Development Part-1

Electricity Price Forecasting and Resource Management in Cloud Based Industrial IoT Systems:

ABSTRACT:

Cloud computing is gaining popularity as a storage platform, allowing organizations to reduce hardware and procurement expenses. The exponential growth in data consumption necessitates more data center requirements, which consume significant electricity. Data centers are responsible for 2% of the total energy consumption worldwide. Furthermore, estimates indicate that this percentage is expected to grow by 12% annually. Cooling accounts for 39% of total electricity use, operating IT infrastructure accounts for 45%, and lighting

INTRODUCTION

Cloud computing is gaining popularity as a storage platform, allowing organizations to reduce hardware and procurement expenses. The exponential growth in data consumption necessitates more data center requirements, which consume significant electricity. Data centers are responsible for 2% of the total energy consumption worldwide. Furthermore, estimates indicate that this percentage is expected to grow by 12% annually. Cooling accounts for 39% of total electricity use, operating IT infrastructure accounts for 45%, and lighting accounts for 13%. In 2008, this level of consumption resulted in a 30 billion dollar loss to the business community [1]. In the logistics context, the adoption of distributed computing with virtualization has the potential to significantly enhance productivity, although its usage is still limited. In the realm of server utilization, Ericsson's insightful research reveals that non-virtualized servers often operate at a mere fraction of their potential, harnessing only 5-14% of their maximum capacity. In stark contrast, virtualized servers shine by unlocking their potential and reaching impressive utilization rates of up to 29% [2]. To fortify reliability, data center operators strategically disperse their facilities across diverse locations, embracing replication techniques as an assurance of seamless operations. While this approach meets latency. requirements, it can lead to unforeseen expenses due to fluctuating power costs in different regions. Energy markets exhibit high volatility, with prices surging by a factor of 10 within a mere 60 minutes. Therefore, conducting research on leveraging the volatility of deregulated energy markets becomes crucial in order to predict value spikes and optimize power usage, thereby minimizing energy expenditures in the logistics industry [3]. Businesses like Netflix rely on Content Delivery Networks (CDNs) to provide their content, and locating data centers closer to clients can improve service quality and reduce energy costs. This method involves moving capacity from centrally controlled data centers to hubs on the system's outskirts [4]. In recent decades, there has been a growing urgency to prioritize sustainable practices and adopt energy-efficient measures to protect the environment. As a result, researchers have employed a range of traditional and innovative techniques to tackle these issues. For instance, [5] has demonstrated that power costs can be reduced in various locations. This feature significantly enhances the practicality and usefulness of our approach, making it a viable alternative for optimizing energy consumption in data storage facilities.

In the logistics landscape, the growing demands of big data and cloud computing call for the establishment of expansive cloud data centres. Yet, the colossal energy consumption of these facilities presents a pressing challenge to their sustainability and efficiency. In response, researchers are fervently investigating diverse methodologies to curtail energy usage in cloud data centres, all while upholding optimal performance and reliability. In the ensuing section, we delve into pioneering tactics and approaches that spearhead this field, exploring noteworthy research on the reduction of energy consumption in cloud data centres

Researchers have turned to virtual machine consolidation in their pursuit for energy-efficient data centres. This technology tries to save energy use by combining underutilised virtual machines onto fewer servers. This approach has been a subject of intense scrutiny in recent times, with numerous algorithms proposed to achieve optimal VM consolidation. However, the effectiveness of this approach hinges on the workload's inherent characteristics, and it may falter when workloads are highly erratic and unpredictable, thereby limiting its potential benefits.

In the realm of data centres, Dynamic Voltage and Frequency Scaling (DVFS) acts like an intuitive personal assistant, adapting to your work style and conserving energy. This advanced technology efficiently adjusts the frequency and voltage of processors in real-time according to workload demands. By preventing over-exertion, DVFS serves as a valuable energy-saving tool for data centres. This innovative method, meanwhile, also has certain difficulties that need to be resolved. To ensure maximum efficiency, DVFS must accurately interpret each individual workload, which can be hindered by the intricate, non-linear relationships between frequency, voltage, and workload characteristics. If not applied properly, DVFS may lead to performance degradation or instability, much like an ill-designed work schedule may cause exhaustion or injury. The pursuit of energy-efficient task scheduling requires a delicate balance between minimizing energy consumption and meeting the resource demands of high-intensity applications. Energy-aware task scheduling achieves this balance by intelligently scheduling tasks to optimize resource utilization, while ensuring application-level constraints are satisfied. However, the effectiveness of this technique depends on the specific workload characteristics and optimization objectives at hand. Numerous algorithms, such as genetic algorithms, ant colony optimization, and particle swarm optimization, have been proposed to achieve energy-aware task scheduling. Nevertheless, these algorithms may introduce significant overhead or result in suboptimal solutions. Energy effectiveness and performance must be perfectly balanced, which calls for meticulous planning and close attention to detail. When executed correctly, energy-aware task scheduling can lead to substantial energy savings and enhanced system performance.

In order to increase energy efficiency in the constantly changing environment of cloud data centres, researchers have resorted to machine learning-based solutions. The crux of these techniques lies in the use of machine learning models to predict workload demand and resource usage patterns, and subsequently, make dynamic resource allocation decisions that minimize energy consumption while maintaining performance and reliability. One such technique is multi-task learning, which is proving to be an increasingly powerful tool in this space. By leveraging the interdependencies between electricity price forecasting and resource management tasks, multi-task learning is helping to achieve improved accuracy and efficiency in both domains, driving energy savings and better system performance.

Basically, researchers have investigated various techniques to reduce energy consumption in cloud data centres, such as VM consolidation, DVFS, energy-aware task scheduling, and machine learning-based techniques. Multi-task learning is a promising approach that can lead to better results than single-task learning or other approaches by exploiting the interdependencies between electricity price forecasting and resource management tasks.

The ever-increasing demand for cloud computing services to manage and process large volumes of data has compelled cloud providers to constantly seek innovative techniques to reduce the energy consumption required to store this data [14]. Additionally, cloud providers face the challenge of maintaining government expectations and earning profits through Service Level Agreements (SLAs) while ensuring energy effectiveness [15], [16], [17]. The fluctuating nature of deregulated energy prices has created a strong incentive to explore whether these variations can be leveraged to minimize energy costs while preserving optimal performance [18], [19], [20]. This study investigates whether machine learning techniques can effectively capitalize on significant energy price spikes and reduce operational expenses associated with data centres. The above-mentioned is addressed in this article with the following contributions:

• An optimization method DMOA has been used to significantly reduce energy consumption in data centres.

• A new model called Alex Net-DMOA has been proposed to optimize storage location and predict power prices more accurately.

• The model has been trained with 75% of available data to ensure high precision, while the remaining 25% has been used for testing purposes.

• The Alex Net-DMOA model forecasts power prices with an MAE of 2.22% and an MSE of 6.33%, resulting in an average reduction of 22.21% in electricity expenses.

• The proposed algorithm outperforms 11 benchmark algorithms applied in the latest literature in terms of performance metrics, accuracy, time complexity, data processing, and model overfitting issues.

RELATED WORK

The increasing emphasis on sustainability within the logistics industry has raised concerns regarding energy consumption and its environmental impact. This paper provides a concise overview of previous methodologies employed to forecast power usage in logistics operations. It also highlights the limitations of existing research, prompting the exploration of more robust and effective approaches. To address these challenges, researchers have utilized a Multi-Layer Neural Network (MLNN) model, as demonstrated in [21], [22], and [23], to estimate power load and overall electricity consumption in logistics operations. By leveraging the Ensemble technique, which combines multiple machine learning models to reduce errors and eliminate noise, significant improvements have been achieved in the accuracy of energy consumption predictions. These advancements hold promising implications for optimizing energy usage and sustainability in the logistics sector. This combination of techniques allows for a more precise estimation of energy usage. It will enable cloud providers to make better-informed decisions about power usage and resource allocation. Ultimately, this leads to improved energy efficiency and cost savings for cloud data centres. While their approach showed competitive accuracy, it lacked resilience due to longer processing times and high loss rates during live testing

Similarly, in [24], the author proposed a hybrid method called EPNet for energy price prediction, using LSTM and CNN models that produced MSE and MAE of 7.74 and 16.8, respectively. Despite the favourable results, these models had high error rates and required significant computational power for real-time predictions. Moreover, the model's performance was impacted by the heavy normalization of the dataset, and it failed to reproduce the same results when applied to real-time data. In [25], the author proposed a model similar to those above, combining support vector regression with other optimization methods. The model yielded a 6.82 MAE, but only for one-day-ahead forecasts, rendering the results unreliable. Moreover, the model's results are inconsistent and subject to change, making it unsuitable for real-time application. Additionally, the models incur high computational costs.

In [26] and [27], researchers conducted a comparative study of DL-based methods for predicting electricity consumption and green energy. They evaluated the performance of 23 benchmark methods, including CNN, GRU-DNN, and LSTM-DNN. They proposed a DL-based algorithm for power price prediction, demonstrating results comparable to prior studies. Nonetheless, the proposed model incurs high computational costs and generates inaccurate predictions when used in real-time applications, resulting in a significant testing loss. The comparison was based on a single, thoroughly normalized dataset.

In [28], the author proposed a hybrid approach for power price prediction that integrated both SVM and Kernel Principal Component Analysis (KPCA). The proposed technique delivered promising results, with a low error rate of 5.7 percent for one threshold value and a higher but still reasonable error rate of 47.9 percent for another. This hybrid method presented in [29] can reduce energy consumption and costs in data centres by allowing for a more accurate and efficient In [28], the author proposed a hybrid approach for power price prediction that integrated both SVM and Kernel Principal Component Analysis (KPCA). The proposed technique delivered promising results, with a low error rate of 5.7 percent for one threshold value and a higher but still reasonable error rate of 47.9 percent for another. This hybrid method presented in [29] can reduce energy consumption and costs in data centres by allowing for a more accurate and efficient.

In the logistics domain, the proposed method differs from other models as it takes into account the static nature and regional dependencies of energy prices, considering variations across seasons and locations. Researchers in previous studies, as seen in references [30] and [31], demonstrated successful outcomes by adopting location-specific data collection and a combination of Autoencoder models and NN-based models. Additionally, advanced deep learning techniques, highlighted in [32], were employed to enhance the accuracy of energy cost forecasts in the European market. These researchers utilized sophisticated feature selection methods, resulting in promising results using a simplified model. Nevertheless, the MAE and MSE values were relatively high, and the methodology did not tackle the problem comprehensively. The model presented in [33] employed multivariate techniques to estimate energy costs hourly and used dimension reduction to address over-fitting concerns. The author of [34] introduced a DNN-based model that combined LSTM and LSTM-based models to predict power prices and load, but the outcomes were inadequate in predicting power prices. Most of the current research has been centerd around applying established deep-learning techniques. Nevertheless, these methods can be computationally demanding and may yield unforeseeable results, mainly when dealing with large-scale datasets [35]. Alternatively, [36] took a different approach by emphasizing feature selection, which led to an MAE of 3.18. However, using a sizable dataset, their model was only appropriate for offline prediction.

The article [37] delved into the combination of power cost estimation and energy demand prediction, utilizing the Artificial Bee Colony and SVM algorithms with Least Square. On the other hand, [38] proposed an ANN-based approach, and [39] put forward a hybrid methodology employing a model based on a biweight kernel with dynamical system reconstruction to forecast electricity prices using datasets from the ISO of New York, the US, and the South Wales markets. However, these models are computationally expensive, generate inaccurate predictions resulting in significant losses, and are inefficient for real-time use.

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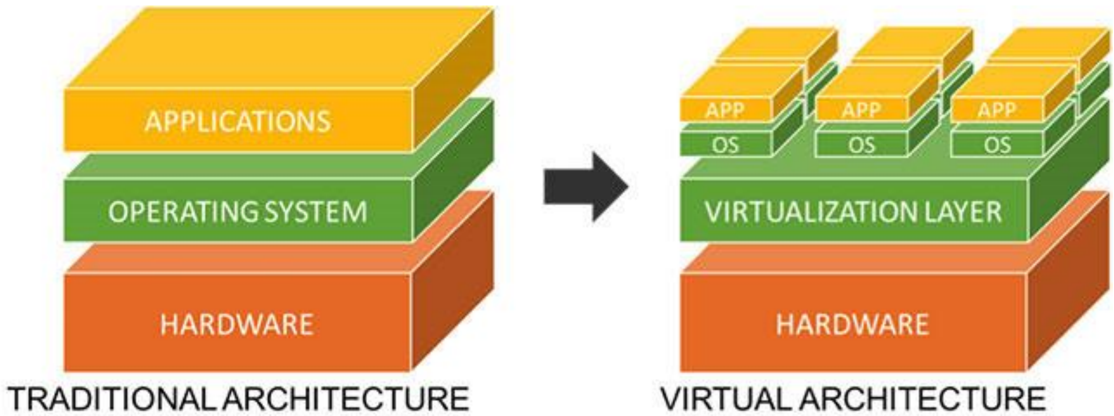
Countless studies have delved into the search for more energy-efficient cloud data centres. They have explored several strategies to lessen energy consumption while maintaining system performance and reliability. A strategy that aims to minimize energy consumption by matching the workload demand with processor performance is dynamic voltage and frequency scaling (DVFS). However, researchers have noted the challenges posed by the non-linear relationship between frequency, voltage, and workload characteristics []. Similarly, the consolidation of underutilized virtual machines (VMs) onto fewer servers has been investigated as a method for diminishing energy consumption. However, its effectiveness is limited when workloads are highly dynamic and unpredictable [39].

The attention of researchers has been drawn towards the potential of machine learning-based methods for reducing energy consumption in cloud data centres. For instance, multi-task learning has been investigated as a powerful machine learning technique for both electricity price forecasting and resource management tasks in cloud-based Industrial IoT systems, leading to improved accuracy and efficiency. In order to enhance feature representations and increase performance, the research suggests a semi-supervised feature analysis method for multi-task learning. The suggested issue of projecting power prices and resource management can be enhanced by taking use of the relationship between the two jobs [42]. Other researchers have proposed using machine learning models to predict workload demand and resource usage patterns, which are then used to dynamically adjust resource allocation to minimize energy consumption while maintaining performance and reliability. In order to translate across languages, this paper suggests an unsupervised multi-modal machine translation strategy that pivots on movies. The proposed approach's multi-task learning component views the tasks of resource management and energy price forecasting as separate languages that require translation. Videos can serve as a springboard for innovative ideas on how to best take advantage of the relationship between the two jobs and produce superior outcomes [43].

III. THEORETICAL AND METHODOLOGICAL ASPECTS

A . CLOUD COMPUTING

The IT industry has undergone a significant transformation due to adopt cloud computing. With the advent of this novel approach, users can now access a communal repository of computing resources that can be promptly allocated and de-allocated with little need for management or intervention from service providers. This alternative paradigm, which diverges from the conventional method of relying on local servers, allows users to obtain immediate access to a plethora of configurable resources, such as services, applications, networks and storage, without necessitating the use of dedicated local hardware [43]. This can lead to cost savings, increased scalability, and greater flexibility in IT resource allocation. As a result, server costs can be reduced by paying for resources on demand rather than making capital expenditures. Meeting the needs of modern data-driven industries requires data center companies to continuously improve their processing, software, and data handling capabilities. Business users can pay for their services, allowing them to concentrate on their core activities while freeing up time to focus on other important business objectives. The amalgamation of these building blocks can deliver better efficiency, decreased overall expenditure, and enhanced returns [43], [44].



Infrastructure-as-a-Service (IaaS) is a category of cloud computing services that operates on a usage-based billing model. This billing method charges customers based on their usage of computing resources. Cloud platforms can be divided into open, closed, and blended types [44]. Cloud providers such as VMware Cloud, Nutanix, and Red Hat OpenShift are examples of blended data centres combining public and private cloud services. Private and public cloud platforms are integrated with hybrid data centres to allow for the flow of information between private and public clouds.

B. CONCEPT OF VIRTUALIZATION

Regarding server management, virtualization architecture is a crucial aspect. This design permits multiple operating systems to operate concurrently on a single server. Data centres can optimize their resources by creating multiple virtual environments on a single machine, including physical servers and energy consumption allocation [45]. The image in Figure 1 illustrates the virtualization design concept.

The impact of virtualization on cloud computing architecture can be observed in Figure 1. Single hardware can be allocated with multiple virtualization layers, resulting in more scalability than a single computer and simpler workflows in the corporate sector. Virtualization enables efficient utilization of IT resources in data centres, regardless of the operating system or the number of applications. Unlike conventional architecture, which is restricted to a single operating system and a few applications, modern architecture is more flexible and adaptable to various operating systems and applications [45].

C.CONTENT DISTRIBUTED DELIVERY NETWORK

The primary components of Content Delivery Networks (CDNs) are distributed edge servers in different regions. These servers are designed to store vast amounts of data with minimal latency and high reliability. CDN services account for over half of all internet traffic, and the number of CDN providers is rapidly increasing. CDNs are utilized by services such as Netflix, Amazon, Facebook, and Dropbox. Distributing data across a geographic region is a technique used to minimize the distance between servers and users [10], [46]. This technique can significantly reduce latency, improving the system's overall performance. Netflix implements this approach by distributing data across multiple locations to ensure users receive data from the closest server. Additionally, Netflix uses intelligent algorithms to anticipate when the desired file will be accessible on the selected server. This enables local servers to manage bandwidth expenses and adapt to the vast geographic scope of data transmission. Furthermore, transferring the requested data to the network's edge helps avoid exceeding data limits in the hubs. Through this technique, Netflix increased its throughput from 7 Gbps in 2013 to more than 90 Gbps in 2019 [47]

D. INTELLIGENT SYSTEMS AND COGNITIVE COMPUTING

In computer-based machine learning (ML), algorithms are used to sift through data to identify patterns and to predict information that was not previously known. It enhances resource efficiency by utilizing processed data. A machine learning algorithm constructs logic and adapts its performance using data without explicit programming. Machine learning issues can be categorized into two groups: the dataset includes labelled data. One is used to train models for predicting future outcomes; the other includes unlabeled data to discover patterns and insights within the data itself [48]. On the other hand, unsupervised learning utilizes input data that has not been classified to detect patterns and extract meaning from them. Machine learning and deep learning capabilities may be intelligently applied in cloud computing. It has the potential to predict energy expenditures and improve energy management accurately. It can also forecast future power costs, significantly impacting the power market. This study aims to develop a method for energy cost prediction by assessing the performance of three main ML classifiers: Support Vector Regression (SVR), Random Forest, XG Boost and 3 DL classifiers CNN [49], Dense Net and proposed ensemble.

E. MOTIVATION AND JUSTIFICATION FOR IMPLEMENTING MULTI-TASK LEARNING IN LOGISTICS

In the realm of logistics, particularly in cloud-based industrial IoT systems, the seamless integration of resource management and electricity price forecasting is paramount. These two interdependent tasks go hand in hand, offering valuable synergies when approached collectively. Accurate electricity price prediction serves as the nurturing sun and rain, fostering effective resource management. As a result, this optimization process enhances the allocation of computing, storage, and network resources, leading to decreased energy consumption and costs, all while effectively meeting the industry's demands. Conversely, resource management decisions can influence electricity prices by modulating system workload and energy usage. To leverage the inherent interdependence of these interconnected activities, a single model can be trained to perform multiple related tasks simultaneously using a multi-task learning technique [50].

Multi-task learning provides several advantages over single-task learning approaches for electricity price forecasting and resource management in cloud-based industrial IoT systems. Firstly, it can improve the performance of both tasks by exploiting their interdependencies. By jointly learning the two tasks, the model can better capture the underlying relationships and dependencies between them, leading to enhanced accuracy and efficiency. Secondly, multi-task learning can enhance the model's generalization and robustness by learning shared representations and features across multiple tasks. Multi-task learning is a potent approach that enables the complexities and uncertainties of real-world events to be successfully negotiated by models [51]. By learning common representations, useful information and patterns can be transmitted between tasks, resulting in improved performance and quicker convergence. Additionally, the capacity to cooperatively learn tasks can greatly reduce the model's computational complexity and training time. This is especially helpful for industrial IoT systems that use the cloud, as the data there is frequently large and multidimensional. The ability of the model to expedite convergence and lower the danger of overfitting by sharing parameters makes it a useful strategy for tackling the difficult problem of energy price predictions and resource management. Overall, the best results can be obtained in this complex environment of cloud-based industrial IoT systems by utilizing multi-task learning as a strong method. possibility of reducing computational complexity and training time.

PROPOSED METHODOLOGY

The article is structured into four distinct phases. Initially, data is gathered and scrutinized from a variety of sources. Secondly, the data is comprehensively, analysed to identify and comprehend various data characteristics. Thirdly, the data is prepared for energy price prediction using a tailored model that incorporates multiple machine learning classifiers, and this process will aid the final phase. The dataset employed in our approach is sourced from IESO Canada [52].

FORECASTING MODEL

We utilized machine learning and deep learning techniques to implement four distinct algorithms to enhance the accuracy of power cost forecasting. These algorithms include SVM, RF, XG Boost, and Alex Net with Dwarf Mongoose Optimization Algorithm (DMOA). To ensure a fair comparison between these techniques, all classifiers were trained and tested on the same data, using the train-test split method with a test size of 0.3. To avoid overfitting and underfitting, we used K-cross validation with K=3. We experimented by utilizing an XG Boost model with defaulting values on varying amounts of data to ascertain the optimal amount of data required. The error metrics were used to evaluate the performance of the models. MAE and RMSE were employed to measure the range of errors in different estimations, with the RMSE always being greater than or equal to the MAE. Lower values of both MAE and RMSE indicate better performance [11] as described in Equations 1 to 4.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{Actual_i - Pred_i}{Actual_i} \right| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} [\text{ Actual }_i - \text{ Pred }_i]^2} \quad (2)$$

To assess the precision of predicted values, we can compute MSE and MAE using the given dataset x1, x2, . . . , xn, and predicted values y1, y2, . . . , yn. Where the actual value is denoted by x, and the predicted value is denoted by y, the formulas presented below can be utilized to compute the MSE and MAE [15]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | Actual_i - Pred_i | \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} | Actual_i - Pred_i |^2 \quad (4)$$

$$TP = \frac{TP}{TP + FP} \quad (5)$$

$$FN = \frac{FN}{FN + TP} \quad (6)$$

Equation 5 assumes that when a positive instance (Class 1) in the dataset is correctly classified as positive by the model, Equation 6 assumes that when a negative instance (Class 1) is incorrectly classified as positive by the model. Our research using Alex Net-DMOA determined that the optimal depth was 4, and the number of estimators was 30. The true positive probability was 0.41, while the false negative probability was 0.58, indicating a significant variance between genuine and forecast values.

DWARF MONGOOSE OPTIMIZATION ALGORITHM

The social behaviour of wild dwarf mongooses served as the basis for developing the Dwarf Mongoose Optimisation Algorithm (DMOA), a relatively recent optimization algorithm. DMOA is a population-based algorithm that mimics the cooperative behaviour of dwarf mongooses to search for the global optimum solution in a multi-dimensional search space. In the context of electricity price forecasting and resource management, DMOA is used to simultaneously optimize the parameters of the forecasting and resource management models. The multi-task learning approach can improve the accuracy of price forecasting and resource management efficiency by exploiting the correlations between the two tasks [54]. The algorithm of DMOA can be described as follows: The equations used in DMOA are as follows: The velocity of each dwarf mongoose, represented by v(i , j , k), is determined by a formula that considers various factors. These factors include the inertia weight w, acceleration constants c1 and c2, the unique best solution of the dwarf mongoosp best(i , j , k), and the global best solution for the task represented by gbest(j , k). The speed of a particular dwarf mongoose can be determined using the Equation 7 [54]:

Algorithm 1 DMOA Algorithm

1: Initialize the population of dwarf mongooses with random solutions.
2: Evaluate the fitness of each dwarf mongoose solution using the objective function.
3: Update the personal best solution for each dwarf mongoose based on its current fitness.
4: Update the global best solution for the entire population based on the best fitness value.
5: Update the position and velocity of each dwarf mongoose using the personal and global best solutions.
6: Apply constraints to the new solutions, if necessary.
7: Evaluate the fitness of the new solutions.
8: Repeat steps 3-7 until the termination condition is met.

$$v(a, b, c) - w * v(a, b, c) + c1 * rand() * (pbest (a, b, c) - x(a, b, c)) + c2 * rand() * (gbest(b, c) - x(a, b, c)) \quad (7)$$

Here, a represents the index of the mongoose, b represents the parameter for the price forecasting task, and c represents the parameter for the resource management task. The constant w represents the inertia weight, c1 and c2 are acceleration coefficients, pbest is the best position found by the mongoose, x is the current position of the mongoose, and gbest is the best position found so far by the mongoose swarm [55]

The inertia weight w, acceleration constants c1 and c2, and random number generator rand() are used in the calculation. The personal best solution of the dwarf mongoose pbest(i,j,k) and the global best solution gbest(j,k) are also taken into account in the formula. The inertia weight, acceleration constants c1 and c2, random number generator rand(), personal best solution pbest(i,j,k), and global best solution gbest(j,k) are also involved in this calculation.

Fitness of the i-th dwarf mongoose: The fitness of the i-th dwarf mongoose may be expressed by the objective function F's function f(i), which is defined. The objective function F plays a crucial role in determining the fitness of the i-th dwarf mongoose. It takes in the parameters for both the price forecasting and resource management tasks and produces a fitness value. The objective function F plays a crucial role in determining the fitness of the i-th dwarf mongoose. It takes in the parameters for both the price forecasting and resource management tasks and produces a fitness value. The function G is defined with parameters x(1,a), x(2,a), . . . , x(n,a), x(1,b), x(2,b), . . . , x(n,m), where a represents the number of parameters required for the task of price forecasting, and b represents the number of parameters required for resource management. The values of x are used to compute the output of function G. By comparing the parameters to the objective function; we can determine the fitness value denoted by f(i) for the i-th dwarf mongoose. By contrasting the parameter u with the goal function F, the fitness of the i-th dwarf mongoose is determined.

AlexNet ENSEMBLE WITH DMOA

Integrating the AlexNet ensemble with DMOA presents a promising technique for precisely and effectively predicting electricity prices and resource management [56]. Fusing deep learning and optimization methods in the AlexNet ensemble with DMOA enhances electricity price prediction and resource management accuracy. The DMOA optimization algorithm is a novel approach inspired by the collaborative behaviour of dwarf mongooses during their food search. The algorithm's exploration, exploitation, and search phases work together to find and refine candidate solutions towards the global optimum. The algorithm further improves the model's accuracy by focusing on the best solutions in the search phase. The AlexNet ensemble with DMOA strategy trains multiple instances of the AlexNet architecture with diverse initializations. It combines their results to create an ensemble, which leads to increased accuracy and resilience of the model.

The formula given below may be used to express the ensemble technique used in this approach:

$$z = 1/n * \text{sumjn}(gj(a)) \quad (8)$$

a indicates the input parameter, g_j stands for the jth model, n is the number of models utilized in the ensemble, and z denotes the predicted result.

The AlexNet ensemble with the DMOA approach has shown promising results in electricity price forecasting and resource management in cloud-based industrial IoT systems. It has the potential to change the field of energy management by increasing resource utilization and decreasing costs using precise and effective forecasting models. The steps for the AlexNet ensemble with DMOA is as follows:

- Collect the historical electricity price data and corresponding environmental data such as temperature, humidity, and wind speed.
- Preprocess the data by scaling, normalizing, and splitting it into training and testing datasets.
- Train multiple AlexNet models on the training data, each with a different set of hyperparameters.
- Evaluate the performance of each AlexNet model on the testing data and select the top-performing models based on a chosen evaluation metric.
- Ensemble the selected AlexNet models by taking the average prediction of their outputs.
- Apply the Dwarf Mongoose Optimization Algorithm (DMOA) to optimize the ensemble weights for the best prediction accuracy.
- Deploy the optimized AlexNet ensemble model in the cloud-based Industrial IoT system for real-time electricity price forecasting.
- Monitor the performance of the deployed model and retrain or re-optimize the model as necessary

Here are the detailed steps with equations for the AlexNet ensemble with the DMOA algorithm:

Algorithm 2 Hyrbid AlexNet-DMOA Algorithm:

1: Input data: a_i - The essential component that breathes life into the AlexNet model.

2: Predicted output: b_i - The result of the AlexNet model's calculations, a product of its determined computations.

3: AlexNet model: f(a_i, w_k) - The algorithm's core, a sophisticated machine that uses deep learning to improve its performance, with w_k as its ever-evolving parameter set.
4: Cost function: C(b_i, f(a_i, w_k)) - The gauge of the model's accuracy, measuring the gap between predicted and actual outputs, guiding the optimization of the algorithm.

5: Optimization method: Technique that fine-tunes the AlexNet model, such as Adam.

6: Ensemble prediction: y_ens = (1/N) * sum_i f(a_i, w_k) - The final output of the ensemble of N selected AlexNet models, a culmination of their collective abilities, where each model contributes an equal share to the ultimate prediction.

7: Ensemble weights: w_ens = [w_1, w_2, . . . , w_N] - The balancing act of the ensemble's abilities, the assigned weights of each AlexNet model that are optimized using the ingenious DMOA technique.

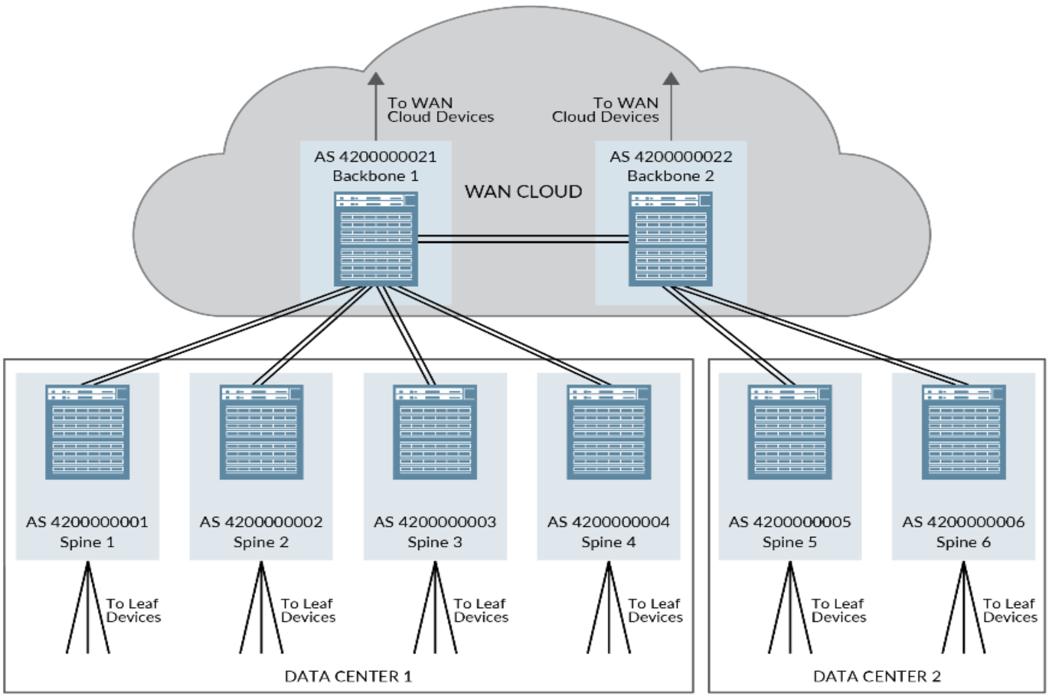
8: Optimization objective function: J(w_ens) = C(b_i, sum_k w_k * f(a_i, w_k)). The DMOA algorithm's guiding concept is a complex function that evaluates the ensemble's performance and the effect of the weights on the result.

9: Optimization algorithm: DMOA: Inspired by the agile and collaborative behaviour of the dwarf mongooses, this algorithm drives the optimization of the weights assigned to each AlexNet model in the ensemble, unlocking their full potential and unleashing their power upon the world.

To improve the precision of energy price predictions and resource management in cloud-based Industrial IoT systems, the AlexNet ensemble with the DMOA algorithm combines the strength of deep learning models with optimization approaches.

DATACENTER SIDE OPTIMIZATION

The study examined the cost benefits of discharging capacity to nodes in a single data center system with varying node distances. Hourly monitoring of electricity costs was conducted to investigate the efficiency of downloading data to nodes. Results indicated that downloading data to nodes was consistently cheaper than other methods. The model will be updated regularly to incorporate new data, such as message traffic from popular social media platforms like Facebook, WhatsApp, and Telegram that reach over a billion users [54]. If a value spike occurs, it may indicate the transfer of data



Notation	Description
A	Server an Index
Yb	Storing data on node b
Cb	Storage cost node
Y	Actual electricity price
X	Predicted electricity price
Ji	Node b Capacity
Xi	Server a Capacity
TM	Servers b total
Xa	Storing data on the server a
TN	Servers a total
B	Server b index

The study involved utilizing a mobile phone as a node to store information without charging the node or connecting it to an energy supplier. The node's energy was based on the owner's usage for loading the node

A graphical depiction of the system configuration is shown in Figure 2, wherein a solitary data center acts as a server that offers cloud computing services to M nodes that are linked to it. A lighting symbol indicating the power source depicts the electrical power that drives the server. The arrows originating from the data center and pointing towards the destination nodes in the network diagram denote the offloading capacity [16], [54]. The cooling and power cost in a data center generally exceeds the price of the IT apparatus. The author concluded that many cloud computing companies use expensive methods when setting up their businesses.

The notations used in the article are shown in Table 1. P0 refers to a set of equations that can describe the problem at hand. The specific equations within this set can vary depending on the values of xa and xb, as illustrated below in Equation 9 and 10 [21]:

$$\begin{aligned} \min \mathrm{w} &= \sum_{a=1}^{TN} x_a \cdot X + \sum_{b=1}^{TM} x_b \cdot c_b \\ \text{subject to } x_a &\leq x_i, \quad \forall a = 1, \ldots, T\,N \\ x_b &\leq j_i, \quad \forall b = 1, \ldots, T\,M \\ \sum_{a=1}^{TN} x_a + \sum_{b=1}^{TM} x_b &= \sum_{a=1}^{TN} x_i \end{aligned} \tag{9}$$