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Efficient Optimization of Energy Consumption at Home through Machine Learning

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***Abstract*— In recent years, the imperative need for efficient energy utilization in residential buildings has become increasingly evident due to the unwarranted wastage of electrical energy. This has spurred significant interest in optimizing energy consumption while maintaining user comfort. Accurate energy prediction is a crucial component of this optimization. This study focus on minimizing energy consumption by accurately predicting it through advanced Machine Learning (ML) models and optimization techniques. The study begins with the collection of energy data from a reliable source, Kaggle, comprising 29 features. To streamline the dataset, unnecessary features are discarded, and data normalization is performed to ensure consistency and reliability. Subsequently, ML models, specifically Long Short-Term Memory (LSTM), are designed and optimized through the Genetic Algorithm (GA) and Grey Wolf Optimization (GWO) to fine-tune hyperparameters. The prediction results are evaluated using error values to assess the accuracy and reliability of the models. Notably, our findings indicate that the GWO-LSTM model outperforms the others, exhibiting minimal errors and therefore showcasing its superior predictive capabilities. Accurate energy prediction not only serves as a valuable tool in its own right but also plays a pivotal role in enabling proactive energy management. By accurately forecasting future energy requirements, it becomes possible to optimize energy consumption further. Such precision paves the way for intelligent scheduling of home appliances, which, in turn, leads to significant reductions in energy consumption.**

Keywords*— *Energy Consumption, Machine Learning, Error Metrics, Optimization

I. INTRODUCTION

The information and communication sector is constantly evolving, leveraging new sensing and communication tools for establishing connectivity from almost anywhere and anytime, a notion referred to as the Internet of Things (IoT) [1]. However, amidst this advancement, the focus has shifted towards addressing critical concerns such as security, connectivity, privacy, and standardized communication protocols within IoT networks. Researchers are actively engaged in resolving these issues to facilitate the practical deployment of IoT networks. One area of specific concern for researchers and scientists is the prediction and optimization of electricity consumption in residential buildings, a key component of IoT-based smart home systems. Traditionally, energy management relied on forecasting methods based on statistical analysis and ML applied to historical energy consumption data collected from electricity meters. However, these conventional methods fall short in predicting energy consumption at an hourly level. To address this limitation, researchers have turned to digital meters and applied advanced ML techniques, enabling the accurate prediction of hourly energy consumption. By leveraging these predictions, homeowners can optimize energy usage, reducing the wastage of precious energy resources. Research in this area has already made significant progress, encompassing energy consumption prediction at various temporal scales, including hourly, daily, weekly, monthly, and yearly levels, using error metrics for evaluation.

The prediction of power consumption remains a significant concern, particularly for power generation companies grappling with the ever-increasing demand for energy driven by rapid population growth [2]. Energy shortages could occur in the near future, according to experts, if energy consumption is not controlled. Two approaches exist for dealing with this problem: the expensive one of expanding energy production, and the more realistic one of lowering energy consumption and cutting waste. Since expanding energy output can be costly in terms of both money and resources, attention has switched to preventative methods that reduce energy consumption. Over the past few decades, scientists have poured a lot of time and effort into figuring out how to forecast and optimize energy consumption.

The first step in optimizing energy consumption is energy prediction [3]. The process is looking at past energy consumption patterns and making upcoming predictions. Energy optimization is extremely useful in smart homes since it makes sure that gadgets only receive the exact amount of electricity they require while also taking into consideration environmental factors like temperature, lighting, humidity, air quality, and more. The goal of this research is to utilize an energy forecasting model to assist homes in saving money on electric bills by lowering their energy consumption. GWO and GA are used to further optimize the LSTM network. A practical and efficient method for managing energy in the home is presented through the identification of the most successful model and the utilization of its results to reduce energy consumption.

II. Literature Survey

Several research works have looked into novel ways of anticipating and optimizing energy consumption. The research [4] focuses on utilizing ML algorithms to forecast annual building energy consumption using a huge dataset of residential constructions. Their research is focused on the impact of cluster building on model efficiency. The study's innovation is the development of a model that allows architects to enter essential building design aspects early in the design phase and obtain an estimate of the annual average energy consumption. These findings highlight building designers' capacity to use Deep Neural Networks (DNN) for informed decision-making, efficient management, and optimum design. They show that DNN is an efficient predictive system for energy usage. The study [5] provides a novel IoT task management strategy for lowering energy consumption in smart homes, with a focus on predictive optimization. This method includes an energy-consumption-minimization optimization module as well as a prediction-based predictive optimization module. The study evaluates the suggested predictive optimization technique to traditional prediction and optimization modules by collecting energy usage data from a wide range of popular household appliances. The outputs are evaluated using regression performance criteria, and a case study demonstrates that including a predictive optimization mechanism in task management produces better results for lowering energy consumption in households than using two independent approaches of prediction and optimization.

A unique optimization approach is proposed in research [6] to establish a happy medium between energy consumption and optimal climate conditions, taking variables such as greenhouse temperature, CO2 concentration, and humidity into account. The suggested model's performance is examined using external environmental data collected over 15 days in Jeju, and the study verifies the ad hoc greenhouse simulator. When the output of the optimization system is compared to that of a reference approach, significant gains are observed. The proposed model's energy consumption is lower than that of the current scheme while still preserving the appropriate interior atmosphere to increase crop output. The study [7] investigated approaches for optimizing energy consumption and forecasting future usage, highlighting innovative solutions to these issues. An improved Particle Swarm Optimization (PSO) algorithm is utilized in one study to construct a model for optimizing tramway energy consumption. The first stage is to create an energy consumption model for tramway operations that incorporates energy-saving methods. The study then provides a Particle Swarm Optimization (CM-PSO) algorithm that improves energy efficiency through a competitive mechanism. To demonstrate the utility of this novel strategy, the Guangzhou Haizhu tramway is used as a case study. The findings of this study demonstrate the model's superior performance in reducing tramway energy consumption as compared to alternative approaches. The research [8] proposes a hybrid Artificial Intelligence (AI)-based system for reliably predicting future electricity consumption and generation. This framework is divided into three major phases. The procedure starts with deciding on the best data preparation approach for upgrading the dataset. It then employs a Convolutional Long Short-Term Memory (ConvLSTM) model to collect spatiotemporal features in order to learn discriminative patterns from historical power data. A bidirectional gated recurrent unit (BDGRU) is utilized next to extract temporal characteristics. The feature descriptors are then processed and predicted using multilayer perceptron layers. Extensive trials using residential and solar energy data show that the model improves dramatically in accuracy, particularly in terms of mean square error (MSE) on hourly data, when compared to the most recent state-of-the-art approaches.

Researchers investigate real-time energy optimization in a grid-connected sustainable smart house using the Lyapunov optimization technique, which is based on the stability of virtual queues and takes into consideration the dynamics of unknown system inputs, in the study [9]. The main goal is to lower the time-averaged cost of energy and the cost of thermal discomfort over time. This sustainable smart house model takes into account changes in home occupancy, desired temperature settings, power consumption, renewable energy generation, outdoor temperature, and electricity pricing. Extensive simulations are performed to demonstrate that the approach works and that the algorithm can successfully optimize energy consumption in real-time. The practice also contributes to lower overall energy costs over time. Significant progress is being made in resolving issues with traditional residential systems such as heating, ventilation, air conditioning, and lighting. This method takes into account environmental factors like as daylight, temperature, and heat gain from within a building. In the research [10], a mathematical framework was developed to anticipate the consumption of energy expenses in residential buildings taking into account factors such as interior heat gains, external temperature, external illuminance, and time-of-use pricing. The Bald Eagle search optimization methods are employed to fine-tune construction features. When compared to baseline models, with or without building energy management systems, this algorithm significantly reduces mean energy consumption costs relative to the worst-performing fireworks algorithm, resulting in significant cost savings.

III. Theoretical Concept

The theoretical concept of energy prediction models, such as GA-LSTM and GWO-LSTM, along with energy optimization, is elaborated below.

A. GA-LSTM

LSTM is a recurrent neural network structure developed to fix the vanishing gradient issue [11]. LSTMs excel at learning intricate long-term dependencies and have shown remarkable performance across a wide range of tasks. LSTMs are characterized by four network layers that interact in a unique manner. These networks typically incorporate "forget" gates, which enable the controlled backpropagation of errors across numerous virtual layers. This mechanism empowers the network to acquire knowledge related to events that transpired many time steps in the past.

GA is a form of metaheuristic and stochastic optimization that is based on the ideas behind natural evolution [12]. GAs are widely employed for seeking nearly optimal solutions to problems characterized by extensive search spaces. The GA method is based on the same concepts of evolution, including crossover and mutation. One key idea in GAs is that of "chromosomes." The binary strings that make up each chromosome stand for different approaches to a problem. These chromosomes are created at random at first, with the more efficient solutions being given a better chance to reproduce. There are six steps involved in the GA process: seeding, fitness testing, termination condition analysis, selection, crossover, and mutation.

In this study, we present a unified method by integrating LSTM and GA to find the best time window size and LSTM unit count. The choice of the time window is critical as LSTM relies on past information during the training process. If the window size is too large, the model may overfit by learning too much from the training data. Conversely, a window that is too small may result in underfitting, where important information is overlooked. This integrated approach involves two stages. In the first stage, we design an LSTM network with appropriate parameters. A Sequential Layer LSTM network with two hidden layers is employed, and the number of neurons in the hidden layers is determined using GA. We use the ReLU as an activation function for the input and hidden nodes. This function is also used for the output nodes, as energy prediction after 10 minutes is a regression problem. Initial weights are set to random values, and the "Adam" optimizer is used for weight adjustment. Adam is a gradient-based optimizer known for its computational efficiency, making it suitable for large datasets and parameters, as well as for addressing problems with noisy and sparse gradients. In the second stage, GA is applied to find the optimal window size and hidden units in each LSTM hidden layer. Different window sizes and numbers of hidden units are evaluated for fitness by GA. The GA process involves the following steps:

1. Population space is initialized with random values representing potential solutions.
2. Genetic operators explore the search space by encoding each chromosome with binary bits. Each chromosome consists of 10 bits, where bits 1–5 indicate the window size and bits 6–10 indicate the number of LSTM units in each hidden layer.
3. Selection is performed using the roulette method, where each chromosome's fitness is evaluated.
4. Crossover is executed using the ordered crossover method, exchanging chromosomes between two individuals with a set crossover probability of 0.8.
5. The mutation is implemented using the basic bit mutation method to introduce diversity in the population.
6. The above steps are repeated for 10 generations of offspring as the stopping condition.

The choice of fitness function is crucial in GA, and in this research, MSE is employed to assess the fitness of each chromosome. The chromosome yielding the smallest MSE value is deemed the optimal solution for the LSTM network.

B. GWO-LSTM

Wolves, notorious for their cunning and ferocity, have developed very effective hunting techniques as a result of living in a hostile ecosystem. Their prowess has inspired researchers to solve practical problems, with historical examples of imitation. Within a grey wolf pack, a strict hierarchy is observed, with four distinct levels [13]. The α wolf, the pack's leader, assumes responsibility for decisions concerning habitat, hunting, and movement. This α serves as the core of the grey wolf pack. The β wolf, second in command, supports the α wolf and assists in decision-making, often becoming the primary candidate for the alpha role when the current leader passes. The δ wolf category includes sentry wolves, young wolves, and caregivers, all obedient to the α and β wolves, providing assistance in pack management. The ω wolf encompasses other members of the pack, representing the lowest tier that complies with the directives of higher-ranking individuals, while also facing increased survival risks.

The proposed method comprises two key stages. In the initial stage, a suitable LSTM network is designed with appropriate network parameters. In the subsequent stage, we employ GWO to evaluate the optimal time window size and the hidden units in each LSTM network layer. Various window sizes and hidden unit numbers are assessed for fitness using GWO, following these steps:

1. Step 1: Using the actual data prediction accuracy of the LSTM as an indicator for assessing each grey wolf's position, set m hyperparameters inside the LSTM as the prey for the grey wolf pack. Model a repetitive hunt for food.
2. Step 2: Determine the LSTM's hyperparameters and the amount of gray wolves. Limit the optimization space by setting upper and lower limits. Make up a pack of grey wolves to roam this area and set the parameters for how many times to search.
3. Step 3: Allocate each gray wolf's position to a unique set of hyperparameters for the LSTM. Separate the data into a training set and a testing set, then use the trends you see in the training set to make predictions about what will happen next in the testing set. Calculate the deviation from the predicted sequence using data from the testing set. The three most accurate wolves are called the wolf, the wolf, and the wolf.

4. Step 4: The grey wolf group, led by the alpha, beta, and gamma wolves, begins a prey search, each individual wolf's position changing according to predetermined formulas.

Do it again, but this time for real this time. The ideal LSTM hyperparameters are the ones that map to the position of the wolf.

C. Scheduling

Energy prediction, particularly when employing methods like LSTM for projecting future energy consumption, provides valuable insights into expected energy consumption patterns. This predictive data can be harnessed to optimize energy utilization through load balancing. Here's how load balancing can be applied based on the results of energy prediction:

Resource allocation optimization within a residential environment constitutes a multifaceted approach aimed at the efficient management and utilization of resources to enhance energy efficiency, cut costs, and elevate overall quality of life. A pivotal element of resource allocation optimization in a home involves the integration of smart home automation systems. These systems can be programmed to oversee various aspects of household operations, including lighting, heating, cooling, and security, in response to occupancy and predetermined schedules. For instance, a programmable thermostat can dynamically adjust indoor temperatures to ensure comfort while minimizing energy consumption. The intelligent control of these resources not only heightens convenience but also contributes to energy conservation and reduced utility expenses. Implementing time-of-use scheduling represents a pragmatic approach to optimizing resource allocation within the home. This strategy revolves around the scheduling of high-energy consumption tasks, such as running dishwashers, doing laundry, or charging electric vehicles, during off-peak hours when electricity rates typically dip. By aligning resource-intensive activities with periods of diminished energy demand, homeowners can maximize cost efficiency and energy effectiveness. Load balancing for electrical appliances offers another method for efficient resource allocation within the home. By spreading the usage of energy-hungry devices, like air conditioners, refrigerators, and electric heaters, throughout the day, homeowners can avert circuit overloads. This not only contributes to a stable supply of electricity but also curbs the risk of electrical surges and breakdowns, enhancing both comfort and safety.

IV. RESULT AND DISCUSSION

The findings of the study "Optimization of Energy Consumption at Home through Machine Learning" are described further below.

A. Data and its processing

The study utilized the dataset [14] depicted in Table 5, comprising a total of 19,735 records and 29 columns. The dataset is classified into indoor and outdoor data categories. Within these categories, certain parameters, denoted as T and H, pertain to factors such as temperature and humidity, both in rooms within a residence and in proximity to a nearby station. Additionally, the dataset encompasses data regarding dew point, light, visibility, wind speed, air pressure, and more, sourced from the weather station. The data taken from Kaggle and used in this research is given in Figure 1.

	A	B	C	D	E	F	G
1	date	11-01-2016 17:00	11-01-2016 17:10	11-01-2016 17:20	11-01-2016 17:30	11-01-2016 17:40	11-01-2016 17:50
2	Appliances	60	60	50	50	60	50
3	lights	30	30	30	40	40	40
4	T1	19.89	19.89	19.89	19.89	19.89	19.89
5	RH_1	47.59666667	46.69333333	46.3	46.06666667	46.33333333	46.02666667
6	T2	19.2	19.2	19.2	19.2	19.2	19.2
7	RH_2	44.79	44.7225	44.62666667	44.59	44.53	44.5
8	T3	19.79	19.79	19.79	19.79	19.79	19.79
9	RH_3	44.73	44.79	44.93333333	45	45	44.93333333
10	T4	19	19	18.92666667	18.89	18.89	18.89
11	RH_4	45.56666667	45.9925	45.89	45.72333333	45.53	45.73
12	T5	17.16666667	17.16666667	17.16666667	17.16666667	17.2	17.13333333
13	RH_5	55.2	55.2	55.09	55.09	55.09	55.03
14	T6	7.026666667	6.833333333	6.56	6.433333333	6.366666667	6.3
15	RH_6	84.25666667	84.06333333	83.15666667	83.42333333	84.89333333	85.76666667
16	T7	17.2	17.2	17.2	17.13333333	17.2	17.13333333
17	RH_7	41.62666667	41.56	41.43333333	41.29	41.23	41.26
18	T8	18.2	18.2	18.2	18.1	18.1	18.1
19	RH_8	48.9	48.86333333	48.73	48.59	48.59	48.59
20	T9	17.03333333	17.06666667	17	17	17	17
21	RH_9	45.53	45.56	45.5	45.4	45.4	45.29
22	T_out	6.60E+00	6.48E+00	6.37E+00	6.25E+00	6.13E+00	6.02E+00
23	Press_mm_hg	733.5	733.6	733.7	733.8	733.9	734
24	RH_out	92	92	92	92	92	92
25	Windspeed	7	6.666666667	6.333333333	6	5.666666667	5.333333333
26	Visibility	63	59.16666667	55.33333333	51.5	47.66666667	43.83333333
27	Tdewpoint	5.30E+00	5.20E+00	5.10E+00	5.00E+00	4.90E+00	4.80E+00
28	rv1	13.27543316	18.60619498	28.64266817	45.4103895	10.08409655	44.91948425
29	rv2	13.27543316	18.60619498	28.64266817	45.4103895	10.08409655	44.91948425

Fig. 1. Energy Data from Kaggle

The dataset pre-processing procedure is a necessary step to improve the performance of the model. The correlation analysis is conducted using Equation (1), which defines the correlation formula. In this equation, X_i denotes the feature under consideration, while Y_i is the corresponding feature. The symbols μ and ν indicate the mean.

$$cov(X,Y) = \frac{\sum(X_i-\mu)(Y_j-\nu)}{n} \qquad [1]$$

Following the correlation analysis, it was determined that certain features needed to be eliminated. As a result, various room humidity and temperature attributes, along with outdoor light and temperature, were removed. Additionally, random features were dropped due to their minimal impact on appliance energy and the prevalence of zero values. The specific columns that were removed include lights, Tdewpoint, T9, T6, RH5, RH4, rv1, rv2, and Visibility. The elimination of the "lights" column was motivated by its high frequency of zeros, which could potentially affect a model's performance. T6 was deemed redundant as it closely mirrored the values found in "Tout." Other columns with correlation scores below 0.02 were also excluded in this study. For experimental purposes, two commonly used scaling techniques, namely min-max scaler and standard scaler, were employed [15].

B. Research Outcome

The goal of this study was to improve energy consumption prediction using LSTM neural networks and two optimization strategies, GA and GWO. Table 1 summarizes the findings of this study, including key metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and predicting time for the various models. Table 1 clearly compares the three models employed in the study.

Table 1. Outcome of DL model on energy prediction

Model	MAE	MSE	MAPE	Predicting Time
LSTM	0.242	0.32	0.408	32
GA-LSTM	0.17	0.153	0.192	45
GWO-LSTM	0.09	0.06	0.115	51

The LSTM model has an MAE of 0.242, MSE of 0.32, and MAPE of 0.408, and is predicted in 32 seconds. While the LSTM model provided moderate accuracy, we attempted to enhance our predictions further. The LSTM model improved significantly in predicting accuracy after being strengthened by the GA. The GA-LSTM model had an MAE of 0.17, an MSE of 0.153, a MAPE of 0.192, and a somewhat longer prediction time of 45 seconds. In our investigation, the LSTM model with GWO proved to be an outstanding performer. It had the lowest MAE of 0.09, MSE of 0.06, MAPE of 0.115, and predicted time of 51 seconds. These findings clearly show that the optimized model outperforms the other methods investigated in this study in terms of energy consumption prediction accuracy.

Figure 2 visually represents the comparison of error values among the models. It is evident that the GWO-LSTM model exhibits minimal errors, confirming its superiority in predictive accuracy over the other models.

Figure 3 provides an illustration of the energy forecast for the day, generated by our developed models. Notably, the energy prediction produced by the GWO-LSTM model closely aligns with actual energy consumption, demonstrating its effectiveness in real-world applications.

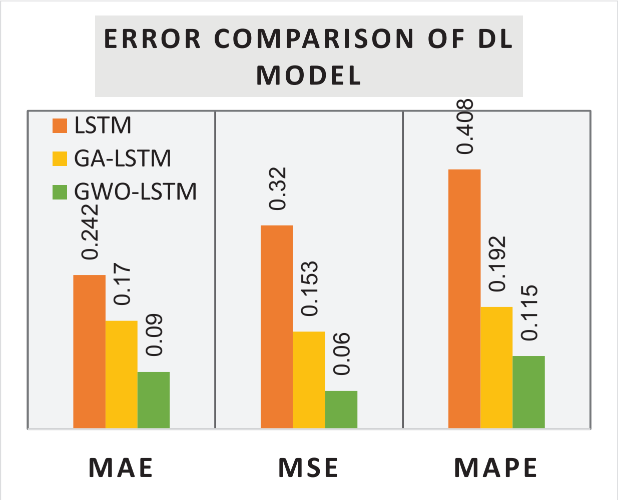

Fig. 2. Error comparison chart

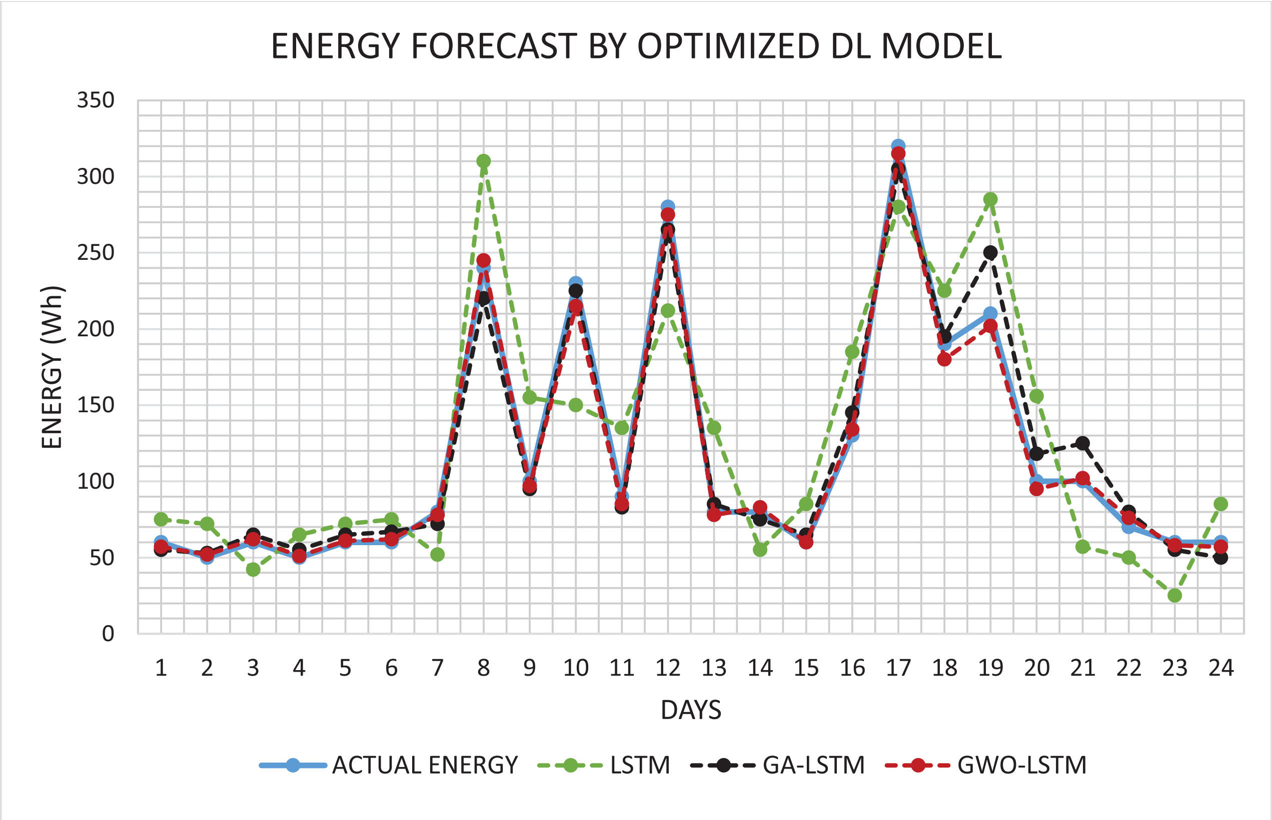

Figure 3: Energy Forecast Comparison

V. Conclusion

Energy optimization, aimed at maximizing energy efficiency while minimizing wastage, holds immense importance in residential buildings. This process involves the identification and implementation of strategies to reduce energy consumption, enhance equipment performance, and optimize energy systems, ultimately leading to several valuable benefits, including cost savings and environmental sustainability. This research contributed to the advancement of energy optimization by developing a reliable GWO-LSTM model for energy prediction. The GWO-LSTM model has demonstrated exceptional predictive capabilities, boasting minimal error scores with an MAE of 0.09, MSE of 0.06, and MAPE of 0.115. Our study indicates that optimizing LSTM models with evolutionary algorithms, particularly GWO, can significantly enhance the accuracy of energy consumption predictions. The GWO-LSTM model excelled in delivering minimal errors and accurate predictions, making it a valuable tool for optimizing energy consumption, reducing costs, and enhancing energy management in various applications such as smart grids and energy management systems. These findings highlight the potential for improved decision-making and resource allocation in the energy sector.

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