Machine Learning Algorithms in Cloud Manufacturing - A Review

Syed Omer Farooq Ahmed[1], Adapa gopi[2]
[1]Research Scholar, Koneru Lakshmaiah Education Foundation, Guntur, India.
[2]Associate Professor, Koneru Lakshmaiah Education Foundation, Guntur, India.

Abstract -
Cloud computing has advanced significantly in terms of storage, QoS, online service availability, and integration with conventional business models and procedures. The traditional manufacturing firm becomes Cloud Manufacturing when Cloud Services are integrated into the present production process. The capabilities of Cloud Manufacturing are enhanced by Machine Learning. A lot of machine learning algorithms provide the user with the desired outcomes. The main objectives are to learn more about the architecture and analysis of Cloud Manufacturing frameworks and the role that machine learning algorithms play in cloud computing in general and Cloud Manufacturing specifically. Machine learning techniques like SVM, Genetic Algorithm, Ant Colony Optimisation techniques, and variants are employed in a cloud environment.

Keywords-Cloud Manufacturing, Machine Learning Algorithms, Optimization Algorithms, Service Optimization, QoS, Industry 4.0

1. INTRODUCTION

The requirement for new cloud service providers is driving corporate innovations across all industries. Web Services and Information Technology integration into manufacturing processes has also grown at an exponential rate. This creates challenges that must be addressed in the sector. With the emergence of research in disciplines such as Internet of Things (IoT), cloud computing, virtualization, and Web 3.0, the manufacturing paradigm has moved from product-focused to service-focused.

This is an innovative approach to supporting several organisations in the deployment and administration of cloud-based industrial services. The term "cloud manufacturing" (CMfg) refers to a manufacturing design model that helps various users—including suppliers, manufacturers, and customers—achieve their business objectives by utilising networks, cutting-edge and novel information technology innovation, and a knowledge base platform.

Industry 4.0 refers to Cloud production's advancement in the production process. The authors presented four-layer architecture in [12].

i. Manufacturing Resource Layer: Overseeing all resources involved in the life cycle of a product's development

ii. The Manufacturing Virtual Service Layer gathers all the virtualization-related resources needed to construct Cloud Manufacturing Services.

iii. Global Service Layer: controlling encapsulated and virtual manufacturing resources and competencies

iv. Application layer: giving end users access to manufacturing services via the cloud

SMEs play an important role in integrating Cloud Manufacturing into their product development process. With the advancement of cloud computing, they established a cloud to handle the charges. Combining Manufacturing Resources and Capabilities with the Cloud Model produced better results. 3D Creation Lab, Quirky, and PhotoBox are just a few examples of companies in this category.

The crucial activities of resource identification, service scheduling, and service matching are efficiently supported by the Cloud Based Design and Manufacturing platform that researchers presented in [41–47]. Resources virtualization technologies, resource and service publication, discovery, service composition, efficiency, dependability, and security

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

management are among the topics that have been the focus of several research projects.

The issues raised by the sudden rise in consumer expectations are covered in [76–81]. The corporations have strong standards and geographical limitations in place to manage their production numbers and/or networks. SMEs are exploiting the digital environment and goal-oriented collaborative approaches to generate new business opportunities. The grid manufacturing business model provides a cluster of distributed and heterogeneous manufacturing resources.

The interaction of Users (consumers), Cloud Based Application Providers, and Physical Resource Providers supports Cloud Manufacturing deployment. Users include large OEMs, private citizens, small groups, and design and testing firms. Cloud-based application providers not only provide apps for product planning that optimise cost, time, and resources, but they also provide a single resource management application that pulls together all of the essential tools to achieve the desired results. Physical resource suppliers own and operate several types of manufacturing equipment, such as testing, machining, finishing, inspecting, and packing technologies.

The details of the participants in each layer can be seen in Table #1

CLOUD MANUFACTURING LAYERS		
Cloud Users Layer	**Cloud Based Application Providers Layer**	**Physical Resource Providers Layer**
Quality Assurance includes Industry Standards and Management of decentralized collaboration ***Cloud Robustness*** ***Configuration Management*** ***Business Models*** comprising Data Ownership with effective collaboration ***Information Security***	***Production Planning*** ***Resource identification*** ***Decentralized Control of Resources*** ***Combination of Resources*** ***Machine to Machine Cooperation*** ***Industry Control System***	***Data Compatibility*** ***Automation***, for System Flexibility, System Logic & Artificial Intelligence* (AI) and Integration with existing technologies * *In this layer the machine learning algorithms play a crucial role to solve real time industry problems to get the most out of Cloud Manufacturing*

Table1. Cloud Manufacturing Layers with the participants

Cloud clients' demands will be matched with the right resources, either software or hardware, through the application layer in order to satisfy the supply-demand component of the market. The global supply chain, cloud computing, information technology research, and the market have all had a significant impact on cloud manufacturing. CMfg services are used to share all available resources and capabilities. The type of industry and how frequently they are

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

implemented dictate how many CMfg services are offered. There are generally a number of CMfg services available. Cloud users' needs are satisfied by these services.

There are two types of service delivery models in Cloud Manufacturing. These are represented in Table #2

Related to Information Technology

a) Infrastructure as a Service (IaaS)
b) Platform as a Service (PaaS)
c) Software as a Service (SaaS)

Related to Manufacturing Resources

d) Hardware as a Service (Haas)

SERVICE DELIVERY MODELS IN CLOUD MANUFACTURING		
Information Technology		***Manufacturing Resources***
Infrastructure as a Service (IaaS),	server, storage space, and networking components	It is Hardware as a Service (HaaS), For consumers of Cloud Manufacturing, manufacturing resources and competencies related to manufacturing processes can be provided through a service model. In the Cloud Manufacturing System, for instance, the service delivery models may include design, production, or communication services.
Platform as a Service (PaaS)	providing the operating system, database, and programming language as a service to the enterprise's computing platform	
Software as a Service (SaaS)	software programmes to users via the Internet via the Cloud, eliminating the need for consumers to buy, install, and manage the application	

Table2. Service Delivery Models in Cloud Manufacturing

The idea behind Manufacturing as a Service (MaaS) is to provide cloud-based manufacturing services that may be used to accomplish tasks. Digital business ecosystems can be subdivided into manufacturing ecosystems. Similar generativity and control structures most likely exist in other digital ecosystems. Several well-known applications primarily rely on 3D printers and additive manufacturing, including but not restricted to

i. 3D Hubs – A privately held company offering more than 6000 3D printers around the world
ii. Thingiverse – A website for sharing user-created designs for printing, milling, and laser cutting
iii. Ponoko – an online manufacturing service for small scale production
iv. Autodesk Forge – cloud based software platform for manufacturing and product design
v. OnShape – A cloud-based CAD system with API and solution providers for manufacturing

The below-mentioned research work in the area of MaaS is presented in [57-62].

i. In [57] - Production planning and scheduling as a service
ii. In [58] - Manufacturing execution system serving multiple factories
iii. In [59] - Providing visibility for supply chain collaboration
iv. In [60] - Collaborative smart process monitoring
v. In [61] - Collaborative delivery of customized products
vi. In [62] - Selling machine capacity

The rest of the paper is organized as follows

i. Section 2 - Related Work
ii. Section 3 - Machine Learning Algorithms
iii. Section 4 - Machine Learning Algorithm in Cloud Manufacturing
iv. Section 5 - Conclusion

2. RELATED WORK

Cloud computing, virtualization, the Internet of Things, ontology, big data, service composition, manufacturing

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

planning, and industry 4.0 are among the elements that make up the cloud manufacturing map.

The foundation for future research advancement is always laid by a methodical literature assessment. The full digitalization of this period has made it possible to have a thorough understanding of the systemic examination of the study field in many ways. However, the challenge is in going through and evaluating all of the study's data.

Industry 4.0, virtualization, digitization, and other recent developments in information technology have altered the structure and mode of operation. There are many different models, references, and definitions for cloud manufacturing. The existing literature uses a structured statistical model to identify the primary study topics of CMFg. Ultimately, clusters with the subsequent study topics of Cloud Manufacturing are created utilising NLP and ML algorithms[18].Henzel and Herzwurm did a thorough study of the literature in [19], proposing a comprehensive analysis of cloud manufacturing and its current paradigm. The review involved the identification, classification, and evaluation of existing research.

In [20], the primary research focuses are visualised using the findings of the research on cloud manufacturing, which is done automatically using a software application. The maps were produced by this software using the data.The manufacturing sector's product life cycle, which is greatly influenced by computing, is presented by Katzel in [21]. According to the needs of the company and its users, cloud computing functions as a utility service that may be utilised as needed. Cloud services can support manufacturing by providing software applications, computational power, data storage, and other resources.

The authors of [22] explain how corporate companies' decisions about data storage are influenced by factors such as data security, cloud performance, quality of service, and regulatory compliance requirements.

In [24-28], the authors proposed parameters to be considered in designing the framework for scheduling algorithms. They are

i. Execution time
ii. Response time
iii. Cost
iv. Makespan
v. Scalability
vi. Trust\
vii. Reliability
viii. Resource utilization
ix. Energy consumption
x. Load balancing
xi. Fairness.

The methods for enhancing dynamic resource management through the application of machine learning algorithms were covered in [31]. Depending on the situation, SVM or ANN techniques can be used to save energy and use resources more efficiently.

Several Selection Strategies in research used Genetic algorithms to solve TSP. They are

i. Elite
ii. Roulette
iii. Rank
iv. Tournament

In [32-37], these strategies have been implemented and run against TSPLIB benchmarks.

A CMfg prototype and the previous relevant research on CMfg carried out by the authors' group are succinctly given in [51]. Using virtual machine mappings as the accessing carrier, scattered resources were mapped into virtual resources (virtual machine). Related technologies are mostly used to accomplish a number of function modules.

A distinct strategy concept for cloud manufacturing is recorded in [52]. Upon comparing the existing status with the strategic vision, recommendations for further development are generated. This review also includes some possible effects and research ideas for the future.

An overview of the development concept for cloud-based and ubiquitous manufacturing is provided in [53]. Architecture, which permits the construction of an advanced manufacturing system or organisation on various complexity levels, is also explored through an informal and conceptual presentation of cloud manufacturing.

A novel virtual COM port technique is put forth in this study in reference [54]. This paper addresses a prototype system to implement the cloud computing notion of service-as-a-software.

The importance of establishing cloud connections and the current status of utilisation in the cloud manufacturing environment are established in [55]. It provides case studies, vision and control monitoring, and manufacturing execution assembly system assistance. The theory portion of the paper aims to provide the cloud connect concept in the context of a manufacturing execution assembly system.

An example of the paradigm change in equipment monitoring systems (EMSs) from Internet-based to cloud-

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

based was provided in [56], whereby an EMS for the Computer Numerical Control (CNC) machine tool industry was built on cloud computing. meant to address the drawbacks of conventional web graphical user interfaces.

3. MACHINE LEARNING ALGORITHMS

Machine learning is a subset of Artificial Intelligence (AI) or Computerised Reasoning. Machine learning is becoming a regular component of all cloud-based settings due to its mathematical modelling capability. Machine learning algorithms enable machines to learn by providing initial data; these algorithms eventually improve in accuracy. More data is regularly added to the mix to boost the machine's overall efficiency.

Machines learn from data, and algorithms fine-tune for each new situation that the machine encounters. Classification, predictive modelling, and data analysis all need the use of ML algorithms. Depending on the data and what we want to achieve with it, we can train the algorithm using a specific learning model.

Machine Learning methods are commonly utilised in Cloud environments/systems for workload prediction.

The authors of [63] predicted the workload of each virtual machine using Neural Network techniques with time delay and regression approaches.

The authors of [64] devised resource management and provisioning algorithms to forecast virtual machine demand in the near future. They employed Neural Networks and Regression Techniques.

It was proposed in [65] to forecast future VM load using NN and Regression Methods.

[66] created a client-side cloud-based prediction model to predict the resource model of each VM using three machine learning models: Support Vector Regression, NN, and Linear Regression.

SVM, NN, and Linear regression models were examined as prediction approaches in [67-68].

SVM is not a superior choice when the data collection is large, according to [69].

[70] suggested a Bayesian Model for each VM's resource prediction and compared it to Linear Regression and Support Vector Machine.

3.1. By The Nature of Learning Style

There are three types of machine learning which are, supervised, unsupervised, and reinforcement learning.

3.1.1. Supervised Learning

The technique of learning where a specified labeled data collection is used to teach the model. A labeled data set is a collection of datasets that have a corresponding solution or response. Forecasting future values based on historical data is one example of how supervised learning algorithms generate predictions based on a set of instances. By analysing the training data using an algorithm, we can discover the function that translates the labeled input to the intended output.

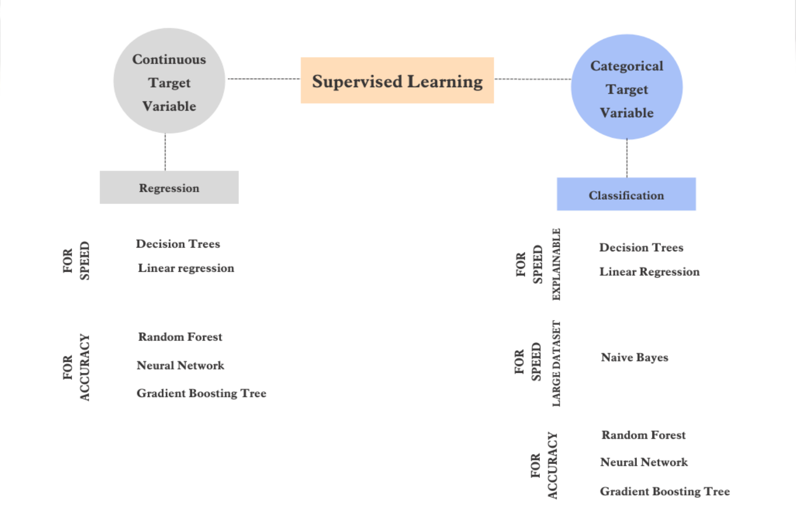

Figure 1. Supervised Learning

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

3.1.2. Un Supervised Learning

We ask an unsupervised learning machine to find the inherent patterns in the given unlabeled data. It is typically a graph, a sparse tree, or a cluster.

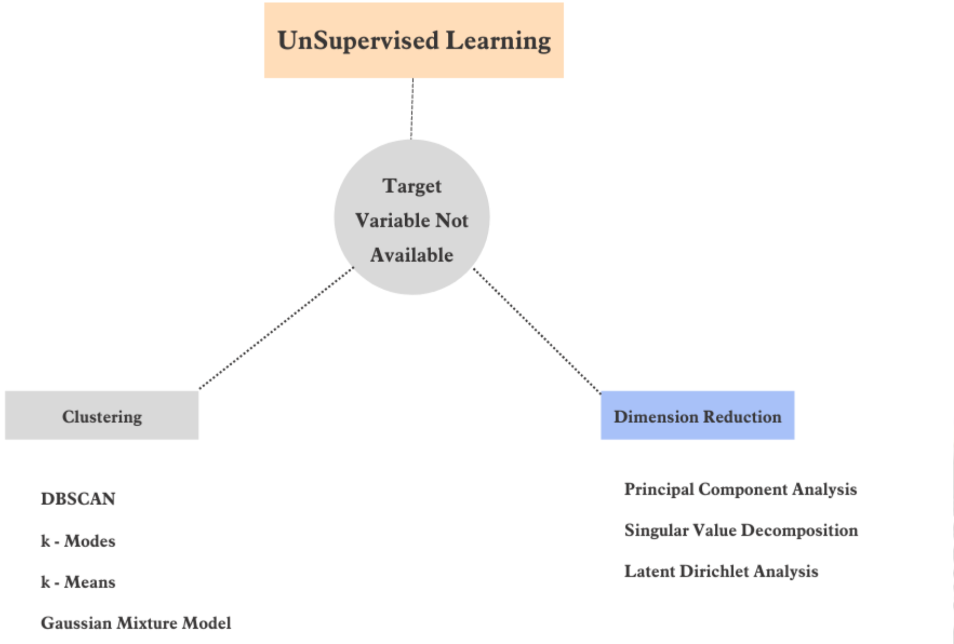

Figure2. Unsupervised Learning

3.1.3. Reinforcement Learning

Reinforcement learning takes place in a setting where computer functionality is required. Reinforcement is the process by which the environment serves as the machine's instructor by giving it feedback, either positive or negative.

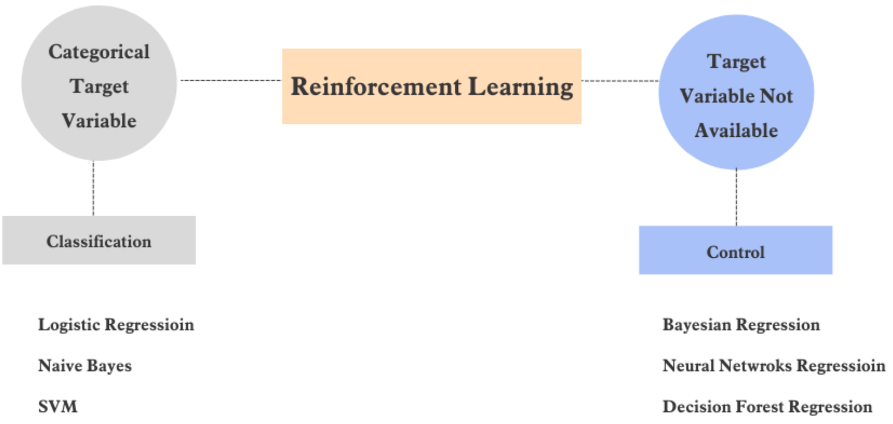

Figure 3. Reinforcement Learning

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

3.2. By The Nature of Similarity

3.2.1. Regression Algorithms

Regression algorithms are widely utilised in machine learning as well as statistical modelling. The independent variable data set is the input data set in regression algorithms, and the dependent variable data set is the output data set. The following lists the three distinct models used in this.

3.2.1.1. System Utilization Based Model

In the system utilization-based model, researchers model the energy consumption of the whole system based on components.

In [1], Hsu and Poole suggested a unitary exponential model for applications requiring a lot of processing; but, because the model's parameters came from experience, it was not applicable to other uses.

3.2.1.2. Performance Counter Based Model

Researchers suggested performance counter-based energy models in tandem with CPU advancement to further increase the energy model's accuracy. Numerous energy models could be constructed by combining attributes of the highlighted components with data from performance counters. For instance, read/write throughput was determined to be the primary energy consumer for memory by researchers analysing memory energy use [1].

3.2.1.3. Environment Oriented Model

For a few particular computing environments, researchers examined environment-oriented energy models. Li et al. [3] used linear regression to build an energy model after looking at the workload data for each Map, Merge, and Reduce phase in the MapReduce context. They looked at two conventional MapReduce applications that required a lot of I/O and compute. An application-centered energy model for CPUs and memory components was created by Wu et al. [4, 5] especially for the MPI/OpenMP environment in large-scale multicore data centres. Their main objective is to differentiate between MPI and OpenMP's energy consumption.

3.2.2. Regularization Algorithms

Regularising old procedures after learning for specific aspects in neural network algorithms is referred to as Consistency Algorithms.

Bias, variance, and irreducible error are three parameters that contribute to the overall error that a machine learning model makes across its predictive capacity. Bias is defined as the amount by which the anticipated value deviates from the true label.

Overfitting arises when, as a result of this proclivity, ML models occasionally memorise the pattern in which the data set is spread in multi-dimensional space rather than comprehending and hence generalising to that pattern. This is an absolutely undesirable situation.

Regularisation enters the picture at this moment. Regularisation is capable of removing overfitting and, as a result, increases model quality. Although it is most commonly observed in linear regression, it is equally applicable to logistic regression models and overfitting artificial neural networks.

Regularisation aims to add an extra term to the target ML or DL model's cost function. This additional term effectively prevents optimisation algorithms such as gradient descent from achieving weight values that minimise the bias error. In other words, it introduces additional bias error into the model. As a result, a significant portion of variance error is reduced, and the model is free of overfitting.

The authors of [6] offer a neural network-based technique for large-scale workload prediction called domain knowledge embedding regularisation neural networks DKRNN. Domain knowledge, which gives additional information about workload changes, is inserted into artificial neural networks ANN for linear regression to increase prediction accuracy based on analysing the statistical features of a real large-scale task. Furthermore, regularisation with noise is integrated to improve artificial neural network generalisation.

3.2.3. Decision Tree Algorithms

The decision tree algorithm can solve regression and classification problems. The choice Tree is used to build a training model that can predict the class or value of a target variable by learning simple choice rules from input data.

Lindell and Pinkas [7] introduced a safe ID3 decision tree technique for horizontally partitioned data in 2002. To achieve privacy-preserving in the distributed ID3 algorithm, they decompose it into multilogarithmic calculation, polynomial evaluation calculation, and data comparison, and then design the security log protocol, polynomial evaluation protocol, and secure comparison protocol.

Emekci et al. [8] established a secure addition computational protocol based on the secret sharing algorithm in 2007, and extended the secure logarithmic computing protocol from two to multiple parties, enabling multiparty involvement in the privacy protection ID3 technique. However, as the number of participants increases, the algorithm's complexity grows exponentially.

3.2.4. Bayesian Algorithms

The Bayesian technique maximises the degree of confidence or trust in a model parameter after training the parameter with new observations and experiments. Another advantage of the Bayesian technique for predictive modelling is its adaptability.

It is simple to fit rational models to complex datasets with measurement errors, censored or missing observations using the Bayesian technique [7].

3.2.5. Support Vector Machine (SVM0

SVM is a supervised machine learning technique that may be used for both classification and regression. The SVM algorithm's goal is to find a hyperplane in an N-dimensional space that clearly classifies the input points.

SVM was utilised as an ML technology in [12] to demonstrate that it is possible to limit overloading during the production process. Furthermore, the authors built, simulated, and successfully implemented a framework called as Cyber Physical System based on ML for Cloud Manufacturing.

The paper [13] proposes a Cloud SVM training method (CloudSVM) for distributed machine learning applications in a cloud computing environment using the MapReduce technique. The findings of this work are significant for training large-scale data sets for Cloud Manufacturing using Machine Learning.

3.2.6. Clustering Algorithms

Modelling approaches like as centroid-based and hierarchical clustering are commonly used to organise clustering procedures. All approaches group data into clusters containing the most comparable features.

In [8,] services are first clustered into abstract services, and then an abstract service clustering network is constructed. As a result, service composition paths and corresponding candidate sets for satisfying manufacturing requirements can be swiftly obtained, reducing the difficulty and improving the efficiency of service composition.

We present a unique clustering-based and trust-aware technique in [9]. To begin, using the clustering-based approach, a set of comparable users can be identified based on task similarity, where task similarity can be computed by including both explicit textual and rating information, as well as implicit context information. Second, because the QoS values may be given by untrustworthy users, we devise a trust-aware CF technique that combines local and global trust values to reconstruct the clustered users' trusted network. Finally, in CMfg, we integrate the clustering-based algorithm and the trust-aware technique to provide a more personalised QoS forecast and dependable cloud service suggestion to active users.

3.2.7. Artificial Neural Network Algorithms

The paper[10] proposes a categorising artificial neural network (ANN) ensemble approach for calculating the time necessary for a simulation activity. Before estimating simulation times, the proposed methodology classifies simulation activities using k-means. Following that, an ANN is built for each task category to estimate the needed task time in the category. To mitigate the impact of ANN overfitting, the needed time for each simulation job is calculated using all categories' ANNs, and the estimation results are then weighted and totaled. As a result, the ANNs create an ensemble. Six statistical and soft computing methodologies were used in real-world applications in addition to the proposed methodology.

S.No	ML Algorithm	Advantages	Disadvantages
1	***Support Vector Machine(SVM)***	It works perfectly with both incomplete data and the speed of classification.	It has a slow learning rate, no human explanation ability, and is used for linear and nonlinear problems.
2	***Decision Trees***	Because of the reliance on data mining for important features, there	It is difficult to discover the best decision tree for the given training data sets, and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

		is a high utilisation in exploration and prediction problems. It is simple to comprehend. The use of graphics facilitates interpretation.	Non-Linear Problems cannot be solved.
3	***Regression Algorithms***	Implementation is simple and efficient. Feature scaling is unnecessary. Hyperparameter tuning is not required.	Poor performance on non-linear data with a high proportion of irrelevant and associated features.
4	***Naive Bayesian***	It requires considerably minimum storage space during training and classification stages	These algorithms are less precise
5	***Artificial Neural Networks***	High Dimensional Data and Variability Supervised, unsupervised, and reinforcement learning can all be used.	It is difficult to get high accuracy. There are also difficulties with overfitting, missing data values, and complexity.
6	***Regularization Algorithms***	Simplicity, Prevents Overfitting and Less Computational Time	Leads to Dimensionality Reduction
7	***Optimization Algorithms***	Simple and less workload, High Training Speed, and Fast Convergence Speed	Poor handling of Discrete Optimization Problems

Table3. Advantages and Disadvantages of Machine Learning Algorithms

3.2.8. Optimization Algorithms

The process of modifying hyperparameters to minimise the cost function using one of the optimisation strategies is known as machine learning optimisation. The cost function must be minimised because it describes the difference between the true value of the estimated parameter and what the model predicted. Before beginning to train the model, hyperparameters are established to specify its structure.

An efficient evolutionary operator is critical in the evolutionary process of optimisation approaches in Multiobjective Evolutionary Algorithms (MOEA). And the operators have a significant impact on the performance of the algorithms. As a result, efficient operators for the MOEAs must be designated. In [48-50], efficient evolutionary operators are devised to improve algorithm performance.

4. MACHINE LEARNING ALGORITHMS IN CLOUD MANUFACTURING

Machine Learning Algorithms such as Neural Networks (NN), Fuzzy Logic (FL), Genetic Algorithm (GA), Simulated Annealing (SA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO) can be applied with nonlinear, multidimensional, and complex engineering scenarios that one can come across in Cloud Manufacturing.

The Machine Learning Algorithms can help to manufacture in the cloud in the following areas.

1. Smart Maintenance
2. Better Product Development
3. Quality Improvement
4. Market Adaptation

The areas in which ML algorithms are being used, which we discuss in this include, but are not limited to Service Composition, Task Scheduling, Framework, Security, and Workload in Cloud Manufacturing.

4.1 Service Composition

Cloud Manufacturing Service Composition is multi extremum, multiobjective, non-linear, and unpredictable. As a result, this is a typical NP-hard issue. Service Composition is a Value Added Service that satisfies the end user's needs.

The performance of Service Composition in Cloud Manufacturing Tasks is determined by

i. The Relationship between any two cloud manufacturing services

ii. The relationship between cloud manufacturing tasks and their respective assigned services.

The optimization factors in Cloud Manufacturing Service Composition, are but are not limited to

1. Collocation Degree - User Needs Can be done by the collaborative participation of customers and cloud service providers
2. Composition Synergy Degree - to meet the requirements of traditional product delivery time and manufacturing cost
3. Service Composition Complexity - Complexity of the manufacturing resources' state changes
4. QoS Parameters - There are several QoS parameters in non-functional Cloud Manufacturing concerns. In this section, we offer quantitative parameters as well as research indices. Each manufacturing process can contain up to n sub-processes (i = 1 to n). To get the best QoS parameters, we must build the most appropriate Service Composition for the end user. Price, Response Time, Availability of Resources and Capabilities, Reliability of Composite Service (a mix of atomic services), and Throughput are the QoS parameters. We must obtain high QoS values in order to meet the end user's needs.

The paper[15] establishes a mathematical model of cloud manufacturing service composition optimisation, with The Objective Function defined in terms of service collocation degree, composition synergy degree, and composition entropy. Manufacturing task execution time and execution cost are the constraints. IGABE, an improved genetic algorithm, is proposed, with improved crossover and mutation operators introduced using a normal cloud model and piece-wise function. The modified roulette selection method is utilised to carry out the algorithm's selection operation, and the fitness function is created by combining Euclidean deviation and angular deviation.

The authors of the study work [16] defined mtDNA as a separate property of the population member class in order to control the crossover function, which can prevent population members from reproducing for some n number of generations (with the same mtDNA). It has no effect on kids because it only inherited from the female parent. The addition of mtDNA to control crossover is regarded as an appropriate adjustment that improves GA optimisation by producing significantly better outcomes. TSPLIB known TSP instances (dantzig42, eil51, rd100, ch150, and kroB200) were used to test the mDNA implementation.Genetic algorithms and variants have been frequently applied in cloud environments. The authors of [38-40] discussed an application of Genetic Algorithms to TSP as well as quality difficulties in implementation.

4.2 Framework

The Cloud Manufacturing Framework with Machine Learning Algorithms aims to provide valuable insights, patterns, and trends from large datasets, resulting in actionable information, situation awareness, and understanding to help with manufacturing planning, scheduling, production, and delivery.

In [22], the authors proposed a framework consisting of five steps:

Step#1 - Defining variables and their relationships;

Step#2 - Designing a probabilistic graphical model;

Step#3 - Collecting data;

Step#4 - Learning the probabilistic graphical model; and

Step#5 - Estimating the collaboration level.

In [22], 23 variables were used across the 8 Dimensions to define Mathematical Model. Designing the Probabilistic Graphical Model (PGM) consists of two steps,

Step#1 - Designing a graph structure - It determines a graph type and connects some nodes by edges

Step#2 - Designing potential functions. - It designs mathematical functions (potential functions) that compose the Probabilistic Graphical Model (PGM).

A framework based on the PGM for measuring the extent of collaboration between CMFg firms. The proposed framework's collaboration levels could be used to tackle a variety of operational difficulties in CMFg.

The paper[24] evaluates the proposed infrastructure using a case study in which industrial demos are practiced in the cloud system as one specific task of process planning service. The suggested framework enables novel and adaptive process planning services via the cloud and service-oriented computing. The event-driven FB technology, in particular, is well suited for onboard adaptive decision making at the machine level in order to achieve real-time responsiveness, adaptability, and overall resource effectiveness.

5. CONCLUSION

A cloud-based manufacturing ecosystem differs from a manufacturing ecosystem or cloud manufacturing. Because of the cloud-based platform that facilitates data and message interchange, cloud-based technologies present additional chances for a normal industrial ecosystem in terms of more natural connection and integration. Furthermore, specialised analytical methods for business optimisation are available on the cloud.

Machine Learning Algorithms increase the productivity of smart manufacturing and solve a number of real-time difficulties. The few areas stated in this study where ML techniques are commonly used include security, throughput, framework, scheduling, and service composition. The current proportion of ML algorithm implementation ensures that there will be a lot of study in this area. In continuation, next study will present a framework for developing and analysing Cloud Manufacturing (CMFg).

REFERENCES

1. C-H. Hsu and S. W. Poole, “Power signature analysis of the SPECpower_ssj2008 benchmark,” in Proceedings of the IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS '11), pp. 227–236, Austin, Tex, USA, April 2011.
2. A.Beloglazov, J. Abawajy, and R. Buyya, “Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing,” Future Generation Computer Systems, vol. 28, no. 5, pp. 755–768, 2012.
3. W. Li, H. Yang, Z. Luan, and D. Qian, “Energy prediction for MapReduce workloads,” in Proceedings of the 9th IEEE International Conference on Dependable, Autonomic and Secure Computing (DASC '11), pp. 443–448, IEEE, Sydney, Australia, December 2011.
4. C. Lively, X. Wu, V. Taylor et al., “Power-aware predictive models of hybrid (MPI/OpenMP) scientific applications on multicore systems,” Computer Science—Research and Development, vol. 27, no. 4, pp. 245–253, 2012.
5. C. Lively, X. Wu, V. Taylor, S. Moore, H.-C. Chang, and K. Cameron, "Energy and performance characteristics of different parallel implementations of scientific applications on multicore systems," International Journal of High-Performance Computing Applications, vol. 25, no. 3, pp. 342–350, 2011.
6. Lei Li, Min Feng, Lianwen Jin et.al, “Domain Knowledge Embedding Regularization Neural Networks for Workload Prediction and Analysis in Cloud Computing, Journal of Information technology and research, vol. 11, Issue 4, October 2018
7. D.B. Dunson, Commentary: Practical Advantages of Bayesian Analysis of Epidemiologic Data, Am. J. Epidemiol. 153 (2001) 1222–1226. doi:10.1093/aje/153.12.1222
8. Feng Li, Lin Zhang, Yongkui Liu, et.al " A clustering network-based approach to service composition in cloud manufacturing April 2017, International Journal of Computer Integrated Manufacturing 30(3):1-12 DOI:10.1080/0951192X.2017.1314015
9. JianLiu, YoulingChen " A personalized clustering-based and reliable trust-aware QoS prediction approach for cloud service recommendation in cloud manufacturing, June 2015, Knowledge Based Systems, vol 174"
10. Toly Chen, Yu-Cheng Wang " Estimating simulation workload in cloud manufacturing using a classifying artificial neural network ensemble approach, Robotics and Computer Integrated Manufacturing, Volume 38, Issue C, April 2016"
11. Xu, X., "From cloud computing to cloud manufacturing", Robotics and Computer-Integrated Manufacturing, vol. 28, no. 1, 2012, pp. 75-86.
12. Hyun-Jun Shin, Kyoung-Woo Cho and Chang-Heon Oh, "SVM-Based Dynamic Reconfiguration CPS for Manufacturing System in Industry 4.0, 2017, Advanced Wireless Communications and Mobile Computing Technologies for the Internet of Things, Volume 2018, Special Edition"
13. Catak, Ferhat Ozgur & Balaban, Erdal. (2012). CloudSVM: Training an SVM Classifier in Cloud Computing Systems. 10.1007/978-3-642-37015-1_6.
14. Yongxiang Li, Xifan Yao , and Min Liu, "Cloud Manufacturing Service Composition Optimization with Improved Genetic Algorithm, July 2019, Mathematical Problems in Engineering, https://doi.org/10.1155/2019/7194258"
15. Yongxiang Li,1,2 Xifan Yao ,2 and Min Liu, "Cloud Manufacturing Service Composition Optimization with Improved Genetic Algorithm, 2018, Mathematical Problems in Engineering, https://doi.org/10.1155/2019/7194258"
16. Ajay Shrestha and Ausif Mahmood, "Improving Genetic Algorithm with Fine-Tuned Crossover and Scaled Architecture, March 2016, Journal of Mathematics, http://dx.doi.org/10.1155/2016/4015845"
17. Chinmai Shetty, Dr. Sarojadevi H and Suraj Prabhu, " Machine Learning Approach to Select Optimal Task Scheduling Algorithm in Cloud, Turkish Journal of Computer and Mathematics Education, 2021, Vol 12"
18. Carsten Elwin, Sascha Neff, Alexander Verl, " Cloud Manufacturing: An Automated Literature Review, 7th CIRP Global WEb COnference Towards shifted production value stream patterns through inference of data, models, and Technology"
19. R. Henzel and G. Herzwurm. Cloud manufacturing: A state-of-the-art survey of current issues. Procedia CIRP Conference on Manufacturing Systems, vol. 51, no. 72, pp. 947– 952, 2018.

20. J. Siderska and K. S. Jadaan. Cloud manufacturing: a service-oriented manufacturing paradigm. A review paper. Engineering Management in Production and Services, vol. 10, no. 1, pp.22-31, 2018.
21. Katzel J. Power of the cloud. Control Engineering 2011;58:16–21.
22. Gilseung Ahn, You-Jin Park and Sun Hur, "Probabilistic Graphical Framework for Estimating Collaboration Levels in Cloud Manufacturing, 2017, MDPI"
23. Xi Vincent Wang, Mohammad Givehchi, Lihui Wang, "Manufacturing system on the cloud: a case study on cloud-based process Planning, The 50th CIRP Conference on Manufacturing Systems"
24. Wenying Zeng, Yuelong Zhao, and Junwei Zeng. Cloud service and service selection algorithm research. In Proceedings of the First ACM/SIGEVO Summit on Genetic and Evolutionary Computation, pages 1045–1048. ACM, 2009
25. Vijendra and Sudhir shenai, "Survey on scheduling issues in cloud computing", International conference on modeling optimization and computing (ICMOC-2012), Procidia Engineering 38(2012) 2881-2888.

Dr.Amit Agarwal and Saloni Jain, “Efficient Optimal Algorithm of Task Scheduling in Cloud Computing Environment”, International Journal of Computer Trends and Technology (IJCTT) – volume 9 Proceedings of the Fourth International Conference on Inventive Systems and Control (ICISC 2020) IEEE Xplore Part Number: CFP20J06-ART; ISBN: 978-1-7281-2813-9 978-1-7281-2813-9/20/$31.00 ©2020 IEEE 730

26. Abdul Razaque, Nikhileshwara Reddy Vennapusa, Nisargkumar Soni, Guna Sree Janapati and Khilesh Reddy V., "Task Scheduling in Cloud Computing", 2016 IEEE Long Island Systems, Applications, and Technology Conference (LISAT).
27. Shubham Mittal, and Avita Katal,” An Optimized Task Scheduling Algorithm in Cloud Computing”, IEEE 6th International Conference on Advanced Computing, 2016.
28. Qi Zhang, Lu Cheng and Raouf Boutaba, "Cloud computing: state-of-the-art and research challenges", Journal of Internet Services and Applications, Volume 1, Issue 1, pp 7–18, May 2010.
29. Rajkumar Buyya, Rajiv Ranjan and Rodrigo N. Calheiros, "Modeling and Simulation of Scalable Cloud Computing Environments and the CloudSim Toolkit: Challenges and Opportunities", Proceedings of the 7th High-Performance Computing and Simulation (HPCS 2009) Conference Leipzig, Germany, June 21 - 24, 2009.
30. Joe Fiala, “A Survey of Machine Learning Applications to Cloud Computing“, http://www.cse.wustl.edu/jain/cse570-15/ftp/cld_ml/index.html.
31. C. Nilsson, "Heuristics for the traveling salesman problem, "Tech. Rep., Link¨oping University, Link¨oping, Sweden, 2003.
32. G. Reinelt, "TSPLIB—a traveling salesman problem library, "ORSA Journal on Computing, vol. 3, no. 4, pp. 376–384, 1991.
33. S. Li, H. Chen, and Z. Tang, "Study of Pseudo-Parallel genetic algorithm with ant colony optimization to solve the TSP, "IJCSNS International Journal of Computer Science and Network Security, vol. 11, no. 3, 2011.
34. X. Yao, “Evolving artificial neural networks,” Proceedings of the IEEE, vol. 87, no. 9, pp. 1423–1447, 1999.
35. D. H. Nguyen and B. Widrow, “Neural networks for self-learning control systems," IEEE Control Systems Magazine, vol.10, no. 3, pp. 18–23, 1990.
36. L. Davis, "Applying adaptive algorithms to epistatic domains," in Proceedings of the International Joint Conference on Artificial Intelligence (IJCAI '85), vol. 1, pp. 162–164, 1985.
37. D. Whitley, T. Starteather, and D. Shaner, “The traveling salesman and sequence scheduling: quality solutions using genetic edge recombination,” in Handbook of Genetic Algorithms, L.Davis, Ed., pp. 350–372, D. Van Nostrand Reinhold Company, New York, NY, USA, 1991.
38. S. F. Gal´an, O. J. Mengshoel, and R. Pinter, “A novel mating approach for genetic algorithms,” Evolutionary Computation, vol. 21, no. 2, pp. 197–229, 2013.
39. L. J. Eshelman and J. D. Schaffer, “Preventing premature convergence in genetic algorithms by preventing incest,” in Proceedings of the 4th International Conference on Genetic Algorithms (ICGA ’91), pp. 115–122, Morgan Kaufmann, San Diego, Calif, USA, July 1991.
40. Tao, F., Cheng, Y., Xu, L. D., Zhang, L., Li, B. H., May 2014. CCIoTCMfg: Cloud computing and internet of things-based cloud manufacturing service system. IEEE Transactions on Industrial Informatics 10 (2), 1435–1442. URL http://dx.doi.org/10.1109/TII.2014.2306383
41. Tao, F., Hu, Y., Zhao, D., Zhou, Z., Sep 2008. Study on resource service match and search in manufacturing grid system. The International Journal of Advanced Manufacturing Technology 43 (3-4), 379–399.URL http://dx.doi.org/10.1007/s00170-008-1699-7
42. Tao, F., Hu, Y. F., Zhou, Z. D., Apr 2007. Study on manufacturing grid & its resource service optimal-selection system. The International Journal of Advanced Manufacturing Technology 37 (9-10), 1022–1041. URL http://dx.doi.org/10.1007/s00170-007-1033-9
43. Tao, F., LaiLi, Y., Xu, L., Zhang, L., Nov 2013. FC-PACO-RM: A parallel method for service composition optimal selection in the cloud manufacturing system. IEEE Transactions on Industrial Informatics 9 (4), 2023–2033. URL http://dx.doi.org/10.1109/TII.2012.2232936
44. Tao, F., Zhang, L., Nee, A., Jul 2011. A review of the application of grid technology in manufacturing. International Journal of Production Research 49 (13), 4119–4155. URL http://dx.doi.org/10.1080/00207541003801234

45. Wu, D., Rosen, D. W., Wang, L., Schaefer, D., feb 2015. Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. Computer-Aided Design 59, 1–14. URL http://dx.doi.org/10.1016/j.cad.2014.07.006
46. Xu, X., Feb 2012. From cloud computing to cloud manufacturing. Robotics and Computer-Integrated Manufacturing 28 (1), 75–86. URL http://dx.doi.org/10.1016/j.rcim.2011.07.002
47. F.-K. Wang and T. Du, "Implementing support vector regression with differential evolution to forecast motherboard shipments, "Expert Systems with Applications, vol. 41, no. 8, pp. 3850–3855, 2014.
48. T. T. Nguyen, Z. Li, S. Zhang, and T. K. Truong, “A hybrid algorithm based on particle swarm and chemical reaction optimization,” Expert Systems with Applications, vol. 41, no. 5, pp. 2134–2143, 2014.
49. F. Valdez, P. Melin, and O. Castillo, “A survey on nature inspired optimization algorithms with fuzzy logic for dynamic parameter adaptation," Expert Systems with Applications, vol. 41, no. 14, pp. 6459–6466, 2014.
50. Zhang, L.; Luo, Y.; Tao, F.; Li, B.H.; Ren, L.; Zhang, X.; Guo, H.; Cheng, Y.; Hu, A.; Liu, Y. Cloud manufacturing: A new manufacturing paradigm. Enterp. Inf. Syst. 2014, 8, 167–187.
51. Wu, D.; Greer, M.J.; Rosen, D.W.; Schaefer, D. Cloud manufacturing: Strategic vision and state-of-the-art. J. Manuf. Syst. 2013, 32, 564–579.
52. Putnik, G. Advanced manufacturing systems, and enterprises: Cloud and ubiquitous manufacturing and an architecture. J. Appl. Eng. Sci. 2012, 229, 127–134.
53. Chen, S.-L.; Wang, H.P.; Chen, Y.Y. Development of software-as-a-service cloud computing architecture for manufacturing management systems based on virtual COM port driver technology. Appl. Mech. Mater. 2013, 1023, 479–480.
54. Giriraj, M.; Muthu, S. A cloud computing methodology for industrial automation and manufacturing execution system. J. Theor. Appl. Inf. Technol. 2013, 52, 301–307.
55. Hung, M.H.; Lin, Y.C.; Huy, T.Q.; Yang, H.C.; Cheng, F.T. Development of a cloud-computing based equipment monitoring system for machine tool industry. In Proceedings of the IEEE International Conference on Automation Science and Engineering (CASE 2012), Seoul, Korea, 20–24 August 2012; pp. 962–967.
56. Helo, P., & Hao, Y. (2017). Cloud manufacturing system for sheet metal processing. Production Planning & Control, 28(6-8), 524-537.
57. Helo, P., Suorsa, M., Hao, Y., & Anussornnitisarn, P. (2014). Toward a cloud-based manufacturing execution system for distributed manufacturing. Computers in Industry, 65(4), 646-656.
58. Manthou, V., Vlachopoulou, M., & Folinas, D. (2004). Virtual e-Chain (VeC) model for supply chain collaboration. International Journal of Production Economics, 87(3), 241-250.
59. Shamsuzzoha, A., Ferreira, F., Azevedo, A., & Helo, P. (2016). Collaborative smart process monitoring within virtual factory environment: an implementation issue. International Journal of Computer Integrated Manufacturing, 1-15.
60. Shamsuzzoha, A., Toscano, C., Carneiro, L. M., Kumar, V., & Helo, P. (2015). ICT-based solution approach for collaborative delivery of customized products. Production Planning & Control, 1-19
61. Wu, D., Rosen, D. W., Wang, L., & Schaefer, D. (2015). Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. Computer-Aided Design, 59, 1-14.
62. T. Imam, F. Miskhat, R. Rahman, and A. Amin, "Neural network and regression based processor load prediction for efficient scaling of grid and cloud resources," in Proc. of ICCIT, 2011.
63. F. Farahnakian, P. Liljeberg, and J. Plosila, “Lircup: Linear regression based CPU usage prediction algorithm for live migration of virtual machines in data centers,” in Proc. of EuroSEAA, 2013.
64. S. Islam, J. Keung, K. Lee, and A. Liu, “Empirical prediction models for adaptive resource provisioning in the cloud,” Trans. on FGCS, 2012.
65. A. Bankole and S. Ajila, “Cloud client prediction models for cloud resource provisioning in a multitier web application environment,” in Proc. of SOSE, 2013.
66. A. Nikravesh, S. Ajila, and C. Lung, "Measuring prediction sensitivity of a cloud auto-scaling system," in Proc. of CSAC, 2014.
67. Y. Nikravesh, S. Ajila, and C. Lung, “Towards an autonomic auto-scaling prediction system for cloud resource provisioning,” in Proc. of SEAS, 2015.
68. T. Joachims, "Training linear SVMs in linear time," in Proc. of SIGKDD, 2006.
69. G. Shyam and S. Manvi, "Virtual resource prediction in a cloud environment: a bayesian approach,” Journal of Network and Computer Applications, 2016.
70. Letaifa, S.B., Gratacap, A., Isckia, T. (2013) Understanding business ecosystems: how firms succeed in the new world of convergence? De Boeck Superieur, Méthodes & Recherches, ISSN 1781-4944.
71. Moore, J. F. (2006). Business ecosystems and the view from the firm. Antitrust Bulletin, 51(1), 31-75.
72. Wulf, A., & Butel, L. (2017). Knowledge sharing and collaborative relationships in business ecosystems and networks: A definition and demarcation. Industrial Management & Data Systems, 117(7), 1407-1425.
73. Rong, K., Lin, Y., Shi, Y., & Yu, J. (2013). Linking business ecosystem lifecycle with platform strategy: A triple view of technology, application, and organization. International Journal of Technology Management, 62(1), 75-94.
74. Cenamor, J., Sjödin, D. R., & Parida, V. (2017). Adopting a platform approach in servitization: Leveraging the value of digitalization. International Journal of Production Economics, 192, 54-65.
75. Panetta, K. (2017). 8 Dimensions of Business Ecosystems. Gartner. Available at:

https://www.gartner.com/smarterwithgartner/8-dimensions-of-business-ecosystems/ [Accessed by 06/19/2018]

76. Rasmus, R. & McKinney, J. (2017). Manufacturing Ecosystems. Accenture Strategy. Available at: https://www.accenture.com/_acnmedia/accenture/conversionassets/dotcom/documents/global/pdf/strategy_8/accenture-manufacturing-ecosystems.pdf
77. Wei, Z., Song, X., & Wang, D. (2017). Manufacturing flexibility, business model design, and firm performance.International Journal of Production Economics, 193, 87-97.
78. Hao, Y., Shamsuzzoha, A., & Helo, P. (2013). Designing of virtual factory information system by enterprise portal. In 17th IEEE International Enterprise Distributed Object Computing Conference Workshops (EDOCW), pp. 258-266.
79. Alfaro Saiz, J., Rodriguez, R., & Ortiz, A. (2005). A performance measurement system for virtual and extended enterprises. In Collaborative networks and their breeding environments. Boston: Springer.
80. Ai, Q. S., Mo, K., Wang, Y., & Zhao, L. (2013). Research of product information sharing system based on cloud manufacturing. In Applied Mechanics and Materials (Vol. 248, pp. 533-538). Trans Tech Publications.