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An Optimized Artificial Neural Network Model Using JAYA Algorithm for Energy Consumption Forecasting in Oman

Zainab Hamed AlSidairi[1,*], Saraswathy Shamini Gunasekaran[1]
[1]Universiti Tenaga Nasional (UNITEN), Kuala Lumpur, Malaysia
Emails: PT20711@student.uniten.edu.my; sshamini@uniten.edu.my

Abstract

The Accurate energy forecasting is vital for strategic planning, particularly in de-veloping economies with rapidly evolving demand patterns. This study pro-poses a hybrid Artificial Neural Network (ANN) model optimized using a modified JAYA algorithm to forecast energy consumption in Oman. The JAYA algorithm's parameter-free, metaheuristic search improves ANN train-ing by enhancing convergence speed and reducing the risk of local minima. Historical data from 2017–2021—comprising GDP, population, and oil and gas production—were used as inputs. Model performance was benchmarked against an ANN trained with the Artificial Bee Colony (ABC) algorithm using mean square error (MSE), mean absolute error (MAE), relative error (RE), and root mean square error (RMSE) as evaluation metrics. Results show that ANN–JAYA consistently outperformed ANN–ABC, achieving lower error rates and greater robustness. The proposed approach offers a reliable deci-sion-support tool for policymakers and energy authorities, enabling more ef-fective resource allocation and long-term planning. Future research will ex-tend the framework to integrate renewable energy indicators and real-time data for adaptive, sustainable forecasting.

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1. Inrtoduction

The world, and Oman, face increasing pressure to adopt renewable energy [1], and this is a fundamental priority in governmental planning for economic diversification [2]. Multiple stakeholder involvement and advanced technologies are essential to meet global challenges, as seen during the COVID-19 pandemic [3]. Renewable energy can be at the forefront of combatting poverty and enabling development [4], but empirical studies proving this, and providing a basis for policy decisions, remain somewhat lacking. Given the immense importance of affordable energy in poverty alleviation, the relatively higher cost of renewable energy has long inhibited the transition to renewables, particularly in developing countries and oil and gas (O&G) producing states (where traditional fuel sources used in conventional electricity generation are far cheaper) [5]. However, as renewables become more cost-competitive, and macroeconomic trends in the global economy and consumer preferences begin to favour renewables, the paradigm is slowly shifting.

Global economic development is closely associated with energy availability and price fluctuations, which influence possible future developmental pathways. The energy crisis of the 1970s exemplified how sudden energy shocks could disrupt economic systems, particularly in developing countries, which predominantly depend on imported energy sources. Despite the emergence of new paradigms aimed at addressing global energy challenges—such as improving energy security—policymakers continue to face considerable uncertainty in this domain. A critical challenge remains: discovering credible potential developments and alternative future trends in energy systems while identifying key driving forces governing energy management. Predicting realistic futures requires analyzing comprehensive historical data that reflect the complex structure of energy consumption and extrapolating these trends accurately. Artificial Neural Networks (ANNs) offer innovative means for modeling these complex patterns and reducing prediction errors. Energy and raw materials constitute fundamental inputs for economic development and natural resource extraction, particularly fossil fuels. Energy consumption in Oman, largely dependent on the country's oil and gas reserves, is increasing steadily. Traditional forecasting techniques exist; however, their effectiveness for Oman's energy data remains under-explored. This study addresses the core problem of whether intelligent models, specifically ANNs optimized with metaheuristic algorithms, can effectively model and predict Oman's energy consumption data.

In recent years, machine learning and artificial intelligence (AI) have gained prominence in forecasting energy consumption across both developed and developing economies. These approaches have been proven to outperform conventional regression and time-series models by capturing non-linear relationships and adapting to evolving consumption patterns. However, the application of hybrid ANN–metaheuristic models tailored to Oman's unique energy structure is relatively unexplored in the literature. Exploring such models is critical, as they may provide more reliable decision-support tools for policymakers seeking to balance energy demand, economic diversification, and sustainability goals.

Furthermore, Oman's rapid urbanization, industrialization, and population growth add layers of complexity to forecasting future energy demand. The country's reliance on hydrocarbon resources creates vulnerabilities to global price shocks and supply volatility, reinforcing the urgency of building robust forecasting frameworks. By applying advanced ANN models optimized through metaheuristic algorithms, this study attempts to fill the gap in accurately forecasting energy demand while providing insights into the potential pathways toward a more secure and sustainable energy future for Oman.
The main Contributions of the Study are:

The main contributions of this research can be summarized as follows:

1. **Development of a tailored ANN–metaheuristic model** capable of accurately forecasting Oman's energy consumption trends, addressing gaps in the current forecasting literature for the region.
2. **Empirical validation of model performance** through comparative analysis with traditional forecasting methods, highlighting the superiority of intelligent techniques in accuracy and robustness.
3. **Policy-relevant insights** into Oman's future energy consumption, supporting governmental strategies for energy diversification, economic planning, and sustainable development.

The remainder of this study is structured as follows. Section 2 outlines the methodology, including data description, model design, and optimization procedures. Section 3 presents the experimental results and comparative performance analysis of the proposed model. Section 4 discusses the implications of the findings for Oman's energy policy and development strategies. Finally, Section 5 concludes the paper with key insights, limitations, and recommendations for future research.

2. Proposed Methodology

2.1 Artificial Neural Networks and Metaheuristics

The multilayer perceptron (MLP) architecture is the most widely used ANN structure [1]. Traditional gradient-based training algorithms like Back-Propagation (BP) suffer from slow convergence and susceptibility to local mini-ma, partly due to dependency on initial parameters [2]. Metaheuristic algorithms, which use randomized exploration and exploitation strategies, provide robust alternatives capable of optimizing MLP weights and structure [1,2].
Metaheuristics such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and JAYA algorithm have been successfully applied for energy consumption forecasting in various countries [3]. These meth-ods generally outperform classical gradient-based approaches by enhancing con-vergence speed and solution quality.

2.2 The JAYA Algorithm

The JAYA algorithm is a population-based optimization technique combining evolutionary survival-of-the-fittest principles with swarm intelligence's global solution attraction [4]. It is characterized by simplicity, a single-phase

process, and the absence of algorithm-specific parameters, which facilitates implementation and robustness against local minima.
In this study, a modified variant of the JAYA algorithm is utilized, incorporating minor parameter adjustments to balance exploration and exploitation better in complex search spaces.
The objective function is minimized by updating candidate solutions based on their relative performance to the best and worst solutions in the population as expressed by:

$$J'_{x,y,z} = J_{x,y,z} + r_{1,x,z}\left(J_{x,best,z} - \left|J_{x,y,z}\right|\right) - r_{2,x,z}\left(J_{x,worst,z} - \left|J_{x,y,z}\right|\right)(1)$$

Where $J_{(x,y,z)}$ represents the value of the xth variable for the yth candidate in the zth iteration, $J_{(x,best,z)}$ is the variable x value of the best candidate, $J_{(x,worst,z)}$ is the variable x value of the worst candidate, $J_{(x,y,z)}^{'}$ is the updated value of $J_{(x,y,z)}$, $r_{(1,x,z)}$ and $r_{(2,x,z)}$ are two random numbers in the range [0, 1] generated for the xth variable during the zth iteration[5].
A new solution replaces the current one if it improves or maintains fitness, with continuous updates to the best and worst solutions to guide the search dynamically.

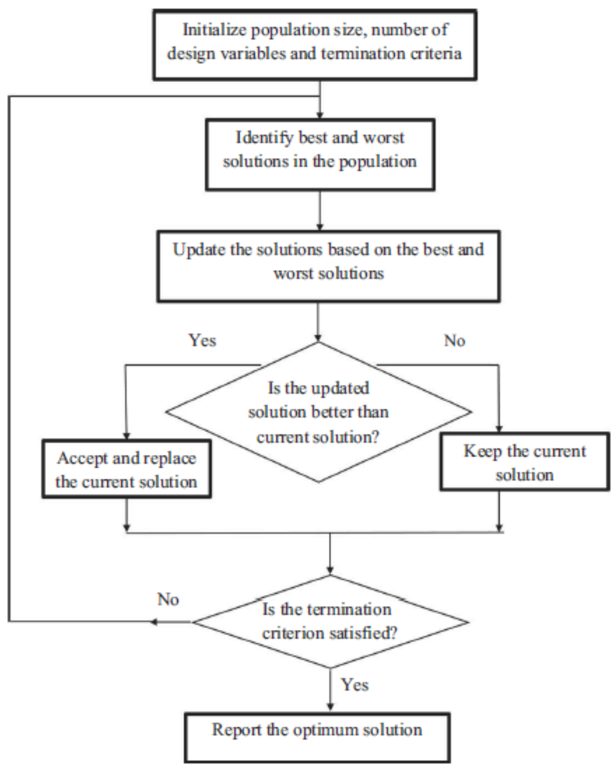

Figure 1. Flowchart of the JAYA Algorithm

2.3 Model Architecture and Training

The ANN model consists of three layers: input, hidden, and output. The tangent sigmoid activation function connects the input and hidden layers, enabling trans-formation of input values from −∞-\infty−∞ to +∞+\infty+∞ into a range of −1-1−1 to +1+1+1. The output layer uses a linear activation function suitable for regression tasks [6].
The JAYA algorithm optimizes the ANN by minimizing the error objective function, adjusting weights and biases to improve forecasting accuracy. This hy-brid approach combines the learning capacity of ANNs with the global search capabilities of metaheuristics.

2.4 Data and Experimental Setup

Data Description The dataset used in this study comprises historical records of Oman's energy consumption collected from the Oman National Centre for Statistics and Information (NCSI) and the BP Statistical Review of World Energy. The data spans the period 2017–2021, covering annual energy consumption val-ues in million tonnes of oil equivalent (Mtoe). Supplementary variables such as GDP, GDP per capita, population, crude oil prices, and oil and gas production levels were included to capture economic, demographic, and industrial influ-ences on energy usage.
All variables were normalized to a [0, 1] range using min–max scaling to im-prove ANN training stability and avoid scale-dominance problems.

2.5 Experimental Environment

All experiments were conducted using Python 3.10 with TensorFlow 2.15 for ANN implementation and NumPy/Pandas for data preprocessing. The JAYA op-timization algorithm was implemented from scratch to ensure flexibility in pa-rameter tuning. Computations were performed on a workstation with Intel® Core™ i9-13900K, 64 GB RAM, and NVIDIA RTX 4090 GPU running Windows 11 Pro.

2.6 Artificial Neural Network Configuration

The baseline ANN model consisted of:

- Input Layer: Number of neurons equal to the number of input features (n = 3: GDP, population, oil and gas levels).
- Hidden Layer(s): Single hidden layer with the number of neurons determined by JAYA optimization.
- Activation Functions: ReLU for hidden layers, linear activation for the output layer.
- Output Layer: Single neuron representing forecasted energy consumption [7].

The JAYA algorithm was employed to optimize ANN parameters, including hidden neuron count, learning rate, and batch size. The maximum number of iterations for JAYA was set to 100, with a population size of 20 candidate solutions.

2.7 ANN Model Accuracy Parameters

[8] To assess the accuracy of the trained ANN model, five statistical parameters were computed:

$$Relative\ Errors\ (RE) = \frac{\sum_{i=1}^{n}\left(\frac{Y_k - O_k}{Y_k}\right)}{n}\ X\ 100 \quad (2)$$

$$Root\ Mean\ Square\ Errors\ (RMSE) = \left[\frac{1}{n}\sum_{i=1}^{n}(Y_k - O_k)^2\right]^{\frac{1}{2}} \quad (3)$$

$$Mean\ Absolute\ Errors\ (MAE) = \frac{1}{n}\sum_{i=1}^{n}|(Y_k - O_k)| \quad (4)$$

$$Correlation\ Coefficients\ (R) = \frac{\left(\sum_{i=1}^{n}(O_k - \bar{O}_k)\,(Y_k - \bar{Y}_k)\right)}{\sqrt{\sum_{i=1}^{n}(O_k - \bar{O}_k)^2\ \sum_{i=1}^{n}(Y_k - \bar{Y}_k)^2}} \quad (5)$$

$$U - statistic = \frac{RMSE}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_k)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_k)^2}} \quad (6)$$

Lower values of Relative Error (RE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) indicate that the model produces estimate closer to observed values. Meanwhile, correlation coefficient (R) values approaching 1 and Theil's U-statistic values approaching 0 denote superior model performance [10].

2.8 Control Parameters

The performance of metaheuristic algorithms such as JAYA is highly influenced by their control parameters, which are often challenging to optimize. This study selected potential control parameter values based on findings from previous lit-erature [5,6].

2.9 Parameter Range

The parameter range for ANN weights was adjusted to [−1, 1]. The mean squared error (MSE) goal was set to 8×10^{-8}. The training process iteratively updated the network weights until the stop criteria were met. The training scheme for the ANN model is illustrated in Figure 2.

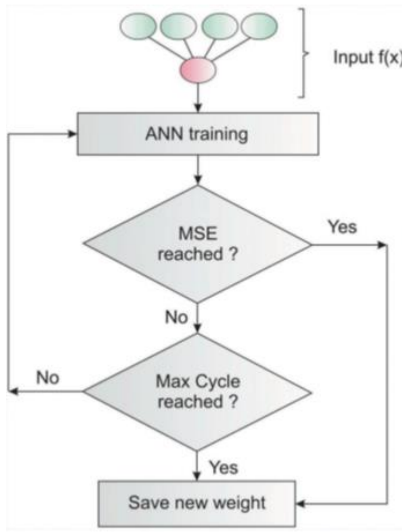

Figure 2. Training scheme for ANN

2.10 Input Variables

Energy planning requires an in-depth understanding of historical and current consumption trends as well as reliable forecasts of future demand. While energy prices influence consumption patterns, they are only one among many determining factors. Other critical variables include supply reliability, technological factors, population growth, income levels, urbanization rates, and social behaviors.

In this study, three independent variables were selected based on literature evidence [15,16,17,18]:

- Gross Domestic Product (GDP)
- National Population
- Oil and Gas Production Levels

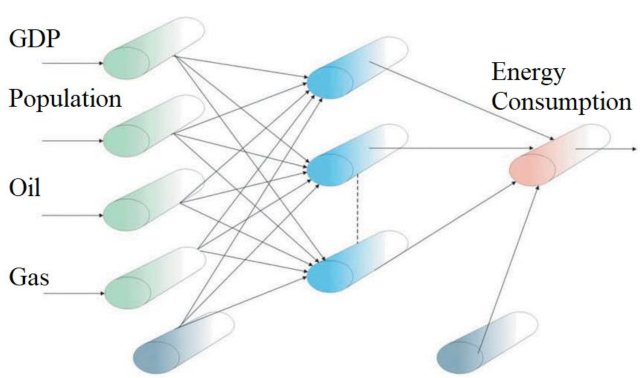

Figure 3. ANN model for energy consumption

GDP is a key macroeconomic indicator reflecting overall economic activity, population growth is a primary driver of long-term energy demand, and oil and gas levels are directly linked to national energy intensity. GDP per capita was also tested as it provides a more accurate representation of living standards com-pared to GDP alone.

2.11 Forecasting Model Development

A three-layer feed-forward Multilayer Perceptron (MLP) neural network was constructed, with the three independent variables (GDP, population, oil and gas levels) as inputs and total energy consumption as the output. The JAYA algo-rithm was used to optimize ANN parameters. Backpropagation was employed to update network weights during training. The general architecture of the model is illustrated in Figure 3. For all metaheuristic optimization methods, initial population values are ran-domly generated within the search space. When initial values are near the opti-mal solution, faster convergence is achieved. Increasing the number of independ-ent runs enhances the probability of initializing close to the optimum.

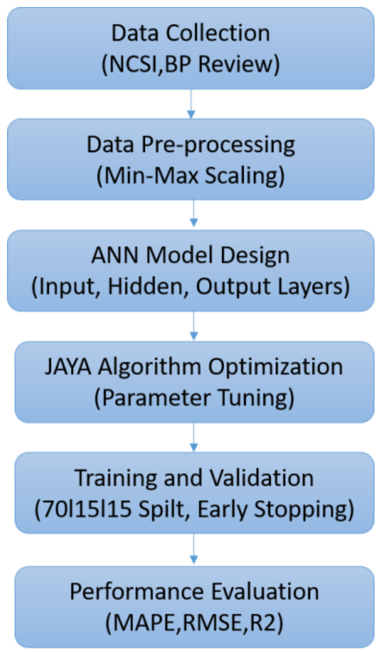

Figure 4. Training scheme for ANN (full process from inputs → normalization → optimization → evaluation

2.12 Comparison Algorithm

The artificial bee colony (ABC) algorithm, introduced in 2005 [12], has been described in detail previously [12]. Briefly, it is an algorithm that was inspired by honey bee foraging behavior and is based on swarm intelligence. Each food source location in the search space refers to one ABC algorithm solution. The ABC algorithm seeks to define the best available food source by searching all source options in the search space. Employed, onlooker, and scout bee subsets of individuals carry out food source searching [13].

The weights in the present ANN model are the solution parameters. The ABC algorithm finds the optimal weights, and its performance depends on three con-trol parameters, namely the food source count (i.e., employed/onlooker bee quan-tity), limit, and maximum cycle count. This algorithm is started by a random food source population, evaluates the population, and repeats.

ANNs will be trained with ABC algorithm. To restrain error functions within a competitive time, this study will be applied ABC and JAYA algorithms to obtain optimal weights and minimize biases. Weights and biases were updated until the objective function error (MSE) will be reduced to an acceptable level.

3. Results and Discussion

Accurate energy consumption forecasting is essential for sustainable energy planning and policy formulation. The primary objective of this study was to de-velop a novel Artificial Neural Network (ANN) model optimized with the

JAYA algorithm (ANN–JAYA) for forecasting energy consumption in Oman, and to benchmark its performance against an ANN model trained using the Artificial Bee Colony (ABC) algorithm (ANN–ABC). The models were trained using Oman's GDP, national population, and oil and gas production levels as input variables, while energy consumption served as the output variable. Forecasts were generated under three different scenarios.
The selected ANN architecture consisted of an input layer, one hidden layer, and an output layer. Previous studies have shown that a single hidden layer can yield high prediction accuracy while reducing computational complexity. The number of neurons in the hidden layer was determined empirically through trial and error, as no universal rule exists for its selection.

For activation functions, a tangent sigmoid was used between the input and hidden layers, and a linear function was employed between the hidden and out-put layers. Both the ABC and JAYA algorithms were applied to minimize the mean square error (MSE), defined as:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(Y_k - O_k)^2 \quad (7)$$

where n represents pattern count, Ok represents the ANN-yielded output value, and Yk represents the exact output value.

Weights and biases were iteratively updated until the MSE was minimized to an acceptable level [11].

3.1 Data Collection

The forecasting models were trained using annual data from 2017–2021 obtained from the Oman Statistical Institute. The dataset comprised:

- GDP (economic growth indicator)
- National population (a primary driver of energy demand)
- Oil and gas levels (indicators of industrial activity and energy intensity)

All input/output data were normalized to the range 0.1–0.9 to match the transfer function's optimal operational range (0–1).

3.2 Data Training

A three-layer ANN was configured with GDP, population, and oil/gas levels as inputs, and energy consumption as the output. The ABC and JAYA algorithms were applied to optimize the ANN parameters.

Table 1: summarizes the MSE values for different hidden-layer neuron counts.

ANN Architecture	ABC Algorithm	JAYA Algorithm
5- neurons	**2.884**	**1.916**
10- neurons	**4.2**	**3.662**
15- neurons	**3.194**	**2.726**
20- neurons	**5.325**	**5.972**

The results indicate that ANN–JAYA consistently achieved lower MSE values than ANN–ABC for all neuron configurations tested. The number of neurons did not show a linear relationship with performance; in some cases, increasing neurons improved accuracy, while in others it did not. This variation is largely attributed to the random initialization inherent in metaheuristic algorithms. Increasing the number of runs can improve the probability of achieving near-optimal initialization.

Table 2: Maximum Relative Error (RE) Results (%)

ANN Architecture	ABC Algorithm	JAYA Algorithm
5- neurons	**2.884**	**1.916**
10- neurons	**4.2**	**3.662**
15- neurons	**3.194**	**2.726**
20- neurons	**5.325**	**5.972**

Both models achieved RE values within acceptable limits, with ANN–JAYA generally outperforming ANN–ABC.

3.3 Performance Evaluation

Performance metrics included Mean Absolute Error (MAE), Relative Error (RE), and Root Mean Square Error (RMSE).

Table3: Mean Absolute Error (MAE) (Mtoe)

ANN Architecture	ABC Algorithm	JAYA Algorithm
5- neurons	**1.253**	**0.703**
10- neurons	**1.431**	**0.264**
15- neurons	**0.522**	**0.507**
20- neurons	**0.662**	**0.599**

Table 3: Relative Error (RE) (%)

ANN Architecture	ABC Algorithm	JAYA Algorithm
5- neurons	**1.117**	**0.627**
10- neurons	**1.324**	**0.231**
15- neurons	**0.456**	**0.445**
20- neurons	**0.594**	**0.549**

Table 5: Root Mean Square Error (RMSE) (Mtoe)

ANN Architecture	ABC Algorithm	JAYA Algorithm
5- neurons	**1.338**	**0.829**
10- neurons	**1.911**	**0.378**
15- neurons	**0.597**	**0.626**
20- neurons	**0.770**	**0.771**

Across all three metrics, the ANN–JAYA model with 10 neurons demonstrated the highest accuracy, achieving the lowest MAE, RE, and RMSE values.

3.4 Predictions of Energy Consumption

The models were used to forecast Oman's energy consumption for 2017–2021, with results shown in Table 6.

Table 6: Actual vs. Predicted Energy Consumption (Mtoe)

Years	**Actual Energy**	
Consumption Values	**ANN-ABC**	**ANN-JAYA**
2017	**102.9**	**104.9**
2018	**105.8**	**110.1**
2019	**114.5**	**115.4**
2020	**120.1**	**118.4**
2021	**120.3**	**119.7**

Model comparison results are summarized in Table 7.

Table 7: Model Performance Comparison

Years	**ANN-ABC**	**ANN-JAYA**
Mean absolute error (Mtoe)	**1.77**	**0.35**
Relative error (%)	**1.60**	**0.31**
Root-mean-square error (Mtoe)	**2.14**	**0.50**

The ANN–JAYA model significantly outperformed ANN–ABC, showing reduced errors across all metrics. The proposed ANN–JAYA model, trained on GDP, population, and oil/gas production data, demonstrated superior forecasting accuracy compared to ANN–ABC. The JAYA algorithm's simplicity, lack of control parameters, and robust search capability allowed for faster convergence and higher accuracy.

Based on RMSE, MAE, and RE values, the ANN–JAYA model proved more effective for short-term energy consumption forecasting in Oman, offering a robust tool for policy and strategic energy planning.

4. Conclusion

This study developed a hybrid ANN model trained by a modified JAYA algorithm to forecast energy consumption in Oman. The approach addresses challenges of traditional ANN training by enhancing convergence and avoiding local minima. Results demonstrate improved prediction accuracy, providing valuable insights for policymakers and energy management authorities. The critical analysis of the JAYA algorithm reveals both its strengths and its limitations in addressing optimization problems. This chapter has outlined the proposed methodology, including the ANN model's accuracy parameters and control parameters, as well as the integration of the JAYA and ABC algorithms for weight optimization. By evaluating these approaches, the chapter provides a clear framework for determining the most suitable domains and applications of ANN models enhanced with the JAYA algorithm. This, in turn, justifies the JAYA-related contributions in the context of energy consumption forecasting in Oman. Future work will consider expanding the model to incorporate renewable energy variables and real-time data for adaptive forecasting.

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