W1 * power(x) / power_total
  If PC_m(x, y) > 0 Then
    KPI_m(x) = (Em1(x) + Em2(x)) / PC_m(x, y)
    KPI_ideal(x) = Em1(x) / PC_m(x, y)
  End If
  If Em1(x) + Em2(x) > 0 Then
    KPI_SCORE(x) = 100 * Em1(x) / (Em1(x) + Em2(x))
  End If
  KPI_total_ideal = KPI_total_ideal + KPI_ideal(x)
  KPI_total = KPI_total + KPI_m(x)
  Sheets("KPI").Cells(y, x + 2) = KPI_m(x)
  Sheets("KPI").Cells(y, x + 9) = KPI_ideal(x)
  Sheets("Sheet1").Cells(y, x) = Em2(x)
Next
For x = 1 To m
  If KPI_m(x) > KPI_indicator Then
    KPI_indicator = KPI_m(x)
    BNE = x
  End If
  Sheets("OW").Cells(y - 1, x + 1) = OW(x)
Next
Sheets("KPI").Cells(y, 17) = KPI_total
Sheets("KPI").Cells(y, 18) = (KPI_total - KPI_total_ideal)
Sheets("KPI").Cells(y, 16) = KPI_total * (KPI_total - KPI_total_ideal)
Sheets("PL").Cells(y, 9) = PL_total
Sheets("Sheet1").Cells(y, 14) = power_total
Sheets("Sheet1").Cells(y, 10) = W1

```

Sheets("Sheet1").Cells(y, 11) = W2
 Sheets("PL").Cells(y - 1, 1) = y
 Sheets("OW").Cells(y - 1, 1) = y
 Sheets("KPI").Cells(y, 1) = KPI_total
 Sheets("KPI").Cells(y, 2) = KPI_total_ideal
 Sheets("calculation").Cells(y - 1, 1) = y
 Sheets("calculation").Cells(y - 1, 2) = BN
 Sheets("calculation").Cells(y - 1, 3) = BNE

Next

Sheets("Inputs").Activate

End Sub

The interface is as followed:

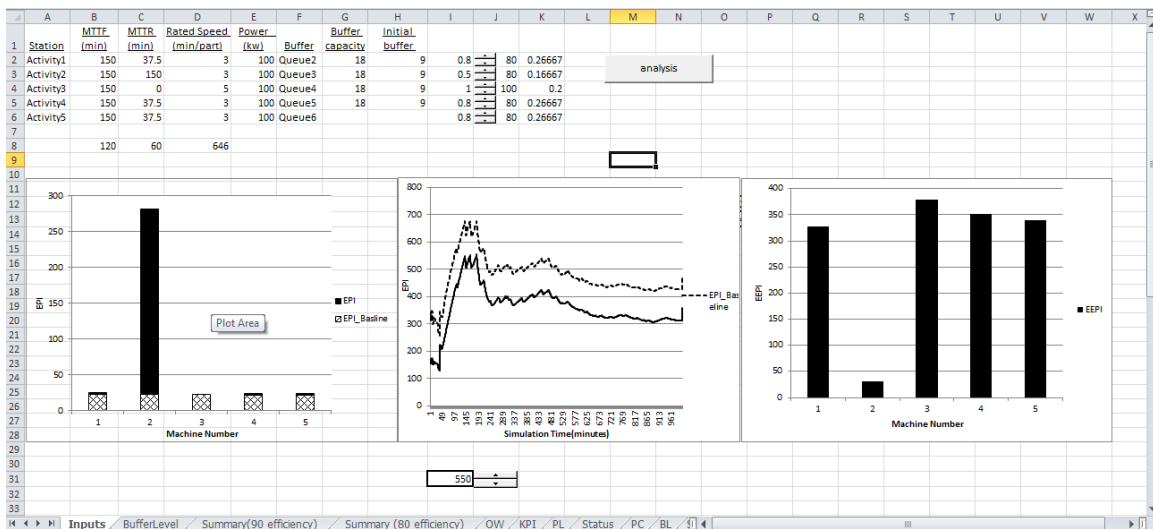


Figure-4