

MODELING AND SIMULATION FOR QUALITY MANAGEMENT IN MANUFACTURING PROCESSES

K. U. S. Somarathna¹, L.K.I Rajapaksha², and K. Y. J. Somarathna³

¹*Department of Textile & Clothing Technology, University of Moratuwa,
Sri Lanka.*

^{2,3}*Department of Management, Auckland University of Technology, New
Zealand.*

*Emails: ¹udaras@uom.lk; ² isuru.rajapaksha@aut.ac.nz;
³yeshika.somarathna@aut.ac.nz*

ABSTRACT

Quality management in manufacturing processes is crucial to improve organizational performance. In order to improve product quality of manufacturing processes, new quality strategies have to be implemented and manufacturing processes have to be re-engineered. The effectiveness of such strategies and process modifications must be evaluated prior to implementation. However, experimentation with the real manufacturing system is constrained as quality and manufacturing related parameters such as fraction defective, inspection strategies, and machine failures cannot be systematically changed in a real manufacturing context. Therefore, modeling and simulation is widely used in operations management to analyze manufacturing and business processes. Though simulation of manufacturing systems is well studied in literature, simulation models that focus on apparel manufacturing and specific aspects of quality management are limited. Therefore, the objectives of this paper are to review the existing simulation models of quality management, identify their limitations and propose areas of study for further research, and demonstrate the simulation of a one-piece-flow apparel manufacturing module. A discrete event simulation technique was adopted in the simulation model, and the effects of fraction defective

and machine failures on throughput, work-in-progress, and cost per unit were evaluated.

Key Words: Quality Management, Simulation and Modeling, Apparel Manufacturing, Simio

1 Introduction

Modeling and simulation is a widely used technique in operations management, where its applications are found in diverse fields including manufacturing, services, healthcare, defense, and public service (Jahangirian, Eldabi, Naseer, Stergioulas, & Young, 2010). Modeling and simulation is the process of developing an abstract model of a real-world system and imitating it over time (Banks, Carson II, Nelson, & Nicol, 2010; Laguna & Marklund, 2013). The real-world system is represented as a network of entities and underlying relationships, where the system is simulated over time so that its behaviors and evolution can be studied. Simulation is particularly a useful technique when the real system being studied is too complex to be analyzed by analytical methods due to the stochastic and dynamic nature of the system (Banks et al., 2010; Laguna & Marklund, 2013). However, the oversimplification of the real system during the modeling process could limit the validity of the insights provided by the simulation model.

Discrete Event Simulation (DES), System Dynamics (SD), and Agent-based Modeling (ABM) techniques have been used by previous authors for manufacturing-related simulation. In DES, the state variables of the system change at discrete points. SD technique utilizes a network of integrated feedback loops to model the causal structure of a system. In ABM, the real-world system is represented as a collection of autonomous agents who interact based on a set of underlying rules.

Simulation plays a key role in the analysis and improvement of manufacturing processes (McLean & Leong, 2001). The quality management process in manufacturing is a complex system. It primarily encompasses materials, machines, people, and procedures. Due to stochastic and dynamic events such as material defects, machine breakdowns, operator inefficiency, and external disturbances, the quality management process may exhibit emergent behaviors. The complex relationships and interdependencies among the system entities make it difficult for the human mind to analyze the interactions

of the system and visualize the outcomes (Somarathna, 2020). Accordingly, it is difficult to easily determine the influence of a quality strategy on quality outcomes (Ruyter, Cardew-Hall, & Hodgson, 2002). Therefore, a tool that can determine the manufacturing and financial performance of a strategy prior to its implementation is required. Thus, modeling the quality management process as a complex system and simulating its interactions can provide useful insights for managerial decision making. However, most of the current research focuses on the application of simulation techniques to optimize the productivity-related aspects of apparel manufacturing systems such as production efficiency and line balancing (Kim & Kim, 2020; Pan, 2014; Rotab Khan, 1999; Sime et al., 2019; Ünal et al., 2009). The impact of man, machine, and materials on quality management aspects has received less attention.

The objectives of this paper are to review the existing simulation models of quality management, identify their limitations and propose areas of study for further research, and demonstrate the simulation of a one-piece-flow apparel manufacturing module.

2 Literature Review

Traditionally, the quality performance of a process was reported based on historical data (Ruyter et al., 2002). This approach is not effective in evaluating quality procedures prior to implementation. Also, experimenting with the real system to understand the influence of quality strategies is not feasible. For example, the impact of fraction defective on manufacturing performance measures cannot be studied on a real system by varying the fraction defectives. Therefore, simulation models were adopted. Primarily, simulation models have been used to model the cost of quality, inspection strategies, statistical process control, and manufacturing disruptions due to quality problems.

The Prevention-Appraisal-Failure (PAF) model was the basis for the simulation of cost of quality in most of the models, where the system dynamics simulation technique was adopted. Visawan & Tannock (2004) adopted the PAF model and incorporated the price-quality relationship in the market to study the economics of quality from a holistic point of view. They used real data of a case study to calculate simulation parameters based on linear regression. Kiani, Shirouyehzad,

Bafti, & Fouladgar (2009) developed a causal loop model based on the PAF model to study the cost of quality, where they reported that the prevention costs had the greatest impact on external failures and total cost of quality. Also, the difficulties in measuring non-conformance costs in a real manufacturing environment were highlighted. Burgess (1996) adopted a similar system dynamics approach and concluded that the classical view of the cost of quality, i.e. the existence of an optimum level of quality, could be justified in time-constrained situations. However, considering an infinite time frame, investment on prevention could be justified to reach zero defects. Alglawe, Schiffauerova, & Kuzgunkaya (2019) adopted a system dynamics approach to model the cost of a quality of a supply chain, where they incorporated the opportunity cost into the PAF model. They observed a significant impact of opportunity cost on new customers and production units in the supply chain, and hence, they stressed the significance of considering opportunity cost for quality management decision making.

Discrete event simulation models were also used to analyze manufacturing processes. Ruyter, et al. (2002) adopted a discrete simulation approach to model a manufacturing process that employs self-inspection quality control. They reported that inspection error could significantly influence the total cost of quality. Clark & Tannock (1999) adopted a similar discrete approach to model a cell-based manufacturing company and highlighted the value of simulation for analyzing quality costs. Freeman (2008) evaluated the effectiveness of micro and macro simulation approaches for quality cost simulation and he emphasized the power of computer simulation to support quality-related management decision making. Gardner, Grant, & Rolston (1995) used simulation to evaluate a manufacturing system, where they considered the effects of defect rate, inspection, and defect removal strategies. They demonstrated that simulation can be used to assess quality costs and thereby justify the investment in quality improvement efforts. Tannock & Saelem (2007) defined a new cost category called disruption costs and incorporated it into the PAF model in their simulation model. They found that the influence of the disruption cost category could be highly significant at higher non-conformance levels.

Tannock (1995) developed a simulation tool which can perform statistical process control related analysis, where process capability analysis, cost of quality, and loss function concepts were integrated. The application only supported the variable quality characteristics of the products. Also, the inspection strategies such as 100% inspection, no inspection, and single sampling scheme could be chosen during a simulation run.

3 Methodology

The simulation of a one-piece-flow apparel manufacturing module based on discrete event simulation technique is demonstrated in this study. A general-purpose simulation package, Simio, was used for the simulation. Three what-if scenarios were considered for simulation: a scenario with workstation-specific fraction defects, a scenario with workstation-specific machine failures, and a scenario with both fraction defective and machine failures. A statistical analysis of the simulation output performance measures was performed, considering 50 independent simulation runs.

4 Results and Discussion

4.1 Simulation Model for an Apparel Manufacturing Module

The model of an apparel manufacturing module was implemented and simulated with what-if scenarios to understand the impact on production and financial measures. The simulation model, which was implemented in Simio, is illustrated in Figure 1.

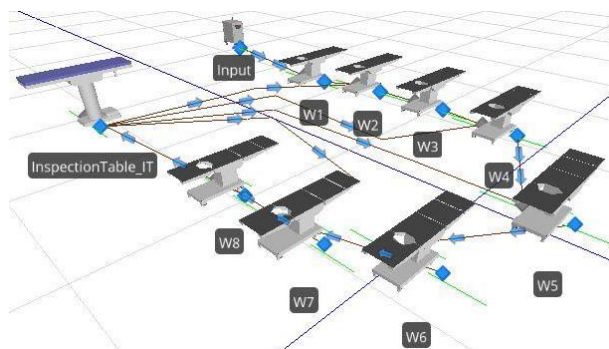


Figure 1. The illustration of the simulation model in Simio.

The model represents an apparel manufacturing module of fixed worker layout, which consists of eight workstations and one inspection table. The material flow is configured as one-piece-flow, where each processed piece is passed onto the subsequent operator without

making a bundle of semi-finished pieces. The module produces identical products. At the inspection table, all completed garments are inspected. If defective products are found, those are returned to the corresponding workstations. It is assumed that there is no inspection error of the operator at the inspection table. The line is perfectly balanced so that the inefficiencies of line balancing are not confounded with the parameters of our interest: fraction defectives and machine unavailability.

In order to incorporate the stochasticity of the real manufacturing context, the input parameters for simulation are sampled from probability distributions. For example, the time taken to complete a job (stitching/inspecting a piece, repair/set up a machine, etc) is assumed to have a triangular distribution. Similarly, the time between machine failures (due to machine breakdown, regular operator-based maintenance such as thread change) is assumed to be exponentially distributed. According to the corresponding fraction defective, the defects occur randomly based on a uniform distribution. Based on the literature, these distribution assumptions are reasonable when real data is not available (for example in case of a start-up company) (Law, 2015). Since our objective is simply to demonstrate the application of modeling and simulation approach to an apparel manufacturing context, we rely on arbitrary values in the current study. However, if real data is available these parameters can also be estimated. In addition, as pieces are processed through each workstation, a cost of processing is attached so that the total value addition for each completed garment can be traced. The simulation parameters used in the current study are shown in Table 1.

Table 1. Simulation parameters

Simulation parameter	Value		
	Scenario 1	Scenario 2	Scenario 3
Time taken to process a piece (W1 - IT) (minutes)	Triangular (0.8,1,1.2)	Triangular (0.8,1,1.2)	Triangular (0.8,1,1.2)
Fraction defective (W2, W4, W5, W7)	1.5%	0%	1.5%
Fraction defective (W1, W3, W6, W8, IT)	0%	0%	0%
Defect occurrences	Uniform (0-1)	Not applicable	Uniform (0-1)

Time between machine failures (minutes)	No failures	Exponential (30)	Exponential (30)
Machine repair/setup time (minutes)	Not applicable	Triangular (2,2.5,3)	Triangular (2,2.5,3)

Source: Author developed

The simulation runs were performed as terminating simulations considering an 8-hour production shift. Three output performance measures were monitored: total throughput (TTPT), total cost per unit (TCPU), average work-in-progress (AWiP). The output data of 50 independent simulation runs were considered for the statistical analysis shown in Table 2.

Table 2. Simulation output analysis

Scenari o	TTPT		AWiP		TCPU (\$)	
	Avg	SD	Avg	SD	Avg	SD
1	422.22	5.78	33.91	3.60	6.77	0.09
2	398.12	6.84	50.34	4.43	6.75	0.09
3	381.16	8.06	58.23	4.69	7.09	0.13

Source: Author developed

An increase in defective products leads to an increase in TCPU because of the additional rework cost. However, the magnitude of the cost increase depends on the fraction defective. Therefore, in scenarios 1 and 3 the TCPU is slightly higher compared to scenario 2, which has zero defects. It seems that the machine failures have a greater influence on TTPT than the fraction defective. The total throughput has been reduced in scenario 3 due to the cumulative effect of defects and machine failures. However, this cumulative effect is not observed with regard to AWiP because the accumulation of WiP in subsequent workstations is compensated by the machine downtime of preceding workstations.

Since each manufacturing system has its unique characteristics, it should be noted that these results are only applicable to the current model and hence cannot be generalized.

4.2 Potential Areas for New Research in Quality Simulation

Based on the review of the existing quality model, several areas for further research have been identified. In most of the studies, a fixed fraction defective is assumed during a simulation run. However, in reality, the fraction defective can vary during a manufacturing shift due to product variations, operator fatigue, and assignable causes of variation. Therefore, a time-dependent rate may be incorporated. The holistic view of the quality system can be considered instead of simulating discrete processes to understand the behaviors of the system as a whole. In such a study, for example, the competing objectives of production and quality departments can be integrated to see the impact on production, quality, and financial indicators so that any existing trade-offs can be identified. Further, more complex multi-product and multi-defect scenarios can be simulated rather than being constrained to much simpler single product and single defect systems.

5 Conclusions

The existing simulation models that attempt to simulate quality management aspects of manufacturing processes were reviewed and potential research areas were identified such as using time-dependent fraction defects, adopting a holistic approach, and considering multi-product and multi-defect scenarios. Also, a one-piece-flow manufacturing module of an apparel manufacturing plant was modeled and simulated. The simulation results of the current model showed that the machine failures had a greater influence on the TTPT. Also, fraction defective and machine failures had a cumulative effect on TTPT, while they showed a neutralizing effect on AWiP.

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