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Integration of Missing Parameters into a DES Tool

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Abstract. Products are usually made by accomplishing a series of manufacturing processes in a sequential flow line that is also known as a manufacturing system. Today, lean methods are widely adopted by many manufacturing plants as a popular model in designing, implementing, operating or managing a manufacturing system. It has been proved as a cost-effective approach to boost system efficiency and productivity by consistently seeking and removing any non-value added activities (i.e., wastes) during a production with a small or without any additional investment. Nevertheless, identification of these wastes using the traditional lean methods does not include such wastes as amounts of energy consumption and CO_2 emissions. For human centered assembly lines, for instance, it is reported that applying highly skilled, flexible and dynamic workers into production lines is also a good practice for implementing a lean manufacturing system in which each worker performs multiple tasks amongst stations. On the other hand, most studies on manufacturing systems using the modelling simulation methods failed to consider parameters of energy consumption, CO_2 emissions and human factors that may also impact the overall system performance. The simultaneous prediction, which relates to amounts of energy consumption and CO_2 emissions and effects of human factors (or human performance) for a manufacturing system evaluation, is often overlooked by researchers or system designers partially due to a lack of existing DES (discrete event simulation) tools that enable incorporating these parameters into an established DES model. This paper presents a study by addressing these issues aiming to incorporate these missing parameters of energy consumption, CO_2 emissions and human factors (age and experience) into a DES model.

1. Introduction

The concept of lean production or manufacturing emphasizes the importance of eliminating "any non-value-added wastes" in every aspect of manufacturing-related activities thereby increasing manufacturing efficiency and productivity at a workplace, reducing time required for manufacturing a product and improving quality of final products. Lean manufacturing can be implemented with lean thinking, which is described as an enterprise culture by recognizing that there is always room for improvement of product design, manufacturing processes or operations, production systems, and management. Thus, any creation of ideas or approaches, which can be utilized effectively and economically for enhancing efficiency and productivity through reduction of system wastes and increase of system responsiveness and flexibility, need to be encouraged. These ideas or approaches must also be embedded in any manufacturing-related activities or organizations. At a typical small-medium enterprise (SME) in manufacturing, multifunctional workers are the key in success of implementing a lean manufacturing system, particularly when the manufacturing system involves a great deal of human-centered operations. Such a manpower production line need also to be designed towards a reduction of the seven wastes (identified by the traditional lean methods), which are the waste of overproduction, the waste of waiting for parts to arrive, the waste of conveyance or transport system, the waste in processing or operations, the waste of inventory, the waste of motion and the waste of rework. Nevertheless, these wastes often do not comprise the environmental wastes in terms of such as energy consumption and CO_2 emissions relating to manufacturing activities; and these environmental wastes also add no value to manufactured products. In practice, the environmental considerations may be addressed as constraints or separately or often overlooked during the design and implementation of a manufacturing system. As for human centred manufacturing systems, most studies have focused on the impact of human factors on human performance in linguistic terms, which are not specifically related to manufacturing activities or production systems. In a human-centred manufacturing system, however, production loss can be caused due to varying human performance that is often affected by a variety of human factors interacting in a complex way, such a phenomenon is often under or overestimated or simply neglected in manufacturing systems design, evaluation and implementation [1]. Moreover, DES (discrete even simulation) tools are often used as an aid for manufacturing systems design and evaluation. These tools, however, are developed focusing on conventional operations of systems and operators. And these tools do not provide facilities that allow system designers to combine parameters of such as energy consumption and CO_2 emissions, and human attributes (or human performance) within an investigation of the overall system performance. This is because, for example, in a DES model, the workers are defined and treated as the same as parts, conveyors and processing machines and so on. The application of DES simulation models is therefore restricted to predicting such variables as the required number of workers, their utilisation percentages or shift patterns and routes [2]. This paper reports a latest development aimed at addressing the above issues by attempting to create a user-friendly method incorporating some parameters of energy consumption, CO_2 emissions and a couple of human factors or attributes into an integrated DES model. With this approach, amounts of energy consumption and CO_2 emissions or effect of human factors on system performance can be quantified.

2. Energy consumption and CO_2 emissions relating to manufacturing systems

The traditional lean approaches can only be used for identifying wastes in terms of manufacturing operations through implementation of management rules (such as 5S rules); these methods do not consider wastes of such as energy consumption and CO_2 emissions in relation to operations or processes of a manufacturing system. In a manufacturing system, energy is used for operating machines, illumination systems, air conditioning systems and other relevant supporting equipment such as compressors which supply compressed air to some of these machines. To describe amounts of energy consumption and CO_2 emissions used for these facility mathematically, the following notations are used [3-4]:

m: number of processes in a manufacturing system
n_i: number of machines involved in process i, where $i \in \{1, 2,...., \mathrm{m}\}$
E_i (kWh): energy consumption for a machine involved in process i
E_i^{cond} (kWh): energy consumption of an air conditioning system
E_i^{illum} (kWh): energy consumption of an illumination system
$E_i^{air\ comp}$ (kWh): energy consumption of compressed air needed for a machine involved in process i
TE (kWh): total energy consumption of a manufacturing system
N_i (kw): installed power for a machine involved in process i
R_i (kg/h): manufacturing rate for a machine involved in process i
τ_i (hr): operating time for a machine involved in process i
μ_i (%): efficiency for a machine involved in process i
∂_i (kg): mass of materials transferred from a machine involved in process i
G_i (kg): mass production per month
$¥_i$ (%): waste ratio for a machine involved in process i

$\underset{\sim}{E}_i$ (kWh): energy consumption of air conditioning per month
$\check{E}_i$ (kWh): energy consumption of illumination per month
$\zeta_i^{air\ comp}$ (kWh/m^3): energy consumption per cubic meter of a compressor
υ_i (m^3/h): compressed air used for a machine involved in process i per hour
$\rho_i^{air\ \mathrm{comp}}$ (m^3/h): capacity of compressed air in cubic meter per hour of a compressor
$N_i^{air\ \mathrm{comp}}$ (kWh): installed power for a compressor
e_i (kg/kWh): amount of CO_2 emissions per kWh released from a machine involved in process i
Te_i (kg/kWh): amount of CO_2 emissions per KWh of a machine, an air conditioning system and an illumination system involved in process i
ω : CO_2 emission factor using different energy sources
Te (kg/kWh): total amount of CO_2 emissions released from a manufacturing system
q_i (kg): mass of materials involved in process i

2.1. Energy consumption

Energy consumption E_i for a machine involved in process i is given by:

$$E_i = \tau_i \times N_i \times n_i \tag{1}$$

And operating time τ_i for a machine involved in process i is calculated below:

$$\tau_i = \frac{q_i}{R_i \times \mu_i} \tag{2}$$

Mass of materials q_i transferred from a machine involved in process i is obtained by:

$$q_i = \partial_i \times (1 + ¥_i) \tag{3}$$

Energy consumption for air conditioning E_i^{cond} in a manufacturing system is given by:

$$E_i^{cond} = \underset{\sim}{E}_i \times \frac{\partial_i}{G_i} \tag{4}$$

Energy used for an illumination system Eiillum is calculated by:

$$E_i^{illum} = \check{E}_i \times \frac{\partial_i}{G_i} \tag{5}$$

Energy consumption of a compressor needed for a machine involved in process i, thus $E_i^{air\ comp}$ is calculated by:

$$E_i^{air\ comp} = \tau_i \times \zeta_i^{air\ comp} \times \upsilon_i \times n_i \tag{6}$$

Where $\zeta_i^{air\ comp}$ can be determined by:

$$\zeta_i^{air\ comp} = \frac{N_i^{air\ \mathrm{comp}}}{\rho_i^{air\ \mathrm{comp}}} \tag{7}$$

Thus, total energy consumption TE for a manufacturing system is given below:

$$TE = \sum_{i=1}^{m} (E_i + E_i^{air\ comp} + E_i^{cond} + E_i^{illum}) \tag{8}$$

Where, $i \in \{1,2,...., \mathrm{m}\}$

Hence, equation 8 can be given below:

$$TE = \sum_{i=1}^{m}\left(\frac{\partial_i \times (1+ \text{¥}_i)}{R_i \times \mu_i} \times \mathrm{N}_i \times n_i + \tau_i \times \zeta_i^{air\ comp} \times \upsilon_i \times n_i + \text{Ȩ}_i \times \frac{\partial_i}{G_i} + \check{E}_i \times \frac{\partial_i}{G_i}\right) \tag{9}$$

2.2. CO_2 emissions

Amount of CO_2 emissions e_i released from a machine involved in process i is calculated by

$$e_i = \omega \times E_i \tag{10}$$

And total amount of CO_2 emissions Te can be calculated as follows:

$$Te = \sum_{i=1}^{m}(e_i \times q_i + 0.6895 \times (E_i^{air\ comp} + E_i^{cond} + E_i^{illum})) \tag{11}$$

Where $i \in \{1, 2,...., \mathrm{m}\}$

Thus, Te can be expressed below:

$$Te = \sum_{i=1}^{m}\left(\omega \times \tau_i \times N_i \times n_i \times \partial_i \times (1+\text{¥}_i) + 0.6895 \times (\tau_i \times \zeta_i^{air\ comp} \times \upsilon_i \times n_i + \text{Ȩ}_i \times \frac{\partial_i}{G_i} + \check{E}_i \times \frac{\partial_i}{G_i}\right) \tag{12}$$

3. Walking workers and human factors

It was reported that approximately one third of all German companies that have invested in highly advanced automaton have recognized that these solutions are not flexible enough and have reduced again their level of automation; 38% of these companies have reduced automation by taking advantage of a more efficient use of their qualified workforce [1]. Figure 1 illustrates a lean manufacturing system using multifunctional, dynamic and cross-trained walking workers. Within such a system, each worker travels with a partially assembled product downstream and stops at each station carrying out the essential assembly work as instructed. Each worker is previously trained to be capable of performing assigned tasks to build a product completely from start to end along the line. This type of system inherently prevents unnecessary in-process inventory thereby decreasing the buffer requirement [5]. For such a human centered manufacturing system, however, the overall system performance can be affected by varying performance of individual workers who have such as different ages and experience. Effects of these human factors or human performance can also be unpredictable and it may alter due to varying psychological and physiological states [6].

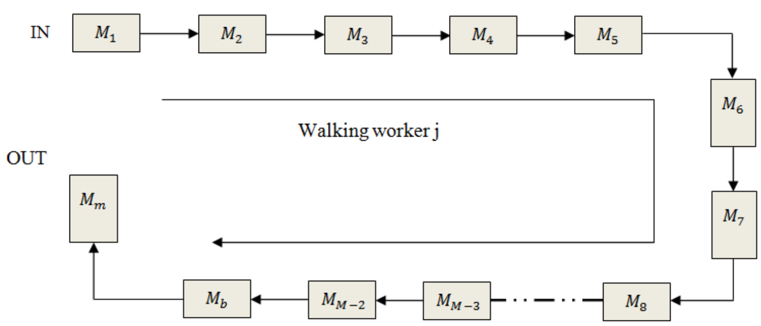

Figure 1. Walking worker production

3.1. Ageing

There are some studies in a view of socio-technical or psychological sciences to evaluate the effects of human factors or human performance relating to the design of manufacturing systems. Nevertheless, these studies are basically described in a form of general language that manufacturing engineers often find difficult to understand. A literature review by authors [7] indicates that that human performance starts to deteriorate at 38 years old as a base line. It also shows the loss rate, which refers to the rate of decline as the remaining functional capacity (%) of his/her peak at the age of 38 using the regression analysis method, can be described below:

$$F_{rm} = k_2 - L_r(k_1 - 38) \tag{13}$$

In which,

L_r = 0.57 + 0.012k

where,
L_r = Loss rate in percentage

k = Age in years

F_{rm} : Remaining capacity in percentage of the peak at 38 years old

k_2: Peak capacity (100%) at 38 years old

L_r: Loss rate in percentage

k_1 : Existing age in years

3.2. Experience

Experience can be defined as the knowledge or a skill to be gained through involvement of a specific task, event or subject. In a human centred assembly line, for instance, experience can be quantified as a learning curve that refers to a trend in reduction of assembly time for an assembly work as quantity of products increases through a learning and forgetting process, which can be denoted as follows [8]:

$$T_n = T_t \, . Q^c \tag{14}$$

Where

T_n: Average time to produce the n^{th} unit

T_t: Assembly time to produce the first unit

Q: Cumulative number of units produced

C : Learning index which determines the speed of learning occurring each time as a cumulative output increases, it is computed as $\frac{\log(R)}{\log(2)}$ where the learning rate R is measured in percentage (0 < R < 1) [9]. Note that the average time towards the steady state decreases with the increase of number of units produced. Thus, the average time towards a steady stage can be given as:

$$T_A = T_t \, . B^R \tag{15}$$

or

$$T_t = \frac{T_A}{B^R} \tag{16}$$

Where

T_A: The average time towards a steady stage

B: Batch size

it yields:

$$T_n = \frac{T_A}{B^R} \, . Q^R \tag{17}$$

Hence

$$T_n = T_A\left(\frac{Q}{B}\right)^R \tag{18}$$

The loss in average assembly time per worker due to ageing is given below:

$$\Delta_{Lt} = T_n \times F_{dl} \tag{19}$$

Where

F_{dl} : Kinematic decline rate (%) of human full capacity

$$\Delta_{Lt} = T_A\left(\frac{Q}{B}\right)^R \times F_{dl} \tag{20}$$

Hence, average total assembly time per worker associated to ageing is computed below:

$$T_{At} = T_A\left(\frac{Q}{B}\right)^R + T_A\left(\frac{Q}{B}\right)^R \times F_{dl} \tag{21}$$

Where

Δ_{Lt}: Average assembly time loss due to ageing

T_{At}: Average total assembly time per worker due to ageing

4. Integration of missing parameters into a DES tool

A feasibility study was carried out by establishing a user-friendly way incorporating identified parameters of energy consumption, CO_2 emissions and effects of human factors into a DES tool, which can permit manufacturing system designers, at the early design stage, to evaluate the overall performance of a manufacturing system with considerations of these parameters. These parameters can be modeled into either external MS Excel worksheets that can be actively linked into a DES tool or the internal program using the DES simulation language or other language like Java. These parameters interact with parameters of physical elements (built in the DES tool) of machines and conveyors etc., together with logical interrelationship for operational activities in a manufacturing system. Thus, this method enables system designers to evaluate the overall performance of a manufacturing system considering not just operational activities but also amounts of energy consumption and CO_2 emissions. This integrated modeling simulation methodology permits users to determine the relevant impact on logical interactions and interrelationships between parameters in manufacturing operations, energy consumption, CO_2 emissions, and human factors within the created manufacturing system model. Figure 2 illustrates the connection interface between the DES model and input/output Excel files in which both input data and output data (simulation results) can be manipulated in an Excel environment.

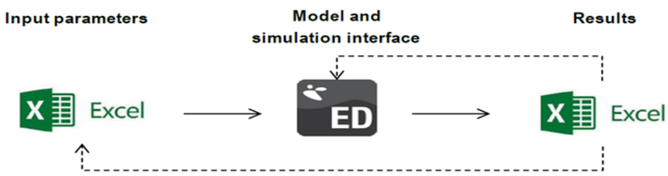

Figure 2. Connection between the DES model interfaced with input/output Excel files

Figure 3 shows the simulation results in terms of amount of CO_2 emissions of each processing task using the alternative energy sources, which are subject to the selection of CO_2 emission factors. It can be seen that the highest amount of CO_2 emissions is 4.08×10^9 kg using oil as indirect energy source, 2.9×10^9 kg using oil as direct energy source and 3×10^6 kg using solar as indirect energy source to generate electricity, respectively. The results shown in Figure 3 also indicate that the total amount of CO_2 emissions using the solar energy is 7×10^6 kg, which is the lowest, followed by 6.5×10^9 kg using oil as direct energy source and 8.4×10^9 kg using oil as indirect energy source to generate electricity. Figure 4 shows the trend in decline of human functional capacity at varying ages after 38 years old. Figure 5 shows the trend of average assembly time corresponding to accumulative number of units produced by workers at the age of 38 years old during a learning process of repetitive operations of assembling a unit. It can be seen that the average assembly time tends to be stabilised after performing assembly of over 480 units.

5. Conclusion

The paper reports a feasibility study by proposing an integrated lean approach aimed at not merely improving efficiency and productivity of a manufacturing system by reducing unnecessary production wastes, which can be identified using the traditional lean methods, but also examining wastes of energy consumption and CO_2 emissions within a manufacturing system. For human centred manufacturing systems, effects of human factors can also be examined using the DES tools. This is because current DES tools in the market do not have functionality allowing manufacturing systems designers to create a DES model that considers parameters relating to energy consumption, CO_2 emissions and effects of human factors or human performance. The paper presents an effective and user-friendly method incorporating some parameters relating to energy consumption, CO_2 emissions and effects of human factors to a DES model. The simulation results demonstrate the applicability of using this method by quantifying the amount of energy consumption, CO_2 emissions or effects of human factors on the overall system performance.

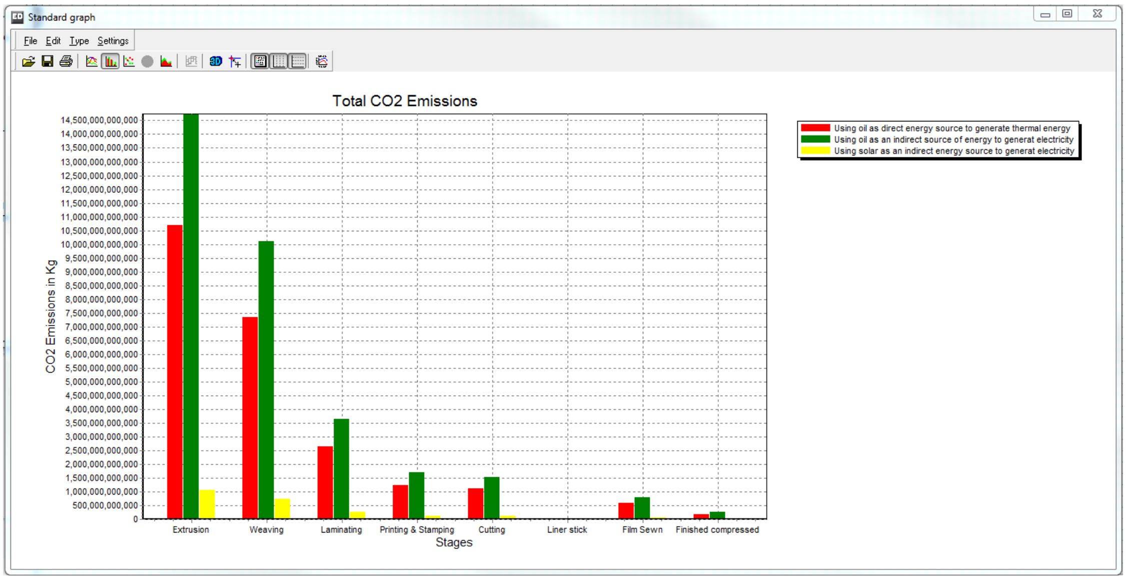

Figure 3. Amount of CO_2 emissions for each process task of the plastic woven-sacks production using alternative energy sources.

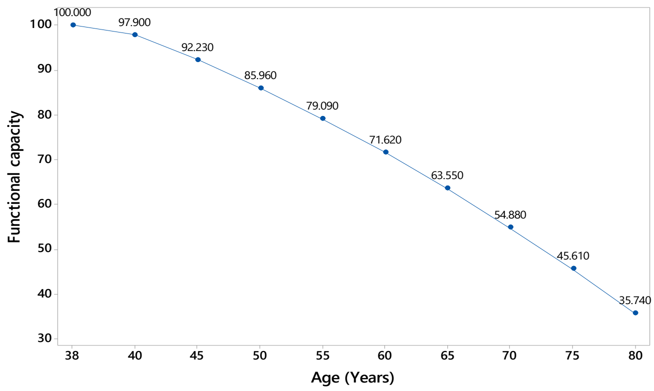

Figure 4. Decline in human functional capacity after 38 years old

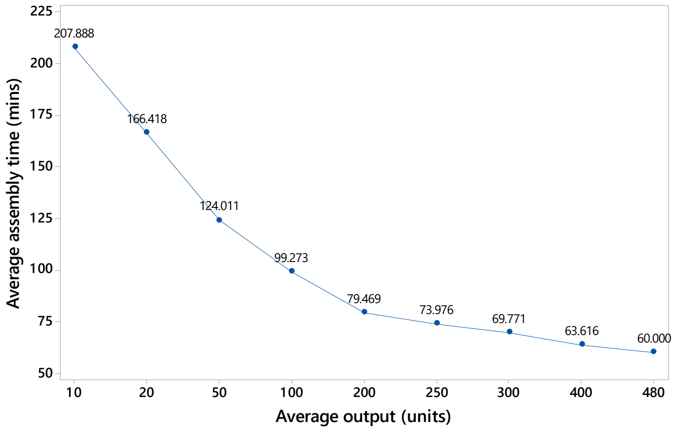

Figure 5. Average assembly time (mins) vs accumulated output of workers at 38 years old

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