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RESEARCH ARTICLE

Convolutional Neural Network With Genetic Algorithm for Predicting Energy Consumption in Public Buildings

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ABSTRACT Due to their capacity to improve energy consumption performance, intelligent applications have recently assumed a pivotal position in the energy management of public buildings. Keeping these buildings' energy consumption under control is a significant issue because of their irregular energy consumption patterns and the lack of design criteria for energy efficiency and sustainability solutions. As a result, it is essential to analyze public building energy consumption patterns and predict future energy demands. Evidence like this highlights the need to identify and categorize energy use trends in commercial and institutional dwellings. This research aims to identify the most effective intelligent method for categorizing and predicting the energy consumption levels of buildings, with a specific study case of public buildings and, ultimately, to identify the scientific rules (If-Then rules) that will aid decision-makers in establishing the proper energy consumption level in each building. The goals of this research were accomplished by employing two intelligent computing models, the Elbow technique and the Davis and Boulden approach, to count the number of clusters of energy consumption patterns. We addressed clustering with K-means and a genetic algorithm. The genetic algorithm was utilized to find the best centroid points for each cluster, allowing the fitting model to function better. Determining which buildings consumed the most energy has been easier thanks to extracting If-Then rules from cluster analysis. Convolutional neural networks (CNNs) and CNNs combined with a Genetic Algorithm (GA) were also employed as intelligent models for energy consumption prediction. At this point, we utilized a genetic algorithm to fine-tune some of CNN's settings. CNN with genetic algorithm outperforms the CNN model regarding the accuracy and standard error metrics. Using a genetic algorithm, CNN achieves a 99.01% accuracy on the training dataset and a 97.74% accuracy on the validation dataset, with accuracy and an error of 0.02 and 0.09, respectively. CNN achieves a 98.03% accuracy, 0.05 standard error on the training dataset, 94.91% accuracy, and 0.26 standard error on the validation dataset. Our research results are useful for policymakers in the energy sector because they allow them to make informed decisions about energy supply and demand for public buildings.

INDEX TERMS Energy consumption, public buildings, convolutional neural network, K-means, genetic algorithm.

I. INTRODUCTION

Inefficient buildings, regarding energy performance, are the primary causes of global energy consumption and greenhouse

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gas emissions [1]; hence we must construct buildings that consume less energy and are better for the environment. Energy use in buildings substantially contributes to global warming, air pollution, and thermal pollution, all of which have far-reaching consequences for human civilization [2]. Population growth and rapid urbanization in the last few

decades have significantly increased the energy demand, notably in public buildings [3].

Researchers' interest in energy efficiency in buildings has sparked innovative machine-learning applications [4], [5], [6], [7], [8]. Predicting how much energy a building will need is crucial for saving resources and making informed choices that will result, in time, in lower energy consumption. However, energy consumption prediction is still challenging due to the many factors that influence such phenomena, such as the physical attributes of a building and the energy-use behavior of its residents [9]. ASHRAE, the American Society of Heating, Refrigerating, and Air-Conditioning Engineers, has divided models for predicting building energy use into two broad classes: forward models and data-driven models [10].

Forward models, also known as physics-based modeling approaches, necessitate numerous inputs about the building and its surroundings, including the HVAC (Heating, Ventilation, and Air Conditioning) system, insulation thickness, thermal properties, internal occupancy loads, solar information, and more [11]. DOE-2, Energy Plus, and TRNSYS are the most common examples of simulation tools that use this technique. Too numerous and often unobtainable parameters are needed by these models. Therefore, these methods can be ineffective because of the design and computing time they take and the lack of data they require [1].

Data-driven models, on the other hand, rely entirely on empirical data analysis. Many researchers have proposed these models for estimating building energy usage using machine learning algorithms [1], [3], [10], [12] since they do not need many specific inputs to the building structure. This technique is honed using data culled from BMSs – Building Management Systems and smart meters to create a large, comprehensive hourly or sub-hourly measurement dataset [13]. Data amount, data quality, and machine learning model selection are the three most important elements in determining how well these models can estimate future building energy usage [9].

Researchers have estimated that public buildings might reduce their overall energy use by 10%-30% if they had access to an energy modeling system with precise forecasts [3], [18]. As a result, efforts to improve building energy prediction must be maintained if we want more energy-efficient structures. Progress in data-driven models has led to accurate energy projections [19]. Greenhouse gas emissions, the development of less energy-efficient buildings, energy demand, and savings will all rise until a reliable algorithm for predicting building energy usage is found [20].

Numerous machine learning techniques for estimating future building energy use have been presented during the past decade [1], [3], [10], [11], [13]. Machine learning algorithms like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees have been used for estimating building energy use or consumption. Most of the data used to train and test these algorithms come

from datasets containing less than 1,000 buildings [1], [21], [22], [23], [24]. Since it is well-established that more quality data leads to more precise results, the limited sample size of these datasets may result in less-than-accurate model predictions [25], [26], [27], [28], [29].

The excellent results of Artificial Neural Networks (ANN) have led to their increased popularity in the field of energy prediction. It is well-documented that large and curated datasets provide the neural network with enough information to train a model and provide a significant advantage [30]. Reviewing the use of ANN for hourly building energy forecasting, Fei [31] found that the ANN algorithm yields good results in both single- and multi-step forward predictions [9]. Using a single dataset consisting of two six-story building blocks, ANN's prediction performance with the energy modeling and simulation tool Energy Plus. The findings indicated that data-driven approaches (ANN) are superior for building energy consumption prediction [32].

To forecast electricity demand in a single hospital based on weather data and time/day fluctuation, Chen et al. investigated the potential of multi-layer perceptron ANN. After being implemented, ANN forecasting excelled during the colder months [24]. Inga [21] was the first to propose a Support Vector Machine (SVM) to predict building energy consumption. When applied to predict monthly electricity consumption using four buildings based on meteorological data, the authors found that the SVM outperformed related research using neural networks, with a coefficient of determination (R^2) greater than 0.99. J. Lee et al. and Y. Long et al. used support vector machines to predict the hourly cooling demand of a single office building. Root Mean Square Error (RMSE) results for hourly load prediction using SVM showed good results [22], [23]. Moreover, Dong et al. tested ANN and SVM for forecasting hourly energy usage of office buildings using a dataset of 507 buildings. The model's input variables were dew point, atmospheric pressure, outside temperature, wind speed, etc., and building data (floor area, building type, etc.). According to Dong et al. [32], the RMSE for ANN was 5.71, whereas it was 7.35 for SVM.

Our study addresses optimization methods like GA to improve the accuracy of the clustering model and the CNN model. A metaheuristic approach is particularly pertinent when solving search and optimization challenges. It represents a procedure that uses one or more heuristics and, as a result, inherits all the characteristics of each heuristic. As a result, a metaheuristic method generally lacks strong evidence of convergence to the optimal solution, (i) is computationally faster than exhaustive search (ii), and (iii) tries to identify a near-optimal solution rather than the precise ideal answer. These techniques are iterative and frequently modify one or more original candidate solutions using stochastic procedures (usually generated by random sampling of the search space).

Despite the importance of precise predicts in comprehending building energy efficiency, none of the literature research

has used more than 1000 buildings in the dataset to train the model for better prediction performance, and based on the performance criterion used, none have achieved great prediction. We've mentioned that accuracy is extremely sensitive to the choice of modeling algorithm, data quality, and data amount [9]. Because diverse data and varied situations would yield distinct outcomes, the accuracy result of algorithms implemented on the different datasets is not directly comparable when assessing the optimal method [35], [36], [37], [38]. Therefore, it is not possible to say that one modeling method is superior to another without first analyzing and comparing them on the same dataset. A few studies have compared the various algorithms using the same data to see which provides the most accurate energy consumption prediction in buildings. To establish the most accurate approach to achieve this goal, our study applies the same dataset and conditions to several modeling algorithms.

Most studies examine the overall energy usage of various buildings. However, other influencing factors have yet to be considered, such as the consumption patterns of the buildings' inhabitants at peak times or during vacant hours (00h00-02h00; 06h00-08h00; 22h00-00h00). This research presents a cognitive computing model that automatically classifies energy use into discrete levels. To further minimize energy consumption and aid decision-makers in guiding the behavior of occupants in public buildings, we offer a hybrid intelligent model that combines a convolutional neural network with a genetic algorithm to predict energy usage. Our paper's impact is multifaceted, encompassing four areas:

- a) Combining K-means (KM) with a genetic algorithm (GA) to create a unique hybrid model for categorizing building energy consumption into levels (e.g., low, medium, and high). In addition, the best possible starting centroids in KM are identified with the help of GA.
- b) Combining a convolutional neural network (CNN) with GA to develop a unique hybrid model for estimating building energy consumption. Additionally, CNN parameters are optimized with the help of GA.
- c) Using a large dataset on the energy usage of public buildings in Portugal, collected in 2018 and 2019, to train and test our suggested models and assess their performance and accuracy (comprising 81 260 public buildings in 238 Portuguese cities).
- d) Proposing a state-of-the-art intelligent model for analyzing building-level energy consumption to improve public building energy efficiency.

The paper is structured as follows. In Section II, we discuss our relevant research. Research questions and methods are presented in Section III. In Section IV, we present and discuss the outcomes of our modeling experiments. In the final section, we conclude and make recommendations for further research.

II. RELATED WORK

The purpose of this section is to provide context for our proposal and to defend the choice of strategies to be compared in the experimental section by reviewing relevant prior work in the field.

To predict building energy use, Ouf et al. [16] fused a Bidirectional Long Short-Term Memory (Bi-LSTM) network with a Convolutional Neural Network (CNN). The dataset's discriminative feature values were extracted using a CNN, and predictions were subsequently made using a Bi-LSTM network. A novel ensemble-based deep learning model for anticipating energy usage and demands was introduced by Park and Son [17]. The dataset was first pre-processed with standard approaches, including transformation, normalization, and cleaning, before being input into the ensemble model, where the CNN and Bi-LSTM network extracted discriminative feature values. To enhance and guarantee the prediction performance of the proposed model, an active learning approach was developed in this study using the moving window. Following this phase, the provided model was evaluated on a Korean commercial building dataset using MAPE, RMSE, MAE, and MSE values to determine its efficacy. For predicting future electrical loads, Wen et al. [18] combined an Extreme Learning Machine (ELM) with Variational Mode Decomposition (VMD) methods. The VMD method was used to decompose the gathered electric load series into components with varying frequencies, reducing the impact of any inherent fluctuations, and improving the whole predictability. Finally, a differential evolution method was used in conjunction with ELM to forecast.

Salam et al. [19] integrated a Deep Belief Network (DBN) with linear regression methods to make predictions about time series data. In this investigation, the time series data's nonlinear and linear behaviors are captured using the linear regression method. The difference between the actual data and the anticipated data was first calculated using linear regression, and then the DBN was given that value to make its predictions. The DBN considerably isolates the characteristics between self-organization qualities and layers, making it useful for time series forecasting. For electric load forecasting, McNeil et al. [20] utilized Support Vector Regression (SVR) on time series data. The SVR method effectively modeled target variables' nonlinear relationship with exogenous factors. Transportation, banking, aviation, and power/energy are just a few of the many fields that have benefited from Inga [21]. 's novel multivariate temporal convolutional network for time series prediction. The provided convolution network markedly improved the outcomes in time series data forecasting. In addition, the balance between forecast precision and system complexity is investigated. To discover the most accurate results for forecasting building energy consumption, Lee et al. [22] used a genetic algorithm with a Particle Swarm Optimization (PSO) method to choose ideal hyperparameters in LSTM.

Long et al. [23] presented a novel oblique random forest classifier for time series forecasting. The created classification method swaps out each node of the decision tree for the best possible orthogonal classifier depending on the features available. Moreover, feature partitioning was accomplished using the least square classification method. The effectiveness of the oblique random forest classifier was studied using five electricity load time series datasets and eight general time series datasets. In addition, a novel deep-learning network for anticipating near-term energy loads was presented by Chen et al [24]. The achieved outcomes demonstrated the deep energy model's sturdiness and great generalization capacity in data series forecasting. Chen et al. [25] also used DBN in tandem with empirical mode decomposition to predict future power usage. Before anything further, the collected data series were decomposed into several Intrinsic Mode Functions (IMFs). Each of the retrieved IMFs was then modeled using the DBN for precise forecasting. Li et al. [26], who used a random forest classifier, predicted energy consumption using short-term energy consumption data. The random forest classifier was evaluated for its efficacy on five datasets spanning a year. As can be seen from the assessment results, the random forest classifier described here achieved higher MAE in terms of predicted accuracy.

Qavidel Fard et al. [27] developed an ensemble classifier for foretelling time series in large datasets using a mixture of random forests, gradient-boosted trees, and decision trees. After being put through its paces, the built ensemble classifier was shown to perform well when tasked with predicting time series data. Goyal et al. [28] introduced a novel stacking multi-learning ensemble model to predict time series data. The provided model incorporates three primary approaches (SVR, linear regression, and a backpropagation neural network), while the presented ensemble model incorporates four basic processes (integration, pruning, generation, and ensemble prediction tasks). For energy consumption prediction, Kabir et al. [29] established a hybrid model that combines a firefly algorithm with an Adaptive Neuro-Fuzzy Inference System (ANFIS) classifier; nevertheless, the enhanced search space diversity in the given model improves its predictive accuracy. For time series forecasting that considers several seasonal trends, Bourhnane et al. [30] presented a novel LSTM Multi-Seasonal Net (LSTM-MSNet). The results of the evaluation demonstrated that the given LSTMMSNet model outperformed state-of-the-art methods in terms of both computing time and prediction accuracy. To make accurate predictions of time series data, Fei et al [31] coupled multi-head attention with LSTM networks. Outlier, redundant, and null values were originally removed from the datasets using min-max and conventional transformation approaches by Dong et al. [32]. Then, a Gated Recurrent Units (GRUs) model was implemented in a Convolutional Neural Network (CNN) to predict energy use. The experimental assessment using MAE, RMSE, and MSE demonstrated the provided model's substantial performance.

Attempts have been made in the written literature to develop a computationally intelligent model for categorizing building energy use according to a variety of parameters that vary with the time of day and the state of the structure in question [6]. Stakeholders that want to increase the energy efficiency of buildings might benefit from identifying and categorizing energy load patterns of users in public buildings based on such consumption profiles. One of the techniques employed in the reviewed literature is K-means clustering. However, it does highlight a few problems. If the data you're trying to group is of varied volume and density, for instance, K-means won't be able to help you [32]. Second, outliers can cause centroids to shift [33]. To sum up, K-mean presumes that every variable is the same in terms of its variance [34], [36]. Therefore, the goal of our study is to improve upon the K-means clustering technique by discovering a more precise way of clustering. In addition, prior studies have shown that big data enabled considerable gains when employing a convolutional neural network to forecast building energy usage. Therefore, this research suggests a convolutional neural network and genetic algorithm (CNN-GA) hybrid intelligent model for estimating future energy needs. To improve accuracy and decrease the error rate, the GA was used to train the network to determine the ideal weights in network training. Therefore, the suggested model's adoption by energy sector stakeholders to make the appropriate judgments regarding high-energy-consumption buildings and to rationalize the inhabitants of such buildings to supply the required energy consumption.

By reviewing the literature, we learned that past research has struggled to locate data depicting building inhabitants' behavior throughout time. Furthermore, some articles employ conventional clustering approaches and statistical models like regression analysis without considering how well these methods cluster energy consumption into comparable groups or make predictions about those groups' levels. The decision-maker can be misled in several ways by inaccurate classification and prediction of energy consumption, including (1) the inability to find buildings with high energy consumption, (2) the inability to anticipate the energy required to cover the needs of public buildings adequately, and (3) the inability to identify the best energy providers. To address these gaps, in 2018 and 2019, a dataset on energy use in Portuguese public buildings was compiled. Public building energy usage classification and prediction models were trained and tested using this dataset. Our approach can help the energy industry's decision-makers make educated choices about the public sector's energy usage.

III. RESEARCH QUESTIONS AND METHODOLOGY

We posed the following questions to guide our investigation:

- RQ1: What data sources may we adopt to profile a building's energy consumption?
- RQ2: Which method(s) of intelligent computing may be adopted and/or modified to determine the energy

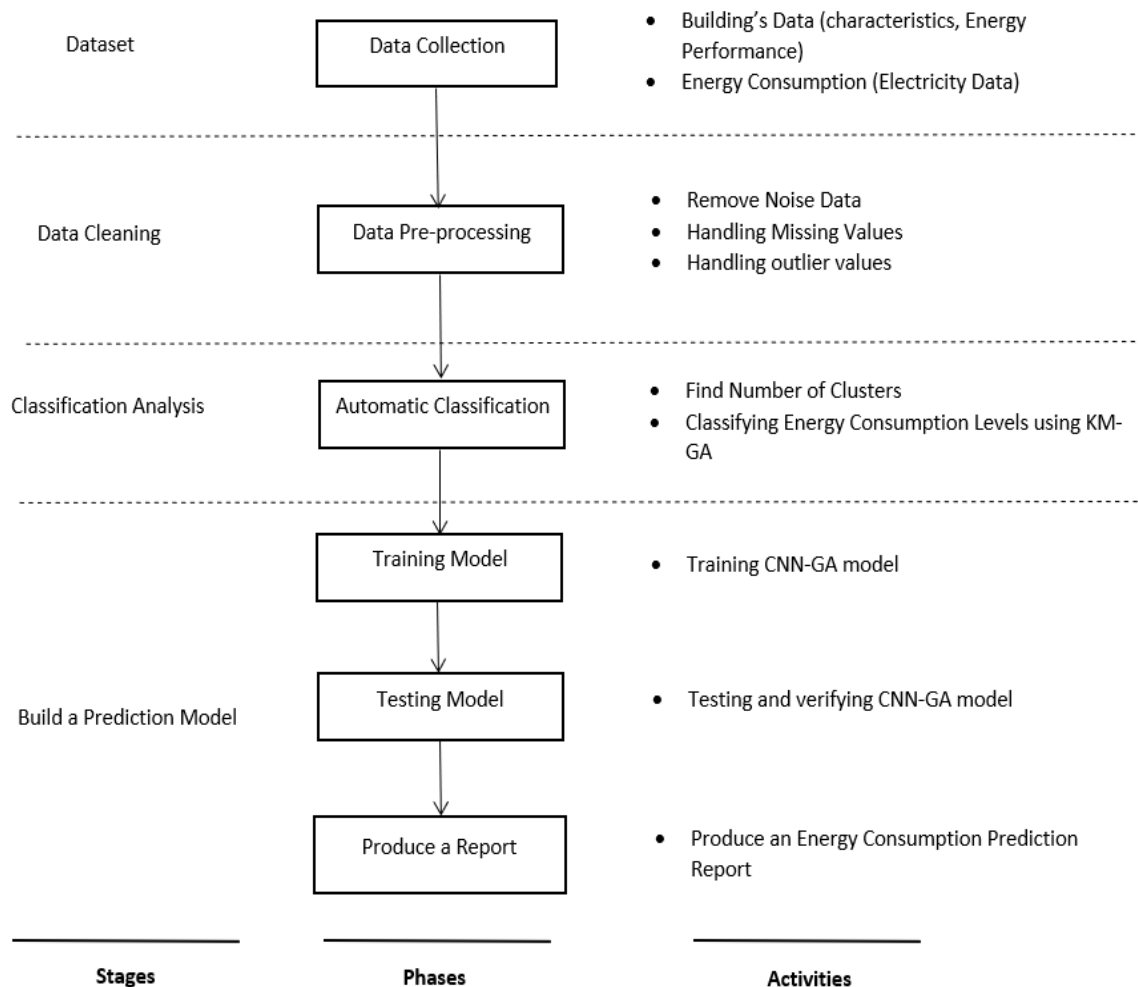


FIGURE 1. Our suggested model for categorizing and estimating building energy use.

consumption dataset’s cluster size and cluster characterization?

- RQ3: Which method(s) of intelligent computing may be adopted and/or modified to cluster and predict building energy consumption?
- RQ4: When analyzing the data on energy consumption, what are the most notable and distinctive trends that have emerged?

A hybrid approach (see figure 1) combining deep learning and optimization techniques, namely KM with GA [4], is proposed to address the posed research questions, with the KM-GA model and the CNN-GA model capable of clustering and predicting energy consumption in buildings, and a proof of concept of its application to public buildings in Portugal.

Steps to cluster and predict building energy use are shown in Figure 1. The stages that will be addressed in the methodologically detailed approach are as follows:

1. We gathered data on variables like energy usage and building features, including but not limited to delivery point IDs, delivery addresses, contractual electrical

power, electricity usage, and billing information broken down by month. The goal of this stage is to check that no significant changes were made to the underlying structure of the data, that all units of measurement are uniform, that sampling rates are sufficient, that the time series is stable over time, and that it is consistent with previous data. There are two parts to this:

- The makeup, behavior, and energy efficiency of the building’s data.
 - Use of resources (electricity data).
2. In this data preparation stage, we performed a thorough analysis of the data and, if necessary, changed it to disclose its information better. Outliers were removed using Isolation Forest (ISF), and missing values were filled in with polynomial interpolation. Three parts make up the whole process:
 - Clean up the data.
 - Treatment of missing data.
 - How to deal with extreme data (e.g., outliers).

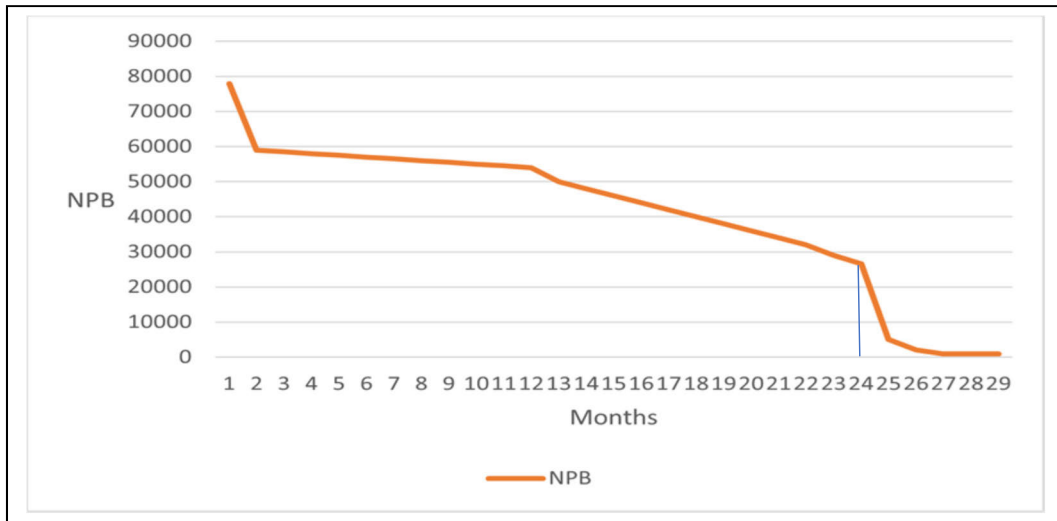


FIGURE 2. Structure counts in our data collection, with usage months ranging from 1 to 29.

3. Profiling energy consumption can be automatically sorted by categorization algorithms applied to the data. The Elbow approach and the Davis and Bouldin method were applied to our dataset to determine the total number of clusters. After this process, all samples (rows) in the energy consumption dataset have had their consumption levels classified using our KM-GA technique.
4. Two deep learning models, CNNs and CNN-GAs were used to train the data on energy use. These two models provided more precise and reliable energy usage predicting.
5. The two suggested models (CNN and CNN-GA) were tested for accuracy and error rate. We then picked the best model and proposed it to cluster energy consumption levels and assist stakeholders in making informed decisions about energy consumption.
6. Use the proposed methodology to build a report that predicts energy use, including which buildings will be more efficient and which will use more energy. As a result, this analysis aids decision-makers in the energy sector in three distinct ways:
 - Identify the highest energy-consuming buildings.
 - Estimating the energy consumption of future buildings
 - Assistance in switching energy providers, given the proper classification, and predicting the energy consumption of buildings.

A. DATA COLLECTION

This section analyses the energy consumption of public buildings (NPB) in Portugal, and the following features are considered in the analysis: The dataset comprises a total of 2,775,082 recordings, gathered monthly between 2018 and 2019, from 77,996 buildings in a variety of public sectors

throughout 238 cities in Portugal. The number of records used in this study was 1,222,695, corresponding to 26,624 public buildings, after excluding records of public lighting (since it is outside the scope of our study) and excluding buildings that do not contain consumption data for the full observed period of 24 months, as shown in figure 2.

Table 1 displays the attributes and dimensions of the two components of our dataset:

building characteristics and energy consumption.

B. DATA PREPARATION

This section presents our approach to data preparation, including treating missing data and addressing the exclusion of outlier values, using the Isolation Forest (ISF) method. Interpolation was adopted as a last resort in our research.

Much like random forests, ISF is constructed with decision trees. Without any externally provided labels, their implementation is unsupervised. The concept of “few and distinct” data points was crucial in developing isolation forests to detect outliers in our dataset. Information criteria like the Gini index or entropy were used to construct decision trees. Subtle differences are found after the more visible ones have been sorted out at the tree’s base and farther into its branches. An isolation forest processes the randomly subsampled data in a tree structure based on randomly selected criteria. There is a minimal chance that samples that go further into the tree and need more cuts to separate them are outliers. Similarly, samples closer to the tree’s root are likelier to be outliers since the tree differentiated them from the rest of the data on energy use.

ISF has two stages: (a) During the modeling stage, subsets of the energy consumption dataset are randomly selected to build the iTrees collection. (b) The evaluation phase uses iTrees to perform tests on data and keeps track of the path length for each test instance before calculating the

TABLE 1. Informational aspects of government buildings’ electrification use.

Dataset Dimensions	Attribute Name	Description
Buildings characteristics	Unique Energy Point Delivery ID	The ID of each public building
	Business Partner	Identification of the institution that owns or rents the building
	Building Address	Address of each building
	Municipality	City Location of each building
	Installation Type	Details of the electrical installation of each building
	Contracted Power	Power in MW which has been agreed with the operator for each building
	Year/Month	Consumption date
Energy consumption (Active Energy (KWh))	Simple	Total of active energy
	Super Empty	Active Energy (02h00-06h00)
	Empty	Active Energy (00h00-02h00; 06h00-08h00; 22h00-00h00)
	Outside Empty	Lighting and plug loads that cannot be turned off
	Peak	Active Energy (09h00-10h30; 18h00-20h30)
	Full	Active Energy (08h00-09h00; 10h30-18h00; 20h30-22h00)
	Total	Total energy consumption (Active plus Reactive Energy)

out-of-the-ordinary result. Then, it separates and detects any out-of-the-ordinary test findings [40].

iTrees are built in the modeling phase by periodically segmenting the provided dataset until all instances are separated or the tree achieves its maximum depth (MaxD) [35]. An abnormality score is then assigned to each instance based on the iTrees obtained in the previous modeling step. Here are the specifics of this stage:

- Let x . go through each iTTree in the model, recording its location at the end. At the root of every iTTree.
- First, using Eq. 1 and 2, calculate the path length of instance x and the abnormality score S ; Then, in Step 2, use the abnormality score to estimate instance x [41].

$$S(x, n) = 2(E(h(x)))/(c(n)) \tag{1}$$

$$c(n) = 2h(n1)(2(n - 1))/n \tag{2}$$

The average path length of instance (x) in each iTTree is indicated in Eq.(1) by $E(h(x))$. The average of $h(x)$ is represented by $c(n)$. It is used to normalize $h(x)$. Three situations can be found in $E(h(x))$ [42]:

- $E(h(x))$ equals zero, (s) equals one, which indicates that the likelihood of an abnormality for (x) increases if (s) score is very close to one.
- This suggests that if (s) reaches 0.5, (x) is not an essential anomaly. $E(h(x))$ equals $c(n)$, (s) equals 0.

- $E(h(x))$ equals ($n,1$), (s) equals zero, which indicates that (x) is more likely to be a standard instance if (s) is smaller than 0.5.

Authors often resort to interpolation, a pliable mathematical approach to determine compensation values or estimate unknown values based on related known values [43]. The energy consumption of public buildings may be represented graphically by computing unknown points using a consistent trend over a dataset.

Analyzing the ISF findings, we found that in some cases, the energy provider added zero and negative numbers to the consumption figures. This was due to compensating for prior consumption estimations in those buildings that lack smart meters and require periodic manual energy consumption readings, that deviate from the real consumption figures. We also understood that if we ignored these values, the total number of public buildings would drop to 10361, significantly reducing our sample size and making it more difficult to apply our models. This necessitated an interpolation technique to impute consumption values replacing the mentioned null and negative numbers. The Difference Table and the Lagrange method are only two of the many accessible interpolation techniques. Considering that the gaps between adjacent data points are not uniformly spaced, we used the Lagrange technique to fix the mentioned problems with negative and zero values. Building A, for instance, has a monthly energy usage of 500 kW in the first month,

TABLE 2. Polynomial degree structure [43] - various forms.

Polynomials	Degree	Examples
Constant Polynomials	Polynomials of a Certain Degree 0	3
Linear Polynomials	Polynomials of a Certain Degree 1	$x + 8$
Quadratic Polynomials	Polynomials of a Certain Degree 2	$3x^2 - 4x + 7$
Cubic Polynomials	Polynomials of a Certain Degree 3	$2x^3 + 3x^2 + 4x + 6$
Quartic Polynomials	Polynomials of a Certain Degree 4	$x^4 - 16$
Quintic Polynomials	Polynomials of a Certain Degree 5	$4x^5 + 2x^3 - 20$

200 kW in the second month, and 280 kW in the third month. Considering this, the disparities between the three months are not comparable.

We used the Lagrange approach to account for negative and zero values in our dataset, which requires three primary inputs, as shown in Algorithm 1 below.

The various types of polynomial degrees are shown in Table 2. Equation (3) [44], shows how the RMSE metric was used to determine the polynomial degree. Set n points at $(x_0, y_0), \dots, (x_n - 1, y_n - 1)$ and provide the corresponding function values in (c) to represent the array of $f(a)$ at each of the n points. Step 6 then involves computing the Lagrange polynomial that is built so that x_i is substituted for x to have a value of zero whenever $(j \neq i)$, and a value of y_i when $j = i$. The Lagrange polynomial obtained by summing these terms has the form $p(x_j) = 0 + 0 + \dots + y_j + \dots + 0 = y_j$ for each of the coordinates (x_j, y_j) . The interpolation results are then displayed using the equation in step 9 in Algorithm 1.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \tag{3}$$

where:

- The predicted value (compensation values for numbers less than 1 and 0 values) for the i th observation in the dataset is represented by the symbol p_i .
- The observed value (energy consumption dataset) for the i th observation in the dataset is denoted by the symbol o_i .
- The size of the sample is n .

Algorithm 1: Calculating offsets for the energy consumption dataset’s negative and zero values using the Lagrange interpolation method.

C. FINDING THE NUMBER OF CLUSTERS

We have utilized two literature approaches to find the best number of clusters for energy usage data: the Elbow method and the Davis and Bouldin method (DB). Finding the ideal number of clusters has been the focus of previous research using these techniques, particularly in the context of building energy use.

Regarding the Elbow method, if we plot the average inner per-cluster sum-squared-error (SSE) distance against the number of clusters, we may see an “elbow,” highlighting the optimal number of clusters. According to Eq. 4 [11], the

average distance between centers inside a cluster equals the average inner whole of squares (4).

$$W_k = \sum_{r=1}^k \frac{1}{n_r} + D_r \tag{4}$$

where:

- The distance between each pair of points *in a cluster* is denoted by D_r .
- Where k is the total *number of clusters* and
- n_r is the total number of *points in cluster r*.

The DB score is defined as the mean similarity between any two clusters. The similarity is defined as the ratio of distances between nodes inside a cluster, and distances between clusters. Thus, a better score is achieved by groups that are further apart and less dispersed. In Eq. (5) and (6) [16], scores closer to zero indicate better grouping.

$$DB(c) = \frac{1}{k} \sum_{i=1}^k (\max_{j \leq k, j \neq i} D_{ij}), k = |C| \tag{5}$$

For the i th and j th clusters, D_{ij} represents the within-to-between cluster distance ratios.

$$D_{ij} = \frac{d_i^- + d_j^-}{d_{ij}} \tag{6}$$

D_{ij} is the Euclidean distance between the centroids of the two clusters; d_{ij} is the average distance of all data points in cluster I to its centroid.

D. K-MEANS WITH GA

Informed by Charles Darwin’s notion of natural evolution, GA is a computing methodology that can be applied to several problems. The strongest and healthiest members of a population are encouraged to have children, ensuring that only the strongest and healthiest members of the following generation are born. Using GA speeds up implementing any fitness function, such as Euclidean distance, in the energy consumption dataset because of its proficiency in dealing with many points and its robustness in noisy situations. The formulae for the three fitness functions—Euclidean distance (ED), Manhattan distance (MD), and Cosine distance (CD)—show how GA was used to locate the best centroids in KM to expedite convergence between energy consumption locations (7, 8, 9). In addition, it contributes to a rise in KM’s precision in our approach.

Algorithm 1 Lagrange Interpolation Method to Find Compensation Values to Negative and Zero Values in the Energy Consumption Dataset

Input: n -Degree, Points: a_1, a_2, \dots, a_n , Function values: $f(a_1), f(a_2), \dots, f(a_n)$,

Evaluation point: X

Output: The value of the n th-degree Lagrange interpolant at point X

1. Answer = 0;
2. **For** I to n **do**
3. Product = 1;
4. **For** j to n **do**
5. **If** $I \neq j$
6. Product = (Product) $\times \frac{X-a_j}{a_I-a_j}$
7. **End**
8. **End**
9. Answer = Answer + (Product) $\times f(a_i)$
10. **End**
11. **Return** Answer

In GA, selecting the fittest members of a population is the first step in natural selection. They give birth to children who carry on their parent’s traits and join the following generation. More physically fit parents will produce children who will outperform them and have a higher chance of surviving. The fittest generation will eventually emerge as this process iterates repeatedly. A GA considers the following five phases: 1) initial population: The process starts with a population group of individuals. Every individual is a component of the answer to the issue we are trying to address. 2) Fitness function.

The fitness function assesses an individual’s level of fitness (the ability of an individual to compete with other individuals). Everyone receives a fitness rating from the system. Based on its fitness score, an individual’s likelihood of being chosen for reproduction is calculated. 3) Selection: During the selection phase, the best candidates are chosen and allowed to pass on their genes to the following generation. Two sets of individuals (parents) are chosen based on their fitness ratings. High-fitness individuals are more likely to be chosen for reproduction. 4) Crossover: The most important stage of a GA is crossover. A crossover point is picked randomly from the DNA for each set of parents to mate. Parents’ genes are exchanged until the crossover point is achieved, at which point offspring are produced. 5) Mutation: In some newly produced offspring, there is a small chance that one or more of their genes will experience a mutation. This suggests that a few bits in the bit string could be reversed. Mutation takes place to preserve diversity throughout the population and avoid early convergence.

The coordinates (x_1, y_1) of one point are used in the ED formula, while the coordinates (x_2, y_2) of another point are used to calculate the distance between the two points (x_2, y_2) .

$$ED = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{7}$$

MD represents the total absolute value of the coordinate differences. Here’s an illustration of how to calculate the MD

between two data sets: say $X = (E, M)$ and $Y = (B, K)$.

$$MD = |E - B| + |M - K| \tag{8}$$

CD determines the cosine of the angle formed by vectors X and Y .

$$CD = \frac{X \cdot Y}{\|X\| \|Y\|} \tag{9}$$

where:

$\|X\|$ = Mean Euclidean Distance of a Vector, $X = (X_1, X_2, \dots, X_n)$

$\|X\|$ = An example of a vector’s Euclidean norm, $Y = (Y_1, Y_2, \dots, Y_n)$

The procedures used by algorithm 2 to calculate the best KM centroids using GA are shown in the following scientific explanation. A sizable number of chromosomes (the energy consumption dataset, or ECD) are present at the outset of the ensemble. The goal of the GA is to select the best ECD centroids via the minimum standard error and the best possible chromosomal variance. This is done by computing ECD’s fitness function (ED, MD, and CD). Assume the execution has terminated after the given number of repetitions. ECD allows us to locate the most suitable centers. In this case, we must run the selection procedure and pick the two best chromosomes (2 ECD) from the population based on their fitness function value. We then choose any two chromosomes (ECD) at random from the population. The next step is to carry out the crossover procedure and locate the point of exchange: the parent exchange is a subset of a set of detached exchange points represented by binary values. We select two unrelated chromosomes at random from the pool of potential candidates. The resulting progeny would next undergo the mutation procedure, but with the bit positions flipped. Finally, we employ an elitist approach to ensure the continued presence of good chromosomes (ECD), create a new population from which to derive a fitness function, and repeat the preceding steps until the best centroids in KM are found.

Algorithm 2 GA Steps for Finding the Optimal Centroids in KM

Input: Size α of population,
Number σ of Iterations

Output: $\beta \leftarrow$ (Optimal Chromosomes (OptimalCentroids)).

1. Count $I = 0$
2. $C_k =$ Create random σ solutions
3. Compute fitness function (i) for each $I \leq C_k$
4. *While* ($\sigma \neq 0$)
5. *For* $I = 0$ to σ *do*
6. Pick chromosomes (ECD) for the contest.
7. Detect chromosomes (ECD) with the lowest fitness value.
8. Avoid chromosomes (ECD) with the lowest fitness value.
9. Estimate novel chromosomes (ECD)
10. *End For*
11. Execute the mutation method.
12. Estimate (mutated chromosomes((ECD))).
13. Compute fitness function (i) for each $I \leq C_k$
14. *End While*
15. $\beta =$ fitness values from C_k

Return β

Algorithm 2: Techniques for Locating the Best Centers in KM Using GA:

Clustering similar data points together to reveal hidden trends is one of KM's primary goals. It faces several difficulties. One of them is finding the sweet spot between the Elbow approach and the Davis & Bouldin method for settling on the ideal number of existing clusters. Secondly, we use GA to find where the centroid should be inside each cluster. For this reason, KM has been employed to predict the labels assigned to clusters across all ECD buildings, effectively clustering the level of energy consumption of each building. We built better KM clustering with the third algorithm by combining the Elbow technique, the Davis & Bouldin method, and the GA. To increase the accuracy of cluster label prediction across all ECD buildings, upgraded KM performs steps 1 through 4 to identify new centroid positions inside each cluster (see algorithm 3).

Algorithm 3: Cluster label predictions in each structure have been improved thanks to enhanced KM:

E. CNN WITH GA

In machine learning, CNN belongs to the deep learning category of algorithms. CNN's format was conceived with the brain in mind. Its name, "Convolutional," comes from the fact that rather than just multiplying matrices, it conducts a linear mathematical process known as convolution [27]. It is well-known for its efficacy in handling data with a grid-like architecture [27]. Dimensions range from one (for processing signals and text) to three (for processing images, audio, and video) and beyond.

To summarize, a CNN has an input layer, an output layer, and a set of hidden layers that comprises numerous convolutional layers, normalization, pooling, and fully connected layers. Consistently, a convolutional layer is used as the

initial hidden layer, and a fully connected layer is used as the final one. The input data's associated characteristics are identified with the help of the convolutional layer and then compared features are combined in the pooling layer. When N is the number of classes being categorized, the fully connected layer transforms the input into a vector with N dimensions [28]. The fundamental structure of a CNN is depicted in Figure 3.

A loss function is used to measure the quality of the classification at each iteration of the learning process. The network predict is compared to the current data, and a similarity measure is computed. The term "Local Receptive Field" refers to the fact that the neurons in the first hidden layer of a CNN are only coupled to a localized portion of the input (LRF). The weights and biases of each LRF are first generated at random [29].

Initialization of the weights is investigated here. Each convolutional layer's output is then subjected to a nonlinear activation function () in the layer that follows it. This is done so that CNN may learn where to draw the limits of its nonlinear decisions [26]. Activation functions like sigmoid, tanh, and ReLU are available and may be applied in many situations. Results may vary depending on the activation function used. The pooling layer will receive the data once the activation function has been applied. Pooling can be either maximal or average. Max pooling is a popular type [30] that uses the biggest value in each patch of each feature map in a matrix. Alternatively, the average pooling method just averages over all the cells in that region. The results of this computation are displayed in Figure 4. It's possible to add more convolutional layers, but the final layer is always a fully linked one, as seen in Figure 3.

The CNN classification model weights will be tuned with a GA optimization technique. While training the data, GA is

Algorithm 3 Improved KM to Predict Cluster Label in Each Building

Input: $K = 3$, // Specify the number of clusters using the Elbow method and the Davis & Bouldin method
 Initialize σ of centroids using GA.

Output: $\beta \leftarrow$ predicting cluster label in each building in ECD

1. **Repeat**
2. Assign each point to its closest centroid.
3. Compute the new centroid of each cluster.
4. **Until** the centroid positions do not change.

Return β

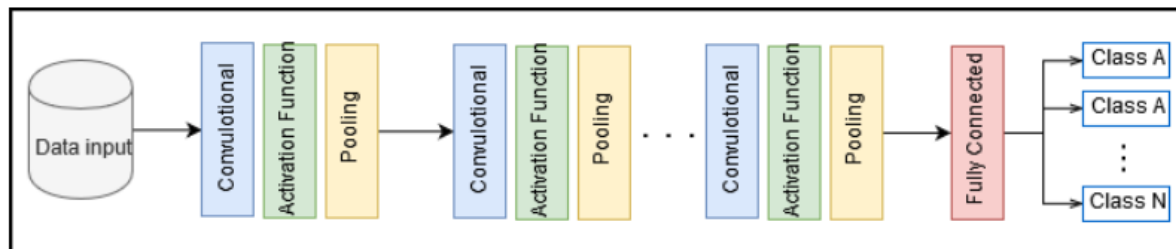


FIGURE 3. CNN architecture.

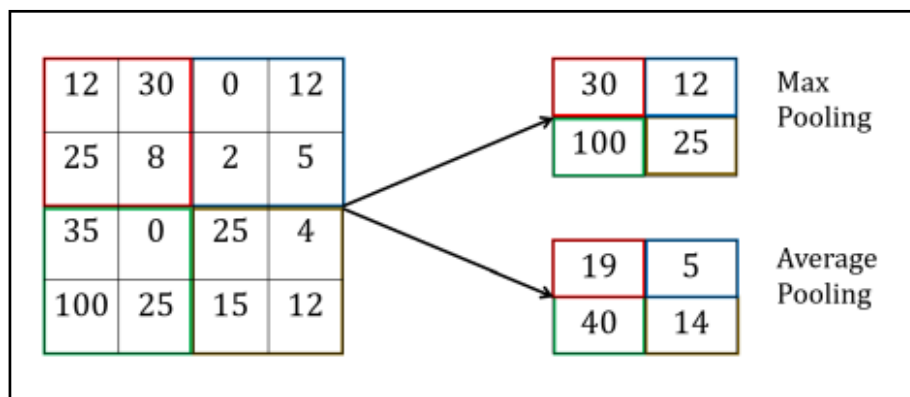


FIGURE 4. The pooling layer types.

used to determine the optimal model and weight values. To determine the classification accuracy, the training phase's best model is used to test data (see Figure 5).

The network weights are encoded in GA's chromosomes. The chromosomal count of the population is chosen at random. There are as many weight vectors as there are chromosomes. The training data's loss function (Mean Absolute Error; MAE) is the fitness function. Accordingly, when employing CNN, reducing the MAE of the training set becomes an optimization problem.

Python code that uses the fitness function to reduce loss has been developed. Eq. shows that the fitness value is the reciprocal of the loss value (10).

$$\text{fitness value} = 1.0/\text{loss} \tag{10}$$

The following procedures determine the model's fitness:

1. Get back the model's parameters from a one-dimensional vector.

2. Indicate the values for the model's variables.
3. In other words, guess what will happen.
4. Determine the monetary worth of the damage.
5. Find out how to fit you are.
6. Provide the fitness score.

With the release of PyGAD 2.8.0, a brand-new module known as Keras GA became available for use. Its full name, Keras Genetic Algorithm, is a mouthful, but the initials KGA suffice. Here are some of the features that may be accessed using the module:

- Use the Keras GA class to construct a starting population of viable solutions. All Keras model parameters are available within each solution.
- Utilize the model weights as vector () method, to display the Keras model's settings as a 1-dimensional vector, or chromosome.

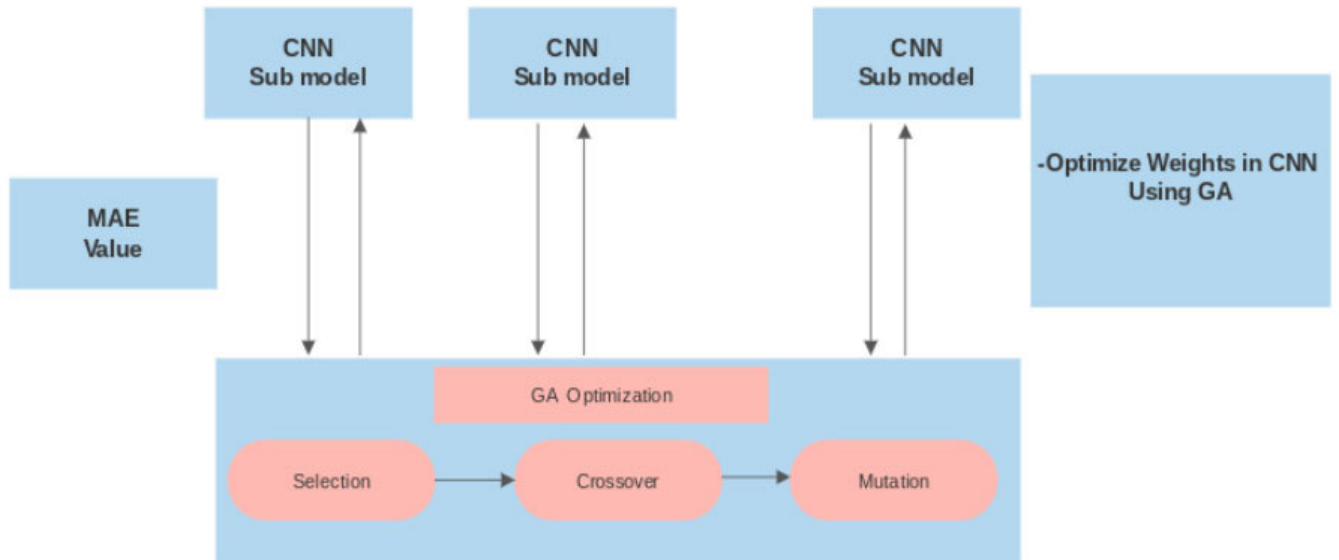


FIGURE 5. The proposed flowchart of the GA-enhanced CNN predictive model.

- The model weights as matrix () method in Keras may be used to get the model’s parameters from the chromosome.

Keras GA class generates three instance characteristics in response to these two parameters:

- Reference to the Keras model.
- Num solutions denote the total number of solutions in the population.
- Population weights: A doubly linked list containing the model’s parameters. When a new generation is created, this list is refreshed.

To get the best weight, use PyGAD and the code below to construct the fitness function. PyGAD’s fitness function is a standard Python function with two parameters. The first stands in for the solution, while the second is the fitness value. Knowing where a solution ranks among the population might be helpful in some circumstances, which is why it appears as the second argument.

A 1-dimensional vector representing the solution is given to the fitness function. Step 1 demonstrates how to use the `pygad.kerasga.model.weights` as a `matrix()` function to get the original Keras model parameters from the provided vector.

```
model = model, weights vector = solution, model weights matrix = pygad.kerasga.model.weights as matrix (Step 1)
```

In step 2, we see how the `set_weights()` function updates the model to use the previously saved values for the parameters.

```
model.set_weights(weights=model.weights.matrix) (Step 2)
```

Step 3 demonstrates how the model uses the `predict()` function to predict future results based on the current set of inputs.

```
model.predict(ECD) = predictions (Step 3)
```

The loss is determined by the accuracy of the predicted outcomes. As seen in Step 4, the MAE is employed as a loss function.

```
tens or flow. keras. losses. Mean Absolute Error () = mae (Step 4)
```

As indicated in Step 5, if the loss value is 0.0, it is best to add a small number, such as 0.00000001, to prevent a division by zero when determining the fitness value.

```
equation: solution fitness = 1.0 / (mae(data outputs, predictions)). numpy() + 0.00000001) (Step 5)
```

After the GA has been run and the optimal weights have been obtained, the CNN is executed to predict the testing set of buildings’ energy usage. CNN may be employed with only a single dimension. Nonlinearity is introduced via various layers, such as Convolutional layers, Pooling layers, Activation functions, and the Fully Connected layer. The Rectified Linear Unit (ReLU) activation function is used. Numerous studies ([22], [41], [42]) have shown its efficacy and excellent accuracy in estimating energy use; hence it was selected. In addition, max pooling is used, and there is a 50% chance of drops. In addition, we use a maximum gradient of 5.0, a learning rate of 0.0005, and 100 epochs to train the model. Due to the one-dimensional nature of the ECD representation, a 1D Convolutional Layer is used.

This is the structure that is used:

- Embedding Layer
- 1D Convolutional Layer (Conv1D)
- Max Pooling Layer (MaxPooling1D)
- Relu Activation •
- 1D Convolutional Layer (Conv1D)
- Relu Activation
- Max Pooling Layer (MaxPooling1D)

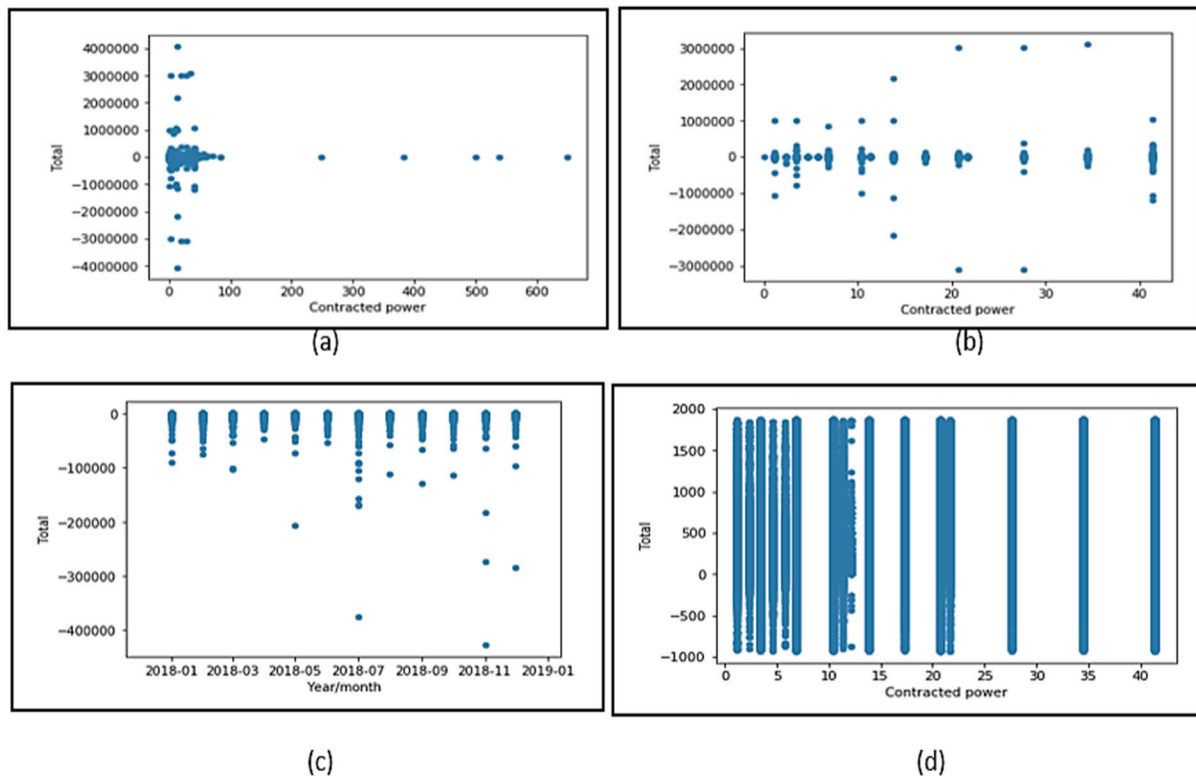


FIGURE 6. Data Pre-processing: (a) raw energy dataset, (b) public buildings that have several months less or more than 24 months and public lighting has been removed, (c) public buildings that contain negative and zero values have been interpolated, (d) outlier values have been removed.

- 1D Convolutional Layer (Conv1D)
- Relu Activation
- Max Pooling Layer (MaxPooling1D)
- Flatten Layer
- Dense Layer

Regarding testing and verifying the proposed model, 70% of the data is used for training, 15% for validation, and 15% for testing. The model is “trained” using the training data. Models are chosen based on the optimal solution (weight vector) that achieves the highest accuracy, as measured by the validation data. The suggested model is tested and evaluated with the help of the testing data. In addition, the accuracy and MAE are used to assess the proposed model, as indicated in Eq (11 and 12).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

$$MAE = \frac{1}{2} \sum_{i=0}^n |\theta - \Psi| \tag{12}$$

where:

TP=how many predictions the classifier made where it properly identified the positive class as positive.

TN=how many predictions the classifier made where it properly identified the negative class as being negative.

FP=the number of forecasts in which the classifier erroneously forecasts a positive class for a negative class.

FN=how many times the classifier misclassifies a positive class as a negative prediction.

θ = the actual/true value

Ψ = the predicted / estimated value

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This part is divided into four sub-sections: (1) data preparation, (2) cluster discovery, (3) K-Means with GA classification of ECD levels, and (4) CNN-GA prediction of ECD levels.

A. DATA PREPARATION

The success of any study involving intelligent machine learning methods depends entirely on the validity and use of the dataset. As a result, the efficiency with which one may construct and refine an intelligent model is greatly enhanced if the given dataset is of high quality. Additionally, the data on energy consumption comes from a real-world setting. As a result, removing noise and outliers is an essential part of the data preparation step. There are two phases in data preparation. Figure 6 depicts the initial stage of the procedure, which entails preprocessing and exploring the energy consumption statistics. In (a), contractual power (X_i) versus total energy consumption (Y_i) is shown for a subset of the

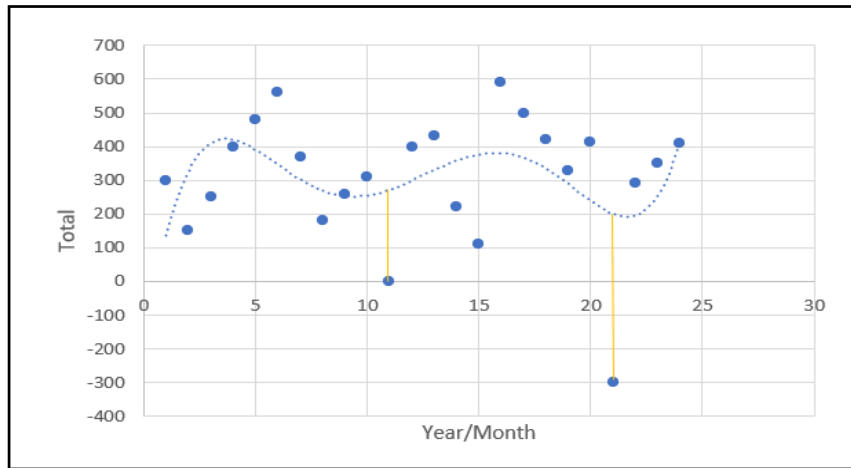


FIGURE 7. Data pre-processing (Stage 2).

raw dataset; (b) depicts public buildings with several energy consumption months less than or more than 24 months. These were eliminated, as were public lighting structures, because they were beyond the purpose of our research.

Figure (c) shows more negative and zero values that appeared in our dataset; therefore, interpolation method has been used to compensate these values to estimated values to keep the volume of our dataset. Finally, in (d) ISF has been used to eliminate outlier values; however, this has also eliminated potentially dangerous or zero values. In our implementation of the ISF technique, we focus on the following criteria:

- The ensemble size, or the total number of trees generated, equals the number of estimators (n estimators = 100). There is a default value of 100.
- The number of samples used to train each simple estimator is denoted by the max samples value (max samples = auto). When max samples are set to “auto,” it will be set to min ($n = 256$ samples).
- The contamination (auto) variable in our dataset reflects the expected fraction of extreme values. When the “auto” setting is used, the contamination level is set to 0.1.
- To train a tree, take as many features as possible from the complete set of features, which is represented by Max features (set to 1 by default).

Stage 2 data pre-processing is shown in Figure 7 by a selection of public buildings that show negative or zero values. To prevent negative and zero readings, polynomial interpolation was used to determine compensation values for (X_i, Y_i) , where $Y_i = f(X_i)$, energy consumption, the dependent variable is a function of Year/month, the independent variable. Figure 7 represents a sample of a Portuguese public building with zero and negative values and how to handle it using polynomial interpolation. Each point in the proposed building represents a month from the beginning of 2018 to the end of 2019; therefore, there are 24 points in Figure 7.

For instance, the point representing November 2018 contains a zero value, and the one representing September 2019 contains a negative value. These points have been fixed by the interpolation method and all zeros and negative values in our public building dataset.

Each degree of the polynomial in the interpolation training was evaluated by its root-mean-squared error (RMSE), and the degree with the lowest RMSE was chosen for training. The degree-by-degree RMSE findings are displayed in Figure 8. Quintic polynomials have been used since they are considered the most reliable degree. There’s no way to reduce overfitting by increasing the degree of polynomials.

Data pre-processing led to the final dataset, which was used to identify distinct trends in energy usage across public buildings.

Figure 9 depicts a subset of the final dataset showing the relationship between contracted power and total energy use. One can notice that there are no zero or negative energy consumption values.

We now compare the Elbow approach with the Bouldin-Davis method to determine the best possible cluster size. As seen in Figure 10, after applying the Elbow and Davis & Bouldin methods to our dataset, we identified three clusters.

We conclude from our analysis of the Elbow technique and the Davis-Bouldin approach that we can cluster the data on energy consumption into three groups: low, medium, and high consumption.

B. K-MEANS WITH GA TO PREDICT ENERGY CONSUMPTION LEVELS

In this section, we present two approaches to calculating the distance between clusters: K-means clustering with K-means++ initialization (KMCKI) is the first technique, while K-means clustering with Gaussian averaging (KMGA) is the second. Table 3 outlines the primary GA parameters used in practice. The distance between clusters can be

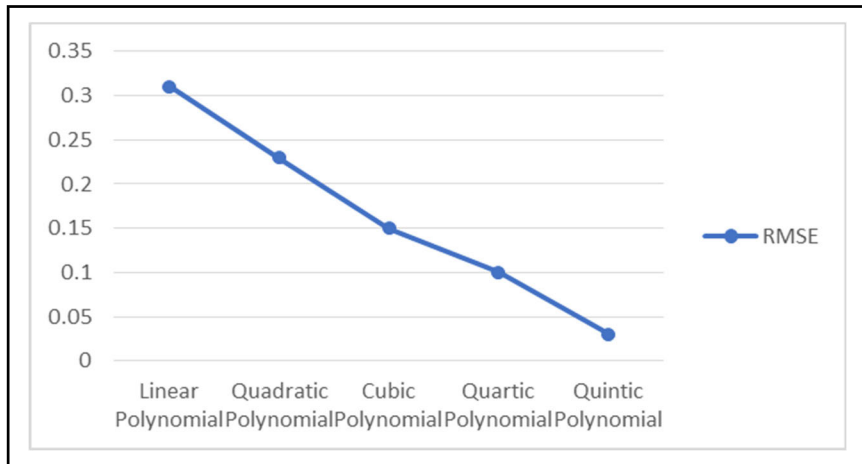


FIGURE 8. Degree of polynomials with root-mean-square-error.

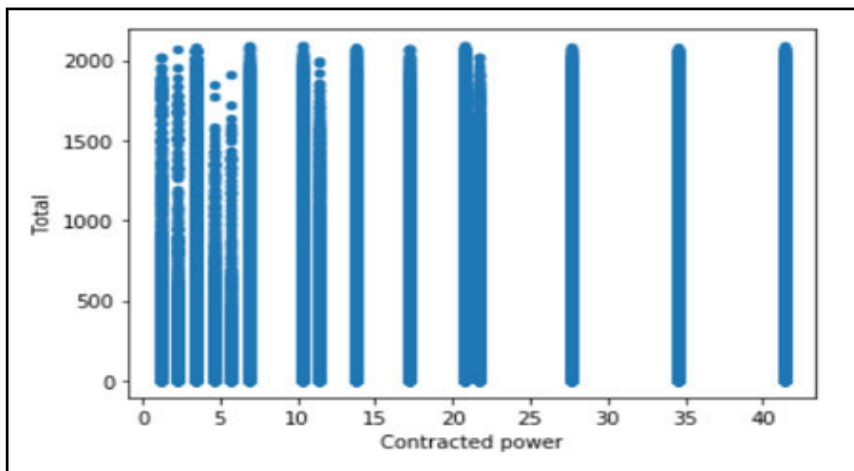


FIGURE 9. Total energy use versus contracted power.

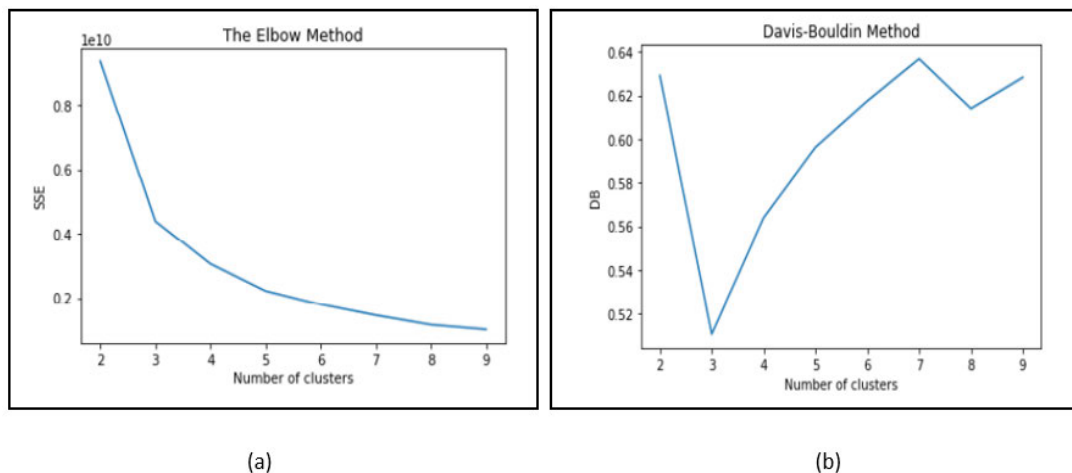


FIGURE 10. Comparison of the Elbow and Davis-Bouldin procedures on a dataset of energy consumption.

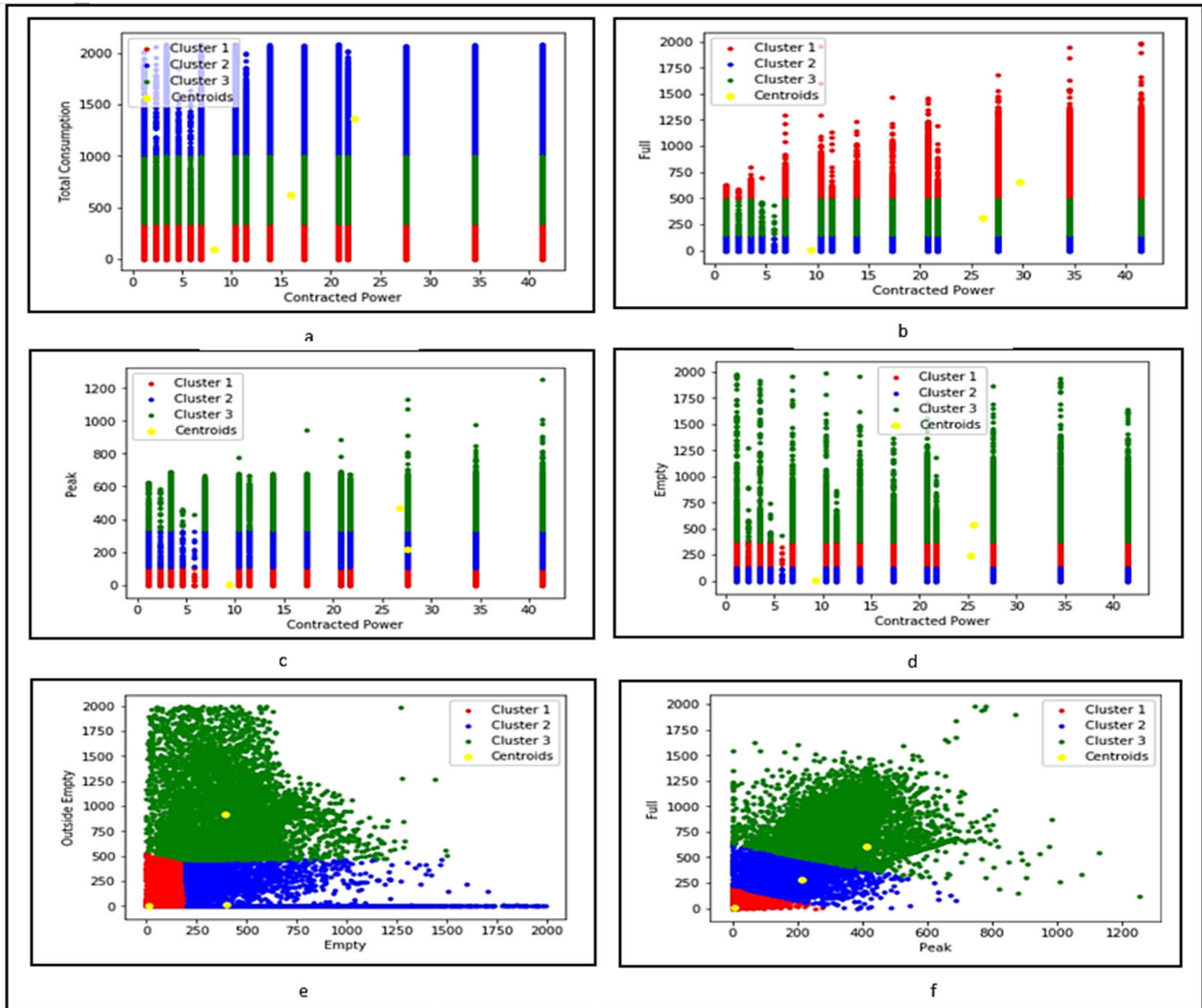


FIGURE 11. Sample of clustering results, (a) between total energy consumption and contracted power (b) between full and contracted power (c) between peak and contracted power (d) between empty and contracted power (e) between outside empty and empty (f) between full and peak.

calculated in three ways: ED, MD, or CD. We compared the accuracy of KMCKI and KMGGA using equation 13’s standard error (SE) [11] and standard deviation (SD) measures of performance. Table 4 demonstrates that CD with KMGGA outperforms all other approaches. Therefore, CD with KMGGA was used in this work to predict cluster labels across all ECD structures and unearth hidden trends.

$$SE = \frac{STDEV(\Omega)}{\sqrt{COUNT(\Omega)}} \tag{13}$$

where:

STDEV = Standard deviation

Ω = Distances between each center of clusters

Analytics on large amounts of data benefit greatly from being visualized. The cluster analysis results have been demonstrated using a variety of approaches, helping energy professionals in Portugal making more informed choices

about the energy they use to power public buildings. In addition, our ECD has contracted power, a crucial consideration for analyzing the time-of-use electricity consumption patterns in public facilities. Figure 11 depicts the visualizations used in ECD through CD using KMGGA, demonstrating the dimensions utilized in each. The centroid for each cluster is calculated by taking the mean of all the data points in that cluster. The algorithm would then repeat the process of assigning data points to clusters based on the new centroids and recalculating the centroids until the clusters no longer change, or a maximum number of iterations is reached. At the end of the process, the algorithm would have grouped the data points into 3 clusters based on their similarity. These clusters could then be used to gain insights into the energy consumption levels in public buildings. As mentioned, 3 clusters (low, medium, and high) can help stakeholders determine the public buildings and municipalities that consume the most energy.

TABLE 3. GA parameters.

No	Parameters	Value
1	Population Size	ECD
2	Crossover Probability	0.5
3	Crossover type	Two points
4	Mutation Probability	0.6
5	Mutation type	Bit flip
6	Number of Iterations	100

TABLE 4. A comparison between KMCKI and SPKG in terms of SE and STDEV.

No	Method	SE	STDEV
1	ED with KMCKI	93.19	465.99
2	MD with KMCKI	184.14	920.73
3	CD with KMCKI	0.004	0.021
4	ED with KMGA	88.49	442.45
5	MD with KMGA	174.94	874.71
6	CD with KMGA	0.002	0.012

Table 5 displays the results of an analysis of the clustering data, from which we derived key rules to aid stakeholders in Portugal’s energy sector in distinguishing between the various types of public buildings. Rules for energy use can help decision-makers pinpoint public buildings in need of direction from their tenants and in switching energy providers for those buildings.

If-then rules can help public buildings control their energy use in several ways, including:

1. Simple and easy to understand: even non-experts can easily understand if-then rules. Building managers and residents will find it simpler to comprehend how their choices affect energy use as a result.
2. Modifiable: If - then rules can be altered to meet the requirements of a structure or organization. This makes it possible to manage energy in a more specialized manner.
3. Real-time feedback: If-then rules can give building managers and residents real-time feedback about their energy usage. They may be able to alter their behavior and choose how to spend energy with better knowledge as a result.
4. Cost-effective: If-then rules are a cost-effective approach to energy management since they can be implemented utilizing current building management systems and sensors.
5. Energy savings: If-then rules can be used to cut down on energy usage and lower energy costs. Building managers and residents can consume less energy and spend less money by giving real-time feedback and supporting energy-efficient behavior.

C. CNN WITH GA TO PREDICT ENERGY CONSUMPTION LEVELS

This section addresses two intelligent computing models for making energy consumption predicts. The first model (CNN) was developed without optimizing the network’s starting weights. In contrast, the second model (CNN-GA) was developed by maximizing accuracy and minimizing the loss curve by adjusting the weights of the network’s initial nodes.

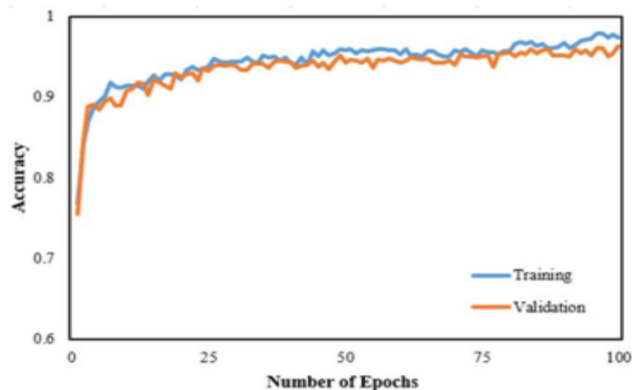


FIGURE 12. Accuracy of CNN architecture.

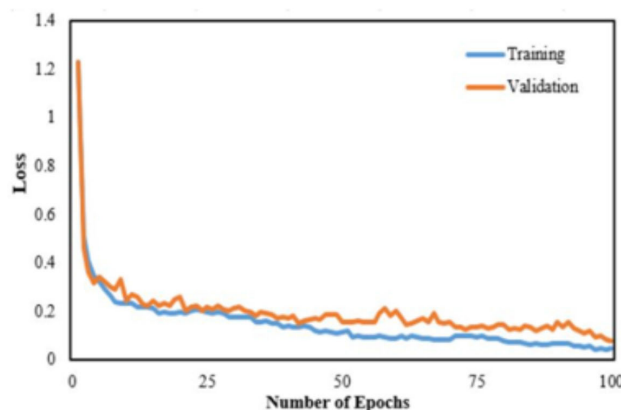


FIGURE 13. Loss of CNN architecture.

We compare these two models to choose the most effective one based on the accuracy and loss curve, which may help stakeholders in the energy sector estimate energy consumption levels.

Training and testing loss and accuracy curves work as follows:

Figures 12 and 13 indicate that at epoch 100, the CNN design achieves the lowest training and validation accuracy of 98.03% and 94.91%, respectively, with a loss of 0.05 and 0.26.

Figures 14 and 15 show that at epoch 100, CNN-GA architecture achieves its largest training and validation accuracies of 99.01% and 97.74%, respectively, with a loss of 0.02 and 0.09.

Figures 16 and 17 represent visually the prediction performance of the CNN-based GA model for the energy consumption dataset. Analyzing these networks, we found that the suggested CNN-based GA model yields reliable predictions of energy use.

D. IMPLICATIONS AND PRACTICAL APPLICATIONS IN BUILDING ENERGY CONSUMPTION PREDICTION

To predict future energy consumption in buildings, this article presents a hybrid intelligent model, trained, and validated

TABLE 5. Sample of energy consumption rules.

No	Rules
1	Total<359 AND Full<157 Then cluster 1 (low energy consumption)
2	359<Total<992 AND 157<Full<484 Then cluster 2 (medium energy consumption)
3	Total>=993 AND Full>=484 Then cluster 3 (high energy consumption)
4	Full<157 AND Peak<111 Then cluster 1 (low energy consumption)
5	157<Full<484 AND 111<Peak<341 Then cluster 2 (medium energy consumption)
6	Full>=484 AND Peak>=341 Then cluster 3 (high energy consumption)
7	Outside empty<245 AND Empty<123 Then cluster 1 (low energy consumption)
8	245<Outside empty <878 AND 123<Empty<386 Then cluster 2 (medium energy consumption)
9	Outside empty >=878 AND Empty>=386 Then cluster 3 (high energy consumption)
10	Total<359 AND Full<157 AND Peak<111 AND Outside empty<245 AND Empty<123 Then cluster 1 (low energy consumption)
11	359<Total<992 AND 157<Full<484 AND 111<Peak<341 AND 245<Outside empty<878 AND 123<Empty<386 Then cluster 2 (medium energy consumption)
12	Total>=993 AND Full>=484 AND Peak>=341 AND Outside empty>=878 AND Empty>=386 Then cluster 3 (high energy consumption)

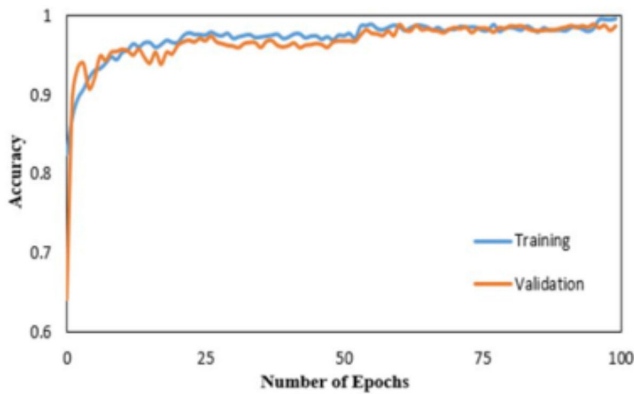


FIGURE 14. Accuracy of CNN-GA architecture.

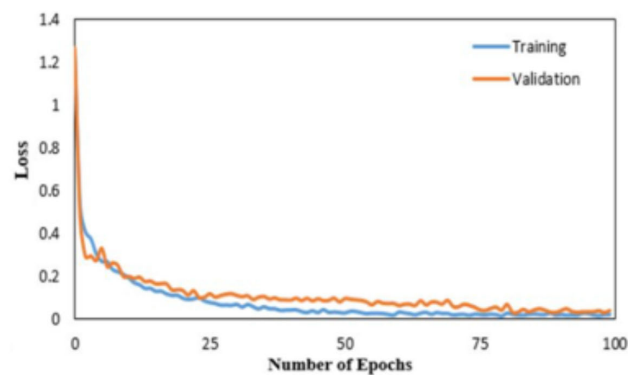


FIGURE 15. Loss of CNN-GA architecture.

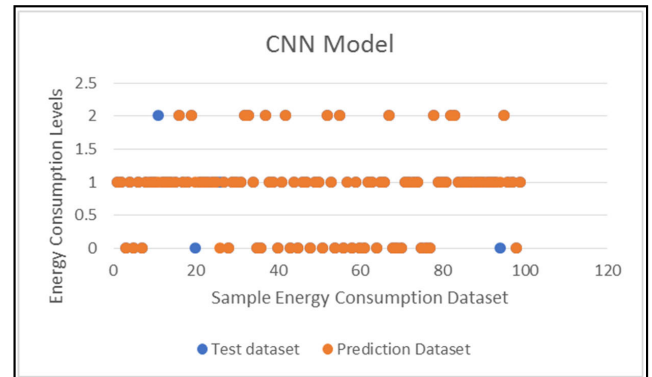


FIGURE 16. CNN model testing and prediction in energy consumption levels.

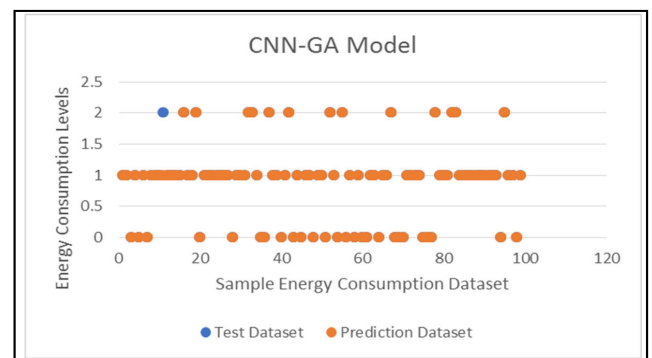


FIGURE 17. Evaluation of CNN-GA models for predicting energy use.

using a dataset of energy consumption of Portuguese public buildings. Essential rules were derived from three distinct categories of energy consumption patterns (cluster 1, cluster 2, and cluster 3). Regarding energy policy, these guidelines aid the decision-maker in ranking public buildings by energy use. This article also facilitated estimates of future energy

consumption in various public buildings. At last, the monthly building energy consumption trends for 2018 and 2019 were calculated. The decision-maker can use these findings to predict future energy needs in each territorial dimension, educate building occupants on efficient energy use, and help switch energy providers with informed decision support.

Regarding experimental design, this paper proposes an accurate and reliable building energy consumption predicting model with an adaptive CNN at its heart. The proposed energy-predicting approach has three distinct innovations over previous deep learning models in that:

1) The energy consumption profiles of public buildings are grouped into several clusters using k-means clustering with GA, and the representative features are then extracted from each cluster. The ideal architecture and weighting parameters for one CNN sub-model can be determined using the datasets in each cluster.

2) Neurons in CNN frequently link to one another. As a result, the complete time correlation in the data series can be revealed.

3) GA has been selected to optimize weights in CNN hidden layers network to improve the accuracy of the proposed network and minimize the MAE metric, compared to the state-of-the-art methods in previous works.

4) The dataset used to train and validate the proposed energy consumption predicting model, spans two years (2018, 2019) and includes data from 26,624 public buildings in Portugal.

Precise energy consumption prediction is crucial for many processes, such as monthly building energy management, facility managers' decision-making, the creation of building information models, net-zero energy operation, and circular economy.

Primarily, reliable energy demand predicting is essential to monthly building energy management. For effective energy device scheduling and management, which can increase the building's energy utilization rate, it is critical to estimate peak and monthly demand accurately. Building managers can make better judgments to judiciously manage all types of energy devices with the help of an accurate building energy consumption prediction.

Secondly, precise energy consumption predictions might be the foundation for smart energy management and building energy efficiency retrofitting. Building facility managers can benefit from such predictions, giving the information needed to estimate future energy expenditures and decide whether to switch to a more efficient pricing structure or reduce anticipated usage.

Moreover, performance-based building requirements are increasingly common because they permit design flexibility while maintaining or even improving the energy performance demanded by prescriptive-based requirements. However, estimating a building's energy performance using precise building energy prediction models is necessary to ascertain whether building information model designs can achieve targeted energy efficiency improvements.

Furthermore, achieving net-zero energy operation in buildings depends on precise energy prediction. Renewable energy is gradually displacing conventional fossil fuels as the global energy sector changes. The output of active energy devices can be calculated using an accurate prediction of the energy demand and different renewable energy generation. As a

result, the building's energy supply and demand can be optimally coordinated to help it operate at net-zero energy costs.

Finally, a key step in developing a circular economy is precisely predicting the electricity load on the power system. Accurate electricity consumption prediction can boost societal and economic advantages by lowering energy usage and costs. Given that the energy demand from several buildings continues to be high, reducing energy consumption is a significant component that may impact economic growth.

The proposed CNN-GA model has been compared to the state-of-the-art methods in previous works regarding the MAE metric. Our proposed model outperforms Adaptive Long-Short-Term Memory neural networks driven by GA [LSTMGA] [37], and GA-enhanced Adaptive Deep Neural Network [GADNN] [43] in terms of this metric. In our proposed model (CNN-GA) MAE reaches 0.02 in training and 0.09 in testing, whereas in LSTMGA figures are 0.51 in training and 1.15 in testing, and in GADNN, this metric was calculated with 0.63 in training and 1.71 in testing.

V. CONCLUSION AND FUTURE WORK

In order to estimate future energy consumption levels in public buildings, this work presented a hybrid intelligent model, focusing on fulfilling the four research objectives we set out to investigate. In 2018 and 2019, raw data was gathered monthly in 77 996 buildings across a wide range of public sectors and 238 cities in Portugal. We employed an isolation forest to eliminate outliers' values from our energy dataset, and we interpolated to discover compensation values or estimate unknown values based on related known values. After this data preparation, the final number of records used in this work was 1,222,695, corresponding to 26,624 public buildings, after excluding records of public lighting (since it is outside the scope of our study) and excluding buildings that do not contain consumption data for the full observed period of 24 months.

K-means using a genetic algorithm was used to predict cluster labels in each building. At the same time, the Elbow technique and Davis and Boulden approach were employed to determine the ideal number of clusters. Further, If-Then rules have been derived from K-means data using a genetic algorithm to aid in identifying the buildings with the highest energy use. Finally, two intelligent computing methods, CNN and CNN-GA, have been developed to predict future energy consumption. There are four areas where this research makes a difference. We present a unique approach for dividing the expected energy consumption of public buildings into tiers (e.g., low, medium, and high). Our research is based on a large data source of public building energy consumption collected in Portugal, in 2018 and 2019. We extracted sound scientific If-Then principles for use by decision-makers in justifying the energy use of public buildings and identifying the largest energy hogs among them. Finally, we propose two intelligent computing models to make predictions about future energy use with an assessment of the models' accuracy and standard error.

Recommendations for future research include using statistical methods like multiple linear regression or logistic regression to identify important factors influencing public building energy consumption, as well as combining clustering and optimization techniques (grey wolf, lion, and whale optimization), to improve the accuracy of predictions for cluster labels describing building energy consumption (low - medium, and high). This study also recommends using machine learning algorithms from the deep learning family, such as long short-term memory and deep forest, to improve the accuracy of predictions about a building's energy use.

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