IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 23, 2020, accepted November 9, 2020, date of publication November 16, 2020, date of current version November 20, 2020.

*Digital Object Identifier 10.1109/ACCESS.2020.3037660*

# An Improved Value Stream Mapping to Prioritize Lean Optimization Scenarios Using Simulation and Multiple-Attribute Decision-Making Method

**QINGQI LIU**[1] **AND HUALONG YANG**[1,2]
[1]College of Transportation Engineering, Dalian Maritime University, Dalian 116026, China
[2]Logistics Research Institute, Dalian Maritime University, Dalian 116026, China

Corresponding author: Hualong Yang (hlyang@dlmu.edu.cn)

This work was supported by the National Natural Science Foundation of China (NSFC) under Grant 72071024.

**ABSTRACT** Manufacturing organizations have been witnessing transformation in business strategy from mass production to lean philosophy. Value Stream Mapping (VSM) is one of the primary analytical tools for identifying waste and transforming the production environment into lean operational state. However, traditional VSM lacks the capability to handle conflicting factors in the improvement scheme and to prioritize multiple improvement initiatives. VSM enables only a static analysis of a system, and a static model does not allow assessing how the system will be affected to various scenarios with different parameters in the future-state map. Moreover, VSM optimization is a typical multiple-attribute decision-making (MADM) problem that involves the evaluation of multiple performance metrics such as inventory levels, lead times and service levels. Therefore, this paper proposes an improved VSM procedure that incorporates simulation and MADM, using grey Taguchi method, to overcome the limitation of standard VSM. Simulation introduces a dynamic dimension to VSM, and grey Taguchi method prioritizes the scenarios with a minimum number of test series. A lean implementation program is conducted in a footwear manufacturing company to validate the improved VSM procedure. Two alternative future-state VSMs are proposed, each with nine different scenarios, and the identified optimal solution realizes the reduction in defect rate, work-in-process inventory and lead time, as well as the improvement in order fulfilment rate. The improved VSM procedure enables practitioners to determine the optimal future-state VSM according to the preference of practitioners on multiple performance criteria.

**INDEX TERMS** Grey Taguchi method, lean production, multiple-attribute decision-making, simulation, value stream mapping.

## I. INTRODUCTION

Lean production, originated from the Toyota Production System, has been receiving great attention from researchers and practitioners since its introduction [1]. It is a systematic approach for identifying and eliminating waste through continuous improvement in pursuit of perfection, using a pull-control strategy derived from customer requirements [2]. Womack and Jones [3] defined five principles that characterize lean: specifying value, identifying the entire value stream, making the product flow, letting the customer pull value from the system, and continuously search for perfection. Therefore, the analysis of the product value stream is always implemented as the first step toward leanness, identifying the areas where the improvement efforts should be concentrated [4]. Value Stream Mapping (VSM) is a visual tool that facilitates the process of lean production system through identifying value-added activities and eliminating wastes [5]. It can be described as "a graphical tool used to map the as-is situation of the organization, to identify opportunities for waste elimination, and to decide the improvements to be implemented to eliminate the waste" [6]. The sources of wastes identified by VSM include over production, waiting, transportation, inappropriate processing, unnecessary inventory, unnecessary motions, and defects [7]. Some of these wastes are generated due to the incoordination between processes, while others, especially defects in most cases, might be associated with the improper parameter settings of some

The associate editor coordinating the review of this manuscript and approving it for publication was Fabrizio Messina.

process [8]. Seven guidelines are to be followed based on the concept of lean production to eliminate these wastes and construct the future-state VSM, including ''produce to your takt time'', ''develop continuous flow wherever possible'', ''use supermarkets to control production where continuous flow does not extend upstream'', ''send the customer schedule to only one production process'', ''level the production mix'', ''level the production volume'', and ''develop the ability to make 'every part every day' (then every shift, then every hour, or pallet or pitch) upstream of the pacemaker process'' [9]. However, these guidelines mainly focus on the coordination of the entire system and the interfaces between processes, while little emphasis is laid on the optimization of a specific working station. This leads to one of the deficiencies of VSM:

- It lacks the involvement of tools or guides aiming at optimizing the parameter settings of individual working stations, consequently, wastes generated by the inappropriate setting of working stations are ignored.

Multiple factors need to be considered according to the guidelines [10], and different combinations of the factors would result in different outcomes. For instance, guidelines ''production mix levelling'', ''production volume levelling'' and ''every part every interval'' promote batch size reduction and facilitate the highest possible flow degree. However, reduction of batch size is always accompanied by increase of changeovers, and more frequent changeover may lead to higher material or energy consumption, which is not in accordance with the principle of lean [11]. Moreover, the implementation of these guidelines usually requires drastic changes to the current setups. Some of the undertaken solutions may be costly and time-consuming to implement or may not necessarily lead to the expected results due to the unintended consequences related to the complexity of the system under observation [12]. Therefore, it is necessary to provide decision makers with visible evidence and quantifying potential gains of committing these lean thinking concepts before real implementation [13]. This generates another two major limitations of VSM:

- It lacks the capability for a rapid development and evaluation of multiple what-if analyses and potential benefits that are required to prioritize different alternatives;
- Multiple improvement areas and their respective multiple improvement proposals would result in too many possible combinations, making it complicated and time-consuming to decide the optimal scenario.

This paper targets the development of an enhanced VSM procedure that overcomes the above deficits. For this purpose, VSM is integrated with simulation and multiple-attribute decision-making (MADM) method to produce an efficient identification of the optimal production parameter settings and the optimal future-state scenario. Simulation dynamically assesses feasibility and evaluates trade-offs in alternative future-state scenarios, and MADM identifies the preeminent combination of controllable variables. The MADM problem is solved by grey Taguchi method that incorporates grey relational analysis (GRA) into Taguchi method to transfer multi-response problems into single-response problems.

The remainder of the article is organized as follows. Section 2 reviews the previous studies relevant to the proposed problem. Section 3 proposes the enhanced VSM procedure. Empirical illustrations following the proposed procedure are describes in Section 4. Finally, conclusions and future research prospects are presented in Section 5.

## II. LITERATURE REVIEW

### A. VALUE STREAM MAPPING

As a practical guiding tool for lean implementation, VSM creates a pictorial representation and common language for the production line [5]. Compared to other mapping techniques, VSM has some specific features, making VSM important and unique for lean manufacturing. For instance, VSM not only manages the manufacturing processes but also optimizes the whole system by creating a holistic view of it [14], [15]. VSM is a door-to-door demonstration for visualizing a production process at the plant level rather the single-process level and illustrating the flow of materials and information in the entire supply chain rather than for separate manufacturing plants [9]. Thus, it includes information related to production times, as well as to inventory levels, and offers a reflection of systemic vision maintaining local details of process by diagrammatically linking material-flow, information-flow and timeline [16]. Moreover, by using operating parameters such as takt time, which determines the production rate at which each processing stage in the manufacturing system should operate, VSM links product planning and demand forecasts to production scheduling and flow-shop control. Through visualized mapping, VSM successfully forms a blueprint for lean implementation and can be integrated into various qualitative and quantitative analyses-based tools to refine and redesign strategic improvements [13].

Due to its effectiveness and advantages in promoting lean manufacturing, VSM has stepwise expanded to a wide range of industries since originated from automotive industry [13], [17]–[19]. However, it is recognized in the application that VSM lacks the capability to handle conflicting factors in the improvement scheme and to prioritize multiple improvement initiatives [20]. Therefore, it is difficult to draw a final decision from different potential scenarios when solely using VSM to guide a lean production system.

To overcome this drawback, Librelato *et al.* [20] presented a process improvement approach based on VSM and Thinking Process of the Theory of Constraints (TP-TOC), providing an integrated view between the losses in the process and the prioritization of the steps for the elimination of such losses. The prioritization of waste elimination solutions identified by VSM was also studied by Behnam, Ayough and Mirghaderi [21] by the usage of analytical hierarchy process (AHP) method. Mohanraj *et al.* [22] integrated fuzzy quality function deployment (QFD) with VSM framework to scientifically prioritize the improvement proposals.

While techniques such as TP-TOC, AHP and fuzzy QFD introduce scenario prioritization to VSM, they fail to overcome the static nature of VSM, thus fail to provide quantifiable evidence in the evaluation of multiple scenarios [23]. The static nature of VSM is one of the fundamental limitations of the tool, making it uncapable on studying a dynamic problem [24]. For example, predicting inventory levels in the production line is usually impossible with just a map of future state, because with a static model one cannot observe how inventory levels will vary for what-if scenarios [25]. In general, a future-state map needs to be complemented by a tool with predictive ability to quantify the inventory levels, lead times, machine utilization and other parameters for different future-state scenarios [26]. In addition, value stream optimization often requires making dramatic changes to the organization. Therefore, it is essential to evaluate the changes suggested by VSM before implementing the improvement initiatives. The above-mentioned complementary tools fail to incorporate such hypothesis testing function to VSM [13]. A very promising add-on is simulation [25].

### B. SIMULATION OPTIMIZATION

Simulation has been widely recognized as one of the best and most suitable methodologies for problem solving in real-word complex systems in order to choose correctly, understand why, diagnose problems, explore possibilities, and find optimal solutions [27]. A simulation model enables analysts to model either an existing system or a system that has not been built yet in real life, and moreover, to test the system under different conditions [28]. Since a simulation model is able to visualize material flows and times, it can detect bottlenecks using waiting times and utilization [13]. Atieh *et al.* [13] introduced simulation as a complementary tool to VSM: simulation adds a dynamic dimension to VSM, and helps in judging changes and evaluating potential scenarios in value stream improvement schemes. Schmidtke *et al.* [11] developed an enhanced VSM procedure with simulation to assess feasibility and analyze trade-offs of the proposed future-state map prior to implementation. Helleno *et al.* [29] integrated VSM with discrete-event simulation to direct the management investment in the best option among the available scenarios. The results showed the efficiency of VSM and simulation integration as decision-making tools. Simulation contributes substantially in supporting the reasoning and prioritizing the alternatives for improvement to derive the future-state VSM [30]. A simulation-enhanced VSM is no longer a snapshot; it is a moving picture that enables ideas to be tested without interruptions [28]. The applicability and benefits of incorporating simulation into VSM have been studied and supported by various researchers [15], [25], [29], [31]. However, though simulation can be used to evaluate the performance of a new design, it cannot provide the optimal design. Moreover, a value stream optimization usually involves multiple Kaizen proposals, each with multiple possible Kaizen schemes, resulting in numerous improvement portfolios. It is laborious and time-consuming to examine the full combination of multiple improvement schemes. Such problem, however, is not fully considered in the above studies discussing simulation-VSM integration.

### C. GREY TAGUCHI METHOD

Taguchi method is extensively used in industrial design to improve product quality through the robust design of products and has been used to address problems in manufacturing [32]. It can systematically determine the effects of all process parameters using only a small number of experiments and can optimize the process parameters by combining the orthogonal array and the quality loss function concept [33]. According to Taguchi [34], a small fraction of setting factors produces the most information from all possible combinations [35]. Taguchi method thus suggests a special design of orthogonal arrays to study the effect of process parameters using a small number of experiments [36]. For instance, if the given problem has 4 independent variables and 4 levels for each, the conventional design requires 256 experiments to find out the optimum setting portfolio, while Taguchi DoE requires only 16 experiments [37]. Thus, the Taguchi method is a powerful approach to improve experimental efficiency and has been used in various industries for designing products that combine reduced cost with enhanced quality [38]. Normally, more than one performance measure needs to be examined in a VSM optimization, which might include production lead time, work-in-process inventory, waiting time, resources utilization, productivity, and order fulfil rate, etc. [13], [23]. However, the conventional Taguchi method does not provide a solution for multiple-response optimization by default. Therefore, Taguchi method needs to be accompanied by a MADM problem-solving procedure to prioritize VSM improvement schemes [39]. GRA uses a grey relational grade to evaluate multiple performance characteristics, and is effective in the problem solving of MADM like value stream improvement [13], [40]. Thus, GRA can be incorporated with the Taguchi method, namely, grey Taguchi, to achieve a single set of optimal level of different parameters for various properties (responses) simultaneously [41], and the grey Taguchi method can be incorporated with VSM simulation to produce an efficient assessment of the performance criteria and a quick decision on the optimal scenario [42].

## III. PROPOSED METHOD

The proposed enhanced VSM is shown in Figure 1. The first step creates a current-state VSM based on the investigation and field research to the case company. The second step identifies the processes that contribute to the most frequent quality failures and their respective control factors, and accordingly, determines the optimal parameter settings to the processes using grey Taguchi method to minimize product defects. The third step highlights the wastes in the current-state VSM, identifies improvement opportunities, and creates the future-state VSM proposals accordingly. In this research, two alternative future-sate VSMs with their respective control factors are proposed at this stage. Next, develop simulation models

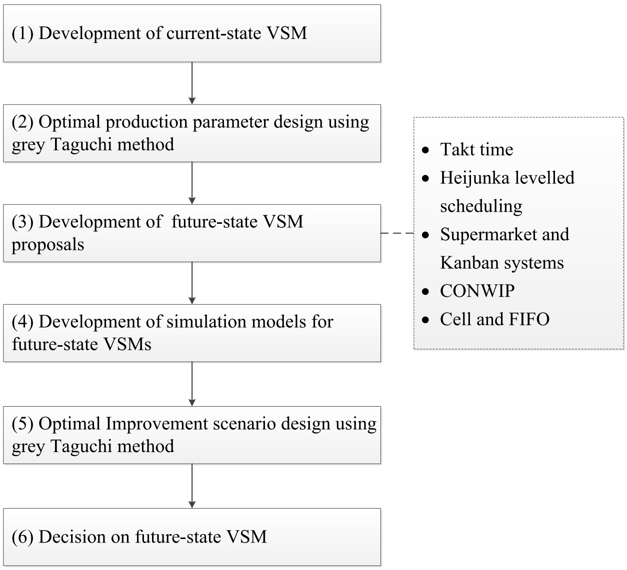



**FIGURE 1. The proposed procedure.**

for future-sate VSMs and search their respective optimal scenario using grey Taguchi method. The final step compares the optimal schemes from two future-sate VSMs in terms of leanness evaluation criteria, and determines the ideal future-state VSM accordingly.

### A. DEVELOPMENT OF CURRENT-STATE VSM

Current-state VSM graphically documents the processes in the current manufacturing system. Related data, including cycle time, changeover time, work-in-process (WIP) levels, etc., is collected from the manufacturing executive system (MES) and the field investigation of the case company. With reference to current-state VSM, analysts identify and measure the wastes generated from incapacity, inefficiency, and the unreliability of information, time, money, space, people, machines, materials and manufacturing tools during the management of processing within an organization, and improvement initiatives are created accordingly [6].

### B. OPTIMAL PRODUCTION PARAMETER DESIGN USING GREY TAGUCHI METHOD

The parameter settings of each process should be optimized prior to optimizing the flow of material and information along the value stream. Multiple factors need to be considered, thus a MADM procedure should be followed. Grey Taguchi method is applied to explore the cause-and-effect relationship between process variables (process parameter settings) and output variables (defect rates). The first step is to maximize the signal-to-noise (S/N) ratio of each control factors, as a greater value for S/N ratio suggests greater robustness of system. The objective function of the S/N ratio is [43]:

$$Y_{ij} = -10\log\left(\frac{1}{r}\sum\nolimits_{k=1}^{r} v_{ijk}^2\right), \tag{1}$$

for the "smaller-the-better" responses; and

$$Y_{ij} = -10\log\left(\frac{1}{r}\sum\nolimits_{k=1}^{r} \frac{1}{v_{ijk}^2}\right), \tag{2}$$

for the "larger-the-better" responses; where $Y_{ij}$ represents the S/N ratio of i$^{\text{th}}$ experiment for j$^{\text{th}}$ response, $v_{ijk}$ denotes the result of i$^{\text{th}}$ experiment for j$^{\text{th}}$ response in k$^{\text{th}}$ replication, and r is the number of replications.

Next, GRA is applied to synthesize the responses and to achieve a single optimal combination of the parameters with respect to multiple responses. The S/N ratio of each response can be transformed into a normalized value using the following equation:

$$Z_{ij} = \frac{\max Y_{ij} - Y_{ij}}{\max Y_{ij} - \min Y_{ij}}, \tag{3}$$

for "smaller-the-better" criteria [44]; and

$$Z_{ij} = \frac{Y_{ij} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}}, \tag{4}$$

for "larger-the-better" criteria [45]; where $Z_{ij}$ is the normalized S/N ratio of i$^{\text{th}}$ experiment for j$^{\text{th}}$ response [44], [46], [47]. Note that $\max Y_{ij} = \min Y_{ij}$ suggests the output variable (response) is insensitive to any input variable (controllable factor). This might be caused by the absence of influencing factors or the mistaken selection of response. In such cases, the missing factors should be included in the experiments, or the improper response should be excluded. For instance, four controllable factors A, B, C, D are identified for response $J_1$ and $J_2$. If the S/N ratio of $J_1$ remains constant in all Taguchi experiments, then the first possible reason may be the influencing factor of $J_1$ is not identified. In such case, additional factors should be included in the experiments. The second possible reason may be $J_1$ is not the suitable output variable to determine the optimal input variable, then response $J_1$ should be excluded, or replaced by other response.

Grey relational coefficient (GRC) gives the relationship between the reference value and normalized value and is calculated using:

$$GRC_{0ij} = \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{0ij} + \rho\Delta_{max}}, \tag{5}$$

where $GRC_{0ij}$ represents the grey coefficient of i$^{\text{th}}$ experiment for j$^{\text{th}}$ response; $\Delta_{0ij}$ is the difference between the ideal value of normalized S/N ratio ($Z_{0j}$) and the normalized S/N ratio ($Z_{ij}$); $\Delta_{min} = min_{\forall i} min_{\forall j} \Delta_{0ij}$; $\Delta_{max} = max_{\forall i} max_{\forall j} \Delta_{0ij}$; $\rho$ is the identification coefficient or distinguishing coefficient that ranges between 0 and 1, and is set as 0.5 in this study [46].

Finally, the grey relational grade (GRG) is computed using:

$$GRG_{0i} = \sum\nolimits_{j=1}^{n} \omega_j GRC_{0ij}, \tag{6}$$

where $GRC_{0i}$ represents the grey relational grade of i$^{\text{th}}$ experiment, $\omega_j$ represents the normalized non-negative weight assigned to j$^{\text{th}}$ response, determined by the judgements of decision makers or the structure of the proposed problem [46], and $\sum_{j=1}^{n} \omega_j$ equals to 1.

With reference to the result of GRG, the alternative scenarios can be prioritized according to GRG in descending order, and the ideal parameter settings can be determined.

### C. DEVELOPMENT OF FUTURE-STATE VSM PROPOSALS

After the parameter settings of individual working station have been optimized, the next step is to redesign value stream to make a leaner production system. The paper proposes two alternative future-state VSMs, both following principles including:

- Takt time: takt time is used to synchronize the pace of production with the pace of customer demand [9], calculated by:

$$\text{Takt time} = \frac{\text{available working time per shift/day}}{\text{customer demand per shift/day}}, \quad (7)$$

Then cycle time should be set according to the takt time: cycle time is the actual time between completion of consecutive units of product or component, which should be less or equal to the takt time. An ideal lean production system is to have cycle time equal to takt time [48].

- Heijunka levelled scheduling: using levelled scheduling (Heijunka) to construct a schedule that matches actual production to takt time and cycle time [48], thus to reduce the variability of the production rate, resulting in a short lead time and a quick response to customer demand [9].
- Supermarket and Kanban systems: Supermarket and Kanban systems are to be applied to the production line in order to replace WIP and prevent overproduction.
- CONWIP: Constant WIP (CONWIP) strategy is to be implemented where Kanban does not perform well (for instance, in uncertain or dynamic environment).
- Cell and FIFO: The layout of the plant is to be adjusted to reorganize adjacent working stations into a single cell where applicable, and replace the WIP buffer with FIFO flow where applicable.

### D. DEVELOPMENT OF SIMULATION MODELS FOR FUTURE-STATE VSMS

Simulation experiments are to be conducted under different scenarios of future-state VSM proposals. This study adopts the simulation software Flexsim 2019 for the empirical illustration. The process flow chart in Flexsim is used to design discrete-event models with block diagram schemes. Abstract objects called "tokens" transit between blocks instantaneously, triggering at their arrival states transitions in the model. The tokens in the simulation model denote two different entities: firstly, they represent the Pitch, that is, the consistent amount of production instruction released at the pacemaker process and the basic unit of the production schedule; secondly, they represent the customer request (of a Pitch), suggesting the arrival of an order to produce a new Pitch chosen from the order-backlog list. Blocks called "activities" define a transition in the state of the model or a delay in the flow of the token. To verify and validate the simulation model, the current-state VSM is modelled and examined, and the outputs of the simulation are compared with the performance of the actual system. The results show the numerical outputs from the simulation are all within the range of the actual data, suggesting the established simulation model is valid as the experimental platform for the VSM optimization experiments. Recording the WIP level, production lead time and order fulfilment rate in each simulation experiment as performance criteria to determine the optimal improvement scheme in the final step.

### E. OPTIMAL IMPROVEMENT SCENARIO DESIGN USING GREY TAGUCHI METHOD

For each future-state VSM alternative, using the same procedure as described in Section III. (B) to determine the optimal value stream parameter settings that produce the best performance in terms of WIP level, production lead time and order fulfilment rate. Practitioners can set the acceptable levels of performance criteria to exclude unsatisfactory scenarios and rank the scenarios according to GRG in descending order.

### F. DECISION ON FUTURE-STATE VSM

The decision on future-state VSM solutions can be made by comparing the performance criteria of the alternatives. The proposed simulation-integrated VSM evaluates the production line using multiple criteria including WIP level, lead time, order fulfillment rate, etc., whereas the conventional VSM performs the assessment based only on the estimated time-related factor. If additional criteria need to be included, or some criteria need to be excluded, data can be easily obtained by adding or removing the outputs from the simulation in step D, and recalculating the GRG in step E accordingly. Moreover, the comparison results between the ideal future-state VSM and the current-state VSM can be given using the performance criteria. This makes the optimized value stream and lean system more visible, providing decision makers with more quantitative evidence of lean initiative implementation. The optimized future-state VSM then becomes the roadmap to make a lean system, which would be achieved by implementing and fulfilling the proposed strategy, as described in Section III. C.

## IV. CASE ANALYSIS

### A. DEVELOPMENT OF CURRENT-STATE VSM

In this study, an athletic shoe manufacturer named EA is investigated. EA outsources the production of soles and imports the raw materials for the uppers in the global market. The uppers are manufactured and attached to the soles in the manufacturing plant. The manufacturing procedure mainly consists of five major steps: (1) cutting, (2) pre-fitting, (3) computer stitching, (4) manual stitching and (5) assembly. Production begins in the cutting room. Here, raw materials for the uppers are cut into prescribed shapes using instruments

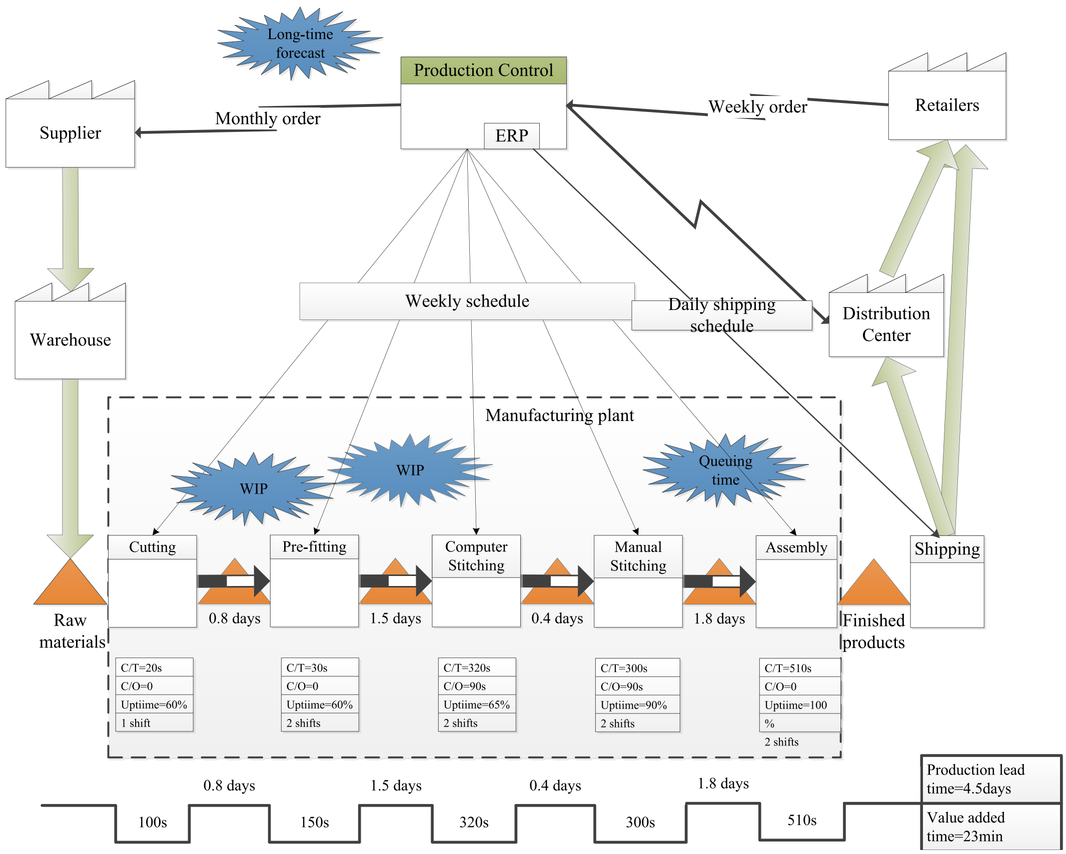



**FIGURE 2.** Current-state VSM.

that look like cookie cutters. After cutting is the process of pre-fitting, in which some of the cut parts are skived for better fit and some are embossed or embroidered with details or logos. Next, the parts are brought to the computer stitching department, where a machine guided by computer vision joins the separate parts to the uppers. Parts that cannot be automatically stitched are taken to a manual stitching workshop. Here, uppers are transformed from a flat form to a three-dimensional form. Finally, the nearly-finished uppers circulate to the assembly line, where the uppers are placed and stretched on foot-shaped moulds called "lasts" and attached to the soles.

According to the historical data from the case company's MES database, the average customer demand for the investigated footwear model is 400 pairs per day, of mixed men's and women's styles and mixed sizes. Men sizes range from 39 to 44, including half sizes, i.e., 39-39.5-40-40.5-41-41.5-42-42.5-43-43.5-44, and the women sizes range from 35-40, including half sizes, i.e., 35-35.5-36-36.5-37-37.5-38-38.5-39-39.5-40 (Note that the 39, 39.5 and 40 sizes for man style are different from those for woman style). The cycle time for cutting, pre-fitting, computer stitching, manual stitching and assembly is 20s, 30s, 320s, 300s, and 510s, respectively. For each shoe, five different parts, including the upper body, shoe tongue, heel counter, and other functional or decorative pieces, need to be cut from the fabric or leather rolls. A cutting

**TABLE 1.** The controllable process factors and their levels.

| Factor | Factor details | Unit | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| A | Stitching line(s) | No. | 1 | 2 | 3 |
| B | Stitching density | Stitches per cm (in average) | 3.8 | 4 | 4.2 |
| C | sewing thread specification | Denier (D) | 19/21 | 20/22 | 21/23 |
| D | Stitching margin | mm | 1.2 | 1.4 | 1.6 |
| E | Sole pressing time | Second (s) | 6 | 7 | 8 |
| F | Sole pressing pressure | Pound (p) | 25 | 30 | 35 |

machine can handle up to ten tiers of flat stock at a time and a pre-fitting machine can process up to ten pieces at a time. For cutting, pre-fitting and assembly, there is no change-over time, and the computer stitching and manual stitching has the same change-over time of 90s. The current-state VSM in the manufacturing plant is shown in Figure 2. At the bottom of the figure, the timeline from raw material receipt till final product shipping is depicted. Note that the valued-added times of cutting and pre-fitting is five times of their respective cycle times because the cutting and pre-fitting operation, respectively, repeats five times to produce the five different parts for

**TABLE 2. Experimental results for inspection defect rate.**

| Exp. No. | A | B | C | D | E | F | Defect (V) (%) | | | AVG (V) (%) | Defect (M) (%) | | | AVG (M) (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3.4 | 19/21 | 1.2 | 6 | 25 | 5.0 | 6.7 | 7.5 | 6.4 | 17.5 | 15.8 | 15.8 | 16.4 |
| 2 | 1 | 3.4 | 19/21 | 1.2 | 7 | 30 | 5.0 | 4.2 | 4.2 | 4.4 | 16.7 | 15.8 | 16.7 | 16.4 |
| 3 | 1 | 3.4 | 19/21 | 1.2 | 8 | 35 | 5.8 | 6.7 | 6.7 | 6.4 | 18.3 | 17.5 | 16.7 | 17.5 |
| 4 | 1 | 4 | 20/22 | 1.4 | 6 | 25 | 5.0 | 5.8 | 6.7 | 5.8 | 13.3 | 11.7 | 10.0 | 11.7 |
| 5 | 1 | 4 | 20/22 | 1.4 | 7 | 30 | 2.5 | 4.2 | 3.3 | 3.3 | 10.0 | 10.8 | 10.0 | 10.3 |
| 6 | 1 | 4 | 20/22 | 1.4 | 8 | 35 | 4.2 | 3.3 | 3.3 | 3.6 | 9.2 | 7.5 | 9.2 | 8.6 |
| 7 | 1 | 4.2 | 21/23 | 1.6 | 6 | 25 | 5.8 | 5.0 | 6.7 | 5.8 | 8.3 | 8.3 | 7.5 | 8.1 |
| 8 | 1 | 4.2 | 21/23 | 1.6 | 7 | 30 | 4.2 | 4.2 | 3.3 | 3.9 | 7.5 | 8.3 | 7.5 | 7.8 |
| 9 | 1 | 4.2 | 21/23 | 1.6 | 8 | 35 | 5.8 | 6.7 | 4.2 | 5.6 | 7.5 | 9.2 | 9.2 | 8.6 |
| 10 | 2 | 3.4 | 20/22 | 1.6 | 6 | 30 | 2.5 | 3.3 | 2.5 | 2.8 | 5.8 | 4.2 | 4.2 | 4.7 |
| 11 | 2 | 3.4 | 20/22 | 1.6 | 7 | 35 | 2.5 | 1.7 | 1.7 | 1.9 | 3.3 | 5.0 | 4.2 | 4.2 |
| 12 | 2 | 3.4 | 20/22 | 1.6 | 8 | 25 | 3.3 | 2.5 | 2.5 | 2.8 | 4.2 | 3.3 | 5.0 | 4.2 |
| 13 | 2 | 4 | 21/23 | 1.2 | 6 | 30 | 0.8 | 3.3 | 1.7 | 1.9 | 4.2 | 5.0 | 5.0 | 4.7 |
| 14 | 2 | 4 | 21/23 | 1.2 | 7 | 35 | 1.7 | 2.5 | 1.7 | 1.9 | 3.3 | 2.5 | 2.5 | 2.8 |
| 15 | 2 | 4 | 21/23 | 1.2 | 8 | 25 | 1.7 | 1.7 | 0.8 | 1.4 | 5.0 | 5.0 | 4.2 | 4.7 |
| 16 | 2 | 4.2 | 19/21 | 1.4 | 6 | 30 | 2.5 | 2.5 | 1.7 | 2.2 | 3.3 | 1.7 | 1.7 | 2.2 |
| 17 | 2 | 4.2 | 19/21 | 1.4 | 7 | 35 | 2.5 | 0.8 | 1.7 | 1.7 | 2.5 | 1.7 | 1.7 | 1.9 |
| 18 | 2 | 4.2 | 19/21 | 1.4 | 8 | 25 | 2.5 | 1.7 | 1.7 | 1.9 | 2.5 | 3.3 | 3.3 | 3.1 |
| 19 | 3 | 3.4 | 21/23 | 1.4 | 6 | 35 | 6.7 | 5.8 | 5.8 | 6.1 | 6.7 | 7.5 | 7.5 | 7.2 |
| 20 | 3 | 3.4 | 21/23 | 1.4 | 7 | 25 | 7.5 | 7.5 | 6.7 | 7.2 | 15.0 | 15.8 | 17.5 | 16.1 |
| 21 | 3 | 3.4 | 21/23 | 1.4 | 8 | 30 | 7.5 | 5.8 | 5.8 | 6.4 | 16.7 | 17.5 | 18.3 | 17.5 |
| 22 | 3 | 4 | 19/21 | 1.6 | 6 | 35 | 3.3 | 3.3 | 2.5 | 3.1 | 8.3 | 6.7 | 6.7 | 7.2 |
| 23 | 3 | 4 | 19/21 | 1.6 | 7 | 25 | 3.3 | 1.7 | 2.5 | 2.5 | 5.8 | 5.0 | 7.5 | 6.1 |
| 24 | 3 | 4 | 19/21 | 1.6 | 8 | 30 | 2.5 | 2.5 | 3.3 | 2.8 | 5.8 | 6.7 | 6.7 | 6.4 |
| 25 | 3 | 4.2 | 20/22 | 1.2 | 6 | 35 | 7.5 | 5.8 | 5.8 | 6.4 | 9.2 | 10.0 | 9.2 | 9.4 |
| 26 | 3 | 4.2 | 20/22 | 1.2 | 7 | 25 | 4.2 | 4.2 | 3.3 | 3.9 | 9.2 | 11.7 | 12.5 | 11.1 |
| 27 | 3 | 4.2 | 20/22 | 1.2 | 8 | 30 | 6.7 | 7.5 | 8.3 | 7.5 | 15.8 | 12.5 | 13.3 | 13.9 |

every single shoe. As a result, the total production lead time in days (TPLT) is 4.5 days, whereas the total value-added time in seconds (TVAT) is only 1,380s, leaving a great margin for improvement. In addition to the low efficiency (measured by the ratio of TVAT with respect to the TPLT, i.e., TVAT/TPLT) of the production line, the company is now suffering from high defect rate, as reported by the quality control manager. As a consequence, the company has to keep a certain level of finished products in their warehouse in case delay in delivery aroused by too many defects. Since the shoes produced by the company are in various series, colors, and sizes, the inventory volume is very huge as the result of the large number of SKU. Head of sales and marketing also pointed out that the frequent customer complaints is a serious impediment to the further expansion of the market.

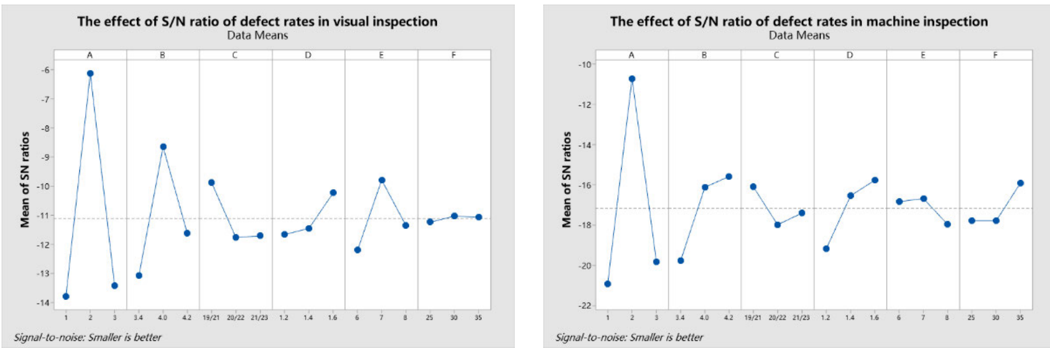
### *B. OPTIMAL PRODUCTION PARAMETER DESIGN USING GREY TAGUCHI METHOD*

It is discovered from the inspection results that the most frequent quality failures come from the stitching (including both computer stitching and manual stitching) and assembly stages. After carefully examining the product defects and referring to the quality guidelines, four controllable factors influencing stitching performance and two factors influencing assembly are identified, as illustrated in Table 1.

Accordingly, DoE-based Taguchi method is employed to determine the optimal parameter settings. An L27($3^6$) orthogonal array (OA) is applied consisting of six controllable factors, with three levels of each factor [49]. Experiments on the shop floor were performed at different parameter settings. Two series of quality examination were conducted: the first was visual inspection performed immediately after assembly, checking the stitching, sewing and upper-sole bonding; the second was machine inspection testing the wearing durability of the manufacturing materials and stitching method. The two different inspections reflect two dimensions of customer satisfaction index: the first influences the rate of order fulfilment and/or the level of safety stock; the second serves as an important indicator of the after-sales satisfaction. For each parameter setting, the sampling and testing experiment was repeated three times to minimize the influence of external uncontrollable factors. The experiment results are illustrated in Table 2. Defect (V) refers to the result of the visual inspection, and Defect (M) refers to result of the

**TABLE 3.** S/N ratio for visual inspection ($Y_V$) and machine inspection ($Y_M$) results.

| Level | A | | B | | C | | D | | E | | F | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_V$ | $Y_M$ | $Y_V$ | $Y_M$ | $Y_V$ | $Y_M$ | $Y_V$ | $Y_M$ | $Y_V$ | $Y_M$ | $Y_V$ | $Y_M$ |
| 1 | -13.79 | -20.93 | -13.08 | -19.77 | -9.87 | -16.10 | -11.67 | -19.17 | -12.21 | -16.83 | -11.24 | -17.79 |
| 2 | -6.12 | -10.73 | -8.65 | -16.12 | -11.76 | -17.98 | -11.45 | -16.54 | -9.79 | -16.69 | -11.03 | -17.79 |
| 3 | -13.44 | -19.83 | -11.62 | -15.59 | -11.71 | -17.41 | -10.23 | -15.77 | -11.35 | -17.96 | -11.08 | -15.91 |
| Delta | 7.67 | 10.20 | 4.43 | 4.17 | 1.89 | 1.88 | 1.44 | 3.40 | 2.42 | 1.28 | 0.21 | 1.88 |
| Rank | 1 | 1 | 2 | 2 | 4 | 4 | 5 | 3 | 3 | 6 | 6 | 5 |




(a) (b)

**FIGURE 3.** The effect of S/N ratio of defect rates.

machine inspection. Accordingly, the AVG (V) and AVG (M) represents their average values, respectively.

Since the defect rate is ''smaller-the-better'' type of property, according to (1), the S/N responses for visual inspection and machine inspection results are calculated and listed in Table 3.

It is observed from Table 3 that, for visual inspection result, A has the greatest impact, followed by B, E and C whereas D and F have insignificant influence. For machine inspection, the greatest influence factor is also taken by A, followed by B, D and C whereas F and E have the lowest impact. According to the S/N ratios in Table 3, the effect of each factor level on visual inspection and machine inspection results is shown in Figure 3. Therefore, the levels of process parameters/factors are decided as $A_2B_2C_1D_3E_2F_2$ to minimize the defect rates in visual inspection, and $A_2B_3C_1D_3E_2F_3$ to minimize the defect rates in machine inspection.

It can be seen from the results that different optimization goals (minimizing defects from visual checking and machine inspection respectively) have different optimal parameter settings. Therefore, GRA is applied to determine the optimal setting scenario with respect to both responses. The results of S/N ratio are transformed into normalized values using (3) for ''smaller-the-better'' response, and GRC for both responses is calculated using (5), respectively. By assuming that equal weight is assigned to visual and machine inspection, i.e., $\omega_1 = \omega_2 = 0.5$, GRG is computed using (6). The results of other attribute weight settings are discussed at the end of this section. The normalized value of S/N ratio, GRC and GRG for visual and machine inspection are listed in Table 4.

It can be observed from Table 4 that the experiment 17 has the highest GRG of 0.96. Accordingly, the optimum factors for minimum total defects from visual and machine inspection is $A_2B_3C_1D_2E_2F_3$, i.e., double stitching lines, 4.2 stitches per cm (in average), 19/21D sewing thread, stitching margin of 1.4mm, sole pressing of 7s and 35p.

To illustrate the impacts of attribute weight settings, GRG is calculated under different weight assignment of visual inspection ($\omega_1$) and machine inspection ($\omega_2$), and experiment with the highest GRG is identified, respectively. The results are summarized in Table 5.

According to Table 5, experiment 17 remains the optimal design unless the weight of visual inspection is overwhelmingly higher than the weight of machine inspection, i.e., (0.8, 0.2) and (0.9, 0.1) settings of ($\omega_1, \omega_2$). However, such occasion is unadvisable and rarely chosen by decision makers in practical operation, as wearing durability has a significantly influence on the after-sale satisfaction of the product, and consequently, on the long-term development of the organization.

### C. DEVELOPMENT OF FUTURE-STATE VSM PROPOSALS

After the process parameter settings related to the product defects are optimized, the next step is to establish an ideal, or optimized, VSM for the future implementation. Two alternative VSMs are proposed, both of which follow the guidelines including takt time of 36s per shoe (calculated by (7): customer demand is 400 pairs per day, and daily working time is 8 hours), Heijunka levelled schedule, supermarket/Kanban leading production and delivery, CONWIP, and cell layout

**TABLE 4. Normalized value of S/N ratio, GRC and GRG for visual and machine inspection.**

| Exp. No. | Normalized value of S/N ratio | | GRC | | GRG | Rank |
|---|---|---|---|---|---|---|
| | $Z_V$ (%) | $Z_M$ (%) | $GRC_V$ | $GRC_M$ | | |
| 1 | 0.18 | 0.07 | 0.38 | 0.35 | 0.36 | 23 |
| 2 | 0.50 | 0.07 | 0.50 | 0.35 | 0.43 | 22 |
| 3 | 0.18 | 0.00 | 0.38 | 0.33 | 0.36 | 25 |
| 4 | 0.27 | 0.37 | 0.41 | 0.44 | 0.43 | 21 |
| 5 | 0.68 | 0.46 | 0.61 | 0.48 | 0.55 | 15 |
| 6 | 0.64 | 0.57 | 0.58 | 0.54 | 0.56 | 14 |
| 7 | 0.27 | 0.61 | 0.41 | 0.56 | 0.48 | 18 |
| 8 | 0.59 | 0.62 | 0.55 | 0.57 | 0.56 | 13 |
| 9 | 0.32 | 0.57 | 0.42 | 0.54 | 0.48 | 19 |
| 10 | 0.77 | 0.82 | 0.69 | 0.73 | 0.71 | 9 |
| 11 | 0.91 | 0.85 | 0.85 | 0.77 | 0.81 | 6 |
| 12 | 0.77 | 0.85 | 0.69 | 0.77 | 0.73 | 8 |
| 13 | 0.91 | 0.82 | 0.85 | 0.73 | 0.79 | 7 |
| 14 | 0.91 | 0.94 | 0.85 | 0.90 | 0.87 | 3 |
| 15 | 1.00 | 0.82 | 1.00 | 0.73 | 0.87 | 4 |
| 16 | 0.87 | 0.98 | 0.79 | 0.96 | 0.87 | 2 |
| 17 | 0.96 | 1.00 | 0.92 | 1.00 | 0.96 | 1 |
| 18 | 0.91 | 0.93 | 0.85 | 0.87 | 0.86 | 5 |
| 19 | 0.23 | 0.66 | 0.39 | 0.59 | 0.49 | 17 |
| 20 | 0.05 | 0.09 | 0.34 | 0.35 | 0.35 | 27 |
| 21 | 0.18 | 0.00 | 0.38 | 0.33 | 0.36 | 25 |
| 22 | 0.73 | 0.66 | 0.65 | 0.59 | 0.62 | 12 |
| 23 | 0.82 | 0.73 | 0.73 | 0.65 | 0.69 | 10 |
| 24 | 0.77 | 0.71 | 0.69 | 0.63 | 0.66 | 11 |
| 25 | 0.18 | 0.52 | 0.38 | 0.51 | 0.44 | 20 |
| 26 | 0.59 | 0.41 | 0.55 | 0.46 | 0.50 | 16 |
| 27 | 0.00 | 0.23 | 0.33 | 0.39 | 0.36 | 24 |

and FIFO where applicable, as listed in the previous section. Differences between the two alternative solutions are as follows.

### 1) FUTURE-STATE VSM$_1$

The first solution of the future-state value stream (see Figure 4) is supposed to change the layout of the plant to move the cutting and the pre-fitting units closer to each other, thus to realize the sharing of the operator between these two units. Such modification is to be made after the productivity of each production process and the takt time of the whole value stream (36s per shoe) are compared. In particular, for cutting and pre-fitting, the processing times of an upper are 100s and 150s, respectively. Because the concurrent output of these two processes is ten items, the times required to produce one item by these two processes are 10s and 15s, respectively. For computer stitching, manual stitching and assembly, the numbers of facilities working concurrently are 10, 10 and 15 while the corresponding cycle times are 320s, 300s and 510s, respectively. Each machine can handle a single shoe at a time. Therefore, the output paces of these three processes are 32s, 30s and 34s per shoe, respectively. The cutting and pre-fitting have the output paces, as measured by the time taken to produce one shoe, of less than half of the takt time of the line. Therefore, the proposal of shift working between cutting and pre-fitting processes is generated, as indicated by the arrow connecting cutting and pre-fitting in Figure 4. In accordance with this hypothesis, the manufacturing line is balanced under the condition that the cutting unit works on half-shift but keeps its original productive rate. Hence, it is necessary to place a buffer immediately after the cutting unit to store the items released at a rate that is double that of the line, and the shift frequency between cutting and pre-fitting units is one of the key factors that influence WIP and production lead time. Such modification reduces both WIP volumes and labor density. A supermarket is placed after the pre-fitting unit to inform the production Kanban of the number of items to be produced. The upper limit of the supermarket is another key factor to be optimized. When it goes to the Computer Stitching, Manual Stitching and Assembly Departments, the batch approach is replaced by the flow approach. First-in-first-out (FIFO) rule is implemented between the cells of two adjacent departments.

**TABLE 5. Sensitivity analysis for different attribute weights of visual inspection ($\omega_1$) and machine inspection ($\omega_2$).**

| $\omega_j$ | | Experiment with the highest GRG |
|---|---|---|
| $\omega_1$ | $\omega_2$ | |
| 0.1 | 0.9 | 17$^{th}$ |
| 0.2 | 0.8 | 17$^{th}$ |
| 0.3 | 0.7 | 17$^{th}$ |
| 0.4 | 0.6 | 17$^{th}$ |
| *0.5 | *0.5 | 17$^{th}$ |
| 0.6 | 0.4 | 17$^{th}$ |
| 0.7 | 0.3 | 17$^{th}$ |
| 0.8 | 0.2 | 15$^{th}$ |
| 0,9 | 0.1 | 15$^{th}$ |

*original weights.

Accordingly, four controllable factors are identified as: (1) shift frequency between cutting and pre-fitting units, (2) upper limit of the finished product inventory, (3) upper limit of the supermarket between pre-fitting and computer stitching units, and (4) level scheduling frequency, to determine the optimal lean implementation rules in this future-state solution. In Table 6, the four controllable factors are donated as A, B, C and D, and the respective level of them are donated as 1 to 3 (from low to high level).

### 2) FUTURE-STATE VSM$_2$

In the second solution (see Figure 5), the hypothesis is to change the overall layout of the plant to unify the cutting and the pre-fitting units into a single cell and the computer and manual stitching units into another to realize a "one-piece" flow within each working cell [50]. Consequently, the new manufacturing line has a "cutting + pre-fitting" cell and ten "computer + manual stitching" cells. The "cutting +

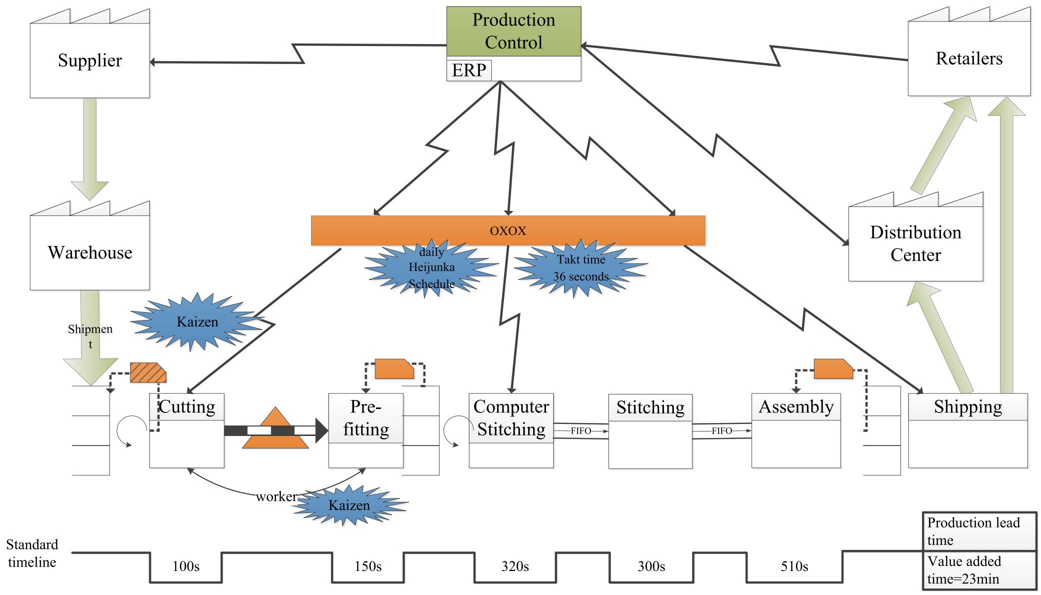



**FIGURE 4.** Future-state $VSM_1$.

**TABLE 6.** Control variables for future-state $VSM_1$.

| Factor | Factor details | Unit | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| A | Shift frequency between cutting and pre-fitting units | Hour | 1 | 2 | 4 |
| B | Upper limit of the finished product inventory | Shoe | 800 | 1600 | 2400 |
| C | Upper limit of the supermarket between pre-fitting and computer stitching units | Shoe | 100 | 200 | 400 |
| D | Level scheduling frequency | Hour | 1 | 2 | 4 |

pre-fitting" cell is operated by one worker: the worker cuts ten tiers of flat stock each time, and immediately takes the ten pieces into pre-fitting without interruption, thus to eliminate the WIP between the two processes and reduce unnecessary transporting due to the isolation of the two departments as in the original plant layout. Similarly, in the "computer + manual stitching" cells, an upper is transferred from the computer stitching directly to the manual stitching without temporary storage. Each "computer + manual stitching" cell is operated by two workers: the computer stitching operators finishes the first shoe, passes it to the manual stitching worker, and starts his work for the second shoe at the same time. Since the computer and manual stitching has similar cycle time (320s and 300s respectively), the two operators in the cell can work in an almost synchronous rhythm without long-time waiting. Afterwards, the stitched uppers are sent to the assembly line following a FIFO lane.

Accordingly, the controllable factors in this scenario are: (1) upper limit of the finished product inventory, (2) upper limit of the supermarket between pre-fitting and computer stitching units, and (3) level scheduling frequency. In Table 7,

**TABLE 7.** Control variables for future-state $VSM_2$.

| Factor | Factor details | Unit | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| A | Upper limit of the finished product inventory | Shoe | 800 | 1600 | 2400 |
| B | Upper limit of the supermarket between pre-fitting and computer stitching units | Shoe | 100 | 200 | 400 |
| C | Level scheduling frequency | Hour | 1 | 2 | 4 |

the three controllable factors are donated as A, B and C, and the level of these factors are donated as 1 to 3 (from low to high level).

### D. DEVELOPMENT OF SIMULATION MODELS FOR FUTURE-STATE VSMS

The proposed future-state VSM is modelled by Flexsim simulation software to test the performance of the production line in different settings of the four controllable factors. (See Appendix for the process flow simulation model.) The daily working time and customer demand is supposed to be consistent with the current state, i.e., 8 hours and 400 pairs per day, with random distribution for man or woman style and normal distribution for respective sizes. The present study adopts WIP, lead time and order fulfilment rate as the performance criteria. The case-study company aims to reduce WIP and production lead time through implementing lean pull strategy, but it is important to keep their order fulfilment rate.

### E. OPTIMAL IMPROVEMENT SCENARIO DESIGN USING GREY TAGUCHI METHOD

#### 1) IDENTIFICATION OF OPTIMAL SCENARIO FOR $VSM_1$

An L9 ($3^4$) Taguchi orthogonal array is applied to facilitate searching for optimal scenario in $VSM_1$ [8]. The experimental scenarios and simulation results are shown in Table 8.

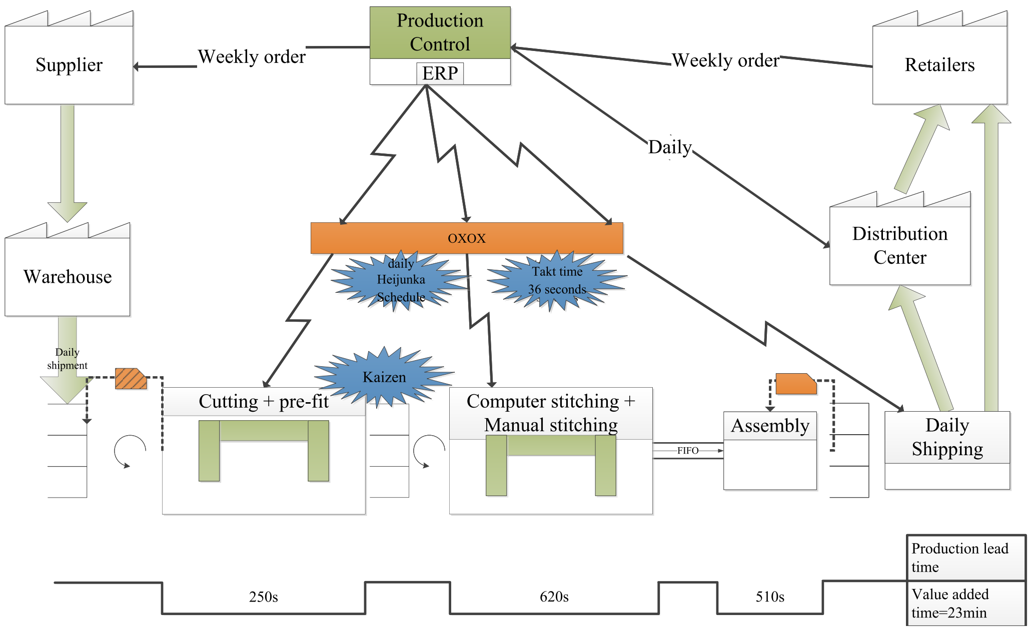



**FIGURE 5.** Future-state $VSM_2$.

**TABLE 8.** The experimental scenarios and simulation results for future-state $VSM_1$.

| Exp. No. | A | B | C | D | WIP | Lead time | Order fulfilment rate |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 800 | 100 | 1 | 190 | 11586 | 64% |
| 2 | 1 | 1600 | 200 | 2 | 277 | 12470 | 97% |
| 3 | 1 | 2400 | 400 | 4 | 424 | 22655 | 92% |
| 4 | 2 | 800 | 200 | 4 | 343 | 16025 | 97% |
| 5 | 2 | 1600 | 400 | 1 | 357 | 17706 | 92% |
| 6 | 2 | 2400 | 100 | 2 | 280 | 14225 | 81% |
| 7 | 4 | 800 | 400 | 2 | 456 | 24863 | 92% |
| 8 | 4 | 1600 | 100 | 4 | 363 | 19832 | 77% |
| 9 | 4 | 2400 | 200 | 1 | 318 | 19802 | 72% |

WIP and lead time is “smaller-the-better” type of property, the S/N for which is calculated using (1). Order fulfilment is “larger-the-better” type of property, thus, the S/N ratio is computed using (2). The results are listed in Table 9 (lead time abbreviated to LT, and order fulfilment rate abbreviated to OFR; the same applies to the tables following).

It is observed from Table 9 that, for WIP level, C has the greatest impact, followed by D and A, whereas B has the lowest significance. For lead time, the greatest influence factor is also taken by C, followed by A and D, whereas B has the lowest impact. For order fulfilment rate, the significance ranking from high to low is C, D, A, B, same with that for WIP. According to the S/N ratios in Table 9, the effect of each factor level on WIP, lead time and order fulfilment rate is shown in Figure 6. It can be seen from the figure that $A_1B_1C_1D_1$ is the best design for the future-state $VSM_1$ to minimize WIP, $A_1B_2C_1D_1$ is the best design for the future-state map to minimize lead time and $A_2B_2C_3D_2$ is the best design for the future-state map to maximize order fulfilment rate.

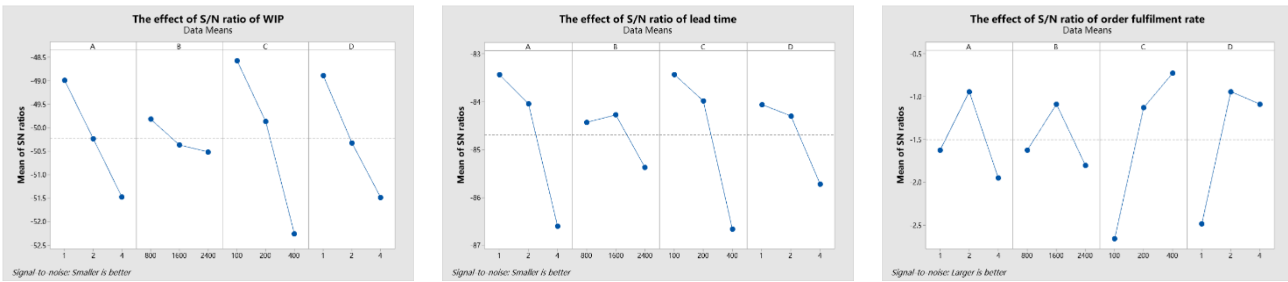
As different optimization goals (minimizing WIP, minimizing lead time and maximizing order fulfilment rate) have different optimal settings, GRA is applied to determine a single optimal combination of the parameters with respect to all responses. S/N ratio for WIP and lead time is transformed into normalized values using (3) for “smaller-the-better” response, and S/N ratio for order fulfilment rate is normalized according to (4) for “larger-the-better” response. The GRC for all responses is calculated using (5), respectively. By assuming that equal weight is assigned to WIP, lead time, and order fulfilment rate, i.e., $\omega_1 = \omega_2 = \omega_3 = 1/3$, GRG is computed using (6). The impact of attribute weight allocation is discussed later in this section. Note that experiments with order fulfilment rate lower than 90% are removed from the decision options, as indicated by “/” in the GRG and Rank column in Table 10, since it is agreed that customer service level should be the prerequisite of all redevelopment plans. The normalized values of S/N ratio, GRC and GRG for WIP, lead time and order fulfilment rate are listed in Table 10.

It can be observed from Table 10 that the experiment 2 has the highest GRG of 0.83. Accordingly, the optimum scenario for future-state $VSM_1$ is $A_1B_2C_2D_2$, i.e., shifting between cutting and pre-fitting units every hour; maximum 1600 shoes (800 pairs) of the finished product inventory; maximum 200 shoes (actually separated parts for 200 shoes) of the supermarket between pre-fitting and computer stitching units; level scheduling every 2 hours.

To illustrate the impacts of attribute weight settings, GRG is calculated under different weight assignment of WIP ($\omega_1$), lead time ($\omega_2$), and order fulfilment rate ($\omega_3$), and experiment

**TABLE 9. S/N ratio for WIP ($Y_{WIP}$), LT ($Y_{LT}$) and OFR ($Y_{OFR}$) in future-state $VSM_1$.**

| Level | A | | | B | | | C | | | D | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ |
| 1 | -48.99 | -83.43 | -1.62 | -49.82 | -84.43 | -1.62 | -48.57 | -83.43 | -2.66 | -48.89 | -84.06 | -2.48 |
| 2 | -50.23 | -84.04 | -0.94 | -50.37 | -84.28 | -1.09 | -49.87 | -83.98 | -1.13 | -50.32 | -84.30 | -0.94 |
| 3 | -51.48 | -86.60 | -1.95 | -50.51 | -85.37 | -1.80 | -52.26 | -86.66 | -0.72 | -51.48 | -85.72 | -1.09 |
| Delta | 2.48 | 3.16 | 1.01 | 0.69 | 1.09 | 0.72 | 3.69 | 3.23 | 1.93 | 2.59 | 1.66 | 1.55 |
| Rank | 3 | 2 | 3 | 4 | 4 | 4 | 1 | 1 | 1 | 2 | 3 | 2 |




(a) (b) (c)

**FIGURE 6. The effect of S/N ratio of WIP, lead time and order fulfilment rate in future-state $VSM_1$.**

**TABLE 10. Normalized S/N ratio, GRC and GRG for WIP, LT and OFR in future-state $VSM_1$.**

| Exp. No. | Normalized S/N ratio | | | GRC | | | GRG | Rank |
|---|---|---|---|---|---|---|---|---|
| | $Z_{WIP}$ | $Z_{LT}$ | $Z_{OFR}$ | $GRC_{WIP}$ | $GRC_{LT}$ | $GRC_{OFR}$ | | |
| 1 | 1.00 | 1.00 | 0 | 1.00 | 1.00 | 33% | / | / |
| 2 | 0.67 | 0.93 | 100% | 0.60 | 0.88 | 100% | 0.83 | 1 |
| 3 | 0.12 | 0.17 | 85% | 0.36 | 0.37 | 77% | 0.50 | 4 |
| 4 | 0.42 | 0.67 | 100% | 0.47 | 0.60 | 100% | 0.69 | 2 |
| 5 | 0.37 | 0.54 | 85% | 0.44 | 0.52 | 77% | 0.58 | 3 |
| 6 | 0.66 | 0.80 | 52% | 0.60 | 0.72 | 51% | / | / |
| 7 | 0.00 | 0.00 | 85% | 0.33 | 0.33 | 77% | 0.48 | 5 |
| 8 | 0.35 | 0.38 | 39% | 0.43 | 0.45 | 45% | / | / |
| 9 | 0.52 | 0.38 | 24% | 0.51 | 0.45 | 40% | / | / |

**TABLE 11. Sensitivity analysis for different attribute weights of WIP ($\omega_1$), lead time ($\omega_2$), and order fulfilment rate ($\omega_3$).**

| $\omega_j$ | | | Experiment with the highest GRG |
|---|---|---|---|
| $\omega_1$ | $\omega_2$ | $\omega_3$ | |
| *1/3 | *1/3 | *1/3 | 2nd |
| 1/2 | 1/3 | 1/6 | 1st |
| 1/2 | 1/4 | 1/4 | 1st |
| 1/2 | 1/6 | 1/3 | 2nd |
| 1/6 | 1/2 | 1/3 | 2nd |
| 1/4 | 1/2 | 1/4 | 2nd |
| 1/3 | 1/2 | 1/6 | 1st |
| 1/6 | 1/3 | 1/2 | 2nd |
| 1/4 | 1/4 | 1/2 | 2nd |
| 1/3 | 1/6 | 1/2 | 2nd |

*original weights.

with the highest GRG is identified, respectively. The results are summarized in Table 11: the first line represents the equal weight of $\omega_1$, $\omega_2$, and $\omega_3$; line 2-4 suggest WIP is given the highest weight, ($\omega_1$ : $\omega_2$: $\omega_3$) = (3: 2: 1), (3: 1.5: 1.5), and (3: 1: 2), respectively; line 5-7 suggests lead time is given the highest weight, ($\omega_1$ : $\omega_2$: $\omega_3$) = (1: 3: 2), (1.5: 3: 1.5), and (2: 3: 1), respectively; line 8-10 suggests order fulfillment rate is given the highest weight, ($\omega_1$ : $\omega_2$: $\omega_3$) = (1: 2: 3), (1.5: 1.5: 3), and (2: 1: 3), respectively.

**TABLE 12. The experimental scenarios and simulation results for future-state $VSM_2$.**

| Exp. No. | A | B | C | WIP | Lead time | Order fulfilment rate |
|---|---|---|---|---|---|---|
| 1 | 800 | 100 | 1 | 40 | 1740 | 74% |
| 2 | 800 | 200 | 2 | 149 | 5835 | 100% |
| 3 | 800 | 400 | 4 | 332 | 15430 | 100% |
| 4 | 1600 | 100 | 2 | 71 | 2658 | 98% |
| 5 | 1600 | 200 | 4 | 203 | 8543 | 100% |
| 6 | 1600 | 400 | 1 | 197 | 6816 | 100% |
| 7 | 2400 | 100 | 4 | 131 | 5100 | 100% |
| 8 | 2400 | 200 | 1 | 79 | 2725 | 86% |
| 9 | 2400 | 400 | 2 | 292 | 12758 | 100% |

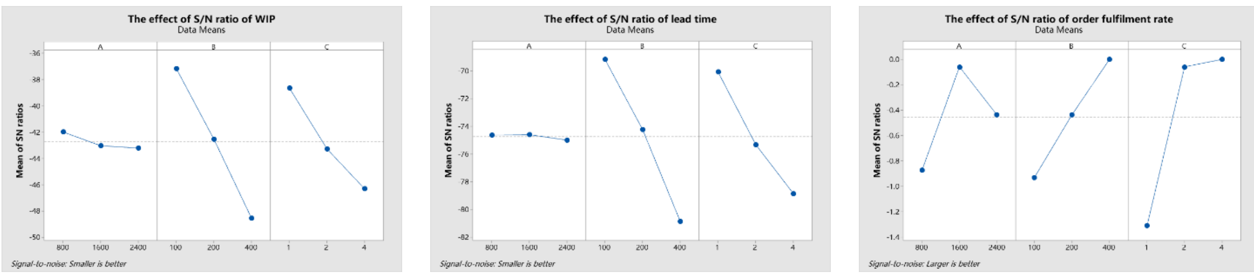
According to Table 11, experiment 1 is identified as the optimal scenario for future-state $VSM_1$ in the (1/2, 1/3, 1/6), (1/2, 1/4, 1/4) and (1/3, 1/2, 1/6) settings of ($\omega_1$, $\omega_2$, $\omega_3$),

**TABLE 13.** S/N ratio for WIP ($Y_{WIP}$), LT ($Y_{LT}$) and OFR ($Y_{OFR}$) in future-state $VSM_2$.

| Level | A | | | B | | | C | | |
|---|---|---|---|---|---|---|---|---|---|
| | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ | $Y_{WIP}$ | $Y_{LT}$ | $Y_{OFR}$ |
| 1 | -41.98 | -74.63 | -0.87 | -37.14 | -69.15 | -0.93 | -38.63 | -70.06 | -1.31 |
| 2 | -43.02 | -74.6 | -0.06 | -42.52 | -74.22 | -0.44 | -43.27 | -75.31 | -0.06 |
| 3 | -43.2 | -74.99 | -0.44 | -48.54 | -80.85 | 0.00 | -46.31 | -78.85 | 0.00 |
| Delta | 1.23 | 0.39 | 0.81 | 11.4 | 11.7 | 0.93 | 7.68 | 8.79 | 1.31 |
| Rank | 3 | 3 | 3 | 1 | 1 | 2 | 2 | 2 | 1 |

**TABLE 14.** Normalized S/N ratio, GRC and GRG for WIP, LT and OFR in future-state $VSM_2$.

| Exp. No. | Normalized S/N ratio | | | GRC | | | GRG | Rank |
|---|---|---|---|---|---|---|---|---|
| | $Z_{WIP}$ | $Z_{LT}$ | $Z_{OFR}$ | $GRC_{WIP}$ | $GRC_{LT}$ | $GRC_{OFR}$ | | |
| 1 | 1.00 | 1.00 | 0 | 1.00 | 1.00 | 33% | / | / |
| 2 | 0.63 | 0.70 | 100% | 0.57 | 0.63 | 100% | 0.73 | 3 |
| 3 | 0.00 | 0.00 | 100% | 0.33 | 0.33 | 100% | 0.56 | 7 |
| 4 | 0.89 | 0.93 | 92% | 0.82 | 0.88 | 87% | 0.86 | 1 |
| 5 | 0.44 | 0.50 | 100% | 0.47 | 0.50 | 100% | 0.66 | 5 |
| 6 | 0.46 | 0.63 | 100% | 0.48 | 0.57 | 100% | 0.69 | 4 |
| 7 | 0.69 | 0.75 | 100% | 0.62 | 0.67 | 100% | 0.76 | 2 |
| 8 | 0.87 | 0.93 | 46% | 0.79 | 0.87 | 48% | / | / |
| 9 | 0.14 | 0.20 | 100% | 0.37 | 0.38 | 100% | 0.58 | 6 |




(a) (b) (c)

**FIGURE 7.** The effect of S/N ratio of WIP, lead time and order fulfilment rate in future-state $VSM_2$.

and experiment 2 is the optimal scenario in other weight assignments. However, 1st experiment has been excluded from the decision options as it fails to meet the minimum order fulfilment rate (90%). Therefore, the optimum scenario for future-state $VSM_1$ remains 2nd experiment, i.e., $A_1B_2C_2D_2$, insensitive to the weight assignment of WIP, lead time, and order fulfilment rate.

### 2) IDENTIFICATION OF OPTIMAL SCENARIO FOR $VSM_2$

An L9 ($3^3$) Taguchi orthogonal array is designed to identify the optimal scenario [8]. The experimental scenarios and simulation results are shown in Table 12.

The S/N ratio for WIP and lead time is calculated using "smaller-the-better" function (1), and the S/N ratio for order fulfilment rate is calculated using "larger-the-better" function (6). The S/N responses are listed in Table 13.

It is observed from Table 11 that the significance ranking of controllable factors from high to low is B, C, A for both WIP and lead time property, and C, B, A for order fulfilment rate. According to the S/N ratios in Table 13, the effect of each factor level on WIP, lead time and order fulfilment rate are

**TABLE 15.** Sensitivity analysis for different attribute weights of WIP ($\omega_1$), lead time ($\omega_2$), and order fulfilment rate ($\omega_3$).

| $\omega_j$ | | | Experiment with the highest GRG |
|---|---|---|---|
| $\omega_1$ | $\omega_2$ | $\omega_3$ | |
| *1/3 | *1/3 | *1/3 | 4th |
| 1/2 | 1/3 | 1/6 | 1st |
| 1/2 | 1/4 | 1/4 | 4th |
| 1/2 | 1/6 | 1/3 | 4th |
| 1/6 | 1/2 | 1/3 | 4th |
| 1/4 | 1/2 | 1/4 | 4th |
| 1/3 | 1/2 | 1/6 | 1st |
| 1/6 | 1/3 | 1/2 | 4th |
| 1/4 | 1/4 | 1/2 | 4th |
| 1/3 | 1/6 | 1/2 | 4th |

*original weights.

shown in Figure 7. It can be seen from the figure that $A_1B_1C_1$ is the best design for the future-state map to minimize WIP, $A_2B_1C_1$ is the best design for the future-state $VSM_2$ to minimize lead time and $A_2B_2C_3$ is the best design for the future-state map to maximize order fulfilment rate.

In order to determine the optimal scenario with respect to all response, S/N ratio for WIP and lead time is

**TABLE 16. Comparing results between current-state VSM and future-state VSM.**

| Comparing items | Current state | Future state (Experiment 4) | Improvement ratio | Future state (Experiment 7) | Improvement ratio |
|---|---|---|---|---|---|
| WIP (shoe) | 3600 | 71 | 98.03% | 197 | 94.53% |
| Lead time | 4.5 days | 2648s | 99.32% | 6816s | 98.25% |
| Order fulfilment rate | 94%* | 98% | 4.26% | 100% | 6.38% |

*drawing from the MES database in EA.

transformed into normalized values using (3) for "smaller-the-better" response, and S/N ratio for order fulfilment rate is normalized according to (4) for "larger-the-better" response. The GRC for all responses is calculated using (5), respectively. By assuming that equal weight is assigned to WIP, lead time, and order fulfilment rate, i.e., $\omega_1 = \omega_2 = \omega_3 = 1/3$, GRG is computed using (6). The impact of attribute weight allocation is discussed later in this section. The results are shown in Table 14. Also, experiments with order fulfilment rate lower than 90% are removed from the decision options, as indicated by "/" in the GRG and Rank column in the table.

It is observed from Table 14 that the experiment 4 has the highest GRG of 0.86. Accordingly, the optimum scenario for future-state $VSM_2$ is $A_2B_1C_2$, i.e., maximum 1600 shoes (800 pairs) of the finished product inventory; maximum 100 shoes (actually separated parts for 100 shoes) of the supermarket between pre-fitting and computer stitching units; level scheduling every 2 hours.

To illustrate the impacts of attribute weight settings, GRG is calculated under different weight assignment of WIP ($\omega_1$), lead time ($\omega_2$), and order fulfilment rate ($\omega_3$), and experiment with the highest GRG is identified, respectively. The results are summarized in Table 15.

According to Table 15, experiment 1 is identified as the optimal scenario for future-state $VSM_2$ in the (1/2, 1/3, 1/6) and (1/3, 1/2, 1/6) settings of ($\omega_1, \omega_2, \omega_3$), and experiment 4 is the optimal scenario in other weight assignments. However, $1^{st}$ experiment has been excluded from the decision options as it fails to meet the minimum order fulfilment rate (90%). Therefore, the optimum scenario for future-state $VSM_2$ remains $4^{th}$ experiment, i.e., $A_2B_1C_2$, insensitive to the weight assignment of WIP, lead time, and order fulfilment rate.

### F. DECISION ON FUTURE-STATE VSM

According to the above analysis, the future-state $VSM_1$ has its best performance, measured by WIP, lead time and order fulfilment rate, in experiment 2, with 277 WIP level, 12470s lead time per shoe, and 97% order fulfilment rate; future-state $VSM_2$ has the ideal performance in experiment 4, with 71 WIP level, 2648s lead time per shoe, and 98% order fulfilment rate. The result indicates that the second solution is superior to the first in terms of all performance criteria, thus is determined to be the optimal improvement scheme. An additional point needs to mention is that the experiment 4 in the future-state $VSM_2$ performs a 98% order fulfilment rate, while the experiment 7 which ranks second in the overall performance has the order fulfilment rate of 100%. Therefore, if order fulfilment is strictly required, the company can adopt the property settings in the $7^{th}$ experiment of future-state $VSM_2$, with 197 WIP level, 6816s lead time per shoe, and 100% order fulfilment rate (still superior to those of any experiment of future-state $VSM_1$). The comparing results between the current-state VSM and the proposed future-state VSM are highlighted using three performance measurements and summarized in Table 16.

## V. CONCLUSION

This article proposes an enhanced VSM procedure that integrates VSM with simulation and grey Taguchi method to achieve the prioritization of lean optimization scenarios. The improved VSM overcomes the weakness of traditional VSM by visualizing the future-state plans in the simulation model and prioritizing these plans using grey Taguchi method. The implementation in a footwear manufacturing company validates the improved VSM procedure, and the identified optimal future-state production line improves performance in terms of defect rate, WIP, lead time and order fulfilment rate in compared with the current state. From the analysis, the integration of VSM with simulation and grey Taguchi method introduces the following benefits:

- incorporating simulation into VSM helps quantify WIP levels, lead times, order fulfilment rate and other parameters in different future-state scenarios;
- grey Taguchi method helps determine the optimal parameter settings in minimizing defects and provides the ranking list of multiple future-state scenarios to aid optimal future-state VSM decision;
- the decision on the optimal future-state VSM can vary according to the specific requirement of the practitioner, for instance, the lower limit of the order fulfilment rate, or different weights for different performance criteria, etc.;
- the comparison and assessment is not limited to multiple scenarios in a single future-state VSM; it can extend to prioritization and decision from multiple future-state VSMs.

Future research can extend the VSM to a supply chain view, possibly encompassing supplier and/or customer considerations. Further, the demand variation could be taken into consideration and the extended VSM with bullwhip effect in the value stream might be an interesting topic to be investigated.

## APPENDIX

See Figures 8–10.

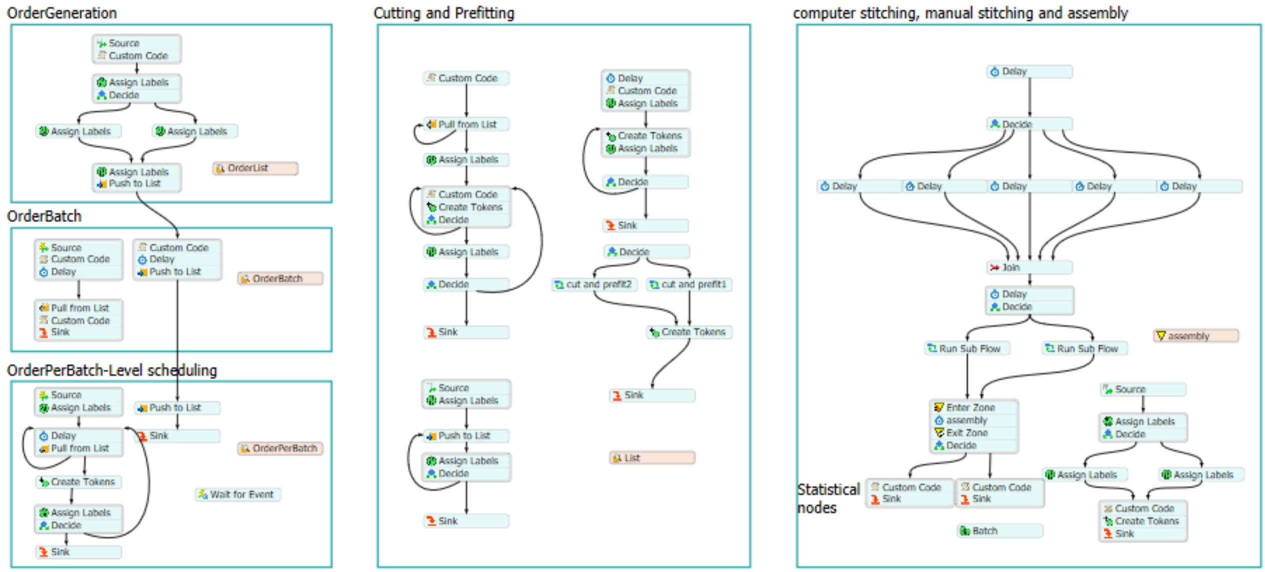



**FIGURE 8.** **Simulation model for future-state VSM: the overall process flow.**

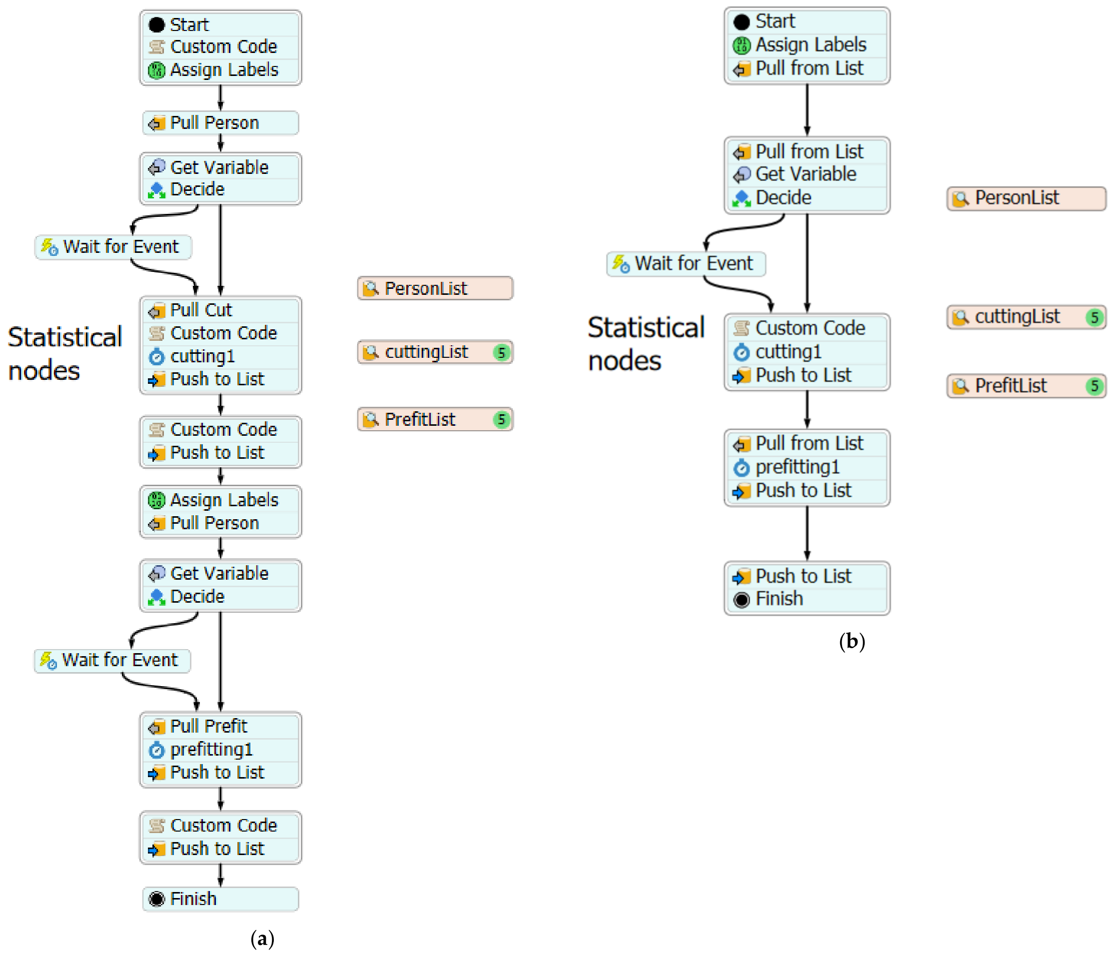



**FIGURE 9.** **Simulation model: cutting and pre-fitting processes in future-state $VSM_1$ (a) and $VSM_2$ (b).**

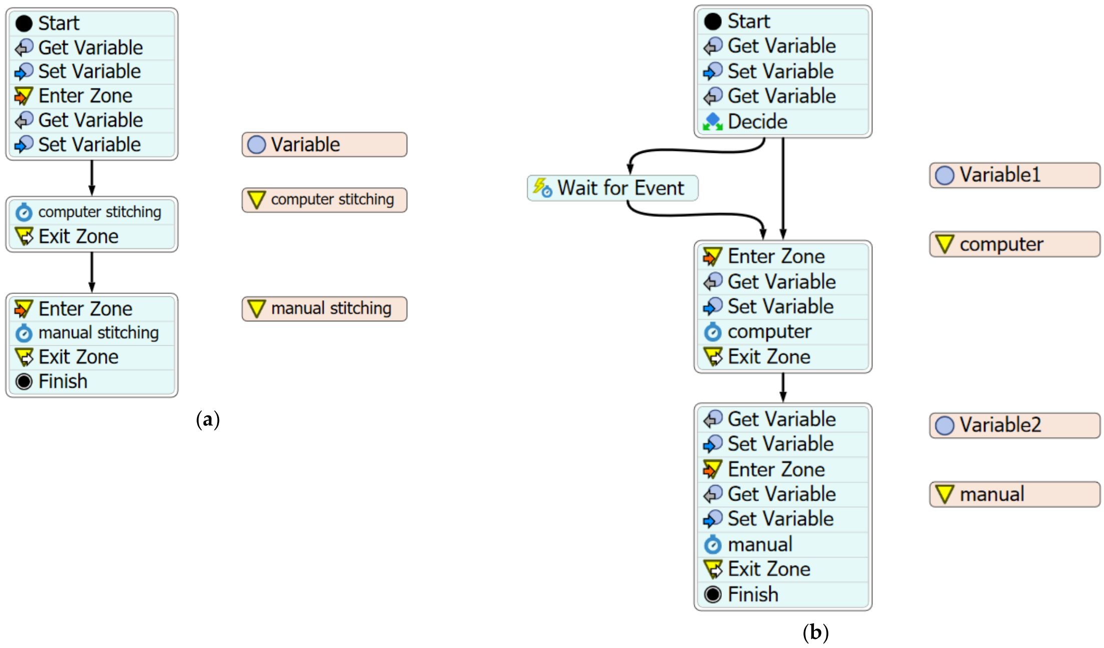



**FIGURE 10.** Simulation model: computer and manual stitching processes in future-state $VSM_1$ (a) and $VSM_2$ (b).


## ACKNOWLEDGMENT

The authors would like to thank the anonymous referees for their valuable comments.


## REFERENCES


[1] A. Susilawati, J. Tan, D. Bell, and M. Sarwar, "Fuzzy logic based method to measure degree of lean activity in manufacturing industry," *J. Manuf. Syst.*, vol. 34, pp. 1–11, Jan. 2015.

[2] Y. H. Lian and H. V. Landeghem, "An application of simulation and value stream mapping in lean manufacturing," in *Proc. 14th Eur. Simulation Symp.* Dresden, Germany: SCS Europe BVBA, 2002, pp. 1–8.

[3] J. P. Womack and D. T. Jones, *Lean Thinking: Banish Waste and Create Wealth in Your Corporation*. New York, NY, USA: Simon & Schuster. 1996.

[4] B. Das, U. Venkatadri, and P. Pandey, "Applying lean manufacturing system to improving productivity of airconditioning coil manufacturing," *Int. J. Adv. Manuf. Technol.*, vol. 71, nos. 1–4, pp. 307–323, Mar. 2014.

[5] D. Seth, N. Seth, and P. Dhariwal, "Application of value stream mapping (VSM) for lean and cycle time reduction in complex production environments: A case study," *Prod. Planning Control*, vol. 28, no. 5, pp. 398–419, Apr. 2017.

[6] S. J. Pavnaskar, J. K. Gershenson, and A. B. Jambekar, "Classification scheme for lean manufacturing tools," *Int. J. Prod. Res.*, vol. 41, no. 13, pp. 3075–3090, Jan. 2003.

[7] T. Ohno, *Toyota Production System : Beyond Large-Scale Production*. Portland, OR, USA: Productivity Press. 1998.

[8] J. C. Chen, Y. Li, and B. D. Shady, "From value stream mapping toward a lean/sigma continuous improvement process: An industrial case study," *Int. J. Prod. Res.*, vol. 48, no. 4, pp. 1069–1086, Feb. 2010.

[9] M. Rother and J. Shook, *Learning to See—Value Stream Mapping to Add Value and Eliminate Muda*. Cambridge, MA, USA: Lean Enterprise Institute. 1998.

[10] A. U. Rehman, M. Alkhatani, and U. Umer, "Multi criteria approach to measure leanness of a manufacturing organization," *IEEE Access*, vol. 6, pp. 20987–20994, 2018.

[11] D. Schmidtke, U. Heiser, and O. Hinrichsen, "A simulation-enhanced value stream mapping approach for optimisation of complex production environments," *Int. J. Prod. Res.*, vol. 52, no. 20, pp. 6146–6160, Oct. 2014.

[12] G. Noto and F. Cosenz, "Introducing a strategic perspective in lean thinking applications through system dynamics modelling: The dynamic value stream map," *Bus. Process Manage. J.*, Sep. 2020, doi: 10.1108/BPMJ-03-2020-0104.

[13] A. M. Atieh, H. Kaylani, A. Almuhtady, and O. Al-Tamimi, "A value stream mapping and simulation hybrid approach: Application to glass industry," *Int. J. Adv. Manuf. Technol.*, vol. 84, no. 5, pp. 1573–1586, Sep. 2015.

[14] S. M. Seyedhosseini, A. E. Taleghani, A. Makui, and S. M. Ghoreyshi, "Fuzzy value stream mapping in multiple production streams: A case study in a parts manufacturing company," *Int. J. Manage. Sci. Eng. Manage.*, vol. 8, no. 1, pp. 56–66, Feb. 2013.

[15] L. Parv, B. Deaky, M. D. Nasulea, and G. Oancea, "Agent-based simulation of value flow in an industrial production process," *Processes*, vol. 7, no. 2, pp. 82–96, 2019.

[16] J. Singh, H. Singh, A. Singh, and J. Singh, "Managing industrial operations by lean thinking using value stream mapping and six sigma in manufacturing unit: Case studies," *Manage. Decis.*, vol. 58, no. 6, pp. 1118–1148, May 2019.

[17] H. De Steur, J. Wesana, M. K. Dora, D. Pearce, and X. Gellynck, "Applying value stream mapping to reduce food losses and wastes in supply chains: A systematic review," *Waste Manage.*, vol. 58, pp. 359–368, Dec. 2016.

[18] R. Barathwaj, R. V. Singh, and G. I. Gunarani, "Lean construction: Value Stream Mapping for residentials construction," *Int. J. Civil Eng. Technol.*, vol. 8, no, pp. 1072–1086, 2017.

[19] N. B. Ali, K. Petersen, and K. Schneider, "FLOW-assisted value stream mapping in the early phases of large-scale software development," *J. Syst. Softw.*, vol. 111, pp. 213–227, Jan. 2016.

[20] T. P. Librelato, D. P. Lacerda, L. H. Rodrigues, and D. R. Veit, "A process improvement approach based on the value stream mapping and the theory of constraints thinking process," *Bus. Process Manage. J.*, vol. 20, no. 6, pp. 922–949, Oct. 2014.

[21] D. Behnam, A. Ayough, and S. H. Mirghaderi, "Value stream mapping approach and analytical network process to identify and prioritize production system's Mudas (case study: Natural fibre clothing manufacturing company)," *J. Textile Inst.*, vol. 109, no. 1, pp. 64–72, Jan. 2018.

[22] R. Mohanraj, M. Sakthivel, S. Vinodh, and K. E. K. Vimal, "A framework for VSM integrated with fuzzy QFD," *TQM J.*, vol. 27, no. 5, pp. 616–632, Aug. 2015.

[23] F. A. Abdulmalek and J. Rajgopal, "Analyzing the benefits of lean manufacturing and value stream mapping via simulation: A process sector case study," *Int. J. Prod. Econ.*, vol. 107, no. 1, pp. 223–236, May 2007.

[24] S. Samant, V. K. Mittal, and R. Prakash, "Resource optimisation for an automobile chassis manufacturer through value stream mapping enhanced with simulation technique and constraint programming," *Int. J. Ind. Syst. Eng.*, vol. 28, no. 3, pp. 379–401, 2018.
[25] P. F. Andrade, V. G. Pereira, and E. G. Del Conte, "Value stream mapping and lean simulation: A case study in automotive company," *Int. J. Adv. Manuf. Technol.*, vol. 85, nos. 1–4, pp. 547–555, Jul. 2016.
[26] L. Mönch, "Simulation-based benchmarking of production control schemes for complex manufacturing systems," *Control Eng. Pract.*, vol. 15, no. 11, pp. 1381–1393, Nov. 2007.
[27] J. Banks, *Handbook of Simulation*. New York, NY, USA: Wiley, 1998, pp. 605–627.
[28] E. Alzubi, A. M. Atieh, K. Abu Shgair, J. Damiani, S. Sunna, and A. Madi, "Hybrid integrations of value stream mapping, theory of constraints and simulation: Application to wooden furniture industry," *Processes*, vol. 7, no. 11, pp. 819–833, 2019.
[29] A. L. Helleno, C. A. Pimentel, R. Ferro, P. F. Santos, M. C. Oliveira, and A. T. Simon, "Integrating value stream mapping and discrete events simulation as decision making tools in operation management," *Int. J. Adv. Manuf. Technol.*, vol. 80, nos. 5–8, pp. 1059–1066, Sep. 2015.
[30] N. B. Ali, K. Petersen, and B. B. N. de França, "Evaluation of simulation-assisted value stream mapping for software product development: Two industrial cases," *Inf. Softw. Technol.*, vol. 68, pp. 45–61, Dec. 2015.
[31] T.-K. Wang, T. Yang, C.-Y. Yang, and F. T. S. Chan, "Lean principles and simulation optimization for emergency department layout design," *Ind. Manage. Data Syst.*, vol. 115, no. 4, pp. 678–699, May 2015.
[32] C.-C. Chen, C.-C. Tsao, Y. . .-C. Lin, and C.-Y. Hsu, "Optimization of the sputtering process parameters of GZO films using the Grey–Taguchi method," *Ceram. Int.*, vol. 36, no. 3, pp. 979–988, Apr. 2010.
[33] F. Mohammadi and T. Mohammadi, "Optimal conditions of porous ceramic membrane synthesis based on alkali activated blast furnace slag using taguchi method," *Ceram. Int.*, vol. 43, no. 16, pp. 14369–14379, Nov. 2017.
[34] G. Taguchi, *System of Experimental Design: Engineering Methods to Optimize Quality and Minimize Costs*. New York, NY, USA: American Supplier Institute, 1987.
[35] M. Jiang and R. Komanduri, "Application of taguchi method for optimization of finishing conditions in magnetic float polishing (MFP)," *Wear*, vol. 213, nos. 1–2, pp. 59–71, Dec. 1997.
[36] P. Sharma, A. Verma, R. K. Sidhu, and O. P. Pandey, "Process parameter selection for strontium ferrite sintered magnets using Taguchi L9 orthogonal design," *J. Mater. Process. Technol.*, vol. 168, no. 1, pp. 147–151, Sep. 2005.
[37] T. B. Kumar, A. Panda, G. Kumar Sharma, A. K. Johar, S. K. Kar, and D. Boolchandani, "Taguchi DoE and ANOVA: A systematic perspective for performance optimization of cross-coupled channel length modulation OTA," *AEU-Int. J. Electron. Commun.*, vol. 116, Mar. 2020, Art. no. 153070.
[38] K.-S. Chang, K.-T. Chen, C.-Y. Hsu, and P.-D. Hong, "Growth (AlCrNbSiTiV)N thin films on the interrupted turning and properties using DCMS and HIPIMS system," *Appl. Surf. Sci.*, vol. 440, pp. 1–7, May 2018.
[39] M. Bosch-Mauchand, A. Siadat, N. Perry, and A. Bernard, "VCS: Value chains simulator, a tool for value analysis of manufacturing enterprise processes (a value-based decision support tool)," *J. Intell. Manuf.*, vol. 23, no. 4, pp. 1389–1402, Aug. 2012.
[40] J. L. Lin and C. L. Lin, "The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics," *Int. J. Mach. Tools Manuf.*, vol. 42, no. 2, pp. 237–244, Jan. 2002.
[41] J. K. Prusty and B. Pradhan, "Multi-response optimization using taguchi-grey relational analysis for composition of fly ash-ground granulated blast furnace slag based geopolymer concrete," *Construct. Building Mater.*, vol. 241, Apr. 2020, Art. no. 118049.
[42] M. R. Galankashi, E. Fallahiarezoudar, A. Moazzami, S. A. Helmi, J. M. Rohani, and N. M. Yusof, "An efficient integrated simulation–Taguchi approach for sales rate evaluation of a petrol station," *Neural Comput. Appl.*, vol. 29, no. 4, pp. 1073–1085, Feb. 2018.
[43] G. P. Syrcos, "Die casting process optimization using Taguchi methods," *J. Mater. Process. Technol.*, vol. 135, no. 1, pp. 68–74, Apr. 2003.
[44] J. Lilly Mercy, S. Prakash, A. Krishnamoorthy, S. Ramesh, and D. A. Anand, "Multi response optimisation of mechanical properties in self-healing glass fiber reinforced plastic using grey relational analysis," *Measurement*, vol. 110, pp. 344–355, Nov. 2017.
[45] M. Y. Lin, C. C. Tsao, H. H. Huang, C. Y. Wu, and C. Y. Hsu, "Use of the grey-Taguchi method to optimise the micro-electrical discharge machining (micro-EDM) of Ti-6Al-4V alloy," *Int. J. Comput. Integr. Manuf.*, vol. 28, no. 6, pp. 569–576, Jun. 2015.
[46] Y. Kuo, T. Yang, and G.-W. Huang, "The use of a grey-based Taguchi method for optimizing multi-response simulation problems," *Eng. Optim.*, vol. 40, no. 6, pp. 517–528, Jun. 2008.
[47] O. L. C. Narong, C. K. Sia, S. K. Yee, P. Ong, A. Zainudin, N. H. M. Nor, and M. F. Hassan, "Optimisation of EMI shielding effectiveness: Mechanical and physical performance of mortar containing POFA for plaster work using taguchi grey method," *Construct. Building Mater.*, vol. 176, pp. 509–518, Jul. 2018.
[48] J. Miltenburg, "Level schedules for mixed-model JIT production lines: Characteristics of the largest instances that can be solved optimally," *Int. J. Prod. Res.*, vol. 45, no. 16, pp. 3555–3577, Aug. 2007.
[49] R. K. Roy, *Design of Experiments Using the Taguchi Approach : 16 Steps to Product and Process Improvement*. New York, NY, USA: Wiley, 2001.
[50] J. Motwani, "A business process change framework for examining lean manufacturing: A case study," *Ind. Manage. Data Syst.*, vol. 103, no. 5, pp. 339–346, Jul. 2003.

**QINGQI LIU** received the B.S. degree in logistics engineering from Dalian Maritime University, Dalian, China, in 2012, and the M.S. degree in supply chain management from The University of Manchester, Manchester, U.K., in 2013. She is currently pursuing the Ph.D. degree in logistics engineering with Dalian Maritime University. She has published research articles in journals, such as *Quality Engineering* and *International Journal of Information and Management Sciences*, and IEEE Conference on Control and Decision. Her research interests include lean manufacturing, value stream mapping, and operation management.

**HUALONG YANG** is currently a Professor with the College of Transportation Engineering, Dalian Maritime University, Dalian, China. He has published research articles in journals, such as *Operational Research*, *Quality Engineering*, *Transport*, *Journal of Traffic and Transportation Engineering*, and *Journal of Transportation Systems Engineering and Information Technology*. His research interests include supply chain management and management science.