AN AGENT-BASED MODEL FOR SUPPLIER SELECTION IN DIGITAL MANUFACTURING MARKET

by

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A thesis submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Master of Science in Technology
with a Major in Industrial Technology
December 2014

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DEDICATION

To my husband, my parents and everyone who helped my wishes come true

ACKNOWLEDGEMENTS

I would like to thank Dr. Ameri for what I have learned from him. I feel very fortunate to have someone like him as my thesis mentor.

I would like to express my appreciation to Dr. Jimenez for the helpful directions and comments and to Dr. Srirman for teaching me the basics of research.

I would like to say my special thank you to my family whom I have not seen them for four years, but their support always helps me to concentrate more on my work.

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ABSTRACT

Manufacturing supply chain is increasingly becoming agile to keep up with the rapid changes in the market. Agility should be imparted to all aspect of supply chain operation including the formation of supply chain. Ability to assess and select new suppliers quickly is a necessity for rapid formation of supply chains. The Digital Manufacturing Market (DMM) is a virtual market for trading manufacturing services in which buyers and sellers are represented by intelligent software agents. The DMM enables rapid and autonomous deployment of service-oriented supply chains from a pool of suppliers that are distributed geographically. Customer agents in DMM can employ different strategies for selecting the qualified suppliers who possess the required capabilities and capacities. The objective of this research is to compare different decision-making scenarios that customer agents may follow for selecting appropriate suppliers. The metrics used for evaluating different supplier selection scenarios include overall customer wait time and utilization rate of the suppliers in the system. In this work, the agent-based model of DMM is implemented in *AnyLogic* simulation software in small and large scale. The results show that by having Dynamic Capacity (DC) in the large-scale market, customers find their desired services with less average time while the suppliers are not overloaded.

CHAPTER I

INTRODUCTION

Background

Product lifecycle is increasingly shrinking in most markets and companies are striving to become more responsive to market changes. Manufacturing supply chains are increasingly becoming virtual and agile to meet the need for rapid and cost-effective product development in today's volatile economy. An agile supply chain can be defined as a network of suppliers that pool their resources to meet short-term objectives and exploit fast-changing market trends (Gunasekaran et al., 2008).The agile supply chain minimizes the excess capacity and capabilities by dynamically adjusting its resources based on the actual requirements of the work orders. The loosely coupled nature of the agile supply chain allows for dynamic addition or removal of the participants as needed. In addition, agile supply chains are short-lived and typically dissolve once the order is fulfilled. Deployment of an agile supply chain is challenging for several reasons. First, operational capabilities are not readily possible because of the virtual relationship between the actors, accurate evaluation of the potential partners in terms of technological. Second, a lack of standard models for formal representation of engineering information; particularly capability information is a hurdle to efficient exchange of information among the participants in the early stages of supply chain formation. Third, human agents cannot efficiently manage the search and evaluation process, because of the large size of supply and demand pools.

For these three reasons, therefore, it is necessary to support the deployment process with the necessary computational tools and information models that enable automated supply chain configuration and customization with high precision in a short period of time. One promising solution for addressing the aforementioned challenges is incorporation of agent technology. A supply chain is a natural application domain for an agent-based framework as a supply chain can be considered as a network of autonomous, distributed, and self-contained business units aiming at the procurement, manufacturing, and distribution of goods. Agent-based systems, due to their automation capabilities, can accommodate the computational complexities of the supply chain deployment problem more efficiently. Previously, the Digital Manufacturing Market (DMM) (Ameri & Patil, 2012) was introduced as an agent-based marketplace that provides the participants, including buyers and sellers of manufacturing services, with advanced computational support for search, evaluation, communication, and negotiation in order to build agile supply chains. Also, a standard information model is used in DMM to facilitate inter-agent communication. The objective of this work is to supplement the DMM research through designing and implementing the agent-based model of DMM *AnyLogic* simulation software in order to study the behavior of the market. The next section provides background information about the DMM and its associated information model.

Digital Manufacturing Market

The Digital Manufacturing Market (DMM) is a virtual market for trading manufacturing services in which buyers and sellers are represented through intelligent software agents. The general view of DMM is shown in Figure1. As can be seen in Figure 1, there exist three main types of agents in the DMM, namely, supplier agent, customer (or work order) agent, and middle (or search) agent. Supplier agents represent the suppliers of manufacturing services and describe the manufacturing capabilities of the supplier they represent. Similarly, customer agents represent the buyers of manufacturing services and describe the manufacturing needs of different work orders owned by the customer they represent. Middle agents are tasked with mediating between supply and demand and ultimately, connecting supplier and customer agents based on their semantic similarities. The standard ontology language of the DMM is called Manufacturing Service Description Language (MSDL) (Ameri& Dutta, 2007). MSDL is an OWL-based ontology with explicit semantics that provides the vocabulary for formal representation of manufacturing services. The content of MSDL is machine-understandable, thus enabling seamless and unambiguous information exchange among machine agents. Several semantic similarity measurement heuristics were developed to quantify the semantics similarities between requested and provided services in the DMM. The similarity score is calculated primarily based on the technological capabilities of suppliers. In the DMM, multiple middle agents can participate with different search logics and similarity measurement.

The term supplier score throughout this paper refers to the semantic proximity of a supplier to a given work order calculated by the middle agent. The DMM framework is particularly suitable for work orders pertaining to short-run production of metallic parts with medium complexity that require machining, assembly and surface treating services.

Beauchamp (Beauchamp, B.S., 2013) developed an optimization model based on Integer Programming with the goal of improving the performance of the DMM. Beauchamp created an integer programming formulation to efficiently and effectively solve the supply chain configuration problem by maximizing the technological competencies of the assigned suppliers, while meeting capacity and distance constraints.

To solve the issue of limited scalability of traditional LP formation, the column generation approach is adopted in his work. In this work, a simulated model of the DMM will be developed to analyze the performance of the market under different scenarios.

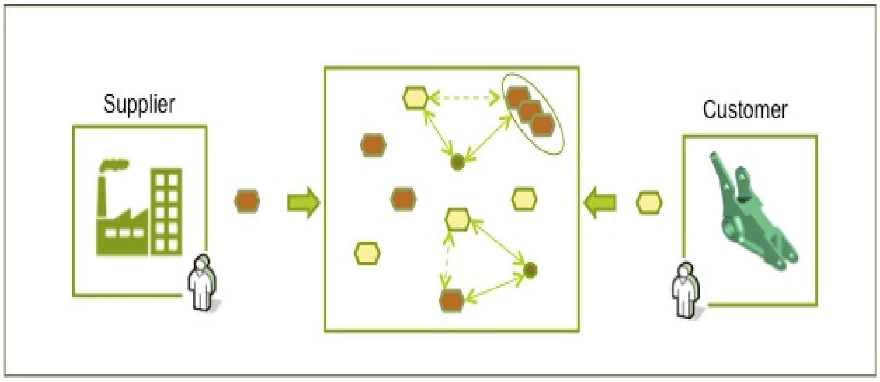

Figure 1. The General Architecture of DMM.

Problem Statement

It is necessary to assess the DMM with respect to multiple performance metrics. Also, the scalability of the system needs to be studied as more suppliers and customers are added to the system. For this purpose, there is a need for developing a simulated model of DMM that can be used for performance analysis. The **objective** of this research is to simulate an agent-based environment for supply chain configuration. The agent-based model of DMM is simulated and implemented in *AnyLogic.*

This research is particularly focused on evaluating different decision-making scenarios that customer agents may follow for selecting appropriate suppliers. The research aim is to study the performance of DMM with respect to **service allocation** efficiency. The metrics used for evaluating different supplier selection scenarios include overall customer wait time, match ratio, and utilization rate of the suppliers in the system.

Assumptions, Limitation, and Delimitations

The Assumptions of this research are:

- Run time for this simulation is 24 hours.
- Each customer agent represents one Work Order (WO).
- Service Time (ST_{ij}) varies depending on service type.
- Cost and geographical location are not considered.
- Order of service allocation does not matter.
- Each customer agent has a predefined Minimum Acceptable Score (MAS_k).

The limitation in this work relates to the number of suppliers because the graphical representation of this version of software does not support more suppliers. One of the delimitations in this work is related to not creating a supplier agent. It is assumed that the supplier agent is passive. Another delimitation concerns the number of services per work order. It is assumed that customer agent asks up to five services per work order.

Research Approach

In this work, **simulation** and **statistical hypothesis testing** are used for comparing models, the agent-based model of DMM is implemented in *AnyLogic7* simulation software. The metrics used for evaluating different supplier selection scenarios include overall customer wait time, match ratio, and utilization rate of the suppliers in the system. The *state chart* is used for implementing the agent-based model. Each block in the state chart represents a state of the system and the entry actions and exit actions can be defined programmatically for each state. The simulated model is generated in three steps. 1) Model A: Fixed Capacity-One service per work (toy problem) 2) Model

B: Fixed Capacity-Up to 5 services per work order3) Model C: Dynamic Capacity (DC)-Up to 5 services per work order. Agent-based modeling simulation is used into 3 main steps as shown in Table 1.

Table 1. Agent-based Modeling Simulation Approach.

Phases of an ABM study	Steps of agent-based modeling	
Model A: Fixed Capacity-One service per work(toy problem)	1	Outline the assumptions of the proposed simulation. Define the model variables and assumptions
		Implementation of toy problem.
		Analysis of Model A.
Model B: Fixed Capacity-Up to 5 services per work order	2	Outline the assumptions of the proposed simulation. Define the model variables and assumptions.
		Implementation of Model B.
		Analysis of Model B.
Model C: Dynamic Capacity (DC)-Up to 5 services per work order.	3	Outline the assumptions of the proposed simulation. Define the model variables and assumptions.
		Implementation of Model C.

Organization of Thesis

The rest of the thesis is organized as follows. Chapter II, “literature Review,” provides an overview of the existing work in the general areas of agent-based systems in supply chain management and also order allocation and supplier selection.

In Chapter III, “Modeling and Simulation,” the proposed model and its implementation are discussed.

Chapter IV, “Conclusions and Future Works,” presents the conclusions of the research and suggests directions for future research.

CHAPTER II

LITERATURE REVIEW

This chapter is intended to provide a critical literature review on supply chain performance measurement and approaches. The purpose of this research is to identify qualified simulation agent-based systems and to develop functional models to solve the agile supply chain deployment problems.

In this literature study, the focus is on two areas: 1) Supplier selection and order allocation 2) Agent-based Modeling Technology for Supply Chain in supply chain management.

Supplier Selection & Order Allocation

This thesis is classified under the general category of supplier selection and order allocation problems with underlying technical problem. Supplier selection problem usually is very complicated, because variety of uncontrollable and unpredictable factors affects the evaluation and the decision-making process. Various decision-making approaches have been proposed to tackle the problem, particularly the multi-criteria analysis approaches which use both quantitative and qualitative data.

Some examples of these methodologies include Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Case-Based Reasoning (CBR), Genetic Algorithms (GA), SMART theory (Simple Multi-Attribute Rating Technique), Data Envelopment Analysis (DEA), and Interpretive Structural Modeling (ISM). For example, ISM is a methodology to identify, rank and find out the interaction among the criteria and sub-criteria which is used to select the supplier for supply chain formation.

There are some research methods that propose using integrated multi-objective decision making approach such as, Analytic Network Process (ANP) and Mixed Integer Programming (MIP) for supplier selection. Ding et al. (2004) mentioned that the methodology for solving supplier problem is composed of three basic modules: a Genetic Algorithm (GA) optimizer, a Discrete-Event Simulator (DES) and a supply chain modeling framework. Moreover, Agent Based Modeling (ABM) is especially suitable for simulating the behavior of complex systems operating in dynamic environments. Ding et al (2004) showed that the GA optimizer continuously searches different supplier portfolio and related operation parameters. In this work, simulation models are automatically created through an object-oriented process. By using the proposed methodology, the supply chain planner is able to optimize the supplier portfolio taking uncertainties into consideration.

Furthermore, Zouggari et al. (2009) proposed a fuzzy multiple goal-programming (FMGP) model to help downstream companies to supply based on knowledge acquisition.

Agent-based Modeling Technology for Supply Chain

Agent-based models have been used since the mid-1990s in various applications which include modeling of organizational behavior and cognition, team working, supply chain optimization in logistics, modeling of consumer behavior, and including word of mouth, social network effects, distributed computing (Crowder et al,.2012). Agent-based modeling is especially suitable for simulating the behavior of complex systems operating in dynamic environments. Agent-based technology has been adopted for solving the problems related to supply chain management as they can capture the realistic characteristics of supply chains and help supply chain modelers analyze the behavior of the system under different circumstances. The first implementation of agent-based technology for supply chain management dates back to the early 1990s when Fox et al. (1993) introduced the Integrated Supply Chain Management System (ISCM) for real-time control and coordination of supply chain functions. Wang et al. (2009) proposed an agent-mediated coordination approach. In this work, agents are involved in various decision making activities at strategic, tactical, and operational levels.

Hyun et al. (2010) used a negotiation-based approach for allocating work orders to participants for supply chain formation. Their model provided a pareto optimal solution. Akanle and Zhang (2008) proposed a methodology which shows that with increasing the importance of supply chain operations on manufacturing successes, an optimum configure their supply chains to meet customer demands with minimum cost. Agents within the supply chain interact with one another, under the coordination of an iterative bidding mechanism, to identify the optimum resource combination to meet the specified needs.

Easwaran and Pitt (2002) used an agent-based model for efficient allocation of services to form a supply chain. Monteiro et al. (2007) used hierarchical architecture for the agent-based system to integrate individual planner, negotiator, and mediator agents with a decentralized control for imparting robustness and flexibility to the supply chain network.

Xialong et al. (2005) and Xue et al. (2005) proposed an agent-based framework for construction supply chain coordination based on multi-attribute negotiation and utility theory. The agents participating in this model include owner, designer, general contractor, sub-contractors, and supplier. In the decision models developed in this work, multiple factors such as cost, time, quality, safety, and environmental impacts are used. A prototype is developed using ZEUS software. Emerson and Piramuthu (2004) developed a framework, supported by machine learning techniques, for Automated Supply Chain Configuration (ASCC). In Emerson's model supply chain agents make decision based on the information received from the previous levels with respect to inventory levels and cost. Nowadays, new gaps are considered for making the agility of supply chain better which means considering dynamic architecture for supply chain to response quickly In other words, .agility in today's dynamic high-mix production environments is the ability to quickly and accurately evaluate new product/subcomponent designs and strategic business decisions (e.g., supplier selection decisions) with regard to capacity and material requirements across the supply chain. In this section, the proposed methods for supply chain creation in dynamic environments.

Kouvelis et al. (2002) showed how changes in supply and demand uncertainty affect the extent of outsourcing. They figured out that greater supply and greater demand have the expected effect on investments. In their multi-period model, the nature of adjustments in capacity is realized based on changes in demand or supply which follows from the comparative statistics of the single-period model.

In 2002, Young Hae and Sook Han considered capacity constraints for production-distribution planning in supply chain. Analytic models have been developed to solve the integrated production-distribution problems in supply chain management. They proposed a hybrid approach combining the analytic and simulation model. Operation time in the analytic model is considered a dynamic factor and adjusted by the results from an independently developed simulation model, which includes general production-distribution characteristics.

Tu and Lie (2012) showed the supply chain's positive development. By revealing the balance between the supplier's production capacity and order load which can facilitate the successful conclusion of orders. Moreover, it is a significant guarantee because it suggests the establishment of a stable and efficient supply chain network through properly adjusting the supplier's load level by the demanding party.

Sadeh et al. (2001) provided an overview of MASCOT (Multi-Agent Supply Chain Coordination Tool) a reconfigurable, multilevel, agent-based architecture for coordinated supply chain planning and scheduling aimed at supporting these functionalities. They attempted to dynamically take advantage of finite capacity considerations.

Recently, Dabbaghianamiri et al. (2014) implemented a new model of customer agent in the small-scale by using anylogic software for a virtual market, to compare different decision-making scenarios that customer agents may follow for selecting appropriate suppliers.

This literature review reveals that very few agent-based models have addressed the supply chain configuration problem in dynamic environments where the size of supply and demand pools constantly change and suppliers can be quickly replaced by more competent peers. This work focuses on supply chain configuration and order allocation problem and the objective is to evaluate various decision-making logics that customers' agents may follow in the Digital Manufacturing Market to rapidly find qualified suppliers.

Research Questions

- This research is motivated by the following questions:
- What is the impact of reducing the expectations of customers (minimum acceptable scores) on the performance of DMM?
- What is the impact of adjusting the capacity of the market based on the number of active customers in the market?
- What is the best strategy for minimizing customer wait time?
- What is the best strategy for improving the utilization of the suppliers in the market?

CHAPTER III

MODELING AND SIMULATION

This chapter provides a description of the simulation model together with its implementation. The described model is implemented in *AnyLogic 7*. The simulation model is developed in three steps: 1) Model A: Fixed Capacity-One service per work order (toy problem) 2) Model B: Fixed Capacity-Up to 5 services per work order 3) Model C: Dynamic Capacity (DC)-Up to 5 service per work order.

Three metrics are used for evaluating the performance of the market under different conditions:

- Average supplier utilization: The average of the available time (percentage) that suppliers are operating in each day.
- Average waiting time: The average waiting time is simply the averages of all the waiting time in system that a customer faces for finding suppliers.
- Number of matched customers: The number of customers which are matched to supplier capability (score and available time) in the market during market's operating time (24 hours).

Model A: Fixed Capacity – One service per work order

The main objective of this model is to compare different decision-making logics the customer agents may follow for assigning their services to suppliers (i.e., discounting vs. not discounting). Two types of agents are involved in the proposed agent model, namely, supplier Agent (SA) and Customer Agent (CA). CAs can own multiple Work Orders (WO) each requiring one manufacturing service such as machining, coating, or assembly. The main simplifying assumption in this model is that each CA conveys only one WO and each WO needs exactly one manufacturing service from the 3 possible types of services. Furthermore, it is assumed that the middle agent assigns a similarity score (a score between 0 and 1) to each supplier upon receiving a request from the customer agent. The similarity score measures the ability of a supplier in providing a particular service requested by a customer agent. More capable suppliers receive higher scores by the middle agent. For the sake of brevity, the middle agent is not included in the present agent model. Instead, a random function is used for generating random scores between 0 and 1 for suppliers.

Model Variables for Model A

- Supplier agent (SA_i): 10 instances (i=1 to 10).
- Customer agents (CA_k): 200 instances (k=1 to 200).
- ST_{ij}: Service time for the *jth* service if provided by the *ith* supplier.
- Score $_{ij}$: The score of the *ith* supplier with respect to service j.
- Ser-Count $_k$: number of services of the *kth* work order.
- F_{ij}=1 If supplier I provides service j otherwise F_{ij} = 0.
- MAS_k: Minimum Acceptable Score for the *kth* customer.
- AWT $_k$: Average Waiting Time for *kth* customer.

Assumptions for Model A

- Run time: 24 hours.
- Number of suppliers in the market is fixed.
- Each customer agent represents one Work Order (WO).

- Each work order may need up to three manufacturing services.
- Service Time (ST_{ij}) varies depending on service type.
- Order of service allocation does not matter.
- Each customer agent has a predefined Minimum Acceptable Score (MAS_k). For example, if MAS=0.75, then it only accepts the suppliers with the score of 0.75 or more. A random MAS value is assigned to each customer agent upon arrival.
- Service time can take the value of 1h, 2h, and 3h which is picked randomly for each supplier-service pair. For examples, casting service if provided by supplier 1 may take 2 hours but if the same service is provided by supplier 2 it may take 1 hour since supplier 2 perhaps uses more advanced casting technology.

Decision Logic for Model A

Any time a customer agent arrives, it contacts the available supplier agent one at a time. For each supplier, the customer agent first verifies if the supplier provides the needed services. For each provided service, a similarity score is randomly generated by the middle agent. The decision of the *kth* customer agent (CA_k) with respect to assigning the *jth* service to *ith* supplier is influenced by the following parameters:

- Score $_{ij}$: The score of the supplier i with respect to service j
- AT_i: The available time (capacity) of the supplier i (AT_i) for the rest of the day

The customer agent selects the *ith* supplier agent (SA_i) only if the supplier's score is more than or equal to the Minimum Acceptable Score and also its available time is sufficient for fulfilling the new order:

$$(Score_{ij} >= MAS_k) \textbf{ AND } (AT_i > ST_{ij}) \qquad (1)$$

In this model, the following scenarios are investigated:

- ***Scenario a***: If the customer agent cannot assign a service to any supplier in the first round after contacting all 10 suppliers, it repeats the service assignment cycle one more time. If the service is not matched to any supplier after the second round, then the service is considered to be unmatchable and the customer agent the customer exits from the market.
- ***Scenario b****:* If the customer agent cannot assign a service to any supplier in the first round, it discounts its Minimum Acceptable Score (MAS) for an arbitrary amount in order to find a qualified supplier. The MAS can be discounted up to 10 times. The lower threshold for the discounted score is .5. The MAS will be reset to the original value when moving on to the same service and customer.

Figure 2 shows the general service allocation procedure used in this agent-based model under the described scenarios.

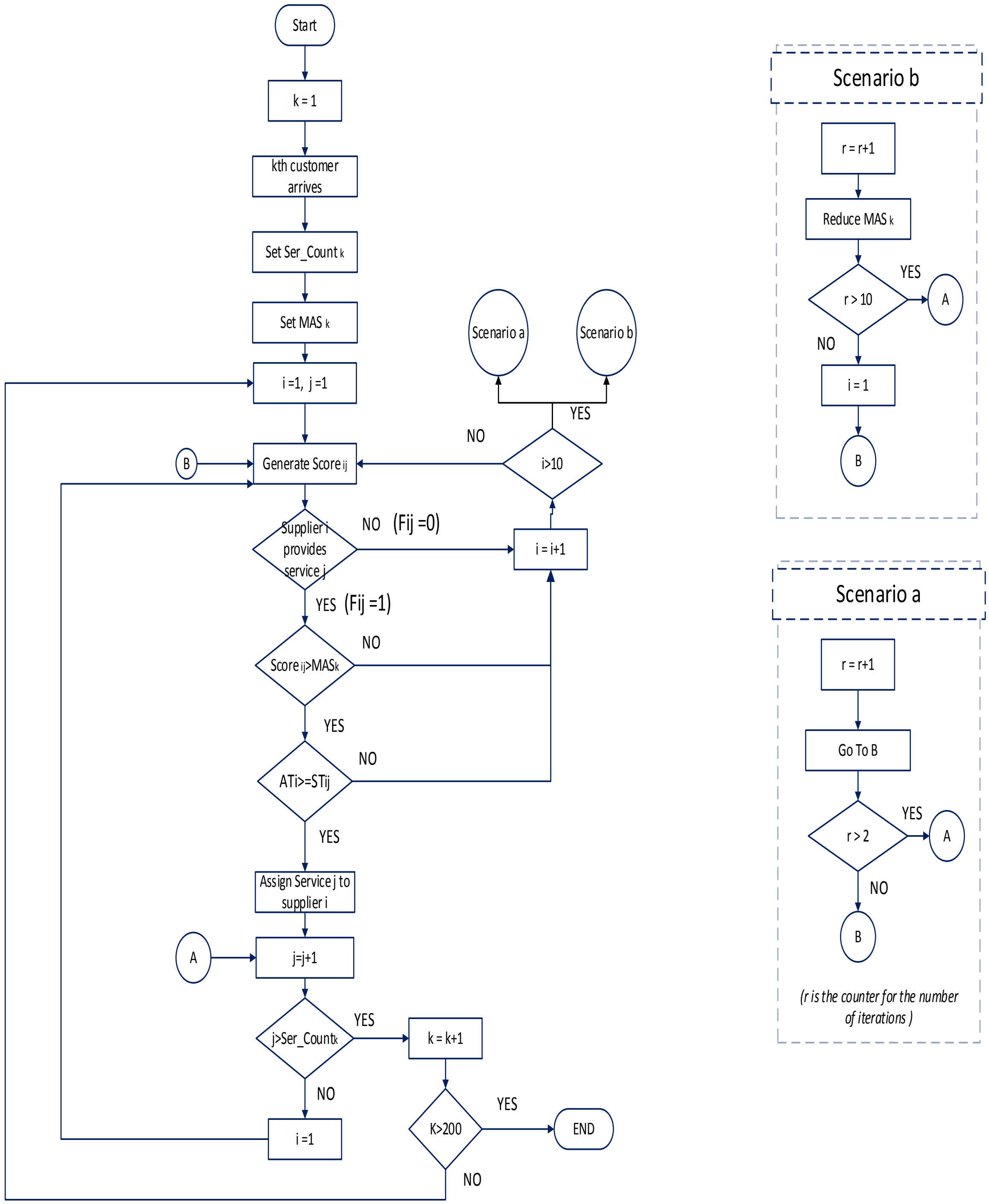

Figure 2. The General Process of Service Allocation for Model A.

Implementation of Model A

In AnyLogic, the *state chart* is used for implementing the agent-based model. Each block in the state chart represents a state of the system. The entry and exit actions can be defined programmatically for each state. Figure 3 shows the early activities of the service allocation process. In the very first step, the customer counter (k) is set to one. Before each iteration, a conditional branch is used for checking the counter of the current customer. If k>200, then the simulation process is terminated and the response parameters (such as average waiting time and supplier utilization) are calculated in the *CalcAveWaitingTime* and *CalcSuppUtiliz* state blocks. Otherwise, the Minimum Acceptable Score (MAS) is generated for the current customer in the *GenerateMAS* state block. The same state block is used for generating discounted MAS in the next iterations. The process continues by approaching the first supplier and entertaining the possibility of allocating the first service (i=1 and j=1) to this supplier in the *FirstSupplierFirstService* state block. Since it is not always guaranteed that a given supplier can provide the requested service, it is necessary to check service availability when the customer agent contacts the supplier agent.

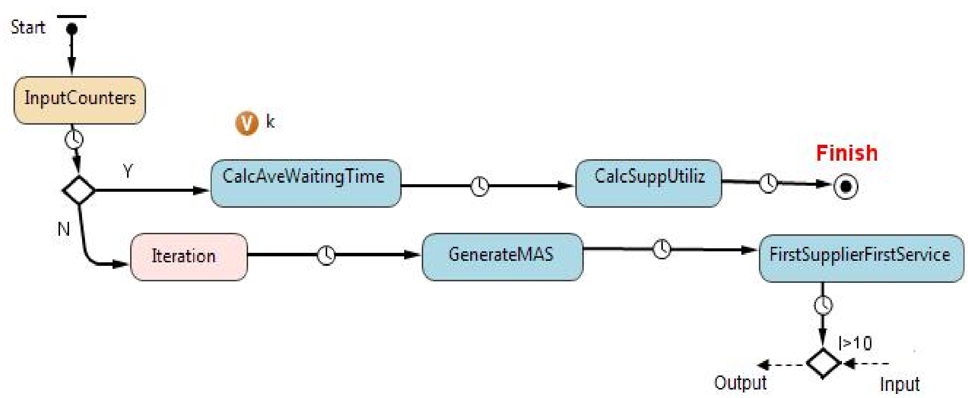

Figure 3. State Chart Related to Calculating Average Waiting Time and Generating MAS.

Figure 4 shows the state chart for checking the availability of the service and assigning service time for a given supplier. When a customer arrives with a need for a particular service such as machining, the supplier may or may not be able to offer the service due to not having the necessary equipment or expertise. This situation is implemented in the *CheckSerAvailability* and *ServAvailable* state blocks. In these states, a random number between 0 and 1 is assigned to Fij and then it is rounded to 0 or 1 depending on its actual value. Fij = 1 implies that the supplier can provide the service. Then a score is assigned to the service-supplier pair in the *AssignScore* state block. This score is generated randomly in this implementation but in the complete implementation of DMM, this score will be calculated by the search (or middle) agent based on the technological capabilities of the supplier. Calculating similarity score is outside the scope of this work and the interested readers are referred to (Ameri& Dutta, 2007).

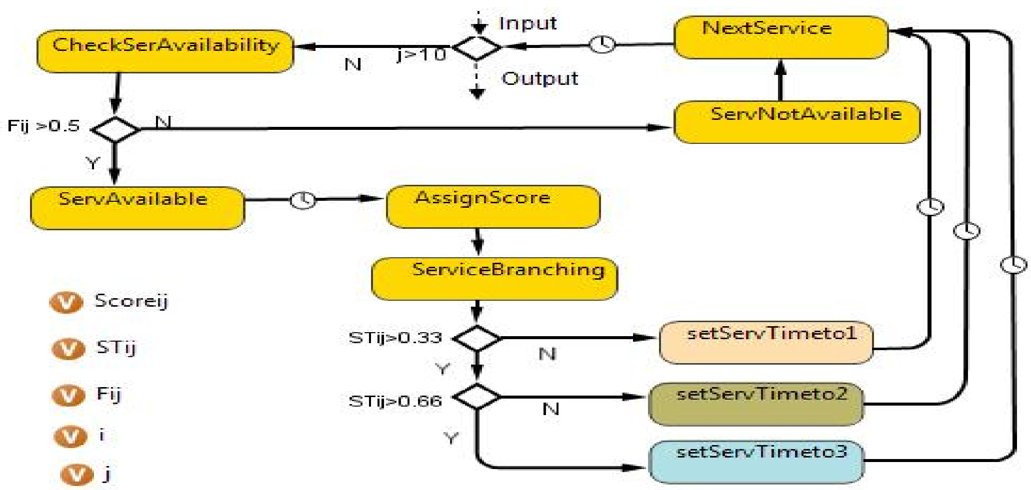

Figure 4. State Chart Related to Checking Service Availability and Assigning Service Time.

The next step is to assign service time to the current service. In this implementation, it is assumed that a service can take the between 1 to 3 hours. This situation is implemented in the *ServiceBranching* and *setServTimeto* state blocks. Once a service time is assigned to the current service, the model moves on to the next service. This step is iterated until the duration of all available services is determined.

Figure 5 shows the service allocation process. To allocate a service to a supplier, it is first necessary to check the score of the supplier and to verify if it meets the minimum score requirements (i.e., if $Score_{ij}$>MAS_k). This step is implemented *checkScore* block. Also it is necessary to verify if the available time of the ith supplier is sufficient for accommodating the *jth* service for the current customer (i.e. if AT_i>ST_{ij}). This step is implemented in the *CheckATi* block. In the *AllocateSupplier* block, the *jth* service of the current customer is assigned to the *ith* supplier if the score and time conditions are met. Then in the *UpdateParameters* block, the number of customers with matched services is incremented by one unit and the average waiting time for the customers is updated. If the *ith* supplier is not available for providing the service, the next suppliers will be contacted. The aforementioned steps are repeated for each customer until the termination condition (k=200) is reached. One of the limitations of the current model is that a customer is considered to be matched only if all if its services are assigned to a supplier. Partial service assignment does not change the status of the customer to full match. Customers with unmatched services exit the market

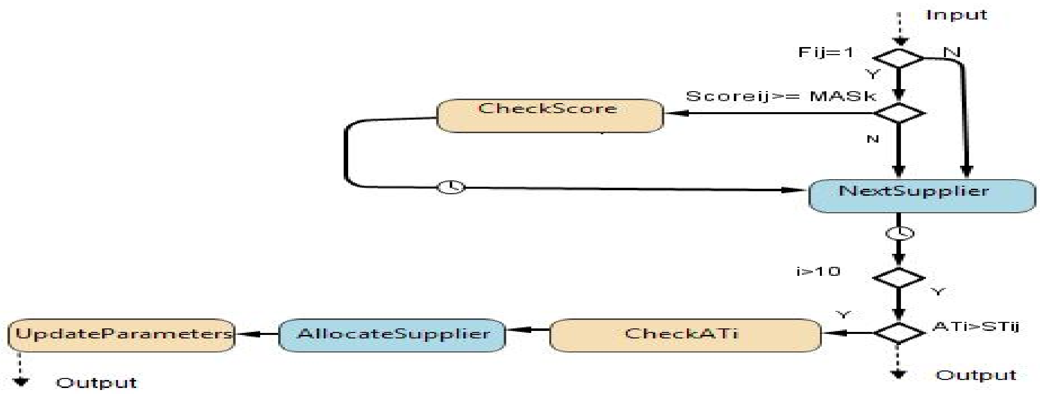

Figure 5. State Chart Related to Checking the Available Time and Score for Suppliers and Allocating Supplier.

Figure 6 shows the Number of Matched (NOM) customers for two scenarios implemented

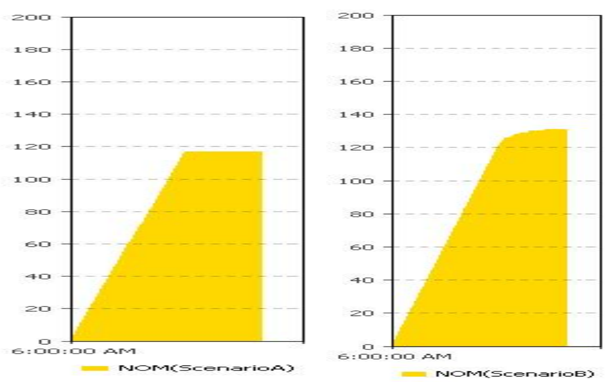

Figure 6. Number of Matched Customer for Scenarios a and b.

Design and Analysis of Experiment for Model A

As mentioned earlier, the main objective of this implementation is to compare different decision-making logics the customer agents may follow for assigning their services to suppliers (i.e., discounting vs. not discounting). To this end, each scenario was run 20 times and the response variables were recorded. The utilization rate of the suppliers under both scenarios was almost identical (around 95%). One explanation is that because the demand level is significantly higher than the supply level (20 to 1 ratio), suppliers will remain over-utilized regardless of the adopted decision-making logic by the customer agents. However, under *scenario b* the average waiting time of the customers in the system is reduced and the number of matched customers is increased.

Average Waiting Time for Model A

As can be seen in Figure 7, under *scenario b*, customers go through a slightly shorter wait time for fully allocating their services to suppliers.

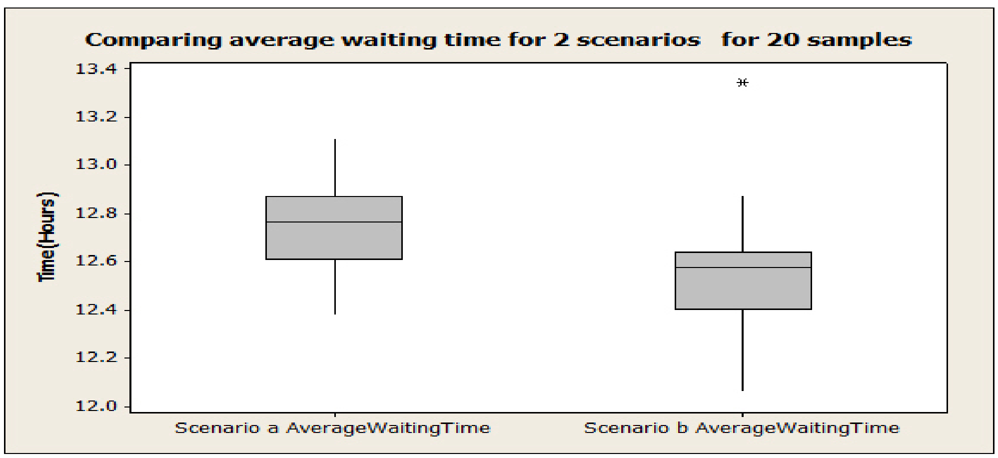

Figure 7. Comparing Average Waiting Time of Model A.

The statistical detail of this experimentation is summarized in Table 2.

Table 2. Statistics of Average Waiting Time for Scenarios a and b for Model A.

Average waiting time (in hours)	Scenario a	Scenario b
Mean	12.73	12.56
Standard Deviation	0.19	0.26

The hypothesis to be tested in this experiment was whether the average waiting time under two scenarios is the same. The results of the statistical hypothesis testing process are shown in Table 3.

Table 3. Hypothesis Testing for Average Waiting Time for Model A.

Two-Sample T-Test

$H_0: \mu_a = \mu_b$

$H_1: \mu_a \neq \mu_b$

	N	Mean	StDev	SE Mean
Scenario a	20	12.733	0.197	0.044
scenario b	20	12.568	0.268	0.060

Difference = mu (1) - mu (2)

Estimate for difference: 0.1643

95% CI for difference: (0.0129, 0.3157)

T-Test of difference = 0 (vs not =): T-Value = 2.21 P-Value = 0.034 DF = 34

The 95% confidence Interval includes zero; therefore, at this level of confidence it was concluded that the means of two populations are not the same. So, the null hypothesis is rejected. In other words, adapting *scenario b* has a meaningful impact on the average waiting time of customers at the 95% level of confidence.

Number of Matched Customers for Model A

As can be seen in the box plot in Figure 8, more customers are matched with suppliers under *scenario b*.

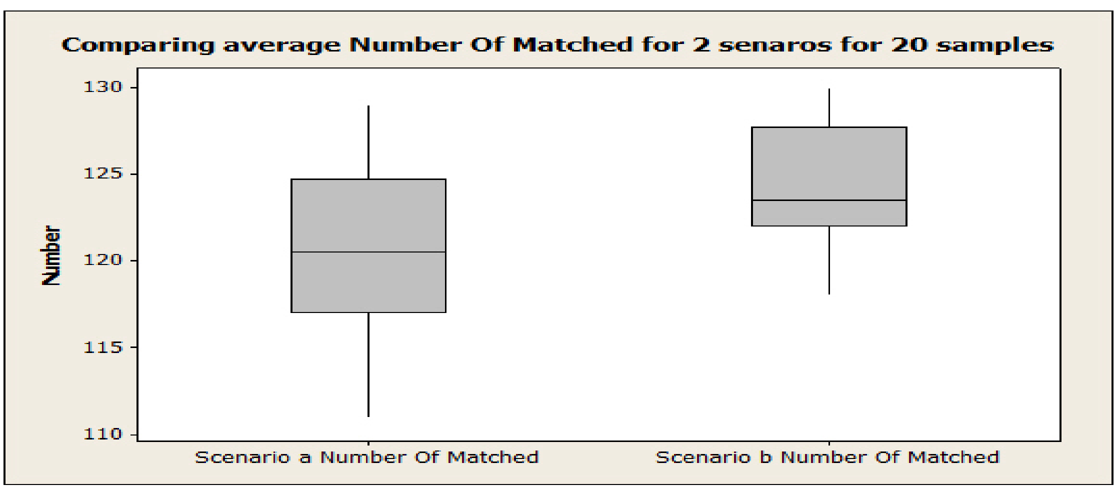

Figure 8. Comparing Number of Matched Customers of Model A.

The statistical details of this experimentation are summarized in Table 4.

Table 4. Statistics of Number of Matched Customers for Scenarios a and b for Model A.

Average number of matched customers	Scenario a	Scenario b
Mean	121	124
Standard Deviation	4.88	3,69

Another experimentation was designed to verify the statistical validation of the observation provided by the box plot. The sample size in this experimentation is 20 as well. The result of this experimentation is shown in Table 5.

Table 5. Hypotheses Testing for Number of Matched Customers for Model A.

Two-Sample T-Test

$H_0: \mu_a = \mu_b$

$H_1: \mu_a \neq \mu_b$

	N	Mean	StDev	SE Mean
Scenario a	20	121.00	4.89	1.1
Scenario b	20	124.05	3.69	0.83

Difference = mu (1) - mu (2)
Estimate for difference: -3.05
95% CI for difference: (-5.83, -0.27)
T-Test of difference = 0 (vs not =): T-Value = -2.23 P-Value = 0.032 DF = 35

Since the p-value is sufficiently small, it can be concluded that there is a significant difference in the mean of the number of matched customers for two populations. Therefore, the null hypothesis is rejected. In other words, adapting *scenario* *b* will have a meaningful impact on the number of matched customers at a 95% level of confidence. The practical implementation is that, with discount, customers have a better chance for matching their services with a qualified supplier.

Model B: Fixed Capacity - Up to 5 services per work order

In the previous model, the services within each work order were assigned to a single supplier. However, in reality, services in a work order can be assigned to several suppliers. Therefore, it is necessary to modify the first model such that a work order can be split among several suppliers.

In this implementation, ten types of services are used. A work order can have one to five services such as machining, coating, milling, cutting, turning, threading, welding, finishing, grinding and assembly. Similar to Model A, the capacity is fixed in Model B. Same to the previous model, there are two types of agents involved in the Model B, namely, Supplier Agent (SA) and Customer Agent (CA). The middle agent (implemented as a random function) is in charge of assigning a similarity score (a score between 0 and 1) to each supplier upon the request from the customer agent.

Model Variables for Model B

- Supplier agent (SA_i): 10 instances (i=1 to 10).
- Customer agents (CA_k): 200 instances (k=1 to 200).
- ST_{ij}: Service time for the *j*th service if provided by the *ith* supplier.
- Score $_{ij}$: The score of the *i*th supplier with respect to service j.
- Ser-Count $_k$: number of services of the *k*th work order.
- F_{ij}=1 If supplier i provides service j otherwise F_{ij} = 0.
- MAS_k: Minimum Acceptable Score for the *kth* customer.

- AWT_k: Average Waiting Time for *kth* customer.

As can be seen in this list, the mentioned variables are the same as the Model A. SY_{ij} is the new variable which refers to service types for the *jth* service when provided by the *ith* supplier.

Assumptions for Model B

- Run time 24
- Each customer agent represents one work order (WO).
- Each work order may need one to five manufacturing services.
- Service time (ST_{ij}) varies depending on service type and it is uniformly distributed between 1 and 3 hours.
- Each customer agent has a predefined Minimum Acceptable Score (MAS_k). For example, if MAS=0.75, then it only accepts the suppliers with the score of 0.75 or more. A random MAS value is assigned to each customer agent upon arrival.
- Service time can take the value of 1h to 3h which is picked randomly for each supplier-service pair. For examples, casting service if provided by supplier 1 may take 2 hours but if the same service is provided by supplier 2 it may take 1.5 hour since supplier 2 uses more advanced casting technology.

Decision Logic for Model B

As seen all parameters and decision-makings are the same as simulated Model A and customer agent select the suppliers according to equation(1) , but in this model CA can ask more services and the work orders will be distributed among different suppliers who are eligible to receive the requested services.

In this model, the following scenarios are considered:

- ***Scenario a***: If the customer agent cannot assign a service to any supplier in the first round, it repeats the service assignment cycle one more time. If the service is not matched to any supplier after the second round, then the service is considered to be unmatchable and the customer agent moves on to the next service.
- ***Scenario b****:* If the customer agent cannot assign a service to any supplier in the first round, it discounts its Minimum Acceptable Score (MAS) for an arbitrary amount in order to find a qualified supplier. The MAS can be discounted up to 0.05 for each cycle. The lower threshold for the discounted score is .5. The MAS will be kept to the original value when moving on to the next service for the same customer.

Figure 9 shows the general service allocation procedure used in this agent-based model under the described scenarios.

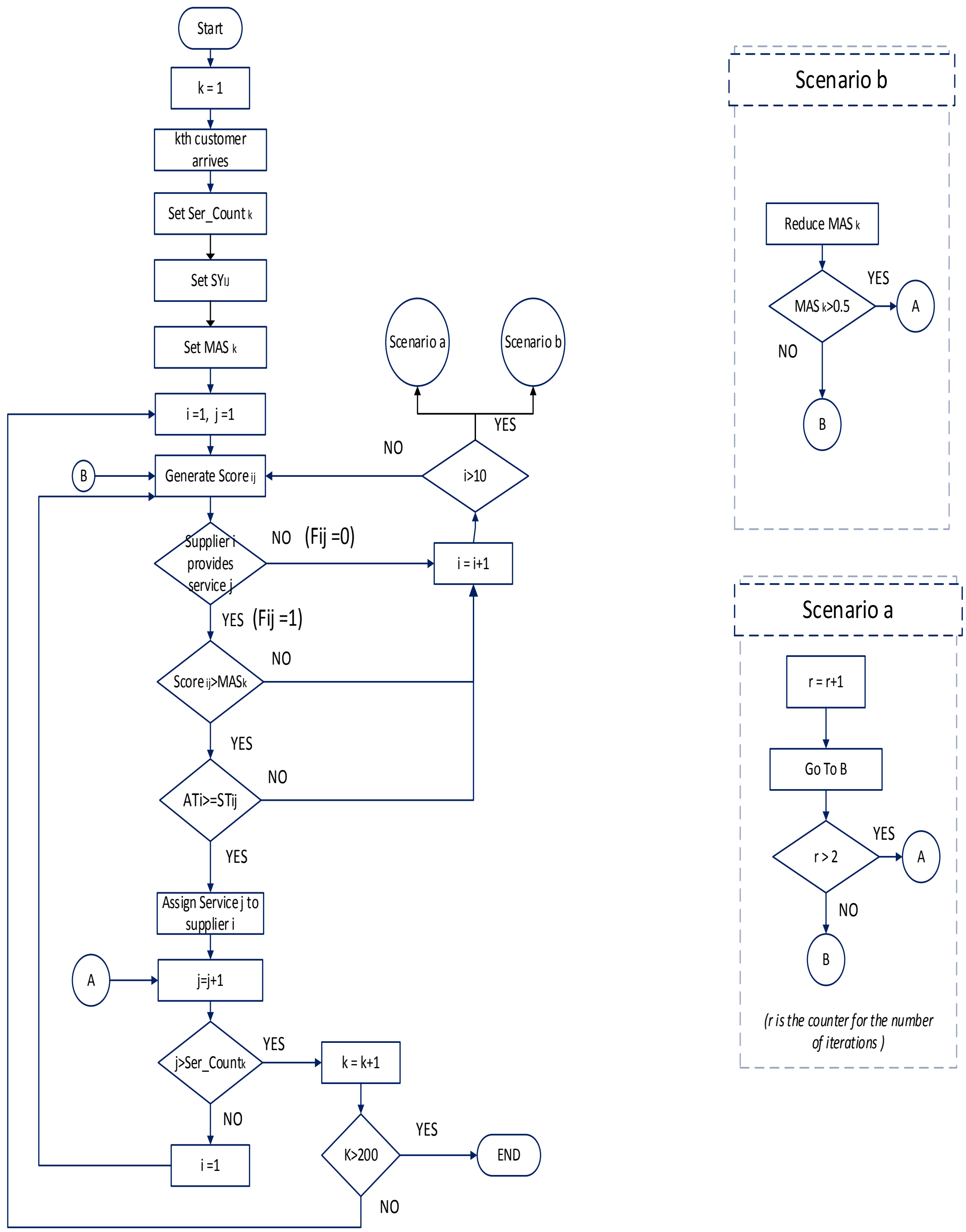

Figure 9. The General Process of Service Allocation for Model B.

<u>Implementation of Model B</u>

Figure 3 shows the early activities of the service allocation process which is the same as the Model A and it was described earlier. But the difference appears in Figure

10, across the counting service process and after Minimum acceptable Score was created in the *GenerateMAS* state block, the different types of services are considered for *kth* customer in the *SetCounterk* state block. In the first conditional branch, types of services is checking to be less than or equal to 10 types .In the second branch, the types of required services will be checked to verify whether they are the same types or not if they are not the same type then, the *jth* services will be allocated in the *AllocateSers* state block and if the services are the same types and they are more than 10 types then those will return again to the *CheckAgain* state block and the number of required services will be counted again.

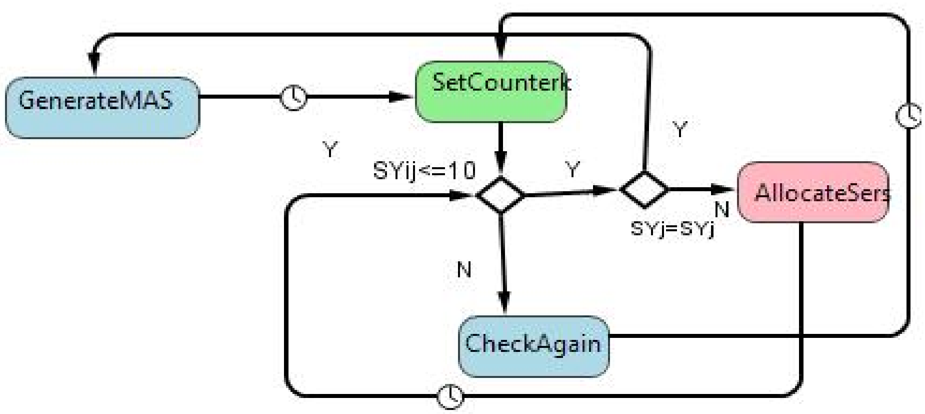

Figure 10. State Chart Related to Counting Services.

Figure 11 shows the state chart for checking the availability of the service and assigning service time for a given supplier. When a customer arrives with a need for a particular service such as machining, the supplier may or may not be able to offer the service due to not having the necessary equipment or expertise. This situation is implemented in the *CheckSerAvailability* and *ServAvailable*state blocks. In these states, a random number between 0 and 1 is assigned to Fij and then it is rounded to 0 or 1 depending on its actual value. Fij = 1 implies that the supplier can provide the service.

Then a score is assigned to the service-supplier pair in the *AssignScore* state block. The next step is to assign service time to the current service. In this implementation, it is assumed that a service can take the between 1 to 3 hours. This situation is implemented in the *setServTimeUniform1to3* state block. Once a service time is assigned to the current service, the model moves on to the next service. This step is iterated until the duration of all available services are determined.

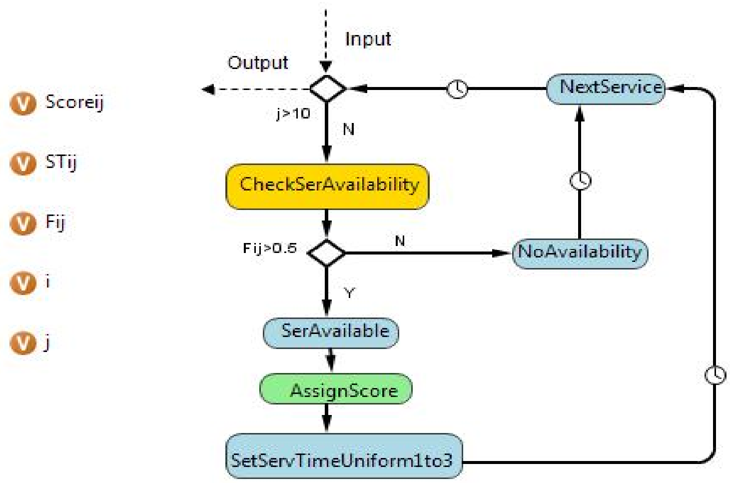

Figure 11. State Chart Related to Checking Service Availability and Assigning Service Time

<u>Design and Analysis of Experiment for Model B</u>

In order to evaluate the performance of the system under new assumptions, each scenario was run 10 times and the response variables were recorded.

<u>Average Waiting Time for Model B</u>

As can be seen in Figure 12, under *scenario* customers go through a shorter wait time for fully allocating their services to suppliers. The reason for this is that there are many requested services and that should be responded by a limited number of suppliers.

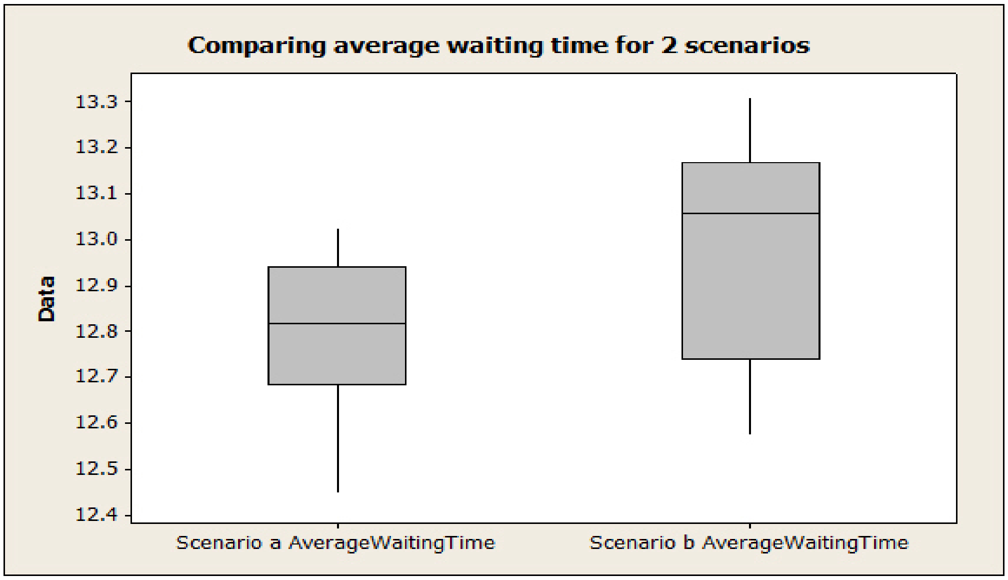

Figure 12. Comparing Average Waiting Time for Model B.

The statistical detail of this experimentation is summarized in Table 6.

Table 6. Statistics of Average Waiting Time for Scenarios a and b for Model B.

Average waiting time (in hours)	Scenario a	Scenario b
Mean	12.8021	12.9674
Standard Deviation	0.181380784	0.255118796

The hypothesis to be tested in this experiment was whether the average waiting time under two scenarios is the same. The results of the statistical hypothesis testing process are shown in Table 7.

Table 7. Hypothesis Testing for Average Waiting Time for Model B.

Two-Sample T-Test

$H_0: \mu_a = \mu_b$

$H_1: \mu_a \neq \mu_b$

	N	Mean	StDev	SE Mean
Scenario a	10	12.802	0.181	0.057
Scenario b	10	12.967	0.255	0.081

Difference = mu (a) - mu (b)
Estimate for difference: -0.1653
95% CI for difference: (-0.3751, 0.0445)
T-Test of difference = 0 (vs not =): T-Value = -1.67 P-Value = 0.114 DF = 16

The 95% confidence interval includes zero; therefore, at this level of confidence it was concluded that the means of two populations are the same. Thus, the null hypothesis is accepted. In other words, adapting *scenario b* has no meaningful impact on the average waiting time of customers at the 95% level of confidence.

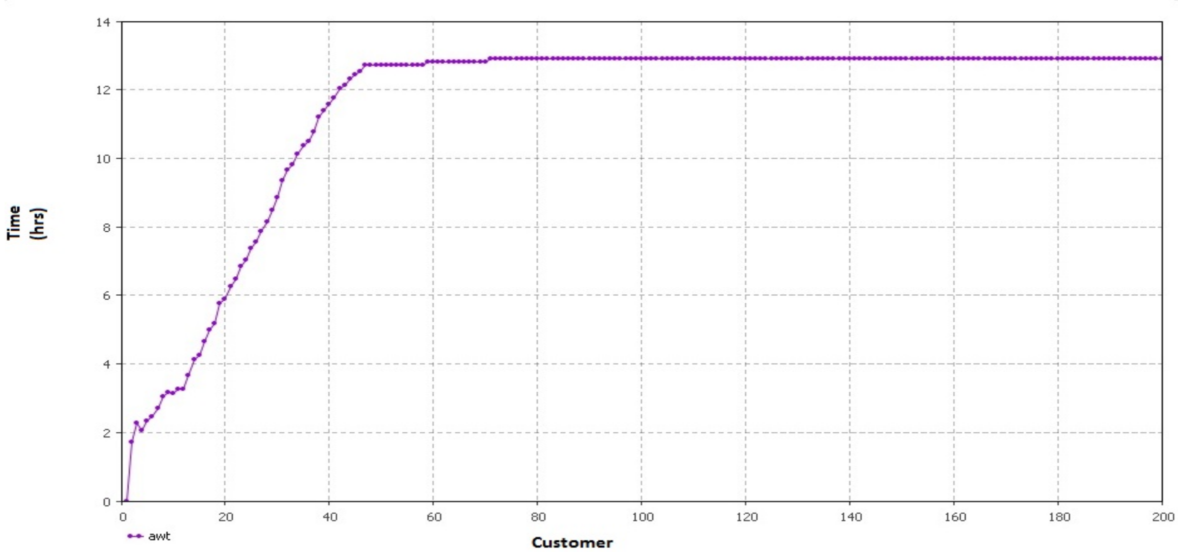

Figure 13. Average Waiting for Customers in Model B under Scenario b.

Figure 13 shows that under the discount policy, the variation of average waiting time as new customers enter the system. This figure shows that the system reaches its steady state with regard to the average waiting time when the 50th customer enters the system. The reason is that after the services belonging to the 50th customers are assigned to suppliers, the available manufacturing capacity is fully assigned and no new customers can be served in the system. Therefore the new customers will be rejected by the system and the average waiting time is calculated based on the first fifty customers (remains fixed after the arrival of the 50th customer).

Number of Matched Services for Model B

As can be seen in the box plot in Figure 14, more services are matched with suppliers under scenario *b*.

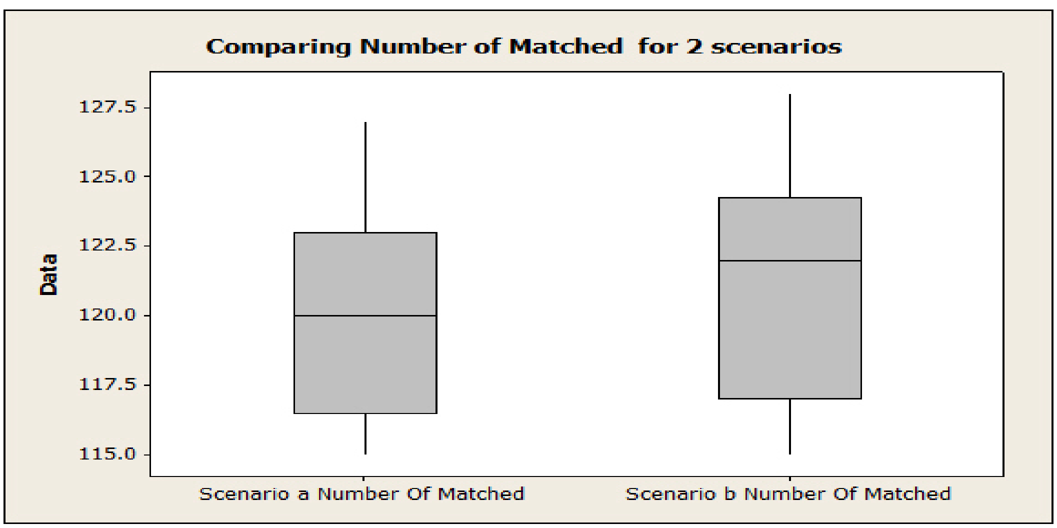

Figure 14. Comparing Number of Matched Services for Model B.

The statistical details of this experimentation is summarized in Table 8.

Table 8. Statistics of Number of Matched Services for Scenarios a and b for Model B.

Average number of matched services	Scenario a	Scenario b
Mean	120	121.5
Standard Deviation	3.858612301	4.089281

To verify the statistical validation of the observation provided by the box plot, a T-Test was conducted as shown in Table 9.

Table 9. Hypotheses Testing for Number of Matched Services for Model B.

Two-Sample T-Test

$H_0: \mu_a = \mu_b$

$H_1: \mu_a \neq \mu_b$

	N	Mean	StDev	SE Mean
Scenario a	10	120.00	3.86	1.2
Scenario b	10	121.50	4.09	1.3

Difference = mu (a) - mu (b)
Estimate for difference: -1.50
95% CI for difference: (-5.25, 2.25)
T-Test of difference = 0 (vs not =): T-Value = -0.84 P-Value = 0.411 DF = 17

The 95% confidence interval includes zero; therefore, at this level of confidence the conclusion is that there is no significant difference in the mean of number of matched services for two populations. So, the null hypothesis is accepted. In other words, adapting *scenario a* or *scenario b has* the same impact on the number of matched services.

Supplier Utilization for Model B

In Model A, the utilization rate of the suppliers under both scenarios was almost identical (around 98%). But in Model B, there is a difference in the utilization rate of the suppliers under two scenarios. As can be seen in the box plot in Figure 15, more services are matched with suppliers under *scenario b*. One explanation is that because the demand level in *scenario b* is higher than *scenario a* due to the effect of discount, suppliers will be busier in general.

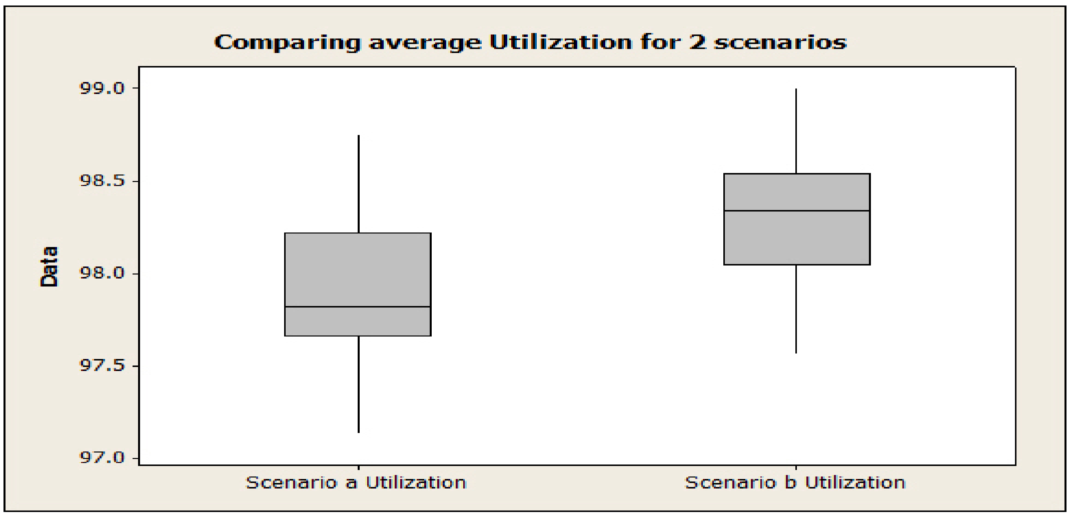

Figure 15. Comparing Supplier Utilization for Model B.

The statistical details of this experimentation is summarized in Table 10.

Table 10. Statistics of Supplier Utilization for Scenarios a and b for Model B.

Average supplier utilization(Percentage)	Scenario a	Scenario b
Mean	97.89969907	98.28542
Standard Deviation	0.44102063	0.412444

Another T-Test was designed to evaluate the impact of scenarios on supplier utilization. The result of this hypothesis testing is shown in Table 11.

Table 11. Hypotheses Testing for Supplier Utilization for Model B.

Two-Sample T-Test

$H_0: \mu_a = \mu_b$

$H_1: \mu_a \neq \mu_b$

	N	Mean	StDev	SE Mean
Scenario a	10	97.900	0.441	0.14
Scenario b	10	98.285	0.412	0.13

Difference = mu (a) - mu (b)
Estimate for difference: -0.386
95% CI for difference: (-0.789, 0.017)
T-Test of difference = 0 (vs not =): T-Value = -2.02 P-Value = 0.059 DF = 17

The 95% confidence interval includes zero; therefore, at this level of confidence the conclusion is that there is no statistically significant difference in the mean of supplier utilization for two populations. So, the null hypothesis is rejected. In other words, adapting *scenario b* or scenario *a* has no meaningful impact on the supplier utilization at a 95% level of confidence.

Experiment on Different Level of Lower Customer Expectations

As shown before, discount policy has no impact on the number of matched services. For this reason, more accurate experiment was done to find the exact reason why discount policy has no effect on the number of matched services. The objective of doing another experiment is to see if changing the initial MAS will have any influence on the number of matched services. Six scenarios were compared with MAS varying between .2 and .8. Same as before, 200 customers were considered in this experiment. For each scenario, if the customer agent cannot assign a service to any supplier in the first round, it discounts its Minimum Acceptable Score (MAS) in order to find a qualified supplier. The MAS can be discounted up to 0.05 for each cycle. The MAS will be rest to the original value when moving on to the next service for the same customer. Figure 16 shows the initial MAS for each scenario.

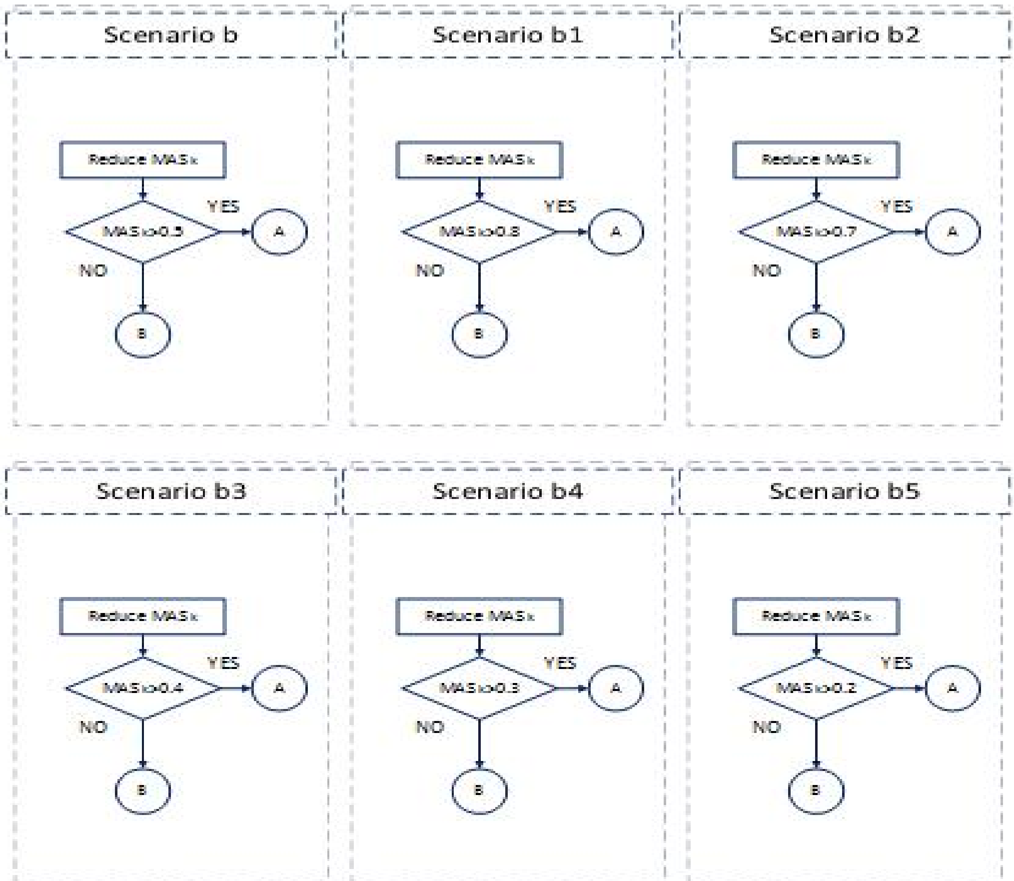

Figure 16. Different Amount of Lower Thresholds for MAS.

Figure 17 shows the result for 200 customers each asking for 5 services. As can be seen in this figure, the discount policy has no impact on the number of matched services because, the market is statured. In other words, the impact of reduction in MAS is hidden due to having overloaded suppliers in the system.

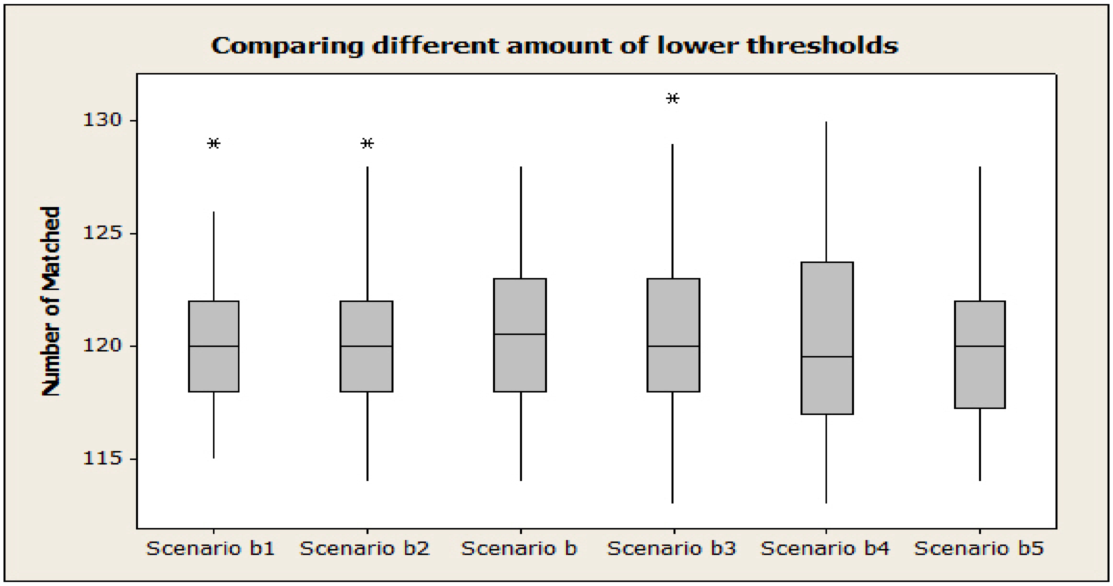

Figure 17. Comparing Number of Matched Services under Different Discounted Lower Bound.

To solve this problem, two solutions are suggested:

1. Increase the number of suppliers
2. Decrease the number of work orders

Figure 18 shows number of matched services under lower bound 0.5 for different amount of customers when second solution was implemented (i.e. decreasing the number of work orders).

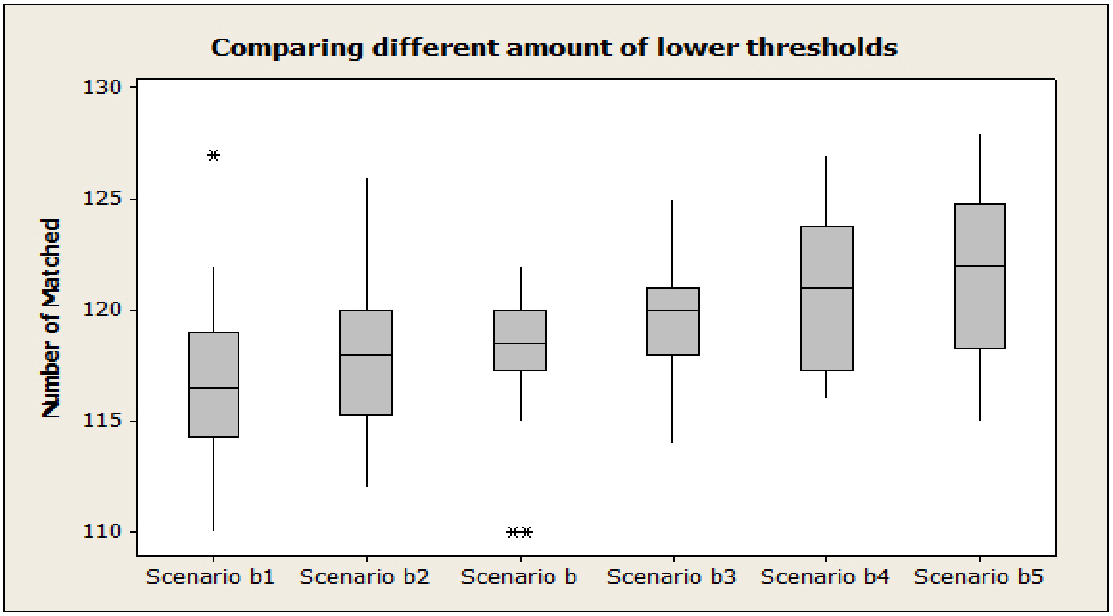

Figure 18. Comparing Number of Matched Services for 50 Customers.

The result shows that the effect of reducing the initial MAS is visible when the market is not saturated.

Model C: Dynamic Capacity (DC) – Up to 5 services per work order

In the previous model, the number of suppliers (i.e., production capacity) in the system was fixed. However, it is necessary to investigate how the system reacts to dynamic addition and deletion of suppliers. With dynamic capacity adjustment, the supplier utilization rate can be maintained in the desirable range. In this model, the number of active suppliers in the system is adjusted according to the average supplier utilization rate. If the utilization rate is high and supplier are overloaded, new suppliers are added to the system and if the average utilization rate is low, the number of available supplier is reduced.

Model Variables for DCA

The agent model in Model C is the same as Model A and Model B. The main difference is dynamic addition and deletion of suppliers in the system based on the average utilization rate. The following variables are used in Model C.

- Supplier agent (SA_i) (i=1 to Nsup)
- Customer agents (CA_k): 80 instances (k=1 to 80)
- ST_{ij}: Service time for the *j*th service if provided by the *ith* supplier
- SY_{ij}: Service types for the *j*th service if provided by the *ith* supplier
- Score $_{ij}$: The score of the *ith* supplier with respect to service j
- Ser-Count $_k$: number of services of the *kth* work order
- F_{ij}=1 If supplier I provides service j otherwise F_{ij} = 0
- MAS_k: Minimum Acceptable Score for the *kth* customer
- AU_i; Average Utilization for *ith* supplier
- Nsup: supplier counter (i=5 to 15)
- AWT $_k$: Average waiting time for *kth* customer

Assumptions for DCA

- Service time (ST_{ij}) varies depending on service type (Uniformly distributed between 1 and 3 hours).
- Up to five types of services are requested by a customer agent in this model (e.g., casting, machining, painting, assembly, and coating).
- Order of service allocation does not matter.
- Each customer agent has a predefined Minimum Acceptable Score (MAS_k).

- At the beginning of simulation, there are 10 suppliers in the system.

<u>Design and Analysis of Experiment for DCA</u>

The first step in designing the dynamic system is to estimate the initial number of suppliers and customers. The objective is to keep the utilization rate of the suppliers in the range of 75-85%. If the average utilization rate is in this range, the market is considered to be *balanced*. It means that suppliers are working most of the time and also they are not over-stressed. For a 24-hours run time with 50 customers in the system, the required processing capacity is expected to be 300 hrs (the average numbers of required services per work order is 3 services, and the average of processing time per service is approximately 2 hrs). Given that each supplier provides 24 hours of processing capacity, approximately 12 suppliers will be needed in average to fully cover the demand. However, the system can start with a smaller number of suppliers since there aren't many customers in the market at the early hours. Therefore, it is assumed that the market starts with ten suppliers. The number of suppliers (Nsup) varies from 5 to 15.

As mentioned earlier, the goal is to have lower average waiting time for customers and, at the same time, have a balanced marker. Also, it is desirable to accommodate a higher number of customers. For finding the initial number of customers in the system that yields a utilization rate between 75% and 85%, several experimentations were designed with different number of customers ranging from 50 to 90. Figure 18 shows how the average waiting time varies with utilization rate when 50 customers enter the system. In this scenario, the least average waiting time happens when utilization (45-55) % range. But, it is not a perfect utilization rate.

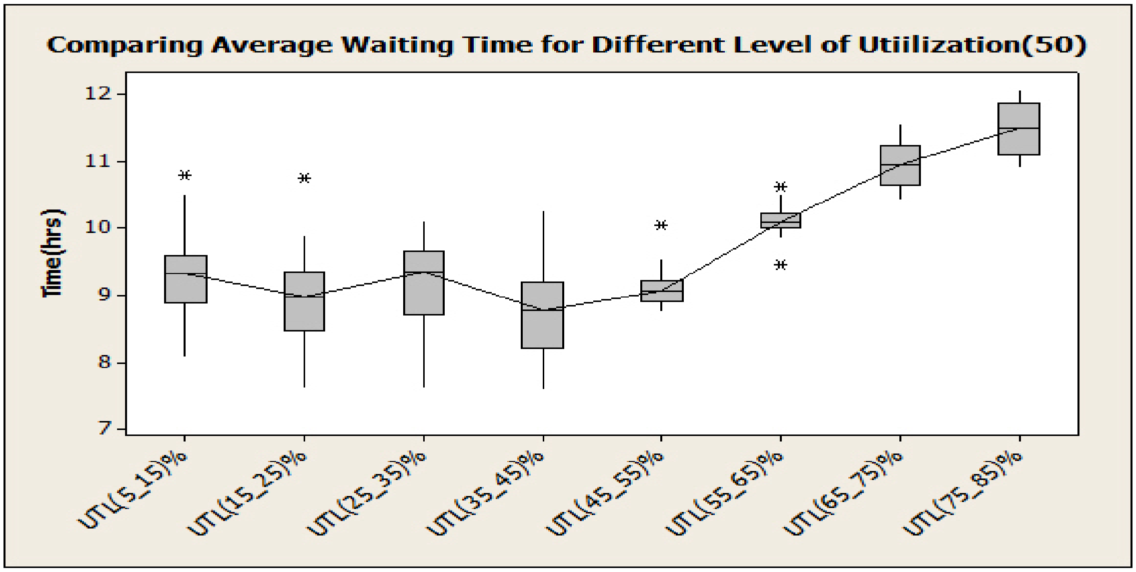

Figure 19. Comparing Average Waiting for Different Range of Utilization for 50 Customers.

Figure 19 shows that having 50 customers is not ideal for this agent model. Thus, another experiment was conducted with 70 customers. Figure 20 shows the least average waiting time happens when utilization is in (55-65) % range. But in this range the market is still not balanced.

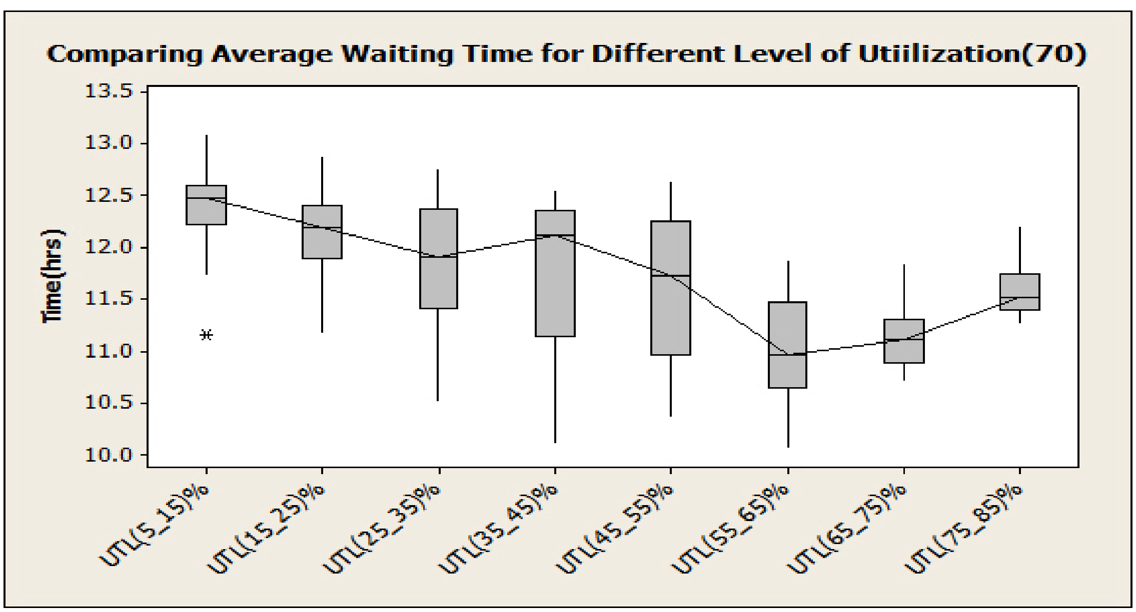

Figure 20. Comparing Average Waiting for Different Range of Utilizations for 70 Customers.

This experiment shows that having 70 customers is not ideal for this agent model again. So, another experiment was done for 80 customers and Figure 21 shows the least average waiting time happens for utilization in range of (75-85) % which is the goal of this modeling as mentioned earlier.

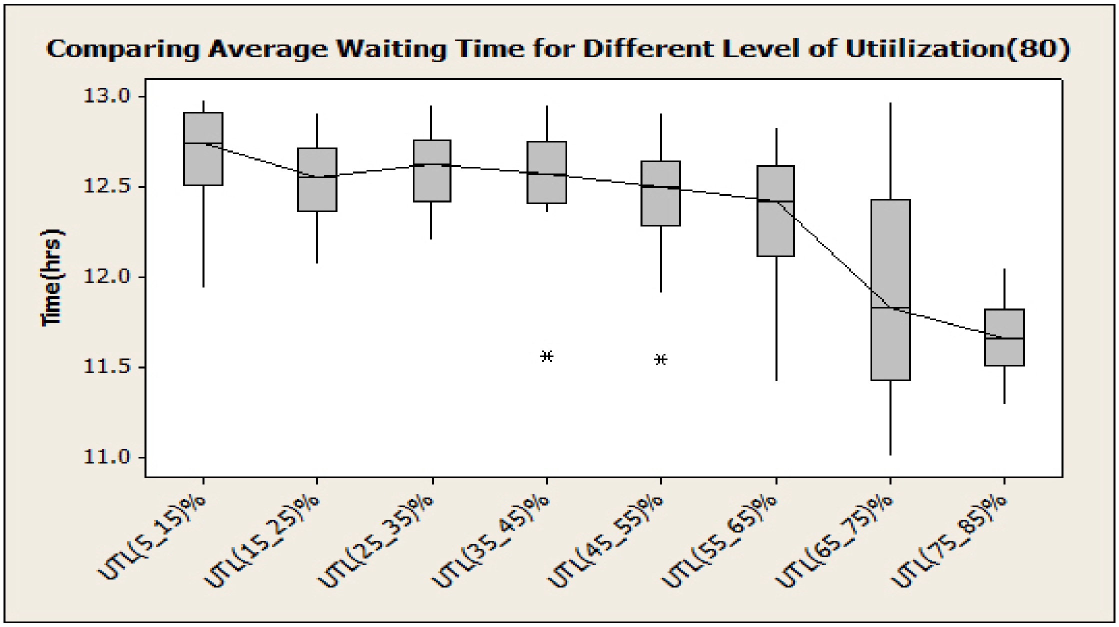

Figure 21. Comparing Average Waiting for Different Range of Utilization for 80 Customers.

This experiment shows that having 80 customers is ideal for this agent model. But, another experiment was done for 90 customers to see what the effect of having 90 customers is. Figure 22 shows the least average waiting time also corresponds to the utilization rate of (75-85) % but the average waiting time is increased. Thus, it was concluded that by having 80 customers in the starting set, the desirable results (balanced market and low average waiting time) will be obtained.

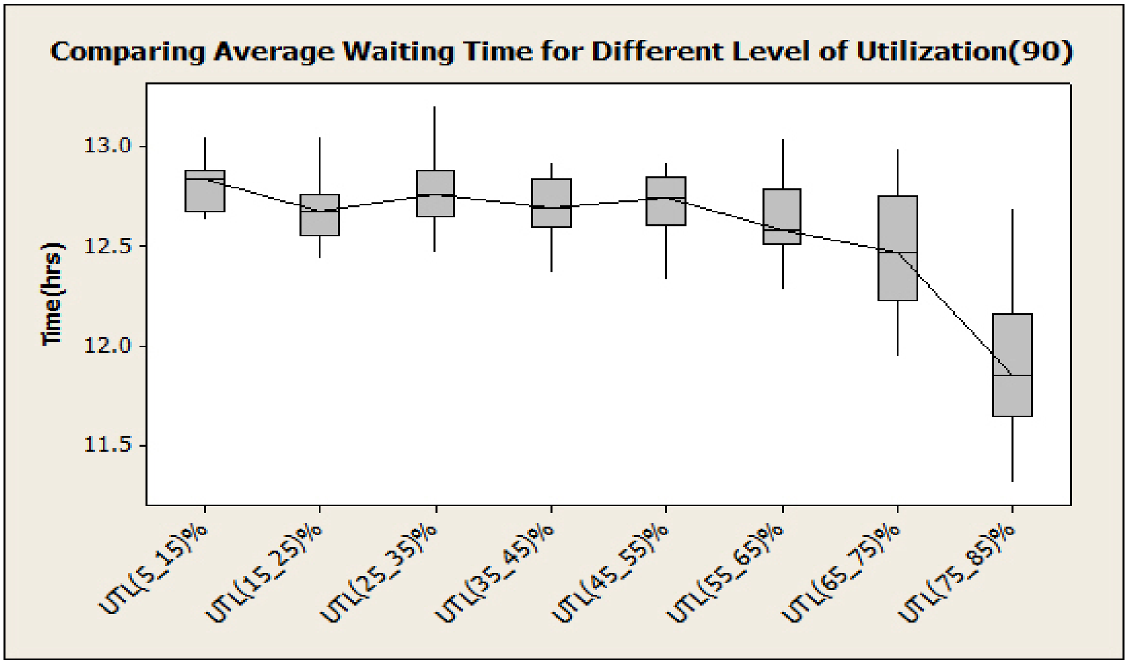

Figure 22. Comparing Average Waiting for Different Range of Utilization for 90 Customers.

<u>Decision Logic for DCA</u>

All parameters and decision logics in Model C are the same as Model B and customer agents select suppliers according to equation (1). Also, in this model work orders will be distributed among different suppliers who are eligible to receive the services. In this model, the number of suppliers (SA_i) is dynamically adjusted to obtain a balanced market based on the following utilization range:

$$75\% < AUi < 85\% \qquad (2)$$

Scenario: If the customer agent cannot assign a service to any supplier in the first round, it repeats the service assignment cycle one more time. If the service is not matched to any supplier after the second round, then the service is considered to be unmatchable and the customer agent moves on to the next service and customers wait to find their matched services. When the average utilization of suppliers is less than 75%, the total number of active suppliers is reduced. Also, when average utilization of suppliers is more than 85%, more supplier are added to the system to bring the balance back.

Figure 23 shows the general service allocation procedure for DCA used in Model C under the described scenario while there is no discount.

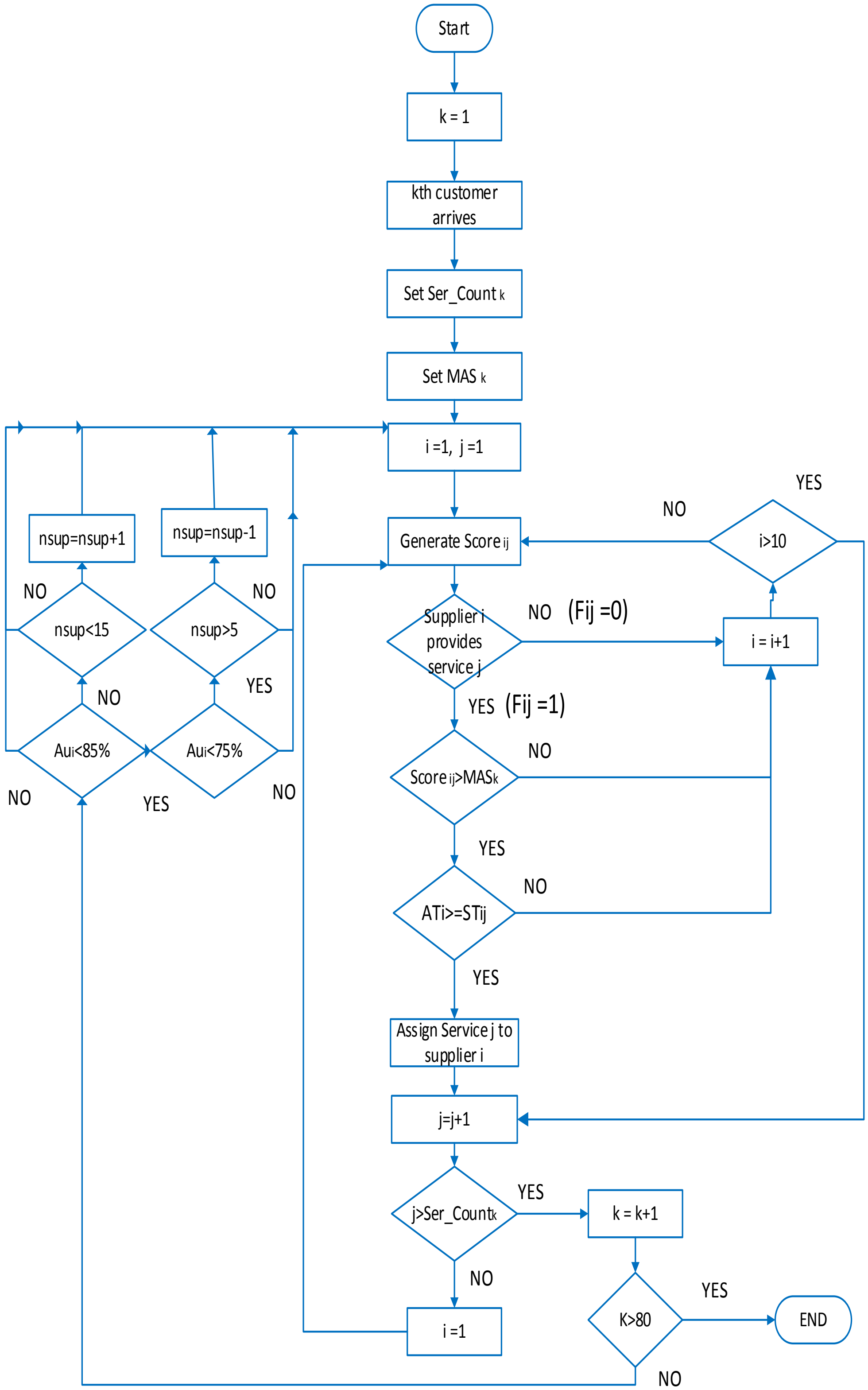

Figure 23. The general Process of Service Allocation for DCA.

Implementation of DCA

Calculating Average Waiting Time and Generating MAS state chart is the same as Model B and Model A. A conditional branch is used for checking the current number of the system. If k>80, then the simulation process is terminated. *Checking Service Availability, Assigning Service Time, Checking the Available Time, Calculating Score for Suppliers, Allocating Supplier, Counting Services* processes are performed similar to Model B. The main difference that the system continuously measures the average utilization rate and adds and removes suppliers accordingly as shown in Figure 24. To allocate a service to a supplier, it is first necessary to check the average utilization of suppliers (i.e., if 75 %<AU_i<85%). In this system, there are at least five and at most fifteen suppliers. If the average utilization of suppliers is more than 85%. Then, in the *pluSup* block the supplier will be added to system which implies there will be enough number of suppliers to response to CA_k. Furthermore, if the average utilization of suppliers is less than 75% Then, in the *subsup* block *the* supplier is added to system and in the *updateutiliz* block the average utilization rate of suppliers is be updated in each iteration.

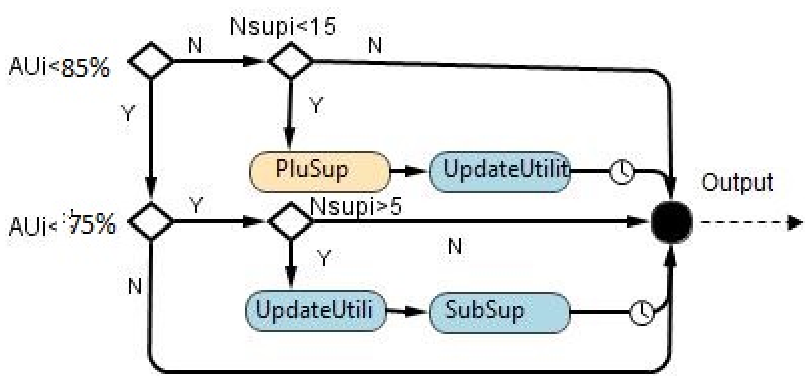

Figure 24. State Chart Related to Checking Utilization and Allocating Supplier.

Figure 25 shows how the number of suppliers varies as new customers enter the system. Note that the initial number of suppliers in the system is ten. Every 1 minute, a new customer enters the system. This figure shows that for the first few hours, the number of suppliers in the system drops from 10 to 5 but it gradually increases after the number of customers in the reaches 20. Towards the end of simulation duration, the number of suppliers in the system reaches 14. Moreover, this figure shows how the workload of each supplier in the system increases with increase in the number of customers. By the time the services related to the 23rd customers are assigned to the available supplier, the system passes the permissible upper limit for average supplier utilization. Therefore, a new supplier (6th) is added when the 24th customer enters the system.

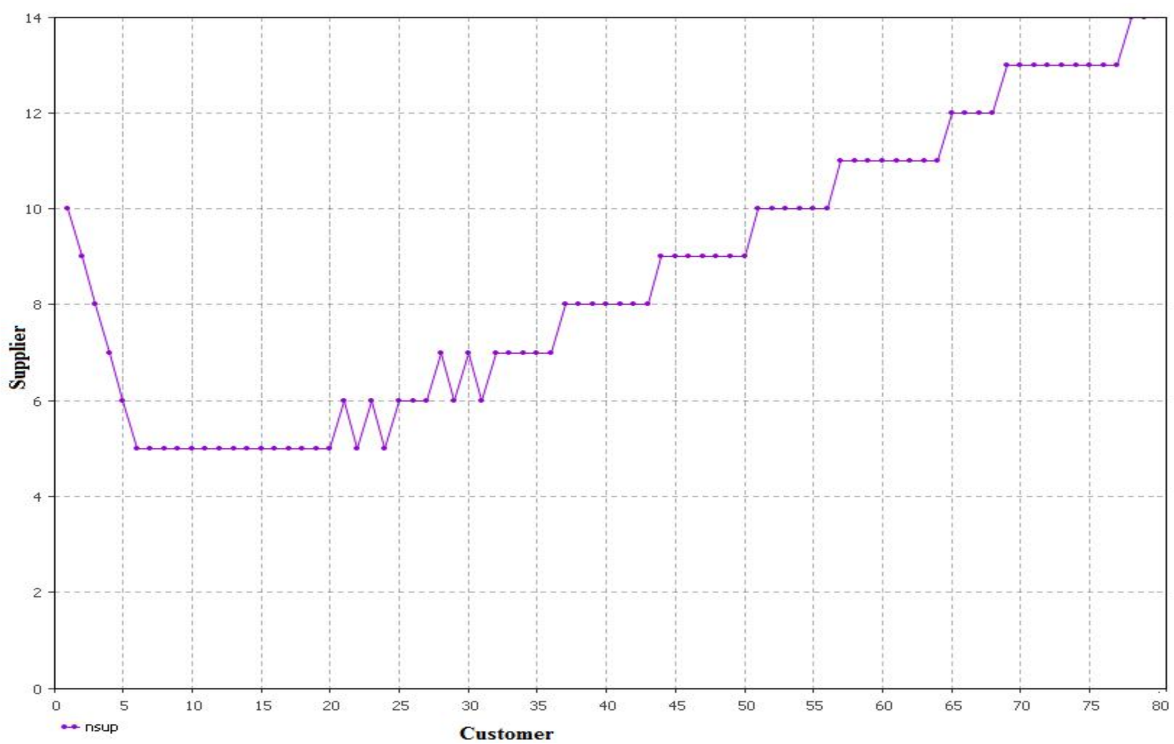

Figure 25. Dynamic Capacity Adjustment (DCA).

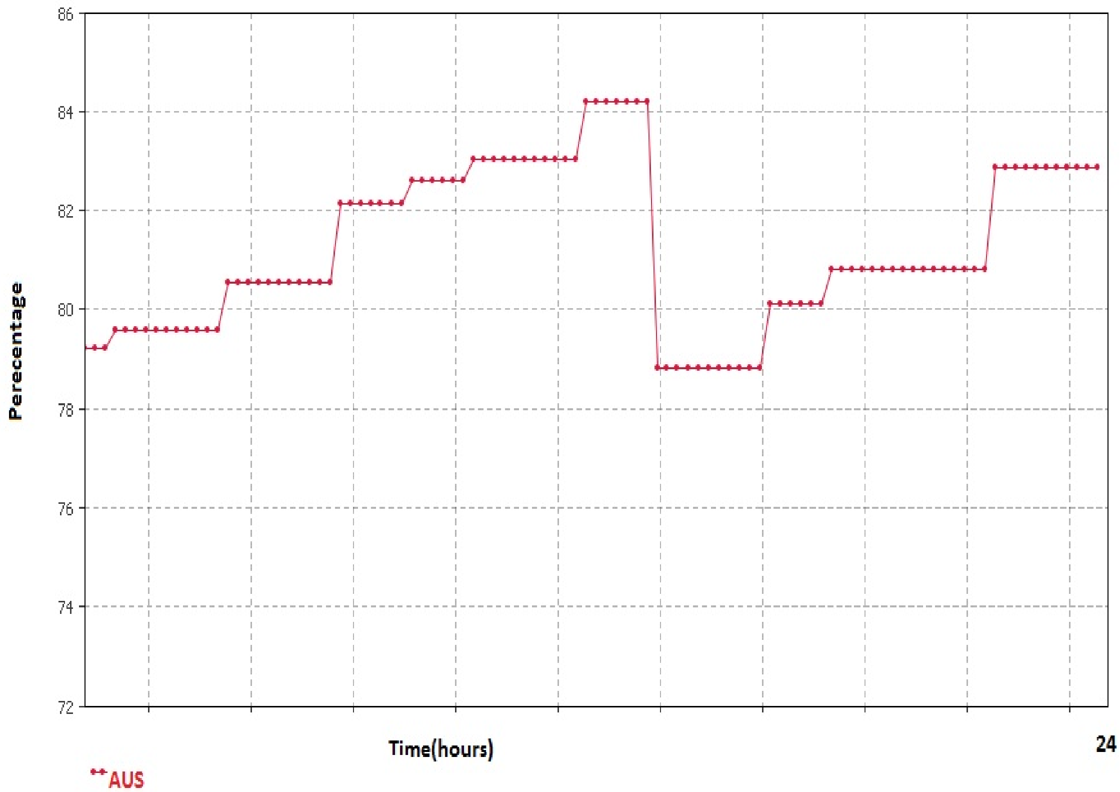

Figure 26. Average Supplier Utilization Rate (DCA).

Figure 26 shows that the average supplier utilization is an ideal range in DCA model.

Figure 27 shows how work orders are distributed among different suppliers, how the number of suppliers varies as new customers enter the system and how much time each work order needs. For example, the 72rd customers are assigned to the available 11th and 12th supplier and this customer needs 4 hours for his/her order, then 2 hours of this work is allocated to 11th supplier and the rest of this (2 hrs) is allocated to 12th supplier.

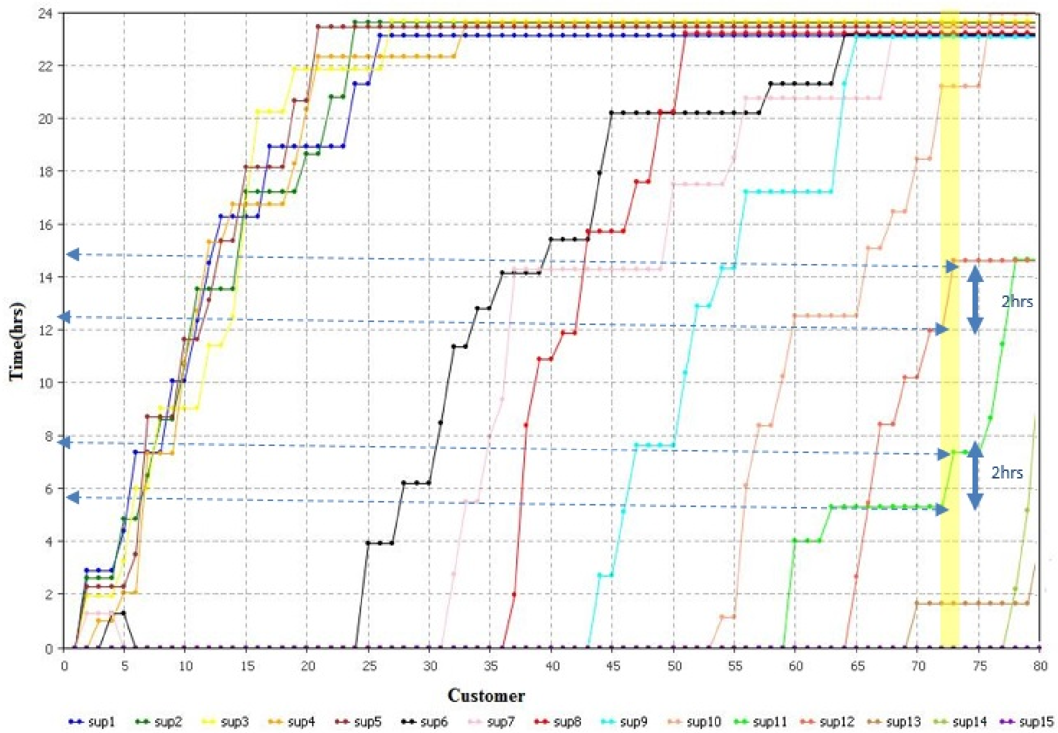

Figure 27. Process Variation of Suppliers in DCA.

Table 12 shows how services from a given customer are distributed among multiple suppliers. A three-digit string is used to indicate each service allocation. The first digit shows the customer number, the second digit shows the service number, and third digit shows the supplier. For example, “1,9,7” means that the first customer has allocated its 9th service to 7th supplier and “1,1,1” indicates that the same customer has allocated its 1st service to the first supplier

Table 12. Distributed Work Orders in DCA.

work orders are distributed among suppliers
1,9,7_1,1,1_1,2,3_1,10,2_1,4,5_2,8,4_3,6,6_4,4,1_4,6,4_4,2,3_4,8,2_5,2,1_5,4,3_5,10,5_6,7,5 _6,2,4_6,1,4_6,4,5_6,9,2_7,1,3_7,5,3_7,9,2_8,1,1_9,3,4_9,6,2_9,10,5_9,8,4_10,7,4_10,6,2_10, 8,1_11,2,4_11,10,5_11,4,3_11,6,1_12,7,5_12,3,1_13,1,3_13,4,4_14,3,5_14,2,3_14,6,3_14,10,2 _14,9,2_15,3,3_15,6,3_16,10,1_18,6,3_18,1,4_18,5,5_19,1,2_19,7,4_20,3,4_20,7,5_21,7,2_23, 6,2_23,10,1_24,9,6_24,8,6_25,10,1_26,2,3_27,1,6_30,5,6_31,8,6_31,3,7_32,9,4_32,3,7_33,5,6 _34,4,7_34,3,7_35,6,6_35,7,7_36,6,7_36,1,8_36,3,7_37,4,8_37,7,8_37,9,8_38,8,8_39,5,6_40,7 ,8_42,6,8_42,7,8_43,9,9_43,1,6_44,8,6_45,5,9_46,8,9_46,1,8_48,8,8_49,10,7_49,8,7_50,8,9_5 0,6,8_51,8,9_53,6,9_53,4,10_54,7,7_55,10,7_55,1,10_55,7,9_55,8,10_56,4,10_57,10,6_58,1,1 0_59,8,11_59,9,10_59,6,11_62,7,11_63,1,9_63,5,6_63,3,9_64,10,12_64,2,9_65,10,10_65,9,12 _65,1,12_66,2,12_67,5,7_67,6,10_68,2,12_69,5,10_69,10,13_70,9,12_71,1,10_71,7,10_72,3,1 1_72,10,12_75,3,11_75,4,10_76,6,11_77,5,11_77,4,14_77,6,11_78,7,14_79,8,14_79,1,14_79,7 ,13_79,3,14_80,3,14_

Figure 28 shows the variation of average waiting time as new customers enter the system. This figure shows that the system reaches its steady state with regard to the average waiting time when the 75th customer enters the system which means the market is saturated later.

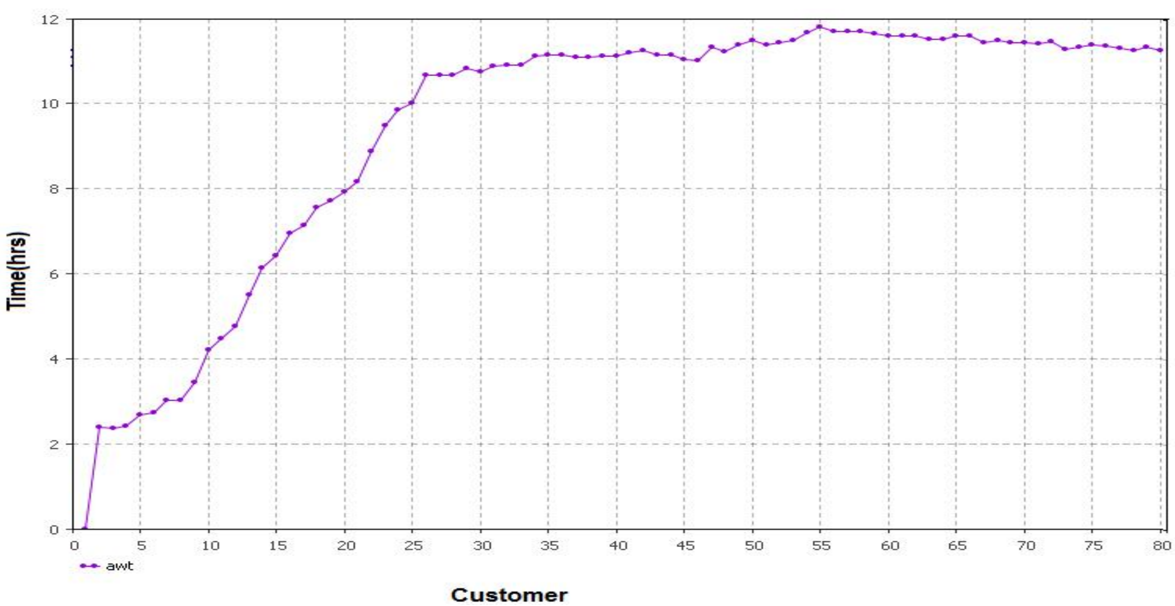

Figure 28. Average Waiting for Customers in DCA.

Table 13 compares the output variables of 10 different runs of the model with 80 customers the DCA model.

Table 13. 10 Runs of DCA.

Run #	Ending Number of suppliers	Average Wait time (hrs.)	Max Wait time (hrs.)	Average Utilization (75-85)%	Number of matched customers
1	14	11.57	22.378	80.67	143
2	13	11.662	22.607	82.787	145
3	15	11.371	22.364	82.07	152
4	14	11.488	22.553	79.416	144
5	14	11.506	22.688	78.479	142
6	14	11.561	22.535	78.78	135
7	11	11.561	22.925	82.971	112
8	15	11.549	22.589	82.35	156
9	14	12.497	22.551	82.720	143
10	14	11.469	22.445	84.64	144

Figure 29 shows the cumulative amount of Work in Process (WIP) for one simulation run. In this run, about 250 hours of service are assigned to the suppliers in the system. The ending number of suppliers in this run was 15 suppliers.

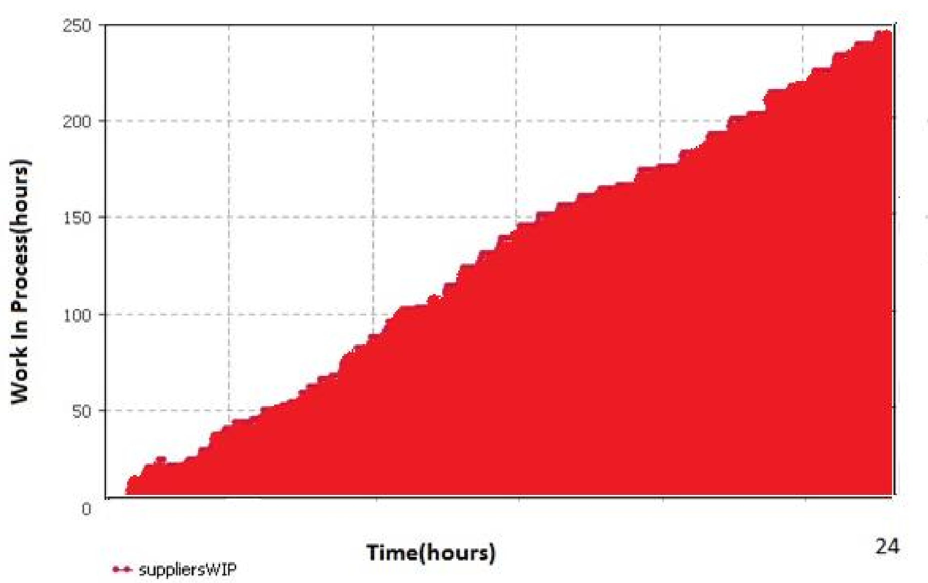

Figure 29. Cumulative WIP Graph.

By comparing figure 13 and 24, it can be concluded that Model C gives better result. Because in DCA Model when there are many services and suppliers are flexible, the average waiting time for customers is less than the average waiting time in Model B. Furthermore, the system in Model C reaches the steady state sooner. Therefore, the DCA works better while the average utilization of suppliers is high, the average waiting time is less, and suppliers are not overstressed or overloaded in this market.

Table 14 shows that Model C (DCA) is the best model in compare of other ones (discount policy was not considered). Because, there is a good range of utilization and suppliers are not overstressed and there is less average waiting time for customers while many services are asked in market from customers.

Table 14. The General Comparing of Models.

Models	Assumptions of Model	Number of Matched Services	Average Utilization Rate	Average Waiting Time (hrs)
Model A	• Service time (1, 2, and 3 hours). • Up to1 types of services • Customer agents :80 instances • Number of Suppliers:12	77	51%	7.013
Model B	• Service time (Uniformly distributed between 1 and 3 hours). • Up to five types of services • Customer agents :80 instances • Number of Suppliers:12	149	98.2%	12.611
Model C	• Service time (Uniformly distributed between 1 and 3 hours). • Up to five types of services • Customer agents :80 instances • Average Utilization Rate(75-85)% • Number of Suppliers:10 to 15	157	80%	11.66

CHAPTER IV

CONCLUSION AND FUTURE WORK

In order to evaluate the performance of Digital Manufacturing Market (DMM), different decision-making scenarios that customer agent may follow were compared. Four main research questions were formulated in Chapter 1. To answer these questions discrete-event simulation and statistical hypothesis testing were used as the research methodologies. This chapter provides succinct and explicit answers to these questions. Future work is discussed in this chapter as well.

Answers to Research Questions

Research Question 1: What is the impact of reducing the expectations of customers (minimum acceptable scores) on the performance of DMM?

Finding: Reducing the expectation of customers in Digital Manufacturing Market when there are not many required services is useful, because the number of matched customers and rate of supplier utilization is high while the customers' wait time is less than when there is no discount policy. However, hypothesis testing shows that when there are many required services in Digital Manufacturing Market the discounting does not work well. Therefore, the discount policy will work efficiently when there are not many services in demand.

Research Question 2: What is the impact of adjusting the capacity of the market based on the number of active customers in the market?

Finding: By adjusting the capacity of the markets based on active number of customers, the market will work efficiently. When the average rate of supplier's utilization is low, reducing the number of suppliers will help the market become more balanced. Furthermore, when the average rate of supplier's utilization is high, adding more suppliers is beneficial, because when the suppliers are overloaded, they are overstressed, and it is not an ideal situation to ask suppliers to work more than their capacity. Furthermore, according to Table 14, customer wait time in this market is less than when the numbers of suppliers are fixed.

Research Question 3: What is the best strategy for minimizing customer wait time?

Finding: As mentioned in previous question, in the small market, average wait time with the discount policy is less than without discount policy. However, while there are many services, by adjusting the capacity of the market dynamically, the average wait time of customer was found to be less compared to fixed capacity.

Research Question 4: What is the best strategy for improving the utilization of the suppliers in the market?

Finding: By applying dynamic capacity adjustment strategy, suppliers were found to be working in the ideal range of utilization while they are not overloaded and overstressed.

Contribution

To assess the DMM multiple, performance metrics were introduced in this work. Furthermore, a simulated model of DMM was developed for performance analysis. This work represents the first agent-based implementation of the DMM. The implementation itself is a contribution as it suggests a new approach for modeling the operation of a market for manufacturing services. The other contribution of this research is related to investigating the impacts of actors such as discount policy and capacity adjustment on the performance of the market. Currently, DMM as described in this work does not exist on the real world and an agent-based system for manufacturing market is a futuristic idea. This simulated model helps supply chain managers gain insight into the performance of a manufacturing market under different circumstances if the idea of such markets becomes a reality in the future.

Future Work

The current simulated models are just dependent on customer decisions but supplier agents were regarded as passive entities. However, supplier agents can also possess their own logic and react to the market conditions proactively to improve their chances for finding jobs. Moreover, middle agent, which is in charge of similarity score calculation, can be simulated separately to measure its accuracy for allocating different scores.

Additionally, the future extension of this agent-based model should allow for more than five services per work order and more complicated scenarios can be modeled for both customers and suppliers. The scalability of the market also needs to be tested when hundreds of customers and supplier are active in the market.

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