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A FRAMEWORK FOR SELECTING AND EVALUATING PROCESS IMPROVEMENT PROJECTS USING SIMULATION AND OPTIMIZATION TECHNIQUES

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ABSTRACT

Selection of process improvement initiatives can be a challenging task. Process improvement projects usually fall into the following categories: Lean, Six Sigma, Lean Six Sigma, Change Management, and Business Process Reengineering. The selection process of these projects is a multi-criteria decision making process which involves multiple conflicting objectives. In this study, we develop an optimization model to select process improvement projects taking into consideration resource availability, required skills, and budget constraints. In addition, discrete event simulation (DES) models are developed to evaluate some of the selected projects. The DES models account for the uncertainty in the system and allow for performing scenario analysis on the selected projects. To validate the proposed approach, we provide a case study from a high-end server manufacturing environment. Results can be used to enhance the decisions on selecting process improvement projects.

1 INTRODUCTION

1.1 Background

In today's globalized and highly competitive market, companies must seek ways to continuously improve their processes and adapt to the new changing market conditions. Continuous improvement is a key factor for the survival of companies and it provides a competitive advantage to these companies. Process improvement activities focus on identifying and analyzing business problems and finding ways to eliminate these problems and prevent their occurrence in the future. The common process improvement methodologies are Lean, Six Sigma, and Business Process Reengineering. The focus of these methods is to improve quality, remove wastes, and sustain the achieved improvements.

However, it is important to note that in every organization or team, different levels of problem complexity exist and there is no 'one-size-fit-all' methodology that can be applied uniformly. Unfortunately, most organizations force all the problems/opportunities to be solved using a standardized approach, such as Lean or Six Sigma even when it is not required, resulting in sub-optimal results. Over the past few years, problem solving practitioners have attempted to provide guidelines to determine when to use the various methodologies, but these guidelines are limited in terms of scalability across domains. In

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this research, we are proposing a framework that can provide clarity on selecting the appropriate process improvement methodology using multi-objective criteria and simulation of the scenarios, prior to making the decision. The case study considered in this research discusses the process improvement initiatives in a high-end server manufacturing environment. The authors have been an integral part of this initiative and have worked closely with the different teams to achieve successful process improvement results. The proposed framework can also be applied to any manufacturing and/or service industry where process improvement initiatives need to be prioritized and evaluated.

1.2 Related Literature

Process improvement methodologies, such as Lean and Six Sigma, have been widely used in manufacturing and service environments. Several studies in the literature have discussed these improvement techniques and their application to improve processes. For example, Aziz and Hafez (2013) presented a study in which they discuss how Lean principles are applied in construction industry in order to reduce wastes and improve process efficiency.

Prioritization and selection of process improvement projects is considered an important decision making process. This topic has been addressed by several studies. Kalashinkov et al. (2017) proposed a bi-objective approach for selecting Lean Six Sigma projects. The study developed an optimization model to select Lean Six Sigma projects taking into consideration resource availability and time and cost constraints. An example of identification and development of Lean projects in healthcare industry was discussed by Crem and Verbano (2016). Implementation of Lean standard work in an automated manufacturing environment was discussed by Lu and Yang (2015). Results from the study showed a 37.5% labor reduction prior to the pacemaker workstation and a 304.7% increase in the daily throughput at the bottleneck workstation. Mourtzis et al. (2016) proposed a framework for classifying, formalizing, and identifying Lean rules in order to create a comprehensive and applicable library of Lean rules.

Ramakrishnan and Testani (2012) proposed a simple framework to assess Lean readiness wherein each project idea (typically a problem or an opportunity) is vetted based on four factors: (a) Clarity of the problem, (b) Frequency of the problem, (c) Ease of solving the problem, and (d) Skill level of the team. Based on the responses, a score is calculated to determine which problem solving method is the most appropriate one for the project. For example, when the project team does not have Six Sigma skills, the framework would recommend that they start off with a Lean approach (fact-based) and then, seek the guidance of team members with Six Sigma down the road. In another scenario, if the team knows the root cause and potential solutions to address the problem, the framework would recommend to implement the known solution. The drawback of this approach is that the heuristic does not account for many other factors that contribute to the decision, such as availability of resources and funding, current quality levels and responsiveness of the process and support from leadership to change the process.

The use of optimization models and discrete event simulation (DES) to support process improvement initiatives has been discussed by some authors in the literature. For example, Bae et al. (2016) have discussed the use of DES to support Lean design of a milk-run delivery system in an automobile emissions system production facility. Zhang et al. (2016) developed a discrete event optimization framework, which is an integrated simulation-optimization approach based on mathematical programming, to optimize buffer allocation in production lines.

There is a limited number of studies in the literature that discussed the selection of process improvement projects and the optimal allocation of operators to these projects. This study develops a framework for selecting and evaluating process improvement projects and allocating operators to the selected projects utilizing optimization and simulation techniques.

2 RESEARCH METHODOLOGY

The proposed research methodology for selecting process improvement projects consists of two main steps: optimization and simulation. In the optimization step, an optimization model is developed to identify the projects that should be implemented taking into consideration project requirements, business constraints, resource constraints, and project impact. The optimization model also assigns the available operators to the different projects based on their skills. In the simulation step, a simulation model is developed to test some the selected projects and their impact on the business processes. The research methodology is shown in Figure 1.

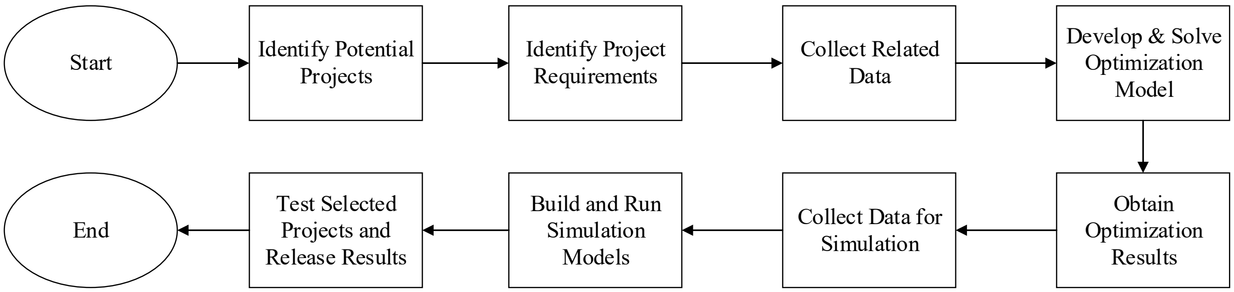


Figure 1: Proposed Research Methodology.

2.1 Optimization Model

The optimization models is described in this section. Because the selection for the process improvement projects is a multi-criteria decision making problem, we develop a multi-objective optimization model for this purpose. The notation of the optimization model is shown in Table 1. We use two decision variables; one to select the projects and another to allocate available operators to the selected projects. The optimization model along with description of the equations is shown in Table 2. There are three conflicting objectives and eight constraints. The calculation of the project difficulty score is shown in Table 3. Project difficulty is based on three main factors: project complexity, implementation time, and project cost.

Table 1: Notation for the optimization model.

Symbol	Description	Symbol	Description
N	Set of process improvement projects to be implemented (index *i, j*)	S_i	Set of skills required for implementing project *i*
N^{mx}	Set of mutually exclusive projects, $N^{mx} \subset N \times N$	S'_k	Set of skills operator k has
N^{mp}	Set of mandatory projects, $N^{mx} \subseteq N$	o_i	Operator time required by project *i*
δ_i	Complexity of project *i*	o_k	The available time for operator *k*
π_i	Benefit of the individual implementation of project *i*; $i \in N$	O	Total available operational time
σ_i	Difficulty of implementation of project *i*; $i \in N$	c_k	Pay rate (per hour) for employee *k*
λ_i	Sustainability of project *i*	M	Set of operators to work on the projects (index *k*)
B	Total available budget for miscellaneous costs	X_i	Binary variable with value 1 when project *i* is selected, 0 otherwise
b_i	Total miscellaneous costs of project *i*; $i \in N$ (doesn't include operator's salary)	Y_{ik}	Binary variable with value 1 when operator *k* is assigned to work on project *i*, 0 otherwise

In order to identify the skills required for the projects, we used the proposed framework shown in Figure 2. The selection of problem solving methodology for a given project depends on several factors including nature of the problem, root causes, required analysis, and frequency of occurrence. Implementation of a process improvement project and applying different problem solving methodologies require different skills. Table 4 shows the different process improvement projects and the associated Lean Six Sigma skills.

Table 2: Optimization model formulation.

Equation	Formula	Description
Objective 1	$Max\ Z_1 = \sum_{i=1}^{N} \pi_i X_i$	Maximize total organizational benefits from implementing the projects.
Objective 2	$Min\ Z_2 = \sum_{i=1}^{N} \sigma_i X_i$	Minimize total difficulty of implementing the selected projects.
Objective 3	$Max\ Z_3 = \sum_{i=1}^{N} \lambda_i X_i$	Maximize the total sustainability of the selected projects.
Constraint 1	$\sum_{i=1}^{N} \left(b_i X_i + \sum_{k=1}^{M} c_k o_i Y_{ik} \right) \leq B$	Budget constraint. This constraint limits the budget to be assigned to the projects. The budget includes the project cost and the operator cost.
Constraint 2	$X_j = 1, j \in N^{mp}$	Mandatory project constraint. Some projects are mandatory to be implemented due to internal and external restrictions.
Constraint 3	$X_i + X_j \leq 1, i, j \in N^{mx}$	Mutually exclusive projects are such that the acceptance of one project excludes the other from consideration. The constraint ensures that only one of the two projects can be implemented (or both not implemented) for the condition to hold.
Constraint 4	$\sum_{k=1}^{M} Y_{ik} = X_i, \forall i \in N$	Only one operator is assigned to a given project. However, one operator can work on more than one project. If more than one operator are allowed to work on a given project, the right hand side of the equation can be set to the number of operators allowed to work on the project.
Constraint 5	$\sum_{k=1}^{M} S'_k Y_{ik} \geq S_i X_i, \forall i \in N$	Operator(s) assigned to a project should have the minimum skills required for the project.
Constraint 6	$\sum_{i=1}^{N} o_i X_i \leq O$	Operational time constraint to ensure total working time of operational employees required to complete selected projects on time does not exceed the maximum available operational time.
Constraint 7	$\sum_{i=1}^{N} o_i Y_{ik} \leq o_k, \forall k \in M$	Operator time constraint. The available total time for an operator should be greater than the time required for the projects to be implemented by that operator.
Constraint 8	$X_i, Y_{ik} \in \{0,1\}, binary$	Binary constraints.

Table 3: Calculating project difficulty score.

Project Complexity (δ)	Implementation Time (o)	Project Cost (b)	Final Difficulty Score (σ)
1	< 1 week	$10,000	10
2	1-2 weeks	$20,000	20
3	2-3 weeks	$30,000	30
4	3-4 weeks	$40,000	40
5	1 month to 2 months	$50,000	50
6	2 month to 3 months	$60,000	60
7	3 month to 4 months	$70,000	70
8	4 month to 5 months	$80,000	80
9	5 month to 6 months	$90,000	90
10	> 6 months	$100,000	100

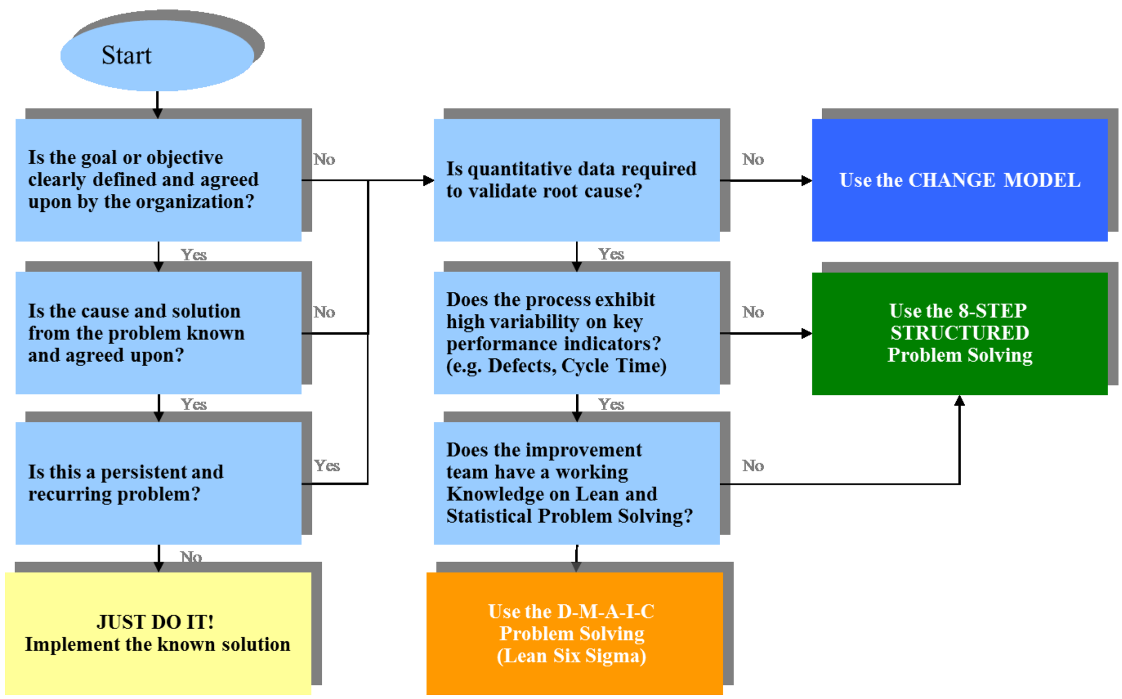


Figure 2: Identification of skills required for process improvement projects.

Table 4: Project types and associated Lean Six Sigma skills.

Project Type	Belt	Pay Rate/Hour	Code
Just Do It	Yellow Belt	$50	1
8-Step Structured Problem Solving	Green Belt	$100	10
Lean Six Sigma	Black Belt	$150	100
Change Model	Master Black Belt	$200	1000

2.2 Simulation Model

In order to test the impact of some projects on the system performance, simulation methods such as System Dynamics (SD) and Discrete Event (DE) can be utilized. System dynamics is used to understand the nonlinear behavior of the system over time. Continuous improvement projects can be considered complex dynamic systems because they involve multiple feedback processes as well as nonlinear relationships. SD is a modeling technique that consists of a stock and flow diagram (SFD). The SFD is a casual loop that maps both the variables of the system and the casual influence of these variables. SFD is based on a set of equations that describe the various casual relationships. DES can also be used to study the behavior of complex systems. Unlike SD, DES is based on events that create changes in the system's state at a specific point in time. DES is considered an important tool for process improvement initiatives and can be used to support the implementation of improvement solutions.

3 CASE STUDY

To test and validate the proposed framework, a case study for process improvement project selection in a high-end server manufacturing is considered. The company has a long process improvement journey that has started about ten year ago. During this period, many process improvement projects were implemented which saved the company millions of dollars. The high-end server manufacturing environment is characterized by aggressive introduction cycles of new products (i.e., every two years), extreme demand skews, significant engineering changes, and high inventory holding cost. The manufacturing processes include fabrication assembly, fabrication test, dekitting and storage, fulfillment assembly and test, and packaging. An overview of the hybrid manufacturing system architecture is illustrated in Figure 3. The manufacturing environment is based on configure-to-order processes which is a combination of build-to-plan and make-to-order processes. This is also known as a fabrication-fulfillment strategy to respond to customer orders rapidly and minimize inventory holding costs. In the fabrication process, components or subassemblies are produced, tested, and assembled based on a projected production plan and are kept in stock until an actual order is received from a customer. In the fulfillment process, final products are assembled according to actual customer orders, such that no finished good inventory is kept.

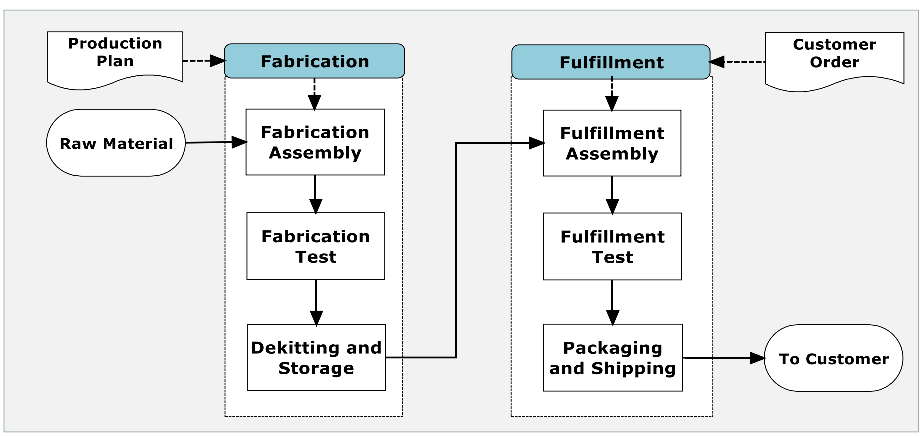


Figure 3: Illustration of server assembly process (Aqlan et al. 2014).

According to Cao et al. (2003), the fabrication-fulfillment model provides the company with the flexibility of mass customization and the speed and efficiency of mass production. However, the randomness (i.e., random yields, system configuration, stochastic lead times, etc.) inherent to this model makes the inventory management and production planning a challenging problem, considering high inventory holding and missing opportunity costs. To deal with the uncertainty in customer demand, some of the key strategies that are implemented are as follows: i) inventory sharing between different plants when there is a shortage of parts and components; ii) localized warehouse for suppliers at manufacturing sites; iii) flexible production planning for internal orders; iv) order fulfillment dashboard; and v) information technology. Ten potential process improvement projects were identified as indicated in Table 5.

Table 5: Process improvement project and their description.

Project	Process Improvement Initiative	Description of the Initiative	Problem Solving Methodology
Project 1	Capacity Planning (Simulation)	Due to the high new product introduction cycles (almost every two years), first pass yield (FPY) and process time (PT) are updated. This process improvement initiative focuses on applying Lean Six Sigma techniques and simulation modeling to identify the optimal numbers of test cells based on the new parameters. The objective is to maximize the test cell utilization.	Lean Six Sigma (DMAIC)
Project 2	Standard Work for Assembly	The process improvement initiative focuses on reducing cycle time and defects in the final product assembly with the application of standard work.	Lean 8-Step Problem Solving
Project 3	Optimal Batch size for Test	Process improvement initiative focuses on using simulation and Lean Six Sigma techniques to study the component test process in order to identify the optimal batch size of components to be tested.	Lean Six Sigma (DMAIC)
Project 4	Process Improvement	This project aims to reduce contamination and defects in the inspection area and reduce the high levels of variation that have been observed in work practices.	Lean 8-Step Problem Solving
Project 5	Capacity Planning (Simulation)	This process improvement initiative focuses on applying Lean Six Sigma techniques and simulation modeling to identify the optimal numbers of test cells that maximize the test cell utilization.	Lean Six Sigma (DMAIC)
Project 6	Component Test Allocation	The objective of this project is to implement a standardized transition process to decrease cycle times and circles of motion. Reduce non-value add circles of motion and wait times by 20%.	Lean 8-Step Problem Solving
Project 7	Practice vs. Procedure Audit	Practice versus Procedure audit (PP) project aims to create and implement standardized process to conduct, respond and execute PP Audits with Manufacturing Teams.	Lean 8-Step Problem Solving
Project 8	Process Improvement	Current process contribute to increased inventory, excess circles of motion, cycle time, and defects. The process initiative focuses on creating a new functional configuration of the components that utilizes the least amount of parts necessary and a standard start-up test process.	Lean 8-Step Problem Solving
Project 9	Product Disassembly Standard Work	The objective of this project is to standardize the product disassembly work and decrease waiting time.	Lean 8-Step Problem Solving
Project 10	Standard Work Project	This project focuses on standardizing the component assembly and test processes as well as identify improvement opportunities to reduce cycle time and improve quality.	Lean Six Sigma (DMAIC)

Table 6 shows the collected data for the ten projects. The input data for the optimization mode is as follows: N = 10 (see Table 6), N^{mx} = 2 (projects 1 and 5), N^{mp} = 2 (projects 2 and 7), B = \$150,000, O = 750 days, and M = 2 Green Belts, 1 Black Belt, 1 Master Black Belt. The rest of the input data is shown in Tables 6 and 7.

Table 6: Collected data for the projects.

Project	o_i (days)	S_i (minimum skills)	b_i (dollars)	δ_i	σ_i
Project 1	190	1000	60,000	10	87
Project 2	85	10	10,000	6	37
Project 3	155	100	30,000	8	58
Project 4	60	10	5,000	5	40
Project 5	90	1000	50,000	9	57
Project 6	190	10	8,000	4	50
Project 7	55	10	6,000	4	23
Project 8	100	10	15,000	5	37
Project 9	120	10	3,000	3	23
Project 10	180	10	10,000	7	60
Total	1225		197,000		

Table 7: Collected data for the operators.

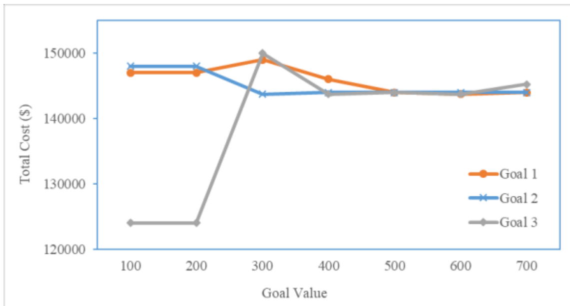
Operator	S'_k (Skills)	c_k (\$/hr)	o_k (hours)
Operator 1	Green Belt	\$100	200
Operator 2	Green Belt	\$100	200
Operator 3	Black Belt	\$150	150
Operator 5	Master Black Belt	\$200	200

3.1 Solution Approach for Optimization Model

The optimization model is formulated and solved using goal programming which is a multi-objective optimization that replaces the multiple objectives with a single objective where deviation variables are used to represent the objectives. Three deviation variables (d_1, d_2, and d_3) are used to represent the three objectives. The goal programming model is shown below.

$$Min\ Z = (d_1^+ + d_1^-) + (d_2^+ + d_2^-) + (d_3^+ + d_3^-)$$
$$s.t.$$
$$\sum_{i=1}^{N} \pi_i X_i + +(d_1^- - d_1^+) = g_1$$
$$\sum_{i=1}^{N} \sigma_i X_i + (d_2^- - d_2^+) = g_2$$
$$\sum_{i=1}^{N} \lambda_i X_i + (d_3^- - d_3^+) = g_3$$
Constraints 1-8
$$d_1^+, d_1^-, d_2^+, d_2^-, d_3^+, d_3^- \geq 0$$

where g_1, g_2, and g_3 are the goal values for the three objectives, respectively. The model was solved in CPLEX (version 12.7). Sensitivity analysis on the goal values was conducted. Figure 4 shows the sensitivity analysis for both total project cost and time.



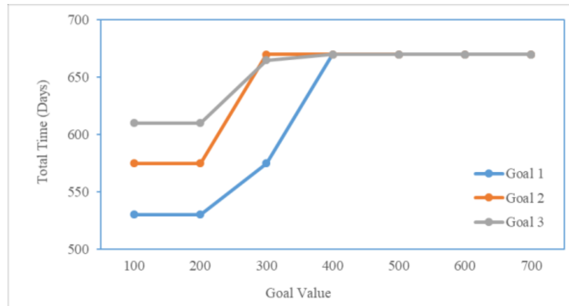


Figure 4: Sensitivity analysis of total project cost (left) and time (right).

Figure 6 shows the sensitivity analysis of the total budget allocated for the process improvement projects. It is noted that the total project cost increases with increasing the allocated budget. This is because more projects (or projects with higher costs) will be selected when we increase the allocated budget. The optimal selection of process improvement projects and the allocation of available operators to the selected projects are shown in Figure 5 and Table 8, respectively.

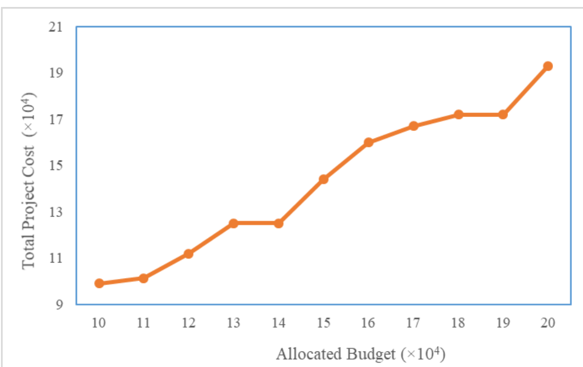


Figure 5. Sensitivity analysis of allocated budged.

Table 8: Operator allocation results.

Project	Decision	Operator
Project 1	No	-
Project 2	Yes	Operator 3
Project 3	No	-
Project 4	Yes	Operator 3
Project 5	Yes	Operator 4
Project 6	No	-
Project 7	Yes	Operator 2
Project 8	Yes	Operator 4
Project 9	Yes	Operator 2
Project 10	Yes	Operator 1

3.2 Simulation of Selected Projects

In order to test the selected projects, a DES model was developed. In this Section, we discuss the simulation developed to test project 5 in which simulation is used for capacity planning in the high-end server manufacturing environment. The project focuses on determining the number of test cells for two main product types. High-end server manufacturing is characterized by the high introduction cycles of new products, almost every two years. Capacity planning should be performed each time a new product is introduced to determine the optimal number of workstations based on the parameters of the new product.
The main product of focus in this study is the main processing unit, also known as book or node, used in the high-end server. There are two main fabrication test processes for the nodes, Fab 1 and Fab 2. Furthermore, the nodes also get inspected in the different stages of the server assembly and are then tested again (while assembled with all the other sever components) in the fulfillment process. A high-level process flow of the server node assembly and test processes is shown in Figure 6. The simulation model was developed using Arena software. The main characteristics of the model are shown in Table 9. Table 10 shows sample statistical distributions for the simulation inputs.

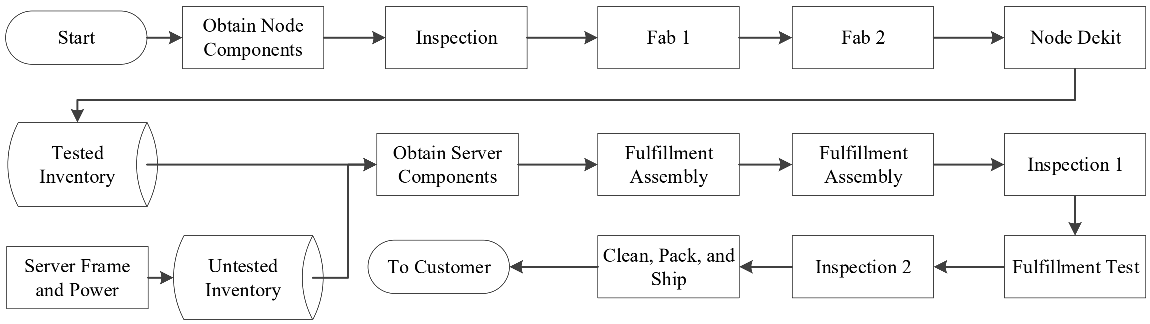


Figure 6: High level process flow of server node assembly and test.

Table 9: Simulation model characteristics.

Item	Entities	Resources	Inputs	Output	Replications	Rep. Length
Description	Servers, Nodes	Assembly Stations, Test stations	Arrival rates, Cycle times, Failure rates, Repair times	Throughput, Work-in-process, utilization	30	90 days

Table 10: Input data for the simulation model.

Simulation Input	Distribution	Data Source
Boards for Product 1	Time between arrivals (days): DISC(0.66,1,.952,2,.976,6,1,10) Entities per arrival: TRIA (1,3,28)	Historical Data
Boards for Product 2	Time between arrivals (days): EXPO(1) Entities per arrival: 0.999+61*BETA(0.915,1.47)	Historical Data
Failure Analysis for Rework	Time between arrivals (days): EXPO(1) Entities per arrival: 1	Historical Data and Time Study
Fab Inspection Time	TRIA(10.1, 11.4, 12.0) minutes	Time Study
Fab Test Time	TRIA(3.01,3.45,3.74) days	Experts
Node Assembly	TRIA(10.02,11.12,12.21) hours	Experts
Dekitting Time	TRIA(15.3, 17.4, 19) minutes	Time Study
Repair Time (Fabrication)	0.25* TRIA(3.01,3.45,3.74) days	Experts
Fulfilment Assembly Time	0.52 + WEIB(1.63,3.84) days	Historical Data
Fulfilment Test Time	1.41 + 1.18 * BETA(1.5,1.76) days	Historical Data
Fulfilment Inspection Time	TRIA (50, 60, 70) minutes	Experts
Fulfillment Repair Time	0.25*[1.41 + 1.18 * BETA(1.5,1.76)] days	Time Study
Clean, Pack, and Ship	TRIA(0.5, 0.65, 1) days	Historical Data

The following assumptions were made during the development of the simulation model: 1) historical data of closest products was projected to be used for the new introduced products, 2) required number of test cells is based on maintaining 55-70% utilization, 3) for the nodes that fail in the test cells, only 5% can be fixed in place and 95% have to be return to node assembly area, 4) the following process parameters for the new products were provided by the Industrial Engineering department:

- Fab 1: 11 test cells are needed for product 1 and 19 test cells are needed for product 2
- Fab 1: expected yield for product 1 is 61.8% and for product 2 is 73.5%
- Fab 2: 17 test cells are needed for product 1 and 20 test cells are needed for product 2
- Fab 2: expected yield for product 1 is 73.7% and for product 2 is 71.1%

The simulation model is a terminating simulation. The model was verified and validated by comparing the simulation results to the data sets collected for the real system. Table 11 shows the validation results for the baseline simulation model. Other performance measures such as cycle time and fab test time were also obtained and validated by the experts.

Table 11: Validating baseline simulation model.

Product Type	Simulation Result	95% C.I. Half Width	Historical Value	% Difference	P-value
Product 1	1302	58.8	1271	-2.4%	0.21
Product 2	768.3	44.08	803	4.3%	0.29

To perform scenario analysis and study the capacity planning for the new products, the simulation model was adjusted to account for the expected new parameters. Table 12 shows the comparison of the expected fab volumes and the simulation results. Table 13 shows the simulation results for capacity planning of the new products. Scenario analysis was also conducted on the capacity of the test cells. Table 14 shows the scenario analysis for product 1.

Table 12: Expected fab volumes for the two products.

Product Type	Simulation Result	Expected Value	% Difference	P-value
Product 1	861	842	-2.3%	0.17
Product 2	1437	1422	-1.1%	0.48

Table 13: Simulation results for capacity planning.

Product	Fab Test Process	Capacity	Utilization	Yield	Cycle Time (hours)
Product 1	Fab 1	11	59.3%	75%	28
	Fab 2	7	63.1%	82%	26
Product 2	Fab 1	14	60.6%	85%	41
	Fab 2	26	60.6%	85%	88

Table 14: Scenario analysis for fab test of product 1.

Scenario	Fab 1 Test Cells	Fab 2 Test Cells	Fab 1 Utilization	Fab 2 Utilization	Throughput
S1	9	7	72.1%	63.8%	846
S2	10	7	63.7%	61.7%	826
S3	11	7	59.3%	63.1%	842
S4	11	6	59.5%	73.6%	839

4 CONCLUSIONS

In this paper, we presented a proposed simulation-optimization framework for selecting and evaluating process improvement projects as well as allocating operators to the selected projects. The proposed approach takes into consideration resource availability and time and cost constraints as well as the required skills. The case study was used to validate the proposed approach and provide valuable insights into the decision making process. For some selected projects, simulation was used to test different scenarios and identify the capacity requirements for new products.

Future work will focus on enhancement of the optimization model by considering the interaction among the different process improvement projects and the resource sharing for these projects. Moreover, system dynamics models will be developed by study the dynamic behaviors and the nonlinear relationships among system parameters.

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