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RESEARCH ARTICLE

Multi-Task Learning for Electricity Price Forecasting and Resource Management in Cloud Based Industrial IoT Systems

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ABSTRACT Cloud computing has gained immense popularity in the logistics industry. This innovative technology optimizes computing operations by eliminating the requirement for physical equipment for calculations. Instead, specialized companies provide cloud-based computing services, relying heavily on computers and servers that consume substantial amounts of energy. Hence, ensuring the availability of affordable and dependable electricity is paramount for the efficient design and management of these logistics services. Cloud centers, which are power-intensive, face the challenge of reducing their energy consumption due to escalating power costs. To address this issue, efficient data placement and node management strategies are commonly employed in logistics operations. An AlexNet model has been designed to optimize storage relocation and predict power prices. The outcome of this initiative has resulted in a considerable reduction in energy consumption at data centres. The model uses Dwarf Mongoose Optimization Algorithm (DMOA) to produce an optimal solution for the AlexNet and increase its performance with a real-world dataset from IESO in Ontario, Canada. 75% of the available data was used for training to assure the model's precision, with the remaining 25% allocated to testing purposes. The 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. Our proposed method has an accuracy of 97% compared to 11 benchmark algorithms, including CNN, DenseNet, and SVM having an accuracy of 89%, 88%, and 82%, respectively.

INDEX TERMS Cloud systems, deep learning, energy efficiency, energy consumption, machine learning, Meta heuristic algorithm, price forecasting, logistics.

I. 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 centre requirements, which consume significant electricity. Data centres 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

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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 centres closer to clients can improve service quality and reduce energy costs. This method involves moving capacity from centrally controlled data centres 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. It is widely accepted among researchers that studying the cost of server installation in multiple locations is critical because the costs can vary significantly. Additionally, [6] investigates node scheduling optimization to lower power costs, while [7] improves data transmission route selection. These studies provide recommendations to address specific aspects of the problem instead of offering a single, comprehensive solution. Moreover, researchers have directed their attention towards assessing the influence of machine learning on energy forecasting and model planning, with a particular focus on the worldwide electricity market. The two primary machine learning techniques are predicting power prices and optimizing energy systems. Common methods include Random Forest (RF) [8], Naive Bayes, Decision Tree [9], [10], and other deep neural networking methodologies [11], [12].

Most prior research on energy price predictions is in its infancy and lacks accuracy or the ability to present real-time data. Our proposed technique evaluates the effectiveness of power price forecasting in Ontario, Canada [13], using the Data Center to reduce energy usage while maintaining confidence and saving high costs. Our forecast model evaluates the impact of various risk factors on data storage price growth and actual energy consumption. Using data from IESO, we assessed the model to predict energy price markets for 14 years. In our study, we developed a novel approach that resulted in a remarkable reduction of up to 24.21% in energy costs for data storage compared to the conventional SVM and RF methods. However, we acknowledge the need for further research and experimentation to validate its potential for delivering acceptable future performance and reliable estimates. Our proposed method offers the added advantage of generating predictions in real-time and offline with minimal effort. This feature makes it a highly convenient and versatile tool for predicting energy consumption in data storage facilities. 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 centers. 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 centers, 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 centers.

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 centers, 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 centers. 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 centers, 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.s

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 AlexNet-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 AlexNet-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.

II. 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 prediction of power prices. This study highlights the significance of integrating advanced machine-learning techniques in the energy sector, emphasizing the need for ongoing research. However, the model incurs significant computational overhead when applied to a large dataset of various fuel cost prices.

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 centred 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.

Energy price prediction has been an essential topic of discussion for many years, with a wealth of literature available to estimate power consumption in DCs and reduce it. However, existing techniques have limitations in providing efficient results for the global market with low MSE and MAE. Most of them are computationally expensive and unsuitable for real-time usage.

Countless studies have delved into the search for more energy-efficient cloud data centers. 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 centers. 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 centre companies to continuously improve their processing, software, and data handling capabilities. Business

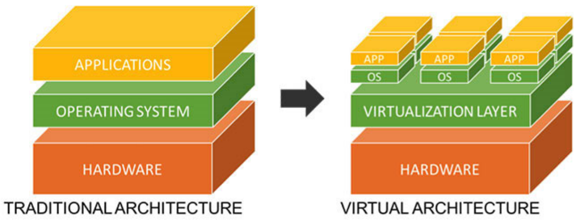

FIGURE 1. Virtualization architecture [45].

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, XGBoost and 3 DL classifiers CNN [49], DenseNet and proposed ensembler.

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.

IV. 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 analyzed 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].

A. 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, XGBoost, and AlexNet 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 XGBoost 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.

$$MAPE = \frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}} \left| \frac{Actual_{\mathrm{i}} - Pred_{\mathrm{i}}}{Actual_{\mathrm{i}}} \right| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}} [\,\mathrm{Actual}_{\mathrm{i}} - \mathrm{Pred}_{\mathrm{i}}]^2} \tag{2}$$

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]:

$$MAE = \frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}} | Actual_{\mathrm{i}} - Pred_{\mathrm{i}} | \tag{3}$$

$$MSE = \frac{1}{n}\sum_{\mathrm{i}=1}^{\mathrm{n}} | Actual_{\mathrm{i}} - Pred_{\mathrm{i}} |^2 \tag{4}$$

$$TP = \frac{TP}{TP + FP} \tag{5}$$

$$FN = \frac{FN}{FN + TP} \tag{6}$$

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 AlexNet-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.

B. 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 mongoose

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.

pbest(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]:

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

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.

C. 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:

$$z = 1/n * sum_j n(g_j(a)) \quad (8)$$

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.

D. DATACENTER SIDE OPTIMIZATION

The study examined the cost benefits of discharging capacity to nodes in a single data centre 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.

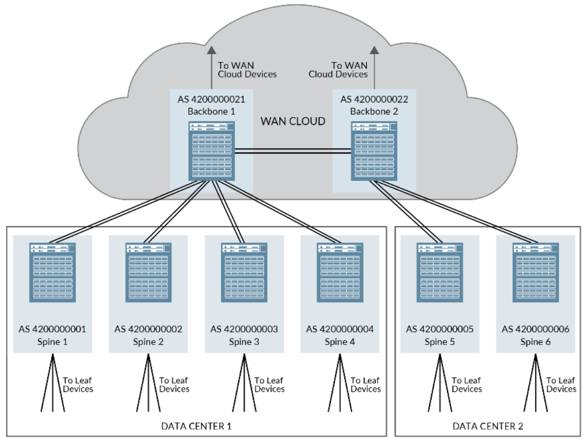

FIGURE 2. Data centers interconnected on cloud.

TABLE 1. Notations used.

Notation	Description
a	Server an Index
y_b	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 centre 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 centre and pointing towards the destination nodes in the network diagram denote the offloading capacity [16], [54]. The cooling and power cost in a data centre 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]:

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

$$x_a, x_b \geq 0, \quad \in \mathbb{Z}^+, \quad \forall a = 1, \ldots, T\,N, \\ \forall b = 1, \ldots, T\,M \tag{10}$$

The optimization model utilizes P0, a collection of formulas that represents the problem. When considering the given scenario, xa is an integer value representing server a's data storage capacity, and xb is a decimal value that signifies the offloading data volume to node B. The cost of electricity is denoted as X, while the cost of data storage at node j is indicated by cb. The symbols designate the limits of server I and node b ai and bj. The value spike threshold is represented by cb, which determines when to store the data set in the data centre instead of on edge. The objective function f(c,d) minimizes the cost estimate to obtain the optimum results of the variables (d) and (d). The node owner's energy cost is assumed to be zero.

The forecast prices impact the storage cost, which can be minimized by achieving the goal w. Equations 9 and 10 are constraints to enable the dynamic data assignment to server capacity and each node [25]. Equation 10 further ensures the distribution of assigned data across multiple nodes and servers in data centres. Furthermore, xa and yb can only assume integer values and forbidden storage.

The procedure of P0 is delineated in this part of the manuscript, which encompasses an algorithmic structure provided underneath:

- The techniques outlined herein can be utilized to anticipate electricity prices.
- It is feasible to estimate the cost by considering the output produced by the P0 function and the prevailing electricity prices.

The precision of price prediction plays a crucial role in determining the actual cost, thereby influencing the effectiveness of the optimization approach. Therefore, the expected price may serve as the basis for the power pricing model, enabling the cost to be estimated at the correct price. This method may then record the hourly cost [27].

$$\text{cost} = \sum_{a=1}^{TN} x_a \cdot \eta \cdot E \cdot 10^{-6} \tag{11}$$

In the Equation 11, E represents a server's energy per hour per p2 server space, and electricity is the adjusted price. The conversion of E to CAD/Wh is carried out to ensure that it can be compared to the hourly energy price in CAD/MWh.

V. SIMULATION AND RESULTS

A. EXPERIMENT SETUP

In this section, we describe the detailed experimental setup employed for evaluating the effectiveness of multi-task learning for electricity price forecasting and resource management in cloud-based Industrial IoT systems, utilizing Python programming language and the Google Colab platform.

Dataset Preparation: The dataset used in the experiments consisted of historical electricity price data and corresponding resource usage data from a cloud-based Industrial IoT system. The dataset was preprocessed, which involved data cleaning, normalization, and feature engineering. Feature sets or lags were created to capture the temporal dependencies and patterns in the data.

Data Split: The dataset was split into training and testing sets to evaluate the multi-task learning model's performance. The standard 80/20 split ratio was used, where 80% of the data was allocated to the training set, and the remaining 20% was assigned to the testing set. This split ensured sufficient data for training the model while leaving a separate portion for evaluating its performance on unseen data.

Model Architecture: A multi-task learning model was designed using Python and TensorFlow frameworks. The model consisted of interconnected neural network layers, with shared layers for capturing standard features across electricity price forecasting and resource management tasks and task-specific layers for capturing the unique characteristics of each task. The architecture and layer configurations were determined based on prior knowledge and experimentation.

Hyperparameter Tuning: Hyperparameter tuning is a crucial step to optimize the performance of the multi-task learning model. This study's hyperparameters were tuned using the Dwarf Mongoose Optimization Algorithm (DMOA). DMOA is a nature-inspired optimization algorithm that mimics the foraging behaviour of dwarf mongooses. It is particularly suited for solving complex optimization problems by exploring the hyperparameter space efficiently.

The hyperparameters tuned using DMOA included:

Learning Rate: The learning rate determines the step size during the gradient descent optimization. Different learning rates were tested to find an optimal value that balances the convergence speed and accuracy of the model.

Batch Size: How many training samples are handled in each iteration depends on the batch size. Various batch sizes were tested to find the optimal balance between computational efficiency and model generalization.

Regularization Techniques Regularisation Methods: To avoid overfitting and increase the model's capacity for generalization, regularisation methods like L1 or L2 regularisation were used. The regularization parameters were tuned to find the optimal trade-off between bias and variance.

The network design underwent thorough optimization, considering layer count, neuron quantity, and activation functions. DMOA was crucial in exploring various architectural configurations to identify the most suitable task method. DMOA helped explore different architectural configurations to find the most suitable one for the given tasks.

Repeated Experiments: In the quest for unwavering reliability and unshakable robustness, the experiments underwent a meticulous ritual of repetition of about 10 times. Each iteration unveiled a new ensemble of randomized parameter initialization and a spirited shuffle of the dataset. This symphony of randomness ensured that no stone was left unturned, capturing the innate variability inherent in the results. The study unravelled a tapestry of statistical significance with each repeated experiment, weaving together the threads of

TABLE 2. Optimized values of the parameters.

Hyperparameter	Tuned Value
Learning Rate	0.001
Batch Size	32
Regularization Method	L2
Regularization	0.01

certainty and unveiling tall and firm conclusions. The optimized parameters are described in Table 2.

The network design went through a meticulous optimization process, exploring various architectural configurations using DMOA. The final configuration for the network design included 5 layers, with 100 neurons in each layer and ReLU activation functions.

To ensure the reliability and robustness of the findings, the experiments underwent a meticulous ritual of repetition. They were performed not once, not twice, but a resounding ten times. Each iteration introduced different random initializations for the model's parameters and a random shuffling of the dataset. This comprehensive approach allowed for a thorough exploration of the variability present in the results, ultimately leading to the emergence of statistically significant conclusions.

B. COMPUTED RESULTS

A three-stage analysis was conducted to forecast daily prices, which involved investigating the data, predicting the price, and optimizing the process. To carry out this analysis, a simulation of the data was conducted using historical data from 2007 to 2022, which was consolidated into a single CSV file. The data was displayed as a time series in Figure 3 to provide an overview of the complete dataset. Key statistics of the dataset, such as the minimum value (−127.69), maximum value (1781.03), mean value (23.21), and standard deviation value (33.44), were calculated to gain further insights into the data. Figure 3 portrays the pricing trends over a limited period. In actuality, this information is utilized for predicting future prices. After analyzing the entire dataset, it becomes clear that the prices exhibit significant fluctuations and sporadic spikes. The volatility of prices is highlighted by the mean being equal to the standard deviation, as indicated by the primary statistics. Moreover, the highest recorded cost exceeds 1550 CAD, and Figure 3 further illustrates multiple instances of significant price levels. Although the highest price is a single data point, it provides valuable insights into the extreme price movements observed in the dataset.

The lags in Figure 4 refer to the time delay between price and date variables. Specifically, the kth lag represents the time difference between the price at a given date and the price k days earlier or later. By examining different lags, we can gain insights into how the price changes over time and identify patterns or trends in the data. In addition to the kth lags, the list of Hour_0 to Hour_23 represents the different hours of the day. This set of variables can be used to examine how price varies over a day. By examining the price at different hours of

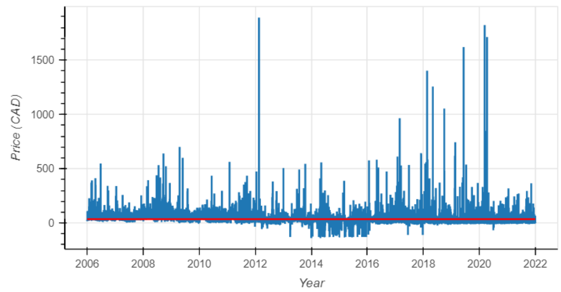

FIGURE 3. Time series data 2006 to 2022.

the day, we can identify patterns and trends in how the price changes over time.

Overall, the lags and hourly variables provide a way to analyze the relationship between price and date over different time scales. By examining the data at different lags and hours of the day, we can gain insights into how different factors may influence the price and how it changes over time. This information can help predict future market trends and make informed investment decisions.

By examining Figure 3, it becomes evident that the price of electricity exhibits fluctuations around the mean value and occasionally experiences sharp spikes. This observation suggests that there may be potential opportunities for offloading data storage during periods of lower electricity prices. Therefore, Figure 5 provides a more detailed analysis of the behaviour of the electricity price and emphasizes the need to optimize storage offloading to reduce operational costs. Figure 6 displays the autocorrelation functions to demonstrate how previous data impacts current prices.

Figure 6 illustrates that the data exhibits seasonality, indicating recurring patterns. Consequently, these time lags may provide valuable information to the model. Additionally, it is noticeable that the correlation weakens as the data ages.

Figure 7 depicts a heatmap illustrating the selected variables' correlation. The intensity of the colours represents the degree of correlation, with brighter colours indicating a stronger correlation between the variables. Figure 7 enables us to pinpoint the variables most closely related to each other and can serve as the foundation for the method. Specifically, It is observed that the contiguous intervals, predictions, and prices from the preceding 24 hours display a strong correlation with each other compared to other variables. The only hour seems to be a relevant predictor for the model regarding the date-related features.

As expected, the correlation decreases as the lag value increases from 1 to 5 since older data should have a decreasing influence on present values. There is a notable difference when comparing this to the data characteristics. As with the lag variables, we observe a decrease in the correlation strength as we move from a granular to a broad level (i.e., from an hourly to a yearly timeframe), implying that the year in which a data point is recorded has a lower impact than the hour of the day. Given that only the Hour variable is deemed

Price	lag k = -1	lag k = -2	lag k = -3	Hour	lag k = 1	lag k = 2	lag k = 3	lag k = 23	lag k = 24	...	Hour_14	Hour_15	Hour_16	Hour_17	Hour_18	Hour_19	Hour_20	Hour_21	Hour_22	Hour_23
30.26	27.86	40.72	58.82	0	27.86	40.72	58.82	26.14	26.13	...	0	0	0	0	0	0	0	0	0	0
27.89	30.26	27.86	40.72	1	30.26	27.86	40.72	25.63	26.14	...	0	0	0	0	0	0	0	0	0	0
26.42	27.89	30.26	27.86	2	27.89	30.26	27.86	25.26	25.63	...	0	0	0	0	0	0	0	0	0	0
25.90	26.42	27.89	30.26	3	26.42	27.89	30.26	24.98	25.26	...	0	0	0	0	0	0	0	0	0	0
25.80	25.90	26.42	27.89	4	25.90	26.42	27.89	25.73	24.98	...	0	0	0	0	0	0	0	0	0	0

FIGURE 4. Feature Set lags and their values.

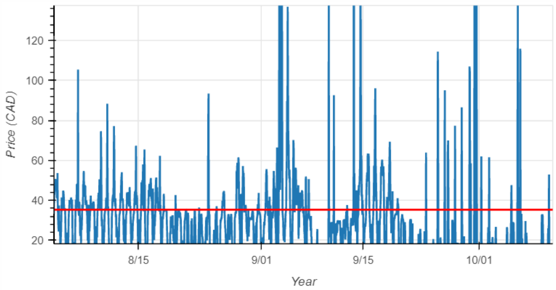

FIGURE 5. Forecasted prices for the period August to October.

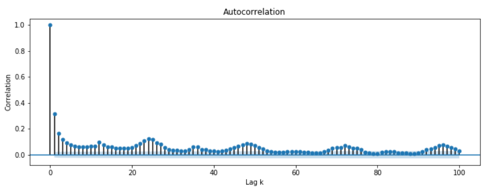

FIGURE 6. Seasonal data patterns.

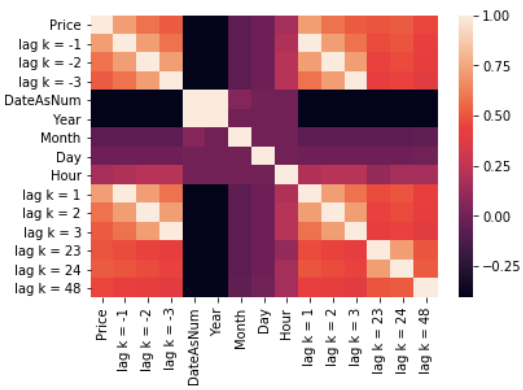

FIGURE 7. Autocorrelation of data.

informative in predicting prices, we will exclude the other data attributes from the model.

C. FORECASTING OF PRICE

The study combined XGBoost with three different power price forecasting techniques: Support Vector Regression (SVR), AlexNet, and Random Forest with XGBoost. Figure 8 presents the results of the AlexNet-DMOA model with optimized parameters, with varying amounts of data, and its corresponding MAE and MSE.

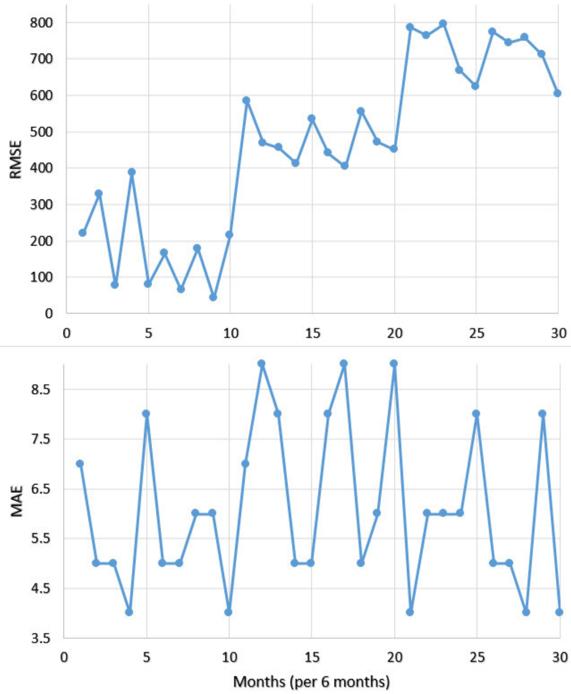

FIGURE 8. RMSE and MAE of AlexNet-DMOA.

TABLE 3. Feature set/lags.

Notation	Set of Features
I	R=-1
J	Spn R=-1, Spn R=1
K	Spn R=-1, Spn R=1, Spn R=-2
L	Spn R=-1, Spn R=1, Spn R=-2, Spn R=2
M	Spn R=-1, Spn R=1, Spn R=-2, Spn R=2, Spn R=-3
N	Spn R=-1, Spn R=1, Spn R=-2, Spn R=2, Spn R=-3, Spn R=24
O	Spn R=-1, Spn R=1, Spn R=-2, Spn R=2, Spn R=-3, Spn R=24, Spn R=3
P	Spn R=-1, Spn R=1, Spn R=-2, Spn R=2, Spn R=-3, Spn R=24, Spn R=3, hour

As depicted in Figure 8, the Mean Squared Error (MSE) significantly increases with a larger dataset, whereas the Mean Absolute Error (MAE) decreases. Therefore, we leverage smaller datasets while using the MSE as it increases significantly compared to the MAE. As the model size increases, the MSE also increases substantially.

The model was constructed iteratively, beginning with the most significant feature identified. Table 3 summarizes the various feature sets used in the study [25], [27], while the tables in the following section present the outcomes of the selection feature process.

R represents the feature, and Spn represents the lag for the respective feature in Table 3. Negative lag refers to the time duration by which the next work can commence before

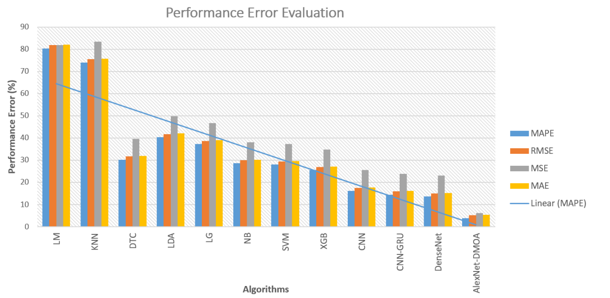

FIGURE 9. **Comparison of error Metrics values for the Ensemble model VS Existing schemes.**

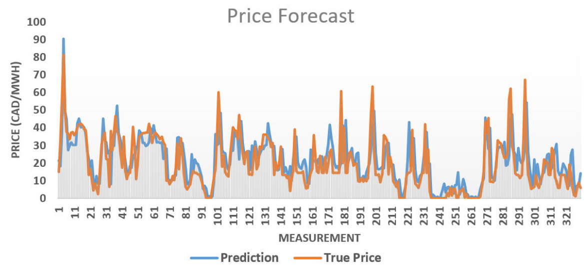

FIGURE 10. **Actual and forecasted value of the proposed tuned model.**

the end of the preceding work. This technique is applied to allow overlapping tasks that would otherwise be sequential or combine tasks that would otherwise be incompatible. Adding a feature to a model does not always guarantee performance improvement. For example, when one additional feature is added from feature set A to feature set B in AlexNet, the MSE improves, as shown in Table 4. As the number of extra features is added, the MSE also increases. However, the MAE decreases gradually as more features are added. This is true for both AlexNet and XGBoost. The best solution for feature set H includes both delays and hours as features.

When introducing features, AlexNet-DMOA behaves differently from Random Forest and XGBoost. Adding more features does not always increase accuracy; it may even decrease accuracy. In most cases, the minimum number of features provides the optimal result, except for the difference between feature sets G and H.

DMOA features were used to optimize the AlexNet-DMOA model. One was selected for future fine-tuning by modifying the layer count, several neurons, the learning rate, and other parameters. The image in the reference tab compares our proposed model and existing techniques, revealing that our model exhibits higher levels of inaccuracy. Patterns in the data may suggest that the proposed model struggles to capture specific patterns or factors that influence pricing, indicating potential areas for improvement.

The proposed model outperforms existing techniques in terms of MAE, RMSE, MAPE, and MSE, as shown in Figure 9. Furthermore, the model is less execution time and is efficient for real-time implementation. The model's accuracy in predicting price spikes is also demonstrated by the values of MAE, MSE, and probabilities P(f/n) = 0.67 and P(t/p) = 0.22. However, it is essential to note that these techniques cannot be cross-validated.

Table 4 presents the results of an evaluation of the proposed hybrid method AlexNet-DMOA and compares its performance with other existing classifiers. The assessment was conducted using error metrics to measure the accuracy of the classifiers in correctly classifying the data.

According to Table 5, the proposed method, AlexNet-DMOA, achieved the lowest error rate of 3% compared to the other existing classifiers, indicating that it has the highest accuracy among all the classifiers evaluated. This means that the proposed method outperformed the other models in correctly identifying the data classes. Therefore, it can be concluded that the proposed method, AlexNet-DMOA, is a better classifier than the other existing models evaluated in this study, as it has demonstrated superior classification accuracy. This result highlights the potential of the proposed method to be used in practical applications of price forecasting in cloud computing.

The graphical representation in Figure 10 succinctly illustrates the simulation outcomes by exhibiting the time sequence for the test set and the estimated pricing. The blue curve precisely portrays the actual cost, whereas the orange curve depicts an estimation that closely corresponds with the actual cost. The recommended model outperforms the power price prediction model, delivering precise predictions with minimal computational complexity.

It is evident that the orange line has a positive impact on the blue line, and the significance of MAE is clear from the graph, making it a valuable metric for evaluating the model's performance. The graph provides sufficient information to determine that the orange line appropriately matches the peaks and lags behind them. It is worth noting that the orange line's extreme values appear perfect and not excessive.

Our recommended model outperforms in terms of accurately predicting the price with low computational complexity, providing reliable results for power price forecasting.

D. OPTIMIZATION OF DATACETERS

Our cost-saving optimization model yielded a significant result of CAD 1805.66, representing a cost savings of 25.31% with the implementation of random capability in servers and nodes. We randomly generated storage sizes for servers and nodes using a normal distribution. Specifically, we set the number of servers as TN=4 and the node capacity as TN(1000,20) xi. We employed a One-and-Off strategy for shutting down servers while downloading to create an energy-efficient and zero-usage system. We used standard servers for more balanced energy usage when activated, with [46] defined as 240 W/h for all active servers. In addition, we used TM = 900 ji TN (4.1) GB capacity nodes, assuming that node storage capacity maximizes energy efficiency to be discharged and prevents energy plant and free storage and node cost. In our analysis, the costs associated

TABLE 4. Forecast error results of all models w.r.t feature set/lag.

Techniques		Feature set							
		A	B	C	D	E	F	G	H
AlexNet-DMOA	MSE	6.234	4.914	3.594	2.274	0.954	0.952	0.95	0.948
	MAE	5.468	4.148	2.828	1.508	0.188	0.186	0.184	0.182
DenseNet [25,26]	MSE	23.037	21.717	20.397	19.077	17.757	17.755	17.753	17.751
	MAE	15.272	13.952	12.632	11.312	9.992	9.99	9.988	9.986
CNN-GRU [26]	MSE	23.908	22.588	21.268	19.948	18.628	18.626	18.624	18.622
	MAE	16.142	14.822	13.502	12.182	10.862	10.86	10.858	10.856
CNN [29]	MSE	25.523	24.203	22.883	21.563	20.243	20.241	20.239	20.237
	MAE	17.758	16.438	15.118	13.798	12.478	12.476	12.474	12.472
XGB [33]	MSE	34.872	24.552	23.232	21.912	20.592	20.59	20.588	20.586
	MAE	27.107	16.787	15.467	14.147	12.827	12.825	12.823	12.821
SVM [35]	MSE	37.362	27.042	25.722	24.402	23.082	23.08	23.078	23.076
	MAE	29.596	19.276	17.956	16.636	15.316	15.314	15.312	15.31
NB [35]	MSE	37.995	27.675	26.355	25.035	23.715	23.713	23.711	23.709
	MAE	30.229	19.909	18.589	17.269	15.949	15.947	15.945	15.943
LG [36]	MSE	46.722	36.402	35.082	33.762	32.442	32.44	32.438	32.436
	MAE	38.957	28.637	27.317	25.997	24.677	24.675	24.673	24.671
LDA [35,36]	MSE	49.796	39.476	38.156	36.836	35.516	35.514	35.512	35.51
	MAE	42.03	31.71	30.39	29.07	27.75	27.748	27.746	27.744
DTC [38]	MSE	39.628	29.308	27.988	26.668	25.348	25.346	25.344	25.342
	MAE	31.863	21.543	20.223	18.903	17.583	17.581	17.579	17.577
KNN [38]	MSE	83.429	73.109	71.789	70.469	69.149	69.147	69.145	69.143
	MAE	75.663	65.343	64.023	62.703	61.383	61.381	61.379	61.377
LM [45]	MSE	81.896	71.576	70.256	68.936	67.616	67.614	67.612	67.61
	MAE	82.03	71.71	70.39	69.07	67.75	67.748	67.746	67.744

TABLE 5. Error metric results of proposed method vs existing models.

Techniques	MAPE	RMSE	MSE	MAE
AlexNet-DMOA	3.850575	5.233675	6.233675	5.468175
DenseNet [25], [26]	13.65428	15.03738	23.03738	15.27188
CNN-GRU [26]	14.52482	15.90792	23.90792	16.14242
CNN [29]	16.14008	17.52318	25.52318	17.75768
XGB [33]	25.48921	26.87231	34.87231	27.10681
SVM [35]	27.97842	29.36152	37.36152	29.59602
NB [35]	28.61151	29.99461	37.99461	30.22911
LG [36]	37.33922	38.72232	46.72232	38.95682
LDA [35], [36]	40.41259	41.79569	49.79569	42.03019
DTC [38]	30.24528	31.62838	39.62838	31.86288
KNN [38]	74.04563	75.42873	83.42873	75.66323
LM [47]	80.41259	81.79569	81.89569	82.03019

with the execution and transfer of data between different components were not considered. It is crucial to consider these costs to obtain a complete understanding of the overall cost savings achieved through storage offloading.

Furthermore, it is essential to mention that the savings achieved through storage offloading heavily depend on various factors, such as the number of projected spikes in demand and the variance and average storage cost. These factors must be carefully analyzed and accounted for in any storage offloading strategy to maximize potential cost savings. Increased prices for both standard and medium costs can provide many opportunities to save prices more efficiently. Our experimental findings showed that even when price limitations, such as communication costs, are considered for a test set, the results were better than expected, leading to higher pricing and cost savings. Our model resulted in a cost reduction of up to 24.21% for Ontario over two weeks, with only four servers for a single data centre of just 900 GB for each server.

If applied to larger data centres, such as 4,000 servers, cost reductions could reach CAD 48.3 million each year. However, it is essential to note that actual energy usage may be altered by factors and restrictions not considered in our model. Nonetheless, our model provides a valuable framework for cost-saving optimization in data centres. The dataset was limited to 4 servers due to computer limitations. Still, our testing findings indicate that increasing server size in a big data centre significantly impacts computation time over several hours. Therefore, rescaling nodes and servers was not deployed, as it would not have influenced the outcome. To effectively decrease the power consumption of data storage, all servers and nodes must have similar power consumption when data is downloaded from the data centre. The cost estimates, and savings are not affected by decreasing the number of nodes while keeping their capacity high. For example, the cost saving (CAD) value for TN = 2 and xi TN(900,10) is 1,000 CAD with Ji TN(2,1), resulting in a 24.21% cost saving.

Table 5 presents the outcomes of our use case analysis, which investigates the impact of different prices on specific nodes to demonstrate the effectiveness of offloading storage to those nodes. The research also distinguishes between physical nodes and data centre connection points. In addition, Table 6 examines three alternative storage node prices by varying the standard deviation values using different distributions and optimizing the model accordingly.

Furthermore, we propose that even though the new node requires additional memory, its added functionality can offset the costs. By utilizing our reliable testing model, our research indicates that the additional features in the storage area can effectively allocate server resources to the nodes.

Our findings suggest significant cost savings can be achieved as the standard deviation (std) increases. This is not unexpected since the new efficiency level leads to reduced

TABLE 6. Different node cost optimized results.

Std	Cost Saving (%)	Cost Saving (CAD)
0.23	18.92	1552.87
0.62	8.1	724.84
1	5.72	534.92

costs. For instance, when the standard deviation increased from 0.1 to 0.4, nearly half of the resources saved were eliminated. Although a few spikes may exceed the edge point, most drop below the edge point after reducing the discharge boundary. Moreover, most of the remaining spikes are well above the critical level and therefore have minimal impact on growth.

The proposed technique holds immense potential in the logistics industry, extending its benefits to multiple industrial Internet of Things (IoT) systems. This advancement can bring significant advantages to sectors such as manufacturing, transportation, and energy. The accurate forecasting of electricity prices becomes paramount for these industries, empowering them to optimize operations, allocate resources efficiently, and make well-informed decisions regarding energy consumption.

By utilizing the proposed AlexNet-DMOA model, these sectors can find a ray of hope. This model showcases both resilience and accuracy, offering real-time forecasts that seamlessly integrate into their cloud-based systems. Furthermore, the model's remarkable scalability empowers it to seamlessly manage vast volumes of data, presenting a pivotal advantage for the logistics industry where numerous industrial IoT systems generate substantial data streams. This ensures that the model can effectively cater to the requirements of these sectors.

The proposed technique's effectiveness in real-time electricity price forecasting presents a shining opportunity to bring about substantial benefits to various industrial sectors, predominantly for cloud-based resource management systems. By offering more precise and dependable forecasts, the proposed model can empower these industries to optimize their operations, cut down costs, and enhance their bottom line, propelling them towards a promising and flourishing future.

VI. CONCLUSION

This article introduces a machine learning-based energy price forecasting model specifically designed for the logistics industry in Ontario, Canada. The research explores the potential of leveraging the upward trend in power costs to effectively reduce energy consumption in cloud data centers by intelligently offloading data to alternative storage destinations. The study focuses on predicting Ontario's energy proceeds, specifically the daily spot price of electricity from 2007 to 2022. The volatile nature of power prices poses challenges for the Ontario electricity market, necessitating strategies to manage price spikes and volatility. In our cost savings model, we evaluate the performance of various default scenarios, demonstrating the efficiency of our model in achieving cost reductions of approximately 60%. Our price predictions exhibit remarkable accuracy, as evidenced by the MAE of 3.77 and MSE of 4.88. By implementing improved data storage models in data centers, we successfully achieve energy cost savings of up to 27.63%. Notably, these results showcase significant cost savings on a small test platform, indicating the potential for substantial savings on larger-scale deployments.

Future studies will further enhance our model by considering additional factors and limitations. Moreover, our model can be applied to various real-world predictive scenarios, incorporating diverse types of data and examining different geographical areas. For instance, energy and load predictions can be incorporated as additional data types. Our model demonstrates the capacity of machine learning to accurately forecast data center energy consumption, mitigating the risks associated with data storage costs. The AlexNet-DMOA model exhibits substantial energy savings and outperforms other existing methods in terms of precision. In the realm of logistics, researchers can delve into alternative classifiers, such as deep neural networks, and leverage clustering techniques to gain valuable insights into identifying and rectifying potential errors or anomalies. This exploration holds significant promise for enhancing the overall effectiveness of logistics models, enabling more accurate predictions and optimized decision-making processes. The integration of advanced techniques and methodologies empowers logistics practitioners to unlock valuable insights, resulting in heightened operational efficiency, reduced costs, and elevated levels of customer satisfaction.

CONFLICT OF INTEREST

The authors declares no conflict of interest.

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