



ARTICLE

## Exploring Multi-Task Learning for Forecasting Energy-Cost Resource Allocation in IoT-Cloud Systems

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Received: 20 February 2024 Accepted: 22 April 2024 Published: 20 June 2024

### ABSTRACT

Cloud computing has become increasingly popular due to its capacity to perform computations without relying on physical infrastructure, thereby revolutionizing computer processes. However, the rising energy consumption in cloud centers poses a significant challenge, especially with the escalating energy costs. This paper tackles this issue by introducing efficient solutions for data placement and node management, with a clear emphasis on the crucial role of the Internet of Things (IoT) throughout the research process. The IoT assumes a pivotal role in this study by actively collecting real-time data from various sensors strategically positioned in and around data centers. These sensors continuously monitor vital parameters such as energy usage and temperature, thereby providing a comprehensive dataset for analysis. The data generated by the IoT is seamlessly integrated into the Hybrid TCN-GRU-NBeat (NGT) model, enabling a dynamic and accurate representation of the current state of the data center environment. Through the incorporation of the Seagull Optimization Algorithm (SOA), the NGT model optimizes storage migration strategies based on the latest information provided by IoT sensors. The model is trained using 80% of the available dataset and subsequently tested on the remaining 20%. The results demonstrate the effectiveness of the proposed approach, with a Mean Squared Error (MSE) of 5.33% and a Mean Absolute Error (MAE) of 2.83%, accurately estimating power prices and leading to an average reduction of 23.88% in power costs. Furthermore, the integration of IoT data significantly enhances the accuracy of the NGT model, outperforming benchmark algorithms such as DenseNet, Support Vector Machine (SVM), Decision Trees, and AlexNet. The NGT model achieves an impressive accuracy rate of 97.9%, surpassing the rates of 87%, 83%, 80%, and 79%, respectively, for the benchmark algorithms. These findings underscore the effectiveness of the proposed method in optimizing energy efficiency and enhancing the predictive capabilities of cloud computing systems. The IoT plays a critical role in driving these advancements by providing real-time data insights into the operational aspects of data centers.

### KEYWORDS

Cloud computing; energy efficiency; data center optimization; internet of things (IoT); hybrid models



## 1 Introduction

Cloud computing has gained popularity as a storage option in the age of rapidly developing technology, providing businesses with the opportunity to reduce hardware and acquisition costs [1]. The need for data centers has grown significantly as a result of this change, which is being caused by the exponential expansion in data consumption. However, rising demand for data centers comes at a price: These establishments currently account for a sizeable 3% of global energy usage. The logistics industry is carefully investigating how distributed computing, virtualization, and the IoT could boost efficiency as companies navigate this new environment.

Virtualized servers utilize up to 30% of their available resources, whereas non-virtualized servers' function at a meager 6%–15% of their capability [2]. Data center operators intentionally distribute their facilities over many sites to guarantee dependability, employing replication techniques to ensure smooth operations. The integration of IoT sensors in data centers becomes imperative to actively monitor critical parameters like energy usage and temperature, providing a comprehensive dataset for informed decision-making. Researchers are addressing the need for sustainable practices in the face of swift advancements in technology [3]. They investigate various methods, such as determining the cost of installing servers in various places and arranging nodes and data transmission routes optimally. Energy forecasting and model planning are critical applications of machine learning, which uses techniques like random forest, naive bayes, and decision trees. The utilization of IoT-generated real-time data seamlessly integrated into machine learning models enhances the accuracy of predictions and aids in optimizing energy efficiency.

Large-scale cloud data center construction is becoming increasingly prevalent in the logistics sector, where big data, cloud computing, and the Internet of Things (IoT) play pivotal roles. However, the high energy consumption associated with these institutions poses a significant environmental challenge. Scholars are currently exploring various approaches to mitigate energy usage while maintaining peak efficiency and reliability. One area of research focuses on Virtual Machine (VM) consolidation, which seeks to reduce energy consumption by consolidating idle virtual machines onto fewer servers. Despite its potential benefits, the effectiveness of this approach varies depending on the nature of the workload and may encounter challenges in unforeseen circumstances [4].

Another innovation aimed at reducing energy consumption in data centers is Dynamic Voltage and Frequency Scaling (DVFS), which adjusts processor voltage and frequency in real-time. However, accurately evaluating the characteristics of each workload remains a challenging task. Energy-efficient job arranging seeks a balance between resource needs and utilization reduction. Suggested algorithms include particle swarm optimization and genetic algorithms [5]. Researchers investigate innovative uses such as distributed fault-tolerant storage, VM consolidation, energy-conscious task organization, and learning algorithms for data centers in clouds that are adaptable. By using the linkages between handling resources and energy price estimation activities, multi-task learning in conjunction with IoT is a viable method for improving performance [6]. The development of novel energy-saving strategies becomes critical given the increasing need for computing services. In the face of fluctuating deregulated energy costs, cloud providers, entrusted with achieving government requirements and profit objectives via service level agreements, oversee the intricacies of energy utilization [7]. To lower data center operating costs and take advantage of energy price variations, researchers are investigating Machine Learning (ML) techniques.

In this work, we have developed a complete framework intended to improve data center energy efficiency and save power costs by integrating incoming IoT data strategically. Our study is a leading

contribution to the area as it highlights how important IoT-generated data is to enhancing data center operating efficiency and obtaining a significant reduction in power costs.

1. IoT-driven data integration: Our work stands out for actively integrating IoT data through strategically placed sensors around data centers. This unique approach allows us to monitor energy usage and temperature, providing a foundational basis for optimizing energy efficiency and elevating predictive capabilities.
2. Innovative Hybrid TCN-GRU-NBeat (NGT) model: We present the NGT model, a novel framework adept at handling diverse data and optimizing storage in data center environments. By seamlessly integrating TCN, GRU, and N-Beat capabilities, NGT emerges as a powerful solution for efficient data processing.
3. Optimization with Seagull Optimization Algorithm (SOA): Notably, we fine-tune NGT parameters using SOA. This optimization process maximizes the potential of incoming IoT data, significantly enhancing NGT's performance in data centers, forecasting, and electricity consumption reduction.
4. Exceptional performance results: Through active IoT monitoring and NGT data processing, our approach achieves a remarkable 2.83% reduction in MAE error and a 5.33% reduction in MSE error. This translates to an impressive 24.87% average reduction in electricity expenses. Importantly, these outcomes surpass existing literature models by 10% to 15%, validating the efficacy of our proposed methodology in optimizing energy efficiency and predictive capabilities.

## 2 Related Work

Energy consumption and its environmental impact have become a growing concern, driven by the increasing focus on sustainability across various industries. This study provides a concise review of previous approaches to electricity demand prediction, acknowledging their limitations and aiming to overcome them through the application of a Neural Network with Multi-Layer (MLNN) model [8]. The study utilizes an ensemble method, combining several ML models to improve the precision of power load and total consumption of electricity projections in logistics processes by utilizing the capabilities of the IoT. The IoT-based method has issues with lengthier processing cycles and notable loss rates in actual testing, despite its competitive accuracy.

In a hybrid approach named EPNet, combining Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) models, presented in [9], energy price prediction is explored with a reliance on the IoT infrastructure. While the models required substantial processing power for real-time predictions and exhibited significant error rates, they produced favorable outcomes. However, the model's applicability to real-time data was limited due to extensive dataset standardization. Another model in [9], incorporating support vector regression with various optimization techniques, reported a 6.82 MAE but faced significant computational costs and limited reliability for forecasts beyond one day. In [10], an assessment of methods that use deep learning for calculating electricity and green energy consumption was carried out. Although the results were competitive, the real-time applications resulted from high computational costs and testing losses. An inventive hybrid strategy for electricity price forecasting, merging SVM and Kernel Principal Component Analysis (KPCA), showed promise with low error rates [11]. However, its application to large datasets posed challenges and incurred substantial processing costs.

In the logistics area, the suggested approach considers seasonal and regional fluctuations in energy costs, utilizing NN-based and autoencoder models, as well as location-specific data gathering

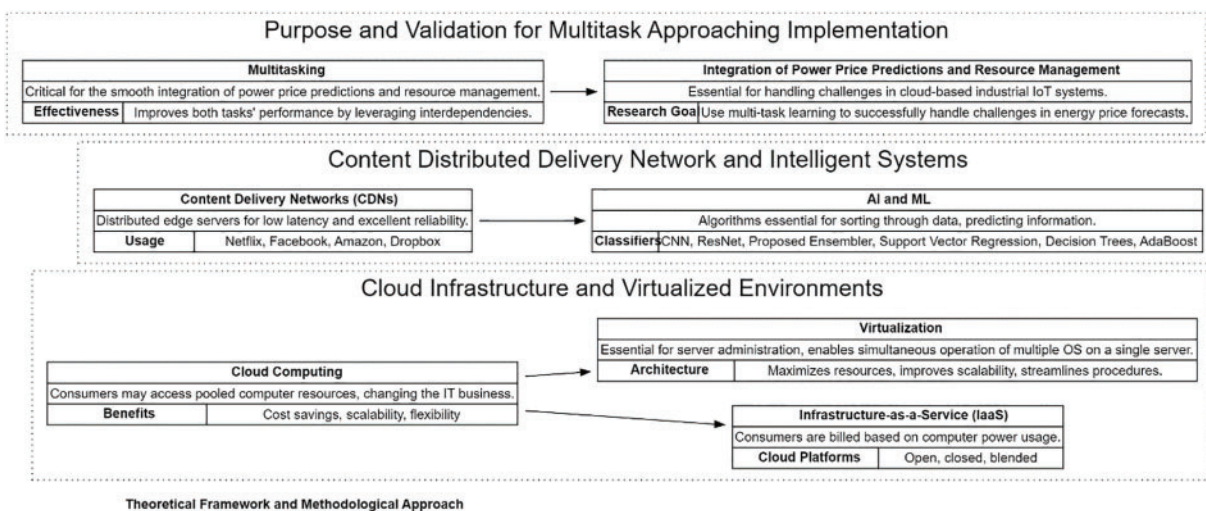
[12]. Harnessing the capabilities of the IoT, despite promising results, sophisticated deep learning methods discussed in [13] face challenges with relatively high MAE and MSE values, leaving room for improvement. A model in [14] employed dimension reduction to overcome over-fitting issues but encountered difficulties in accurately estimating electricity costs. Strategies including DVFS and the relocation of inactive VMs on lesser number of servers are used in the pursuit of energy-efficient cloud data centers [15]. Nevertheless, there are issues with these methods, such is the curvilinear link that connects the workload's rate and voltage parameters.

With multi-task learning showing potential to enhance accuracy and efficiency, researchers explore ML-based techniques for cutting energy use [16]. Feature selection-focused models, like the one, achieved an MAE of 3.18 but were limited to offline prediction using a large dataset.

Studies combining power cost estimation and energy demand prediction with different algorithms, such as Artificial Bee Colony and SVM [17], weighted kernel hybrid methodology [18], and Artificial NN based strategy [19], have embraced the integration of the IoT in their methodologies. These studies, while advancing the field, encountered challenges like computational costs, imprecise forecasts, and inefficiency for real-time applications. Despite the abundance of research on energy price prediction, most existing approaches are not computationally cost-effective for real-time application and struggle to yield good results for the entire market with low error rate. Researchers emphasize the need for ongoing research to precision improvement, effectiveness, and application of energy consumption forecasting models in real-time scenarios [20].

### 3 Theoretical Framework and Methodological Approach

This section encapsulates the core concepts that underpin our research projects, elucidating the systematic approaches employed in conducting our investigations. The theoretical foundations serve as guiding principles, facilitating our comprehension as we delve into the realms of cloud computing, virtualization, content distribution delivery networks, intelligent systems, and the IoT. Simultaneously, our methodology delineates the techniques applied to unravel the intricacies inherent in these technological fields, as illustrated in Fig. 1.



**Figure 1:** Theoretical framework: a visual representation

### ***3.1 Cloud Infrastructure and Virtualized Environments***

With cloud computing, users can access pooled computing resources, revolutionizing the IT industry. This paradigm enables rapid allocation and deallocation of resources with minimal management overhead. Departing from the traditional reliance on local servers, cloud computing offers on-demand access to configurable resources, resulting in cost savings, scalability improvements, and enhanced flexibility in resource allocation [21]. This shift in focus from capital expenditures to pay-as-you-go models based on actual usage contributes to reduced server expenses. Furthermore, the integration of the Internet of Things (IoT) further amplifies the transformative potential of cloud computing in the modern technological landscape. To meet the demands of today's data-driven businesses, data center organizations must continuously enhance their processing capabilities, software programs, and data processing capabilities while incorporating IoT functionalities to keep pace with evolving technological demands. The integration of IoT and cloud computing, particularly in Infrastructure as a Service (IaaS), revolutionizes infrastructure management. IaaS billing is tied to computing power usage, and various cloud platforms, such as open, closed, and mixed types (e.g., VMware and Nutanix), offer diverse infrastructure approaches [22]. Mixed-data centers, blending private and public cloud services, demonstrate efficiency by seamlessly integrating resources. Hybrid data centers, which integrate IoT with shared and private clouds, enhance data processing and communication. In shared data centers, where multiple organizations utilize shared resources, IoT optimizes resource allocation with real-time usage data, promoting efficient sharing. In private data centers dedicated to a single organization, IoT enhances security, monitors equipment health, and optimizes energy usage, thereby improving overall performance. Hybrid data centers, combining shared and private elements, benefit from IoT's comprehensive approach, enabling seamless communication and data processing across the hybrid environment [23,24]. This results in an adaptive, efficient model that combines the advantages of both setups.

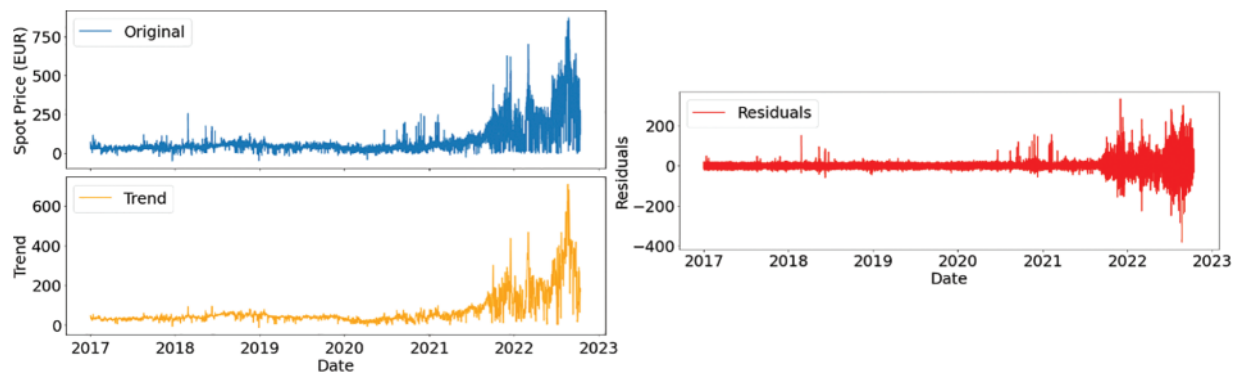
Virtualization streamlines server management by allowing multiple operating systems to run concurrently, thereby improving efficiency. Collaborative IoT integration into the NGT model optimizes energy efficiency and resource allocation in cloud computing, leading to significant cost reductions. The IoT's role involves collecting real-time data from strategically placed sensors to inform decisions, enhancing predictive capabilities, and optimizing energy usage.

### ***3.2 Content Distributed Delivery Network (CDN), Intelligent Systems, and Multi-Task Approaching Implementation***

Content Distributed Delivery Network (CDN) and Intelligent Systems: CDNs are integral for optimizing data delivery, strategically placing edge servers to reduce latency and enhance reliability. Major platforms like Netflix and Amazon leverage CDNs, efficiently managing bandwidth costs through clever algorithms. In cloud-based industrial IoT systems, integrating power price predictions and resource management is crucial. Multi-tasking proves beneficial, enhancing performance by collaboratively addressing dependencies, reducing training time, computing complexity, and improving resilience [25]. The research focuses on leveraging multi-task learning to navigate energy price forecast complexities in cloud-based industrial IoT systems, demonstrating its effectiveness in handling real-world occurrences. The study explores integrating ML and deep learning skills in cloud computing to anticipate future electricity prices and improve energy management. Neural network classifiers and primary ML classifiers are evaluated, highlighting the potential of Artificial Intelligence (AI) and ML techniques in addressing challenges in diverse scenarios.

## 4 Proposed Model

This section discusses the application of forecasting methods for hourly and day-ahead power price forecasting, employing single and hybrid models, as illustrated in Fig. 2. The Nord Pool spot market, a crucial data source, provides hourly time series data, collected through IoT devices [26]. An in-depth data examination focuses on understanding information properties, with a particular emphasis on insights derived from IoT-generated data. The testing and training process involves meticulous data selection, incorporating the enriched dataset from IoT sources. Various ML models, both single and hybrid, are deployed for evaluation, leveraging IoT-enhanced data to enhance model robustness. Section 4 briefly covers the study of each model, highlighting the pivotal role of IoT-generated data in advancing power price forecasting accuracy.



**Figure 2:** Data components of the time series data used

### 4.1 Dataset Description (Time Series Price Data)

The dataset under consideration, crucial for energy price forecasting (EPF) in Denmark and surrounding nations, is acquired through IoT devices, enhancing its relevance and richness. It adheres to a time series structure, with consecutive observations grouped chronologically at regular intervals, such as hourly or daily readings. Fig. 2 portrays the decomposition of a time series dataset representing spot prices in Euros (EUR) into its essential components: Trend and residuals. At the top of the plot, the original time series data is depicted, showcasing the observed spot prices over time without any decomposition. This visual representation offers insights into the fluctuations in spot prices across different periods. Moving to the middle plot, the trend component is illustrated. This component reflects the underlying long-term behavior or tendency in the data, smoothing out short-term fluctuations to reveal the overall direction of spot prices over time. In the bottom plot, the residuals are displayed. These residuals capture the variability or randomness in the original data after removing the trend and any seasonal patterns, highlighting the unexplained fluctuations or noise present in the dataset. By examining these residuals, analysts can gain deeper insights into the random elements influencing spot price fluctuations.

The historical time series dataset encompasses hourly averages of day-ahead spot prices in both DKK and EUR, with timestamps presented in Danish and UTC time zones. Geographical boundaries, categorized by pricing regions (DK1 and DK2) based on the Great Belt, make this dataset notable [26,27]. Its significance lies in its pivotal role in EPF, influencing decisions within the energy industry over the last fifteen years. The dataset elements encompass Hour DK and Hour UTC, representing

time intervals in Danish and UTC time zones, respectively, and the integration of IoT data further enriches its potential applications in energy analytics and forecasting.

These prices represent the fragile equilibrium between demand and supply in the market. This dataset is a significant source for in-depth analysis of time series and multivariate single and multistep power price forecasting because it has a huge count of 50,000 instances. The abundance of cases opens the possibility to a thorough investigation of patterns, developments, and variances, providing a deep understanding of the dynamic retail energy market environment.

#### 4.2 Proposed Hybrid Model

**N-Beats Component:** The N-Beats component is constructed as a collection of fully connected blocks, each adept at capturing diverse temporal patterns across different time scales. The core equation governing the output of a single block is articulated as follows [28]:

$$\hat{Y}_t^{(k)} = G^{(k)}(X_t) \sum_{j=1}^k F_j^{(k)} \left( \hat{Y}_{t-h_j}^{(j)} \right) \quad (1)$$

where,  $\hat{Y}_t^{(k)}$  denotes the predicted output at time  $t$  for the  $k$ -th block. This output amalgamates information from both the generic neural network  $G^{(k)}$  and the forecast functions  $F_j^{(k)}$ .  $G^{(k)}(X_t)$  signifies the contribution from the generic neural network linked with the  $k$ -th block. This component captures overarching patterns and trends in the time series data. The summation term  $\sum_{j=1}^k F_j^{(k)} \left( \hat{Y}_{t-h_j}^{(j)} \right)$  encapsulates forecasts from individual forecast functions  $F_j^{(k)}$ , each applied to a lagged version of the output  $\hat{Y}_{t-h_j}^{(j)}$  from a specific block  $j$ . The inclusion of multiple forecast functions allows the model to comprehend various aspects of temporal patterns at diverse time horizons [28].  $h_j$  denotes the backcast horizon linked with the  $j$ -th forecast. This parameter specifies how far back in time the model looks to make predictions, accommodating various time scales [28].

In essence, the N-Beats component exhibits a modular and adaptive structure, with each block contributing to the overall prediction by capturing patterns specific to different temporal contexts. This adaptability makes the N-Beats component highly effective for forecasting tasks in time series analysis.

**Gated Recurrent Unit (GRU) Component :** A particular kind of Recurrent Neural Network (RNN) called the GRU is made to successfully capture temporal relationships while overcoming issues like vanishing gradients and computing efficiency. The GRU achieves this through the incorporation of an update gate, a reset gate, and a memory cell, facilitating a dynamic balance between retaining past information and adapting to new input [29].

- Update Gate  $U_t$ : The update gate  $U_t$  functions as a controller for determining the extent to which the previous hidden state  $H_{t-1}$  should be retained based on the current input  $X_t$ . Mathematically,  $U_t$  is computed as:

$$U_t = \tanh(WU \cdot [G_{t-1}, L_t]) \quad (2)$$

- Reset Gate  $R_t$ : The gate that resets in accordance of the current input  $L_t$ ,  $R_t$  determines how much of the previous hidden state  $H_{t-1}$  can be reset or forgotten.  $R_t$  is scientifically computed as:

$$R_t = \text{sigmoid}(WR \cdot [G_{t-1}, G_t]) \quad (3)$$

- **New Memory Content  $M_t$ :** By combining data from the reset gate, previous hidden state, and current input, the updated storage capacity  $M_t$  serves as a potential hidden condition. This can be stated as:

$$M_t = \tan h (WM \cdot [R_t \cdot L_{t-1}, L_t]) \quad (4)$$

- **Update State\_Hidden  $H_t$ :** The last concealed condition  $H_t$  is the product of the newly acquired memory storage ( $M_t$ ) scaled by  $U_t$  and the old concealed state ( $H_{t-1}$ ) scaled by  $1 - U_t$ .  $H_t$  is determined by:

$$H_t = (1 - U_t) \cdot H_{t-1} + U_t \cdot M_t \quad (5)$$

This equation illustrates how the GRU selectively updates and retains information over sequential data, with the weight matrices  $WU$ ,  $WR$  and  $WM$  being trainable parameters optimized during the training process to enhance the model's performance on specific tasks.

**TCN Component:** At the core of the NGT model lies the Temporal Convolutional Network (TCN), a crucial component that utilizes causal dilated convolutions for robust temporal dependency modeling. The TCN generates the output  $Z_t$  by applying a sequence of convolutions with dilated filters. The expression for the TCN output is defined as follows [29]:

$$z_t = \text{ReLU} \left( \sum_{k=1}^L F_k \times H_{t-dk} \right) \quad (6)$$

where  $\text{ReLU}$  introduces non-linearity through the Rectified Linear Unit ( $\text{ReLU}$ ) activation function.  $\sum_{k=1}^L$ : Signifies the summation across  $L$  convolutional layers.  $F_k \times H_{t-dk}$  denotes the convolution operation,  $F_k$  denotes the learnable convolutional filters and  $H_{t-dk}$  denotes the input sequence shifted by a dilation factor  $d_k$ .

#### **Key Considerations:**

- **Convolution Operation (\*):** This operation involves sliding a filter ( $F_k$ ) across the input sequence ( $H_{t-dk}$ ), performing element-wise multiplication, and summing the results. This operation is executed for each convolutional layer.
- **Number of Layers (L):** L signifies the depth or the count of convolutional layers within the TCN. Each layer captures distinct levels of temporal information.
- **Learnable Convolutional Filters ( $F_k$ ):** These filters represent trainable parameters that the model adapts during the training phase. They play a pivotal role in extracting temporal features from the input sequence.
- **Dilation Factors ( $d_k$ ):** These factors dictate the spacing between values in a convolutional filter. Dilated convolutions extend the receptive field without a surge in parameters.

The TCN component amplifies the NGT model's proficiency in modeling prolonged dependencies, capturing intricate temporal patterns in input data. Thoughtful adjustments to dilation factors and the layer count contribute to the model's prowess in understanding temporal dynamics, offering adaptability across diverse time series forecasting scenarios.

**Integrated NGT Model (A Fusion of Strengths):** The Integrated NGT model brings together three powerful components—N-Beats, GRU and TCN—to create a robust forecasting framework for electricity prices. This integration is a strategic decision aimed at harnessing the unique strengths of each component.



- **N-Beats Contribution:** In the energy price period series, the N-Beats component performs exceptionally well at identifying relationships over time and worldwide trends. Its predictions  $y_t(k)$  contribute a high-level understanding of overarching trends.
- **GRU's Temporal Insights:** GRU, focusing on temporal dynamics, provides contextual information through its hidden state ( $H_t$ ). This encapsulates short to medium-term patterns, enriching the model's temporal understanding.
- **TCN's Local Feature Extraction:** TCN, with its strong ability to extract local features, contributes the output ( $Z_t$ ) that captures intricate details within the electricity price time series.

The integration function, denoted as *IntegratedNGT*, orchestrates the combination of N-Beats predictions, GRU hidden state and TCN output. The integration equation,  $Y_t = \text{IntegratedNGT}(y', H', Z')$ , unifies these diverse components strategically. The integration is not a simple summation; it's a strategic blending of global, temporal, and local perspectives. This holistic approach ensures a comprehensive understanding of intricate patterns within the time series.

**Crucial Benefits of Integration:** The success of integrated NGT lies in its ability to capture a broad spectrum of patterns. This integration allows the model to address both overarching trends and subtle local features, leading to superior forecasting performance. The integrated NGT model stands as a testament to the power of integration, combining diverse components into a unified and potent forecasting tool. This model is designed to provide accurate and robust predictions for electricity price forecasting.

#### 4.4 Optimizing Parameters with Seagull Optimization Algorithm (SOA)

In our integrated NGT model, fine-tuning hyperparameters and optimizing parameters are crucial for peak forecasting performance. The SOA [15], inspired by seagulls' foraging behavior, excels in navigating intricate solution spaces, proving effective in various optimization tasks. SOA mimics seagulls' strategic foraging, adapting search patterns based on resource availability. Integrated with the NGT model, SOA becomes vital in exploring the hyperparameter space, employing a population of seagull agents to represent potential solutions, as in Algorithm 1.

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##### Algorithm 1: SOA parameter optimization algorithm

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###### 1. Initialization:

Initialize a population of seagull agents with different sets of hyper parameters for the NGT model.

###### 2. Initialize Iteration Counter:

Set iteration to 0.

###### 3. While Not Converged:

###### a. Objective Function Evaluation:

i. Assess the performance of each seagull agent using the NGT model's forecasting accuracy as the objective function.

ii. Adaptation and Exploration: Dynamically adjust the positions of seagull agents based on evaluation results, striking a balance between exploiting promising areas and exploring uncharted regions.

###### b. Communication Mechanism:

i. Agents communicate and share information about promising regions, fostering collaborative exploration of the parameter space.

ii. Update Iteration Counter: iteration + 1.

###### 4. Optimal Solution Identification:

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(Continued)

**Algorithm 1** (continued)

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Converged to optimal or near-optimal solutions, leading to finely tuned hyper parameters for the NGT model.

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**4.5 Benefits of SOA in Parameter Optimization**

- **Global Search Capability:** SOA's exploration strategy enables a global search in the hyper parameter space, avoiding local minima.
- **Adaptability:** The approach to searching of the algorithm is continually adjusted, enabling it to explore complicated and dynamic solution spaces with efficiency.
- **Convergence Speed:** SOA often demonstrates faster convergence to optimal solutions compared to traditional optimization algorithms.

The incorporation of the Seagull Optimization Algorithm (SOA) in parameter optimization enhances the overall performance of the NGT model, contributing to its accuracy and robustness in electricity price forecasting. The proposed framework process is shown in Algorithm 2.

**Algorithm 2:** Integrated NGT model

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- > **Input:** Time series dataset for electricity price forecasting.  
 > **Processed Input:** Preprocessed time series dataset.  
 > **Output:** Forecasted electricity prices.
1. N-Beats Component: Function  $f_{NBEATS}(Y_t^{(k)}, X^t)$ .
  2. GRU Component: Function  $f_{GRU}(H_{(t-1)}, X^t)$ .
  3. TCN Component: Function  $f_{TCN}(Z_t, X^t)$ .
  4. Integrated NGT Model: Function  $IntegratedNGT(y^t, H^t, Z^t)$ .
  5. SOA Optimization: Seagull Optimization Algorithm (parameters).
  6. Procedure Data Preprocessing:
    - (a) Address missing values.
    - (b) Apply necessary imputation strategies.
    - (c) Conduct data scaling or normalization as required.
    - (d) Handle outliers or anomalies in the dataset.
  7. Procedure N-Beats Component:
    - (a) Define the N-Beats forecasting function:  $f_{NBEATS}(Y_t^{(k)}, X^t)$ .
  8. Procedure GRU Component:
    - (a) Define the GRU forecasting function:  $f_{GRU}(H_{(t-1)}, X^t)$ .
  9. Procedure TCN Component:
    - (a) Define the TCN forecasting function:  $f_{TCN}(Z_t, X^t)$ .
  10. Procedure  $IntegratedNGT$  model:
    - (a) Define the integration function:  $IntegratedNGT(y^t, H^t, Z^t)$ .
    - (b) Combine the outputs of the  $NBEATS$ ,  $GRU$  and  $TCN$  components.
  11. Procedure SOA Optimization:
    - (a) Initialize parameters for the SOA.
  12. Procedure Optimization Objective Function:
    - (a) Independent Function Def:  $O_1(w_{NGT}) = V[n^t, IntegratedNGT(y^t, H^t, z^t)]$ .
    - (b) Evaluate the performance of the Integrated NGT model.
  13. Procedure Optimization Algorithm:
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(Continued)

**Algorithm 2** (continued)

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- (a) Implement the SOA optimization: SOA (parameters).  
 (b) Fine-tune weights and parameters of the Integrated NGT model.
14. Procedure Ensemble Prediction:  
 (a) Combine predictions from the optimized Integrated NGT models.  
 (b) Ensemble prediction:  $z^{hyb} = \left(\frac{1}{M}\right) \times \sum IntegratedNGT (y^t, H^t, Z^t)$ .
15. Procedure Ensemble Weights:  
 (a) Define *weight<sup>val</sup>* ensemble:  $w^{hyb} = [w_{GRU}^e, w_{NBEATS}^e, w_{TCN}^e]$ .  
 (b) Optimize ensemble weights using the Seagull Optimization Algorithm.
16. Procedure Optimization Objective Function for Ensemble:  
 (a) Define the ensemble objective function:  
 $O_J (w_{hyb}^e) = V(b^i, \sum_{t=0}^k w_L^e \times [n^t, IntegratedNGT (y^t, H^t, z^t)])$ .
17. Procedure Final Integration:  
 (a) Combine outputs of N-Beats, GRU and TCN with optimized ensemble weights.  
 (b) Final integration:  $IntegratedNGT (y^t, H^t, Z^t) = w_{NBEATS} \times f_{NBEATS} + w_{GRU} \times f_{GRU} + w_{TCN} \times f_{TCN}$ .
- Output:** Obtain the final forecasted electricity prices using the integrated and optimized NGT model.
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**5 Cost-Effective Data Center Management**

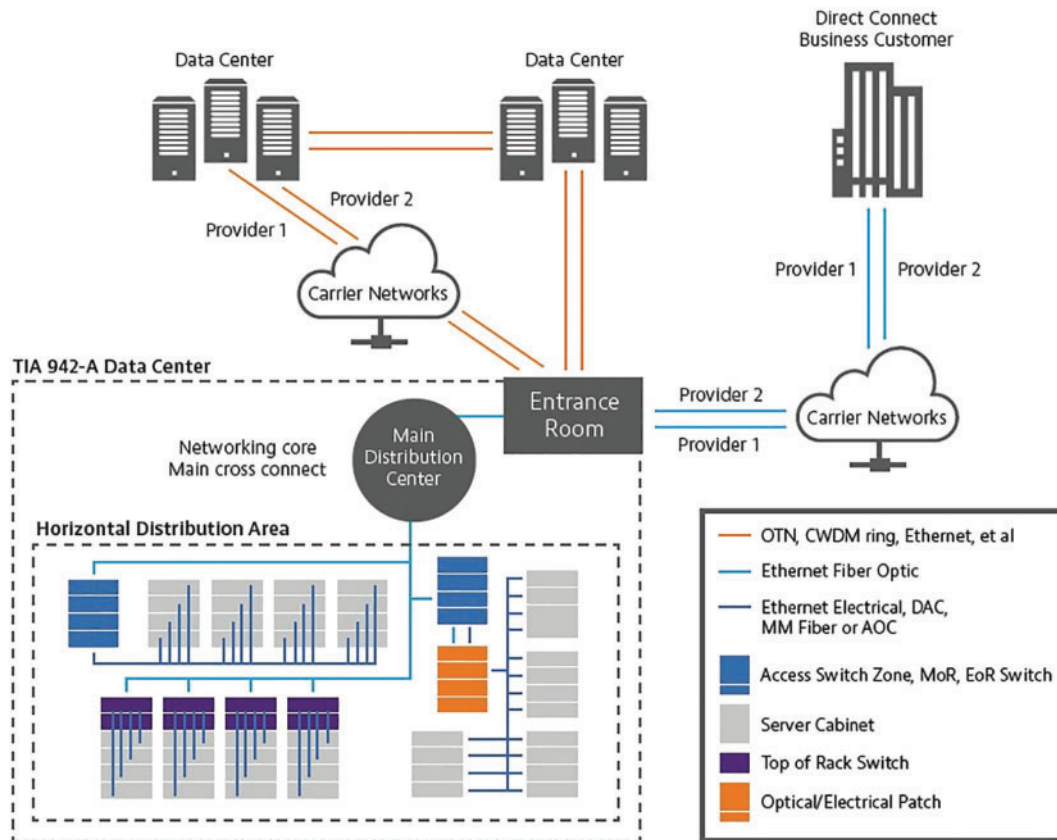
This paper examines, considering varying node measurements, the economic value of capacity discharge to nodes inside one data center system. Data downloads to nodes are constantly more economical than other options, as demonstrated by hourly energy cost analysis. Updates to the model can be accommodated by adding additional data sources, such as message traffic from widely utilized social networks. Using a cell phone as an input device, the technique mimics real-world settings; Fig. 3 illustrates the framework's cost-effective setup and adaptability.

Eq. (7) describes constraints related to server data storage capacity and offloading data volume to nodes, considering integer and decimal values, respectively. Eq. (8) represents the objective function for minimizing overall costs, ensuring the server data storage capacity matches predefined values. Constraints involve offloading data to nodes with specified integer ( $\alpha_i$ ) and decimal ( $\beta_j$ ) values. The optimization model employs P0 formulas to address the problem, where  $\alpha_i$  represents server  $i$ 's storage capacity and  $\beta_j$  signifies offloading volume to node  $J$ . The cost factors include  $\Gamma$  for electricity and  $\gamma k$  for node data storage. Symbols designate limits for servers ( $K$ ) and nodes ( $k$ ). The value spike threshold ( $\gamma k$ ) determines dataset storage decisions. The objective function ( $\gamma, \delta$ ) minimizes cost estimates for optimal  $\gamma$  and  $\delta$ . The optimization process integrates algorithmic structures. These techniques anticipate electricity prices by considering P0 outputs and real time prices of electricity. The efficacy of optimization is influenced by price forecast precision. A strength of pricing framework that records hourly expenses is based on anticipated prices [17].

$$\text{minimize}_{cost} = \sum_{i=1}^N \alpha_i (\beta \cdot \Gamma \cdot 10^{-6}), \text{ Subject to } \begin{cases} \alpha_i \leq \alpha_k, \forall i = 1, \dots, N \\ \beta_j \leq \gamma_k, \forall j = 1, \dots, N \end{cases} \quad (7)$$

$$\sum_{i=1}^N \alpha_i + \sum_{j=1}^M \beta_j = \sum_{i=1}^N \alpha_k, \alpha_i, \beta_j \geq 0, \in \mathbb{Z}^+, \forall i = 1, \dots, N, \forall j = 1, \dots, M \quad (8)$$

$$\text{cost} = \sum_{i=1}^N \alpha_i (\beta \cdot \Gamma \cdot 10^{-6}) \quad (9)$$

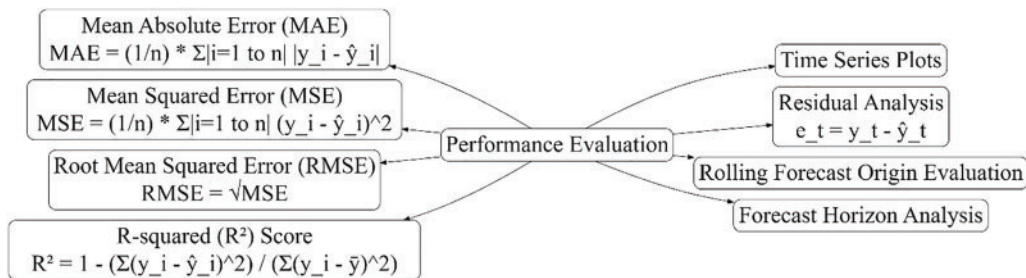


**Figure 3:** Interconnection of data centers on cloud

The energy usage of a server every hour per P2 space on the server is represented by the symbol  $\Gamma$  in Eq. (9), where electricity denotes the modified cost in EUR. To make comparisons with the hourly price of electricity in EUR/MWh easier,  $\Gamma$  is converted to EUR/Wh.

**5.1 Performance Evaluation**

A set of metrics and visuals is employed in the performance assessment for the regression analysis conducted on time series information to gauge the forecasting models’ accuracy and efficacy. The goal is to assess the models’ ability to accurately represent the temporal trends and variances in the power price time series. The performance evaluation metrics are shown in Fig. 4.



**Figure 4:** Performance metrics formulas used for evaluation the proposed model

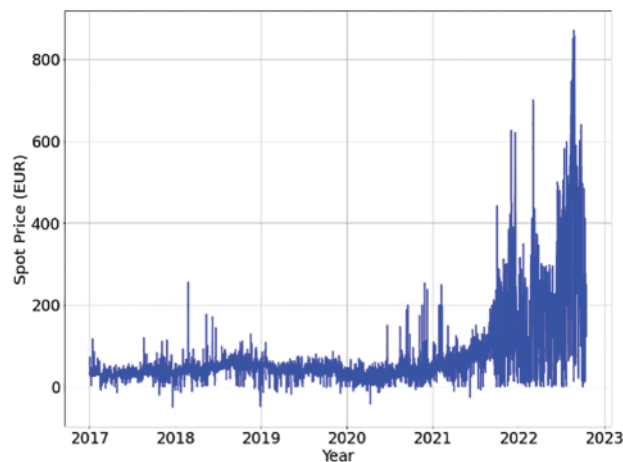
## 6 Simulation Results

This section details the analysis conducted to achieve the stated objective and describes the comprehensive experimental setup. The experiments executed using Python on the Google Colab platform aimed to assess the efficiency of parallel execution of task for resource management and power price predictions in fog based industrialized mechanism with IoT real-time data. Employing a time series dataset from Nord Pool Spot market data, with 50,000 instances of hourly power price observations in DKK and EUR. The collection of data was divided between 20% testing and 80% training samples in a chronological order. The NGT architecture that is integrated, incorporating N-Beats, GRU, and TCN components, was implemented based on the proposed hybrid model, with hyperparameters and configurations outlined in [Table 1](#).

**Table 1:** Obtained optimized parameter values

Component	Parameter	Configuration
N-Beats	Block structure, learning rate, training epochs	4 blocks, 2 fully connected layers, 0.001, 100
GRU	Hidden units, learning rate, training epochs	64 hidden units in GRU layer, 0.01, 50
TCN	Number of layers, dilation factors, learning rate, training epochs	3 layers in the TCN, for the three layers, 0.005, 80

The Seagull Optimization Algorithm (SOA) fine-tuned the model's hyperparameters with a population size of 20, terminating at a convergence threshold of 0.001. Ensuring robustness, experiments were repeated around ten times, introducing new parameter sets and dataset shuffles in each iteration, capturing inherent variability for statistically significant conclusions. An individual CSV file including data from the past from 2017 to 2022 had been generated for data analysis, and [Fig. 5](#) shows the combined data as a time sequence, forming the basis for a three-stage study involving data investigation, price prediction, and process optimization.



**Figure 5:** Data distribution 2017 to 2022

Key dataset stats: Mean 69.84, std. dev. 89.55, min  $-50.00$ , max 871.00. [Fig. 5](#) depicts price trends, emphasizing forecasting utility and pricing volatility. Occasional spikes above 871 EUR suggest

data storage outsourcing opportunities during lower power cost periods. Examining power price behavior stresses optimizing storage offloading for cost savings. The heatmap in Fig. 6 identifies closely connected factors, emphasizing the model’s effectiveness in forecasting a single hour based on date-related variables.

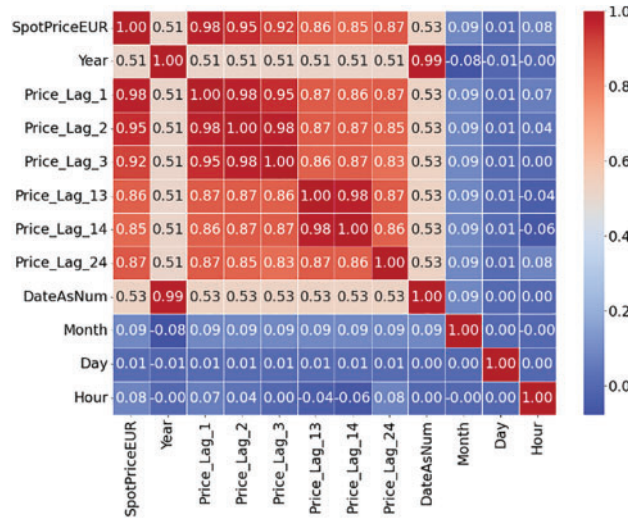


Figure 6: Autocorrelation of the dataset lags

**Price Forecasting Results:** Initially, the most important characteristic that was found that it was used to build the model repeatedly. While the data sets in the next section show the results of choosing the feature method, Table 2 summarizes the various feature sets employed in the study [26,28]. Table 2 uses the notation R for the matching attribute and Spn, which stands for the lag. The time interval that allows the following task to start before the previous one is finished is known as the negative lag. Tasks that would normally be sequential can overlap or be combined using this approach if they would not otherwise be incompatible.

Table 2: Set of features

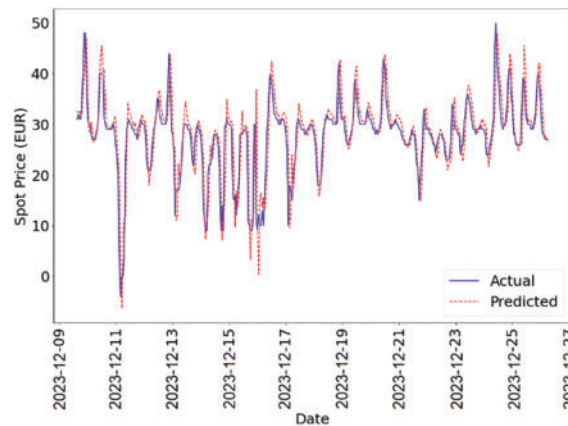
Notation	Set of features	Notation	Set of features
$\alpha$	A = -1	$\epsilon$	E = -1, E = 1, E = -2, E = 2, E = -3
$\beta$	B = -1, B = 1	$\zeta$	F = 1, F = -1, F = -2, F = 2, F = -3, F = 24
$\gamma$	C = -1, C = 1, C = -2	$\eta$	G = -1, G = 1, G = -2, G = 2, G = -3, G = 24, G = 3
$\delta$	D = -1, D = 1, D = -2, D = 2	$\theta$	H = -1, H = 1, H = -2, H = 2, H = -3, H = 24, H = 3, hour

Enhanced functionality is not always a guarantee of better model performance. More features from set A are added to set B in NGT, which raises Mean Squared Error ( $MSE_R$ ) but decreases Mean Absolute Error ( $MAE_R$ ) as shown in Table 3. Hours and delays are important characteristics of the best options for set H. Different from SVR and DenseNet, NGT-SOA demonstrates that many times adding more features does not improve accuracy. When NGT-SOA is optimized using the SOA, the fewest characteristics often yield the best results. Our model shows better accuracy when compared to existing approaches.

**Table 3:** Computed forecasting error in according to different lags

Techniques	Feature set	$\alpha$	$\beta$	$\gamma$	$\delta$	$\epsilon$	$\zeta$	$\eta$	$\theta$
Decision Trees	MSE <sub>R</sub>	40.638	30.318	28.998	27.678	26.358	26.356	26.35	26.352
	MAE <sub>R</sub>	32.873	22.553	21.233	19.913	18.593	18.591	18.59	18.587
DenseNet [16]	MSE <sub>R</sub>	24.918	23.598	22.278	20.958	19.638	19.636	19.63	19.632
	MAE <sub>R</sub>	17.152	15.832	14.512	13.192	11.872	11.87	11.87	11.866
AlexNet [27]	MSE <sub>R</sub>	26.533	25.213	23.893	22.573	21.253	21.251	21.25	21.247
	MAE <sub>R</sub>	18.768	17.448	16.128	14.808	13.488	13.486	13.48	13.482
SVR	MSE <sub>R</sub>	38.372	28.052	26.732	25.412	24.092	24.09	24.09	24.086
	MAE <sub>R</sub>	30.606	20.286	18.966	17.646	16.326	16.324	16.32	16.32
NGT-SOA	MSE <sub>R</sub>	4.331	3.799	3.119	2.688	2.108	1.997	1.886	1.775
	MAE <sub>R</sub>	2.46	1.885	1.244	0.997	0.664	0.553	0.442	0.331

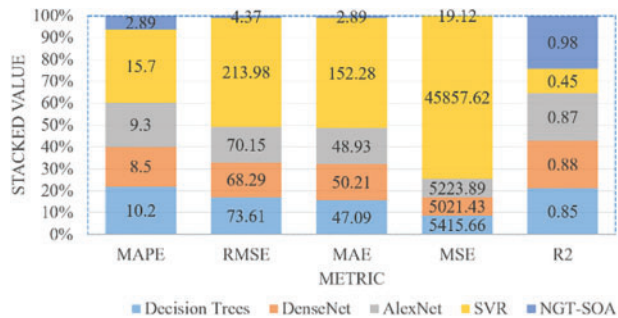
This study employed Decision trees, DenseNet, AlexNet, Support Vector Regression (SVR), and other power price forecasting methods. The NGT-SOA model, with optimized parameters, displayed accurate forecasts as seen in Fig. 7 for December 2023. Fig. 8 compares various regression techniques, highlighting NGT-SOA’s consistent superiority with higher R2, lower MAE and MSE values, and improved accuracy and recall. These results affirm the effectiveness of NGT-SOA in providing precise and reliable hourly spot price forecasts.



**Figure 7:** Forecasted price of last month of 2023

**Optimization of Cloud Datacenters:** Our cost-saving model, employing NGT-SOA and incorporating the IoT real-time data, achieved a notable 25.31% reduction (CAD 1805.66). The model introduced randomness in server and node capacities, implementing a One-and-Off strategy for efficient server shutdowns during downloads. TN(4.2) GB capacity nodes, optimized for energy efficiency, were utilized. The analysis excluded data execution and transfer costs, underscoring the importance of a comprehensive understanding of cost savings through storage offloading. Despite limitations, our results demonstrated better-than-expected outcomes, yielding up to 24.21% cost savings over two weeks for a four-server data center. Scaling to larger data centers (4,000 servers) could potentially result in annual savings of CAD 48.3 million, accounting for potential alterations in actual energy

usage. Our findings underscore the impact of increasing server size on computation time in large data centers, discouraging node and server rescaling as it would not significantly influence outcomes. Maintaining consistent power consumption during data download is crucial for reducing storage-related power consumption. Reducing nodes does not change estimated expenses or savings but ensures high throughput. For example, with Ji TN(2,1) and YN = 3 and ji YN(910,20), a 25.21% cost savings of CAD \$1,000 was achieved, emphasizing the efficiency gains facilitated by IoT integration.



**Figure 8:** Performance metrics results

Table 4 demonstrates the effectiveness of offloading storage to specific nodes, exploring varying storage node prices and emphasizing potential cost savings. Our research suggests that increasing standard deviation (std.) leads to significant cost savings. For instance, increasing it from 0.2 to 0.5 removed roughly a half of the resources that were saved. The NGT-SOA technique, proposed here, holds substantial potential, especially in logistics and industrial IoT, benefiting sectors like manufacturing, transportation, and energy with real-time electricity price forecasting for optimized operations and informed decisions. The scalable model offers a promising future for cloud-based resource management systems.

**Table 4:** Optimized results of cost of every node

Standard dev.	Cost_saving (%)	Cost_saving (EUR)
0.3	19.23	1450.22
0.7	9.22	710.22

## 7 Conclusion

This study introduces a specialized deep learning model for predicting energy prices in Oslo's unique Norwegian energy market, incorporating the transformative potential of the IoT. The focus is on using the upward trajectory of power expenses to enhance energy efficiency in cloud data centers through strategic data offloading. Addressing the challenges posed by fluctuating power prices in the Nord Pool market, the study estimates Ontario's power revenues, specifically the typical spot price, for 2016–2023. Our cost-saving model, rigorously tested in various default settings, demonstrates a significant 65% cost reduction. Innovative data storage technologies, coupled with IoT real-time data integration, yield accurate price projections (MAE 5.42, MSE 2.89), resulting routinely in energy cost reductions of up to 29.66% in data centers. While these outcomes are from a smaller-scale platform, they suggest even higher savings in a larger scenario. Our framework will evolve by incorporating additional variables and addressing shortcomings, enhancing its applicability to a broader range of



real-world situations. Including load and energy forecasts, particularly leveraging IoT data, holds potential to further enhance forecasting performance in future iterations.

**Acknowledgement:** The authors would like to thank the Deanship of Scientific Research, Prince Sattam bin Abdulaziz University, Al-Kharj, Saudi Arabia, for supporting this research.

**Funding Statement:** The authors extend their appreciation to Prince Sattam bin Abdulaziz University for funding this research work through the Project Number (PSAU/2023/01/27268).

**Author Contributions:** The authors confirm contribution to the paper as follows: Study conception and design: M.A, H.A.A, and N.A; data collection: N.A; analysis and interpretation of results: M.A, H.A.A, and N.A; draft manuscript preparation: M.A, H.A.A, and N.A. All authors reviewed the results and approved the final version of the manuscript.

**Availability of Data and Materials:** The authors confirm that the data supporting the findings of this study are available within the article.

**Conflicts of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

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