CREATION OF A CLOUD SERVER-BASED OPERATIONAL DATA MANAGEMENT SYSTEM FOR POWER SYSTEMS

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Abstract:
The current paper introduces a operational data management system of power systems based on cloud computing, big data analytics, and service-oriented architecture (SOA) using cloud servers. The system combines cloud service supply platform and application platform to facilitate the effective processing of data, real-time monitoring, and automated power dispatch control. One of the proposed algorithms deals with the operational risk, cost-effectiveness, and energy usage and enhances the resource use by means of dynamic method of the virtual machine migration and scheduling. The system also improves the scalability, reliability and decision making in power dispatch operations. The experimental data show that efficiency is enhanced, and the scheduling errors are minimized, and the support to smart power system management is provided.

Keywords: Cloud Computing, Power Dispatch System, Big Data Analytics, Smart Grid, Resource Scheduling, Energy Optimization.

I. INTRODUCTION

It is anticipated that power consumption will rise in the future decades, which would strain the current power infrastructure and may lead to power quality decline. Due to inefficient monitoring, fault detection, and automation approaches, the current electricity grid is unreliable. It is also very difficult to integrate decentralized power sources with the current infrastructure. Intelligent power infrastructures, or "Smart Grids," can make power systems safer, more dependable, more efficient, more adaptable, and more sustainable, all of which are necessary to address these issues. Due to the critical nature of data management and communication to the smart grid's operation, numerous projects are underway in different parts of the world to better manage the data related to the grid. The term "Internet of Energy" (IoE) describes the network of interconnected electronic devices that monitor and control electrical power systems. This includes things like smart meters, wireless sensor networks (WSNs), and actuators. Internet of Everything (IoE) makes advantage of the smart grid's two-way flow of data and energy to learn more about power consumption, make predictions about what to do next to improve efficiency and keep costs down. Through the Internet of Things (IoT), a smarter grid can be implemented, allowing for greater data and connectivity throughout the infrastructure and to households.

Electricity supply and demand between consumers and utility providers must be balanced by the current system due to the dynamic nature of energy demand. To accomplish this, Energy Management Systems (EMS) like HEM, DSM, and BEMS (Building Energy Management Systems) can be implemented. A smart grid enables the efficient control of supply and demand for a variety of renewable energy sources. The DR, distributed generation, resource scheduling, and real-time pricing model that make up a smart grid's heterogeneous architecture are what set it apart. Several publications have explored the issue of smart grid distributed energy management from the generation and demand perspectives. Smart meters, sensors, and phasor measurement units (PMUs) are examples of smart information subsystems that provide raw data on the health and operation of the network in Smart Grid. Deployed in numerous countries since the start of the 21st century, smart meters come equipped with characteristics such as defect detection, tamper proof, and more. In recent times, Advanced Metering Infrastructure (AMI) has supplanted the idea of Automated Meter Reading (AMR). The data system in AMI has progressed from a one-way communication system to a two-way system, allowing for the collection of meter data in AMR. One of the main reasons smart meters work is smart meter data analytics, which is concerned with collecting, transmitting, processing, and interpreting data in a way that benefits everyone involved.

Power System Operation

The economical running of the electricity system is crucial if the capital investments are to provide a profit. One way to accomplish this is by economic dispatch, which involves producing power at the lowest possible cost. The key to maximizing profit is minimizing power loss when delivering generated power to load centers. Efficiently minimizing costs per unit of active power generation from various generating stations (GS) while meeting load conditions and transmission losses is the primary goal of economic dispatch. In 1962, Carpentier presented a modified nonlinear programming (NLP) version of the economic dispatch problem that incorporates voltage and additional restrictions. An essential part of operating and planning power systems is dealing with this issue, which was dubbed Optimal Power Flow (OPF). There are a number of variables that contribute to the OPF problem, including dependent variables such as node voltage and phase angle as well as control variables such as actual and reactive power output from generators, voltage settings for voltage control nodes, tap positions of transformers, and so on. As part of OPF, there are a number of limitations.

Following is a list of potential equality or inequality constraints.

i. Power flow equation
ii. An electrical generator's active and reactive power output at its highest and lowest conceivable levels
iii. Power limitations of reactors and shunt capacitors
iv. Maximum and minimum allowable tap positions of phase shifters and transformers
v. Boundaries of the branch's transfer capacity
vi. Limits of node voltage

Historically, PGCIL was in charge of overseeing the operation of India's electricity system. Eventually, in March 2010, a new entity called electricity System Operation Corporation Ltd (POSOCO) was established as a subsidiary of the PGCIL. Its purpose is to operate the electricity grid and is made up of a network of load dispatch centers (LDCs) at the national, regional, and state levels. New Delhi is home to the national load despatch centre (NLDC), which oversees the activities of the five RLDCs that serve the northeast, west, south, and east sectors. State load despatch centers (SLDCs) come after RLDCs and are in charge of ensuring consistent functioning across the state via the supervision of one or more sub-LDCs. To keep things running well in West Bengal, WBSLDC collaborates with a number of sub-LDCs, such as the LDCs of WBSEDCL (the main beneficiary), CESC, DVC, etc. Figure 1 shows the load dispatch center hierarchy.

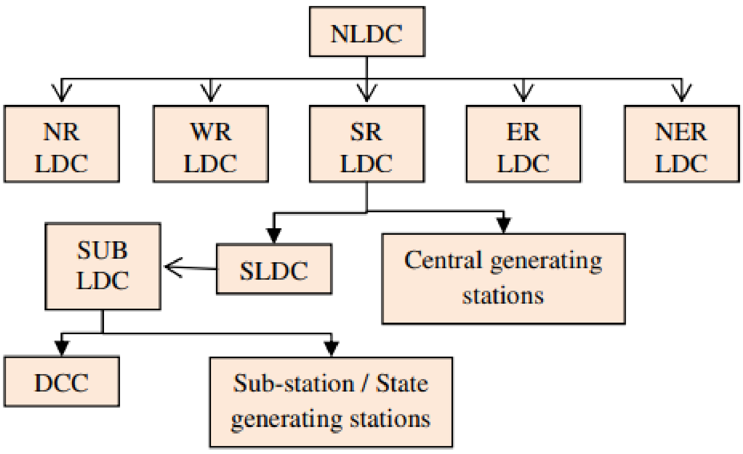

Figure 1. LDC Hierarchy in India for power system operation

All utilities in India that are linked to or use the Inter State Transmission System (ISTS) are required to adhere to the Indian Electricity Grid Code (IEGC), which unites a single set of commercial and technical regulations.

II. REVIEW OF RELATED STUDIES

Yucheng, Shu et al., (2024). With the proliferation of smart grids, power dispatch systems have expanded their remit to include numerous informational functions, such as data fusion, integration of heterogeneous systems, and big data analytics, in addition to the more conventional dispatch services. Unfortunately, the present power dispatch system has a hard time keeping up with the ever-increasing demands of enterprises that deal with complex information, such as big data analysis. In response, we present a method for managing automation in power dispatch that is based on cloud computing and big data analytics. The solution guarantees quick processing and analysis of massive amounts of power dispatch data by utilizing the distributed computing capabilities of cloud computing platforms. Further, the system provides insights for improving the Electric Power System's (EPS) operations by exploring historical data, finding possible operational patterns and danger areas, and utilizing big data analytic methodologies. Results from experiments show that the system is very good at improving data processing, real-time control, and automated management, which is great for intelligent power dispatch systems because it means they have strong technical support.

Muhlheim, Michael & Pradeep, Ramuhalli. (2022). One reason nuclear power stations (NPPs) are being decommissioned too soon is because the operations and maintenance (O&M) costs of light-water reactors are too high. Part of the blame for this lies with the monitoring system. Cloud computing's adaptability in computing and storage, along with its low costs and ability to host applications over numerous types of virtual infrastructures, has made it a dominant technology in recent years. When compared to on-premises storage and diagnostics, cloud computing often offers significant cost savings. An interim cloud deployment architecture for an NPP predictive monitoring (PdM) system is evaluated from a techno-economic perspective in this article. With the help of the cloud-based monitoring system, authorized plant users and maintenance and diagnostics (M&D) analysts could remotely check how the equipment is working, allowing for PdM practices and early fault detection. Data processing and storage, networking of sensor devices, and database management are all part of the suggested cloud architecture, which uses the Microsoft Azure platform. However, this study might be applied to other cloud computing providers instead. In the techno-economic analysis, operational costs and capital expenditures are used to determine economic feasibility, while network performance indicators like throughput, latency, and response time are used to analyze technical feasibility. The paper concludes by discussing some security and regulatory considerations that licensees may have when deciding to use cloud computing. The study identifies technical and financial challenges linked to transitioning to a cloud-computing-based architecture, applies cloud resources to PdM, and integrates storage for sensor databases.

Kanaan, Raed et al., (2019). Several entities, primarily those associated with the government, have implemented management information systems. They are seen as being particularly useful for complex, large-scale undertakings. This means that with the right cloud-based management information solutions in place, most businesses, particularly in developing nations like Jordan, can focus on what they do best. Several studies have examined management information systems using cloud computing, and this study mainly aims to systematically review those studies. To accomplish this study's goal, a comprehensive literature assessment of publications devoted to management and business process analysis is carried out. Understanding the fundamental operation of information systems, their management applications, and the adaption of cloud-based MIS are all goals of the evaluation and assessment of the returned results. We have gathered all of the evaluation results and produced a collective conclusion regarding the use of cloud-based MIS for this research. Results show that large corporations, government agencies, and SMEs are all heavily investing in cloud-based management information systems. Consequently, this study investigates and emphasizes the usefulness of cloud-based MIS in management operations. This review draws on relevant literature to provide a comprehensive overview of cloud-based MIS and its many benefits and uses in management and outsourcing.
Sarkar, Subhra et al., (2019). Data management becomes more difficult as the transition to smart(er) grids accompanies a dramatic increase in data volume. Both the differential binary encoding technique (DBEA) and its extended variant, E-DBEA, are capable of efficiently compressing operational data of power systems. The suggested smart DBEA encryption (S-DBEAE) algorithm encrypts the resultant string after data compression using DBEA or E-DBEA. Data management is accomplished by prefixing encrypted information with a small number of identification characters that comprise various data elements. Despite S-DBEAE's

somewhat lower compression ratio compared to DBEA (or E-DBEA), S-DBEAE is better than DBEA or E-DBEA since it provides data management. The power system operational data management cloud-based real-time test bench consists of four Internet-connected personal PCs. The economic load dispatch problem for a system with two generating stations was solved using the inertia weight-particle swarm optimization technique, which was applied while managing generation schedule information. It is also possible to realize the system for managing system monitoring data with S-DBEAE, since it can significantly minimize the volume of data. Thanks to the straightforward design of the suggested system, it is feasible to make certain adjustments and extend the operation to even low-level microcontrollers.

Sugumar, Hemavathi & Nithiyananthan, K.. (2017). The primary objective of this study is to examine and evaluate how Power System applications use Cloud computing. An alternative solution for massive data handling and excessive computational load in power systems, cloud computing provides a new perspective on easy access to larger scale computer resources over the Internet. Currently, it is available around the clock via the internet and has three main capabilities: load flow, contingency analysis, and an ODM (Open Data Model) power system for transforming simulation data. Due to its important benefits of low cost, flexible & redundant architecture with quick reaction, this article has investigated the employment of Cloud Computing (CC) into power system applications. Security, interoperability, and optimal execution are all benefits of cloud computing that are necessary for large-scale, complicated, keen system applications.

Mu, L. et al., (2011). This paper presents the evolution of the cloud computing method and the various ways it provides services, and then discusses the need and viability of using cloud computing to power system applications. In this article, we will go over the power system's intended use of a cloud computing center, its unique traits, and the specifics of the cloud computing center's architecture, breaking it down into its constituent parts: infrastructure, data management, simulation, cooperation, and consulting services. Data standards, model integration for power systems, mass data management, cooperative work, dynamic job dispatching, and cloud computing center for power systems are some of the important technologies and standards studied. Lastly, a real-world example of its use is provided.

III. PROPOSED STUDY METHOD

Proposed system

Our power dispatch data processing and automation management system is built to achieve high reliability, scalability, flexibility, and security. It draws on the service-oriented architecture (SOA) principle and uses cloud computing and big data analysis. An SOA bus connects the two platforms that make up this system: the cloud service application platform and the cloud service supply platform. Computing, storage, and networking are all part of the supply platform's infrastructure services, which guarantee stable and dependable services. Power dispatch data processing and automation, including data processing, analysis, optimization, and dispatch control, is housed in the application platform. Physical and virtualization resources are managed and scheduled dynamically at the lowest level of the cloud resource layer. To make sure resources are used efficiently and services are always available, the cloud management layer keeps an eye on things like resource allocation, monitoring, dynamic scaling, load balancing, and fault recovery.

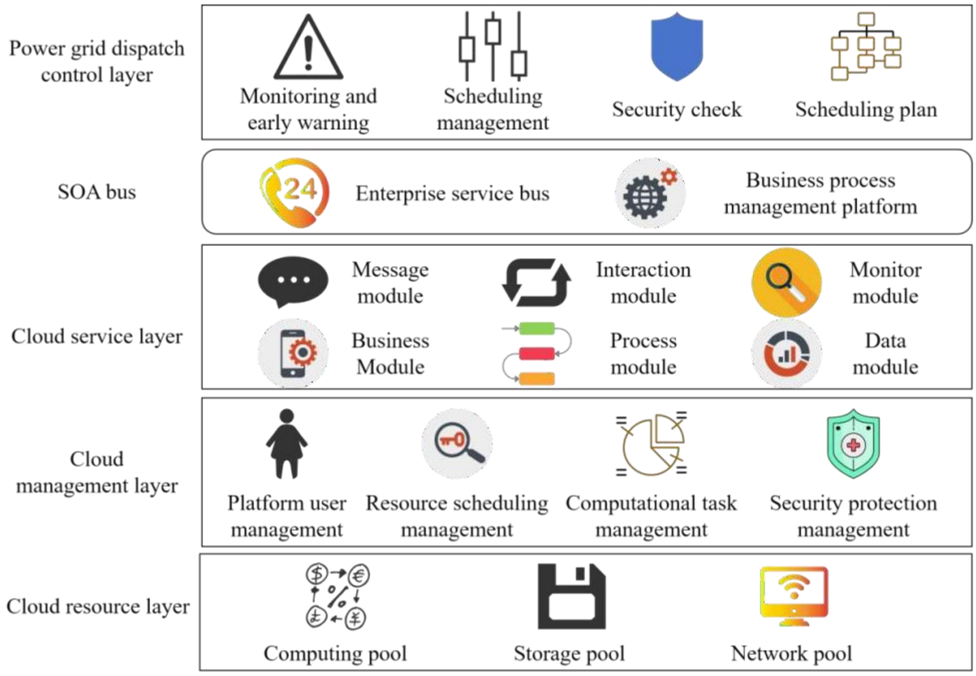

Figure 2: Architecture of Power Dispatch Data Processing and Automation System

Included in the cloud service layer are software services, platforms, and infrastructure. The power grid dispatch control layer is the brains of the operation, handling power dispatch decisions and their execution. Utilizing big data analysis, this layer processes grid data in real-time, forecasts generation and load trends, and creates scientific scheduling plans. Furthermore, it guarantees a safe and reliable grid by supervising grid activities and quickly detecting and fixing anomalies. Connecting several layers of a system through a service-oriented architecture, the SOA bus acts as the communication hub. The design makes it easy to register, discover, invoke, and manage services, which allows for efficient cooperation and seamless integration between application platforms and cloud service providers. Power dispatch data processing and automation rely on big data analysis, which sifts through mountains of grid operation data in search of meaningful insights to guide scheduling decisions. The efficient processing of massive data is guaranteed by cloud computing technology, thanks to its strong computational and storage capacities. In addition, the system can dynamically adjust to suit changing needs thanks to its elastic scalability, which further enhances its flexibility and scalability.

IV. PROPOSED ALGORITHM

Due to the inherent instability of EPS output power and the inherent uncertainty of cloud computing technology, several hazards may develop during the use of cloud computing. The penalty cost condition risk value is a commonly used tool for EPS to evaluate risk and make proper decisions. In this case, the earnings per share penalty costs based on risk are:

$$F_{\beta.t}\left(P_j^{ws}, P_j^{wl}\right) = \left(a_{1j}^{w} + \frac{1}{M(1-\beta)}\sum_{l=1}^{M} Z_{jl}\right) + \left(a_{2j}^{w} + \frac{1}{M(1-\beta)}\sum_{l=1}^{M} Z'_{jl}\right) \quad (1)$$

Z'_{jl} is the auxiliary variable in the equation, and M is the number of sample values.

The following is a typical way to express the operational cost of the electricity grid system:

$$minF_{ccos\ t} = R_{cj}P_j^{cs.t} \quad (2)$$

The cost coefficient of the smart grid system is denoted by R_{cj} in the formula, and the output of the smart grid system is represented by P_{jcst}.

The energy consumption of data centers is complex and includes many different components, such as information technology devices, cooling systems, and distribution equipment. It is worth mentioning that a considerable amount of the total energy consumption in data centers comes from IT equipment, especially servers. It is crucial to develop a data center energy consumption model that zeroes in on server energy consumption since server energy consumption is directly related to the data load processed by the data center. The data center's energy consumption during the b period is:

$$e_i^t = E_i^{\text{usage}} e_{\text{server},i}^t \tag{3}$$

The data center's energy efficiency coefficient, denoted as, is calculated as the ratio of the data center's total energy usage to the server's energy consumption. The total energy consumption of the data center and the server's energy consumption are represented by eib and ib, respectively, in the given formula.

Determine the nodes' load conditions using CPU utilization and set a preset threshold. A node has to move some virtual machines to relieve its burden when its CPU utilization exceeds this threshold, which shows that the node is overworked. In contrast, if the utilization rate is lower than the threshold, it could mean that the node isn't making enough use of its resources. To mitigate the effects of unexpected data, it may be prudent to transfer all virtual machines hosted on the node. The smoothing index approach of time series is used for estimating the CPU use of nodes in different time frames. Predicting future trends by smoothing exponents is a typical use case for this method when processing time series data.

$$Q = \alpha x_t + \alpha x_{t-1} + \cdots \alpha^{n+1} x_{t-1} + \alpha_t \tag{4}$$

Several variables are involved in the formula: Q, which represents the expected CPU utilization of the node; α, a predicted parameter less than 1; φ, a random variable following a smooth exponential normal distribution; n, a table controlling the shifts of the time window; and x_t, which indicates the node's historical load weight at a specific time.

An important step in dynamic migration is choosing the right virtual machine when it is determined by equation (4) that a data node needs to be relocated suddenly. Selecting the smallest virtual machine for migration can help minimize the time and resources needed for the process, which in turn ensures efficiency and stability. The following is the formula for calculating the volume of a virtual machine:

$$V = \frac{1}{1-V_1} \times \frac{1}{1-V_2} \times \frac{1}{1-V_3} \tag{5}$$

The algorithm takes into account V_1, V_2, and V_3, which stand for the virtual machine's CPU, memory, and hard drive utilization rates, respectively. A smaller volume means a reduced miss rate, and that's what we're aiming for. A lower virtual machine volume is indicated by a larger result derived from this calculation.

It is a difficult effort including hardware design and performance optimization to connect data storage in the processor's control circuit and to establish an equal number of tightly connected nodes for operational transmission in each transmission channel. If you want faster processor speeds and better data transmission, you should employ tightly connected nodes. We can learn about the performance and utilization of each node by calculating its access value. The exact formula is given below:

$$P = \beta + \sqrt{2} + 2d \tag{6}$$

In the above formula, $\boldsymbol{U}$ stands for the value of node access, β for the peak of the exchange, and d for the parameter of the shared processing metric.

Creating a model that pinpoints the required physical nodes and virtual machines for scheduling is essential for dynamically migrating EPS's unexpected data processing activities. To make the most of scheduling algorithms in cloud computing, this model takes into account a number of parameters, including virtual machine performance, network bandwidth, task completion time, and scheduling limitations. Once the restrictions for scheduling jobs are defined, the time constraint function formula can be calculated by setting the master node as i and the slave node as b.

$$P = A(i) + B(j) + C(i,j) \tag{7}$$

In the given formula, P is the time it takes for the master node to communicate with the slave node in order to assign cloud tasks, A is the time it takes for the master node to send resources, B is the time it takes for the slave node to receive burst data processing tasks, and $\mathbf{O}(i,b)$ is the time it takes for the burst data processing tasks to be transmitted via Ethernet from the router at node i to the router at node b. A formula for the dependability constraint function is as follows:

$$D = \frac{\sum_{k=1}^{O} M_k}{\xi} \quad (8)$$

In this formula, D stands for the scheduling scheme's reliability for unexpected data processing tasks, ξ for the number of such tasks running on the virtual machine, O for the total number of cloud tasks, and M_k for the possibility of choosing an unexpected data processing task for the k cloud task following scheduling.

V. RESULTS OF THE STUDY

Using the conventional intelligent distribution network large data scheduling technique that uses grey fuzzy prediction as a benchmark, a comparative experiment was conducted to evaluate the performance of the system presented in this research.

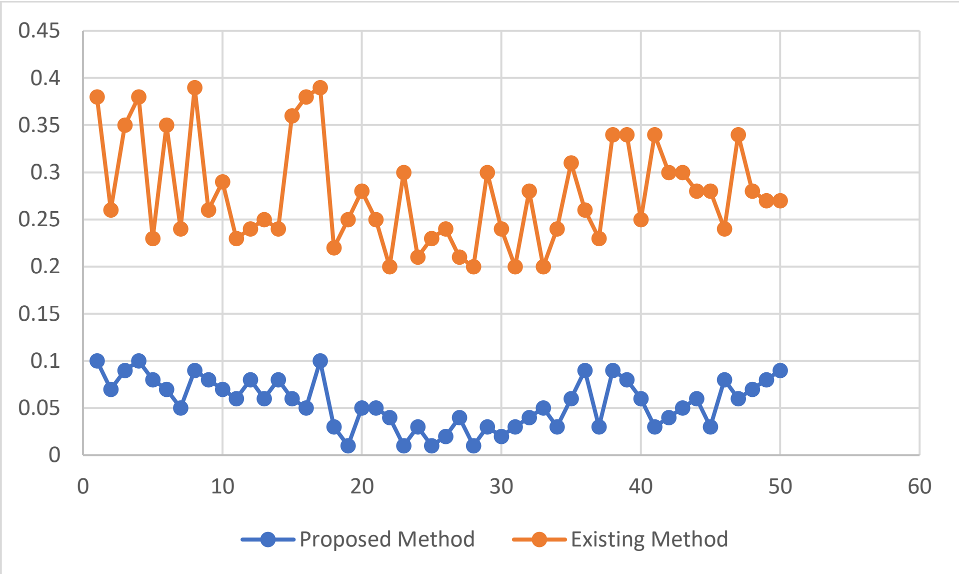

Figure 3. Graph showing Scheduling Error Rate Comparison Between Systems

Figure 3 shows how our suggested technique compares to more conventional approaches in terms of scheduling error rates. To measure how often a scheduling system does not react correctly or quickly to scheduling activities, the scheduling miss rate is an important indicator. The distribution network's operational demands are better met when the scheduling error rate is lower, since this indicates more system stability and reliability. Figure 3 shows that proposed approach outperforms standard methods in scheduling with a significantly reduced scheduling error rate.

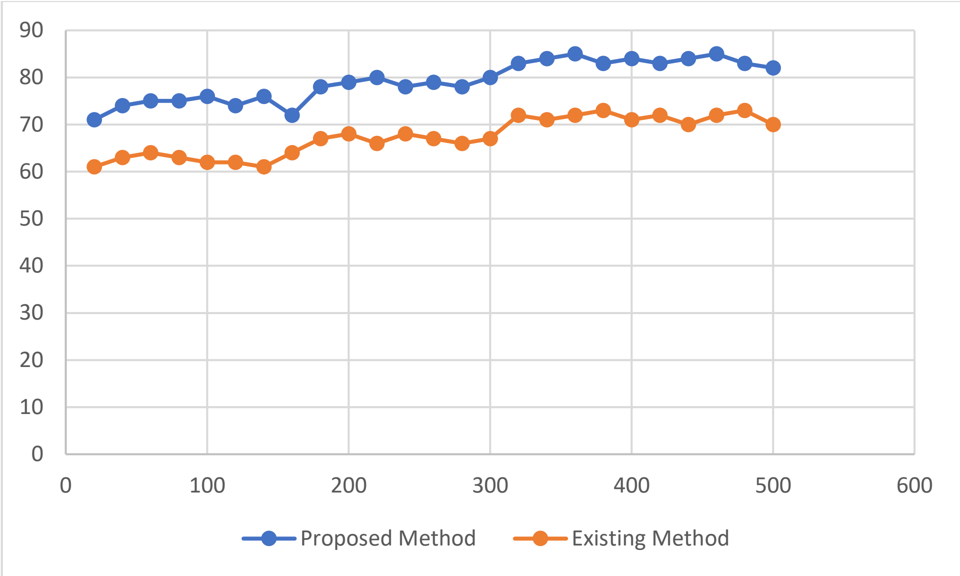

Figure 4. Graph showing task completion Rate Comparison Between Systems

The system's benefit in scheduling job completion rate is further demonstrated in Figure 4 of this research. Another important metric for scheduling system efficiency is the scheduling task completion rate, which shows what proportion of scheduling jobs the system really finishes. When scheduling chores are completed quickly, the system is better able to handle and respond to scheduling needs, which improves the overall power grid's operational efficiency and stability. Figure 4 shows that when compared to older intelligent distribution network large data scheduling methods that rely on grey fuzzy prediction, this system's completion rate of scheduling activities is much greater. The system in this study primarily benefits from cloud computing and big data analysis, which allow it to handle and analyze a vast amount of power dispatch data more rapidly and precisely. As a result, it makes dispatch decisions with greater precision and in less time.

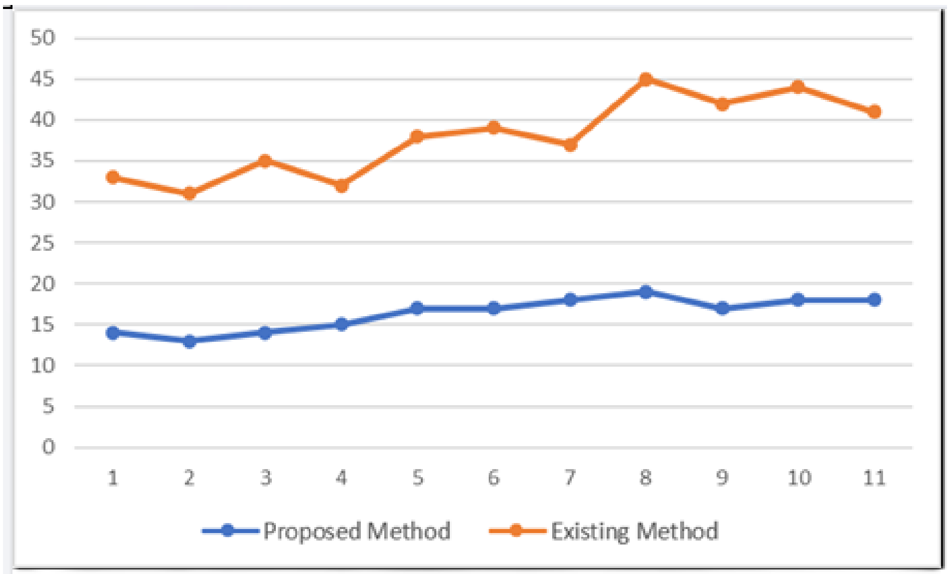

Figure 5: Graph showing Load balance Comparison Between Systems

Our system's superior resource management and optimization capabilities are highlighted by the comparison of resource load balancing in Figure 5. This statistic is essential for determining how well a system manages and makes use of its storage, network bandwidth, processing power, and other resources. Improving the system's overall operational efficiency and stability, a lower load balancing degree suggests more efficient resource use by preventing idle or overloaded resources. While the conventional intelligent distribution network large data scheduling technique relies on grey fuzzy prediction, our system's resource load balancing degree is significantly lower, as shown in Figure 5. The integration of cutting-edge cloud computing and big data technologies into our system is largely responsible for this. These technologies allow us to track and analyze resource utilization in real-time and implement dynamic strategies to allocate resources based on job needs and current conditions.

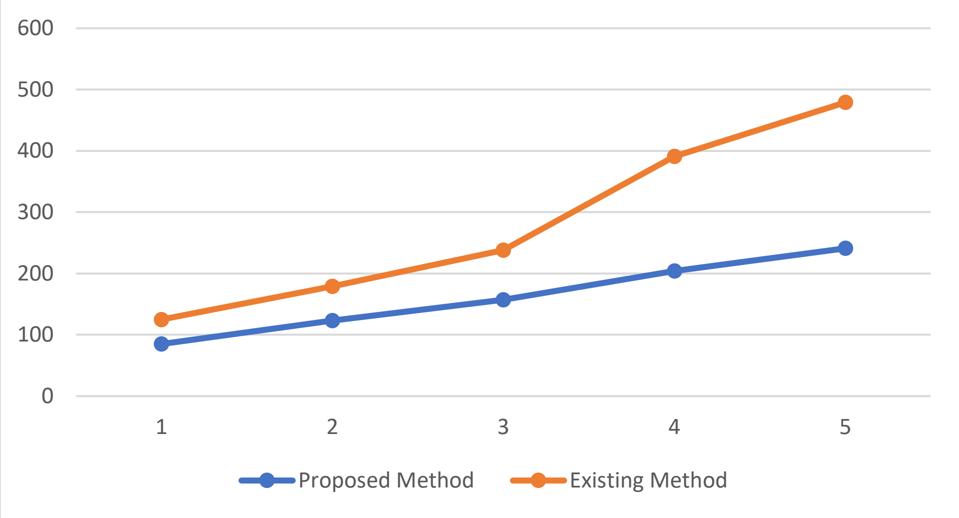

Figure 6: Graph showing task processing time/ms Comparison Between Systems

We can see that our system is far superior in terms of task processing time from the comparison data in figure 6. Because it provides an immediate indication of how efficiently the system manages scheduling tasks, task processing time is a crucial parameter for evaluating scheduling systems. The power grid's real-time and dynamic responsiveness is improved with a faster processing time, which guarantees a more rapid response to scheduling requirements. Table 1 shows that when comparing the task processing times of the various algorithms, the system described in this paper accomplishes a far better job than the conventional intelligent distribution network large data scheduling techniques that rely on grey fuzzy prediction. The main reason for this significant benefit is that our solution incorporates cloud computing and big data technologies. Our solution quickly analyzes and processes massive volumes of scheduling data by utilizing the power of big data technology and the high-performance computing capabilities of cloud computing platforms. This eventually speeds up the processing of tasks.

Figure 7: Graph showing recall rates Comparison Between Systems

The benefits of our system in managing power dispatch duties are once again highlighted by the comparison findings of recall rates in Figure 7. You can tell how well a system is doing in identifying and processing related scheduling tasks by looking at its recall rate, which is a key performance metric. The less room there is for error and omission when the recall rate is high, as the system is able to complete scheduling duties more thoroughly. Compared to the conventional intelligent distribution network large data scheduling algorithm that uses grey fuzzy prediction, the recall rate attained by the system described in this paper is significantly higher (Figure 6). The use of big data analysis tools has been crucial to this development, since they improve scheduling jobs' detection and processing capacities by learning from past data. In order to further improve recall rates, the system also makes use of the powerful computing capabilities of cloud computing platforms to speed up the processing and analysis of large amounts of scheduling data.

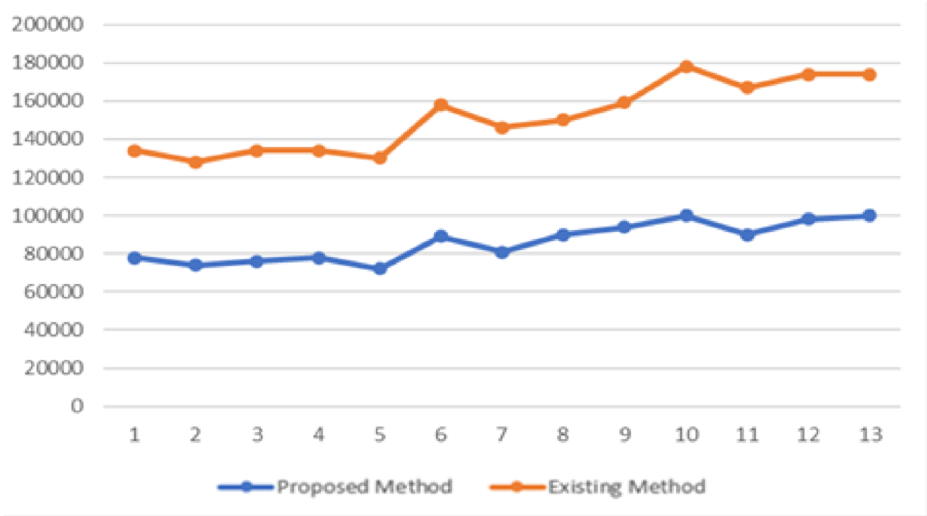

Figure 8: Graph showing scene throughput Comparison Between Systems

Figure 8 shows a comparison of scene throughput, which further demonstrates how our system excels at managing complicated scheduling scenarios. An essential measure of a system's ability to manage large or diversified datasets in the face of complex scheduling duties is scenario throughput. A higher scene throughput indicates that the system is more powerful and scalable, allowing it to handle scheduling demands on a bigger scale. In comparison to the conventional intelligent distribution network large data scheduling technique that makes use of grey fuzzy prediction, the system outlined in this paper displays significantly higher scene throughput (Figure 8). This benefit is mostly attributed to the system's adoption of cutting-edge technology and architectural design, as discussed in this article. This system may dynamically adapt computing resources to schedule scenarios of varied scales and complexities through the elastic scalability of cloud computing platforms.

VI. CONCLUSION

In this paper, a cloud server based operational data management system in power systems has been introduced that combines cloud computing, big data analytics and service-oriented architecture (SOA) to meet the complexity of the present-day power dispatch operation. The suggested system can successfully integrate scalable infrastructure with intelligent data processing to provide real-time monitoring, analysis, and unattended control of the activities of the power system. The algorithm formed integrates risk evaluation, operation cost modelling, energy use analysis and dynamic movement of virtual machine to maximize system effectiveness and dependability. The system provides better allocation of resources, lesser processing delay, and better management of burst data tasks by using prediction of CPU utilization based on load forecasting and efficient assignment of scheduling constraints. The outcomes show that the suggested method is a great way to enhance the volume of data processing, precision of timing, and generally increase the sphere of automation without compromising the stability of the system and decreasing the operational risks.

Moreover, cloud-based architecture is flexible, scalable and cost-effective and is thus appropriate when it comes to large scale smart grid. In general, the paper defines the opportunities of applying cloud technologies and big data analytics to the ways to make traditional power dispatch systems smarter, more effective, and resilient infrastructures and thus contribute to the evolution of smart grids of the future.

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