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Seminar Report
on

THE SUPPLY CHAIN NETWORK ON CLOUD MANUFACTURING ENVIRONMENT BASED ON COIN AND Q-LEARNING

Submitted in partial fulfillment for the award of degree of

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in
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CERTIFICATE

Certified that the seminar entitled "**The Supply chain network on cloud manufacturing environment based on COIN and Q-Learning**" carried out by **G Sumuka** bearing the USN **1BG14CS033**, a bona fide student of VIII Semester B.E., **B.N.M. Institute of Technology** in partial fulfillment for the Bachelor of Engineering in COMPUTER SCIENCE AND ENGINEERING of the **Visvesvaraya Technological University,** Belagavi during the academic year 2017-18. It is certified that all corrections / suggestions indicated for internal assessment have been incorporated in the report. The seminar report has been approved as it satisfies the academic requirements in respect of technical seminar prescribed for the said degree.

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ABSTRACT

Cloud manufacturing is applied to a lot of fields to innovate more advanced development structure for industrial 4.0 while the supply chain network in cloud manufacturing context displays more transparent information communication with each agent. At the same time, each participant in this kind of environment can make decisions refer more information and adapt more advanced algorithm to raise the profit and reduce the cost. Here, the COIN (collective intelligence) model is used to simulate a dynamic market with basic four roles and access the Q-learning algorithm to manage the supply chain.

The manufacturer initially produces goods, auxiliary units based on the requirements of the end customer. The Distributors and the retailers are liaisons. Manufactures take place in very huge volumes, whereas customers ideally consume single units. The distributors are responsible to spread the volume of units manufactured to various positions in the country. Distributors tend to have godowns in various parts of the country to manage the inflow and outflow of goods. They also supply these goods to the retailers in every locality of a city. Customers in turn, seek goods from the retailers. The entire network is based on a feedback mechanism.

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CHAPTER 1

INTRODUCTION

1.1 SUPPLY CHAIN MANAGEMENT

Supply chain management (SCM) is the broad range of activities required to plan, control and execute a product's flow, from acquiring raw materials and production through distribution to the final customer, in the most streamlined and cost-effective way possible. Through this supply chain, manufacturing resource can be provided to any company or any person as a service.

Technology is critical in managing today's supply chains, and ERP (Enterprise Resource Planning) vendors offer modules that focus on relevant areas. There are also business software vendors that focus specifically on SCM. A few important areas to note include:

- Supply chain planning software for activities such as demand management.
- Supply chain execution software for activities such as day-to-day manufacturing operations.
- Supply chain visibility software for tasks such as spotting and anticipating risks and therefore proactively managing them.
- Inventory management software for tasks such as tracking and optimizing inventory levels.
- Logistics management software and transportation management systems for activities such as managing the transport of goods, especially across global supply chains.
- Warehouse management systems for activities related to warehouse operations.

1.2 CLOUD MANUFACTURING

Cloud manufacturing (**CMfg**) is a new manufacturing paradigm developed from existing advanced manufacturing models and enterprise information technologies with the support of cloud computing, Internet of Things (IoT), virtualization and service-oriented technologies, and advanced computing technologies.

Cloud-based design and manufacturing (CBDM) refers to a service-oriented networked product development model in which service consumers are able to configure products or services and reconfigure manufacturing systems.

Examples of CDBM's are :

1. **Infrastructure-as-a-Service (IaaS)** - Infrastructure as a service (IaaS) is a form of cloud computing that provides virtualized computing resources over the internet.
2. **Platform-as-a-Service (PaaS)** - It is a category of cloud computing services that provides a platform allowing customers to develop, run, and manage applications without the complexity of building and maintaining the infrastructure typically associated with developing and launching an app.
3. **Hardware-as-a-Service (HaaS)** - Hardware-as-a-service (HaaS) is a procurement model that is similar to leasing or licensing.
4. **Software-as-a-Service (SaaS)** - It is a software licensing and delivery model in which software is licensed on a subscription basis and is centrally hosted.

- The first category concerns deploying manufacturing software on the Cloud, i.e. a "manufacturing version" of Computing. CAx software can be supplied as a service on the Manufacturing Cloud (MCloud).

- The second category has a broader scope, cutting across production, management, design and engineering abilities in a manufacturing business. Unlike with computing and data storage, manufacturing involves physical equipment, monitors, materials and so on. Here, both material and non-material facilities are implemented on the Manufacturing Cloud to support the whole supply chain. Costly resources are shared on the network. This means that the utilisation rate of rarely used equipment rises and the cost of expensive equipment is reduced.

Supply chain in cloud manufacturing environment is a network structure covering cloud computing, network of things, human-computer interactions.

1.3 MOTIVATION

The increasingly global nature of today's supply chains and the rise of e-commerce, with its focus on nearly instant small deliveries straight to consumers, are posing challenges, particularly in the area of logistics and demand planning. A number of strategies such as lean and newer approaches (demand-driven material requirements) planning may prove helpful. Technologies such as big data, predictive analytics, internet of things (IoT) technology, supply chain analytics, robotics and autonomous vehicles -- is also being used to help solve modern challenges, including areas of supply chain risk and disruption and supply chain sustainability.

1.4 PROBLEM STATEMENT

To make supply chain management more effective and dynamic in the cloud manufacturing environment using concepts such as predictive analytics and COIN (Collective Intelligence) model with Q-Learning algorithm

CHAPTER 2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

[1] Prediction Markets as a vital part of Collective Intelligence

Many definitions of collective intelligence exist nowadays. Authors define collective intelligence as “the capacity of human collectives to engage in intellectual cooperation in order to create, innovate and invent.” This fact is a major advantage of collective intelligence because whichever method would be used collective intelligence has the boundary that cannot be passed. The more accurate forecast could be priceless for many companies, therefore nowadays so many companies use collective intelligence.

It is important to realize that determining collective knowledge is one of the most important processes. Sometimes it is not an easy task to determine collective knowledge, therefore the properly chosen consensus function is so important for the properly functioning collective intelligence.

The author empathies that human computation could include tasks, in which human participation is directed by the computational system or process, and the problem solved by humans fits the general paradigm of computation. The interplay between persons' social behaviors and their interactions with computing technologies. Authors in emphasize that the key distinction between human computation and social computing is the fact that social computing makes the human interaction easy, that is mediated by technology, whereas people in human computation are directed by human computation systems.

The author has defined ten postulates that should be met by consensus function:

- Reliability - each nonempty profile should have at least one consensus.
- Unanimity – for homogeneous profile (in homogeneous profile all elements are the same) exists only one consensus: it is the element belonging to this profile
- Simplification - consensus of a profile should also be a consensus of any of its multiples
- Quasi-unanimity – “if an element x is not a consensus of the profile X, then it should be a consensus of a new profile X′ containing X and n elements x for some n”
- Consistency - if some element x is a consensus for the profile X, and if x is added to the profile X, x should still be a consensus for the new profile
- Condorcet consistency - “if two disjoint subsets of voters V and V would choose the same alternative using (social choice function) f, then their union should also choose this alternative using f”
- General consistency – “common consensus of two profiles should also be a consensus of their sum, and a consensus of the sum of two profiles should be a consensus of at least one of them”
- Proportion - difference between consensus and its elements is greater for a bigger profile
- 1-Optimality - requires the sum of the distances between a consensus and elements of the profile to be minimal
- 2-Optimality – it is similar to requires 1-Optimality but in this case the sum of the squared distances between a consensus and the profile elements to be minimal.

They distinguish five principles of prediction markets :

- Incentive - Prediction markets must provide strong incentives for a good use of market information. They should neither reward status nor dominance, which are common in organizations.
- Indicator - Prediction markets employ a clear information indicator. In particular, price is used to convey aggregation information to all participants.

- Improvement - Prediction markets encourage individuals to improve their knowledge
- Independence - Prediction markets benefit from independent information sources
- Crowd - Prediction markets work best in a large crowd.

The authors analyze two theories:

- “large markets offer higher returns to informed trading, and therefore more information is acquired, traded upon, and incorporated into prices.”
- “information is by its nature distributed across the population, and not held by just a few individuals, and therefore prices in a broader market will harness the wisdom of these crowds and prove to be more accurate.”

In conclusion, The size of the prediction market is a great example of that, in literature all authors agree that bigger crowds usually give more accurate predictions, but it is still required to understand why large crowd produces more accurate results. As the result of constant improvement of the knowledge about collective intelligence, the accuracy of predictions given by artificial intelligence agents used in prediction markets will increase correspondingly.

[2] Fundamental Q-Learning Algorithm in finding Optimal Policy

Based on the off-Policy TD Control-Q learning, an agent is trained by reinforcement learning to find the optimal policy to reach the terminal state in the paper, which includes exploring the five factors affecting the learning efficiency and the results .

The reinforcement learning aims to solve a problem: At the current state, there are series of actions to choose and agent will get reward and move to the next after a certain action. We focus on the problem that how to get the maximal reward under certain condition.

As for the agent, it knows nothing about the environment, and what agent can do is taking actions and judging the feedbacks itself. And the agent will generate a sub-optimal policy at the very beginning. With the agent taking more episodes, it will promote the policy gradually.

First of all, as for Reinforcement learning (Q-learning), we should consider the following factors:

- S: a set of states
- A: available actions to the agent
- R: reward function R
- T: transition function T(s, a, s')
- α: (learning rate) the scale of how much agent
- can enlarge and in which direction. (range from 0 to 1)
- γ: Discount factor (range from 0 to 1)
- Living reward: the reward of being alive (could be positive or negative.
- Epsilon: Act randomly or act on current policy (range from 0 to 1)
- Noise: a factor that will influence the agent takes action correctly (range from 0 to 1)

Based on all of above computing process, we have a conclusion that how can we make the exploration more effective instead of doing the repetitive work. In this program, it uses an exploration function to improve the effectiveness of exploration.

In order to realize this function, we build an array to store the times of accessing every state. And then, we need to take the access time of available state when we compute the max$Q(s',a')$ value. Therefore, the a' access time is lower, the exploration bonus is higher. Besides, we need to think about that the noise factor. If there is no any noise in the program (noise factor = 0), the value of Q-table will be converged very quickly, but with the value of noise increase, the Q-value will be very unstable.

As for the Alpha (D) and Discount factor (J), these two values should not be too small. Because the smaller the Alpha is, the slower the speed of convergence is. Generally speaking, the Alpha factor should be changeable during the process of compute every episode. In terms of Discount factor (J), it judges which one of immediate feedback and future feedback is more important. J =1 means that future feedback is as important as immediate feedback, while J=0 means that we can only consider the immediate feedback. Therefore the factor(J) also need to think twice according the rule of the specified game.

[3] A Novel automated construction scheme for efficiently developing

Aimed at facilitating rapid construction of CMfg services, this letter proposes a novel automated construction scheme for developing CMfg services, called Manufacturing Service Automated Construction Scheme (MSACS). Finally, we apply MSACS to conduct industrial case studies to build the automatic virtual metrology cloud service and intelligent yield management cloud service for an intelligent manufacturing platform.

BY LEVERAGING and extending the characteristics of cloud computing (CC), cloud manufacturing (CMfg) (i.e., cloud-based manufacturing) has become a hot research topic in both academia and industry. The field of services computing has proposed a large number of methods to address the problem of service composition whose main concept is to integrate multiple existing web services into workflows to create new value-added services. They proposed a scalable architecture for automatic service composition to create new value-added services from existing services in cloud computing environments. The works did propose systematic approaches for constructing CMfg services using standalone software library packages (SSLP) that can support manufacturing activities, but they needed developers to manually construct CMfg services.

Aimed at facilitating rapid construction of CMfg services, this letter proposes an automated construction scheme of CMfg services called Manufacturing Service Automated Construction Scheme (MSACS) by adopting a text-based-template and automated-code-generation approach and leveraging technologies of JSON, RESTful Web Service, and Command Script- ing. In industrial case studies, we apply MSACS to build the AVM cloud service and the IYM (Intelligent Yield Management) cloud service on the intelligent manufacturing platform AMCoT.

An SSLP used in this study is restricted to be a library archive file that aggregates many class files and associated metadata and resources into one file for distribution and code reuse. For instance, the work [6] employed a Jar SSLP to develop a CMfg service for inferring proper machine tools and cutting tools for machining tasks of workpieces.

In Conclusion, this paper proposes a novel automated construction scheme for developing CMfg services, called MSACS, from standalone software library packages (SSLPs) of two mainstream languages, Java and C#. Finally, we apply MSACS to conduct industrial case studies to build the AVM cloud service and IYM cloud service on the intelligent manufacturing platform AMCoT.

CHAPTER 3

SYSTEM ARCHITECTURE

3.1 SYSTEM MODEL

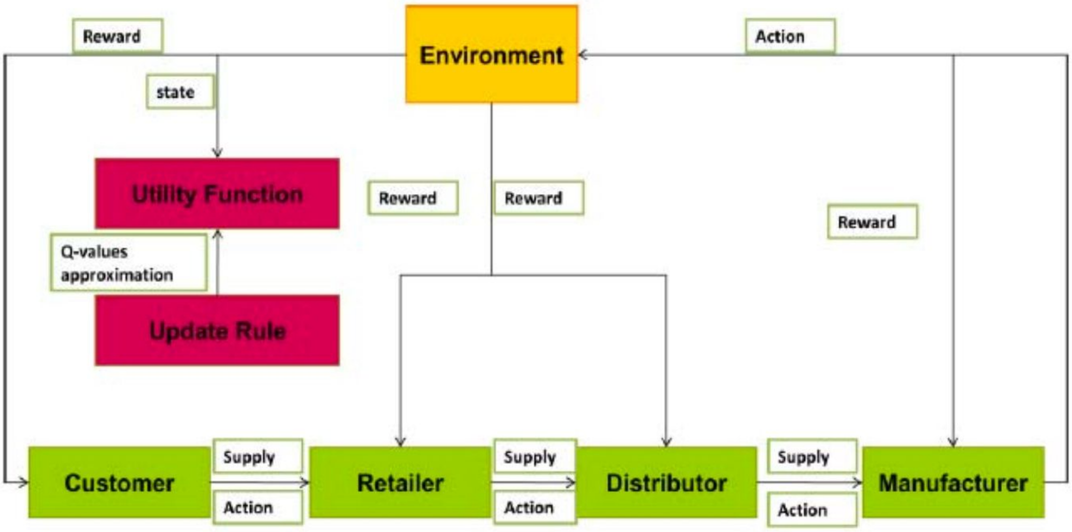

Fig 3.1 The structure of supply chain in cloud manufacturing environment

The participants present in the supply chain network environment are the manufacturer, distributor, the retailer and the end customer. We assume that the interaction between all participants in the supply chain network and the environment influence are transferred to the cost of each agent. The first are the customers who will order a certain number of service or products daily or periodically according to their strategies. The retailers are the next, providing service or products to customers and updating their demand forecast by calculating the difference between the sales and the lost sales. Then the distributors who are ready to send service or products to retailers do the third role. Finally, there are the manufacturers that start producing once their inventory level is lower than some reorder point. At last, the manufacturers watch their inventory level and start providing service or producing if some reorder point is reached. We call roles that send products or provide service suppliers including retailers, distributors and manufacturers. Then the clients are defined as roles that order product or service to upstream participants consisting with customers, retailers and distributors.

Through the whole procedure, each role has its own utility function and tries to get enough information to evaluate all the parameters to make right strategies to achieve a better performance in several trials.

We set the distribution of customers' demand can be chosen from 3 different types: standard normal distribution, poisson distribution and deterministic distribution. The clients' role can measure the service provided by suppliers and score them after all the trade procedures are completed. The score can be used as an indicator for clients to choose the best supplier to order service. At first, the distance between clients and suppliers is considered as the only parameter of score standard. As the trials go, clients can influence other participants by stopping ordering service to suppliers with lower score. The market will remove the suppliers that without any order to punish them.

At the same time the suppliers will forecast the next order from downstream neighbors according to previous orders as a parameter in Q-Learning algorithm to guide them to choose right strategy for calculating the quantity to order or produce. The model above follows the framework of COIN letting agents interact with each other out of control of centralized process.

To achieve optimization of global utility in the environment of cloud manufacturing, we set the current state of retailers using Q-Learning algorithm in this research context in trade t as s(t) consisting the total cost the difference of score between its score and the highest one the inventory level the forecast number for next trade. These four elements mentioned in current state of suppliers are all known till one trade is totally completed. The action depends on order strategies and the lead time. The reward of this situation is given as feedback by environment.

A Q-learning agent has to make a trade-off between exploring new state-action combinations and exploiting the Q-values already learnt. The exploration means that the agent may select a seemingly sub-optimal action given its current Q-table. Usually, the Boltzmann exploration strategy is used for exploration. Here, the probability of choosing an action in a state s is given by the cost function. We set the cost of suppliers includes stock holding costs and order cost.

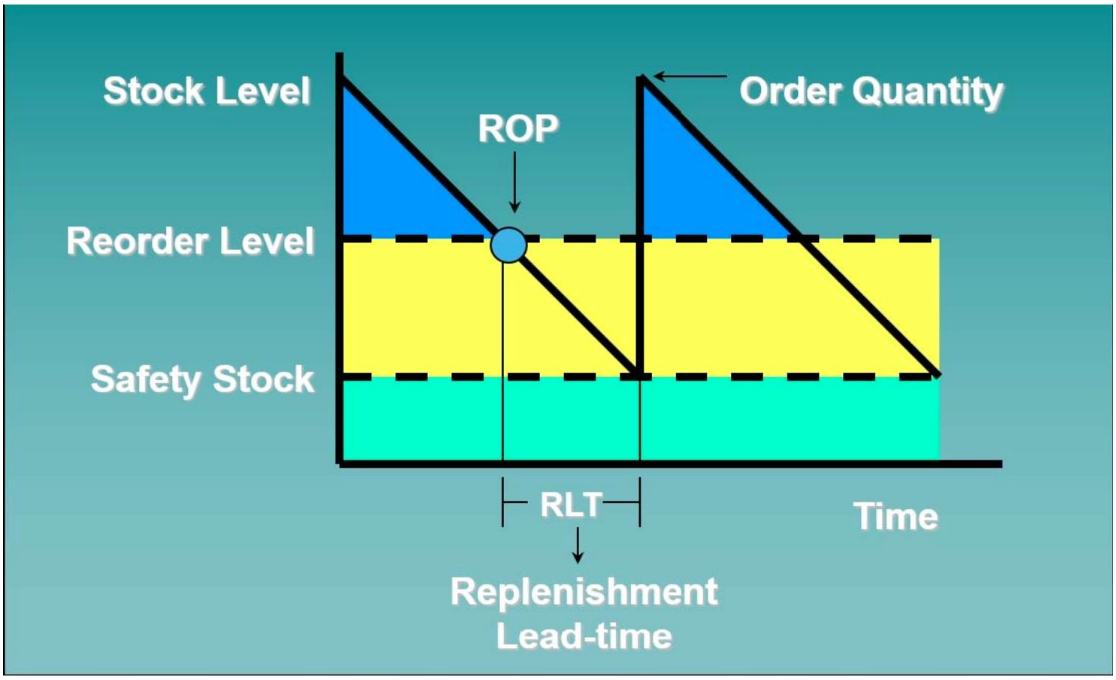

Fig 3.2 Economic Order Quantity Theory

EOQ (Economic Order Quantity) model assumed that suppliers need to replenish the stock when the inventory level reaches the reorder point like Fig.2.The reorder point (ROP) is defined as follows.

ROP = Demand in Lead time + Safety stock

Demand in Lead time = Average Daily Usage x Lead time

There are three options for EOQ models. The first option is simply asking or the difference between the actual stock and EOQ. The second one also considers the daily demand during the lead time. The last option is to repeat the second one but periodically.

CHAPTER 4

EXPERIMENTS

4.1 INTRODUCTION

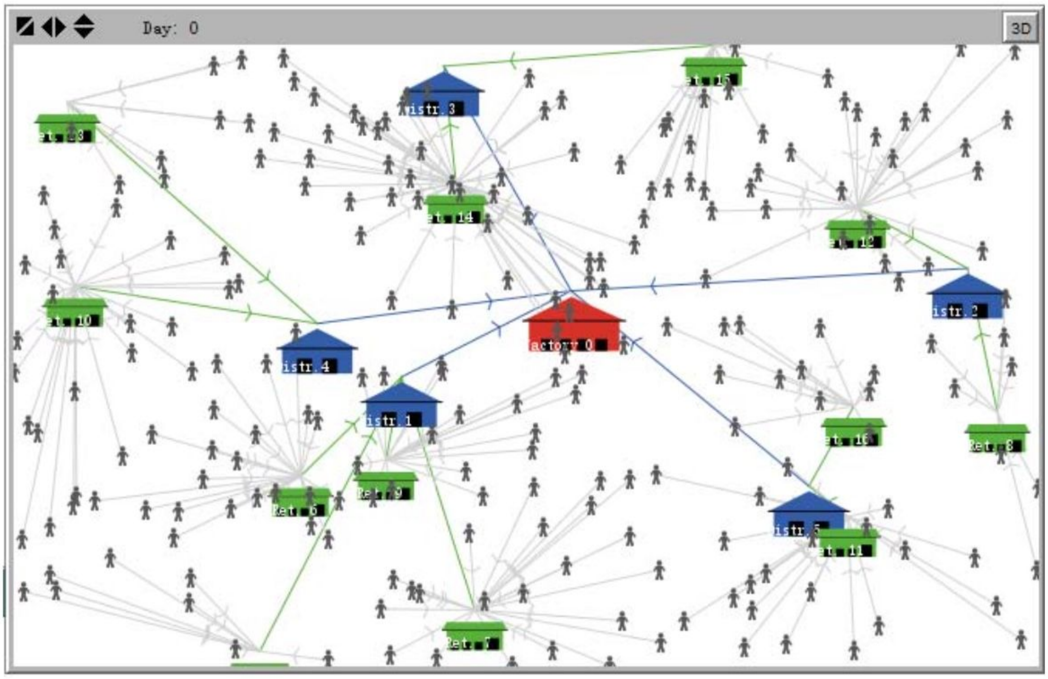

Fig 4.1 Visualization of the supply chain network

The human figure represents customer and the houses are symbolized to be suppliers. Retailers are in green, distributors are in blue and manufacturers are in red. The lines between two participants mean they have business partnership in this trade.

In each trial, we play the model at least 720 periods to get stable results to collect statistic to analyze the changes and patron of all roles in the simulation.

In next part, we show the statistic from three different sets of experiments with a single Q-learner in the supply chain. The sets of each experiment are shown in the table.

Experiment	Distribution	Attributes
1	deterministic	20
2	normal	mean:20 std:4
3	Poisson	mean:20

Fig 4.2 The 3 experiment model

4.2 RESULT ANALYSIS

In experiment 1, the demand of customers is only a constant deterministic number. In experiment 2, there is a normal distribution order from customers daily. The last experiment is conducted in Poisson distribution demand while the customers can choose purchase daily or periodically (order every four days).

We measure the performance of the Q-learning agent by analyzing the tendency of the global utility. The global utility is defined as the total cost of the whole supply chain network. From three experiments, initially all the global utility start in a very high place as the inventory level of all suppliers is zero at first causing suppliers to store a large stock.

The global utility in experiment 1 shows that with the deterministic demand, the retailer with Q-learning algorithm keep fluctuating in a range and the distributors also follow this trend.

Finally, the Poisson distribution of customers' demand obviously leads a longer round circle and the recovery time for factories is also longer. It may be caused by the characteristic of poisson distribution that the rate becomes higher (as the occurrence of the thing we are watching becomes commoner), the center of the curve moves toward right.

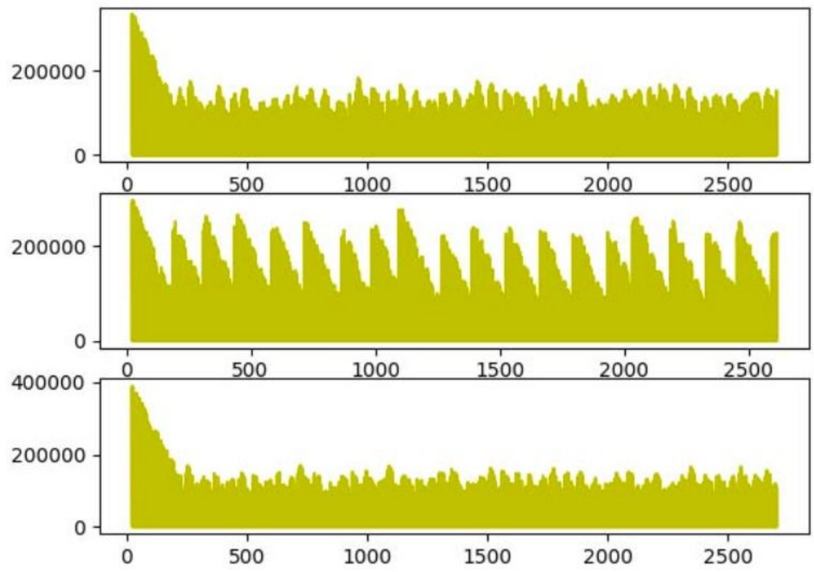

Fig 4.3 Global Utility of 3 experiments

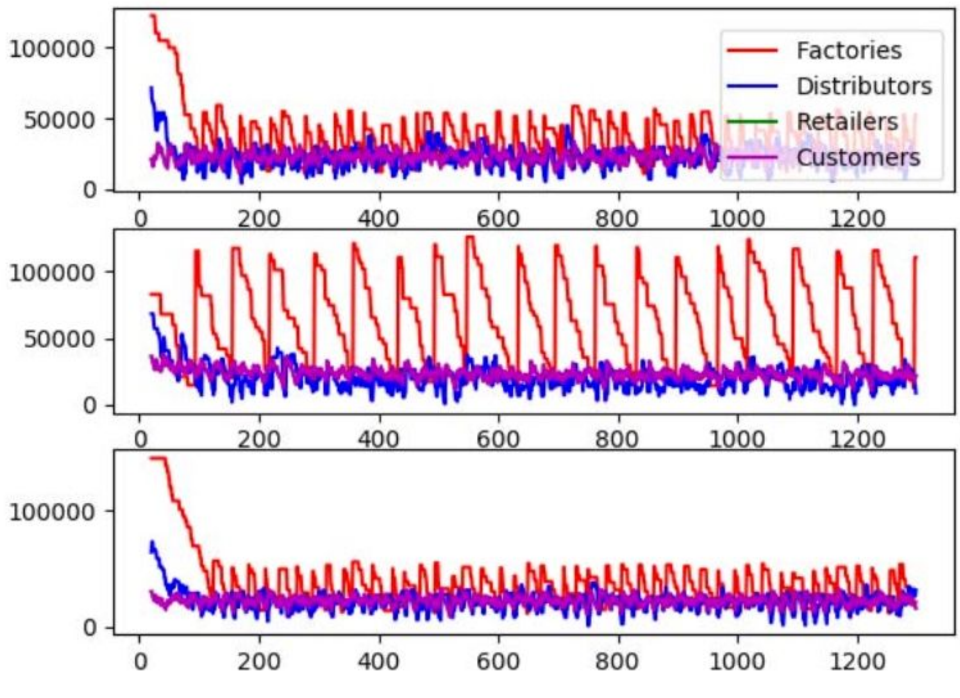

Fig 4.4 Daily stock plot of experiments

From analysis above, the COIN and Q-learning algorithm used in supply chain on cloud manufacturing environment can adapt it to dynamic setting and economic demand.

CONCLUSION

Trying to conduct a simulation model for supply chain in cloud manufacturing environment by using the COIN model and Q-learning algorithm has proved to be effective, as it is treated as a multi-agent system without centralized control in this context, all the participants in supply chain network can make decisions referring to more information about the whole environment and try to set strategy facing different situations. The different distribution of customers' demand is set to be the dynamic origin of the system and the results of experiments show that the agent adapting Q-learning algorithm can lead the system to a stable state although it differs in different conditions.

A study shows that the supply chain network in the context of cloud manufacturing can be simulated to analyze the interactions between each agent and research some problem that has been solved in traditional supply chain. The simulation performance shows that agents can fit itself to dynamic situation and reduce the cost in round circle. There is still further work to do for this field to set more sophisticated forecasting models and add more products to the models specified in more complicated situation used in particular industry. Furthermore, the strategies and findings in research can be used in production process.

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