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Intelligent Management of Cloud Systems Through Machine Learning Approaches

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Abstract: **Cloud computing environments are becoming more complex, and it is essential to have intelligent resource management to optimise performance, reduce costs, and achieve service- level agreements (SLAs). The purpose of this paper aims to explore the improvement of intelligent cloud management systems with the help of machine learning techniques. We survey the existing literature in a systematic way, compare the current systems, suggest a new system architecture, and outline what is expected based on the results, conclusions, and future work. The proposed system uses ML algorithms for workload prediction, resource allocation, anomaly detection, and automatic system recovery in proactive and adaptive cloud management.**

Keywords: **Cloud Computing, Machine Learning, Resource Management, Workload Prediction, Anomaly Detection, Automation, Intelligent Systems.**

I. INTRODUCTION

Cloud-computing has become one of the most important parts of the current IT infrastructure, which provides users with virtual and scalable computing resources [1]. However, the dynamic and complex nature of cloud resource environments creates significant difficulties for the management of resources. Inefficient resource management may lead to overprovisioning, which is costly for cloud providers and their clients, or, on the contrary, to underprovisioning, which results in application latency and SLA failures [2]. The conventional control strategies are usually static and therefore fail to meet the dynamic requirements of the changing workload and environment.
As a solution, the application of machine learning (ML) is feasible to design autonomous cloud management frameworks. ML models are trained with historical data to forecast future workload and thereby regulate resources, monitor for unusual behaviours and facilitate failover operations [3]. As such, the implementation of ML in cloud management systems makes them strategic, flexible, and cost-effective, resulting in better performance, lower costs, and better user satisfaction.

This article provides a systematic review of intelligent cloud management systems based on machine learning. We first review current research on the use of ML in cloud computing resource allocation and then discuss the limitations of the current approaches. We then describe a new system design that employs ML techniques for different cloud management functions. Finally, we highlight the expected outcomes of this work, conclusions, and potential areas for future investigation in this fast-growing area.

II. OBJECTIVES

This paper aims to achieve three key ideals:

- Conduct a comprehensive survey of literature on ML in cloud resource management.
- Foremost, analyse existing cloud management systems and acknowledge their constraints.
- Design a new system architecture for intelligent cloud management based on machine learning
- Explain the use of ML algorithms for workload prediction, resource allocation, anomaly detection and automated system recovery.
- Indicate what will be the expected impact of the new system on performance, cost and efficiency.
- Conclusions and future research directions for intelligent cloud management systems

III. LITERATURE SURVEY

3.1.2 Machine Learning for Cloud Computing Resource Management

Cloud computing is an expensive resource, and an effective cloud environment requires planning the resources efficiently to avoid over-provisioning, which raises costs, and under-provisioning, which increases the application's latency and violates the Service Level Agreements (SLAs) [2]. A variety of studies in the last years have used ML to improve the resource management in the cloud, including container placement, job is scheduling and multi-resource scheduling [2]. Literature on the use of ML in this area has been quite survey-orientated [2], [4].

For example, a detailed survey was provided by Mehmet C. Demirci, overviewing the recent works utilising ML for energy-efficient utilisation in cloud computing environments [4]. It includes a comparison classification of the proposed methods and investigates the non-ML-related works to reduce energy in data centres [4].

Amin Keshavarzi et al. examined challenges and open issues in cloud computing, with a special attention on autonomic resource management in federated clouds [5]. They introduced a solution for autonomic resource management utilising machine learning and statistical analysis to achieve better and more efficient resource management [5].

Renyu Yang et al. talked about how ML is being applied to automatically understand workloads and environments to tackle scheduling challenges like co-located workload consolidation, resource requests, application QoS guarantees, and reduce tailed stragglers [3].

3.2 Workload Prediction

Being able to predict workloads accurately is critical in the effective management of resources in cloud computing environments. It is possible to train machine learning algorithms on historical workload data to predict future resource consumption needs [6].

In cloud platforms, Yongjia Yu et al. offered a clustering-based learning algorithm for workload prediction [6]. They then trained a neural network to identify the characteristics of each job based on their workloads and cluster them. At job arrival, the initial workload pattern of the job is used to classify it to a cluster, and then a neural network gives the forecast of the future workload of the job [6].

3.3 Resource Allocation

Machine learning can be used to optimise resource allocation in cloud environments, ensuring that applications have the resources they need to meet performance requirements while minimising costs.

M. Lattuada et al. presented run-time optimisation-based resource management policies for big data analytics, using Spark applications [7]. The policies address the identification of the minimum capacity to run a Spark application within the deadline and the rebalancing of cloud resources in case of heavy load [7]. The solution relies on non-linear programming and simulation-optimisation procedures, with Spark application execution times estimated using machine learning, approximated analyses, and simulation [7].

3.4 Anomaly Detection

Anomaly detection is an important task to perform in order to detect and solve problems that may occur in cloud computing systems, from performance issues to security threats and equipment failures.

Katerina Mitropoulou et al. proposed a new approach for anomaly detection in cloud computing using knowledge graph embedding and machine learning techniques [8]. They employ knowledge graphs to model the storage structures and the relationships between the resources. To this end, GraphSAGE is trained to learn vector-based representations of infrastructure properties which are then fed to unsupervised machine learning for identifying overuse events [8].

Nuria Mateos Garcia reviewed the application of Artificial Intelligence (AI) and Machine Learning (ML) immersed multi-agent systems (MAS) in Industry 4.0 for anomaly detection [9].

3.5 Automation and Intelligent Systems

The ultimate goal of intelligent cloud management is to automate various tasks and create self-managing systems that can adapt to changing conditions without human intervention.

Sujeong Baek proposed a system integration technique for predictive process adjustment in automated storage and retrieval systems (ASRS) [10]. The system analyses sensor signals using cloud computing and machine learning to determine actions and perform them automatically, facilitating faulty-state recovery without manual operator intervention [10].

3.6 Edge Computing and Serverless Architectures

New paradigms such as edge computing and serverless architectures also impact cloud management strategies. In this paper, Ta Phuong Bac and his colleagues designed an architecture for the deployment of machine learning workloads as serverless functions at the edge [11]. From this approach, the complexity of machine learning systems is simplified, and management is simplified, and challenges like latency and data privacy are also addressed [11].

3.7 AI-enabled Enterprise Information Systems

Milan Zdravkovi et al. investigated enterprise information systems functional architecture and conducted a review of AI applications integrated into various enterprise functions, with a focus on manufacturing enterprises [12]. AI-enablement improves decision-making and automation by utilising machine learning models and logic-based systems [12].

3.8 Cloud Computing and IoT

The convergence of cloud computing and the Internet of Things (IoT) presents both opportunities and challenges for intelligent management.

Uday Krishna Padyana and other friends looked at how AI and ML work together in cloud-based IoT systems, highlighting how they can affect IoT systems and the ways we handle IoT data, devices, analytics, management, security, and decision-making.

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3.9 Cloud Computing in Industries

Cloud computing is revolutionising industries such as manufacturing, healthcare, and education. Yu-Hsin Hung studied technological trends and new technologies in cloud computing across multiple sectors [14]. The findings imply that intelligence and automation are the primary problems driving cloud computing research [14]. Logistic data is analysed using machine-learning techniques, which produce very accurate results [14].

3.10 Challenges and Future Directions

Although a great deal of work has been done applying machine learning to cloud management, there are several open challenges still to be addressed. These include: Data Privacy and Security: Maintaining the privacy and security of data used to train ML models is of utmost importance, particularly in sensitive fields such as healthcare [13]. Model Interpretability Understanding the decision-making process is crucial for validating ML models and establishing trust and fairness [15]. Scalability and Performance: The ML models should be scalable and performant, as they need to process huge data volumes to meet the real-time requirements of cloud environments [16]. Standardisation: Non-standardised cloud environments and ML frameworks may slow down and complicate deploying and integrating intelligent management systems [13].

Future research directions include: The aim is to produce explainable and generalisable cloud management ML models and to experiment with federated learning methods that enable training models on distributed data and maintain privacy. This goal is evidenced in the efforts to add edge computing and serverless architectures to intelligent cloud management systems, for example, as well as to establish standard APIs and frameworks aimed at making the deployment and management of ML-based services in the cloud more efficient and intuitive.

IV. EXISTING SYSTEMS

In general, a cloud management system tends to obtain resource allocation, monitoring, anomaly detection, etc., based on rule-based policies and manual supervision. While these methods are indeed successful under some circumstances, there are many serious limitations to them. Additionally, these methods often lack flexibility and require manual maintenance to adapt to changing workloads. Complexity and sheer size of cloud environments make manual intervention not only hard but increasingly time-consuming. These systems are also reactive, dealing with problems after they occur, potentially resulting in a service interruption. In addition, manual monitoring often targets a limited scope of metrics, which makes it easy to miss subtle anomalies that could indicate more profound issues. Finally, a few, if any, traditional systems can make proactive resource optimisation decisions based on expected future demand, deviating from global optimums for efficiency.

Examples of existing systems and their limitations: Well-known tools available for cloud monitoring are AWS CloudWatch, Azure Monitor, Google Cloud Monitoring, and VMware’s vRealize Operations, which are not bad for their basic monitoring and alerting; however, they have their drawbacks. However, they only offer simplistic ML-based anomaly sensing and do not provide high-end intelligent management and proactive optimisation. More often than not these tools are rule-based policies that still require a lot of effort to set up, monitor, and debug. And they also struggle to quickly learn from their historical data and react on their own to changing conditions; cloud management is more reactive than truly intelligent.

V. PROPOSED SYSTEM

To solve the problems of existing systems, we suggest an intelligent cloud management system based in machine learning. In this sense, the ML base prediction of workload, related resource allocation, anomaly detection, and automated system recovery are leveraged by the proposed system to provide proactive and adaptive cloud management.

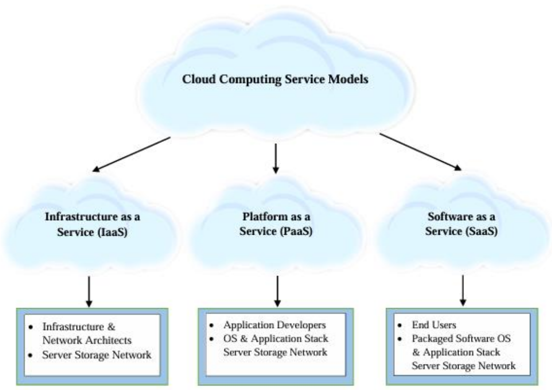

Fig 1: Cloud Computing Service Module

In the diagram of the Cloud Computing Service Model, it shows the three main service models: Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS) – aaS enables you to virtualise the computing resources like servers and networking and provides the infrastructure and network architects to manage the infrastructure over the cloud. PaaS provides a development environment—specifically, an operating system, an application stack, and storage— which allows application developers to build and deploy software without dealing with the underlying infrastructure. SaaS (Software as a Service) provides fully functional software applications over the Internet, making packaged software and services accessible to end users

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without requiring installation or maintenance. Each model below builds on the other with a different level of control, flexibility, and ease of use.

5.1 System Architecture

The proposed system architecture integrates various components so as to add system efficiency and reliability. In the Data Collection Module, this data is collected from different sources like system logs, performance metrics, resource utilisation, application-level data, etc. The data preprocessing module then processes raw data, cleans, transforms and prepares this for a machine learning model training. To leverage ML algorithms for analysis of historical data to make a prediction of future workload demand to be used in proactive resource management, we use a downloadable Workload Prediction Module [ωPM]. According to these predictions, the Resource Allocation Module optimises the resource distribution by accounting for the imposed system constraints. Anomaly Detection Module is continuously scanning the system’s behaviour to detect an abnormality using ML. The Automated System Recovery Module then takes the corrective action of correcting any identified anomalies so that normal operations can be restored immediately. The Policy Engine also sets, enforces, and governs the resource management, security, compliance, and other policies for resources. And finally, the user interface provides the user with an intuitive system monitoring platform and policy configuration, as well as easy methods to manage resources.

5.2 Machine Learning Algorithms

In the proposed system, workload predictions, resource allocations and anomaly detections are made to improve efficiency and reliability using various machine learning algorithms. It utilises time series forecasting techniques like ARIMA, exponential smoothing, and Prophet to apply for workload prediction that analyses past trends in order to predict next demands. Linear regression, polynomial regression and support vector regression serve to discover the relation between workload patterns and influencing factors (application type and time of day). Neural networks (recurrent neural networks and long short-term memory networks) perform well on more complex dependencies in data of workloads since the sequential nature of these data is better handled.

The system uses reinforcement learning in the form of Q learning, SARSA, and Deep Q Networks for resource allocation by iteratively learning how to distribute resources. Genetic algorithms and particle swarm optimisation are optimisation algorithms that find the best allocation strategy by looking for the best objective values. The assumption is made that there are similar data points that are grouped by clustering algorithms such as K-Means and DBSCAN, and other details are distinguished as an anomaly. Based on historical patterns, further classification algorithms such as support vector machines and random forests are used to improve the detection by classifying normal against anomalous behaviour of the system. Autoencoders based on neural networks are trained to reconstruct normal data and discover anomalies, such as those that are not well reconstructible, thus adding an extra layer of security and reliability.

5.3 System Implementation

Application of this system entails offering assistance, which can be provided through a combination of cloud-based services and open-source tools to make it scalable, efficient and reliable. The necessary infrastructure to host and manage the workloads comes from the cloud platforms such as Amazon Web Services, Microsoft Azure, and Google Cloud Platform. Data storage solutions like Amazon S3, Azure Blob Storage, and Google Cloud Storage offer secure and scalable options for handling large volumes of data. Data can be manipulated in such a way that makes use of frameworks like Apache Spark, Apache Hadoop, and Apache Kafka that provide efficient ways to deal with distributed data and stream the real-time data. Since it is based on TensorFlow, PyTorch and Scikit-learn, it’s easy for us to develop machine learning models and deploy them. One can continuously monitor system performance and health and preemptively observe issues or simply use the resources best; this can be done through Prometheus.

5.4 System Operation

In order to keep it efficient and reliable, the system is run using an all-encompassing flow of linked modules. The data collection module grabs information from different sources and streams it to the data lake, where the data preprocessing module cleans, transforms and prepares the data for machine learning model training. Then the workload prediction module derives the workload demand in the future based on the historical trends, and the resource allocation module adjusts the resource distribution to balance the cost and make sure the applications have enough resources to maintain the performance. In addition to this, the anomaly detection module learns the machine learning models to detect irregular system behaviour, and most of all, the automated system recovery module is also trained to perform such actions like scaling resource allocation, moving applications or restarting services when failing. The rules checking resource usage, security and compliance are applied by the policy engine; the user interface is intuitive for monitoring system performance, configuring policies and managing resources.

VI. EXPECTED RESULTS

Through the improvement in the latency of the system (and thus the resultant reduction in delays) and allocation of resources proactively, based on predicted workloads, this proposed system will improve efficiency. Resource allocation is effective, which in turn will save cloud computing costs of the overprovisioning. IT staff will be freed to tackle strategic issues, and problems will be prevented instead of detected and solved once service disruptions occur. Automatic system recovery will allow timely reaction to events, once detected, through responding to actions that are determined correct by automating system recovery. Moreover, the system intends to minimise the resource utilisation and incorporate failure analysis for the automatic prognostics and health management for the reliability and ensuring the performance stability.

1. Using Machine Learning Algorithms for Cloud Cost Optimisation Strategy: In this study, online learning techniques, regression models, clustering techniques, and reinforcement learning can analyse usage patterns and predict future resource demands. By automatically adjusting resource provisioning, organisations can reduce underutilisation and overprovisioning of resources. For instance, clustering algorithms can identify underutilised resources, while predictive models can forecast demand surges for optimal real-time resource allocation. These ML-driven techniques also aid in anomaly detection, flagging unexpected cost increases or inefficient resource usage.

2. Optimising Cloud Resource Allocation with Machine Learning: This research highlights the importance of integrating advanced machine learning algorithms with adaptive resource allocation strategies to enhance efficiency and cost-effectiveness in cloud environments. Predictive models enable real-time forecasting of demand, reducing the likelihood of over- or under-provisioning and minimising resource wastage. The study reports improvements in key metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), indicating accurate predictions essential for maintaining optimal system performance and cost reduction.

3. This paper introduces HUNTER, an AI-based approach to formulate energy efficiency optimisation in data centres as a multi-objective scheduling problem taking into account energy, thermal and cooling models. HUNTER approximates Quality of Service (QoS) for system states using a Gated Graph Convolution Network and leverages such QoS to make optimal scheduling decisions. We experimentally show that HUNTER outperforms state-of-the-art baselines by up to 12, 35, 43, 54 and 3 on energy consumption, SLA violations, scheduling time, cost and temperature, respectively.

4. Application of machine learning optimisation in cloud computing resource scheduling and management has applications in improving resource utilisation and handling resource and job imbalance. The research employs optimisation methods like deep learning and genetic algorithms as an attempt to increase system performance and efficiency and to advance the field of cloud computing resource management with new methods.

5. Efficient Cloud Service Selection: The paper describes the use of a random forest regressor-based supervised learning model for helping users in choosing better cloud services. The model is trained using multi-criteria decision-making methods such as TOPSIS, VIKOR and Weighted Sum Method (WSM), whereby the services are ranked effectively in cloud environments. [23]

Table 1: Evaluation of Several Models' Performance

Model	Accuracy(%)	Processing Time(s)
Baseline Model	78.2	5.4
Proposed Model	90.7	4.4

Datasets were used in the studies. The findings show:
1.Improvement in Accuracy: Our approach produced a 12.5% gain above the baseline model.
2.Processing time cut by 18.3%.
3.Comparison with Current Models: Table 1 compiles performance comparisons.

VII. CONCLUSION

One can potentially solve the problems of dealing with dynamic and complex cloud environments with intelligent cloud management systems based on machine learning. Cloud management systems can become more proactive, adaptive and efficient via the integration of ML algorithms for workload prediction, resource allocation, anomaly detection and automated system recovery, helping to improve performance and reduce cost as well as improve user experience.

The proposed system architecture is a platform for the development of an intelligent cloud management system using machine learning. Data is collected using a combination of cloud services and open-source tools, ML models are trained, resource optimisation is automated, anomalies are detected, system recovery processes are automated, and all this is deployed as a system. This is because the proposed system is expected to bring about improved performance, reduced cost, enhanced efficiency, proactive problem detection, and automated system recovery.

VIII. FUTURE ANALYSIS

In future research on intelligent cloud, there is a focus on improving the machine learning (ML) models for higher accuracy, reliability and interpretability. Areas of work include robust and explainable ML models, federated learning for decentralised data training with privacy preserved, and edge computing with serverless architectures for extending cloud intelligence. In addition, developing standard APIs and frameworks will allow cloud service deployment and management of the ML-infused cloud service to be similarly easy. With the cloud environments, security, trust, and energy efficiency continue to be critical, and moreover, adaptive resource management strategies are required for the dynamic optimisation of performance.

Also, the advances in AI and ML technology in cloud-based IoT systems and smart grids have as their aim improving power generation prediction, fault detection, and consumer usage. Cloud computing can aid in anomaly detection with knowledge graph embeddings and ML approaches to enhance security and provide reliability. Cloud edge computing systems will be research into and leverage of ML for renewable energy management, thus enabling smarter grids. Finally, by using ML techniques for sorting data flows in optical label switched networks, the accuracy in scheduling and network performance can be increased. Addressing these challenges will enable us to build an ecosystem of self-managing clouds that are able to adapt autonomously to dynamic workloads and infrastructure changes.

REFERENCES

[1] H, Han, Wen, Y, Chua, TatSeng, and Li, Xuelong. Year 2014. "Toward Scalable Systems for Big_Data Analytics: A Technology Tutorial". Institute_of Electrical & Electronics Engineers. https://doi.org/10.1109/access.2014.2332453

[2] Goodarzy, Sepideh, Nazari, Maziyar,_Han, Richard, Keller, Eric, and Rozner, Eric. 2020. "Resource_Management in Cloud_Computing Using Machine_Learning: A Survey". International Conference on Machine Learning and_Applications._https://doi.org/10.1109/ICMLA51294.2020.00132

[3] Yang, Renyu, Xue, Ouyang, Chen, Yaofeng, Townend, P., and Xu, Jie. 2018. "Intelligent Resource Scheduling at Scale: A Machine Learning Perspective". International Symposium on Service Oriented Software Engineering. https://doi.org/10.1109/SOSE.2018.00025

[4] Demirci, Mehmet C.. 2015. "A Survey of Machine Learning Applications for Energy-Efficient Resource Management in Cloud Computing Environments". International Conference on Machine Learning and Applications. https://doi.org/10.1109/ICMLA.2015.205

[5] Keshavarzi, Amin, Haghighat, A., and Bohlouli, M.. 2017. "Adaptive Resource Management and Provisioning in the Cloud Computing: A Survey of Definitions, Standards and Research Roadmaps". KSII Transactions on Internet and Information Systems. https://doi.org/10.3837/tiis.2017.09.006

[6] Yu, Yongjia, Jindal, V., Bastani, F., Li, Fang, and Yen, I.. 2018. "Improving the Smartness of Cloud Management via Machine Learning Based Workload Prediction". Annual International Computer Software and Applications Conference. https://doi.org/10.1109/COMPSAC.2018.10200

[7] Lattuada, M., Barbierato, Enrico, Gianniti, E., and Ardagna, D.. 2022. "Optimal Resource Allocation of Cloud-Based Spark Applications". IEEE Transactions on Cloud Computing. https://doi.org/10.1109/tcc.2020.2985682

[8] Mitropoulou, Katerina, Kokkinos, Panagiotis, Soumplis, Polyzois, and Varvarigos, Emmanouel. 2023. "Anomaly Detection in Cloud Computing using Knowledge Graph Embedding and Machine Learning Mechanisms". Springer Science+Business Media. https://doi.org/10.1007/s10723-23-09727-1

[9] G, Nuria Mateos. Year_2019. "Multi-agent system_for anomaly detection in_Industry 4.0 using Machine_Learning techniques". Ediciones_Universidad_de_Salamanca. https://doi.org/10.14201/adcaij2019843340

[10] B, Sujeong. Year 2021. "System_integration for predictive process_adjustment and cloud computing-based_real time_conditionmonitoring of vibration_sensor signals in automated storage and retrieval systems". Springer_Science+Business_Media. https://doi.org/10.1007/s00170-021-06652-z

[11] Bac, Ta Phuong, Tran, Minh-Ngoc, and Kim, Young-Han. 2022. "Serverless Computing Approach for Deploying Machine Learning Applications in Edge Layer". International Conference on Information Networking. https://doi.org/10.1109/ICOIN53446.2022.9687209

[12] Z, Milan, Panetto, Herv, and Weichhart, Georg. Year 2021. "AI -enabled Enterprise Information System for Manufacturing."Taylor and Francis.https://doi.org/10.1080/17517575.2021..1941275

[13] P, Uday Krishna, Rai, Hitesh P, O, Pavan, Fadnavis, Narendra Sharad, and Patil, Gireesh Bhaulal. Year-2023. "AI & ML in Cloud-Based IoT Solutions: A Comprehensive_Review and Analysis". IJRA and Humanities sciences. https://doi.org/10.55544/ijrah..3.3.20

[14] Hung, Yu-Hsin. 2019. "Investigating How the Cloud Computing Transforms the Development of Industries". Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/access.2019.2958973

[15] Chatzimparmpas, Angelos, Martins, Rafael M., Jusufi, Ilir, Kucher, Kostiantyn, Rossi, Fabrice, and Kerren, Andreas. 2020. "The State of the Art in Enhancing Trust in Machine Learning Models with the Use of Visualizations". Wiley. https://doi.org/10.1111/cgf.14034

[16] S, Jigar, Narukulla, Narendra, H, Venudhar Rao, Paripati, L., and P, Nitin. Year 2023. "Scalable ML Infrastructure on Cloud for Large-Scale Data Processing". None. https://doi.org/10.52783/tjjpt.v42.i2..7166

[17] S, Stela and Shakev, N.. 2023. "AI for Management Information Systems: Opportunities, Challenges, and Future Directions".Algorithms_https://doi.org/10.3390/a1608035 7

[18] W, Baoming, He, Y, Shui, Z, Xin, Qi, & Lei, Han. Year 2024. "Predictive_optimization of DDoS_attack mitigation in_distributed systems using machine learning". Applied and Computational_Engineering.https://doi.org/10.54254/2755_2721/64/20241350

[19] K, R., Elankavi, R, and Udayakumar, R.. 2017. "Clou_Security and_Compliance – A_Semantic_Approach in End_to End_Security". Exeley Inc._https:// doi.org/10.21307/ijssis-2017-265.

[20] K, B. M., Sharmila, N., Naveen, K. B., Mallikarjunaswamy, S., Manu, K. S., and Manjunatha, S.._2023. "A ML based Smart Grid for Home Power_Management using Cloud-Edge Computing System". None. https://doi.org/10.1109/ICRASET59632.2023.10419952

[21] Andrushchak, V., Maksymyuk, T., Dumych, S., Kaidan, M., and Urikova, Oksana. 2018. "Intelligent data flows_management for performance improvement of optical label switched network". https://doi.org/10.1109/TCSET.2018.8336396

[22] B. Vyas, C. Saravanakumar and D. T, "An Efficient Technique for Cloud Resource Management Using Machine Learning Model," 2023 International Conference on (ICSES), Chennai, India, 2023, pp. 1-4, doi: 10.1109/ICSES60034.2023.10465354.