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Research Article

Integrating AI-Driven Deep Learning for Energy-Efficient Smart Buildings in Internet of Thing-based Industry 4.0

Mohamed C. Ghanem [1,*], Said Salloum [2]

[1] *Cybersecurity Institute, University of Liverpool, Liverpool L69 7ZX, United Kingdom, UK.*
[2] *School of Science, Engineering and Environment, University of Salford, United Kingdom, UK.*

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ABSTRACT

The integration of Industry 4.0 technologies has paved the way for rapid advancements in smart, energy-efficient buildings. This research focuses on optimizing energy consumption in IoT-enabled infrastructures through the application of data-driven modeling techniques. A comparative analysis is conducted using several machine learning and deep learning models, including Random Forest (RF), Gradient Boosting (GB), Deep Neural Networks (DNN), and Artificial Neural Networks (ANN). These models are trained and validated using real-world datasets, with appropriate preprocessing methods applied to enhance data quality. Evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Scatter Index (SI) are used to measure performance. The findings suggest that RF and GB models strike a practical balance between accuracy and computational efficiency, while DNN delivers the highest predictive accuracy but demands significantly more processing power.

1. INTRODUCTION

Integrated cutting-edge technologies like IoT, AI, and Big Data have transformed industries around the world in recent years thanks to Industry 4.0[1]. Buildings that are energy-efficient and smart are becoming increasingly important in a world that demands sustainable and intelligent infrastructure. IoT-enabled smart buildings are using AI-driven deep learning methodologies to optimize energy consumption and improve operational efficiency. Data analytics, predictive algorithms, and automation will enable us to coexist in harmony with energy sustainability and technological advancement in the future. AI-driven deep learning, IoT, and smart buildings are explored as synergies within Industry 4.0, illustrating their combined potential to redefine energy efficiency and environmental responsibility in industrial and residential environments. Many industries, including energy management, have become more innovative due to artificial intelligence (AI) [2]. Global urbanization and climate change have made it increasingly important for urban areas and buildings to optimize energy efficiency [3]. In smart buildings, AI-driven technologies can reduce energy consumption, operating expenses, and environmental impact by using cutting-edge sensors and automation [4]. Artificial intelligence-driven innovations extend not only to individual buildings but also to the development of smart urban areas that integrate digital technologies for energy efficiency and sustainability [5]. As this trend continues to grow, it is essential to understand how artificial intelligence and digital transformation can revolutionize energy efficiency practices [6]. This literature review investigates how smart buildings and metropolises are being transformed by AI-driven innovation. This paper examines the implications for urban development in the future of integrating AI and digital technologies into energy management systems, along with the advantages and challenges of integrating AI and digital technologies into energy management systems. As a result of the review, policymakers, urban planners, and technology providers will have greater insight into how AI-powered solutions can enhance the efficiency of the energy grid. Based on academic and industrial sources, it examines how artificial intelligence is impacting energy management. With the help of artificial intelligence and digital transformation, smart meters, building sensors, and weather data are being analyzed to improve energy management [7]; as a result of these technologies, predictive maintenance, real-time monitoring, and automated energy adjustments can be achieved to maintain comfort and functionality while optimizing energy use [8]. Integration ensures more efficient energy use and reduces waste, improving the overall efficiency of buildings' energy systems [9], [10]. Buildings and urban areas can benefit from this transformation as they will become more energy-efficient, sustainable, and adaptable to the demands of modern life. An overview of the progress being made in energy efficiency

*Corresponding author. Email: mohamed.chahine.ghanem@liverpool.ac.uk

through AI will be presented in the first half of the article, followed by a discussion of the drivers driving demand for better energy management systems. Smart buildings are being revolutionized by Artificial Intelligence (AI), particularly by optimizing energy usage and increasing operational efficiency [11], [12]. Using Artificial Intelligence (AI) to predict maintenance, adjust control, predict loads, create demand response strategies, and analyze occupancy and behaviour is revolutionizing energy management in modern buildings [13]. The use of AI in smart HVAC systems, energy-saving algorithms, and occupancy monitoring can significantly reduce energy costs and improve building performance.

2. RELATED WORK

There are significant gaps in the literature despite the use of artificial intelligence and the Internet of Things (IoT) in optimizing energy systems. Despite offering valuable insights, [14] and [15] indicate areas that need more investigation. A useful method for detecting faults in wind farms is to use AI-assisted inspections, as discussed in this article. It focuses primarily on human-AI interactions, neglecting the wider human factors in AI adoption. The effectiveness of AI in maintenance settings can be affected by a variety of factors, including user interfaces, training protocols, and cognitive load [16]. Furthermore, integrating human expertise with AI-driven decision-making tools across different sectors could offer deeper insights into improving predictive maintenance. Author [14] discusses the impact of artificial intelligence on renewable energy, including predictive maintenance and energy optimization [6]. When managing intermittent energy sources such as wind and solar, it is still unclear whether different AI methods are more effective than those when managing more stable energy sources. Integrated grid technologies and emerging AI technologies need to be explored further to overcome these challenges[17].
The author [15] focuses on how artificial intelligence and neural networks can be used to forecast solar energy. However, the authors' recommendations on forecasting techniques and standardized datasets are still far from being implemented. In the study, benchmarking and standardized evaluation methods are emphasized, but no detailed strategies are provided for integrating them into practice. There is a need to develop frameworks for standardizing datasets and evaluation metrics, making sure that these standards are applied consistently across different forecasting models and applications in the future. In the same way as traditional machine learning approaches, deep learning approaches rely heavily on data in order to optimize their hyperparameters. In the same way as traditional machine learning approaches, deep learning approaches rely heavily on data in order to optimize their hyperparameters.
Author [18], used LSTM to develop a prediction model for renewable energy production. South Korea's renewable energy supply was estimated using a hybrid model combining LSTMs and variation autoencoders [19]. Wind energy utilization was predicted by the author through the use of a nonlinear mapping system [20]. Researchers in [21] evaluated the performance of LSTMs, RNNs, and GRUs in energy utilization forecasting. LSTM-RNNs, such as the one used in this study, are capable of improving individual neural networks' prediction ability [22]. There are several areas where the authors [23] have shown considerable promise to promote sustainability. Artificial intelligence and deep learning are discussed in this article, emphasizing their contribution to the Sustainable Development Goals. AI and DL are discussed in this article, emphasizing their contribution to the Sustainable Development Goals[24]. The article discusses recent developments in AI and DL, emphasizing how these technologies contribute to the Sustainable Development Goals. In spite of these rapid developments, strict regulations are required to ensure that these technologies are ethical, safe, and transparent. With the help of artificial intelligence and deep learning, renewable energy systems remain stable. Moreover, they may aid in improving waste management and predicting the performance of solar power plants. In the field of environmental health, AI and DL are useful for predicting illness, enhancing exposure modelling, and analyzing complex geographical data. Although these developments have been made, a number of issues still need to be addressed. Data scalability, high dimension, ethics, privacy, and understanding and utilizing AI and DL models transparently are some of the critical issues that must be addressed. As part of the implementation of these technologies, it will be necessary to address the following important issues. As technology advances, engineering and construction businesses are being impacted by big data. In response to this confluence, two paradigms have emerged: Intelligent Construction 4.0 and Sustainable Construction 5.0 [25]. Building processes are made more efficient and sustainable by using big data, sophisticated computational models, and IoT technologies. In 4.0 and 5.0, construction is integrating and becoming more intelligent by relying heavily on data-driven decision-making and automation.

3. METHODOLOGY

In India, efforts are being made to increase the efficiency of buildings. As part of the National Mission for Enhanced Energy Efficiency, the Government approved a policy in 2009. The Energy Conservation Building Code (ECBC) has been adopted by the Ministry of Power and Bureau of Energy Efficiency (BEE), and a minimum building standard was established in 2007 [26]. A mandatory ECBC will be implemented in upcoming years by the Ministry of Urban Development and the Bureau of Economic Empowerment. Furthermore, the Ministry of Environment and Forests undertakes environmental projects in addition to environmental impact assessments. Environmental impact assessments are just one of the environmental projects undertaken by the Ministry of Environment and Forests. GRIHAs (integrated habitat assessments) are the responsibility of the Ministry of New and Renewable Energy. A three-star building will receive Rs. 2.5 lakhs, a four-star building will receive Rs. 5.0 lakhs and municipal corporations may receive Rs. 50 lakhs for a five-star building.

3.1. Energy Conservation Building Code (ECBC)

Energy conservation building code (ECBC) is a standardization guide prepared by India's Ministry of Power. The ECBC provides energy efficiency guidelines for buildings as one of its key functions. Buildings with ECBC are estimated to consume 40 to 60% less energy than those without. In addition to buildings with more than 500kW of load, ECBC applies to complexes of buildings as well. In general, buildings or complexes with an area of more than 1000 m2 belong to this category [26], [27].

3.2. Data sizes

We collected energy consumption data from two weeks [28] to 4-year energy [29], [30]. If you process a small dataset, you might not get a representative sample, and if you process a large dataset, you may have to spend a lot of time calculating results. In 56% of the studies, datasets were 1 month or longer. In 9%, they were shorter than 1 month, and in 31%, they were longer..

3.3. Data preprocessing

In order to avoid problems with inaccurate or inconsistent data, it is essential to preprocess data before using it [30]. As part of preprocessing, data may be cleaned, integrated, transformed, and/or reduced. Data cleaners correct (complete, modify, replace, and/or remove) information that is incomplete, inaccurate, irrelevant, or noisy. Sensor data is typically noisy and incomplete, for instance [31]. Integrating data from multiple sources involves combining them. The outdoor weather conditions and hourly electricity consumption data for training and testing, for instance, come from different sources. An algorithm for learning transforms data into the format it needs. It is possible to normalize, smooth, aggregate, disaggregate, and/or generalize data. Reducing the dataset can make a machine learning algorithm more efficient and improve its performance by removing non-discriminating features. Data reduction can also be achieved using kernel component analysis (KPCA) instead of principal component analysis (PCA). For instance,[32] used PCA and KPCA to reduce the data's dimensionality and compared SVM presentation with PCA, SVM performance with KPCA, and SVM performance without any data reduction. C-means clustering was also compared with fuzzy C-means (FCM), fuzzy SVM, and FCM-SVM.

3.4. Machine Learning Algorithm

Analyzing input data and making predictions from it is the purpose of a machine learning algorithm. It is generally the case that these algorithms make more accurate predictions as new data is fed into them. While there are some variations in how to categorize machine learning algorithms, they can generally be categorized by their purposes and how they are taught.

XGBoost Machine Learning: The purpose of this section is to illustrate how a decision forest can be used to generate an appropriate decision tree. Forest-based trees (FBT) are extended and refined in the presented method [33]. Combination set generation has been refined, allowing multiple building blocks to be included in the decision forest. The data properties were refined to consider them parallel to the previously trained trees' dependencies on the base trees. As opposed to its previous version, which focused on ensembles with independent base models (such as random forests and extra trees), the present method addresses ensembles with dependent base models. The method needs to be adjusted in order to take into account the relationship between the source decision forest and the original training set instead of focusing solely on its internal structure. Further, the user can adjust the maximum tree depth to achieve an optimal balance between prediction performance and tree complexity.

This observation has (x, y) being an m-dimensional vector of m features, $y \in [0, C]$ being a target variable, and C being the number of classes. A decision forest $\tilde{f}$ is built by aggregating the K base tree outputs for a given feature vector x using g, which generates class probability vectors on the basis of K base trees $\{T_1, \ldots., T_k\}$. A trained decision forest can be used to infer new instances by following the steps below:

$$\tilde{f}_x = g(\{h_{i[x]\ldots\ldots}h_{k(x)}\}) \tag{1}$$

A forest's type determines g functionality. A random forest would calculate G using the average of a base tree's probabilities, while an XGBoost would compute G by maximizing the base tree's logarithms. As an input, F is used to generate a new tree T with the following approximate predictive performance:

$$\forall x, t_x \approx f_x \tag{2}$$

By making decision trees interpretable without compromising their predictive performance, this method expands the toolbox of machine learning practitioners. According to their main premises, both decision trees and decision forests are finite conjunctive rules. A new [33] is updated to be compatible with GBDT, allowing users to control prediction performance and complexity better.

Random Forest: Random Forests (RF) are ensemble classifiers made up of many DTs, just like forests are made up of many trees [26]. When deep DTs are trained, they are often overfit to the training data, causing a high variation in the classification outcome. Due to their sensitivity to training data, they make mistakes in testing. Training datasets are divided into different parts and used to train different DTs of an RF. Every DT of a forest must pass down a new sample's input vector for classification. The classification results are then determined by each DT taking into account a different part of the input vector. For discrete classifications, the classification is chosen based on which tree has the most votes (for numeric classifications, the average of all trees is used). RF algorithms take into account the outcomes from many different DTs, reducing the variance caused by considering a single DT per dataset. This figure illustrates how the RF algorithm works.

3.5. The Generalized Linear Model

As a result of combining the systematic and random components of our model, we have finally produced a generalized linear model. The characteristics of this are as follows:

- Section 1.1 describes dependent variables z whose distributions have the parameter θ
- An independent variable $x_1, \dots, x_m$ and a predicted variable $Y = \sum \beta_i x_i$ (see Section 1.2)
- An $\theta = f(Y)$ linking function connecting the z parameters with the linear model's Y parameters

$\theta = Y$ corresponds to θ, σ^2, and when $\theta = Y$ corresponds to normal errors in a linear model

The various exponential distribution types will be described in Section 3, along with other examples of these models. As the next step, we will use iterative weighted least squares to solve the maximum likelihood equations for the parameters of the generalized linear models.

3.6. Artificial Neural Network (ANN)

As a test dataset (RT), ANN is used to detect the fitness of each particle based on an accurate classification of records. Test records can be selected randomly from the entire dataset; however, in this study, only high-ranking records are considered. This dataset now includes a 'ranking' column to help identify high-ranking records. Rank is incremented if this record is included in the dataset received. To determine the accuracy of classification, RTs determine how many records are used. An adaptive neural network is proposed as a tool for learning. A proposed PSO's evaluation process includes both past and future experiences with the proposed PSO. To improve its accuracy, the proposed ANN can be retrained as new datasets are created. Data is initially used to train the proposed ANN. Smart devices, like computers and smartphones, are used to conduct training. Once the ANN has been trained and its internal weights have been determined, it enters the running mode, which is where it makes decisions based on the sensors' readings and its weights. The new dataset is preprocessed and summarized when it appears. Once that is complete, adaptive ANN training will begin again. In Figure 1, we show the proposed structure for an adaptive ANN. The input layer and output layer sizes are adaptive, meaning they can be adjusted based on the data available. A fully interconnected ANN is proposed. Initially hidden layer units are connected to input layer units. Each unit in the first concealed layer has a connection to the next one, and so on. An ANN with sigmoid units is proposed. Construction of the sigmoid unit takes place. An input set is calculated linearly by the sigmoid unit's first part. A threshold is then stratified according to the computed value. With the help of the backpropagation algorithm, the proposed ANN was trained to remove the affluent diversity of nonlinear decisions.

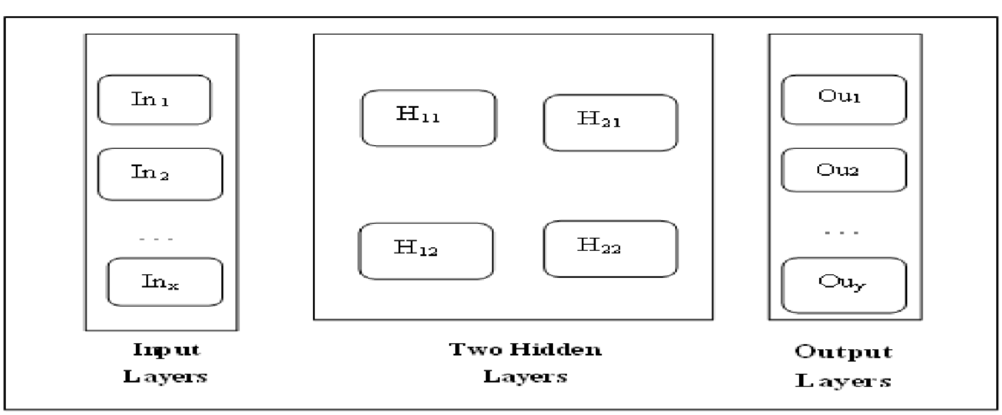

Fig. 1. Adaptive neural networks: a proposed structure.

Our reliance on backpropagation algorithms is due to their excellent results in many real-world applications. As part of the algorithm, the output value is compared with the target value and the squared error is reduced. An altered weight updating rule has been incorporated into the proposed ANN's backpropagation algorithm. Equation (3) shows how it is affected by momentum, another term:

$$\Delta w_{ij}(n) = \eta \sigma_j x_{ij} + \alpha \Delta w_{ij}(n-1) \tag{3}$$

When n is the loop iteration in the backpropagation algorithm, $\Delta w_{ij}(n)$ is the calculated value to update the weight value, η , is a constant positive learning rate, σ_j is the error term of unit j, and represents the momentum that is constant between zero and one. When a momentum term is used, the wind will keep winding in the same direction as before. A local minima can also be dealt with using this method. Local minima are also remedied using another method. A proposal for an ANN is developed in multiple versions. The same dataset is used for both training and testing, but at the beginning of the process, random weights are applied. In the classification process, high-performing versions are selected.

3.7. Support Vector Machine

SVMs with support optimization are used when there are multiple data classes. Malicious and benign classes exist in our case. A training set $x_t \in R^n$ has two classes $i = 1, \dots\dots, l; x_i, y \in R^l$, and $y_l \in \{1, -1\}$, each representing an active local node. Equation (4) illustrates how SVM solves optimization problems [34].

$$\begin{aligned} \min_{w,b,\xi} \quad & \frac{1}{2} w^T w + c \sum_{i=1}^{l} \xi_i \\ \textit{subject to} \quad & y_i(w^T \phi(x_i) + b \geq 1 - \xi_i \\ & \xi_i \geq 0, i = 1, \dots, l \end{aligned} \tag{4}$$

Equation (4) indicates that $\phi(x_i)$ is mapped into a higher-dimensional space by $C > 0$ and is a regularization parameter. Because the weights may have a high dimensionality, we solve the equation (2) [34].

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2} \alpha^T Q \alpha - e^T \alpha \\ \textit{subject to} \quad & y^T \alpha = 0 \\ & 0 \leq \alpha_i C, \qquad i = 1, \dots, l \end{aligned} \tag{5}$$

A semidefinite vector $e = [1, \cdots, 1]^T$, an l by l positive matrix Q, and a kernel function $Q_{i,j} \equiv y_i y_j K(x_i, x_j))$ are used in Equation (5). This section discusses our use of the kernel function. Equation (5) is solved first, then Equation (6) is solved to find the optimal value for w

$$w = \sum_{i=1}^{l} y_i \alpha_i \phi(x_i) \tag{6}$$

3.8. Deep neural networks (DNNs)

As with IoT communication networks, DNN inference networks have multiple layers. The IoT nodes represent the shallow layers of the entire DNN, extracting the information that enables data transmission and, therefore, can be viewed as DNNs. Based on the information sent from the IoT nodes, the base stations and cloud represent the deep layers of the DNN, which infer. The compression function $C_i(.)$ and the inference function $T(.)$ can be learned simultaneously using machine learning. In a DNN, layers are designed with and include the number of neurons in each layer. Following that, the DNN is taught its model parameters based on the compression and inference functions.

An example of a fully connected layer would be a function $\sigma(W_{x_{in}} + b)$, where x_{in} indicates the input of this layer, b indicates its previous layer, and $\sigma(\cdot)$ indicates the activation function, such as a sigmoid. If it is a fat matrix, the output will have a smaller dimension than the input, so the layer represents a compression; if it is a zero-dimensional matrix, it will create a high-dimensional vector by projecting a low-dimensional one. Composing multiple functions to represent each layer of the DNN is the first step in generating the compression and inference functions after the model parameters have been trained, as discussed in Section III.C.

3.9. Evaluation settings

A common statistical measure of the RF model's predictive performance in this study is the MAE, RMSE, and MAPE. As a normalization measure, the SI is calculated by combining the MAE, RMSE, and MAPE factors. These statistical measures are represented mathematically in equations (3) and (6) based on actual and predicted data. To evaluate the data mining tool WEKA, we used open-source software. We set the parameters of the RF model as follows. In accordance with the data mining tool's recommendation, batch sizes were set at 100. Prediction models are trained using the entire training dataset.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y - y'}{y}\right| \quad (7)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y - y')^2} \quad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y - y'| \quad (9)$$

$$SI = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{P_i - P_{min,i}}{P_{max,i} - P_{min,i}}\right) \quad (10)$$

y' and y represent predicted and actual data for hourly energy consumption; n characterizes the size of the data; m represents the number of performance measures; and Pi = i^{th}performance.

4. RESULTS AND DISCUSSION

A comparison of six machine learning models is presented in Figure 2 using five performance metrics: SI, MAPE, RMSE, MAE, and execution time. In spite of its high accuracy and low error rate, DNN has a very long execution time. Contrary to this, GB and RF are highly efficient and accurate. In comparison to ANN, SVM and GENLIN are less accurate and take longer to run, while SVM provides a moderate balance between accuracy and computational cost.

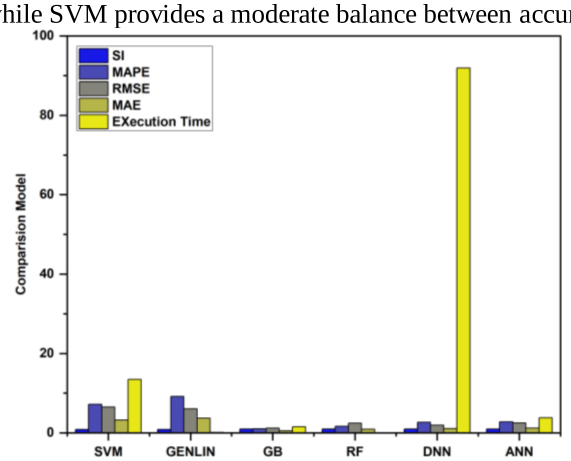

Fig. 2. An evaluation of machine learning models based on performance metrics and execution time.

As shown in Figure 3, a comparison between predicted and true values is shown across 31 samples using the Support Vector Machine (SVM) model. A blue line represents predicted values, while a yellow line represents true values. According to the SVM model, in most cases, the predicted and actual values align closely. In some instances, however, the model will underestimate or overestimate the actual value, particularly around samples 15, 17, and 30. Despite SVM's ability to track the overall pattern, it has difficulty predicting sudden fluctuations or peaks in data.

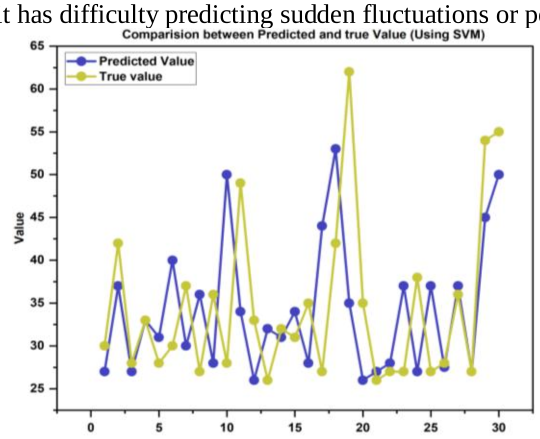

Fig. 3. Comparing the predicted value with the true value (using SVM).

Based on 31 samples, figure 4 shows the comparison between predicted and true values with Gradient Boosting (GB). A close correlation exists between predicted and true values, capturing both trends and sharp fluctuations as accurately as possible. With minimal deviations, the GB model provides accurate and reliable predictions.

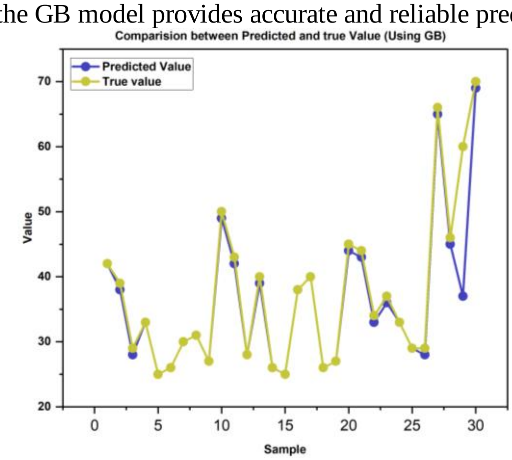

Fig. 4. GB will be used to compare the true values with predicted values.

An example of using the Generalized Linear Model (GENLIN) across 31 samples is shown in Figure 5. Generally, the predicted values tend to follow the true values, but there are some noticeable deviations, particularly around samples 19 and 26, where the model significantly underestimates the actual values. As a result, GENLIN is less efficient in scenarios with high variability since it suffers from difficulties predicting sudden fluctuations or outliers.

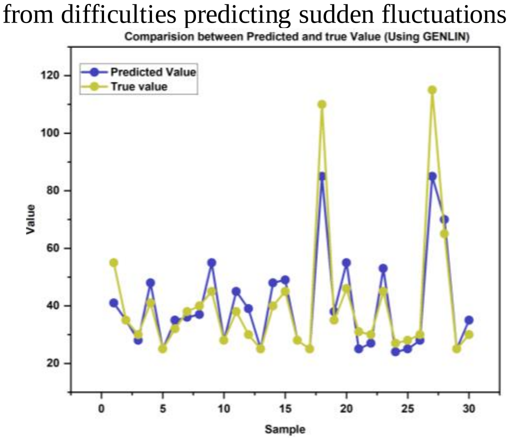

Fig. 5. Comparing predicted and actual values (with GENLIN).

Based on 31 samples, figure 6 compares predicted and true values based on the Deep Neural Network (DNN) model. Predicted values are close to true values, shown in yellow, indicating an accurate model. In addition to capturing overall trends, the DNN captures sharp variations like peaks around samples 2, 7, and 18. As a result of these close alignments across most of the samples, the DNN model was able to learn and replicate complex patterns in the data, providing highly accurate predictions.

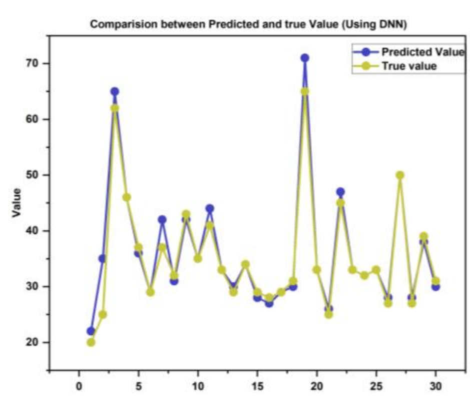

Fig. 6. In this example, we compare the predicted and actual values (using DNN).

As shown in Figure 7, 31 samples were used to compare the predicted and true values using Artificial Neural Networks (ANN) to optimize with Genetic Algorithms (GA). Blue indicates predicted values that are close to yellow values, demonstrating good predictive accuracy. A significant peak around samples 1, 3, 17, and 30 can be identified by the model, which effectively captures both the general trend and sharp fluctuations in the data. Based on this alignment, it appears that ANNs combined with GAs can learn complex patterns and make reliable predictions across a wide range of variables.

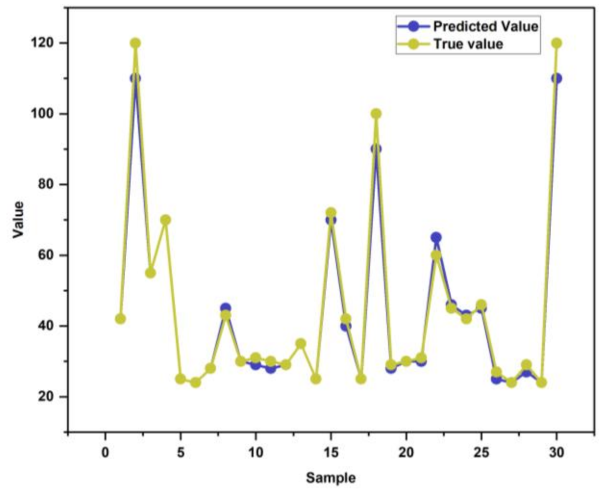

Fig. 7. A comparison of the true value and the predicted value using ANN and GA.

5. CONCLUSION

The advancement of smart buildings under Industry 4.0 can be significantly enhanced by leveraging deep learning techniques to optimize energy efficiency. A comparative evaluation of various models revealed that Deep Neural Networks (DNNs) deliver the highest accuracy in forecasting energy consumption. However, their substantial computational requirements may limit their applicability in scenarios requiring rapid processing. In contrast, models like Gradient Boosting (GB) and Random Forest (RF) strike an effective balance between prediction accuracy and execution speed, making them more practical for real-time applications. Additionally, combining Genetic Algorithms (GA) with Artificial Neural Networks (ANN) has shown considerable potential, especially in handling complex and nonlinear energy consumption patterns. The integration of IoT and intelligent modeling approaches offers a path toward more sustainable and responsive building management. Moving forward, the development of hybrid modeling strategies, the use of more diverse datasets, and the inclusion of ethical considerations in algorithm design will be essential for creating smart, energy-conscious urban environments.

Conflicts Of Interest

The paper states that there are no personal, financial, or professional conflicts of interest.

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