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Comparative Analysis Of Ant Lion Optimization And Jaya Algorithm For Feature Selection In K-Nearest Neighbor (Knn) Based Electricity Consumption Prediction

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Abstract

The increase in demand for electrical energy is in line with increasing population, urbanization, industrial deployment, and technology. Accurate prediction of electrical energy consumption plays an important role in planning, analyzing, and managing electricity systems to ensure sustainable, safe, and economical electricity supply. K-Nearest Neighbors (KNN) is a simple and fast prediction algorithm based on the quality and relevance of the features used. This research proposes to improve the accuracy of energy consumption prediction through feature selection based on metaheuristic algorithms, namely Genetic Algorithm (GA), Ant Lion Optimization (ALO), Teaching Learning Based Optimization (TLBO), and Jaya Algorithm (JA). The dataset used is Tetouan City Power Consumption, with a preprocessing process of time feature extraction, min-max scaling normalization, and feature selection. The ALO+KNN and JA+KNN combinations delivered the best and most stable prediction performance, while TLBO+KNN performed poorly. GA+KNN showed the worst overall results among all combinations. The evaluation of model performance was based on RMSE, MAPE, and R^2 metrics. These findings highlight the importance of selecting a feature selection algorithm that aligns well with the characteristics of the model and dataset to enhance prediction accuracy.

Keywords: *Ant Lion Optimization, Feature selection, Genetic Algorithm, Jaya Algorithm, K-Nearest Neighbors, Teaching Learning Based Optimization.*

1. INTRODUCTION

One of the main sources of energy for society is electrical energy [1]. This can be seen by the continuous increase in demand for electrical energy along with increasing population, urbanization, industrial deployment, and technology [2]. Electricity demand prediction plays an important role in planning, analyzing, and managing electricity systems to ensure sustainable, safe, and economical electricity supply [3]. Therefore, developing an accurate prediction model is a challenge in research.

One machine learning algorithm that can be used for prediction is K-Nearest Neighbor (KNN) as a simple and fast algorithm [4]. Some studies show the performance of KNN outperforms other techniques [5], [6]. Research by Goopyo Hong et al. [7] used KNN to predict electrical energy consumption. The results obtained the coefficient of variation of the root mean squared error (CVRMSE) value in summer and fall ranged from 12-13%. This value range is acceptable based on the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) guidelines of 14%. In spring and winter, the CVRSME value is higher than 30%. Abdullahi Abubakar Mas'ud [5] predicting photovoltaic (PV) power resulted in the KNN algorithm being able to outperform other models with a

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root mean square error (RMSE) of 18.68%, mean absolute error (MAE) of 80.6%, and normalized root mean square error (nRMSE) of 13.2%. Liang et al. [8] predicts the long-term and high-resolution demand for thermal loads in buildings at the pre-design stage. Predictions are used for operational efficiency in the proportion of heating, ventilation, and air conditioning (HVAC) energy consumption. The algorithm used is KNN with data of 16,384 building models simulated using EnergyPlus. Performance evaluation showed an RMSE value of 3.01 W/m², Mean Absolute Percentage Error (MAPE) of 5.63%, and R^2 close to 0.999 for annual thermal load.

Prediction results can be affected by poor dataset quality [9]. A dataset is a collection of data that contains information on a particular problem. Datasets may have very large dimensions, excessive or multiple attributes so that pre-processing techniques are needed in the form of feature selection. Feature selection aims to select features that need to be retained or not. Irrelevant features can have a negative impact on model performance [10] . Feature selection based on metaheuristics in the last few decades is widely used [11]. The application of the Genetic Algorithm (GA) metaheuristic algorithm can improve the performance of Random Forest classification with an Area Under the Curve (AUC) value of 0.98 [12]. The main characteristic of GA is its ability to explore the solution space widely through population approaches and evolutionary mechanisms. In the context of feature selection, GA is able to find the optimal combination of features by evaluating many possible subsets simultaneously. Ant Lion Optimization (ALO) algorithm combined with Support Vector Machine (SVM) to predict groundwater level (GWL) showed superior performance compared to other combinations [13]. In feature selection, ALO has the main characteristic of a good balance between exploration (exploring new solutions) and exploitation (improving the best solution that has been found). ALO uses a random and adaptive ant trap mechanism to guide the solution to the optimal area in the search space. This characteristic makes ALO effective in avoiding local solution traps and finding relevant feature combinations more stably. Teaching Learning Based Optimization (TLBO) algorithm is one of the most efficient and practical optimization techniques [14]. The Jaya Algorithm (JA) has the advantage of requiring fewer control parameters and being easy to implement, making it well-suited for solving optimization problems. Based on experimental results, JA can effectively eliminate redundant features, which contributes significantly to improving model performance. [15].

Although several studies have used metaheuristic algorithms for feature selection and KNN to make predictions, there is still a gap in research, namely research has not conducted a comparative study of metaheuristic algorithms in optimizing feature selection for KNN in predicting electrical energy consumption. The benefit of this research is to contribute theoretically by enriching the literature on KNN optimization using metaheuristic methods and knowing the combination of feature selection that is suitable for predicting electrical energy consumption.

2. METHOD

The CRISP-DM (Cross-Industry Standard Process for Data Mining) method is a de-facto standard method and an industry-independent process model for data mining [16]. The CRISP-DM method provides a systematic framework in guiding the data analysis process. The CRISP-DM diagram includes the stages of Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment [17], [18] . These stages ensure the research process, starting from understanding the business context to model implementation. The CRISP-DM phase is presented in Figure 1. The figure illustrates the CRISP-DM process consisting of six iteratively interconnected stages. The process starts from Business Understanding to understand business objectives, followed by Data Understanding to explore available data. Both influence each other because data understanding can change business perspectives. Furthermore, the data is processed at the Data Preparation stage so that it is ready to be used in Modeling, namely the development of a predictive model. The resulting model is evaluated at

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the Evaluation stage to ensure its suitability for the initial objectives. If feasible, the model is implemented through Deployment. This process is cyclical, where the results of each stage can trigger iterations to the previous stage for continuous improvement.

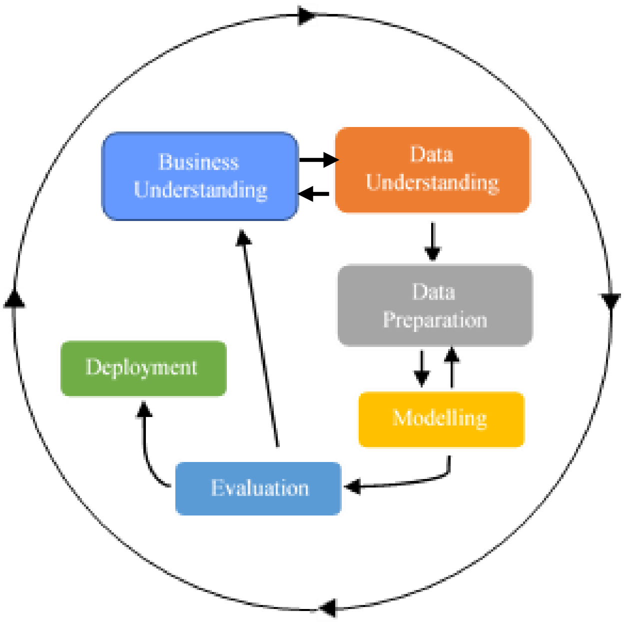

Figure 1. CRISP-DM Phases

2.1. Business Understanding

Accurate consumption prediction requires a wide variety of data with their respective contributions to the prediction model. The selection of diverse data or features is the most important thing in machine learning. The purpose of feature selection can reduce dimensions and reduce computational load which can improve model performance [19], [20], [21]. The purpose of this research is to improve the accuracy of predicting electrical energy consumption using KNN optimized by metaheuristic-based feature selection methods. The methods compared are the performance of four metaheuristic algorithms, namely GA, ALO, TLBO, and JA.

2.2. Data Understanding

The data used in this study comes from Kaggle with the file name Tetouan City power consumption. The dataset consists of 52,417 data with 9 features, namely DateTime, Temperature, Humidity, Wind speed, General Diffuse Flows, Diffuse Flows, Zone 1 Power Consumption, Zone 2 Power Consumption, and Zone 2 Power Consumption. The dataset description is presented in Table 1.

Table 1. Dataset Attribute

Attribute	Data Type	Missing Values	Description
DateTime	Date	no	Date and time in ten-minute intervals
Temperature	Continuous	no	Weather temperature
Humidity	Continuous	no	Weather humidity
Wind Speed	Continuous	no	Wind speed
General Diffuse Flows	Continuous	no	General diffuse flows
Diffuse Flows	Continuous	no	Diffuse flows
Zone 1 Power Consumption	Continuous	no	Zone 1 Power Consumption

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Zone 2 Power Consumption	Continuous	no	Zone 2 Power Consumption
Zone 3 Power Consumption	Continuous	no	Zone 3 Power Consumption

2.3. Data Preparation

Effective data preparation can ensure that the data used is robust, relevant, and easy to manage resulting in more reliable and precise training results [22]. In machine learning (ML) models, the most effective numerical feature normalization method used is min-max scaling [23], [24], [25]. Min-max scaling transforms numerical values to fall within the range of 0 to 1 [26], [27]. Min-max scaling (x') is calculated by the original data value (x) minus the minimum data among all attributes of the original data set (x_{min}), divided by the maximum data among all attributes of the original data set (x_{max}) minusx_{min}. The min-max scale is calculated by the equation (1).

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{1}$$

The application of min-max scaling can also improve accuracy and performance efficiency. KNN relies heavily on distance metrics so that differences in scale between features can affect distance calculations and reduce model performance [28], [29]. In addition to the min-max scaling method, the process in data preparation is feature selection.

Feature selection is a dimension reduction technique used to select relevant features in ML. Feature selection can reduce the size of the data set by removing redundant and irrelevant features so as to improve model performance and speed up the learning process [30], [31]. Feature selection methods are classified into 4 groups, namely evolution based algorithms, swarm intelligence based algorithms, physics based algorithms, and human behavior related algorithms [32]. GA is a popular optimization technique in the evolution based algorithm group [33]. A widely used method from the swarm intelligence based algorithms group is ALO [33]. Feature selection methods based on popular human behavior related algorithms inspired by the teaching and learning process in the classroom are TLBO [34], [35]. JA is a new metaheuristic technique and has a simple form and does not use specific parameters [36], [37]. The selected features are then measured for the linear relationship between two variables and the strength of the relationship using the Pearson correlation method. The value obtained is between -1 and +1, where the resulting coefficient is denoted as "r " [38]. The interpretation of the Pearson correlation coefficient is presented in Table 2.

Table 2. Interpretation of Pearson's Correlation Coefficient.

Range of r	Degree of Relationship
-1.0 to -0.7	Strong negative
-0.7 to-0.3	Distinct negative
-0.3 to -0.1	Weak negative
-1.0 to +0.1	Not a linear relationship
+0.1 to +0.3	Weak positive
+0.3 to +0.7	Distinct positive
+0.7 to +1.0	Strong positive

2.4. Modeling

The research methodology consists of several stages, namely data preprocessing, where standardization is carried out using min-max scaling to ensure that the data is within a certain range. Next, feature optimization is performed to improve the prediction quality by applying several methods, namely GA, ALO, TLBO, and JA. The parameter settings of the Genetic Algorithm (GA) for feature

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selection include the number of iterations of 20 generations (n_gen = 20) and the population size of 10 individuals (n_pop = 10), where each individual represents a different feature subset. The evolution process includes the selection of the best individual, one-point crossover, and mutation with a rate of 10% to maintain the diversity of solutions. The parameter settings for the Ant Lion Optimization (ALO) algorithm include the number of agents (n_agents = 10) and the number of iterations (n_iter = 20), which determine the population size and the duration of the optimal solution search process, respectively. Each agent represents a candidate feature subset, and at each iteration, the agent is updated through a movement mechanism towards the best antlion position (elite). The convergence criterion in this program is not explicitly defined, so the process is stopped after all iterations are complete. The Teaching Learning Based Optimization (TLBO) algorithm uses two main parameters, namely the number of students (n_students = 10) as the population size, and the number of iterations (n_iter = 20) which determines how many times the learning process takes place. This parameter controls the two-stage process in TLBO, namely the teaching phase and the interaction phase between students (learner phase), to direct the search for the optimal solution. The Jaya algorithm uses two main parameters in the feature selection process, namely the number of agents (n_agents = 10) which functions as the size of the solution population, and the number of iterations (n_iter = 20) which determines how many times the solution is improved. In each iteration, agents are updated by gradually directing their positions towards the best solution and away from the worst solution. After the features are obtained, prediction modeling is performed using KNN. Evaluation of model performance is carried out with three metrics, namely Root Mean Square Error (RMSE) to measure the deviation of predictions from actual values on a quadratic scale, Mean Absolute Percentage Error (MAPE) which provides an interpretation of errors in percentage form, and accuracy (R^2). Figure 2 is the method of research conducted.

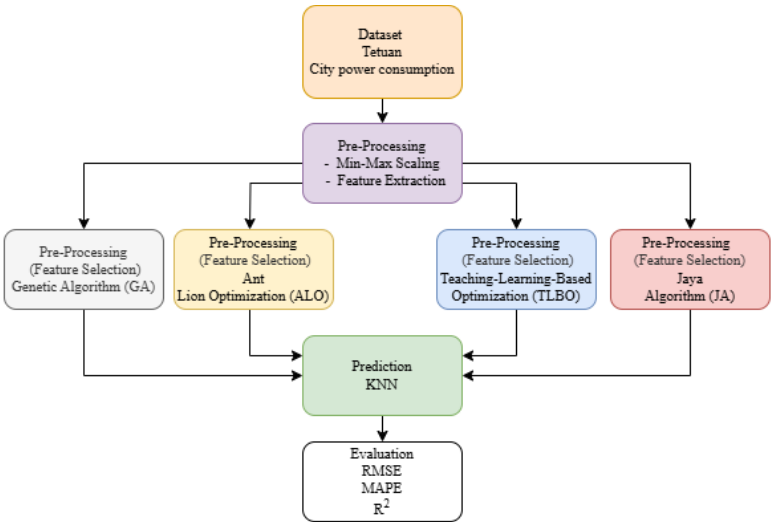

Figure 2. Research Diagram

2.5. Evaluation

Performance evaluation of prediction models is essential to determine their accuracy and reliability [39]. The metrics used to measure model performance are RMSE, MAPE, and R^2. RMSE is a metric that measures the average squared error between the predicted value ($\hat{y}_i$) and the actual value (y_i), which is then taken as the square root, equation (2) to calculate RMSE. MAPE is used to evaluate the relative error in percentage form so that it is easier to compare between datasets with different scales. The MAPE value is obtained by calculating the average of the absolute percentage errors, equation (3) is used to calculate the MAPE value, where M is the amount of data, y_t is the actual result value, and $\hat{y}_t$

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is the predicted value. Evaluation results using RMSE and MAPE are seen from the smallest error value to the best error value [40]. Equation (4) to find the value of R^2, where y_i is the original value. $\widehat{y_i}$ is the predicted value, $\bar{y}$ for the average value of the actual value. $\bar{\hat{y}}$ is the average predicted value and N is the amount of data. If the value of R^2 is close to 1, then the observed and predicted values have a very close correlation [41].

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2} \tag{2}$$

$$\text{MAPE}=\frac{1}{M}\sum_{t=1}^{M}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \text{X } 100\% \tag{3}$$

$$R^2=\frac{\sum_{i=1}^{N}(y_i-\bar{y})(\widehat{y_i}-\bar{\hat{y}})}{\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2}\sqrt{\sum_{I=1}^{N}(\widehat{y_i}-\bar{\hat{y}})^2}} \tag{4}$$

2.6. Deployment

This research focuses on analyzing and comparing methods so that the deployment stage is not carried out. However, the best model obtained can be implemented in IoT-based energy consumption monitoring systems or energy prediction applications for smart grids.

3. RESULT

3.1. Dataset

The dataset is taken from the Kaggle platform with DateTime, temperature, humidity, wind speed, general diffuse flows, diffuse flows, Zone 1 Power Consumption, Zone 2 Power Consumption, and Zone 3 Power Consumption features. Each zone will be predicted. The original data used is shown in Table 3.

Table 3. Dataset

DateTime	Temperature	Humidity	Wind Speed	General Diffuse Flows	Diffuse Flows	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
1/1/2017 0:00	6.559	73.8	0.083	0.051	0.119	34055.7	16128.88	20240.96
1/1/2017 0:10	6.414	74.5	0.083	0.07	0.085	29814.68	19375.08	20131.08
1/1/2017 0:20	6.313	74.5	0.08	0.062	0.1	29128.1	19006.69	19668.43
…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…
12/30/2017 23:30	6.9	72.8	0.086	0.084	0.074	29590.87	25277.69	13806.48
12/30/2017 23:40	6.758	73	0.08	0.066	0.089	28958.17	24692.24	13512.61

3.2. Data Preparation

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In the data preparation stage, there are two activities, namely DateTime data extraction and min-max Scaling. In the DateTime feature, data is extracted into Year, Month, Day, Hour, and Minute. The DateTime feature on the dataset is removed because it has been represented by the DateTime data extraction results. Table 4 is a dataset that is ready to be used for further processing.

Table 4. DateTime Extraction Result Data

Tempera ture	Humi dity	Wind Speed	General Diffuse Flows	Diffuse Flows	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption	Year	Mon th	Day	Hour	Min ute
6.559	73.8	0.083	0.051	0.119	34055.7	16128.88	20240.96	2017	1	1	0	0
6.414	74.5	0.083	0.07	0.085	29814.68	19375.08	20131.08	2017	1	1	0	10
6.313	74.5	0.08	0.062	0.1	29128.1	19006.69	19668.43	2017	1	1	0	20
...	...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...
6.758	73	0.08	0.066	0.089	28958.17	24692.24	13512.61	2017	12	30	23	40
6.58	74.1	0.081	0.062	0.111	28349.81	24055.23	13345.5	2017	12	30	23	50

After preprocessing the DateTime extraction data, the numeric features in the dataset are normalized using the min-max Scaling method to change the data values into a certain range, usually between 0 and 1. This normalization aims to ensure that all features have a uniform scale so that no feature dominates the modeling process due to significant differences in the value range. Table 5 is the result of min-max scaling normalization.

Table 5. Min-Max Scaling Result Data

Tempera ture	Humi dity	Wind Speed	General Diffuse Flows	Diffuse Flows	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption	Year	Mon th	Day	Hour	Min ute
0.0901	0.7484	0.0051	4.04E-05	1E-04	0.526251	0.262361	0.343368	0	0	0	0	0
0.0861	0.7568	0.0051	5.67E-05	8E-05	0.415545	0.374886	0.340731	0	0	0	0	0.2
0.0834	0.7568	0.0047	4.99E-05	1E-04	0.397623	0.362116	0.329626	0	0	0	0	0.4
...	...	...	...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...	...	...	...
0.0955	0.7388	0.0047	5.33E-05	8E-05	0.393187	0.559197	0.181874	0	1	0.966667	1	0.8
0.0907	0.7520	0.0048	4.99E-05	1E-04	0.377306	0.537116	0.177863	0	1	0.966667	1	1

3.3. Feature Selection

3.3.1. Genetic Algorithm (GA) Feature Selection

Feature selection using the GA algorithm in Zone 1 Power Consumption gets temperature, humidity, wind speed, general diffuse flows, month, and hour features. Based on the selected features, hour has a strong positive linear relationship correlation level of +0.73. This shows that hour has a strong influence on electrical energy consumption. Feature selection in Zone 2 Power Consumption obtained temperature, wind speed, general diffuse flows, month, hour, and minute. The correlation value between features to electricity consumption at hour is +0.66, which means that energy consumption is strongly influenced by time. The correlation level value of distinct positive linear relationship is temperature of +0.38, and month of +0.32. Zone 3 Power Consumption has four features selected, namely temperature, diffuse flows, month, and day. Temperature has a correlation level of distinct positive linear relationship of +0.49. Diffuse flows have a correlation level of not a linear relationship with a value of -0.04, which means there is no significant linear relationship to the target. Table 6 is the correlation value between

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features for each zone, where the Temperature and hour features are strong factors in influencing energy consumption, while other selected features have varying influence in each zone. The results of the Zone 1 Power Consumption heatmap graph are presented in Figure 3.

Table 6. Correlation Analysis of Power Load Value from Zone

Feature	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
Temperature	+0.44	+0.38	+0.49
Humidity	-0.29	-	-
Wind Speed	+0.17	+0.15	-
General Diffuse Flows	+0.19	+0.16	-
Diffuse Flows	-	-	-0.04
Year	-	-	-
Month	-0.005	+0.32	-0.23
Day	-	-	+0.01
Hour	+0.73	+0.66	-
Minute	-	+0.00	-

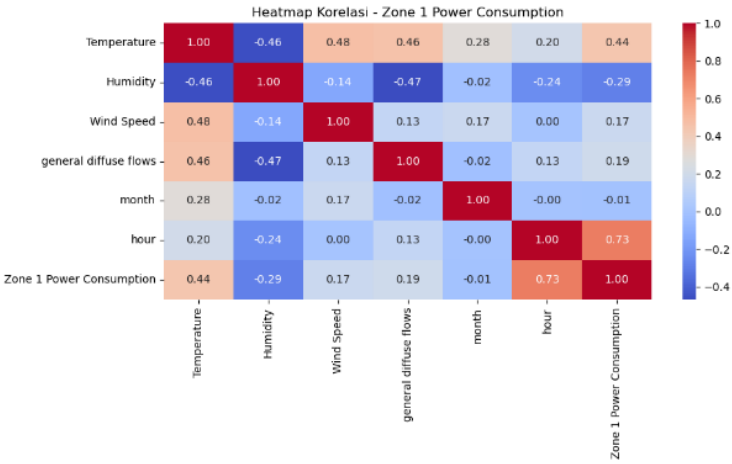

Figure 3. Heatmap of Zone 1 Power Consumption Correlation using GA

3.3.2. Ant Lion Optimization (ALO) Feature Selection

The results of feature selection using the ALO algorithm, in Zone 1 Power Consumption there are features of temperature (+0.44), humidity (-0.29), wind speed (+0.17), general diffuse flows (+0.19), month (-0.01), day (-0.07), and hour (+0.73). Zone 2 Power Consumption selected features temperature, humidity, wind speed, month, weekday, and hour. The correlation value of each feature is +0.38, -0.29, +0.15, +0.16, +0.32, -0.12, and +0.66. While Zone 3 Power Consumption features selected temperature, humidity, wind speed, general diffuse flows, diffuse flows, month, and day. The magnitude of the correlation value of temperature is +0.49, humidity is -0.23, wind speed is +0.28, general diffuse flows are -0.04, month is -0.23, day is +0.01, and hour is +0.45. In each zone the temperature feature enters into a distinct positive linear relationship level. The hour feature enters into a strong positive linear relationship level in Zone 1 Power Consumption, while in the other two zones it enters into a distinct positive linear relationship level. Diffuse flow in Zone 3 Power Consumption gets a value of -0.04 which means this feature does not really affect the target value. Table 7 is the value of the correlation between features in each zone. Figure 4 is a heatmap graph of the correlation between features in Zone 1 Power Consumption.

Table 7. Correlation Analysis of Power Load Value from Zone

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Fiture	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
Temperature	+0.44	+0.38	+0.49
Humidity	-0.29	-0.29	-0.23
Wind Speed	+0.17	+0.15	+0.28
General Diffuse Flows	+0.19	+0.16	+0.06
Diffuse Flows	-	-	-0.04
Year	-	-	-
Month	-0.01	0.32	-0.23
Day	-0.07	-0.12	+0.01
Hour	+0.73	+0.66	+0.45
Minute	-	-	-

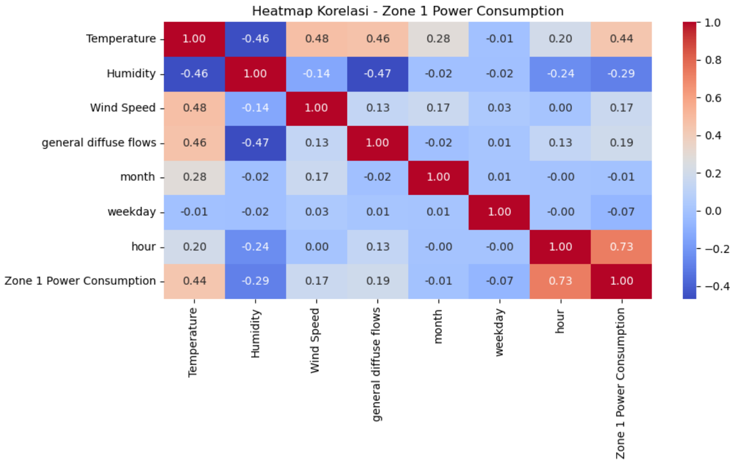

Figure 4. Heatmap correlation of Zone 1 Power Consumption using ALO

3.3.3. Teaching Learning Based Optimization (TLBO) Feature Selection

Feature selection using the TLBO algorithm on Zone 1 Power Consumption found seven features that are considered influential in predicting electrical energy consumption. The selected features are temperature, humidity, wind speed, month, day, and hour. Hour has a very high influence with a score of +0.73 entering into a strong positive linear relationship correlation level. Temperature correlation gets a value of +0.44. Wind Speed of +0.17 is included in the weak positive linear relationship level. While the month of -0.01, and the day of -0.07 entered into the level of not a linear relationship. Humidity of -0.29 entered into a weak negative linear relationship.

Zone 2 Power Consumption there are five features that are considered to have an influence in predicting energy consumption, namely temperature with a correlation value of +0.38, wind speed of +0.15, diffuse flows of +0.04, month of +0.32, and hour of +0.66. Zone 3 Power Consumption has four selected features, namely wind speed with a correlation value of +0.28, month by -0.23, hour by +0.45, and minute by +0.00. Table 8 shows the correlation value of each zone, while Figure 5 displays one of the heatmap graphs in Zone 1 Power Consumption.

Table 8. Correlation Analysis of Power Load Value from Zone

Fiture	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
Temperature	+0.44	+0.38	-
Humidity	-0.29	-	-
Wind Speed	+0.17	+0.15	+0.28
General Diffuse Flows	-	-	-

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Diffuse Flows	-	+0.04	-
Year	-	-	-
Month	-0.01	+0.32	-0.23
Day	-0.07	-	-
Hour	+0.73	+0.66	+0.45
Minute	-	-	+0.00

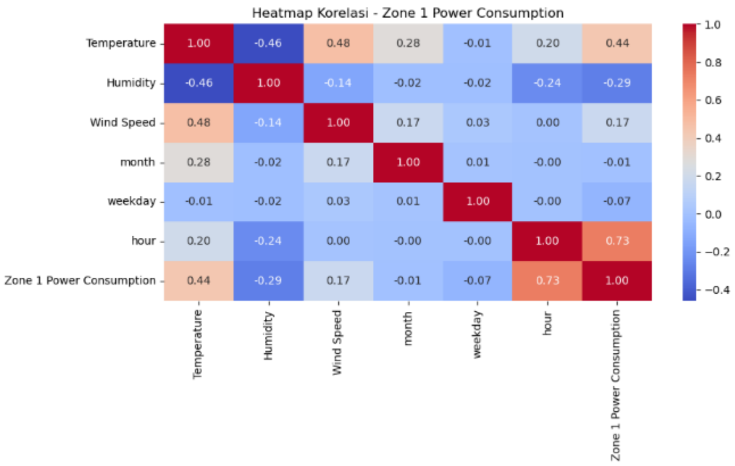

Figure 5. Heatmap correlation of Zone 1 Power Consumption using TLBO

3.3.4. Jaya Algorithm (JA) Feature Selection

The JA algorithm found seven features that are considered to have a correlation in predicting energy consumption. Zone 1 Power Consumption the correlation value of the selected features is temperature of +0.44, humidity of -0.29, wind speed of +0.17, diffuse flows of +0.08, month of -0.01, day of -0.07, and hour of +0.73. Zone 2 Power Consumption features that have a correlation of feature selection results are temperature worth +0.38, humidity worth -0.29, wind speed worth +0.15, diffuse flows worth +0.04, month worth +0.32, day worth -0.12, and hour worth +0.66. Zone 3 Power Consumption features selected are Temperature with a correlation value of +0.49, Humidity of -0.23, Wind Speed of +0.28, month of -0.23, day of +0.01, and hour of +0.45. Based on the feature selection results, temperature shows a distinct positive linear relationship correlation in each zone. Table 9 presents the feature preservation results and correlation values in each zone. Figure 6 is a heatmap graph that shows the level of correlation between features in Zone 1 Power Consumption.

Table 9. Correlation Analysis of Power Load Value from Zone

Fiture	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
Temperature	+0.44	+0.38	+0.49
Humidity	-0.29	-0.29	-0.23
Wind Speed	+0.17	+0.15	+0.28
General Diffuse Flows	-	-	-
Diffuse Flows	+0.08	+0.04	-
Year	-	-	-
Month	-0.01	+0.32	-0.23
Day	-0.07	-0.12	+0.01
Hour	+0.73	-	+0.45
Minute	-	+0.66	-

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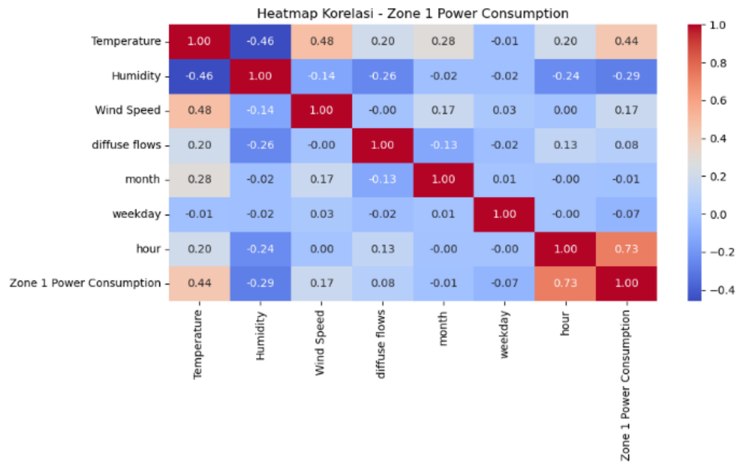

Figure 6. Heatmap correlation of Zone 1 Power Consumption using JA

3.4. Modeling and Evaluation

KNN is one of the supervised learning algorithms used for classification and regression. The evaluation compares various feature selection methods to improve the performance of KNN, namely GA, ALO, TLBO, and JA. The training and test data ratio used is 90:10, which means 90% of the data is used for training and 10% for testing.

Performance comparison based on RMSE values shows that the KNN model without feature selection produces the highest error in Zone 1 Power Consumption. The GA+KNN model records the highest error in Zone 2 and Zone 3. In contrast, the integration of ALO+KNN and JA+KNN shows stable RMSE results in all zones. The JA+KNN model excels with the smallest RMSE value, which is 856.1696 kW in Zone 1 and 598.8744 kW in Zone 2. While ALO+KNN records the smallest RMSE in Zone 3 of 699.5722 kW. Compared with KNN without feature selection (for example, assuming its RMSE in Zone 1 is 1300 kW), JA+KNN provides a reduction in RMSE of 443.83 kW in Zone 1. If GA+KNN produces an RMSE in Zone 2 of 3350.7657 kW, then JA+KNN reduces the error by 2751.89 kW. For Zone 3, if GA+KNN has an RMSE of 3350.7657 kW, then ALO+KNN reduces the error by 2651.19 kW. This significant difference shows that choosing the right feature selection algorithm can drastically improve the prediction accuracy of the KNN model. Table 10 is the RMSE value data of all prediction models.

Table 10. RMSE of each Prediction Model

Prediction Model	Zone 1 Power Consumption (kW)	Zone 2 Power Consumption (kW)	Zone 3 Power Consumption (kW)
KNN	1871.4290	1394.7660	1574.9974
GA+KNN	1221.0346	1829.6050	3350.7657
ALO+KNN	874.6656	638.9848	**699.5722**
TLBO+KNN	904.3016	1375.2004	1703.2814
JA+KNN	**856.1696**	**598.8744**	718.0008

The Mean Absolute Percentage Error (MAPE) values of each prediction model indicate that the integration of feature selection algorithms significantly improves the accuracy of the KNN model. In Zone 1, the baseline KNN model records a MAPE of 4.32%, whereas the JA+KNN model achieves the lowest MAPE of 1.80%, resulting in an improvement of 2.52%. In Zone 2, JA+KNN reduces the MAPE from 4.99% to 1.93%, indicating a gain of 3.06%. Likewise, in Zone 3, JA+KNN demonstrates superior

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performance with a MAPE of 2.34%, improving prediction accuracy by 3.93% compared to the baseline KNN value of 6.28%. The ALO+KNN model also shows competitive performance with MAPE values of 1.82% in Zone 1, 1.99% in Zone 2, and 2.38% in Zone 3. These results correspond to improvements of 2.50, 3.00, and 3.90% points, respectively. The TLBO+KNN model yields a MAPE of 1.85% in Zone 1, reflecting an improvement of 2.47% points, although its accuracy in Zones 2 and 3 is less stable compared to other models. On the other hand, the GA+KNN model performs poorly, with MAPE values of 6.60% in Zone 2 and 12.49% in Zone 3. These figures exceed those of the baseline KNN and indicate a decline in performance by 1.61 and 6.21% points, respectively. Overall, the results confirm that the use of feature selection algorithms, particularly JA and ALO, can significantly enhance the prediction accuracy of the KNN model. Table 11 summarizes the MAPE values of each model across all zones.

Table 11. MAPE of each Prediction Model

Prediction Model	Zone 1 Power Consumption (%)	Zone 2 Power Consumption (%)	Zone 3 Power Consumption (%)
KNN	4.3203	4.9895	6.2790
GA+KNN	2.5816	6.6034	12.4876
ALO+KNN	1.8204	**1.9914**	2.3821
TLBO+KNN	1.8549	4.6538	6.1906
JA+KNN	**1.8006**	1.9323	**2.3444**

The R^2 values of each prediction model show significant performance improvements when KNN is integrated with a feature selection algorithm. In Zone 1, the baseline KNN model achieves an R^2 of 0.9299, while the JA+KNN model reaches 0.9853, representing an improvement of 0.0554. The ALO+KNN model follows closely with an R^2 of 0.9847, which indicates an increase of 0.0548, and the TLBO+KNN model achieves an R^2 of 0.9836, reflecting a gain of 0.0537. In Zone 2, JA+KNN again demonstrates superior performance with an R^2 of 0.9866, which is 0.0588 higher than the KNN value of 0.9278. ALO+KNN also shows strong results with an R^2 of 0.9849, marking an increase of 0.0571, while TLBO+KNN reaches 0.9299, offering only a slight improvement of 0.0021. Conversely, GA+KNN results in a reduced performance in Zone 2, obtaining an R^2 of 0.8758, which is 0.0520 lower than the baseline KNN. In Zone 3, ALO+KNN achieves the highest R^2 value of 0.9887, improving upon KNN's 0.9428 by 0.0459. This is followed by JA+KNN with an R^2 of 0.9881, reflecting an improvement of 0.0453. In contrast, TLBO+KNN yields an R^2 of 0.9331, indicating a slight decline of 0.0097, and GA+KNN performs the worst with an R^2 of 0.7410, which represents a substantial decrease of 0.2018 from the baseline. These results highlight that the JA+KNN and ALO+KNN models provide the most consistent and significant improvements in prediction accuracy, whereas the GA+KNN model tends to degrade model performance in several zones. Table 12 presents the detailed R^2 values for each prediction model.

Table 12. R^2 of each Prediction Model

Prediction Model	Zone 1 Power Consumption	Zone 2 Power Consumption	Zone 3 Power Consumption
KNN	0.9299	0.9278	0.9428
GA+KNN	0.9701	0.8758	0.7410
ALO+KNN	0.9847	0.9849	**0.9887**
TLBO+KNN	0.9836	0.9299	0.9331
JA+KNN	**0.9853**	**0.9866**	0.9881

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4. DISCUSSIONS

The research proved that metaheuristic based feature selection has a significant impact on improving the accuracy of KNN performance in energy consumption prediction. The dataset used is Tetouan City Power Consumption, consisting of 52,417. The dataset consists of nine features, namely datetime, temperature, humidity, wind speed, general diffuse flows, diffuse flows, Zone 1 Power Consumption, Zone 2 Power Consumption, and Zone 3 Power Consumption. The datetime feature is extracted into year, month, day, hour, and minute. The purpose of extraction is to optimize temporal information, so that consumption patterns based on time can be analyzed more deeply. The datetime attribute in the dataset is removed, so as not to redundant with the results of data extraction. The next step is to normalize the data using min-max scaling, because KNN depends on distance calculations so that the same scale is needed.

The feature selection process using GA, ALO, TLBO, and JA shows that the hour, temperature, and humidity features are almost always present in the feature selection results. These three features show that the features have a dominant influence on energy consumption. The results of feature selection using ALO and JA are able to select features that have an influence in predicting energy consumption, so this algorithm is more effective than TLBO and GA.

Energy consumption prediction is carried out in each zone, namely Zone 1 Power Consumption, Zone 2 Power Consumption, and Zone 3 Power Consumption. Prediction results using KNN without feature selection show RMSE values in each zone of 1871.4290 kW, 1394.7660 kW, and 1574.9974 kW. The evaluation results based on the MAPE value, in each zone are 4.3203%, 4.9895%, and 6.2790%. In addition, the R^2 value for KNN without feature selection is quite low compared to other models, namely 0.9299 in Zone 1 Power Consumption, 0.9278 in Zone 2 Power Consumption, and 0.9428 in Zone 3 Power Consumption. This shows that KNN without feature selection is less than optimal in modeling energy consumption patterns.

Employing metaheuristic algorithms for feature selection contributes to improving the effectiveness of predictive modeling. The combination of ALO+KNN and JA+KNN provides excellent performance. In JA+KNN, the RMSE value in each zone drops to 856.1696 kW, 598.8744 kW, and 718.0008 kW. Based on the MAPE value in each zone, the values are 1.8006%, 1.9323%, and 2.3444%. The R^2 value in each zone reaches 0.9853, 0.9866, and 0.9881, indicating that JA+KNN has a very good level of precision in representing actual data. The ALO+KNN model also shows good performance with RMSE values in each zone of 874.6656 kW, 638.9848 kW, and 699.5722 kW, and MAPE in each zone of 1.8204%, 1.9914%, and 2.3821%. The R^2 value achieved was even higher in Zone 3 Power Consumption at 0.9887, while in Zone 1 Power Consumption it reached 0.9847, and Zone 3 Power Consumption reached 0.9849. Based on the evaluation results, it strengthens the evidence that ALO is very effective in finding the optimal feature subset.

The GA+KNN model shows inconsistent performance, even producing the largest RMSE in Zone 3 Power Consumption of 3350.7657 kW, MAPE reaching 12.4876%, and R^2 only 0.7410, showing that GA is less effective in predicting energy consumption. This is in line with the findings of Allemar Jhone P. Delima and Guilian Feng [42] who revealed that GA, when not combined with additional optimization strategies, is prone to overfitting and premature convergence. While the TLBO+KNN model provides intermediate results, better than KNN without feature selection, with RMSE for each zone of 904.3016 kW, 1375.2004 kW, and 1703.2814 kW. MAPE values for each zone are 1.8549%, 4.654%, and 6.1906%. The R^2 values for each zone reached 0.9836, 0.9299, and 0.9331.

Overall, the integration of ALO and JA-based feature selection is proven to significantly reduce prediction error (RMSE and MAPE) while increasing model accuracy (R^2) compared to using KNN

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without feature selection. This confirms that feature selection plays a crucial role in building a more accurate energy consumption prediction model. In the context of computer science, these methods contribute to the advancement of intelligent data preprocessing techniques, particularly in high-dimensional data environments where irrelevant features can degrade model performance. ALO and JA not only improve prediction quality but also enhance computational efficiency by reducing the number of input features, leading to faster training and inference times. Their ability to select optimal feature subsets without exhaustive search demonstrates their practical value in real-world applications, especially in energy systems where accurate and efficient forecasting is vital for operational planning and resource optimization.

5. CONCLUSION

The results show that feature selection plays a significant role in improving the accuracy of the K-Nearest Neighbor (KNN) model for predicting electrical energy consumption. Among the evaluated models, the integration of ALO+KNN and JA+KNN demonstrates the most consistent and effective performance in this scenario, as reflected by reduced RMSE and MAPE values and increased R^2 scores across the three zones. The JA+KNN model achieves the lowest RMSE in Zone 1 at 856.1696 kW and in Zone 2 at 598.8744 kW, along with the smallest MAPE values of 1.8006 percent in Zone 1 and 2.3444 percent in Zone 3. The ALO+KNN model yields the lowest RMSE in Zone 3 at 699.5722 kW and the smallest MAPE in Zone 2 at 1.9914 percent. In terms of R^2, JA+KNN achieves the highest values in Zone 1 and Zone 2 at 0.9853 and 0.9866 respectively, while ALO+KNN records the highest R^2 in Zone 3 at 0.9887. Conversely, the GA+KNN model exhibits inconsistent and less reliable performance across the zones. These findings indicate that, under the tested conditions, ALO+KNN and JA+KNN offer strong potential for enhancing predictive accuracy in energy consumption modeling. For future research, it is recommended to explore the integration of hybrid prediction approaches, such as combining KNN with deep learning models like Long Short-Term Memory (LSTM), and applying JA-based feature selection to further improve both temporal learning and feature relevance. Additionally, evaluating the robustness of these models under real-time or streaming data environments could provide valuable insights for practical deployment.

CONFLICT OF INTEREST

The authors confirm that there are no conflicts of interest related to the authorship or the subject matter discussed in this study.

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