# Synergistic Neural Network and Velocity Pausing Particle Swarm Optimization for Enhanced Residential Building Energy Efficiency: A Case Study in Kuwait

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**ABSTRACT**

**The global energy demand of buildings is on the rise, driven by factors such as rapid population growth, increasing comfort, technological advances, and ongoing developments in building construction. This escalating energy consumption in buildings is a major contributor to the energy crisis and climate change. Accurate prediction of building energy consumption is essential for gaining insight into energy utilization, reducing waste, and enhancing comfort conditions. This study aimed to introduce a reliable technique for predicting and optimizing the energy consumption of residential buildings, with a focus on a case study in Kuwait. A robust Artificial Neural Network (ANN) was developed, meticulously trained, and rigorously tested to provide accurate energy consumption predictions. Subsequently, an innovative variant of the Velocity Pausing Particle Swarm Optimization (VPPSO) algorithm was employed to identify optimal energy consumption solutions. This novel optimization technique can achieve significant reductions in building energy consumption, with potential savings of up to 43%. Additionally, a sensitivity analysis was performed using the Garson method to assess the impact of input parameters on energy utilization. The results reveal that the insulation and cooling setpoint exert the greatest influence on the objective function, followed by the outdoor airflow. The proposed model, which combines the power of ANN with VPPSO, can be applied to similar buildings, offering precise predictions and optimizing energy consumption. This**

**approach holds promise in addressing the pressing challenges of energy efficiency in building environments.**

***Keywords-building energy consumption; Artificial Neural Network (ANN); VPPSO; optimization; sensitivity analysis***

## I. INTRODUCTION

The energy demand of buildings is a pressing global concern that has attracted significant attention due to its far-reaching environmental, economic, and social implications. With urbanization and population growth continuing to accelerate, the energy consumed by buildings has surged dramatically, straining energy resources and exacerbating the problem of climate change. Buildings account for a substantial portion of global energy-related carbon dioxide emissions, underscoring the critical role of energy efficiency in this sector in the pursuit of sustainability goals [1]. According to data from the International Energy Agency (IEA), buildings consume approximately 40% of the world's energy and are responsible for almost a third of global greenhouse gas emissions [2]. Moreover, the IEA projects that global building energy demand is set to increase by 50% by 2050 if substantial measures to enhance Energy Efficiency (EE) are not implemented promptly.

EE stands as one of the most promising solutions to the world's energy and environmental challenges. Investments in EE yield long-term and cumulative benefits in terms of energy savings and cost reductions [3]. Among the sectors with significant potential for energy savings, the building sector emerges as a particularly promising one [4]. Therefore, it has become increasingly imperative to predict and comprehend building energy consumption to realize EE goals. Experts suggest that this sector has the potential to save up to 50% of the electrical energy currently utilized [3]. In recent years, the prediction and optimization of building energy consumption have attracted considerable attention due to the urgent need for enhanced EE and sustainable practices. Accurate predictions of energy consumption play a crucial role in enabling effective energy management and decision-making processes. Simultaneously, optimization techniques offer the potential to minimize energy usage and reduce environmental impact. In this context, the integration of Artificial Neural Networks (ANNs) and optimization algorithms has emerged as a promising approach to tackle these challenges.

ANNs have shown remarkable effectiveness in modeling and predicting complex systems, including energy consumption in buildings [5-7]. Their ability to capture intricate relationships between input variables and energy consumption patterns makes them a valuable tool for achieving accurate predictions. ANNs can analyze huge amounts of data to identify patterns and features and, in many cases, can make sense of incomplete or inaccurate information. In [8], the most significant advantages of ANNs were highlighted as their ability to efficiently represent complex problems by simplifying certain factors. ANNs have consistently achieved success rates ranging from 90 to 99%. In [3], Deep Neural Networks (DNN) and ANNs were identified as the most effective predictive models for energy consumption, particularly in the early design phase, with the lowest Mean Squared Error (MSE) values approaching zero. In [9], the potential to reduce energy consumption in office buildings was evaluated using data-driven models. The findings indicated that the ANN approach proved to be the most accurate, with an average absolute error of 14.8%. In [10], a comparative analysis was performed on the effectiveness of Random Forest (RF) and feed-forward back-propagation ANN in predicting Heating, Ventilation, and Air Conditioning (HVAC) electricity use in a hotel in Spain. ANN exhibited slightly better performance compared to RF. In [11], five distinct methods were used to predict power usage in an administrative building in London. The proposed ANN outperformed the other four approaches, including Multiple Regression (MR), Genetic Programming (GP), DNN, and Support Vector Machine (SVM). Due to their rapid processing, high accuracy, and capacity to handle nonlinear relationships between different variables, ANN models have become the most widely used method in the field of optimizing building performance [12].

ANN research has experienced remarkable growth, finding extensive applications in various aspects related to building energy consumption [13]. ANNs have proven to be a valuable tool in predicting thermal needs for both residential and commercial buildings, including heating and cooling requirements, optimizing HVAC systems, and achieving energy savings [14-16]. Additionally, ANNs play a crucial role in predicting and analyzing electrical energy consumption, supporting energy planning, emission reduction, and efficient energy use [17-23]. Moreover, ANNs are employed to anticipate the thermal insulation features of building materials, helping to minimize energy usage by optimizing insulation and reducing dependence on HVAC systems [24-26]. The versatility and effectiveness of ANNs in these applications demonstrate their importance in accurately predicting and optimizing energy consumption, contributing to sustainable building practices.

Predicting building energy consumption effectively is crucial for optimizing energy use and improving overall energy efficiency. The accuracy of energy consumption predictions is heavily dependent on the selection of appropriate input parameters. These parameters act as the building blocks of predictive models, and their relevance and representativeness directly influence the model's performance. Choosing the right input parameters involves a thorough understanding of the building's characteristics, occupancy patterns, and environmental factors. Some fundamental input parameters include building size, orientation, insulation levels, construction materials, HVAC systems, lighting fixtures, and number of occupants. Additionally, weather data, such as temperature, humidity, and solar radiation, play a crucial role in capturing the impact of the external environment on energy consumption. Sensitivity analysis is a powerful tool to investigate the impact of these factors on building energy consumption [27]. By systematically varying individual input parameters while keeping others constant, the sensitivity and relative importance of each parameter in the model output can be assessed [28]. Sensitivity analysis helps identify which parameters significantly influence energy consumption and which have a lesser impact. This knowledge enables interested parties to prioritize interventions and investments to achieve substantial energy savings.

In [29], a sensitivity and energy analysis was performed to explore the influential factors that affect energy consumption. This study focused on the building form, geometric variations, and materials as crucial factors. The results showed that the outer zone had a substantial influence on energy use, whereas considering both horizontal and vertical geometries along with material choices exhibited similar effects. In [30], the influence of weather fluctuations on energy consumption was explored by analyzing data collected from two residential houses. The second house showed lower sensitivity to changes in weather variables compared to a conventional house. Notably, non-temperature factors such as solar radiation and humidity affect energy usage, with the second house consistently showing lower sensitivity than the first. Moreover, this study showed that the sensitivity of energy consumption to weather conditions varies with different seasons and specific times of day and night. Additionally, it is important to note that building energy consumption is significantly influenced by occupant behaviors. In [31], the effects of spatio-temporal occupant behavior on energy use in residential buildings were studied. The results showed that residential building energy use is strongly affected by thermostat setpoints.

Optimizing building energy consumption is a critical area to achieve energy efficiency and sustainability. By employing various techniques and strategies, it is possible to optimize energy use and minimize waste. Optimization approaches include the utilization of advanced algorithms, such as GA, Particle Swarm Optimization (PSO), and various ML techniques, to explore the vast solution space and identify energy-efficient configurations. The objective is to reduce energy consumption and operational costs and minimize environmental impact by achieving a harmonious balance between occupant comfort, operational requirements, and energy efficiency. In [32], GA was used to optimize indoor lighting in an office setting, achieving enhanced illuminance uniformity, reduced luminaire count, and lowered maximum Unified Glare Rating (UGR) values. These results serve as compelling evidence for the effectiveness of GAs in the field of lighting design. In [33], PSO was used to address both single and multiple objectives, integrated with EnergyPlus, to improve building energy performance. This study emphasized the importance of building window size, glazing, wall material properties, shading, and orientation in achieving energy reduction. The results showed that the optimal design led to a reduction of 1.6 to 11.3% in the total annual demand for electricity. This optimization approach proved to be a valuable and efficient tool, allowing the exploration of optimal solutions with conflicting objective functions in a time-saving manner. In [34], four optimization algorithms were used, namely PSO, GA, Gravitational Search Algorithm (GSA), and Firefly Algorithm (FA), and three methods were used to optimize the design of a building situated in a calm (low wind speed) and hot climate.

In the context of optimizing building energy consumption, ANNs have attracted significant attention among ML methods. A literature review [33] revealed a significant increase in the integration of ANN models with heuristic optimization algorithms since 2017. This combination aims to derive optimal renovation strategies or achieve optimal building designs, considering the limitations associated with simulation-based optimization methods. The primary innovations and goals of this study can be summarized as follows:

- Develop, train, and utilize an ANN to accurately forecast energy use for an existing building located in Kuwait.
- Perform an exhaustive sensitivity analysis employing the Garson method to assess how input factors influence energy consumption.
- Identify the most influential factors that contribute to reducing building energy consumption.
- Implement the Velocity Pausing PSO (VPPSO) algorithm to minimize building energy consumption. The aim is to optimize the influential parameters and facilitate the identification of optimal solutions.
- Employing a previously unused VPPSO algorithm in the building energy use field achieves higher energy efficiency and sustainability in building operations.

## II. DATA SOURCES AND METHOD

### A. *Case Study and Dataset*

The data used in this study originate from a two-story residential villa situated in Kuwait [35, 36], as shown in Figure 1. Kuwait is characterized by an arid and hot climate. The building has a total floor area of 214 m². The 3D model of the case study building was developed using Revit software.

TABLE I. KEY CHARACTERISTICS OF THE STUDIED RESIDENTIAL BUILDING

| Features | Description |
|---|---|
| Location | Latitude 29.31°N<br>Longitude 47.48°E |
| Climate zone | Categorized as 1B according to the ASHRAE climate zones classification [37] |
| Exterior wall | Internal gypsum plastering, concrete, Extruded Polystyrene (XPS) insulation, and layers of brick.<br>Wall thickness 30cm<br>U-value 0.351W/m²-K |
| Roofing | U-value 0.25W/m²-K |
| Windows | Double-glazed windows featuring clear glass panels and frames made of Unplasticized PolyVinyl Chloride (UPVC). |
| Window-to-wall ratio (%) | 17.56 N<br>1.99 E<br>20.56 S<br>4.57 W |
| Occupancy | 0.229 people/m² |
| Cooling setpoint | 25°C |
| lighting power density | 5 W/m² |
| Internal equipment power density | 3.58 W/m² |
| Air conditioning system | Energy Efficiency Ratio (SEER): 18.8 |

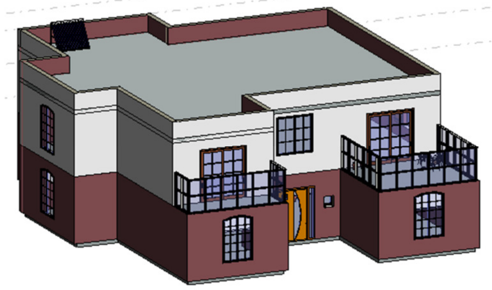

Fig. 1. Axonometric view of the building.

Table I provides a summary of the building's most notable design features, including details about its location, envelope characteristics, internal gains, type of air conditioning system, and other relevant information. This comprehensive overview serves to highlight the key aspects of the building's design and systems, enabling a better understanding of its energy performance and potential areas for optimization.

### *B. ANN Model*

ANN is a nonlinear approach that is mostly used for prediction. This artificial intelligence method is derived from the biological nervous system to understand information and make decisions in a human-like way. ANNs have been employed to establish a connection between the input and output variables. Using the input dataset for training an appropriate ANN structure, output variables can be predicted [38]. This study used a three-layer feed-forward ANN. The dataset was divided into three sets: training data (70%), validation data (15%), and testing data (15%). The Levenberg-Marquardt algorithm was used as an optimizer for the neural network. The input variables considered include insulation levels, cooling setpoint, maximum allowable discomfort glare index, equipment gains, window solar transmittance, outdoor airflow, and economizer maximum limit dry bulb temperature. Table II presents the input factors and their minimum, maximum, and average values. The objective function is energy consumption. Figure 2 illustrates the topology and details of the ANN model, showing the input factors and the resulting output variable. Training the ANN model on these data aims to predict and optimize building energy consumption by identifying optimal values for these input variables.

TABLE II. INPUT FACTORS, AND THEIR MINIMUM, MAXIMUM, AND AVERAGE VALUES

| Item | Name | Min | Max | Average |
|---|---|---|---|---|
| $x_1$ | Cooling set point (°C) | 22 | 26 | 24 |
| $x_2$ | Outdoor airflow (m3/s) | 0.05 | 0.2 | 0.125 |
| $x_3$ | Insulation (m) | 0.05 | 0.14 | 0.095 |
| $x_4$ | Internal equipment heat gains (W/m2) | 2 | 14 | 8 |
| $x_5$ | Window solar transmittance (-) | 0.6 | 0.9 | 0.75 |
| $x_6$ | Economizer maximum limit dry bulb temperature (°C) | 25 | 28 | 26.5 |
| $x_7$ | Maximum allowable discomfort glaring index (-) | 13 | 28 | 20.5 |

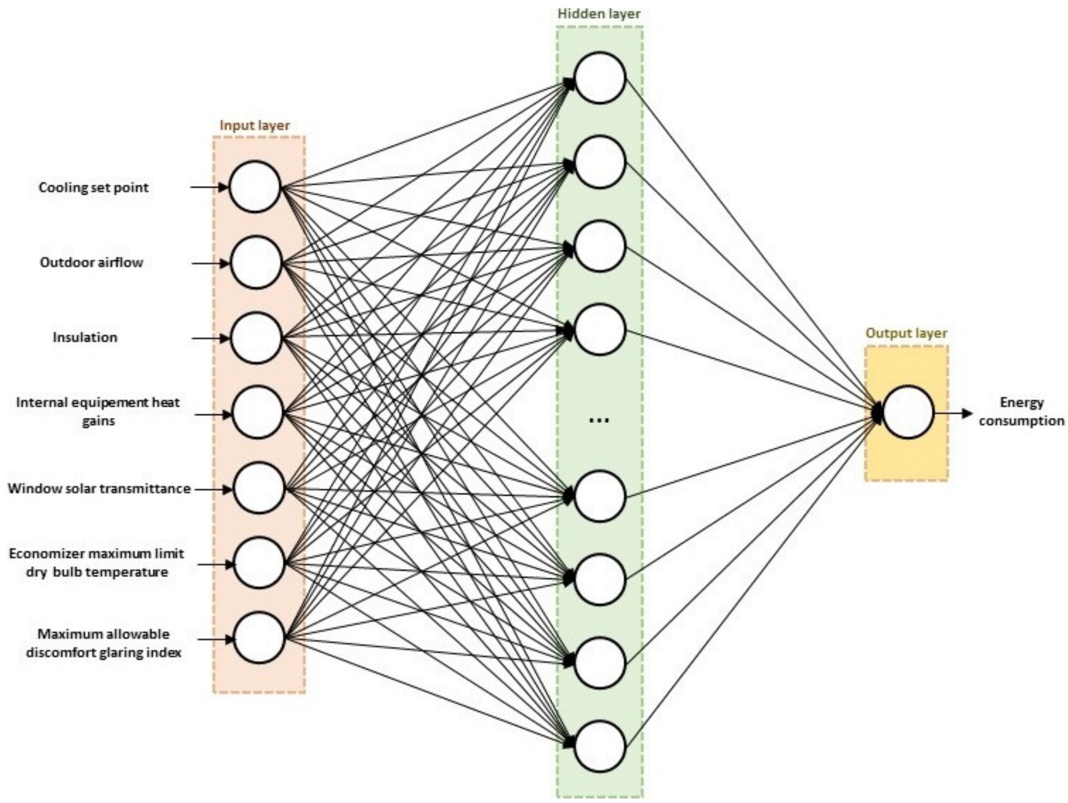


Fig. 2. Topology of the proposed ANN, depicting the network's architecture and connections between input factors and the target output variable.

Performance evaluation is crucial in assessing the effectiveness of any model. This study chose the coefficient of correlation (R) [39] and Mean Absolute Percentage Error (MAPE) [13] as the key metrics to measure the performance of the models, as shown in (1) and (2). The coefficient of correlation provides insights into the strength and direction of the relationship between predicted and actual values, while MAPE measures the average percentage difference between the model's predicted values and the actual values.

$$R = \frac{N(\sum_{i=1}^{N} y_i \hat{y}_i) - (\sum_{i=1}^{N} y_i)(\sum_{i=1}^{N} \hat{y}_i)}{\sqrt{[N \sum_{i=1}^{N} y_i^2 - (\sum_{i=1}^{N} y_i)^2]}\sqrt{N \sum_{i=1}^{N} \hat{y}_i{}^2 - (\sum_{i=1}^{N} \hat{y}_i)^2}} \quad (1)$$

$$MAPE = \frac{100\%}{N} * \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (2)$$

In the context of this analysis, $y_i$ represents the measured energy, $\hat{y}_i$ denotes the predicted energy, and $N$ is the total number of observations.

### *C. VPPSO Algorithm*

In the field of building energy consumption, optimization is a crucial technique that aids in achieving the greatest performance. Therefore, it is essential to apply efficient optimization algorithms. PSO is a widely respected metaheuristic algorithm known for its remarkable performance in tackling various optimization problems [40, 41]. However, two significant issues hamper its efficacy: slow convergence and local optima entrapment. Additionally, PSO performance significantly deteriorates in high-dimensional problems. To address these challenges, a novel variant of the PSO algorithm, known as velocity pausing, was developed [42]. This variant equips the particles with a third movement option, allowing them to maintain the same velocity as in the previous iteration. Contrary to the usual PSO method, which only permits particles to travel at faster or slower rates, this concept enables particles to potentially move at slower, faster, and constant speeds. The inclusion of a third movement option (constant speed) is the primary benefit of velocity pausing. This enables VPPSO to strike a better balance between exploration and exploitation. To address premature convergence more effectively, VPPSO introduces modifications to the first term of the PSO velocity equation. Furthermore, the population in VPPSO is divided into two swarms to preserve diversity. The idea of velocity pausing can be expressed mathematically as

$$V_i(t+1) = \begin{cases} V_i(t) & if\ rand < \alpha \\ wV_i(t) + c_1 r_3 \big(P_{besti}(t) - X_i(t)\big) + c_2 r_4 (g_{besti}(t) - X_i(t)) & otherwise \end{cases} \quad (3)$$

where:

- $V_i(t)$ and $V_i(t+1)$ are, respectively the velocities of particle $i$ at iterations $t$ and $t+1$
- $X_i$ is the position vector of particle $i$ at iteration $t$
- $\alpha$ refers to the parameter for velocity pausing
- $g_{best}$ is the global best particle and $P_{best}$ is the personal best position
- $w$ is the inertia weight
- $c_1$ and $c_2$ are the cognitive and the social acceleration coefficients
- $r_3$ and $r_4$are the random variables.

To assess its capabilities, VPPSO has been evaluated on a set of 43 benchmark functions and applied to address four real-world engineering problems, demonstrating its exceptional capability in effectively solving intricate high-dimensional problems. Consequently, VPPSO holds promise for addressing diverse real-world optimization problems. In this work, the main objective of the VPPSO algorithm is to choose input parameter values that minimize building energy usage.

Figure 3 presents the proposed VPPSO algorithm's flowchart. The VPPSO changes are highlighted in gray. The flowchart illustrates the initial modification in VPPSO, involving updating PSO particle velocities using a newly proposed equation [42]. This equation alters the first term of the original PSO velocity equation, effectively avoiding premature convergence. Additionally, the proposed velocity equation incorporates velocity pausing, contributing to a better balance between exploration and exploitation. Another significant modification in VPPSO is the introduction of a second swarm, where particles update their positions differently. This two-swarm strategy is crucial to enhance diversity within the algorithm.

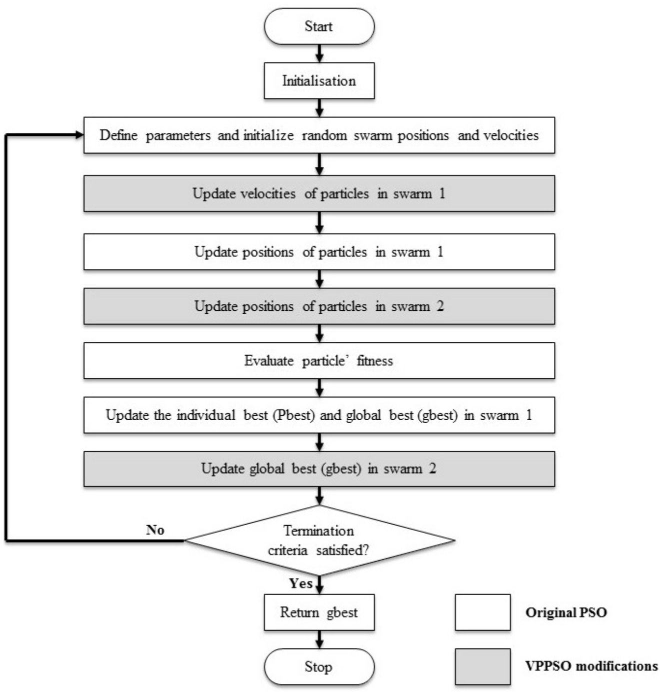


Fig. 3. Flowchart of VPPSO, providing a visual representation of the algorithm's sequential steps and decision points.

## III. RESULTS AND DISCUSSION

This section discusses in detail the results obtained. Subsequently, using the Garson index approach for sensitivity analysis, the effects of decision parameters on the objective function were assessed. Finally, the VPPSO optimization findings based on the ANN results were proposed for decision-making.

### *A. ANN Results*

The dataset used consisted of 26,000 samples, of which 70% were allocated for training, 15% for validation, and 15% for testing. The ANN model's topology was structured as 7, 10, and 1 with 7 inputs, 1 hidden layer containing 10 neurons, and 1 output. Figure 4 illustrates the results obtained from the ANN model. The findings of this study showcase a high-performing ANN model with regression index values close to one, 0.99956 for training, 0.99954 for validation, and 0.99958 for testing. Table III outlines the performance metrics of the ANN model, indicating that MAPE values ranged from 2.71 to 2.76%, while the average R-value across all data was 0.99956. These results indicate the proposed ANN model exhibited high performance. Therefore, this ANN model shows promising results and can be utilized to predict energy consumption.

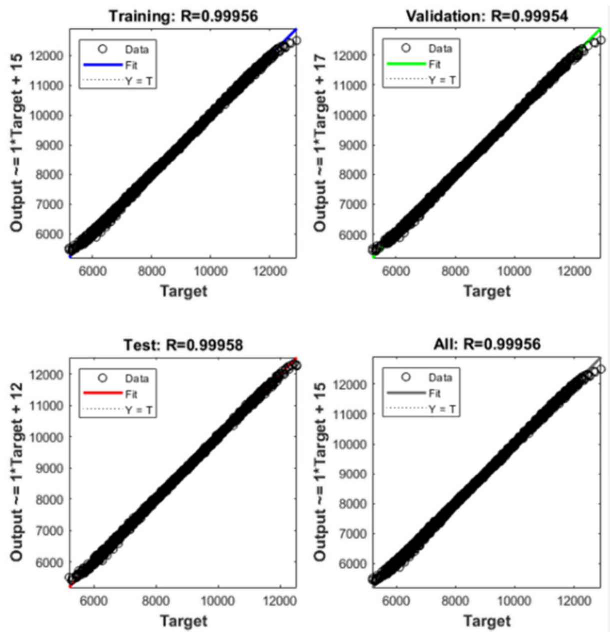


Fig. 4. Regression plots.

TABLE III. MAPE AND R INDICES OF THE ANN MODEL

| Items | Samples | MAPE (%) | R |
|---|---|---|---|
| Training | 17920 | 2.71 | 0.99956 |
| Validation | 3840 | 2.73 | 0.99954 |
| Testing | 3840 | 2.76 | 0.99958 |

The weights of the ANN model were extracted from MATLAB to calculate the importance of each input parameter by analyzing its weights within the neural network layers. This involves multiplying the weights linked to the variable of interest by those of all input variables for each neuron in the hidden layer. Squared products are summed and normalized, yielding a relative importance measure for each input variable. This sensitivity analysis aids in understanding the relative influence of various input parameters on the model's predictions, providing valuable insights into the factors driving the ANN model's performance.

### *B. Sensitivity Analysis Results*

Sensitivity analysis is significant for building performance analysis, as it can be used to identify the primary design elements that directly affect energy consumption [43]. Typically, it is conducted during the early design stage, benefiting from greater design flexibility. It is usually performed before the optimization process to identify the most important design parameters, streamlining the optimization problem and considerably reducing the required time [44].

This study used seven design variables, and optimization was performed directly without simplifying them. However, performing a sensitivity analysis remains valuable to explore the individual contributions of each variable to the variance of the building performance metrics. Table IV shows Garson's relative importance, as well as the rank of the seven input variables for energy performance. Figure 5 provides a clear demonstration of the importance of each input parameter in predicting energy consumption. A higher relative importance means that the variable is more important in energy consumption.

TABLE IV. GARSON'S RELATIVE IMPORTANCE AND RANK OF INPUT VARIABLES

| | Variables | Garson's relative importance (%) | Rank |
|---|---|---|---|
| $x_1$ | Cooling set point | 32.014127 | 1 |
| $x_2$ | Outdoor airflow | 18.034043 | 3 |
| $x_3$ | Insulation | 31.734819 | 2 |
| $x_4$ | Internal equipment heat gains | 8.695349 | 4 |
| $x_5$ | Window solar transmittance | 2.843613 | 6 |
| $x_6$ | Economizer maximum limit dry bulb temperature | 0.013736 | 7 |
| $x_7$ | Maximum allowable discomfort glaring index | 6.664313 | 5 |

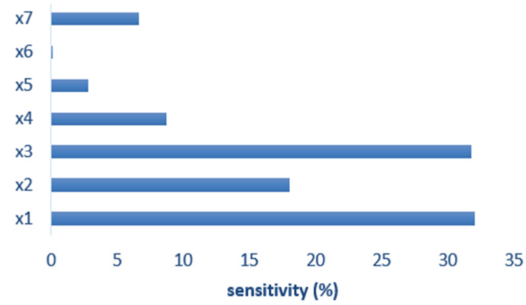


Fig. 5. Sensitivity analysis using the Garson method.

The two most influential variables that affect building energy consumption are cooling setpoint ($x_1$) and insulation ($x_3$). These variables have a somewhat equal impact on energy use. Cooling setpoint contributes 32.01%, which is comparable to insulation's contribution (31.73%). Outdoor air flow ($x_2$) was identified as the second most impactful parameter, contributing 18.03% to energy consumption. The economizer maximum limit dry bulb temperature variable ($x_6$) was determined to be the least influential factor, with a contribution of only 0.013%.

### *C. VPPSO Optimization Results*

40 iterations were used to determine the optimal energy consumption, as shown in Figure 6. Details of three optimal energy consumption iterations and their associated effective parameters are presented in Table V. Additionally, variability ranges were selected for each optimized variable based on the specific characteristics of the case study. From the best 40 iterations of energy-use percentages, as obtained by VPPSO and shown in Figure 7, the energy-use percentage decreased between 37.14% and 43.78% (5,317.7 kWh to 4,756.03 kWh). In terms of overall optimal results, annual energy consumption decreased by 43.78%, from 8,460.87 kWh to 4,756.03 kWh, by modifying the values of the factors. The ANN model not only helped to establish the relationships between inputs and outputs but also help identify the influential parameters in energy consumption. Although a linear relationship between inputs and outputs indicates that the lowest value is the best option, this applies to iteration 40.

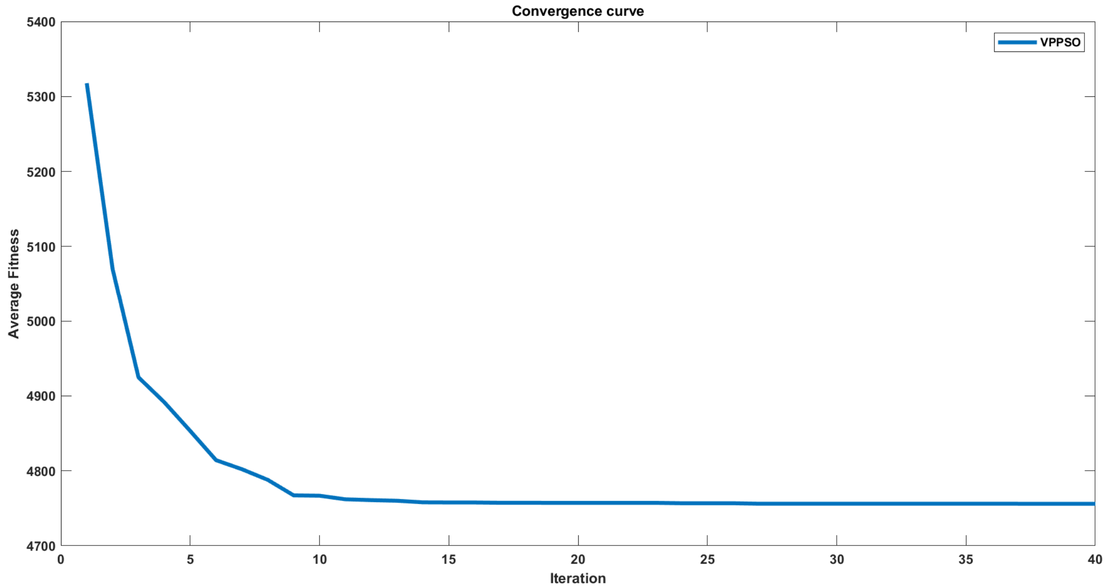


Fig. 6. Optimum energy consumption of the studied building (40 iterations).

TABLE V. DETAILS OF THREE OPTIMAL ENERGY CONSUMPTION ITERATIONS AND THEIR ASSOCIATED EFFECTIVE PARAMETERS

| Iteration number | Cooling setpoint | Outdoor airflow | Insulation | Internal equipment heat gains | Window solar transmittance | Economizer maximum limit dry bulb temperature | Maximum allowable discomfort glaring index | Energy consumption (kWh) |
|---|---|---|---|---|---|---|---|---|
| 40 | 26 | 0.05 | 0.14 | 2 | 0.6 | 25 | 13 | 4756.03184 |
| 14 | 26 | 0.05 | 0.14 | 2 | 0.6 | 26.013766 | 13 | 4757.971392 |
| 3 | 26 | 0.05 | 0.14 | 3.366342 | 0.6 | 27.812098 | 13.699375 | 4924.803432 |

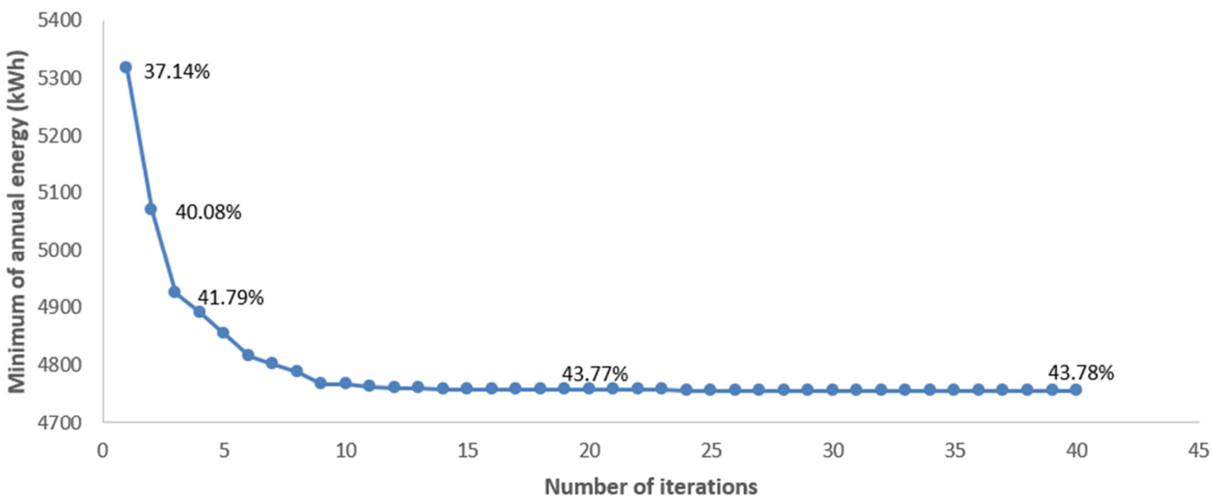


Fig. 7. Percentage of energy consumption optimization (40 iterations).

Based on Table V, iteration 40 achieved the minimum energy consumption rate at a cooling setpoint of 26°C. Optimal cooling setpoints can vary depending on specific building characteristics, climate conditions, and energy efficiency goals. In general, the recommended range for optimal cooling setpoints aims to strike a balance between occupant comfort and energy conservation. During occupied hours, a typical optimal cooling setpoint is often suggested to be around 24°C to 26°C. In [45], it was found that a room temperature of 26°C provides the most comfortable thermal condition, with a thermal sensation closest to neutral. This study also observed that increasing the temperature setpoint from 23°C to 26°C resulted in a substantial improvement in thermal acceptability and significant energy savings of 44 kWh/m²/year in electrical energy used for comfort cooling.

Furthermore, the optimal values for insulation and outdoor airflow were 0.14 m and 0.05 $m^3$/s, respectively, which resulted in minimal energy consumption. These findings indicate that increasing the insulation thickness to 0.14 m and maintaining the outdoor airflow at 0.05 $m^3$/s are crucial factors in achieving the most energy-efficient performance for the building. Table VI displays the optimal values for the remaining decision variables as follows: Internal equipment heat gains ($x_4$) with a value of 2 W/m², Maximum allowable discomfort glaring index ($x_7$) with a value of 13, Window solar transmittance ($x_5$) with a value of 0.6, and Economizer maximum limit dry bulb temperature ($x_6$) with a value of 25°C. These optimal values were identified through the VPPSO optimization process and are associated with minimal energy consumption, contributing to the overall energy efficiency of the building. The proposed solutions for maintaining the decision variables at their optimal values include implementing energy-efficient equipment for lower heat gains, using shading devices and adjustable blinds to control glare, opting for energy-efficient glazing materials to reduce solar transmittance, setting the economizer's maximum limit dry bulb temperature to 25°C, etc.

In conclusion, the VPPSO optimization method presents a promising and innovative approach to reducing energy consumption in building renovations. The proposed parameters can be effectively applied to a wide range of existing building renovations and newly constructed buildings, leading to improved energy efficiency, cost savings, and environmental sustainability. The versatility of this optimization technique makes it a valuable tool for enhancing the energy performance of various building types and meeting the evolving demands of the modern built environment.

## IV. COMPARISON TO THE LITERATURE

In [46], the optimization of the heating energy demand of a shelter in Iran was studied using various protective zones and optimizing occupant heat. This study employed ANNs trained with backpropagation and enhanced the models with GWO and PSO algorithms. Galapagos and Silvereye were used as optimizer engines to minimize the heating energy demand, resulting in satisfactory results. Sensitivity analysis revealed that occupant density significantly influenced the reduction of energy consumption. In [47], a building performance optimization process was proposed, which evaluated daylighting and energy performance for multiple design options, generating optimized designs using GA, building simulation modeling, and parametric design. The effectiveness of this approach was validated through a case study involving a small office building located in three distinct climates (Miami, Atlanta, and Chicago). After optimization, daylighting performance improved by 38.7%, 31.6%, and 28.8%, while energy demand was reduced by 20.2%, 18.5%, and 17.9% compared to average values. Sensitivity analysis identified skylight width and length as crucial variables at all locations, while others show varying levels of influence. In [48], the focus was on optimizing three parameters: occupant schedule, occupant density, and Wall-U value. The results revealed a reduction in energy consumption of up to 13%.

In [49], the aim was to propose a reliable method for optimizing building energy consumption. By identifying crucial input parameters, this study focused on a case study of a research center building in Iran. EnergyPlus software was used to evaluate energy consumption, while an ANN was trained to accurately simulate energy use. The Galapagos plugin, utilizing a GA, was used for energy optimization, leading to a notable reduction of 35% in energy consumption. Additionally, sensitivity analysis revealed that the number of occupants exerts the most significant influence on the building's energy consumption, followed by the wall U-value, which is linked to wall insulation. The findings of this study confirm that insulation is a critical parameter that influences energy consumption. Furthermore, both the insulation and the cooling setpoint exhibit similar effects on energy use, followed by outdoor airflow as the second most impactful parameter. In this study, the utilization of the VPPSO algorithm demonstrated the potential to reduce energy consumption by an impressive 43%, with the energy use decreasing significantly, ranging from 37.14% to 43.79%, showcasing the effectiveness of this algorithm in minimizing energy consumption.

## V. CONCLUSIONS

This study aimed to optimize energy consumption in buildings to reduce energy demand. This led to the derivation of design solutions or recommendations that are not only readily comprehensible but also easily implementable by architects in practical scenarios. In this context, this study selected a representative building in Kuwait to exemplify the optimization process. Seven crucial input parameters, including Insulation levels, Cooling setpoint, Maximum allowable discomfort glare index, Equipment gains, Window solar transmittance, Outdoor airflow, and Economizer maximum limit dry bulb temperature, were employed in the ANN model with energy consumption as the objective function.

This study encompassed the development, training, and application of an ANN model to accurately predict the energy consumption of the building. It also involved an extensive sensitivity analysis to assess the influence of input variables on energy consumption, along with the identification of the most influential factors using the ANN. Additionally, the VPPSO algorithm was utilized to minimize energy consumption. Moreover, the Levenberg-Marquardt algorithm was used to train the ANN model to estimate the most effective building parameters on energy consumption, with a sensitivity analysis conducted considering the case study. The application of the

VPPSO algorithm ultimately led to the optimization of the energy consumption of the studied building, resulting in an average decrease in energy consumption of 43%. Notably, architectural parameters were found to hold a crucial significance in determining the energy performance of the building, and the selection of appropriate design parameters remarkably contributed to reducing energy consumption.

The results of this study showcase a high-performing ANN model with a MAPE of 2.71% for training, 2.73% for validation, and 2.76% for testing, along with regression index values close to one (0.99956 for training, 0.99954 for validation, and 0.99958 for testing). These findings make the model highly promising for predicting energy consumption. The sensitivity analysis highlighted the cooling setpoint and insulation as the most impactful parameters in building renovation with a similar effect on energy use (32.01% and 31.73%, respectively), followed by outdoor airflow (18.03%). By optimizing the proposed model using the VPPSO algorithm, a substantial reduction of 43% in energy consumption was achieved, underscoring the effectiveness of the algorithm. Consequently, this approach has significant potential as a method to reduce energy consumption in building renovation projects, and its proposed parameters can be applied to enhance energy efficiency in other building renovations.

Future research should explore and apply additional input parameters to evaluate more complex and intricate buildings. This would not only help regulate energy consumption but also enhance various vital aspects of building performance, including heating and cooling efficiency, as well as thermal comfort, among others.

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