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Cloud Manufacturing with Fuzzy Inference System: A Supply Chain Approach to Post COVID-19 Economy

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Abstract

The COVID-19 pandemic shocked the managerial team with unprecedented fluctuations in supply, demand, and transportation of goods and services. The lessons learned from the COVID-19 pandemic proved the urgent need for agility and flexibility in response to similar future crises. This paper proposes a cloud manufacturing model as a clustered supply chain approach that incorporates fuzzy inference systems to provide a platform for the post-COVID-19-economy. Cloud manufacturing is a way to standardize and increase the system's reliability, and a fuzzy inference system is suited to deal with highly uncertain circumstances. A fuzzy inference system is integrated into a cloud manufacturing model to incorporate uncertainties related to *Time*, *Quality*, *Cost*, *Reliability*, and *Availability* in finding the optimum supply chain of manufacturers and service centers. The model is illustrated via a simulation in the manufacturing context. The proposed approach provides a tool to address the uncertainties and disruptions resulting from wide-scale crises such as the COVID-19 pandemic.

Keywords: COVID-19 Pandemic, Cloud Manufacturing, Supply Chain, Fuzzy, Simulation

1. Introduction

One of the top barriers to adopting digital supply chain management is "*no sense of urgency*" (Agrawal, Narain, and Ullah, 2020). With the dawn of the COVID-19 pandemic and the subsequent global disruptions, the need to have an agile, flexible, innovative, and interconnected digital supply chain management system is imminent. The pandemic has undermined the feasibility of production processes and endangered the output quality (including timeliness) for products and services. Given the intense competition and the drastic fluctuations in demand and supply due to the pandemic, the necessity to lower production and service costs while increasing the system's reliability is evident more than ever. Selecting the optimal composition of manufacturing services considering the utilization of the unused capacity of production centers can reduce the fixed production cost. As a computer-assisted integrated production and service centers technology, cloud manufacturing is one path to this goal. Prior research shows the positive impact of cloud computing on the performance of supply chain networks (Willcocks, Venters, and Whitley, 2013; Cao, Dara G. Schniederjans and Schniederjans, 2017). In cloud manufacturing, each product development process is considered a service. By developing each specialized service, firms can lower costs while maintaining the system's accuracy, quality, and reliability.

Our paper proposes an integrated platform with manufacturers registered after assessment from impartial institutions using a fuzzy inference system to reduce uncertainties and set the scene for integrating all production and service processes on the national and global levels. Prior literature in supply chain management has benefited from fuzzy logic in optimizing supplier selection models (Jahani et al., 2015; Kaviani et al., 2020; Yazdani et al., 2021). Recent studies on the effect of the COVID-19 pandemic on supply chain management suggest using fuzzy logic to calculate the values of activity parameters such as time and cost (Hajiagha et al., 2021).

We focus our discussion on manufacturing services, but the concepts and findings are generalizable to businesses and institutions. The simulation environment tests our proposed model of cloud manufacturing to optimize manufacturing services within several constraints and criteria. Manufacturing services involve a wide range of constraints, such as manufacturing costs, manufacturing times, end-product quality, reliability, and availability of resources. All these constraints will be analyzed and discussed in the simulated case offered in the paper. The quality of manufacturing services and resources is ranked based on a fuzzy inference model, and the scores are quality scores in the cloud manufacturing model.

The remainder of the paper is as follows: discussion of cloud manufacturing as a solution to supply chain disruptions, proposed model, problem statement, problem objectives, problem boundaries, model specifications, model assumptions, objective functions, the use of

Meta-Heuristic Algorithms, testing the model via simulation, results and sensitivity analysis, and finally, the conclusion.

2. Cloud Manufacturing: a Solution to the Supply Chain Disruptions

Dramatic or disruptive events can create significant swings in supply and demand, which can likely shape firms' behavior. The emergence of a highly contagious disease in early 2020 quickly transformed into a pandemic that led to a deep crisis affecting all aspects of the economies around the world. Most countries worldwide experienced deficient industrial production and very high unemployment rates on the supply side. Moreover, there has been a significant reduction in international freight volume and trucking capacity to ship goods from factories to ports. As inventories run down faster, parts shortages will likely become why plants cannot operate fully. On the demand side, customers who have pre-booked logistics capacity may not use it or may compete for prioritization in receiving a factory's output. The unpredictability of the timing and extent of demand rebound and rapid and profound fluctuations in the global demand market mean confusing signals for the near future. For instance, in the oil sector, the global demand will be reduced by approximately 9.5 by 2020, according to OPEC (Hodari, 2020).

The unexpected global supply chain disruptions are challenges that traditional supply chain management systems can hardly tackle. According to event system theory (EST), in the presence of novel changes, the supply chain processes are altered to create coping capabilities for affected firms (Morgeson, Mitchell, and Liu, 2015). This paper explores integrated manufacturing services on a cloud platform, considering quality as a fuzzy criterion. The model seeks the optimum composition of a clustered supply chain in the form of a digital supply chain management system.

Cloud manufacturing enables ubiquitous, convenient, and on-demand access to a shared pool of configurable manufacturing resources - such as manufacturing software tools, equipment, and capabilities - that can be rapidly provisioned and released with minimal management effort or service provider interaction (Xu, 2012). Tao, Zhang, and Nee (2011) define cloud manufacturing as a service-oriented manufacturing model wherein various technologies such as network manufacturing, cloud computing, the internet of things, virtualization, service-oriented technologies, and resource management are presented within an integrated framework. In this framework, the business partnerships between companies in a cluster supply chain serve as a manufacturing service composition (Manvi & Shyam, 2014; Towers & Burnes, 2008). In such a clustered supply chain, suppliers of similar characteristics fall into the same cluster on the chain. The outcome will be a multilevel, multidimensional, multifunctional, and multi-objective cooperation network (Villa & Antonelli, 2009).

In our proposal, the old goal of "optimal cooperation for meeting the customer's specific demand" transforms into the goal of "finding the optimal composition from a network of integrated manufacturing services to meet the customers' specific demand." Our proposed manufacturing service composition is a three-element model: First, all the resources from all manufacturers (including the research and development, manufacturing services, and processes) are in a confined cluster supply chain called the manufacturing services, which are registered and accessed through an integrated platform. Second, through the platform, customers communicate diverse needs (such as product type, transportation route, and macro and micro-service quality standards) to the manufacturers. Furthermore, a bridge between customers' needs and manufacturing services results in an optimal solution for each customer concerning their needs (Ardagna and Pernici, 2005; Chen, Sohal, and Prajogo, 2013; Liu, Li, and Shen, 2014).

The advantages of the proposed system over the traditional manufacturing systems involve the structure of fixed costs, the ability to adapt to rapid technological changes, the level of productivity and specialization, and the time needed from product development to mass production. Cloud computing allows suppliers to have inventory information updated instantly without waiting time. The efficient data processing system of cloud computing reduces the cycle time from order to delivery, a crucial element in the global supply chain network (Cao, Dara G Schniederjans, and Schniederjans, 2017). The new system does not require significant upfront investments and enjoys lower fixed costs. In a cloud manufacturing system, manufacturers can produce the product, and firms can service the end-user without physical infrastructure. In addition, the speed of response to rapid changes surrounding the firm is high. Cloud manufacturing also increases productivity through an integrated platform updated with all production or service units.

Furthermore, cloud processes drastically reduce the time needed for industrializing a prototype. In this network, many manufacturers provide independent, responsible groups for the manufacturing process, and entrepreneurs can focus on devising new ideas and designs. Again, another benefit to the economy at the aggregate level.

The implementation of cloud platforms is already on the agenda of the top management team in many companies. In a recent report by *Salesforce*, 750 leaders in different manufacturing industries worldwide identified long-lasting impacts of the COVID-19 pandemic. Interestingly, manufacturing leaders who feel well-prepared for the next decade already have most of their sales and operations in the cloud (*Inside Salesforce's New Trends in Manufacturing Report*, 2021). The top management's intention and effort in implementing cloud technology removes a significant barrier to actualizing the digital supply chain systems using cloud computing (Büyüközkan and Göçer, 2018; Agrawal, Narain, and Ullah, 2020).

3. Proposed Model

3.1 Cloud Manufacturing System with a Fuzzy Service Composition

A cloud manufacturing system comprises some components with uncertainties related to the design of the system, the existing hardware, the quality of the human resource, and the product or service of a manufacturing or service unit. Fuzzy Logic and Fuzzy Sets express the inaccuracies and uncertainties in solving problems (Zadeh, 1965). These uncertainties are measured as fuzzy factors, such as the quality of a manufacturing unit. To this end, the output quality of the manufacturing unit is classified as high, average, and low based on fuzzy criteria. A fuzzy set is a class of members, with each member having a different membership degree ranging from 0 to 1. When a member's degree of membership in a fuzzy set is 1, that member is definitely part of the set. When the membership degree is zero, the member is definitely not a member of the set. The model seeks the optimum solution based on the objective function, the best combination of manufacturing units.

3.2 Fuzzy Inference System

A fuzzy inference system is a method in which a definite input is mapped to another definite output under such a system to obtain the desired result. Figure 1 depicts the system's workflow, where a fuzzy inference system receives a definite input and then converts it into fuzzy output using expert knowledge. The decision is made using the rules and inference system in the next step. Next, a fuzzy set of solutions is obtained from the possible solutions set through a union. Finally, definite data and a definite decision are obtained through the defuzzification of the final solution. This system facilitates the process of modeling a complex set.

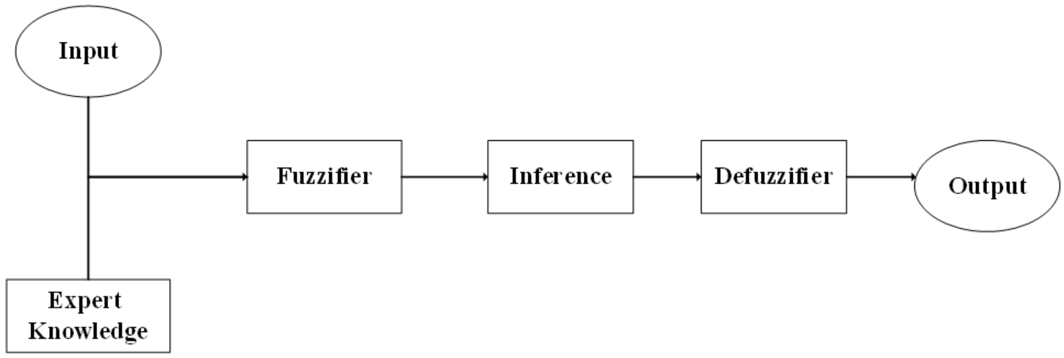

Figure 1. Explaining a fuzzy inference system (input, Fuzzifier, expert knowledge, inference, Defuzzifier, and output)

4. Problem Statement

In a cloud system, everything is a service. A cloud platform consists of three components: the server, the cloud manager, and the client. Both suppliers and customers are constantly trying to increase the productivity of their operations to survive in the competitive environment. With the invention of cloud platforms, manufacturers and suppliers can offer all their services on the platform and fully utilize their spare capacities. Customers, who may also be part of the production chain, try to reduce costs while improving the quality of their products and services. Cloud platforms enable customers to post their orders and choose among the suppliers who offer their desired quality level and are within their limited budget. Therefore, cloud platforms allow suppliers and customers to fulfill their needs. This paper shows that the optimization feature in cloud platforms can help us navigate the current COVID-19 crisis. We continue our discussion of cloud platforms in a manufacturing context.

The model needs a set of criteria and constraints that customers determine. Based on those criteria, the platform computes and offers the optimal composition of services (manufacturing services). The criteria we assume in this paper for optimizing the service providers' composition are Quality, Delivery Time, Costs, and Reliability. The end product needs to be delivered to the customers on time and according to the qualities demanded. The constraints we assume are Capacity and Availability. We assume that these constraints are excluded from the customer utility objective function. We use a fuzzy inference system to assess and score the output product quality to rank factories and estimate output product quality to be presented to the customers by the system.

Although our proposed approach is demonstrated in a manufacturing setting, it is well extendable to the services sectors. In other words, our proposed model applies to any procedure with identifiable steps/sub-categories. For example, the process of air freight services can be divided into these simplified steps: 1) transferring the parcel from its origin to the departure airport, 2) transferring the parcel from the departure airport to the destination airport, 3) transferring the parcel from the destination airport to the regional shipping distribution center, and 4) shipping the parcel from the regional shipping center to the final destination address. Multiple qualified shipping companies and carriers can complete each of these steps. Each supplier has unique advantages and disadvantages in terms of time, quality, reliability, and cost of their services. Our proposed platform considers the supplier's information and the customers' utility function and generates an optimal operating flow for the desired service. In the next part, we resume the analysis and model proposition in the manufacturing setting.

5. Problem Objectives

The optimum composition of manufacturing services on the cloud platform is the overarching goal of the problem. Since quality and cost play a significant role in attracting customers, and perceived quality directly affects estimating costs, this paper tries to provide an optimal composition of manufacturing services to the customers depending on the demanded quality. Several studies measure and analyze perceived quality using fuzzy logic and fuzzy sets (Tsaura, Chang and Yen, 2002; Wu, Hsiao, and Kuo, 2004; Kraus, Ribeiro-Soriano and Schüssler, 2018; Miranda, Tavares and Queiró, 2018). Given the high uncertainty of quality assurance in today's world, a fuzzy inference system estimates the output quality of each manufacturer. Moreover, considering the global Corona pandemic, the proposed cloud platform can use the spare capacity of the servers (manufacturing service providers) at the national and international levels to increase manufacturers' productivity.

In summary, our proposed system consists of the following components: First, a virtual manufacturing system where all machinery and movements from all manufacturing service providers are simulated so that the estimation of Time and Cost takes place with high accuracy. Second, a fuzzy inference system for assessing the quality of each factory and assigning a quality score ranging from 1 to 10. Third, the assignment of quality coefficients for factories (in the problem) is according to the fuzzy inference system, such that the output meets the minimum required quality. Fourth, an optimization problem to maximize customers' utility based on the following six criteria: 1) Output quality, 2) Reliability of the machinery for estimating the failure of the end product, 3) Time, 4) Cost, 5) Capacity, and 6) Availability. Please refer to Table 2 for variable and parameter definitions. Among the six criteria, the first four contribute to customer satisfaction and thus are part of the customer's utility or objective function. The last two are goals that need to be met.

Moreover, it is the computation of the optimum solution. This paper uses a genetic algorithm to solve this optimization problem. The system's output (the proposed model) is optimal for manufacturing the products based on the abovementioned criteria.

6. Problem Boundaries

6.1 The Cloud Space Boundaries

The cloud space has several different characteristics; hence, to accurately set the problem boundaries, we need to define the cloud space precisely.

6.2 Manufacturing Cloud Space

In the cloud space defined in this paper, we only consider manufacturing services and do not include other services such as design or maintenance. Using the cloud space, we simplify the model to receive a production process plan and product specifications.

6.3 Decision-making Cloud Space

The cloud space, designed in the paper, receives required information about factories enrolled in the cloud space from information experts and reveals the optimal manufacturing path based on customer requirements. These requirements are expressed by customers who do not interact with factories. In other words, customers only communicate their needs to the system, which is responsible for the decision-making. For example, the product delivered to the customer has one cloud space indicator, and the customer is unaware of its manufacturing path at the beginning.

6.4 Virtualization of Physical Equipment

The system completely simulates all the equipment items and the machinery movements, so manufacturing cost and time can be estimated with high accuracy. The estimation of Time and Cost requires a database that records information on:

- Manufacturer capabilities: machinery and human resources
- Manufacturer quality: scores and rankings based on fuzzy logic. Please refer to Table 1 for the manufacturers' quality scores.
- Product reliability: based on the quality of each manufacturer's output history.
- Manufacturer's Cost: Cost of production separately for each manufacturer
- Manufacturer's production time: obtained using the historical data on the duration of the production

Table 1. Manufacturers' quality scores

Score	10	9	8	7	6	5	4	3	2	1	0
Quality Rating	A++	A+	A	A-	B+	B	B-	C+	C	C-	D

6.5 Services Offered by the Cloud Manufacturing Platform

Manufacturing service: The platform offers manufacturing services to the customers according to the required design and manufacturing method.

6.6 Cost Assessment Service

The mathematical program behind the model acquires necessary information from the database about each production unit (factory) cost and estimates the cost of the operations for the new operating process.

6.7 Reliability Assessment Service

Similar to the previous service, the reliability of historical outputs is used to estimate the reliability of new products. The required data is retrieved from the database by the software on the platform.

6.8 Time Measurement Service

The platform collects information about manufacturers' spare capacities to shorten the production period to a possible extent through coordinating manufacturing steps and assigning production tasks among several manufacturers. This level of cooperation and coordination is near impossible in traditional systems.

6.9 Product Quality Assessment Service

Throughout the product manufacturing process, the desired quality of the end product is assessed against the customers' quality requirements. Factories capable of manufacturing products with the desired quality are identified and used in the optimum production path.

Figure 2 provides an overview of services provided by the proposed cloud system.

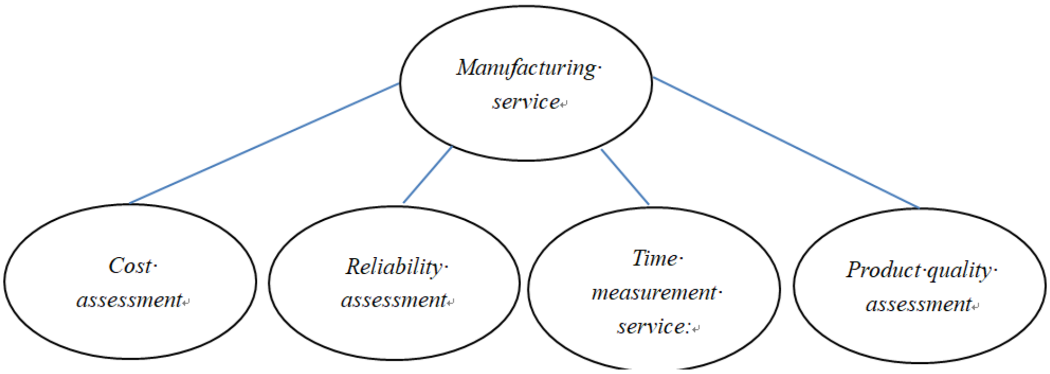

Figure 2. An overview of the services provided by the cloud system

7. Model Specifications

7.1 Availability

Availability of a factory (*Av*) refers to the hours the factory is ready to operate during a process, expressed in percentage. For example, 99% availability means that only one out of every hundred working hours is spent on situations wherein the machines are turned off and the factory is not manufacturing. The lower the rate of availability, the higher the likelihood of delayed order recording. Availability of services in the cloud space during time t is a criterion of concern. Assume t_a during time slot [t_1, t_2] denotes the length of time that the cloud-based service can be successfully delivered, then the availability is calculated as follows (Zhou & Yao, 2017a).

$$Av = \frac{t_a}{(t_2 - t_1)} \tag{1}$$

7.2 Reliability

Reliability (R) refers to executing a cloud manufacturing service successfully within a given time and specific condition. Including the success rate and the average failure rate of cloud manufacturing services, reliability is calculated as below:

$$R = \beta_1 R_{s-exe} + \beta_2 R_{no\ failure} \tag{2}$$

$R_{s\text{-}exe}$ is the successful execution rate of the requested cloud manufacturing within a specific time. $R_{s\text{-}exe}$ is expressed as $R_{s\text{-}exe} = S_{exe(t)} / E(t)$, where $S_{exe(t)}$ is the successful execution times within t and $E(t)$ is the number of times cloud manufacturing service is invoked within t. The average failure rate $R_{failure}$ refers to the probability that a cloud manufacturing service works with no failure at a particular time, and after that time, failure occurs. $R_{failure,}$ also known as failure rate function, is a function of t. According to (Zhou & Yao, 2017b), β1 and β2 can be set according to the actual situation to ensure 0 < R < 1.

7.3 Manufacturing Cost at the Factory

We followed (Zhou and Yao, 2017) for the calculation of the cost of operation (C) for the required service in a cloud system:

$$C = (C_{online} + C_{offline}) \tag{3}$$

Where, C_{online} is the cost of the system being online, including the cost of data transmission, accesses, and computations. $C_{offline}$ is the cost of offline processes and includes performing the processes costs in a physical environment. Offline costs are determined as:

$$C_{offline} = (C_{management} + C_{excution}) \tag{4}$$

The offline cost is the sum of the costs for management and execution.

7.4 Process Time in the Factory

The process time is between registering a process in the cloud manufacturing platform and the delivery of the system. This time is calculated via the following equation.

$$T = (T_{online} + T_{offline}) \tag{5}$$

Following (Zhou & Yao, 2017b), T_{online} refers to the operation duration. The online time is the time spent from the moment the request is answered until the process is completed in the virtual cloud space. It is divided into two sections: process completion and transmission time.

$$T_{online} = (T_{process} + T_{trans}) \tag{6}$$

$T_{process}$ is the process completion time, and T_{trans} is the transmission time in the transport network. $T_{offline}$ refers to cloud manufacturing services performed offline in the physical space. The offline time is the sum of the times needed for management, waiting, and execution, including logistics and operation times on offline activities in the cloud system.

$$T_{offline} = \left(T_{management} + T_{wait} + T_{excution}\right) \tag{7}$$

7.5 The Capacity of Each Factory

Capacity refers to the maximum amount a manufacturer on the platform can produce. Note that capacity is different from availability, as the availability of a factory refers to the number of hours the factory is ready to operate during a process. In contrast, capacity refers to the manufacturing power to produce a product. The capacity criterion is a constraint and is not part of the objective function.

7.6 Quality

Quality refers to the degree of accuracy and accord in the end product based on the parameters required by the customer. Note that Quality and Reliability are two different concepts in our proposed model. Reliability indicates the rate of non-defect products per every hundred pieces manufactured and sent to the customer by a production unit (manufacturer). On the other hand, quality has to do with the conformity of the output quality with the customer's requirements (expectations). We designed and proposed a fuzzy inference system to analyze and rank factories' quality as the model's input. This fuzzy inference system uses four input variables and one output variable. Input variables are manufacturing environment, state of the machinery, flexibility of machinery, and human resource skillfulness. The output variable is a number between 0 to 10, determining the quality of the factory (production unit on the platform), which will be used as input for the mathematical model we will discuss in the following section.

The manufacturing environment deals with the proper layout for the machinery pieces and the factory environment's cleanliness. The state of the machinery is gauged based on the machinery technology, proper installation, tuning, and performance accuracy. The flexibility of machinery has to do with the range and flexibility of outputs that the machinery can produce and the range of options it gives the operator. Human resource skillfulness deals with the personnel's knowledge, expertise, efficiency, and effectiveness.

8. Model Assumptions

We assume all processes are sequential, and the tasks in each step are accomplishable in parallel. With these assumptions, there are several candidate manufacturers in each step. We also assume that the factories in each step are in the same vicinity, and thus the transportation costs are not notably different. Therefore, this value is unchanged and separated from the objective function.

9. Objective Functions

There are two objective functions: The ultimate goal function, which seeks lower cost and time ratios values, and higher quality and reliability ratios. The utility function increases with a decrease in Time and Cost and an increase in Quality and Reliability.

9.1 The Ultimate Goal Function

The objective function is a normalized objective function for each variable.

$$\text{Max Z} = W_1 \times (TimeRatio) + W_2 \times (CostRatio) + W_3 \times (ReliabilityRatio) + W_4 \times (QualityRatio) \tag{8}$$

9.2 Utility Objective Function

$$Max\ Utility = Ln(TimeRatio) + \ln(CostRatio) + e^{ReliabilityRatio} + e^{QualityRatio} \tag{9}$$

TimeRatio is the ratio of process time to the maximum process time needed to carry out the process and is a value less than one. We run the model to maximize the manufacturing time using equation 9 with other coefficients set to zero to find the total possible time. *CostRatio* is the ratio of the cost of carrying out the process to the total cost. This ratio is always less than one. To find the total (or, in other words, the maximum) cost of a process, we run the model intending to maximize the manufacturing cost using Equation 9 with other coefficients set to zero. *ReliabilityRatio* is the ratio of the process reliability to the maximum reliability of performing the process, which is smaller than one. To obtain the highest possible level of reliability, we need to run the model to maximize reliability using Equation 9, holding other coefficients as zero. Finally, *QualityRatio* is the ratio of the process quality to the maximum process implementation quality. This ratio is always less than one. The numerator represents the process implementation quality, and the denominator represents the maximum quality of the process. To find the highest possible level of quality, we need to run the model to maximize the manufacturing quality using Equation 9 while setting other coefficients to zero.

9.3 Constraints

9.3.1 Operation Time

This constraint makes sure that the operation time in each step is lower than or equal to the maximum time allowed for the operation for that step.

$$max(t_{ij}x_{ij}) \leq T_i \quad \forall i = 1 \ldots I \tag{10}$$

Where t_{ij} denotes the processing time of step i in factory j, and x_{ij} is the number of times (iterations of) operations of step i at factory j. T represents the maximum time allowed for the manufacturing of step i. Note that the assumption is that operations of a step can be carried out sequentially by one factory or parallelly at multiple factories.

9.3.2 Operation Cost

Whether a factory completes a process several times or several factories complete a process in parallel, the operational cost is the total operational cost.

$$\sum_{J=1}^{M} c_{ij}x_{ij} \leq C_i \quad \forall i = 1 \dots I \tag{11}$$

Where c_{ij} is the cost of operation in step i at factory j, and C_i is the total operational cost for step i.

9.3.3 Availability

Availability constraints deal with the availability of the production for step i. Given that the availability capability in each step can be done in parallel and each step is sequentially related to its next step, each factory's iteration coefficient functions as the power (Zhou & Yao, 2017b). The following constraint is used for availability.

$$\prod_{J=1}^{M} a_{ij}^{x_{ij}} \geq A_i \quad \forall i = 1 \dots I \tag{12}$$

In the above inequation, a_{ij} represents the extent of availability of factory j for step i, and A_i represents the minimum availability degree required for step i.

9.3.4 Reliability

Reliability constraints show whether the reliability of the production for step i is greater than the minimum acceptable reliability for that step. Since each step's reliability is done in parallel and each step is sequentially related to its next steps, each factory's iteration coefficient functions as the power (Zhou & Yao, 2017b). The following limitation is used for reliability:

$$\prod_{J=1}^{M} r_{ij}^{x_{ij}} \geq R_i \quad \forall i = 1 \dots I \tag{13}$$

Where r_{ij} denotes the reliability of factory j for step i, and R_i represents the minimum reliability level required for step i.

9.3.5 Capacity

Capacity constraint ensures that the total capacity of the service suggested by the platform is greater than or equal to what is needed for step i.

$$\sum_{J=1}^{M} k_{ij}x_{ij} \geq K_i \quad \forall i = 1 \dots I \tag{14}$$

9.3.6 Quality

We define a binary variable that gets one if factory j is used and 0 otherwise. In the following constraint, y_{ij} gets one if factory j accomplishes i^{th} activity (step i) and gets 0 otherwise.

$$min(q_{ij}y_{ij}) \geq Q_i \quad \forall i = 1...I \tag{15}$$

Equation 15 determines if, at each stage, the minimum product quality of the factory must be higher than the minimum quality expected by the customer at that stage. Furthermore, equation 16 ensures that y_{ij} gets 1 when x_{ij} is 1.

$$x_{ij} \leq My_{ij} \quad \forall i = 1...I, j = 1...J \tag{16}$$

Where M is a large number.

9.4 The Criterion-specific Maximum and Minimum Identification Function

We need an objective function to calculate the exact value of each criterion and identify the maximum and minimum values of each. We used the following objective function.

$$max\, z = W_1 * (\textstyle\sum_{i=1}^{I} max(t_{ij}x_{ij})) + W_2 * (\sum_{i=1}^{I} c_{ij}x_{ij}) + W_3 * (R_{ij}{}^{x_{ij}}) + W_4 * (min(q_{ij}\forall i)) \tag{17}$$

The weight of each variable is determined according to the needs of each customer. For example, many countries face a toilet paper crisis in pandemic conditions, in which supply time is critical. Hence, the weight of this variable is much higher than other variables. Or in the case of a vaccine, its cost is of little importance, so the weight of the cost is considered less.

Table 2 provides the list of definitions for variables and parameters.

Table 2. Definitions of variables and parameters

Parameter	Definition
Z	Objective Function value
W_i	Weight of the variable i in the objective function
TimeRatio	The ratio of process time to the maximum process time needed to carry out the process
CostRatio	The ratio of the cost of carrying out the process to the total cost of the process
ReliabilityRatio	The ratio of the process reliability to the maximum reliability of performing the process
QualityRatio	The ratio of the quality of performing the process to the maximum process implementation quality
Utility	Utility Function value
x_{ij}	The number of iterations of step i in jth factory
y_{ij}	Binary variables that get one if factory j accomplishes ith activity (step i), and gets 0 otherwise
t_{ij}	Process time in step i at factory j
T_i	Maximum time allowed to be spent on manufacturing in step i
c_{ij}	Cost of completing step i in factory j
C_i	Maximum allowable cost to be paid for manufacturing the product in step i
a_{ij}	The extent of availability of factory j for step i
A_i	The minimum availability degree for step i

r_{ij}	The reliability of factory j in stage i
R_i	The minimum reliability level for step i
k_{ij}	The capacity of factory j in stage i
K_i	Minimum capacity required for step i
q_{ij}	Quality of factory j for step i
Q_i	Minimum quality required in step i
M	Very large number

10. The Use of Meta-Heuristic Algorithms

As the number of manufacturing steps and service providers in each step increases, the number of candidates for a composition of manufacturing services increases drastically. The mathematical model that the proposed cloud manufacturing platform needs to solve is an example of NP-Hard models; in such models, the solution time increases exponentially as the number of variables increases. Therefore, we need improved optimization methods such as meta-heuristic algorithms to solve complex mathematical problems and find the desired solution. Otherwise, finding the optimal manufacturing path will be highly time-consuming. The genetic algorithm is among the meta-heuristic algorithms practitioners and academicians use in many problems, especially in optimizing cluster supply chains (Wang, Makond, and Liu, 2011). The advantage of this algorithm is the ability to work with integer forms and find a near-optimal solution.

11. Testing the Model - Simulation

This section tests the proposed model in a simulated environment where the product of interest is the "toolbox." The proposed cloud manufacturing system requires three phases: 1) constructing the manufacturers' database, 2) receiving an order from customers, and 3) incorporating customers' requirements.

Phase 1) Construction of manufacturers' database

This dataset records: 1) The machinery type and quantity; 2) The factory output quality; 3) The end product reliability; 4) The manufacturing cost for one working day in the factory; 5) The manufacturing capacity of one working day in the factory.

Experts measure the quality of the manufacturing environment and pieces of machinery and the level of personnel's skills and competencies to assess the factory output quality using the designed fuzzy inference system.

Phase 2) Ordering the product

11.1 Sub-operations

The customer enters production orders of 500 products within a maximum period of d days and with a certain level of quality (for example, A-, which equals a score of 7 in our system) at a maximum cost of C per unit. Please refer to tables 18 to 22 for the customer's order assumptions.

This step will determine the sub-operations needed to produce one unit of the ordered product. In our simulation, we assumed that manufacturing a toolbox requires eight sub-operations. Table 3 summarizes the number of factories running these sub-operations in the simulation.

Table 3. Number of factories per sub-operation in the simulation problem

	Sub-operations							
	1	2	3	4	5	6	7	8
Number of factories	6	3	5	6	3	8	5	9

11.2 Execution Time

Operation time is the duration of one round of operations in a factory according to its capacity. Table 4 tabulates the operation time for each sub-operation at different factories in the simulation. We need to emphasize that factories are independent of each other in each step, such that Factory 2 in sub-operation 1 is not necessarily the same in sub-operation 2. Here, M refers to the absence of the given factory. Hence, it could be set to a very large value.

Table 4. Execution time for each sub-operation in each factory

	Sub-operations							
	1	2	3	4	5	6	7	8
Factory 1	6	15	8	4	43	4	3	4
Factory 2	5	13	12	3	24	5	3	4
Factory 3	8	10	20	6	67	3	8	6
Factory 4	3	M	15	8	M	4	7	8
Factory 5	5	M	8	2	M	4	6	7
Factory 6	4	M	M	4	M	5	M	6
Factory 7	M	M	M	M	M	2	M	9
Factory 8	M	M	M	M	M	4	M	3
Factory 9	M	M	M	M	M	M	M	4

11.3 Cost of Operations

The cost of operation j^{th} in the factory i^{th} is listed in Table 5. This cost is related to a period with a specified capacity.

Table 5. Cost of operations in each factory

	Sub-operations							
	1	2	3	4	5	6	7	8
Factory 1	12	24	50	56	89	23	87	19
Factory 2	41	34	45	60	101	38	98	14
Factory 3	32	54	23	32	95	47	65	16
Factory 4	65	M	40	70	M	38	43	18
Factory 5	25	M	55	40	M	47	37	24
Factory 6	65	M	M	19	M	29	M	24
Factory 7	M	M	M	M	M	64	M	10
Factory 8	M	M	M	M	M	57	M	23
Factory 9	M	M	M	M	M	M	M	27

11.4 Quality of Operations

Experts assess different quality criteria to calculate the quality of each factory. In order to achieve the quality of each operation in each factory, a fuzzy inference system has been used. The system takes in the values of 1) quality of tools, 2) quality of the workforce, 3) quality of machines, and 4) quality of work environment from experts and returns the output value to the optimization problem. Input values are generated randomly by the author and assumed to be the experts' input in the fuzzy inference system. Please refer to tables 6 to 14 for the input and output values. We use MATLAB to program the fuzzy inference system with the following specifications:

Name='ranking'

Type='mamdani'

Version=2.0

NumInputs=4

NumOutputs=1

NumRules=30

AndMethod='min'

OrMethod='max'

ImpMethod='min'

AggMethod='max'

DefuzzMethod='centroid'

Table 6. Quality assessment in factories related to the 1st operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	10	8	7	8	8	3			
Machine Quality	7	7	8	7	7	8			
Tools Quality	5	6	9	8	6	9			
Human Skills	9	4	5	9	5	6			
Quality Score	7.68	6.68	7.07	8.24	6.77	5.1			

Table 7. Quality assessment in factories related to the 2nd operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	8	9	9						
Machine Quality	7	9	6						
Tools Quality	8	10	7						
Human Skills	7	6	8						
Quality Score	7.44	8.67	7.68						

Table 8. Quality assessment in factories related to the 3rd operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	9	8	7	8	9				
Machine Quality	7	7	8	7	6				
Tools Quality	6	9	4	6	8				
Human Skills	8	8	9	7	7				
Quality Score	7.68	8.39	7.02	7	7.63				

Table 9. Quality assessment in factories related to the 4th operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	8	6	10	4	9	5			
Machine Quality	7	6	8	6	8	4			
Tools Quality	6	8	10	9	8	6			
Human Skills	8	7	10	9	6	9			
Quality Score	7.4	6.8	9.38	7.03	7.11	6.79			

Table 10. Quality assessment in factories related to the 5th operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	8	5	10						
Machine Quality	7	8	9						
Tools Quality	5	9	10						
Human Skills	6	9	9						
Quality Score	6.83	8.47	9.11						

Table 11. Quality assessment in factories related to the 6th operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	9	8	9	8	9	9	10	9	
Machine Quality	7	9	10	9	9	8	10	9	
Tools Quality	10	9	8	10	8	10	10	9	
Human Skills	9	10	8	7	10	10	10	9	
Quality Score	9.11	8.73	8.58	8.16	8.69	9.32	9.39	8.75	

Table 12. Quality assessment in factories related to the 7th operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	5	8	7	9	9				
Machine Quality	6	9	8	6	3				
Tools Quality	7	6	9	5	9				
Human Skills	8	4	5	9	7				
Quality Score	6.75	7	7.07	7.13	5.74				

Table 13. Quality assessment in factories related to the 8th operation

	Factories								
	1	2	3	4	5	6	7	8	9
Environment	5	7	6	6	5	9	8	9	9
Machine Quality	8	8	8	9	7	7	7	6	8
Tools Quality	4	8	7	7	8	6	9	8	9
Human Skills	9	9	6	5	9	10	8	7	5
Quality Score	7	8.21	6.87	7	7.95	7.54	8.39	7.63	7.14

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Table 14. Fuzzy inference system output related to the quality of each factory

	Sub-operations							
	1	2	3	4	5	6	7	8
Factory 1	7.68	7.44	7.68	7.4	6.83	9.11	6.75	7
Factory 2	6.68	8.67	8.39	6.8	8.47	8.73	7	8.21
Factory 3	7.07	7.68	7.02	9.38	9.11	8.58	7.07	6.87
Factory 4	8.24	0	7	7.03	0	8.16	7.13	7
Factory 5	6.77	0	7.63	7.11	0	8.69	5.74	7.95
Factory 6	5.1	0	0	6.79	0	9.32	0	7.54
Factory 7	0	0	0	0	0	9.39	0	8.39
Factory 8	0	0	0	0	0	8.75	0	7.63
Factory 9	0	0	0	0	0	0	0	7.14

Phase 3) Assessing customer demands

11.5 Demanded Quality

The customer requested quality A-, which is the same as a score of 7 or higher.

11.6 Demanded Capacity

The capacity requested by the customer is 500 units. Table 15 summarizes the capacity of factories for each sub-operation, considering the inventory levels in manufacturing steps. Table 18 shows the minimum capacity required per operation.

Table 15. Capacity of factories (units of products)

	Sub-operations							
	1	2	3	4	5	6	7	8
Factory 1	200	350	500	400	350	300	400	300
Factory 2	300	300	400	600	600	650	650	450
Factory 3	600	500	300	450	450	350	300	500
Factory 4	800	0	600	700	0	450	600	350
Factory 5	650	0	600	550	0	550	750	350
Factory 6	870	0	0	500	0	500	0	400
Factory 7	0	0	0	0	0	600	0	550
Factory 8	0	0	0	0	0	500	0	570
Factory 9	0	0	0	0	0	0	0	600

Table 18. Minimum capacity required per operation

	Sub-operations							
	1	2	3	4	5	6	7	8
Capacity	480	500	450	420	500	500	480	500

In order to ensure timely delivery of the output, the system needs to estimate the availability, the maximum process time, and the reliability of each process's parameters and integrate them all in the optimization process on the cloud platform. The cloud manager provides these estimates.

11.7 Demanded Reliability

Demanded reliability by the customer is 93%. Table 16 summarizes the reliability of factories for each sub-operation, considering the inventory levels in manufacturing steps. Table 19 tabulates the minimum reliability required per operation.

Table 16. Reliability of factories

	Sub-operations							
	1	2	3	4	5	6	7	8
Factory 1	100%	100%	99.97%	99.95%	99.99%	95%	99.95%	99.99%
Factory 2	99.99%	99.97%	99.93%	99.50%	99%	99.99%	100%	99.95%
Factory 3	99.98%	99.95%	99.85%	99.99%	98.50%	99.95%	99.99%	100%
Factory 4	99.99%	0	100%	100%	0	99.50%	99.25%	99.30%
Factory 5	98.98%	0	99.25	99.96%	0	100%	99.99%	96.50%
Factory 6	100%	0	0	99.35%	0	99.45%	0	99.99%
Factory 7	0	0	0	0	0	100%	0	99.60%
Factory 8	0	0	0	0	0	99.99%	0	99.65%
Factory 9	0	0	0	0	0	0	0	99.95%

Table 19. Minimum Reliability required per operation

	Sub-operations							
	1	2	3	4	5	6	7	8
Reliability	98%	97%	99%	95%	96%	95%	94%	93%

11.8 System Availability

The availability per operation is determined considering the delivery time and capacity. Table 17 summarizes the availability of factories for each sub-operation, considering the inventory levels in manufacturing steps. Table 20 shows the minimum availability required per operation.

Table 17. Availability of factories

	Sub-operations							
	1	2	3	4	5	6	7	8
Factory 1	99%	98%	99/98%	97%	95%	97.98%	96.60%	95.50%
Factory 2	95.60%	99.75%	98%	98.50%	97%	99.99%	100%	93%
Factory 3	97.60%	97.85%	99%	96.70%	98.95%	97.55%	98.90%	100%
Factory 4	96.50%	0	98.98%	95.57%	0	98.56%	96%	94%
Factory 5	95.77%	0	96.90%	93.94%	0	99.50%	99.95%	98.40%
Factory 6	94.95%	0	0	95.50%	0	93.90%	0	93.50%
Factory 7	0	0	0	0	0	99%	0	98.50%
Factory 8	0	0	0	0	0	100%	0	99.50%
Factory 9	0	0	0	0	0	0	0	95.70%

Table 20. Minimum availability required per operation

	Sub-operations							
	1	2	3	4	5	6	7	8
Availability	98%	98%	98%	99%	97%	96%	97%	95%

11.9 Requested Delivery Time

The time of completing each step, the delivery time, is shown in Table 21.

Table 21. Maximum Time available for each operation

	Sub-operations							
	1	2	3	4	5	6	7	8
Time	7	20	18	10	90	10	12	12

11.10 Requested Cost

According to the total requested cost, the cost of each operation is calculated and shown in Table 22.

Table 22. Maximum Cost available for each operation

	Sub-operations							
	1	2	3	4	5	6	7	8
Cost	100	120	70	65	150	70	100	50

Phase 4) Problem-solving

11.11 Determining the Denominators of Ratios

As explained in the previous section, first, we calculate the maximum value of each variable using Equation 17, which results in the maximum values of 97 days, 593 units' cost, 7.13 quality out of quality coefficient of 10, and 0.98931 reliability out of reliability coefficient of 10.

This problem's two objective functions are optimized utilizing the roulette method, and the results are according to the optimal state of each function. Note that the value of the objective function of optimization of ratios does not have a special meaning, and its only goal is to optimize existing ratios. The solution after 500 iterations is as below:

$$X = \begin{bmatrix} 0\,0\,0\,1\,0\,0\,0\,0\,0 \\ 0\,0\,1\,0\,0\,0\,0\,0\,0 \\ 1\,0\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,1\,0\,0\,0\,0 \\ 0\,1\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,1\,0\,0\,0 \\ 0\,0\,0\,1\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0\,0\,1\,0 \end{bmatrix}$$

Table 23 provides the weights of each variable in the initial objective function. We should reiterate that these weights reflect an example of the customers' preferences. Depending on the importance and superiority of the four variables of Quality, Reliability, Cost, and Time, our proposed model produces an optimized plan tailored to the customer's desires. Table 24 shows the answers for each parameter that optimizes the initial objective function. Table 25 summarizes optimal ratios based on optimization of the objective function. Figure 3 shows the problem's solution after 500 iterations.

Table 23. Weights of the variables in the objective function

Variable	Quality	Reliability	Cost	Time
Weight	0.1	0.1	0.4	0.4

Table 24. Answer based on various parameters to optimize the initial objective function

	First Run	Second Run	Third Run	Fourth Run
Gamma	0.3	0.3	0.6	0.8
Mutation Percentage	0.3	0.3	0.3	0.3
Crossover Percentage	0.8	0.8	0.8	0.8
Mutation Rate	0.02	0.1	0.1	0.1
Population Size	1000	1000	1000	1000
Value of Utility Function	0.83629	0.87119	0.87119	0.87119
Value of Objective Function	-0.3369	-0.3303	-0.3303	-0.3303

Table 25. Optimal ratios of variables based on optimization of the objective function

Variable	Quality	Reliability	Cost	Time
Ratio	0.98794	0.99719	0.68297	0.63918

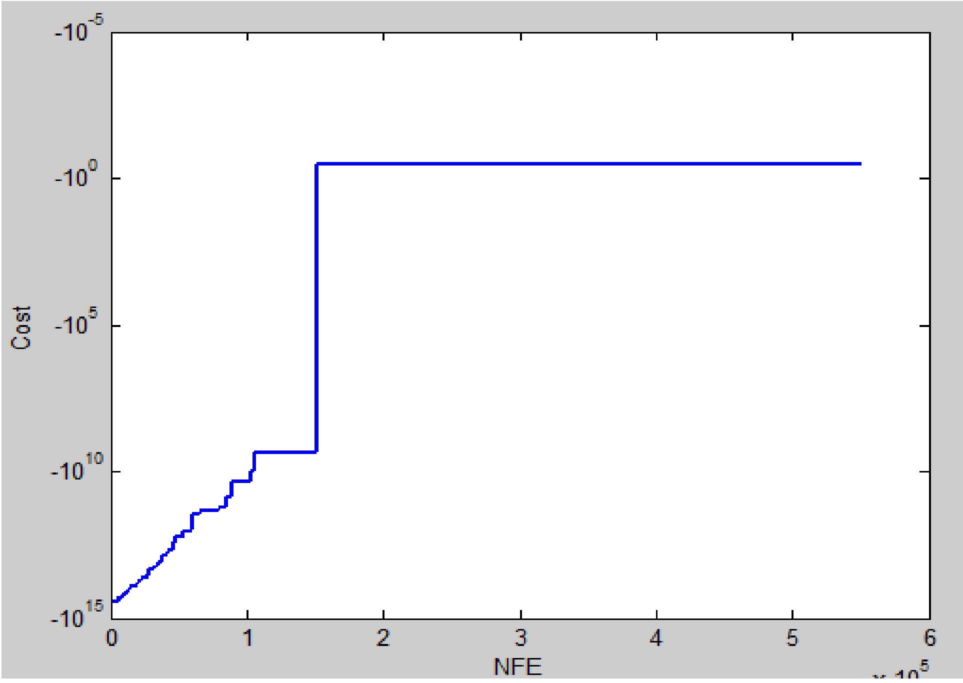

Figure 3. Finding the problem solution after 500 iterations

Now we optimize the utility function of the customer using the roulette method. The utility function is determined based on the customer's needs, and a higher utility function reflects higher customer satisfaction. The model parameters are the same, except that the goal is to optimize the customer's utility.

We set the coefficients for ln (TimeRatio) and ln (CostRatio) to 3, and exp (ReliabilityRatio) and exp (QualityRatio) to one. Table 26 shows the results of different runs based on optimization of the utility function. In this table, the number of iterations for different parameters is tabulated. Following, we will focus on the ratios from the best solution.

Table 26. Results of different runs based on optimization of the utility function

	First Run	Second Run	Third Run	Fourth Run
Gamma	0.3	0.3	0.6	0.8
Mutation Percentage	0.3	0.3	0.3	0.3
Crossover Percentage	0.8	0.8	0.8	0.8
Mutation Rate	0.02	0.1	0.1	0.1
Population Size	1000	1000	1000	1000
Value of Utility Function	0.83629	0.83629	0.87119	0.87119
Value of Objective Function	-0.3536	-0.3536	-0.3303	-0.3303

Table 27 summarizes the final solution by tabulating the optimal ratios of variables based on optimizing the utility function. The problem specifications are the same as the previous objective function. Figure 4 shows the problem's solution after multiple iterations of optimization.

Table 27. Optimal ratios of variables based on the optimization of the utility function

Variable	Quality	Reliability	Cost	Time
Ratio	0.98794	0.99719	0.68297	0.63918

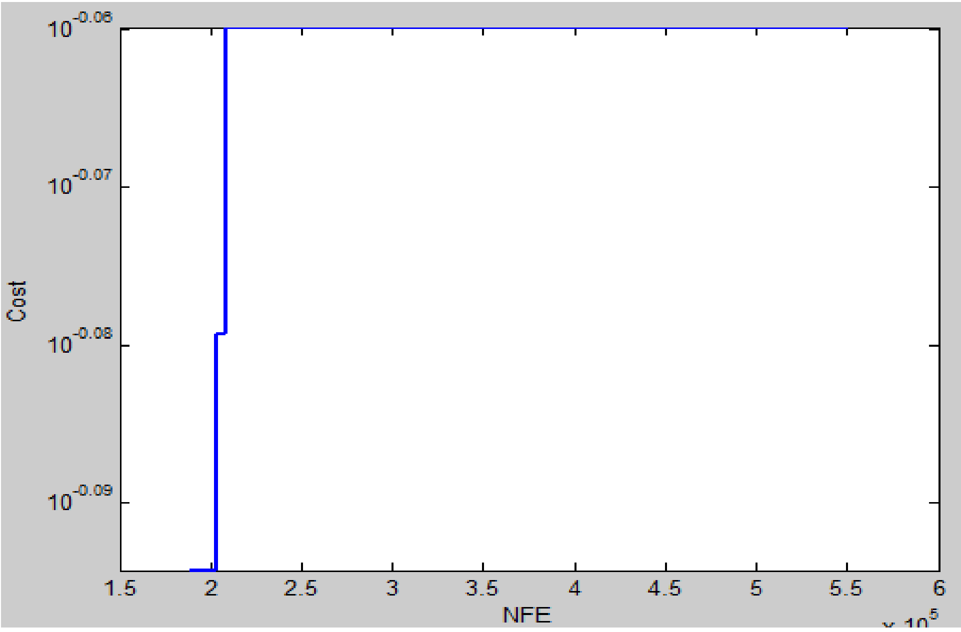

Figure 4. Obtaining the desired solution after multiple iterations of the algorithm

12. Results and Sensitivity Analysis

The objective function of the problem seeks to improve customer satisfaction, and its value is not significant. We use MATLAB for simulation and solving the optimization problem. As mentioned above, we test our proposed cloud manufacturing model by simulating the production of a specific toolbox that involves eight manufacturing steps (sub-operations). We assume that several factories can perform the required operations in each step. In this section, we are conducting a sensitivity analysis of the solution by varying the parameters of the optimization function. We run two iterations for each objective function by alternating the weights, and we summarize the results as follows. The two iterations serve as random examples of possible customers' preferences and are used as input for our proposed model.

First, we change the weights to 45% for quality, 45% for reliability, 5% for cost, and 5% for time. Table 28 summarizes the weights for each variable in the objective function. Table 29 tabulates the results of maximizing the utility function.

Table 28. Weights of the variables in the objective function

Variable	Quality	Reliability	Cost	Time
Weight	0.45	0.45	0.05	0.05

Table 29. Results based on maximizing the utility function

	First Run	Second Run	Third Run	Fourth Run
Gamma	0.8	0.9		
Mutation Percentage	0.3	0.3		
Crossover Percentage	0.8	0.8		
Mutation Rate	0.1	0.1		
Population Size	1000	1000		
Value of Utility Function	2.4738	2.4738		
Value of Objective Function	0.8277	0.8277		

The optimal state using optimization of the utility function is as follows:

$$X = \begin{bmatrix} 0&0&0&1&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1 \end{bmatrix}$$

Table 30 summarizes the results of the optimization of the objective function. The optimal solution from optimization of the objective function is as follows:

$$X = \begin{bmatrix} 0&0&0&1&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1 \end{bmatrix}$$

Table 30. Results based on objective function optimization

	First Run	Second Run	Third Run	Fourth Run
Gamma	0.8	0.8	0.9	
Mutation Percentage	0.3	0.3	0.3	
Crossover Percentage	0.8	0.8	0.8	
Mutation Rate	0.02	0.1	0.02	
Population Size	1000	1000	1000	
Value of Utility Function	2.47	2.4738	2.4738	
Value of Objective Function	0.82487	0.8277	0.8277	

Optimal ratios are 99.12% for Quality, 100% for Reliability, 67.62% for Cost, and 69.07% for Time. Table 31 shows the optimal ratios of variables based on optimizing the utility function. Figure 5 pictures the schematic analysis of the results. The optimized utility results in a manufacturing plan showing the optimal selection and order of each step. In our example of eight steps/sub-categories in producing the optimal product, our model suggests factories 4, 3, 1, 3, 2, 6, 4, and 9 for steps 1 through 8 of the manufacturing process.

Table 31. Optimal ratios of variables based on the optimization of the utility function

Variable	Quality	Reliability	Cost	Time
Ratio	0.9912	1	0.6762	0.6907

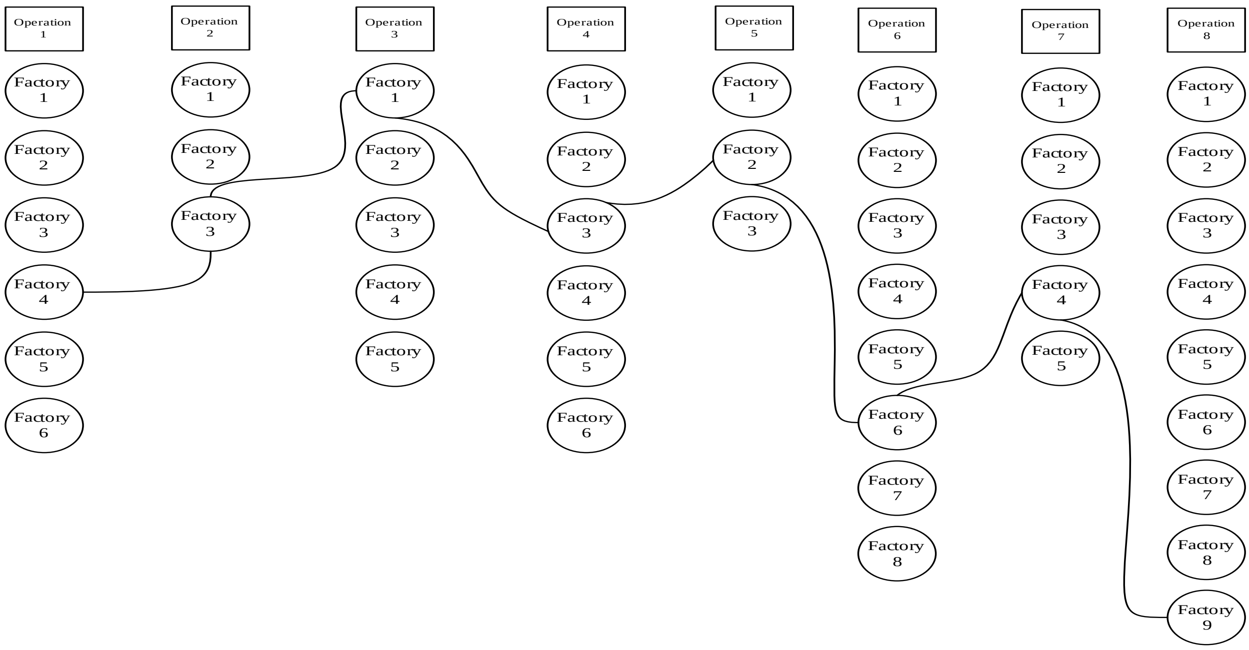

Figure 5 – Schematic analysis of the result

Second, we change the weights to 25% for quality, 25% for reliability, 25% for cost, and 25% for time. Table 32 summarizes the weights for each variable in the objective function. Table

33 tabulates the results of maximizing the utility function. The optimal state using optimization of the utility function is as follows:

$$X = \begin{bmatrix} 0&0&0&1&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 1&0&0&0&0&0&0&0&0 \\ 0&0&1&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0&0 \\ 0&0&0&0&0&1&0&0&0 \\ 0&0&0&1&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&1 \end{bmatrix}$$

Table 34 tabulates optimal variables ratios based on the utility function's optimization. In the optimal state ratios are: 98.79% for Quality, 99.72% for Reliability, 68.30% for Cost, and 63.92% for Time.

Table 32 - Weights of the variables in the objective function

Variable	Quality	Reliability	Cost	Time
Weight	0.25	0.25	0.25	0.25

Table 33 - Results based on utility function optimization

	First Run	Second Run	Third Run	Fourth Run
Gamma	0.8	0.9		
Mutation Percentage	0.3	0.3		
Crossover Percentage	0.8	0.8		
Mutation Rate	0.1	0.1		
Population Size	1000	1000		
Value of Utility Function	1.5563	1.5563		
Value of Objective Function	0.16575	0.16575		

The second iteration of the variable weights shows a different optimal selection and order of each step compared to the first iteration of weights. In other words, our model changes the choice of the last factory from 9 to 8 and generates the flow of factories 4, 3, 1, 3, 2, 6, 4, and 8 for steps 1 through 8 of the manufacturing process when all four variables are equally important.

Table 34 - Optimal ratios of variables based on the optimization of the utility function

Variable	Quality	Reliability	Cost	Time
Ratio	0.98794	0.99719	0.68297	0.63918

Table 35 summarizes the results of the optimization of the objective function. Figure 6 is the schematic view of the result. As seen in the tables above, the solution equals the previous objective function.

As illustrated, an increase or decrease in the weight of each criterion in the objective functions changes the optimal path. The two random examples illustrate the model's flexibility in suggesting optimal routes tailored to customers' needs and preferences. Considering the customer's demand and the degree of importance of each criterion in the customer utility function, our model proposes a different path for the customer to maximize customer utility. For example, the optimal path for factory selection changes as the weight of Quality and Reliability grows.

Table 35 - Results based on objective function optimization

	First Run	Second Run	Third Run	Fourth Run
Gamma	0.8	0.9		
Mutation Percentage	0.3	0.3		
Crossover Percentage	0.8	0.8		
Mutation Rate	0.1	0.1		
Population Size	1000	1000		
Value of Utility Function	1.5563	1.5563		
Value of Objective Function	0.16575	0.16575		

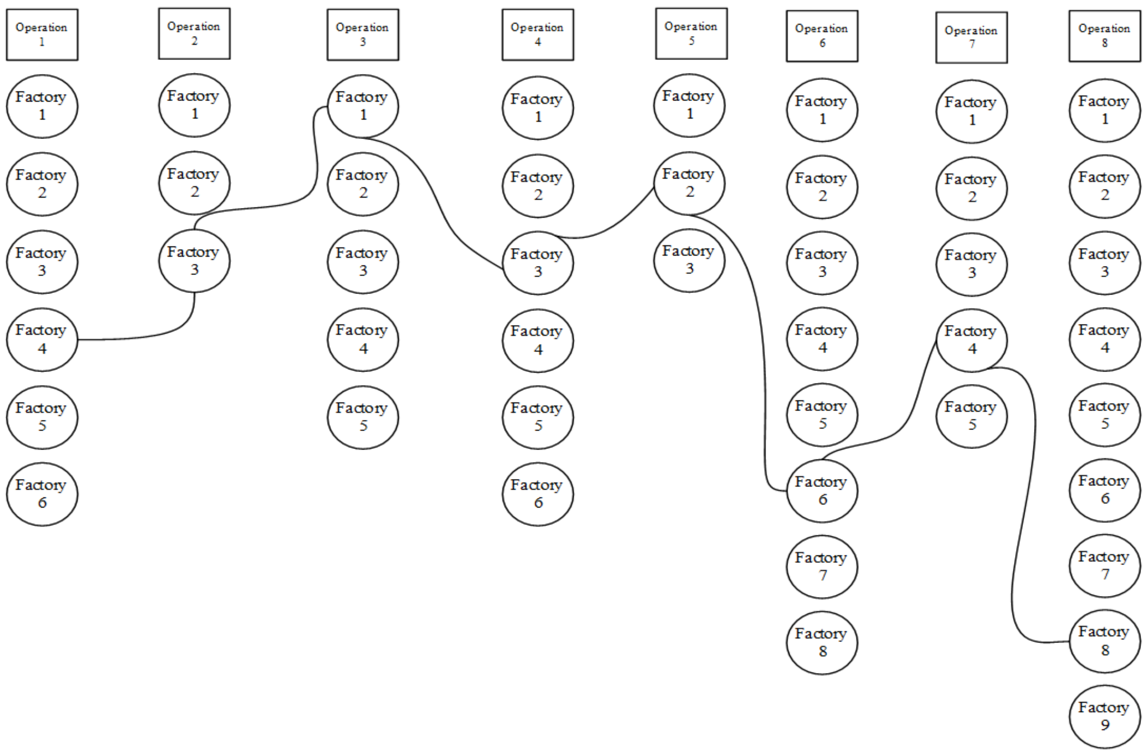

Figure 6. Schematic analysis of the results

13. Conclusion

The COVID-19 pandemic has created an unstable environment, and the only certainty is the possibility of similar crises that will continue shocking global operations and create uncertainties in supply chains. Climate change, seasonal storms, widespread wildfires, and wars, to name a few, will create similar disruptions and intensify fluctuations in supply and demand. Therefore, the readiness for change, standardization of activities, and smartening of all processes with technology become inevitable ingredients in strategic planning for all players in the supply chain system.

We propose that cloud manufacturing is an approach to navigating the current disruption in supply chain and manufacturing activities. The proposed clustered supply chains are interconnected parallelly and sequentially on a smart cloud platform coupled with a fuzzy inference system. The fuzzy approach is adopted to conduct a qualitative analysis of all suppliers/factories. The system then uses a mathematical program that incorporates the suppliers' qualitative scores and customer requirements for utility maximization.

Overall, the numerous benefits of our proposed model help create a more sustainable supply chain system. There are, however, some limitations that are important for consideration. Changing laws and government restrictions are challenging variables to be incorporated into the model. However, these uncertainties can be addressed indirectly by incorporating reliability or transportation costs. Measuring the quality of factories is also a challenge in implementing the proposed model, which is overcome by using the fuzzy inference system. In other words, the fuzzy inference system generates a quality score for each supplier using experts' opinions on the quality of suppliers' manufacturing environment, labor skills, and machinery condition and flexibility. The resulting quality score is then incorporated into the process of generating the outcome of the optimal objective function. In addition, the security of information shared in a cloud platform, especially in multinational supply chains, is a significant concern of the participants (Marston et al., 2011). Future researchers can also add to this area of knowledge by adding transportation time and cost to the models. Moreover, alternative meta-heuristic or heuristic algorithms could study the solution. Comparing our algorithm's efficiency with other methods is another avenue for further exploration.

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