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Novel Approach to Enhance the Performance of Production Systems Using Lean Tools

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Abstract

Value Stream Mapping (VSM) is a tool used for analyzing the current state of a production system and designing a future state by analyzing and improving the flow of material and reducing inefficiencies. However, aiming at improving performance without considering potential machine failures and other uncertainties in the production process may lead to an inaccurate future value stream map.

The purpose of the present study is to introduce a novel approach that combines discrete event simulation, Design Of Experiments (DOE), and Failure Modes and Effects Analysis (FMEA) to enhance the VSM processes. Simulation modeling is utilized to evaluate production system performance and the severity of potential failure modes under several operational conditions. FMEA and DOE are then used to select the best systems enhancements which can be used to generate future map. The results of our approach show that failure modes can drastically affect the system performance if not taken into consideration, resulting in a non-representative future VSM. The proper selection of operational levels can reduce the severity of failures and at the same can provide high performance levels.

Keywords: *Value Stream Mapping (VSM); simulation; Design Of Experiments (DOE); Failure Mode and Effect Analysis (FMEA); process flowchart; enhancement algorithm; glass fabrication case study.*

1. Introduction

Value stream mapping, design of experiments, and simulation are three independent lean tools that are used in industrial engineering. Failure mode and effect analysis has been used to detect potential failure modes in engineering systems. A conceptual infusion model that integrates the four tools is proposed in the present study.

Rother and Shook (1999) provided the guideline for the procedure of VSM in manufacturing. VSM is a process-oriented tool that helps visualize the processes where both materials and information are mapped (Bin et al., 2016; Rohac and Januska, 2015; Tyagi and Vadrevu, 2015). VSM includes two themes; Current State Map (CSM) and Future State Map (FSM) (Ar and Al-Ashraf, 2012). The CSM includes the current production health status and any potential non-value added activities. The non-value added might include long lead-times, processing delays, and improper handling/utilization of resources. The second theme is FSM, which might be considered as an updated version (with reduced non-value adding activities) of the current value state map. The FSM produces a more lean principle system, that will result in more balanced production line and is more focused towards “pull system” where each process only produces the quantity and quality that is required by the following process (Lu et al., 2011; Rother and Shook, 1999). It has been argued that sometimes VSM is not capable of standing alone due to its static nature; thus, for VSM to be efficient, other tools are necessary to improve the efficiency of VSM (Flores, 2015). While these tools are numerous, common examples include discrete event simulation and design of experiments (Abdulmalek and Rajgopal, 2007; Agyapong-Kodua et al., 2009; Ali et al., 2015; Gurumurthy and Kodali, 2011; Jasti and Sharma, 2014; Lu et al., 2011; McDonald et al., 2010; Rohana et al., 2013; Woehrle and Abou-shady, 2010; Xia and Sun, 2013; Xie and Peng, 2012).

Simulation is a great tool that makes it possible to visualize processes, helps in alternative selections, and optimizes operations (Alrabghi and Tiwari, 2014). It has become as a proved tool for enhancing performance in facilities and organizations. Furthermore, simulation provides a virtual environment that can mimic the actual

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environment. Thus, simulation not only complements lean concepts, but also highlights feasible options. This last point can solve the fundamental limitation of VSM (static manual nature), giving it a dynamic perspective (Abdulmalek and Rajgopal, 2007; Gurumurthy and Kodali, 2011; Khalid et al., 2014; McDonald et al., 2010, 2002; Sigari and Clark, 2013; Swallmeh et al., 2014; Xia and Sun, 2013).

Design Of Experiments (DOE), also referred to as designed experiment or experimental design, is a useful tool used to predict the interrelation between experimental factors by developing proper factorial design. Factorial design facilitates the study of the effects that several factors may simultaneously have on a process. When performing an experiment, varying the levels of the factors at the same time is both time and cost efficient, and allows for the study of interactions between the factors. DOE is performed under controlled conditions where a selected process' inputs (factors), which may have impact on the selected process' outputs (responses), are investigated. Depending on the number of factors and the size of the problem, two types of factorial designs can be used. Full factorial experiments are used when dealing with a small number of levels, as responses are measured at all combinations of the factor's levels. For larger problems, it is not feasible to do that, hence fractional factorial design is used to minimize time and cost where information about high order interactions are excluded (Montgomery, 2015).

Conventional VSM does not take into consideration potential failures of the production system explicitly; faults or failures can significantly disrupt the production. These failures are usually listed under what is known as failure modes. For example, a machine breakdown in the system can be considered a failure mode. The degradation of the quality of the produced parts, or incorrect dimensions can be considered as a failure mode or a failure mode effect depending on whether the cause is known or not. For instance, if the latter is caused by the degradation of the machine tool through usage, the degradation of the machine tool itself is the failure mode and the degradation of the quality is a failure mode effect.

While these failures are mostly potential possibilities, their impacts are important enough to affect the decision-making. Failures in the production system have received significant attention in the literature. The efforts targeted the prevention or reduction of these failures (and in some cases accommodating their occurrence) over two main levels. The higher-level is concerned with maintenance-related decision-making (such as the evolution of maintenance policies, paradigm, and maintenance-influenced production policies) (Du et al., 2014; Liu et al., 2015; Paciarotti et al., 2014).

The lower-level is concerned with process-related maintenance (such as the continuous development in sensory and fault detection and estimation techniques).

Tools were developed to assist in each of these levels and in many cases to link them together. For example, the Remaining Useful Life (RUL) is estimated from techniques developed in the lower level and represents an important asset (tool) for the decision-making in the higher level.

One of the most useful tools that join both levels is the Failure Modes and Effects Analysis (FMEA). FMEA is a step-by-step systematic tool for identifying all possible failures in a design, a manufacturing or assembly process, or a product or service (Almannai et al., 2008; Chen and Ko, 2009; Chen and Wu, 2013; Ekmekcioglu et al., 2012; Paciarotti et al., 2014; Wu et al., 2014). FMEA ranks them, and prioritize the highest impact item on the system (Paciarotti et al., 2014).

It studies one failure mode in the system at a time, as complex systems with multi-failures components are impractical to analyze especially when the a series of different effect combination exists (Paciarotti et al., 2014; Xiaoa et al., 2011). FMEA, could be applied in many different industries (Oldenhofa et al., 2011; Paciarotti et al., 2014; Xiaoa et al., 2011). Information gathered and listed in FMEA can be of qualitative (descriptive) or quantitative forms. For instance, in addition to listing all potential failure modes, a description of their potential effects, their potential causes or mechanisms, the current process controls, and the recommended actions can be incorporated in the FMEA presentation.

Literature reveals that several efforts have been made to integrate the previously mentioned tools towards achieving enhancements. Integrating simulation and DOE is found in (Avenida et al., 2007; Li et al., 2014). VSM and simulation (Ali et al., 2015; Helleno et al., 2015; Tyagi and Vadrevu, 2015), and FMEA with DOE (Fahmy et al., 2012; Senthilvelan, 2014; Shishebori et al., 2015).

The objective of the present study is to integrate VSM, DOE, FMEA along with discrete event simulation. Figure 1 clarifies the mutual added value of using these tools simultaneously. The benefit of VSM in both stages, CSM and FSM, is to visualize the processes and identify the potential areas of enhancement. DOE provides the variable input of the simulation model. Simulation helps to assess the current state map, compare the output scenarios of DOE, and provide information for FSM. FMEA will assess the severity of failures, and its impact on Key Performance Indicators (KPI). The approach, detailed in an algorithmic setup in the next section, is capable of achieving a more efficient and a less costly process improvement. It is worthwhile to mention that this approach was evaluated using a real case study in a leading glass-fabrication facility.

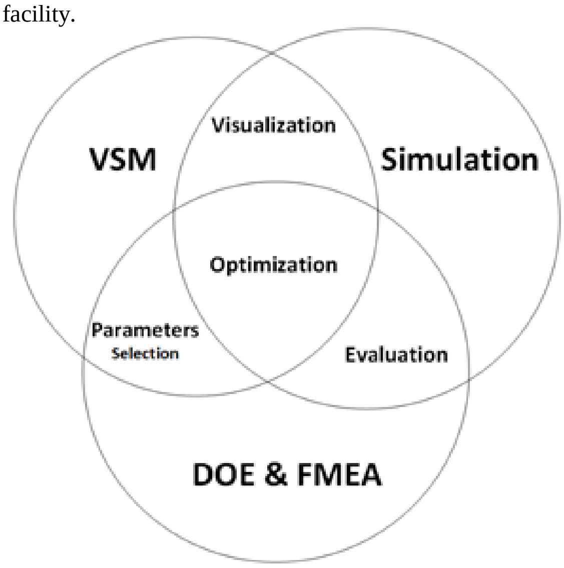


Figure 1. Integration of VSM, Simulation, DOE and FMEA

2. Methodology

The integrated approach is detailed in Figure 2. The production operations of a major glass factory in Jordan are considered as the main example, but the approach is generic enough to allow for numerous applications and setups. After the data is collected, product families, process boundaries, and material flow are identified.

2.1. VSM-CSM

Initially, a VSM representing the CSM of the production facility is established (see Figure 3). It will help to visualize process flow as well as identify production status and any potential alerts (Andons) that might cause problems to the production system. For example, the CSM in Figure 3 illustrates the different processes involved in the glass production. Details of these processes are available in previous work (Atieh *et al*., 2015). According to the production logbook (historical data) and CSM, four processes are identified as major (shown in blue in fig. 3); these are Cutting, Edging, Drilling, and Tempering. The other five processes are

identified as minor as their contribution to the total production represents less than 10%

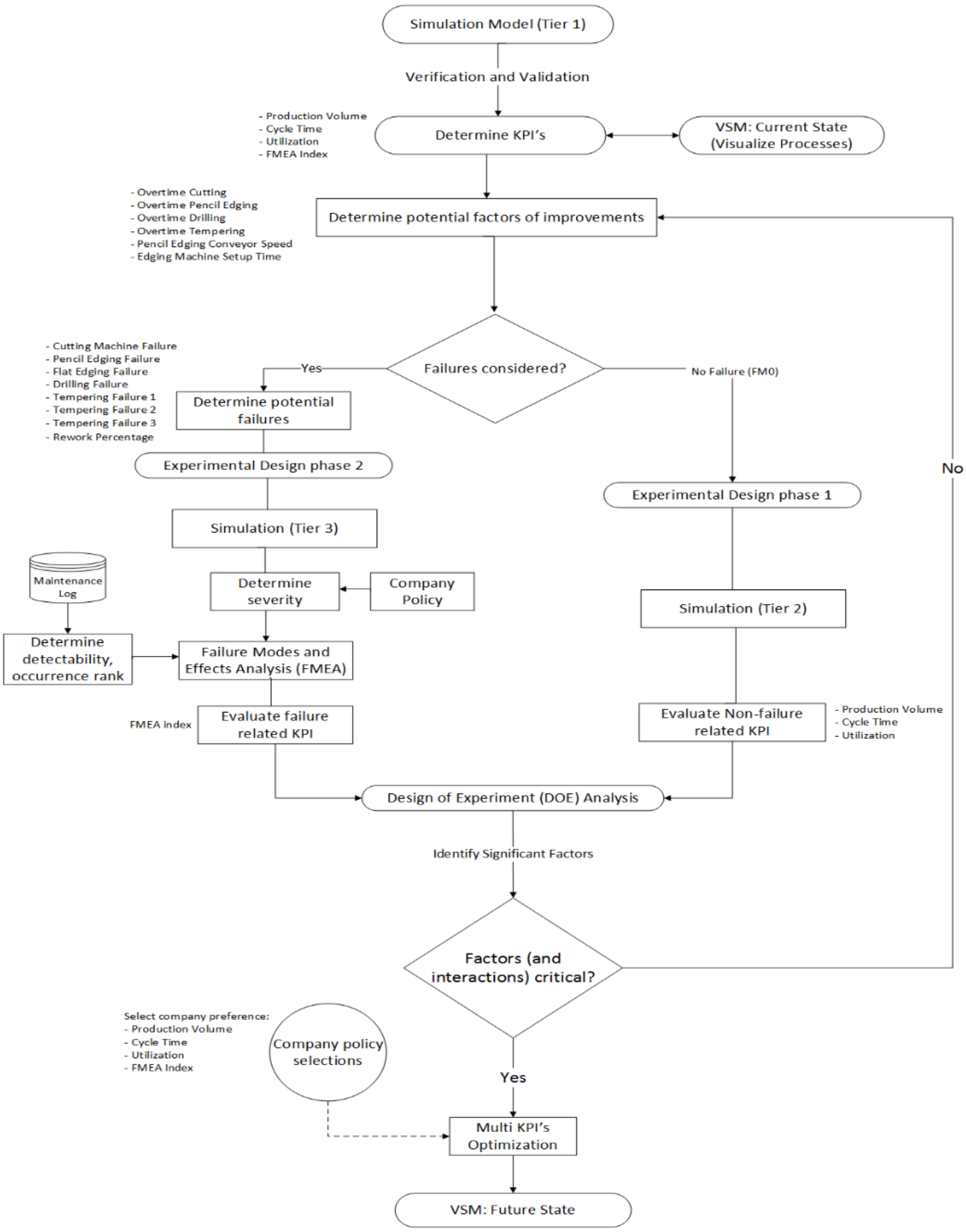


Figure 2. Algorithm Framework

2.2. Simulation Model

After analyzing historical data related to production rates, available resources, setup times and process times, a simulation model representing the current operations at the production facility is created. The model of the case study, which was built using Arena-Rockwell Automation Technologies Software version 14.7, was developed to incorporate rework as it reflects in terms of cost that is added to the process. The model covers all production resources at the glass factory and was verified to mimic the logic of the actual production flow at the factory. Validation was also performed by comparing results to real production data. It is recommended that any simulation model is set to run for several replications with ample run length to achieve steady state. In the present study, 10 replications and 160 days were chosen, respectively. Preliminary tests indicate that 14 days warm-up period is needed to remove any bias in the results. The model is capable of evaluating different KPIs given any combination of input factors' levels (detailed in next section). Three variations of the simulation model are created: Tier 1, Tier 2, and Tier 3. Tier 1 is used in the preliminary runs to evaluate CSM for potential problematic areas. Tier 2 is used after the design of experiments, and Tier 3 is used with the FMEA analysis.

2.3. Determining Input Factors and Responses (KPIs)

In order to analyze and improve the process in any system, two sets of information have to be identified: the outputs (responses or KPIs) with which improvement can be measured, and the input factors, which can affect the outputs. Only feasible factors need to be considered.

Based on company policy, it is found that three performance measures: daily production volume (KPI-1), resources utilizations (KPI-2), and production lead times (KPI-3) are the most desirable in terms of evaluating the system performance. While it is customary to evaluate these KPIs within the normal healthy operational conditions, one can anticipate the severity of the numerous potential failures on them. Therefore, while these KPIs will be evaluated at the healthy conditions, an additional KPI has been devised (FMEA index: KPI-4) to cover for the failure modes and their potential effects. Details of this KPI are provided in Section 2.5.

With regard to KPI-1, the daily production volume is estimated from simulation by averaging the production of one month. The assessments of utilizations are not straightforward, especially with unavailable quality data (for the calculation of the Overall Equipment Efficiency (OEE)). Therefore, we devise the utilization index (KPI-2) which is discussed separately in Section 2.3.1. The production lead time (KPI-3) is calculated based on the average flow time of all products produced during a one month period.

In our case study, the following input factors are considered as being feasible. First, overtime is introduced on the following machines: cutting machine, pencil edging machine, drilling machine, and tempering machine. For all machines, overtime manifests in an additional four operational hours to the 8-hour shift. Additionally, and as indicated in the previous work (Atieh *et al*., 2015), pencil edging represents a challenge in the production time due to long setup and process times. Therefore, the company is interested in evaluating the option to reduce the setup time and/or increase the conveyer speed by investing in a new setup through certain machine upgrades. This results in six feasible input factors.

2.3.1. Utilization Index

The utilization index is adopted as KPI-2. It compares the improvement (or worsening) of the utilization of the resources in the system against its nominal value in the default setup (all factors at low level). On the one hand, it is known that excessive utilization of resources (or machines) reduces their life expectancy, and increases the probability of failures. On the other hand, under-utilized resources represent investment, which has not been fully exploited. Therefore, popular optimal utilization values are in the range of 80-90%.

We propose to evaluate the utilization index for every experiment (combination) through the following equation:

$$U_i = \sum_{j=1}^{N} w_j \left[\left| U_j^* - U_{0j} \right| - \left| U_j^* - U_{ij} \right| \right]$$

$$\forall j = 1, \dots, N \ \ resources\ (machines)$$
$$\forall i = 1, \dots, n\ experiments\ (combinations)$$

where U_i is the utilization index for the ith experiment (combination);

w_j is the weighted factor associated with the utilization of the jth resource (or machine) in the system;

U_j^* is the optimal utilization value of the jth resource (or machine);

U_{0j} is the nominal utilization value of the jth resource (or machine) in the default setup (all factors at low level);

U_{ij} is the utilization value of the jth resource (or machine) in the ith experiment (combination).

U_j^* can be determined from Original Equipment Manufacturer (OEM) recommendations or from the organization's policy. The weighted factors reflect the importance of a particular resource in reference to the collective resources. For example, the percentage of the production, which utilizes a specific resource, can be used to determine its utilization-weighted factor.

The target optimal utilization value was set to 75% for all the resources (machines); it is considered in our case study based on the company's policy. The targeted resources (machines) in the utilization index are from the four major processes (5 machines) indicated earlier: cutting, edging (pencil or flat), drilling and tempering.

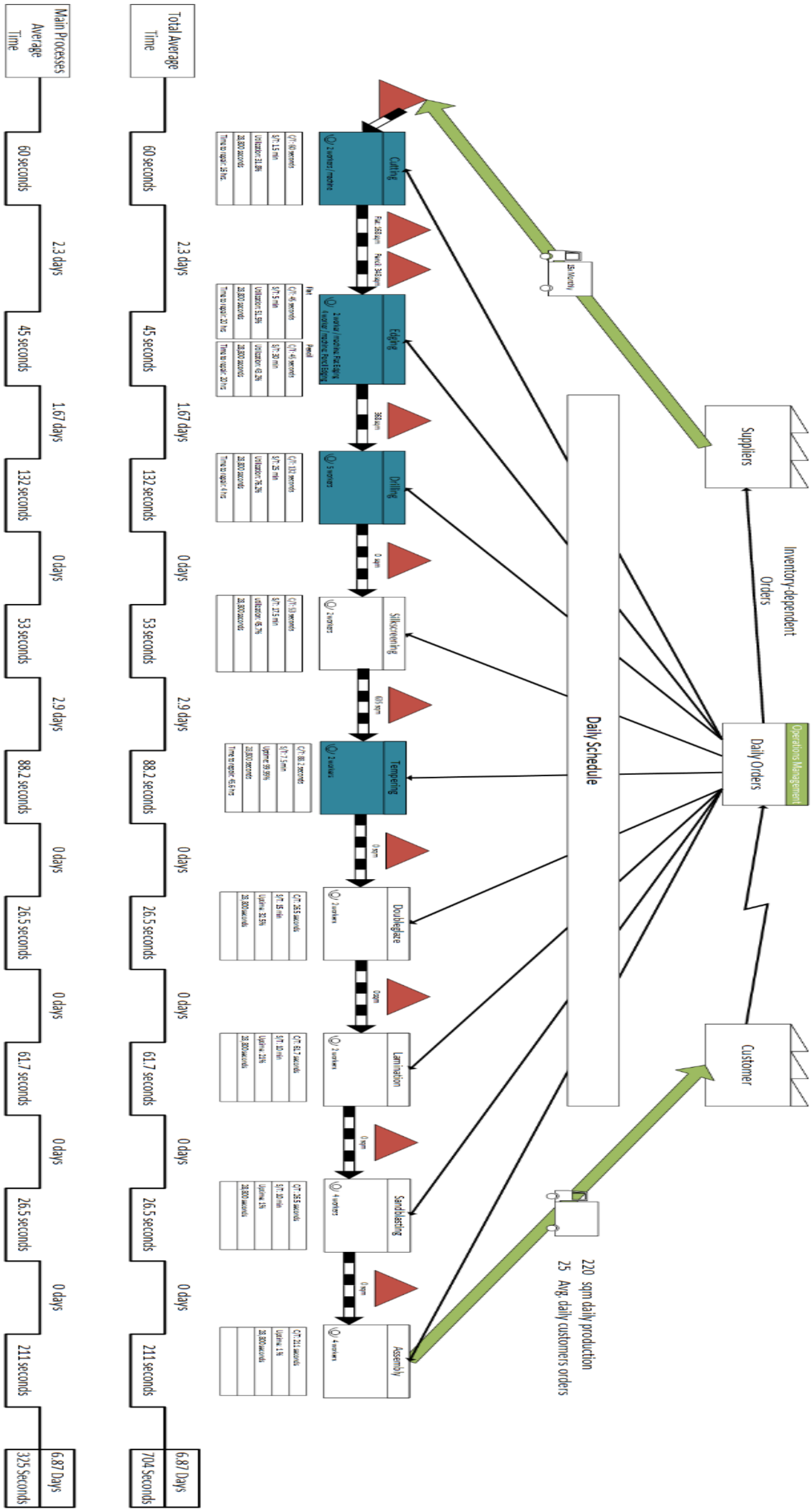


Figure 3. VSM- current state map (CSM)

2.4. Design of Experiments

The DOE is used to create the factorial design for the experimental runs on the input factors and their levels. The DOE considered all the input factors, with a suitable number of levels for each. For our case study, we consider the above six input factors, with each at two levels, resulting in a total of 64 runs for full factorial design. Two phases of DOE are performed; Phase 1 is concerned with experimental design and analysis of the production system behavior without considering effect of failure. Responses KPI-1, KPI-2, and KPI-3 are evaluated at all combinations of the experimental factors' levels using simulation model Tier-2.

After analyzing the factorial deign, the best design is found using the desirability approach (Derringer G, 1980; "Design of Experiments, Minitab user Manual," 2005).

For the scenarios when at least one failure mode exists, DOE phase 2 utilizes the same input factors mentioned above but uses KPI-4 as a response variable, namely failure modes and effects analysis index (FMEA-Index). KPI-4 takes into consideration the effect of failure mode severity on system performance and is obtained by applying Severity Analysis, which is explained in section 2.5. Simulation Tier 3 is used to evaluate severity of potential failures on system performance for the given 64 experimental runs.

If the input factors and their interactions are found to be non-significant or do not provide a reasonable enhancement, another set of feasible factors must be considered. Otherwise, the DOE phase is finished with the understanding of the relationship between the input factors (and their interactions) and the responses.

2.5. Failure Mode and Effect Analysis (FMEA)

Potential failures, which may affect the KPIs, have to be identified. Their potential effect is to be studied in order to assist the DOE phase and what follows it in terms of analysis. A modified FMEA procedure (in reference to the standard one (Defeo, 2014)) is utilized. The procedure transforms the severity rate into a measure for the failures effects on the KPIs under study. Details of this are available in Section 2.5.1. The rest of the FMEA standard procedure (potential effect(s) of failure, its cause(s)/mechanism(s), occurrence and detectability rates) can be obtained from historical data and/or maintenance logs. Occurrence rates are calculated by counting the number of incidents that a certain failure has occurred.

Then this number is normalized to the standard range of FMEA (1 for the failure mode with least frequency of occurrence and 10 for the most frequent one).

The detectability rate indicates how much design control can detect potential cause/mechanism and subsequent failure mode. This is very dependent on the

process/system at hand and the potential failures of concern.

After calculating the severity rate (Section 2.5.1), the Risk Priority Number (RPN) of each failure mode at each combination of input factors/experiment can be easily obtained by multiplying the severity rate, the occurrence rate, and the detectability rate.

In order to combine all the RPNs for a specific experiment into one representative value (namely FMEA-Index), a weighted average can be used if all the RPNs are within the same order. However, averaging is well-known to be sensitive to extreme values. Therefore, while this method statistically covers for the failure modes with high RPN (important to take into consideration), it is also affected by the low RPNs. Therefore, a simple augmentation to the previously mentioned method of combining the RPNs is to exclude the lowest 10% of RPNs from the averaged pool.

In reference to our case study, failures in production systems are quite common, leading to major production problems (Andons) in terms of reduced production rates and/or increased production lead time. Table 1 lists the FMEA for our case. These failure modes are identified based on historical data including the maintenance logbook of machine failures and feedback provided by production personnel regarding the most critical failures. Insignificant failures with extremely low occurrences and/or related to extremely underutilized resources have been disregarded, and only the most frequent eight have been listed. Table 1 lists as well, times to repair machines. Since these times do not depend on previous repair tasks, the Exponential distribution is used to simulate the Mean Time To Repair (MTTR).

2.5.1. Severity Analysis

The association of a severity rating in the FMEA is extremely important as it

directly affects the risk priority number from which the FMEA index will be

calculated. While the occurrence rating and the detectability rating can be evaluated from maintenance logs, the severity is almost ambiguous and can only be estimated when joining maintenance logs with production ones. To overcome such a problem, we introduce a simulation-based severity rating procedure that takes into consideration the organization's policy.

First, the maintenance logs are used to identify the time to repair for the main failure modes chosen in the design of the FMEA. Then, the failures are input into the simulation model, and runs are made to estimate the impact of each of these failure modes on the KPIs of interest. Expectedly, the period during which the failure mode is introduced, and the days after it are studied extensively. The failure modes are as well introduced to each experiment (combination) of enhancing factors.

The KPIs of interest resulting from the healthy (no fault) mode and the ones resulting during the failure mode are compared for each combination. In order to combine the contributions of the different KPIs, a weighted average inspired from the organization's policy can be used. For example, a production facility can have a severity index which focuses on the production volume, lead time, and combined resources utilization. This will result into an equation such as:

$$S_{ik} = w_1' * \frac{L_{ik} - L_{i\varphi}}{L_{i\varphi}} + w_2' * \frac{P_{i\varphi} - P_{ik}}{P_{i\varphi}} + w_3' * \left[\sum_{j=1}^{N} w_j \left[\left| U_j^* - U_{ij\varphi} \right| - \left| U_j^* - U_{ijk} \right| \right] \right]$$

$\forall k = 1, \dots, M\ Failure\ modes\ ;\quad \forall j = 1, \dots, N\ \ resources;$
$\forall i = 1, \dots, n\ experiments\ (combinations)$

where S_ik is the kth severity index for the ith experiment (combination);

w_1^' ,w_2^',and w_3^' are the weighted factors associated with the different KPIs (lead time, production volume, resource utilization) changes because of failure;

L_ik is the lead time in the ith experiment during the kth failure mode;

L_iφ is the lead time in the ith experiment during the no failure (no fault) mode;

P_ik is the production volume in the ith experiment during the kth failure mode;

P_iφ is the production volume in the ith experiment during the no failure (no fault) mode;

w_j is the weighted factor associated with the utilization of the jth resource (or machine) in the system;

U_j^* is the optimal utilization value of the jth resource (or machine);

U_ijφ is the utilization value of the jth resource (or machine) in the ith experiment (combination) during the no failure (no fault) mode;

U_ijk is the utilization value of the jth resource (or machine) in the ith experiment (combination) during the kth failure mode.

Finally, the severity index for each failure mode at each combination are transformed to the standard FMEA one to ten rating with ten being the most severe failure mode.

No.	Potential Failure Mode	MTTR (Hrs)	Potential Effect(s) of Failure	Sev	Potential Cause(s)/ Mechanism(s) of Failure	Occur	Detec	RPN	Recommended Action(s)
1	Cutting Machine Failure	16	Non-straight cuts (Harder to Edge), Incorrect product dimensions	Function of experiment (combination)	Degraded machine tool and/or parts: Oil pump, knives, etc. miscalibration	2	2	Sev x Occur x Detec	Replace or calibrate cutting diamond
2	Flat Edging Machine Failure	20	Rough Edges Or breakage of panels / Increased WIP		Conveyor system: loose conveyer belt, motor dysfunction, jammed , miscalibration, etc.	9	3		Replace polishing and/or diamond wheels OR Adjust feed rate
3	Pencil Edging Machine Failure	20	Rough Edges Or breakage of panels / Increased WIP		Conveyor system: loose conveyer belt, motor dysfunction, miscalibration, etc.	8	4		Install Tool Detectors
4	Drilling Machine Failure	4	Panels breakage / Increased WIP		Degraded machine tool: Broken Drill Pneumatic press failure	8	7		Ensure the table is stable OR replace cutting diamond OR adjust feed rate
5	Tempering/ Furnace Failure 1	16	Stalling products/Increased WIP		Conveyor system	8	5		Check and/or replace rollers (if they absorb heat differently they affect the heat distribution)
6	Tempering/ Furnace Failure 2	45.6	Excessive unbalanced expansion of glass leading to breakage		Heating system: Heaters malfunction, relays, chiller, etc.	7	2		Check and/or replace heaters (heat distribution needs to be equal)
7	Tempering/ Furnace Failure 3	16	Products characteristics that do not meet customer requirements (e.g. strength)		Control/sensors	7	4		Install new detectors and frequent calibrations
8	Rework% increase	N/A	Increased WIP, increased cost, increased product lead time		Various: Human errors, improper machine set up. cumulative machine tools degradation, etc.	7	10		Systematic inspections of tools and products, Modify manufacturing procedure, Apply lean manufacturing tools

2.6. Optimal Solution

While DOE provides the statistical analysis to describe the relationship between the responses (KPIs) and the input factors, it does not explicitly provide the optimal solution for a given response or a combination of responses. Nonetheless, it facilitates it through the regression equations generated in the DOE analysis stage.

The optimization can be achieved using the desirability function approach to find the best solution. First individual desirability is obtained for each KPI according to the targets set for each. Second, the composite desirability is determined using weighted geometric mean of the individual desirabilities. Finally, a reduced gradient algorithm with multiple starting points that maximizes the composite desirability is applied to determine the numerical optimal solution (Derringer G, 1980; "Design of Experiments, Minitab user Manual," 2005).

Optimized solutions are obtained for several scenarios by setting different weights for the response variables. The weights should be selected according to the organization's policy. The more failure-conscious the organization would like to be, the larger the weight assigned to the FMEA-index must be. The methodology will be more efficient if solutions for individual KPIs are investigated first then different combinations using several weights are considered. Finally, a subjective selection of one of solution will be made by consulting with the organization's management.

For our case study a solution that will maximize KPI-1 and KPI-2, and minimize KPI-3 and KPI-4 is sought.

3. Results and Discussion

Implementing the algorithmic procedures detailed above for our case study and using Arena® simulation software version 14.7 and Minitab® 17.1.0, the following results are obtained.

3.1. DOE Factorial Plots

DOE factorial plots are generated for individual response variables to determine significant input factors for each of these responses individually.

3.1.1. Production Volume

Inspection of Figure 4 reveals that the most critical factor to improve the daily production rate is the tempering overtime factor indicating the necessity of increasing the availability of tempering resources, mainly the furnace. All other factors were found to be insignificant in terms of our case study. We also note here that inspection of the interaction plots showed that the input factors do not interact with each other in terms of this response variable.

3.1.2. Utilization-Index

Unlike the production volume, the Utilization-Index KPI is affected by all input factors. It can be improved by adding more overtime to the bottleneck tempering machine and reduce time on the other less-busier machines; drilling, pencil edging, and cutting. This is expected since Utilization-Index measures the deviation of machine utilization from the company's target utilization of 75%.

The results show that drilling station current utilization is about 70% and increasing time availability of this machine reduces the utilization to 31% distancing it further from the target value. Once again, the interaction between different input factors was found to be minimal.

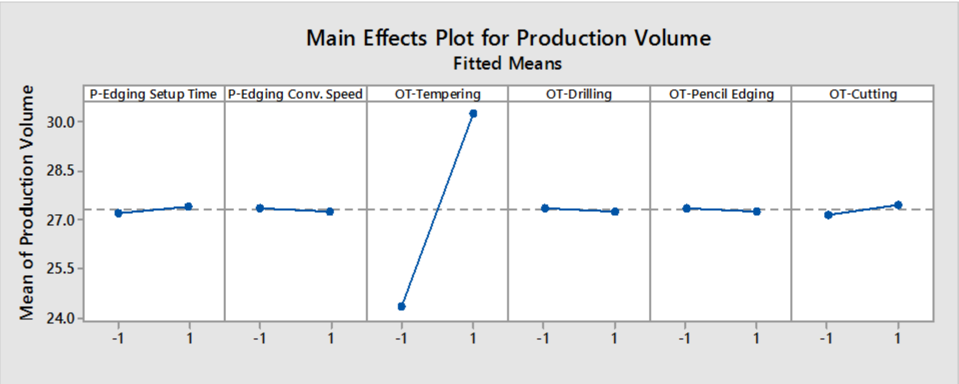


Figure 4. Main Effect plot for production volume

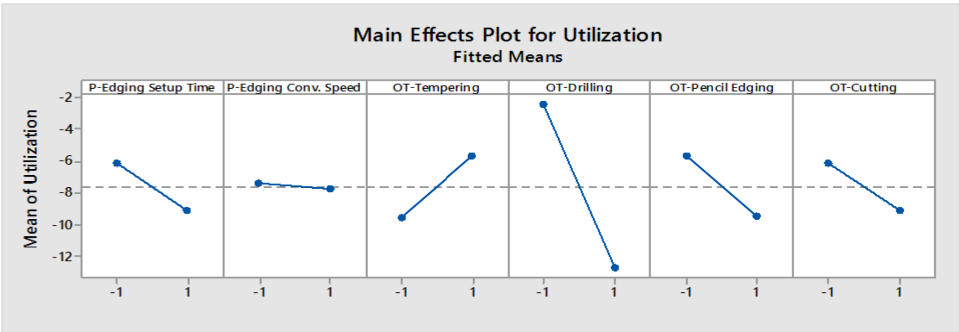


Figure 5. Main Effect plot for utilization

3.1.3. Lead Time

Similar to Production Volume, this KPI is mainly affected by overtime on tempering input factor. To reduce lead time it is imperative to increase tempering machine availability. This is intuitive, as the tempering machine has been shown to be a primary bottleneck (Atieh *et al.*, 2015). Once again, the interaction between different input factors was found to be minimal.

3.1.4. FMEA-Index

As the production system at hand has several under-utilized machines, failure modes have been found to be significant particularly for the lead time. Additionally, the lead time is considered one of the most important performance measures the company is looking to enhance. Therefore, the severity index has been chosen to evaluate the severity of the failure over the lead time.

Unlike the previous KPIs, this response variable indicates complex behavior with the different input factors. For example, on the one hand overtime on tempering is shown in Figure 7 to increase the FMEA-Index as a single response affected by a single factor. However, interaction between input factors (see Figure 8) is shown to be strong and in our case can invert the effect of the single factor. The figure shows that the reduction of the setup time on the pencil edging machine will reverse the effect of the overtime on tempering.

This outcome is explained by the fact that both resources have high utilizations and are considered as potential bottlenecks in the production system. Overtime on tempering will generally relieve the production system (enhancing all its KPIs). Therefore, failures will result in a potential loss of this relief, and hence the FMEA-Index will increase when this input factor is considered on its own. Nonetheless, this factor can (with the interaction of other factors) reduce the FMEA-Index. Particularly, there is a strong cross over interaction between overtime on tempering machine and setup time of pencil edging machine with P-value of 0.019.

This explains why overtime on tempering will be chosen for all the optimal solutions detailed later coupled with a reduced pencil edging setup time or increased conveyer speed. If both have been selected together, the rate of work flow will increase and once the failure occurs (for example at tempering), the WIP increases at the other resources leading to an increase in waiting times. That will reflect on the lead time and consequently worsens the FMEA-Index value. Furthermore, not selecting both input factors will once again highlight the criticality of the tempering machine during failure in a similar manner to not having overtime on tempering (default setup-all factors at low level).

Pencil edging overtime is also a significant factor and Figure 7 shows that it should have higher value to reduce FMEA-Index. In addition, Figure 8 shows that overtime on drilling and cutting machines have strong crossover interaction indicating that having overtime on either one of them should be sufficient.

It is clear that since the FMEA-Index is designed to measure the potential loss of enhancement a change of input factor(s) can provide, in addition to the fact that the enhancement is measured in terms of several KPIs, it will be almost impossible to track physically every input factor's effect. Therefore, statistical analysis such as this approach becomes important. This is in line with the fact that changing an input factor will have dynamic effects on the whole production system and not only on a single machine or component. This can only be captured through simulation which results were used in the DOE analysis.

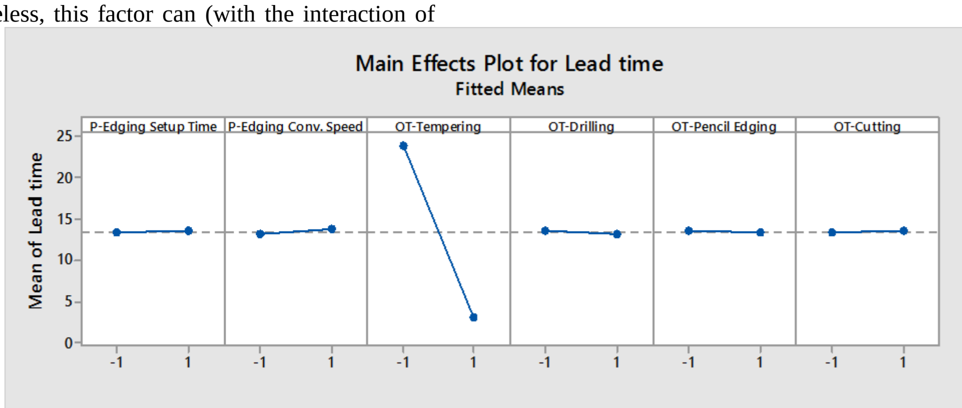


Figure 6. Main Effect plot for lead time

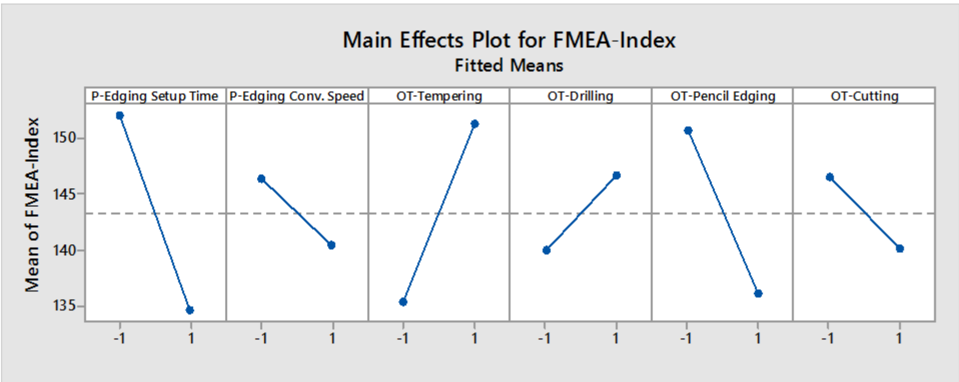


Figure 7. Main Effect plot for FMEA-Index

3.1.5. Joint View

For all four KPIs, the input factor; over time on tempering is the most significant one with highest slope indicating the urgent need to increase the availability of the tempering machine. This result is expected as the preliminary analysis showed that this process is considered as a bottleneck. Introducing overtime on tempering will not only increase productivity and decrease lead time but also the utilization mean effect plot indicates that it is not recommended to have any overtime on other machines except for the tempering as all other machine are underutilized and increasing availability time will reduce their utilization way under the target value of 75%. However, the FMEA-Index plots illustrate some important interactions that can help reduce it, and consequently reduce the risk of failure. To decide the best combination of input factors, optimization is performed using several scenarios as illustrated in the following section.

3.2. Optimization Analysis

Optimization analyses are performed and compared for each single response variable individually and for a selection of weighted combinations of all responses together. The three best solutions for each scenario are considered in the comparison.

3.2.1. Single Response

Optimization analysis for each response separately resulted in a slightly different set of combination factors as illustrated in Figure 9. The numbers between brackets represent the response value for each solution. Some of the obtained levels of input factors were common among most solutions, for example, all solutions show that overtime on tempering is needed for all scenarios, pencil edging overtime is needed considering Production volume, Lead Time, and FMEA-Index but not recommended when considering Utilization-Index. All four charts show significant enhancement in the value of each response variable compared to no-improvement scenario. Best production volume obtained was 33.51 panels/day while best lead time was 1.73 days. To decide what would be a good combination of input factors that will optimize all four responses simultaneously multiple-response optimization is discussed in the following section.

3.2.2. Multiple Responses

To find a solution that will enhance all responses simultaneously, optimization was carried on several combinations of response variables using different weights. The weights were selected carefully to be in line with company policy. Mainly three of these combinations are illustrated in Figures 10, 11, and 12.

In Figure 10, the optimization was performed mainly on the three traditional responses; Production volume, Utilization, and Lead time while a 0% without consideration of the FMEA-Index. First, it can be clearly seen that the results drastically enhances the two main KPIs, lead time and production volume. The optimizer was switching between focusing on enhancing the production volume, lead time and utilization. For example, the production volume has the best value in solution 1, the lead time has the best value in solution 3, while the utilization has the best value in solution 2. One important issue regarding the provided solutions is the large value of the FMEA-Index associated with them, indicating that these solutions present preferable outcome in the healthy mode and are susceptible to failure.

Figures 11 and 12 consider all KPIs including FMEA-Index. Therefore, different sets of solutions have been generated with set in Figure 12 focusing on the production volume. It can be seen from the figures that a solution which does not compromise the enhancements in the traditional KPIs and the FMEA-Index can be attained. We note that achieving the best possible value in all KPIs simultaneously is not achievable. While some solutions achieve excellent levels in some KPIs, other KPIs are less or not enhanced at all. Nonetheless, we recommend generating enough solutions with different sets of weights in order to create a reasonable pool of alternatives from which one solution is subjectively selected.

In the case study, the best solution was selected to be solution 1 produced with weights as; 40% for production volume, 20% for overall resources utilizations, 20% for lead time, and for 20% FMEA-Index.

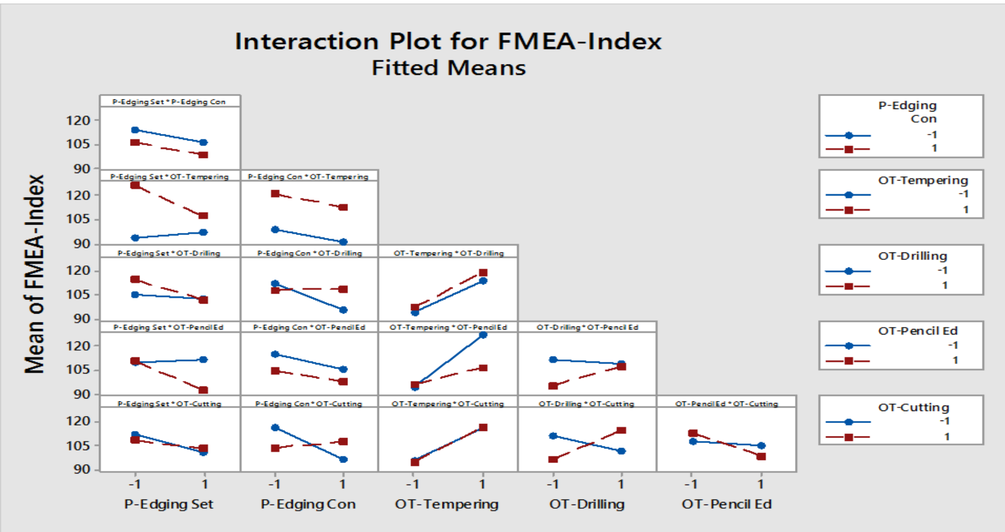


Figure 8. interaction plot for FMEA-Index

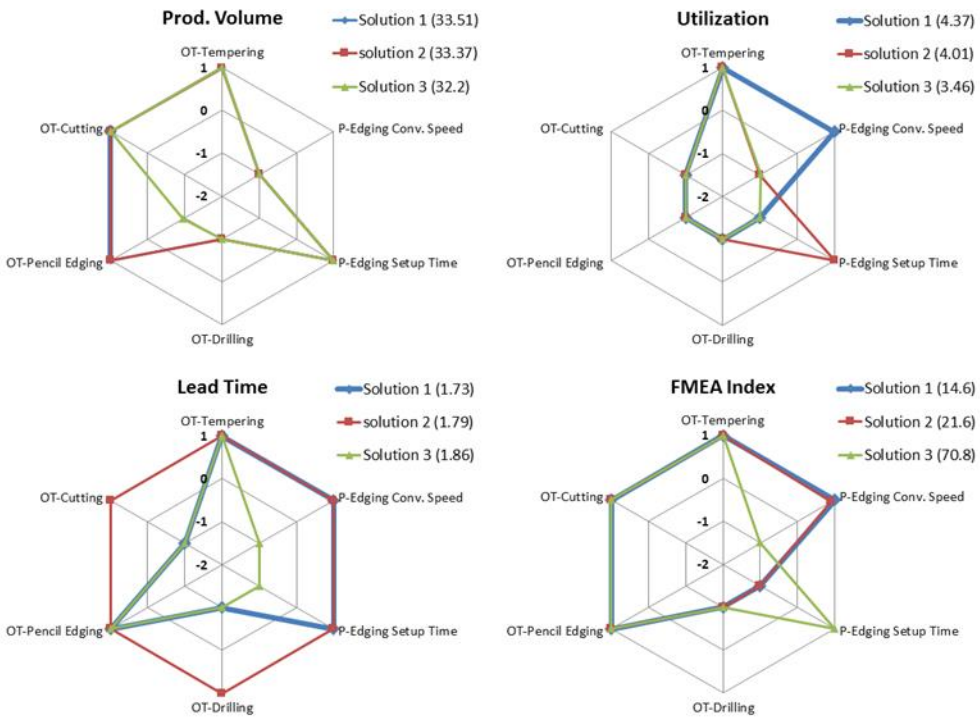
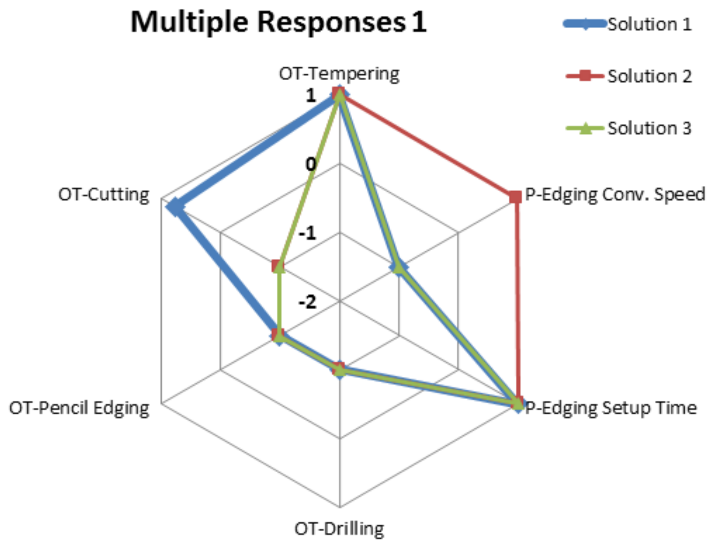
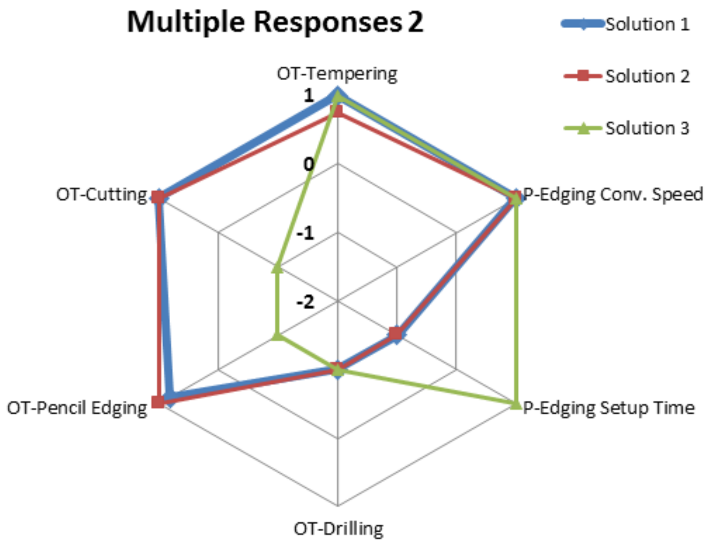


Figure 9. Single response optimization



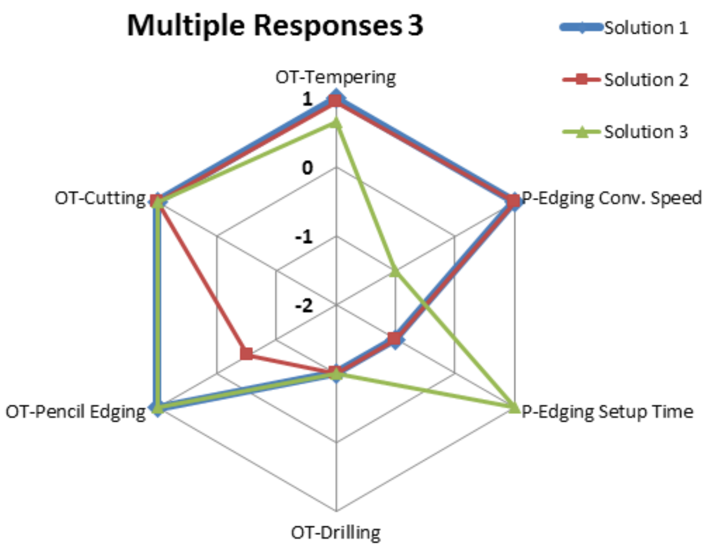
	Vol. Production	Utilization	Lead Time	FMEA Index
Weight in Opt.	40%	30%	30%	0%
Solution 1	31.9	-1.07	3.12	159.1
Solution 2	31.6	0.13	4.80	90.5
Solution 3	30.2	4.37	2.66	148.9

Figure 10. Multiple responses optimization 1



	Vol. Production	Utilization	Lead Time	FMEA Index
Weight in Opt.	40%	20%	20%	20%
Solution 1	33.4	-5.47	6.09	21.2
Solution 2	32.4	-6.08	8.86	27.4
Solution 3	31.6	0.11	4.80	90.5

Figure 11. Multiple responses optimization 2



	Vol. Production	Utilization	Lead Time	FMEA Index
Weight in Opt.	70%	10%	10%	10%
Solution 1	33.5	-5.83	6.38	14.6
Solution 2	32.2	-2.87	4.54	72.6
Solution 3	32.1	-6.15	9.52	30.9

Figure 12. Multiple responses optimization 3

3.3. VSM-FSM

VSM-FSM was constructed as an extra evaluation methodology to measure the enhancement in the production system. The FSM values were updated using the output of simulation model as illustrated in Figure 13. Based on the selected optimized solution described in Section 3.2, for multiple-response variables, a significant enhancement in system performance was observed. Considering the production volume, the daily production in square meters was increased from 24.7 panels/day (220 sqm) to 33.4 panels/day (298 sqm). This increase, represent a 35% enhancement in daily production volume. In addition, the work in process WIP for all four major processes (highlighted in blue) were dramatically reduced except for tempering. For example the WIP for drilling, was reduced from 368 to 35 sqm. While tempering process WIP increased from 635 to 831 sqm, this increase is justified by the increase in daily production volume. Consequently, the overall lead times was reduced for all processes by 56%. While cycle times were enhanced by 5%. This enhancement is a result of the infusion of all previous mentioned tools described above in the new proposed methodology. The utilization of all machines was observed to either be reduced or stayed constant. The major reduction in machine utilization was on tempering which was reduced from 99.99% to 89.9%. Hence, this case study can prove that the application of proposed algorithm can result in major enhancement of production performance.

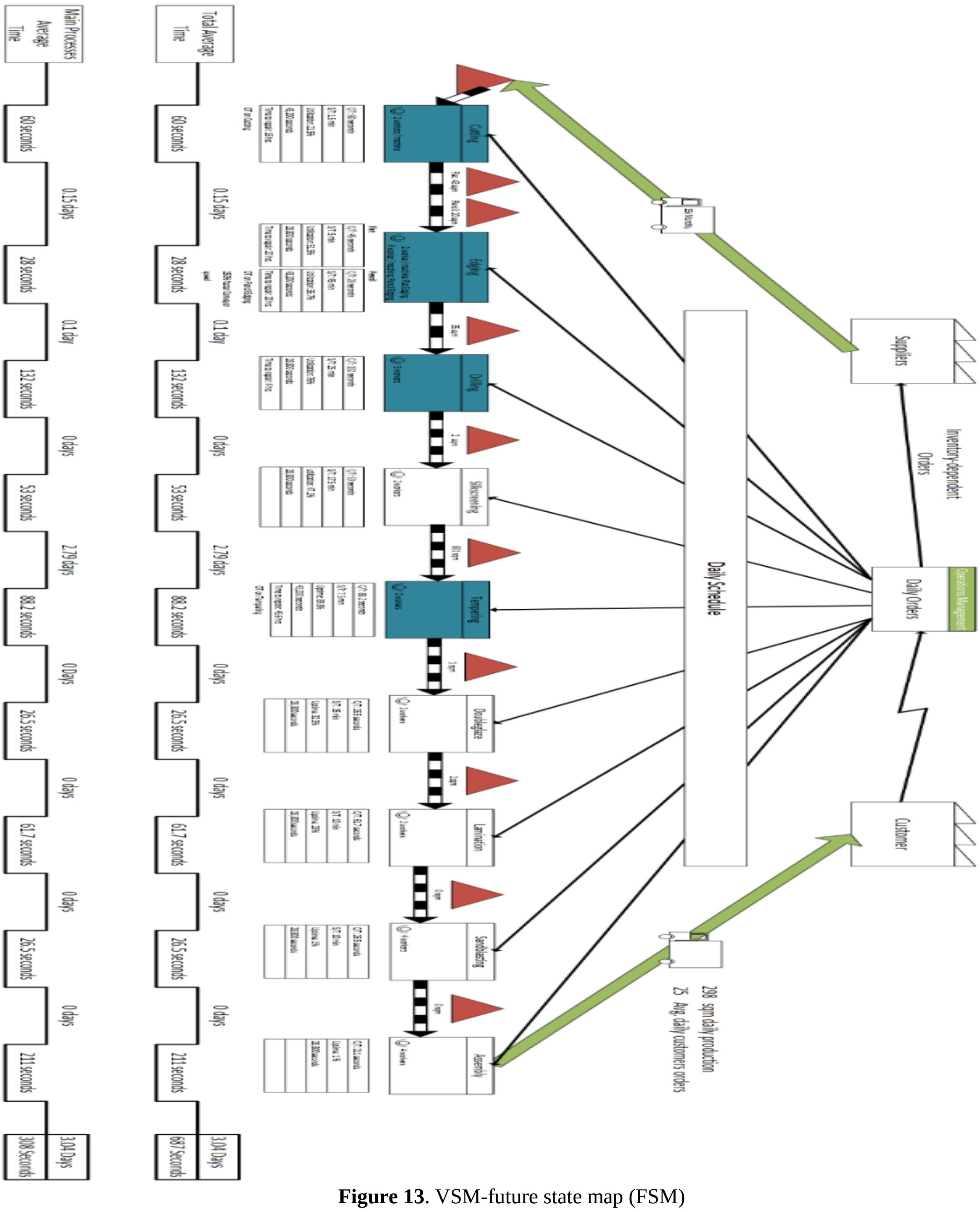


Figure 13. VSM-future state map (FSM)

4. Conclusion

Different types of failures can occur in any production system, causing interruptions to production process, leading to lower production rates and increased lead times. Planning resources to meet production requirements without considering the risk of failures can lead to catastrophic consequences to any organization. Although VSM is used for planning future system improvements, it does not explicitly take into consideration risk of failures. In the present study, we

show that the VSM procedure can be improved considerably by utilizing three lean tools: FMEA, discrete event simulation, and DOE. The proposed methodology offers a valuable contribution since it helps to optimize several KPIs simultaneously, identify critical factors affecting production, assess severity of different failures, and select the best levels of factors that will maximize performance and reduce risk of failures.

We have demonstrated the effective use of our methodology by applying it to a real case study of glass-fabrication facility. Results show that introducing four-hour overtime on a tempering station will enhance system performance considerably. This is expected as the utilization of the furnace is very high, over 95%, and is considered a bottleneck in the production process. However, the Utilization-Index and FMEA-Index plots show that other factors are also significant. Improving the Utilization-Index will help in having a more balanced production system, but should not be considered alone as it may deteriorate important performance measures, like production volume and lead time. In addition, several interactions between input factors were identified which can help in selecting proper levels of input factors. Results also show that neglecting to consider risk of failure might lead to an unrealistic estimate of production volume. Selecting input factors carefully can reduce the failure risk, but still produce good values of other KPI's.

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