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Improvement of Value Stream Mapping by Integrating a Monte Carlo Simulation: A Conceptual Model

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Abstract
Value stream mapping (VSM) is a well-known lean analytical tool in identifying wastes, value, value stream, and flow of materials and information. However, process variability is a waste that traditional VSM cannot define or measure since it is considered as a static tool. For that, a new model named Variable Value Stream Mapping (V-VSM) was developed in this study to integrate VSM with risk management (RM) using Monte Carlo simulation. This model is capable of generating performance statistics to define, analyze, and show the impact of variability within VSM. The platform of this integration is under Deming's Plan-Do-Check-Act (PDCA) cycle to systematically implement and conduct V-VSM model. The model has been developed and designed through literature investigation and reports that lead in defining the main four concepts named as; Continuous Improvement, Data Variability, Decision-Making, and Data Estimation. These concepts can be considered as connecting points between VSM, RM and PDCA.

Keywords
Value stream mapping, Lean manufacturing, Risk management, Monte Carlo simulation, Plan-Do-Check-Act.

Introduction

Value stream mapping (VSM) is a lean manufacturing (LM) tool that maps a process and identifies its main criticalities. Unfortunately, although there are many advantages of VSM, there are some drawbacks in using it (Schmidtke et al., 2014). One of these drawbacks is that it fails to involve process variability for both the current state map (CSM) and future state map (FSM). In other words, VSM shows only the static picture of the process at one single moment of time, instead of the true dynamic nature of the process. Hence, this makes VSM inaccurate as it does not capture the real happenings of the process (Braglia et al., 2009).

Variability can be defined as a lack of consistency or fixed pattern or liability to variation or changes. It refers to how spread out or closely clustered a set of data is (Oxford English Dictionary, 2017). It is a well-known fact that there are different types of variability in all processes. For example, there is variability in customer demand and variability in processes (Taleghani et al., 2013). The variability in this study focuses on the variability in processes. Process variability includes all time durations that a typical process deals with, such as cycle time (CT), lead time (LT), changeover time (CO), takt time (TT), and available time. It also includes variability in inventory, which impacts the variability of all the time durations of a process.

The sources of this type of variability could be from all aspects of the value stream including, but not limited to, equipment (machine failure, tool failure, etc.), processes (consumables shortage, power outages, etc.), work force (worker fatigue and stress, etc.) and material (low specifications, low quality, etc.). In addition, variability is a significant noise factor for a pull system in processes, demands, random breakdowns and random setup times (Braglia et al., 2009).

This type of variability leads to unstable work as well as being unable to deliver on time, which is contrary to the concept of LM. In addition, the constant change in customer demand causes the problem of overproduction which leads to the increase in the lev-

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els of inventories and therefore it is also contrary to the concept of LM.

Uncertainty can be defined as a lack of scientific knowledge that is assumed to be important to make a decision (Willows et al., 2003). All decisions are intended to bring about some future benefit to someone or something, and involve choices. Without uncertainty, these decisions would be straightforward. The uncertainty in manufacturing process is typified by reliability issues, LT uncertainty, CT uncertainty, breakdowns, and process and/or output yield uncertainty. Frequently, managers protect against the impact of process uncertainty by producing larger lots and through maintaining inventories from which their contractual obligations were met which was clearly not lean thinking (Kamrad & Ord, 2006).

Another related term is risk. A risk can be defined as a type of uncertain event which itself, or its consequences, is considered negative to someone in a given context. Risk is the core of risk management (RM) science. RM is one of the areas of knowledge that is increasingly used in tandem with LM. RM is the art and science of identifying, analysing, and reporting risks throughout the life of a project and in the best interest of meeting project objectives (Schwalbe, 2012).

Waste is affected by variability, and variability is affected by uncertainty and risk. Thus, in order to minimize or eliminate current and potential wastes, variability, uncertainty and risk should be reduced or removed. Risky futuristic events call for employees to perform futuristic NVAA as potential non-value-added activities (PNVAA). This way, all risks would be identified, analysed and treated so that waste could be minimized.

This study presents a way in developing a conceptual model that defines, analyses, and presents the process variability through defining, analysing, and presenting the uncertainties and risks. For this purpose, tools and techniques such as Monte Carlo simulation, PDCA, probability distribution, risk register, sensitivity analysis, risk ranking matrix, and correlation matrix were used.

Methodology

The conceptual model is a visual or written product; one that explains, either graphically or in narrative form, the main things to be studied (the key factors, concepts, or variables) and the presumed relationships among them (Miles & Huberman, 1994). The methodology of this study is shown in Figure 1. The literature review part was shown through defining the concepts of the V-VSM model. Although developing the model was achieved and explained in this study, further future studies are needed to verify and validate the V-VSM model.
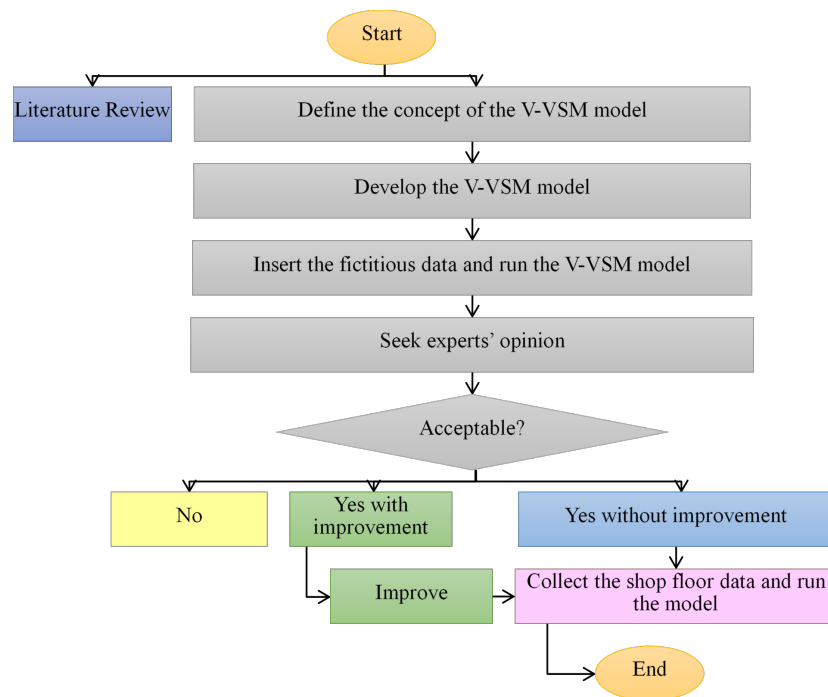

Fig. 1. The Methodology of Designing the V-VSM Model

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Defining the concepts of the model

Understanding the development of value stream and the action category for each step in the process is necessary to enable the wastes to be analyzed. Other considerations in developing the value stream include the understanding of what will flow, what is the information needed to be gathered taking into consideration the variation in time and how this variation affects both cost and inventory.

The main building blocks of V-VSM are three components; i.e. value stream mapping (VSM) as the most important tool in lean manufacturing (LM), risk management (RM) as one of the important knowledge in project management, and plan-do-check-act cycle (PDCA) as one of the methods used in businesses for the control and continuous improvement of processes and products. From the literature, the PDCA cycle has been proven to successfully integrate with each VSM Popoola, 2000; Qassim et al., 2015; Garza-Reyes et al., 2018; Milosevic et al., 2021) and RM (Borkovskaya et al., 2018; Labodová, 2004; Okada, 2004; Ren et al., 2017; Qiu, H., & Du, 2021) separately. In this study, the PDCA was used to integrate both VSM and RM and to emphasize the connecting concepts (characteristics) between them. The integration of these three components strengthens these concepts or complements each other if one component is lacking in one of the concepts, as shown in Figure 2.
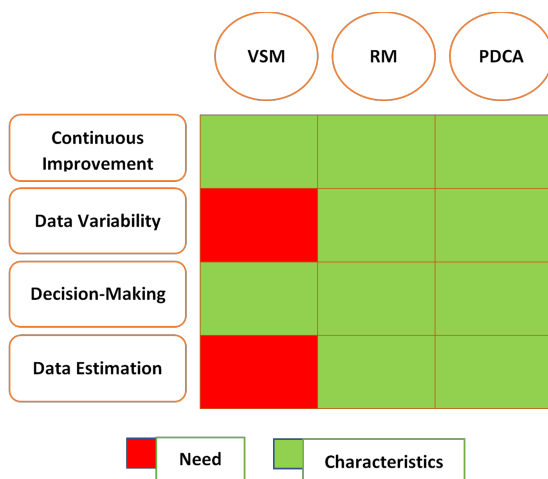

Fig. 2. VSM, RM and PDCA Connecting Points
Relationships

Figure 2 shows the three components of the V-VSM model and the four connecting concepts between these components. These concepts are considered as the characteristics of the components and are represented by the green blocks. Meanwhile, the red blocks represent the need of the components to these characteris-

tics. Thus, the integration of these three components in the V-VSM model will distribute their characteristics among each other. It means all the red blocks (need) will be replaced by the green blocks (characteristics). These concepts can be explained by the following:

Continuous improvement

The continuous improvement for perfection is the aim that drives both LM (Pampanelli et al., 2014; Souza & Alves, 2018; Björnfot et al., 2011; Garza-Reyes et al., 2018; Gill, 2012) and RM (Granerud & Rocha, 2011; Ren et al., 2017). VSM, as one of LM tools, is a process of continuous struggle to minimize waste by supporting the value and offer it at minimum costs (Granerud & Rocha, 2011). RM is a process that protects the value continuously. Continuous improvement is a fundamental element to treat uncertainties. Since both RM and LM are systematic and data driven, the Deming's PDCA cycle is a structure to conduct VSM and RM in a systematic, repeatable and continuous cycle of improvement. It is well known that the RM process cycle equates to a continuous improvement process of PDCA. Furthermore, LM adopts the continuous problem solving from PDCA. Thus, this study uses the PDCA cycle as a base to integrate both VSM and RM into one model (V-VSM) for the purpose of strengthening the continuous improvement characteristic.

Data variability

Both LM and RM support dynamic manufacturing environment and response to changes that translates its goals (zero waste and risks, flow, and pull through a response plan) into combined techniques that should be implemented throughout the entire organization (Paez et al., 2004; Rasmussen, 1997). The dynamism is represented by the data variability (time, cost, inventory, etc.) and customer order variability. Practitioners of VSM have challenged the problem of data and customer variability. As a matter of fact, data displayed by the current state map (CSM) are average values computed by taking snapshots of the process. Still, this simple approach prevents a thorough comprehension of the process and so a complementary tool; i.e. simulation is needed in order to account for the manufacturing variability (Abdulmalek & Rajgopal, 2007). Although risks are usually dynamic, their characteristics, probabilities and impacts can vary during the application of the manufacturing processes. PDCA is suitable for dynamic changes such as customer needs, which forces the continuous

improvement of processes and overall performances. Since PDCA works well with each VSM and RM, the use of it as a base to integrate both VSM and RM will bring benefit in solving the problem of the lack of identifying process data variability in VSM. This variability will be represented in process times (CT, LT, TT, etc.), inventory and cost.

Decision-making

This study emphasized the rule of decision-making for a better choice of variable future state map (V–FSM) by building multiple scenarios of V–FSM based on several data collections for a realistic variable current state map (V-CSM) which supports the decision making process for a better VSM. VSM is known to be useful in supporting decision making process because of its ability in identifying VA activities and highlighting the improved efficiency in a plant. However, the traditional VSM sticks to one plan of FSM depending on a snapshot of one CSM, thus giving no choice for the decision maker to have many alternative plans if the FSM did not work. For RM, decision makers are faced with uncertainty when more than one outcome is possible for each alternative and the probabilities of these outcomes are unknown. Without uncertainty, these decisions would be straightforward (Aven, 2016). PDCA helped the decision makers establish the best possible solution for improvement (Aven, 2016). Thus, in this study the decision making process was supported by the integrated V-VSM model through generating different scenarios of V–FSM depending on V-CSM. The number of the scenarios and the differences between them are given by the decision maker. Then, the decision maker will be given the opportunity to study the differences of these scenarios through the development of V-VSM. Furthermore, many alternatives are ready to be used if the chosen scenario does not work as planned.

Data estimation

The estimation of input data is needed when the output data of an event, process or activity is uncertain. Whenever there is futuristic uncertainty, risk, variability, and probability, there will be an estimation of data presented in a range of possibilities.

V-VSM lists all the expected risks that bring potential non-value-added activities (PNVAA) with their probabilities and impacts by estimating them. The impact of PNVAA on LT will be calculated and shown in the V-VSM drawing. For the PDCA cycle, continuous improvement means continuous change and the estimation process is needed when there is always an

ambiguity and uncertainty in knowing which one of these changes and improvements will bring benefit. Following the PDCA cycle will help solve these uncertainties. This will be through planning the change and applying it or by performing an experiment. The next step is to check the results and analyse where the changes lead to. Finally, the last step is deciding whether to keep the changes or redo the entire cycle again (Choo et al., 2007).

Developing the V-VSM model

The conceptual model in this study is a logical sequence enhanced by quantitative tools in order to create a continuous improving flow. The VSM helps to observe all the areas including value-added activities (VAA) and non-value-added activities (NVAA), as well as, helps to understand how specific processes contribute to the overall satisfaction of the customer. Furthermore, RM provides an additional analysis to all inputs; VAA, NVAA and risks to prevent, mitigate or eliminate potential wastes or PNVAA that might happen in the future. These inputs are identified using probability distributions through Monte Carlo simulation to calculate their probability and impact on the operating parameters. The flow of the model is shown in Figure 3 and, as have been mentioned previously, the PDCA cycle role is very important as a base of integration for both VSM and RM.

As shown in Figure 3, the Plan phase is the understanding and identification of the expected benefits and objectives of applying V-VSM. The goals and objectives for the selected families are represented by the expected time delivery and quantity, which are decided by the decision-maker. This will be through identifying the customer Takt time (CTT). However, the real Takt time (TT) is varied into three values depending on the variable of available time, which in this study is named as operational Takt time (OTT).

Collecting the available data from the decision-maker was achieved under the Do phase. The decision-maker is represented by the stakeholder who is anybody directly impacted by the value (such as the sponsor, manager, team, support staff, customer, user, and supplier). The data collection can be through both primary techniques using questions, interviews, and observations, and secondary technique using the data of the examples from the literatures. Adding to that, the collected data must include all the variations. This variation is to be counted from observations, expert's opinions, and stakeholders. The variability inside the processes depends on the process type itself. Therefore, if the process is manual, it will be more exposed to variability when compared it to an automated ones
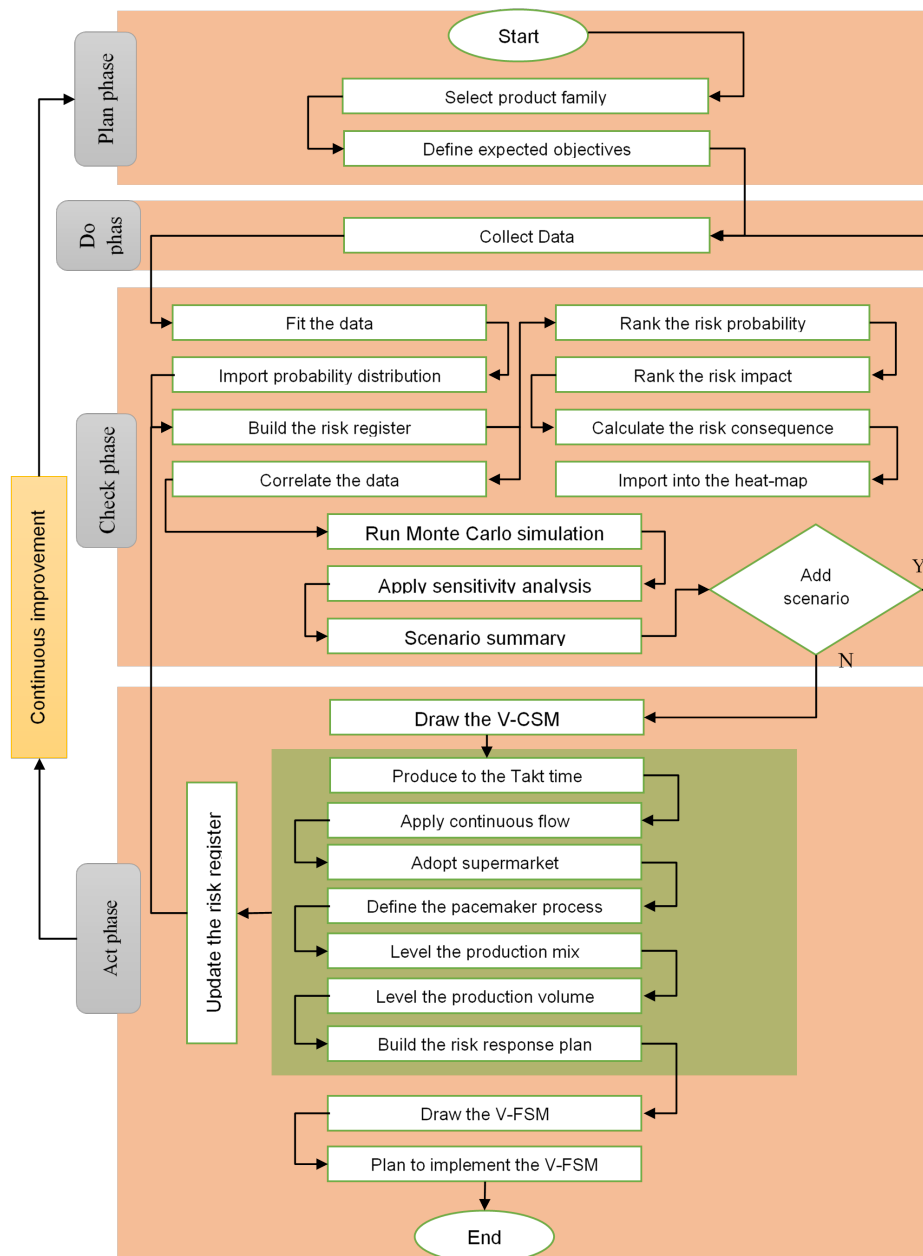
Fig. 3. Variable Value Stream Mapping (V-VSM) Model Structure

(Groover, 2006; Andrecioli & Lin, 2008). Thus, the variability in time will affect work in process (WIP) level, as well as, WIP time.

The Check phase is the application of assessment quantitative and qualitative techniques along with collecting additional appropriate data represented by risks for each process or step along the production processes. The Check phase is the summarization, analyzation and review of a scenario of data through Monte Carlo simulation. Subsequently, the V-CSM will be drawn through this phase.

Fitting the data is needed to specify the variability limits by using Probability Distribution. To do so, it is important to know what type of distribution will best fit the data. The probability distribution is a tool to perform calculations that deal with variability and the results of these calculations are used as a base for business decisions. Thus, applying inappropriate tools will bring wrong results and bad impacts.

The best-fit probability distributions were imported to all the input data. The reasons for identifying the input data with probability distribution are: 1 – The

input data in the model consists of two types of data, first is the variability of observed data, and second is uncertain data. Both types are represented in the probability distribution to define their range of data. 2 – To acknowledge whether the data patterns are accurate enough to fit well in a probability distribution. 3 – Brings further analysis between correlated inputs, and helps to see how the variability range of one variable can effect in incrementing and/or decreasing the variability of other variables. 4 – The probability destitution during the simulation helps to sample the most convening input value considering sampling constrains such as the best fit of the probability distribution, the variance around the mean (standard deviation), the correlated data, and the added time as the impact of the risk data. It means the process of selecting a sample during the simulation is not a random selection. 5 – Different analysis techniques that used in V-VSM model such as Monte Carlo simulation, sensitivity analysis, scenario generating, data correlation, and risk analysis cannot be performed without the identification of probability distribution.

The risk register was used to record all the probabilities, impacts and consequences of risks with their calculations (Mace et al., 2015). Probability refers to how often an event occurs, and is measured in terms of number of events per time units given in percentage. It is described by a discrete distribution. Impact depends on the consequences of the event occurrence, and is described by a continuous distribution (Normal distribution, Gamma distribution, Exponential distribution, beta distribution, etc.). Risk registers are relatively simple tool for capturing risk related data like the type of risk, probability, impact and other information (O'Har et al., 2017).

For correlating the data, Spearman's rank correlation coefficient can be used to identify the relationships between inputs (VAA, NVAA, and risks). This will enhance the sampling process during the run of Monte Carlo simulation to avoid nonsensical results.

The risks probabilities and impacts are anticipated using the risk register. This step evaluates these risks using an established semi-qualitative, quantitative uncertainty analysis called "Risk Probability-Impact Ranking Matrix technique" by ranking and assessing the degree of seriousness of the identified risks (Nicholas, 2018).

All input data will be simulated using Monte Carlo simulation technique. The simulation will run with a certain number of iteration using @Risk software. A higher number of iterations will bring better results because it will consider all the possible outcomes, which make it accurate and real.

After the simulation ends, all the identified inputs

and outputs were shown in a variability way as three values (min, mean or most likely, and max). The outputs need to be identified in order to be collected from simulation result, which, in this study, consists the following:

- The total cycle time (CT): represents the summation of the possible outcomes of the processes' cycle times (VAA).
- The total lead time (LT): represents the summation of the possible outcomes of the VAA and NVAA.
- Impact on time: represents the additional time added as the risk's impact.
- Impact on cost: represents the additional costs added to the plan as the risk's impact.

The simulation was followed by a sensitivity analysis, which was presented as a tornado graph. In this study, the sensitivity analysis tornado graph was displayed using Spearman rank correlation coefficient. It shows a clear image of the most significant sampled input variables that affect the outputs. That means any change in those inputs could directly affect the decrease and increase of that output.

In order to give the decision-maker the permittivity in building the appropriate V-VSM with preferable criteria, this step presents all the scenarios suggested by the decision-maker. Each scenario concentrates on the variability of total CT, total LT, added delay value, and added cost value.

Finally, the Act phase will be through communicating the results with the decision maker. If the results are appropriate, then the V-CSM will be optimized through building the V–FSM for the dynamic manufacturing environment where these phases will be continuously repeated to get continuous improved results.

After inserting the collected input data into the model and processing them, the expected outputs for each phase are shown in Figure 4. The first phase will produce one table having all the wanted data including their variability. Each variable will have three values representing the min, most likely, and max value. The Do phase outputs will include building the risk register and correlate all the input variables including all the ranked risks to know what the most effected risk that needs to be focused on in order for it to be minimized or eliminated. In the third phase, the check phase will show the different scenarios of the Monte Carlo simulation results, followed by drawing the V-CSM by considering the selected scenarios from the simulations. Finally, the V-CSM is used to draw the V–FSM and then initiate a plan to implement the V–FSM.
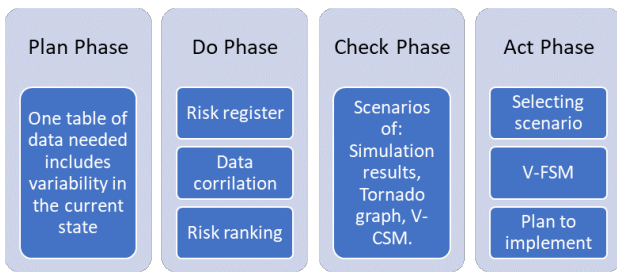
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Plan Phase	Do Phase	Check Phase	Act Phase
One table of data needed includes variability in the current state	Risk register / Data corrilation / Risk ranking	Scenarios of: Simulation results, Tornado graph, V-CSM.	Selecting scenario / V-FSM / Plan to implement

Fig. 4. Expected Outcomes from Each Phase
of V-VSM Model

Results and discussion

In order to test the developed model, the Acme Stamping Bracket value stream mapping example from the book "Learning to See" (Rother & Shook, 2003) was considered as a partial validation in this paper. To specify the variability limits, a probability distribution needs to be imported for each VA, NVA, and PNVA. To do so, it is important to know what type of distribution will best fit the data. Since the variables in this case are all about time and costs which are continuous variables, symmetrical, positive, have upper and lower limits, and relative to the middle values, thus making the Pert distribution the best fit distribution as shown in Figure 5.

The Monte Carlo simulation ran with 100 iterations using @Risk software. The input variables for each iteration were sampled according to the current needs and identified limitations. Thus, the simulation findings were not defined by certain values, but rather they can be regarded as possible outcomes across their minimum-maximum range. At the end of the simulation, all the identified inputs and outputs were shown

in a variability way by three values (min, mean or most likely, and max). Figure 6 shows the simulation results of the outputs, including cycle time, lead time, and both added time and cost as an impact of the risks.

The simulation process was followed by a sensitivity analysis, which was presented as a tornado graph. The sensitivity analysis showed the most significant sampled input variable affecting the outputs. The results were displayed as a graph consisting of bars with different lengths. The longest bar represented the largest effective range input variable and vice versa. Figure 7 shows the tornado graph for all the outputs while the V-CSM with all the variabilities in the input values is shown in Figure 8.

Producing the Takt time (TT) is the first step towards drawing the future state map (FSM). The expected time delivery and quantity are decided by the decision-maker. The decision-maker could give one value of delivery date, which helps in calculating the TT in one value known as customer TT (CTT). However, the real TT and the operating TT (OTT) could vary by the three values of minimum limit, mean, and the maximum limit depending on the varied available time. Formula (1) was used to calculate the OTT by having a fixed value for customer demand, and the available time as the variable value.

$$OTT(\min, \text{mean}, \max)$$
$$= \frac{\text{total daily operating time}(\min, \text{mean}, \max)}{\text{total production demand}} \quad (1)$$

This created three values of TT from the chosen example. The usage of these three values of OTT served the expected CTT in drawing the V–FSM, making the CTT the target. The total daily operating time per shift was (25800, 27600, and 29400) seconds as the
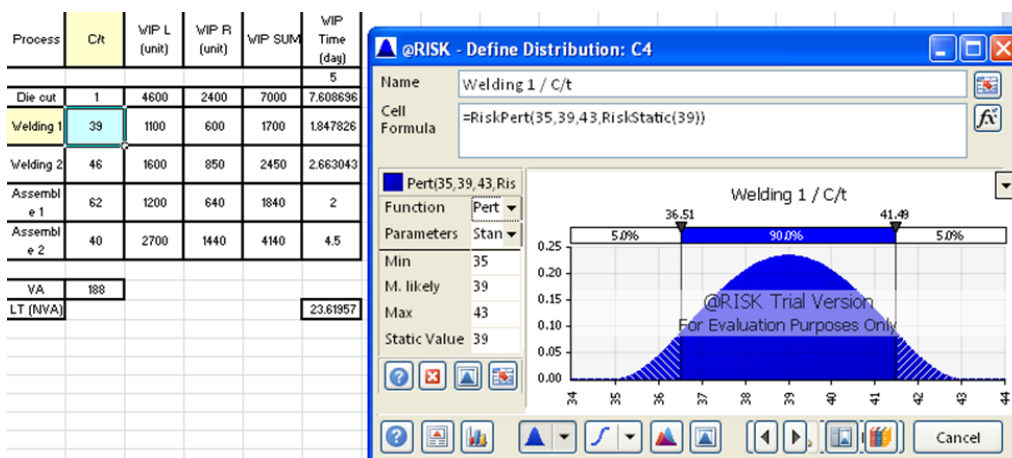

Fig. 5. Importing Probability Distribution into V-CSM

@RISK Scenario 1: Output Results

Name	Worksheet	Cell	Graph	Min	Mean	Max
VA / C/t (Sec)	Sheet2	C9		179.7921	188.0005	196.9282
LT (NVA) / WIP Time (day)	Sheet2	G10		22.92316	23.62004	24.33227
Added time (hr)	risk	L12		0	3.342587	11.48623
Added cost (hr)	risk	R12		0	436.1854	1179.691

Fig. 6. Simulation outputs

Fig. 7. Tornado graph for all outputs

(minimum, mean, and maximum) values respectively, or shown as (7.5, 8, 8.5) hours respectively, per shift. By dividing the range of the total daily operating time by the daily customer production demand which was 460 units, the OTT was calculated to be (56, 60, and 64) seconds. The CTT was 60 seconds, which made it a target to be achieved using the OTT. In order to produce one product according to CTT, the minimum and the mean value of OTT were used neglecting the maximum value as it exceeded the CTT. Thus, the company needed to minimize the range of CT into equal or as close to the minimum and the mean values of OTT to reach CTT as shown in Figure 9. To achieve the target of CTT, the focus was on the min-

imum and mean values of OTT. The maximum value was neglected since it was larger than the target.

From Figure 9, it shows that the minimum range of OTT is equal to 56 seconds, making the range of assembly 1 process exceeding the CTT. Thus, the CT of assembly 1 process needs to be reduced to be equal or less than 56 seconds to be able to produce the minimum limit of OTT.

The next step was to adjust the number of the operator for the cell by adding the minimum CT of all the combined processes and dividing it by the minimum OTT (179.7/56) which was equal to (3.2) operators. However, dividing the mean values of both CT and OTT was equal to (3.1) operators. Thus, the number
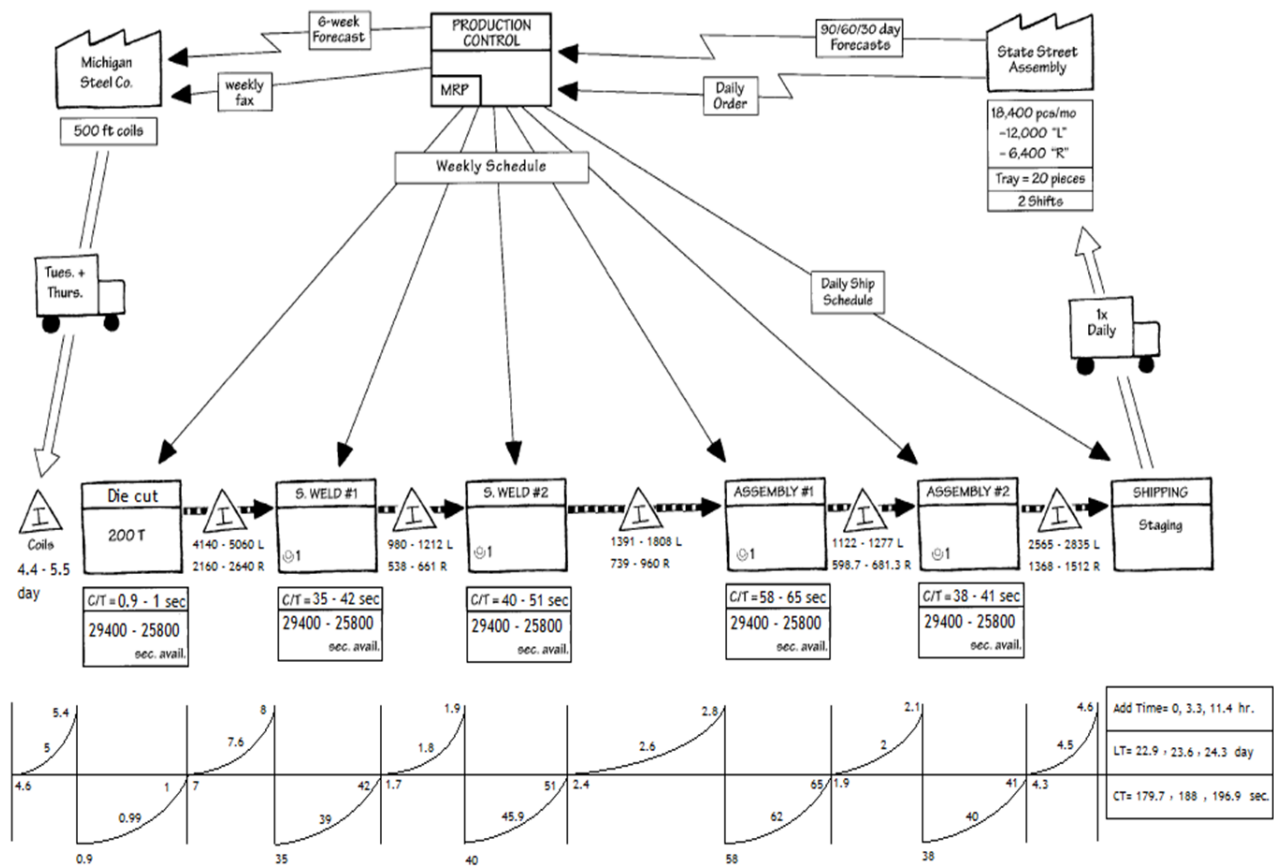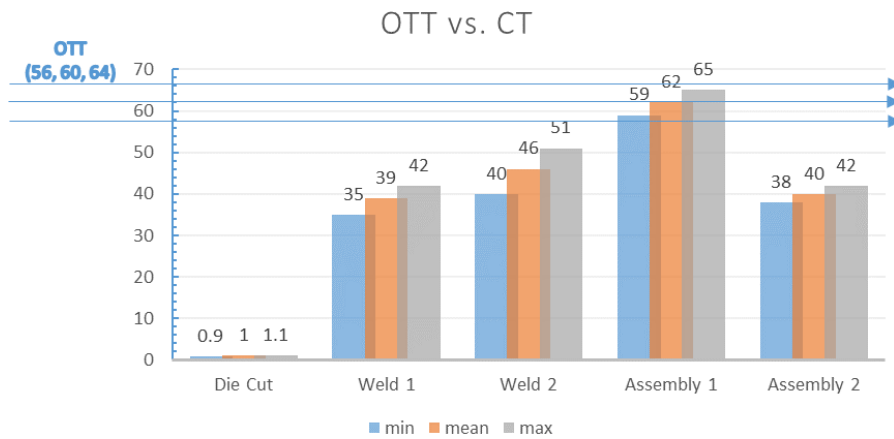
Fig. 8. The Variable Current State Map (V-CSM)

Fig. 9. Operating Takt Time (OTT) Against Process Cycle Time

of workers required was 3 in numbers. If this was not the case, then another scenario would be built.

Since the goal here was to minimize the CT and LT, there were 4 working operators. One for Die cut process and three for the combined cell. By using the minimum OTT of (56) seconds, the working time of each worker should be less than 56 seconds. On the other hand, each worker was spending 56 seconds as a minimum time (169/3). Thus, the work time for each worker was to be reduced to (50 seconds) or less, so that the total CT of the cell would become 150 seconds as shown in Figure 10.

Figure 10 shows the flow of processes using the minimum CTs with the minimum OTT of (56) seconds.

Fig. 10. CT for Continuous Flow Cells Using the Minimum Limits Comparison to Minimum OTT

This scenario could be considered as the first scenario of V–FSM.

Figure 11 shows the mean OTT of (60) seconds with the mean CT of the process. The work time of each worker should be equal or less than 56 seconds to guaranty producing within the CTT of (60) seconds. This scenario could be considered as the second scenario of V–FSM.

The third scenario of V–FSM is shown in Figure 12. It depends on the minimum limits of CT for each worker's work time of (50) seconds. These times were compared to the mean value of OTT of (60) seconds. Thus the workers have more space between CT and OTT to guaranty producing the CTT.

After setting all the previous steps, drawing the V–FSM was done in three scenarios considering the three arrangements when applying the continuous flow step. The three scenarios used minimum and mean values of CT and OTT. The maximum values were neglected since it exceeded the CTT.

The first scenario in Figure 13 used the minimum CT of both the die cut process (0.9) second and the combine cell (50) seconds, and they were compared to the minimum OTT of (56) seconds. The minimum OTT was set as the maximum limit for the cell CT. However, this did not mean the workers had all the freedom to work within that range, but rather carrying on with the work with the specified CT as much as they can despite the maximum limit. This would guarantee producing the OTT to reach the goal of CTT. In the first scenario, reaching the maximum limit of OTT was still within the CTT unless there were no
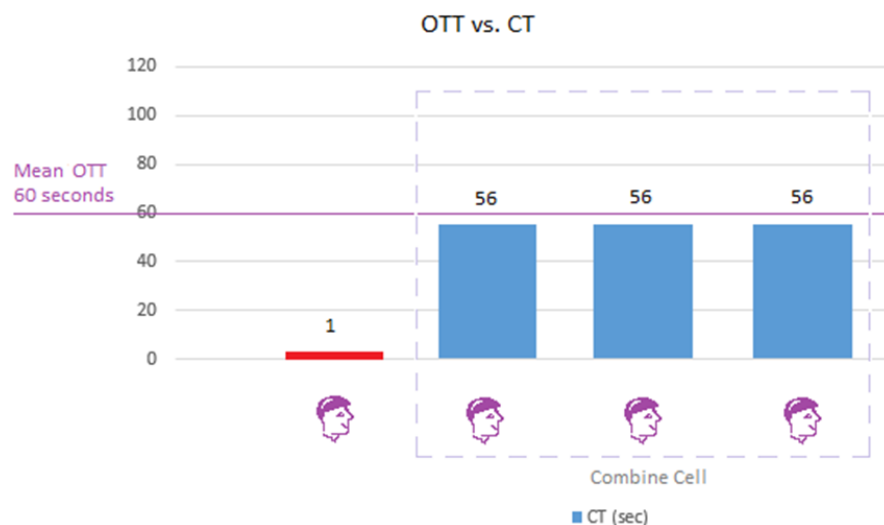

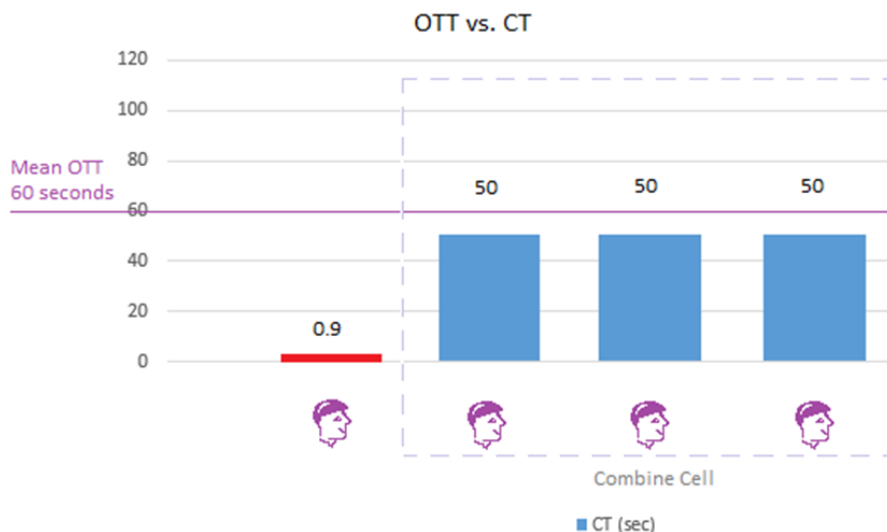Fig. 11. CT for Continuous Flow Cells Using the Mean Limits Comparison to Mean OTT

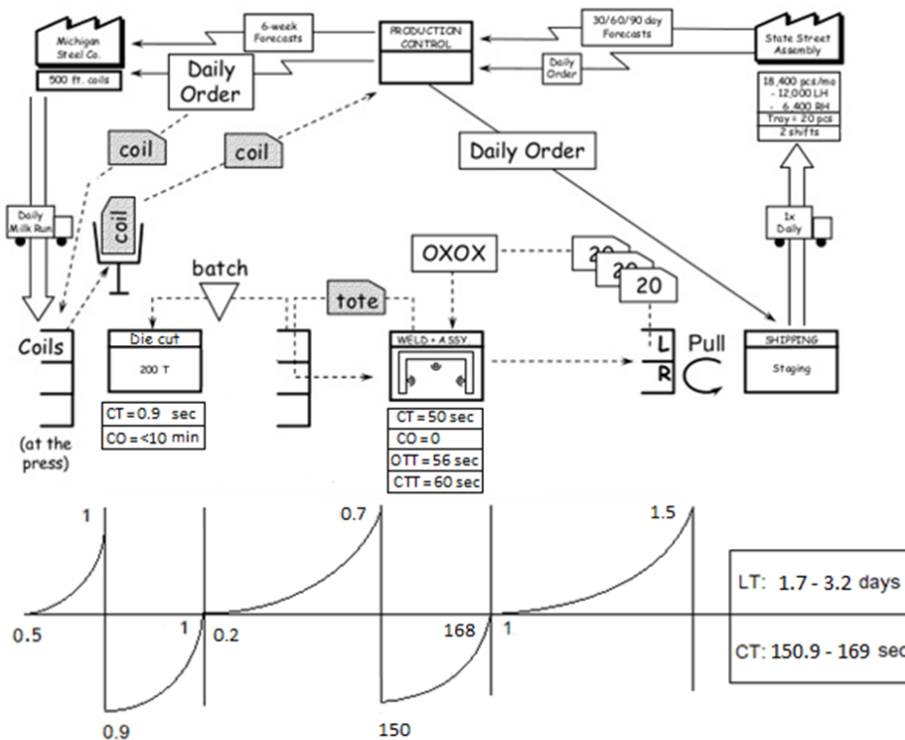Fig. 12. CT for Continuous Flow Cells Using the Minimum Limits Comparison to Mean OTT

Fig. 13. The Variable Future State Map (V–FSM) Scenario 1

risks involved. Any risk occurring during the production needs time to solve it. Thus, the benefits of these ranges between the CT and OTT will save the problem of delaying. Identifying these ranges of variability and the probabilities of risks, impacts, and solutions reduce the time needed in each supermarket, subsequently reducing the total LT as shown in the figures of F-VSM's scenarios.

Since the FSM is a futuristic, predictive map, the supermarkets' times were given as a range of numbers. This brought about the flexibility in applying the V–FSM especially in the first stages of application. The supermarkets' times were all the same in the three scenarios of V–FSM since they were defined in a range. This gave a wider space in the application stage.

The second scenario used the minimum CT of both the die cut process (0.9) second and the combine cell (50) seconds, and were compared to the mean OTT (60) seconds as shown in Figure 14. The mean OTT was set as the maximum limit for the cell CT which made the range between them higher than the first scenario of V–FSM. This gave extra space to solve undefined risks that could occur, and for that, the supermarkets' times could be used as the minimum limit.

The third scenario used the mean CT of both the die cut process (1 second) and the combine cell (56 seconds), and they were compared to the mean OTT (60 seconds) as shown in Figure 15. The total CT in this scenario was considered to be the highest value since it depended on the mean values of the CTs. The mean OTT was set as the maximum limit for the cell CT which made the range between them to be the least compared to the other scenarios of V–FSM.

The outputs of the V–FSM using the developed model was compared to the traditional future state map (T–FSM) of the Acme example are shown in the Table 1.

Table 1 shows the difference between the T–FSM and the developed model V–FSM. Three scenarios of the V–FSM were built according to the variabil-

Table 1
V–FSM Scenarios Outputs Compared to the T–FSM of Acme Example

Model	CT (sec)	LT (day)	Added Time	Added Cost
T–FSM	169	4.5	–	–
V–FSM – Scenario 1	150.9–169	1.7–3.2	0	0
V–FSM – Scenario 2	150.9–181.1	1.7–3.2	0	0
V–FSM – Scenario 3	169–181.1	1.7–3.2	0	0

ity in the V-CSM. Since the FSM is a predictable plan to follow, it is important to show flexibility in the application of it. By this, the map can reflect the dynamic environment of the manufacturing system. Comparing the two models of T–FSM and V–FSM, the latter can show the ranges of values that can fit the varied manufacturing environment. The CT in the T–FSM gave 169 seconds, and the LT was equal to 4.5 days. Meanwhile, the V–FSM was performed in three different scenarios in terms of both the CT and LT.
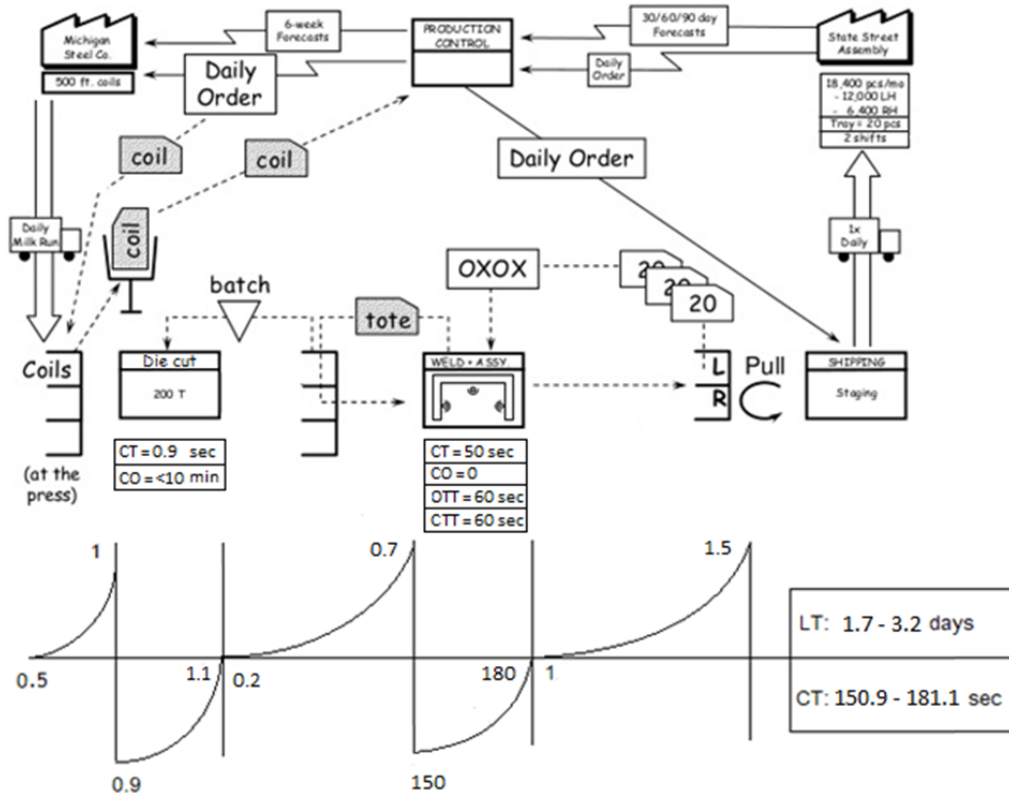

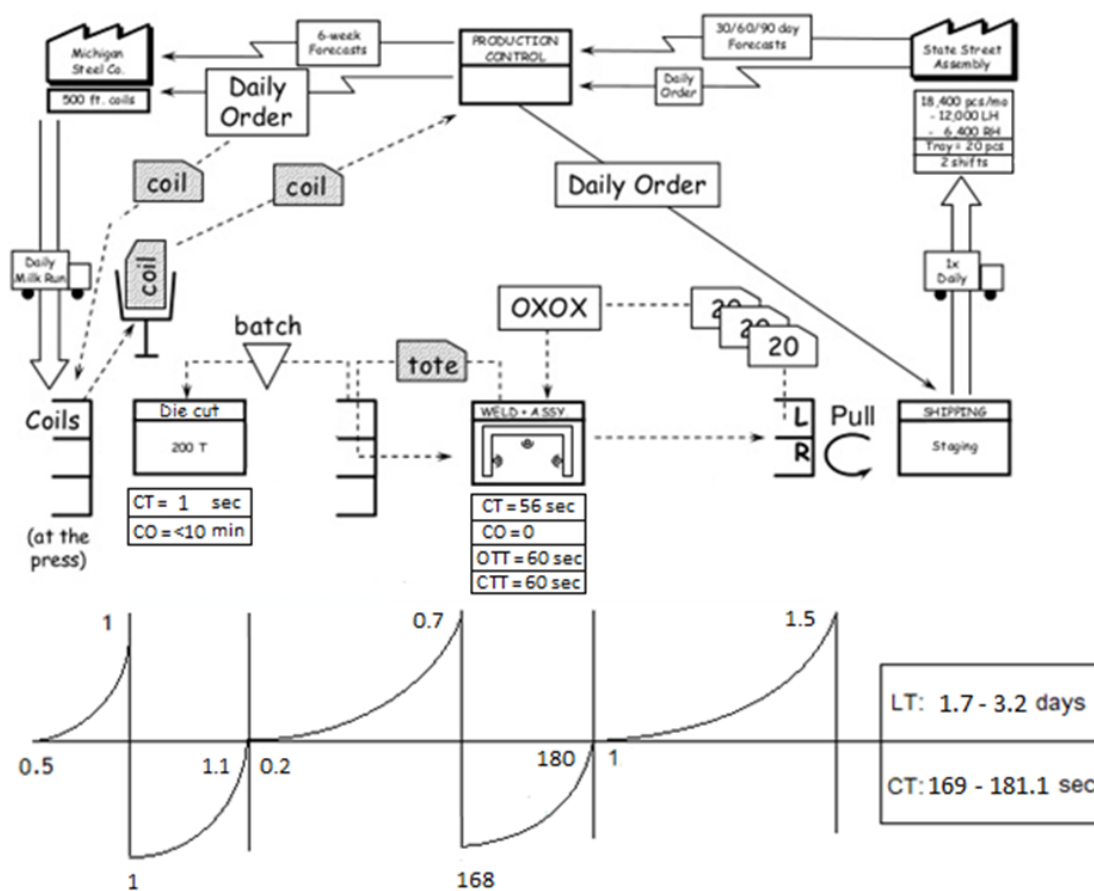Fig. 14. The Variable Future State Map (V–FSM) Scenario 2

Fig. 15. The Variable Future State Map (V–FSM) Scenario 3

As shown in Table 1, the added time and cost gave zero points to the added time and cost, as it was assumed that all the identified risks were eliminated and controlled. The LT was also reduced in all scenarios because of the previous identifying, analyzing, and solving of all the risks. Adding to that, the time between the CT and TT can be used for fixing any undefined risk.

Conclusions

The VSM displays a picture of the manufacturing system in a specific day. However, manufacturing environment tends to vary depending on the state in which the factory is in. If the variation in production process is neglected during the preparation of current state map, the future state map will be inaccurate. It can affect the operating parameters such as machine cycle times as well as the measurement of the performance such as Takt time (TT) of the manufacturing system. Thus, this paper has provided the phases and steps in developing a model that can be used to present the current and future state of a dynamic manufacturing environment through the integration of VSM, Risk Management (RM), and Plan-Do-Check-Act (PDCA) cycle. The model can specify the ranges of variability in the production processes as well as the potential risks by generating scenarios of current state map using Monte Carlo simulation. The results of applying the model shows the difference between the traditional VSM where it gave 4.5 days for the lead time (LT) and the developed V-VSM model where the LT shows in a range of (1.7–3.2) days in three different scenarios of the future state map (FSM). By this, the V-VSM can reflect the dynamic environment of the manufacturing system.

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