Computer Simulation with TOPSIS Approach for Improvement Solutions Ranking: A Case Study

Low Shye-Nee, Shahrul Kamaruddin, and Ishak Abd Azid

***Abstract*—This paper focuses on presenting a multi-criteria decision aid to rank and select the best improvement solution with integration using technique for order preference by similarity to ideal solution (TOPSIS) and data of computer simulation. The proposed decision aid in this paper provides industrial practitioners with a structured and formalized evaluation process when considering multiple criteria. A case study company was used to illustrate the operation of the decision support process through the selection process of improvement solutions. Based on the analysis, the selected improvement solution has been increased 29.3% of the line efficiency. The multi – criteria decision aid has been shown to assist the industrial practitioners when deciding to select and adopt the best improvement solutions.**

***Index Terms*—Decision making, improvement solutions, multi-criteria, simulation, TOPSIS.**

I. Introduction

Competitive pressures increasingly force companies to continuously refine and improve their production floor by adopting the improvement solutions [1]. During the improvement project, it is common to generate a wide range of the improved areas and their solutions [2], [3]. The company might have simulated all the possible solutions and get the whole set of multiple results. Simulation is one of the ways to ensure the feasibility and applicability of the improvement solutions. It is the important step in making decision before implementing it in an existing assembly process [4]. For example, Richard and Jon [5] had used simulation to quantify the benefits of lean manufacturing by providing the estimate saving of the shop floor in the alternative scenarios. Anand and Rambabu [6] used Queing Event Simulation Tool to show the changes after implementing lean manufacturing elements with simulation besides analyzing the effect of the improvement.

However, industrial personnel faces many difficulties in identifying, ranking and selecting the best improvement solutions because of various improved areas with multi criteria are needed to be taken into consideration. It become dilemma situation when no improvement solutions performance the best outcome in all multiple criteria. This challenge occurs due to most companies lack a simple, systematic, and effective selection model for selecting best improvement solutions.

In addition, the comprehensive evaluation process needs to be worked out by considering multiple performance measures such as utilization, throughput rate, process output, idling time and so on. Thus, the selection process becomes complicated when the improvement solution set is not performed well in performance measures. The difficulties and complexity of the selection process increase when it involves the combination of conflicting performance measures such as producing maximum output with lesser number of operators assigned. Due to the difficulty in ranking and selecting best alternative solution, different multi-criteria decision-making (MCDM) methods had been developed [7]-[9]. The MCDM provide a structured interactive step-by-step process for evaluating preferences and providing outputs ranking [10]. Azadeh *et al*. [11] proposed data envelopment analysis (DEA) and analytical hierarchy process (AHP) with computer simulation in selecting the best alternative for improving the railway system. Kuo *et al*. [12] used the grey relational analysis to improve the shop floor in term of selecting the best facility layout. Mahmoodzadeh[13] implemented technique for order preference by similarity to ideal solution (TOPSIS) algorithm to assess, rank and select the industrial project for investment. By adopting MCDM models in the selection process, various technical aspects could be considered simultaneously. It means that larger numbers of performance measures that influence improvement solutions selection can be covered, and more accurate results can be generated. However, it is hard to find the work from published literatures that focus on ranking and selecting the improvement solutions in the simulated production floor.

A decision-support tool is needed to allow industrial practitioners to solve their problems by evaluating, rating, and comparing different improvement alternatives on multiple criteria. Thus, the main objective of this paper is to propose a multi-criteria decision aid model (simulation-TOPSIS) that could assist industrial personnel in ranking and selecting the best improvement solution. The paper is arranged as follows: Section II describes the development of multi-criteria decision aid. Section III deals with the case study including simulated results in an assembly line and the ranking of best improvement solutions. Section IV describes the comparison of the before and after improvement results. Finally, Section V ends with conclusions.

II. Methodology

There are two phases in the proposed methodology

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(simulation-TOPSIS) in order to rank the improvement solutions: simulation model development (Phase 1) and improvement solution ranking (Phase 2). Phase 1 is to design and conduct the simulation experiment for line improvement in the production floor while Phase 2 is used to evaluate and rank the range of improvement solutions.

The tree diagram was used in Phases 1 to display and determine all the possible outcomes of simulated experiment involving more than one improved areas with multi criteria. Example is given in Fig. 1; there are a total of eight combination outcome of simulation model from three improved areas with multiple criteria. The number of combination can be confirmed by using (1).

$$\text{Number of outcome} = NA \times Nb \times \ldots.. \tag{1}$$

where Nt= number of criteria in improved area t

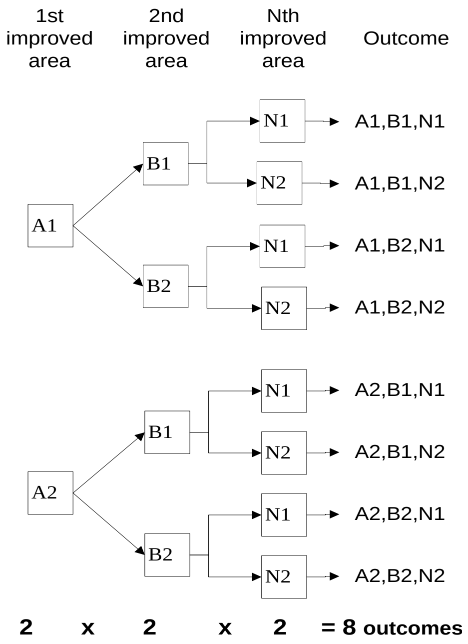

Fig. 1. Determination of possible outcome experiments

For Phase 2, multiple performances have to be determined in order to perform the evaluation of each simulation of the experimental sets. Then, the ranking of the simulation model will be identified by adaptation of TOPSIS. The performances measures can be evaluated from few factors including production output, busying, blocking, work in progress (WIP) and operator required. Followings are the description of the performance measures:

Production output of the improvement model should not be lower than that of the current condition. It is the total amount of unit product produced in certain working hour per 10 working days.

Idling occurs due to the process cycle time of the current workstation is shorter than that of upstream. This implies that the upstream process should be improved.

Busying occurs due to the process cycle time of the current workstation is greater than that of upstream. This implies that the process of the current workstation should be improved.

Blocking occurs due to the conveyor reaching the maximum capacity between the current workstation and the next workstation, in which the conveyor is slow or the conveyor capacity is insufficient. This implies that there is a need to adjust the capacity of the conveyor speed.

WIP of the assembly line reflects the time of a part staying in the assembly line. The faster part flow will reduce the number of WIP needed in the assembly line. The increase in conveyor speed, the reduction in process cycle time and the reduction in the length of the assembly line can reduce the number of WIP needed in the assembly line.

Number of operator required in the simulation model means that the total numbers of workers work in the particular assembly line start from first process until last process.

Once the performance measures are obtained, the decision matrix is constructed to organize the indexes into systematic form. The structure of the decision matrix can be expressed as follows:

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} F_1 & F_2 & \cdots & F_j & \cdots & F_n \end{array} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1j} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2j} & \cdots & f_{2n} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{i1} & f_{i2} & \cdots & f_{ij} & \cdots & f_{in} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mj} & \cdots & f_{mn} \end{bmatrix} \end{array} \tag{2}$$

where A_i denotes the simulation experiment sets stated in Phase 1; i=1… m; F_j represents the performance measures factors; j= 1,…,n; and f_{ij} is a value of simulated performance data of each simulation experiment sets A_i with respect to each performance measures factors F_j. This performance index is based on the data collected from Witness simulation model sets.

Once the matrix representation of the information has been achieved, it will be normalized. The normalization process is to transform different scales and units among various performance measures factors into comparable and measureable units to allow comparisons across the criteria. In TOPSIS analysis, the outcome of each criterion is divided by the norm of the total outcome vector of the criterion at hand. The normalized value r_{ij} is calculated as:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{j=1}^{n} f_{ij}^2}}, \; i = 1,\ldots,m; \; j = 1,\ldots, n. \tag{3}$$

where r_{ij} is the normalized preference measure of the i^{th} simulation experiment sets in terms of the j^{th} performance measures factors. Consequently, all performance measures factors have the same unit length of vector.

After normalization, a set of weights is accommodated to the normalized decision matrix. The weights are generated from rating of personal in charge in the case study company. Each of the performance measures factors are rated by using 5 point Likert scale, where 1 indicates not important at all and 5 indicates highest important level in the production floor. The performance measures are the evaluation factors of simulation experimental sets, which represent the different significant towards the production lines. So, performance measures that obtain higher values of rating will carry higher weighting in this evaluation.

With the set of weights W= ($w_{1,}$ w_2...w_n) the weighted normalized matrix V can be generated by multiplying each column of the matrix R with its associated weight W as follows:

$$V = RW = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & & & \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \quad (4)$$

where m is the number of simulation experimental sets and n is the number of performance measures factors.

The following step is the determination of the ideal and negative ideal solutions. The ideal solution indicates the most preferable solution and the negative ideal solution indicates the least preferable solution.

Ideal solution:

$$\begin{aligned} A_*^+ &= \{v_{1^+}, v_{2^+}, \ldots, v_{n^+}\}, \\ &= \left\{ \begin{matrix} (\max \; v_{ij} | j \in J); \; (\min \; v_{ij} | j \in J), \\ i = 1,2,3\ldots,m \end{matrix} \right\} \end{aligned} \quad (5)$$

Negative ideal solution:

$$\begin{aligned} A_*^- &= \{v_1, v_2, \ldots, v_{n^-}\} \\ &= \left\{ \begin{matrix} (\min \; v_{ij} | j \in J); \; (\max \; v_{ij} | j \in J), \\ i = 1,2,3,\ldots,m \end{matrix} \right\} \end{aligned} \quad (6)$$

where v_{ij} is the weighted normalized value indicating the performance rating of each simulation of experimental sets; A_i with respect to each performance measure

The following process is to calculate the separation measure. The separation distances of each simulation of experimental sets from the ideal solution and the negative ideal solutions are reached by the n-dimensional Euclidean distance method. That means A^+ is the distance of each alternative from the ideal solution and is defined as:

$$A^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \; for \quad i = 1,2,3,\ldots,m \quad (7)$$

And the distance from the negative-ideal solution is defined as follows:

$$A^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2}, \; for \quad i = 1,2,3,\ldots,m \quad (8)$$

After obtaining the simulation experimental sets separation distance, the relative closeness of each simulation experimental sets to the ideal solution is calculated. The relative closeness to the ideal solution can be defined as:

$$RC = \frac{A_i^-}{A_i^+ + A_i^-} \quad (9)$$

where $0<RC<1$ and i=1,2,3,…,m

The simulation of experimental sets can now be preferably ranked according to the descending order of RC. The larger the index value means the better the performance of the simulation of experimental sets in improving the assembly line. The value of the relative closeness will be recorded. The simulation of experimental sets which obtains the highest performance index will be selected and proposed as the best improvement solutions for the assembly line.

III. Case Study

In this study, a manual assembly line (Line X) was selected by the top management of Company R for the production improvement. This assembly line assembles the electronic communication plastics part which form from five workstations as illustrated in Fig. 2. Each workstation is operated by an operator. The layout of assembly line is a straight line equipped with continuous conveyor for transferring the electronic communication plastics part.

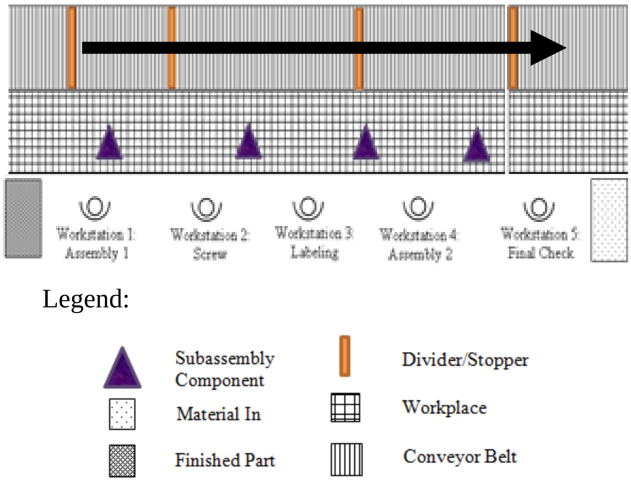

Fig. 2. Current workstation layout and process flow

From the analysis of problems and brainstorming, the company has decided to improve the conveyor speed and combine the process of Workstation 3 and 4 to become a single workstation. However, the improvement team is facing the difficulties to conduct the simulation experiment and evaluate its result. Therefore, the multi-criteria decision aid as presented in this paper has been proposed and implemented in this case study.

A. *Phase 1: Simulation Model Development*

In Phase 1, the design of experiment has been conducted to identify the number of set of simulation experiment needed to be run. There are two improved area determined in this case study, which are conveyor speed with 3 criteria, and combination of process with 2 criteria. Total six sets (3×2) of simulation models have been designed as shown in Table 1. Each model consists of different improved areas. The base model is simulated based on the current situation. The simulation experimental set is run with the aid of simulation software, Witness Manufacturing Performance. The simulation results for 10 days with 8 hours working time per day are recorded.

TABLE I: Information of Improvement Models

Experiment model	Conveyor Speed	Combination of Workstation 3 and 4
Base model(BM)	18.95 sec/pc	No
Set 1	17.25 sec/pc	No
Set 2	18.95 sec/pc	Yes
Set 3	17.25 sec/pc	Yes
Set 4	16.85 sec/pc	No
Set 5	16.85 sec/pc	Yes

B. Phase 2: Improvement Solution Ranking

Five criteria of the improvement model with respective goals have been identified to compare the effectiveness of the improvement model, which are production outputs, percentage of busying, percentage of blocking, WIP and operator required. Table II shows each of the performance measures with its weight. The result of each simulation model is gathered in Table III. Then TOPSIS that has been described in Section II is applied to calculate the relative closeness score of each simulation sets.

TABLE II: PERFORMANCE MEASURE FACTORS

Performance measures		Weight	Goal achieve
F1	Production Output (units per day)	22	Maximum
F2	Busying (%)	22	Maximum
F3	Blocking (%)	16	Minimum
F4	WIP	23	Minimum
F5	Operator required	17	Minimum

TABLE III: RESULTS OF SIMULATION

Performance measures	Average					
	BM	**Set 1**	**Set 2**	**Set 3**	**Set 4**	**Set 5**
F1	1549	1702	1461	1698	1758	1616
F2	48.38	53.15	57.28	64.29	51.63	61.15
F3	15.44	13.42	21.27	18.52	13.63	19.05
F4	30.98	31.096	26.374	27.058	31.022	25.988
F5	5	5	4	4	5	4

TABLE IV: RANKING OF THE SIMULATION MODEL

Experiment model	RC	Ranking
BM	0.38	6
Set 1	0.54	3
Set 2	0.42	5
Set 3	0.65	1
Set 4	0.53	4
Set 5	0.58	2

From the result of TOPSIS in Table IV, it clearly concludes that Set 3 is the best production plan among the six alternative models since the RC score is the highest. Set 3 consisting of 4 workstations, one operator operated one workstation and with the conveyor speed of 16.80sec/unit shows the best production performances in terms of operator utilization (highest percentage in busying) and number of operators. This is to reduce the idling time of the operator as well as the idling of WIP on the conveyor belt. The accumulation of WIP is changed to one piece flow concept. Indirectly, the maximum productivity can be improved. Therefore, the objective of this project can be achieved with reduced manpower to optimum level and improved production output. Furthermore, the line efficiency is increased from 50.5 % to 65.3%.

Fig. 3 is the new layout and process flow after implementation of the multi-criteria decision aid. The distance of the whole assembly line will be reduced since the number of the workstation is reduced. This improvement contributes to the company where more space is available for other product family and other beneficial use. The assembly line is suggested to be moved to a shorter line so that the original space can used for other longer process assembly line.

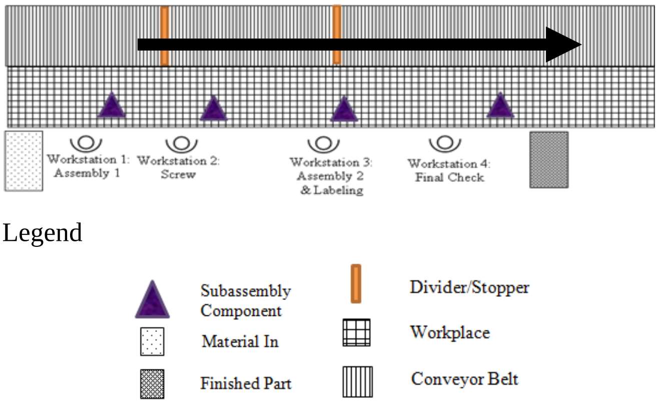

Fig. 3. Improved layout and process flow

With proposing the simulation experiment design method, top management able to get the best possible shop floor operating condition. The simulation with TOPSIS has assisted the industrial personnel, especially the decision maker to plan and make the accurate decision based on the simulated result because the consequences of the wrong decision are serious and costly. For example, assigning wrong number of operators, providing inappropriate work structure procedure, design inappropriate layout or workstation, and so on will have worst consequences for shop floor performance and will directly affect the whole organization. Therefore, through the effective planning and analysis of improvement project, the shop floor operating condition can be improved and become more effective.

IV. CONCLUSION

The multi-criteria decision aid has been integrated with the simulation design with TOPSIS in order to rank and select the best improvement solutions. The use of simulation in the manner prescribed in this paper helps to verify and validate the improvement model generated in the earlier stages. From the simulation, the unpractical model is filtered to reduce the chance of failure of implementing the improvement model. The result obtained from the simulation verifies the practicability of the accepted idea being executed in industry. The best improvement solution based on multiple performance measure factors can be determined by TOPSIS method. The result of this case study shows the improvement in manpower reduction, process cycle time reduction, idling time reduction, WIP reduction and at the same time increase in production output, resource utilization and line efficiency.

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