

RESEARCH PAPER

Testing Artificial Intelligence Models for Solar Cook Stove Performance Prediction: Case Study of Agadez, Niger

Abubakar Danjuma Maiwada,^{*}¹ Sagir Jibrin Kawu,¹ Abba Bashir,^{2,3} and Umar Danjuma Maiwada⁴

¹Centre for Renewable Energy Research, Bayero University, Kano

²Department of Civil Engineering, Federal University, Dutsin-ma, Katsina, Nigeria

³School of Civil Engineering, Tianjin University, Tianjin 300072, China

⁴Computer Sciences Department, Faculty of Natural and Applied Science, Umaru Musa Yar'adua University, Katsina, Nigeria

^{*}Corresponding author. Email: admawada.crer@buk.edu.ng

(Received 24 February 2024; revised 05 April 2024; accepted 10 April 2024; first published online 30 April 2024)

Abstract

Solar cook stoves are becoming an increasingly popular and sustainable option for cooking food, especially in areas where access to traditional cooking fuels is limited or where deforestation is a concern. However, the performance of solar cook stoves can be affected by various factors such as weather conditions, time of day, and geographic location. The developed stove was tested in Agadez, Niger Republic on 9th December 2022, in the cold season, and obtained a temperature of 76.4°C with radiation at noon of 727 W/m² and a total daily radiation of 5044 W/m². To improve the performance of solar cook stoves, researchers have turned to artificial intelligence (AI) based models, specifically artificial neural networks (ANN), for prediction. In this research, ANN was adopted to predict the performance of solar cook stoves. The ANN model employed the use of feed-forward back propagation as network type, trainlm as a training function, learnqdm as learning function, and Mean Square Error (MSE) as performance function, best result was obtained with 2 layers, 10 neurons in the hidden layer and tansig as a transfer function. For the algorithms, Levenberg-Marrquadt was used in training. The experimental data were divided by 70% for training and 30% for testing. Based on the various interpretations provided, it appears that the Artificial Intelligence (AI) based models for the prediction of Solar Cook Stove performance have shown promising results. In the sensitivity analyses, M11 was the function for the Test Temperature, and M12 was for Test Temperature and Solar Radiation. Model M11: Training Phase: MSE \approx 0.1, RMSE \approx 0.2, Testing Phase: MSE \approx 0.05, RMSE \approx 0.15, Model M12, Training Phase: MSE \approx 0.05, Testing Phase: MSE \approx 0.05, RMSE \approx 0.1, RMSE \approx 0.45, Model M12 has a higher RMSE during testing compared to Model M11, indicating lower predictive accuracy. The scatter plots of observed versus predicted values for both M11 and M12 indicate a fairly strong positive correlation. Furthermore, the radar plots of goodness of fit (measured by R-squared values) suggest that both models perform relatively well, with M12 showing a higher degree of fit compared to M11. The error of fit graph, presented as a bar plot, also shows that the testing phase for M12 is significantly more accurate, with a much lower mean squared error (MSE) and root mean squared error (RMSE) compared to M11.

Keywords: Artificial Intelligence; Neural Networks; Solar Cook Stoves; Solar Cooker; Solar Box Type Cooker; Renewable Energy; Cold Season

1. Introduction

Solar cook stoves are a sustainable and eco-friendly alternative to traditional cooking methods that use fossil fuels. They utilize solar energy to cook food and are particularly useful in areas where electricity or fuel sources are scarce. With the increasing demand for sustainable and renewable energy solutions, the use of solar cookstoves is gaining popularity worldwide. The aim and objectives of implementing box-type solar cookers in Nigeria revolve around promoting sustainable development, improving public health, enhancing energy security, and mitigating climate change impacts while harnessing the abundant solar energy resources available in the country.

The research's significance lies in presenting real-world evidence and valuable insights regarding the practicality and dependability of AI-driven models for forecasting the performance of solar cook stoves in Agadez, Niger. By assessing these models using actual data, the research can advise decision-makers, scholars, and professionals about the viability and efficiency of employing AI technologies to optimize the use of solar energy for cooking in resource-limited environments.

Moreover, the research's discoveries can contribute to progressing renewable energy studies by pinpointing ways to enhance AI-based modeling methods, refining input factors, and improving the precision of predictions tailored to Agadez's distinctive environmental and socio-economic conditions. This information can ultimately promote the broader acceptance and integration of solar cookstoves as a sustainable solution for cooking and tackling energy poverty in similar regions across Africa and other areas.

A box-type solar cooker, also known as a solar box cooker, is a device that uses the sun's energy to cook food. It consists of an insulated box with a clear lid, which allows sunlight to enter and heat up the box. The box is also lined with a reflective material, such as aluminum foil or reflective panels, to reflect and concentrate the sunlight onto the cooking pot. Box-type solar cookers are designed to be easy to use and require minimal supervision. Once the food is placed inside the cooking pot and the lid is closed, the cooker will begin to heat up, and the food will cook gradually. Cooking times may vary depending on the intensity of the sunlight and the type of food being cooked, but generally, it takes longer to cook with a solar cooker than with traditional stoves. One of the advantages of box-type solar cookers is that they do not require any fuel to operate, making them an environmentally friendly and sustainable option. They are also safe to use, as there is no open flame or smoke involved. Additionally, they can be used in areas where there is no access to electricity or gas, making them ideal for camping, picnics, and outdoor activities.

AI-based models have been developed to predict the performance of solar cook stoves. These models use machine learning algorithms to analyze data related to the design, construction, and usage of solar cook stoves. By analyzing this data, AI models can predict the efficiency and effectiveness of a particular solar cook stove design under different environmental conditions. AI-based models for the prediction of solar cook stoves have numerous benefits. They can help researchers and designers optimize the design and performance of solar cook stoves, making them more efficient and effective in various conditions. Additionally, these models can provide insights into the behavior of solar cook stoves and identify potential areas for improvement.

2. Literature Review

In a study published in the *Journal of Solar Energy*, researchers developed an ANN-based model for predicting the performance of a solar box cooker under different weather conditions [1]. The model used input variables such as solar irradiance, ambient temperature, and wind speed, and was trained on experimental data collected from a solar box cooker. The results showed that the ANN model was able to accurately predict the cooking time and the temperature of the food, with a mean absolute error of less than 3%. This model used input variables such as ambient temperature, wind speed, and solar irradiance, and was trained on experimental data collected from a solar box cooker. The results showed that the ANN model was able to accurately predict the cooking time and the

temperature of the food, with a mean absolute error of less than 5% [2].

Another study published in the *Journal of Energy Storage*. The authors developed an ANN-based model for predicting the performance of a phase change material (PCM)-integrated solar box cooker [3]. The model used input variables such as PCM melting temperature, solar irradiance, and ambient temperature, and was trained on experimental data collected from a PCM-integrated solar box cooker. The results showed that the ANN model was able to accurately predict the cooking time and the temperature of the food, with a mean absolute error of less than 5%. In a study published in the *Renewable Energy Journal*, researchers developed an ANN model for predicting the performance of a multi-layered solar box cooker [3]. The model used input variables such as the number of layers, the thickness of each layer, and solar irradiance, and was trained on experimental data collected from a multi-layered solar box cooker. The results showed that the ANN model was able to accurately predict the cooking time and the temperature of the food, with a mean absolute error of less than 5%. ANN-based model was developed for predicting the performance of a solar box cooker with different glazing materials [4]. The model used input variables such as the type of glazing material, solar irradiance, and ambient temperature, and was trained on experimental data collected from a solar box cooker with different glazing materials. The results showed that the ANN model was able to accurately predict the cooking time and the temperature of the food, with a mean absolute error of less than 4]%. The study's findings may have limited generalizability due to the specific experimental conditions used for training and testing the Artificial Neural Network (ANN) model. The model's accuracy and reliability heavily depend on the quality and quantity of the experimental data used. The model's performance may be influenced by the specific design and configuration of the solar box cooker used in the experimental setup. The study also reports a mean absolute error of less than 3% for predicting cooking time and food temperature, but other performance metrics could provide a more comprehensive assessment of the ANN model's accuracy and robustness.

In the light of the presented literature review, this study showcases a methodical strategy for overcoming the challenges linked to AI-based models used to predict the performance of solar cook stoves. Through the integration of thorough experimental methods, strong validation techniques, and clear reporting standards, the research contributes to enhancing the comprehension and use of AI in renewable energy studies.

3. Research Methodology

This research Artificial Intelligence Based Models for the prediction of Solar Cook Stove performance tested in Agadez, Niger Republic (AIBMSCSP) was carried out in Agadez, in Niger Republic. Agadez is a city located in the northern part of Niger Republic, in the Sahara Desert. It is situated at an altitude of 520 meters above sea level and covers an area of about 36,000 square kilometers. The city is known for its unique geography and is surrounded by Rocky Mountains, sand dunes, and desert plains.

The climate of Agadez is classified as arid or desert climate. It is characterized by hot and dry weather, with little or no rainfall throughout the year. The temperature in Agadez during the cold season (December) can drop to as low as 10°C at night and rise to around 30°C during the day. The weather is generally sunny during the day, with clear blue skies and low humidity. Dust storms are common during this season due to the dry and windy conditions. The aridity of the region is due to the location of Agadez in the Saharan Desert, which receives very little rainfall and has high evaporation rates.

Locally available materials were used in constructing the Parabolic and Box Type Solar Cooker. Plain wood, battery bank, sensor box, reflector polyethylene, metal sheet, nails, metallic door adjuster, and glue were some of the materials used. The box-type solar cooker was made up of some components: a wooden container, an absorber plate (heat collector), a reflector, and a glass lid.

A basic box container (0.61m x 0.45m) with a height of 0.2m was fabricated. An absorber metal

plate with a dimension of 0.61m x 0.45m was fabricated and painted black, and internally placed at the bottom of the cooker on top of the bottom wood to absorb the directed and reflected solar radiation. As a reflector, all of the interior walls of the box were coated with glowing polyethylene. A clear perplex glass- with good transmissivity, of 4mm thick was fixed to the top of the created box. To reflect more solar energy, a 0.63m x 0.47m reflector hinged at the top of the cooker was used. For tracking, an adjustable lever was used. Two temperature sensors in a box powered by a battery were placed one inside the cook stove and the other outside to get both temperatures. Hourly temperatures with irradiance and the two temperatures were recorded for ten hours beginning from 07:00 hrs. In summary, the box cooker was taken out in the sun, and the cover lid was left open at angle of 60oC. Two temperature sensors were used in the experiment, one was inserted in the cooker, recording internal cookstove temperature and the other recording outside ambient temperature (Figure 1 and 2). The readings including solar irradiance were recorded on hourly basis for ten hours.



Figure 1: *Temperature Control with Battery Bank.*

Incorporating stratification and randomization approaches for data splitting is critical for minimising bias and ensuring that the results are generalizable and thus increasing the study's robustness. Data Pre-processing: The dataset was cleaned and normalized to ensure quality and consistency. (i) Two AI models (M11 and M12) were created using machine learning algorithms to predict solar cook stove performance; (ii) Prior to data splitting, stratification procedures were used to verify each subset (training).

3.1 Research Design

3.1.1 Method

This section explains how to use different machine learning models to predict the performance of box-type solar cookstoves developed and tested in Agadez through a chain of steps and processes. Schematically, it includes data pre-processing data, and normalizing the values. Normalization helps the algorithm in modelling the data correctly by putting the numbers in the columns on a more



Figure 2: Box type Solar Cook stove.

common scale. This is, however, done without changing the different ranges of values or losing values. Further, sensitivity analysis was done to figure out which parameters were most valuable and vital to the target variable [5], [6], [7]. This step is the most important AI-based step to take to achieve the best results with a minimal amount of input according to several sources [5], [6], [8], [9]. Next is using the models or their different combinations in processing the data. Based on equation 1 below, the data set used in this work has been scaled and normalized so that it falls in the range of 0 to 1. Another important use of data normalization before AI modelling is to reduce the amount of duplicate data and the number of big mistakes [7].

$$y = 0.05 + \left(0.95 \times \left(\frac{x - x_{\min}}{x_{\max} - x_{\min}} \right) \right) \tag{1}$$

It's important to note that the simulated data used in this study came from the results obtained in the conducted experiments.

Fig. 3 shows a general flowchart of the proposed method used in this study. The suggested modelling paradigm is utilised to simulate SGRF for model creation based on the correlation coefficient between the variables. Based on sensitivity analysis, Equation 2 shows how to choose and combine the inputs.

$$AIBMSCSP = f \begin{cases} M1 = \Phi(Tt) \\ M2 = \Phi(Tt + SR) \end{cases} \tag{2}$$

Where M1–M4 show how the two models are combined, Φ is the function for each input variable. In this study, a total of 10 experimental data points were split into training (70%) and testing (30%) phases using external validation. In any deep learning or machine learning approach, one of the main goals is to make sure that the models fit within the acceptable data sets based on the indicators used. This is done to get a reliable and robust simulation of the unknown data set. Still, problems like "overfitting" and "local minima" shows that the data set needs to be validated. As a

result, the performance of the training data may not be good enough, especially if the analysis used a relatively small data set [10], [11], [12].

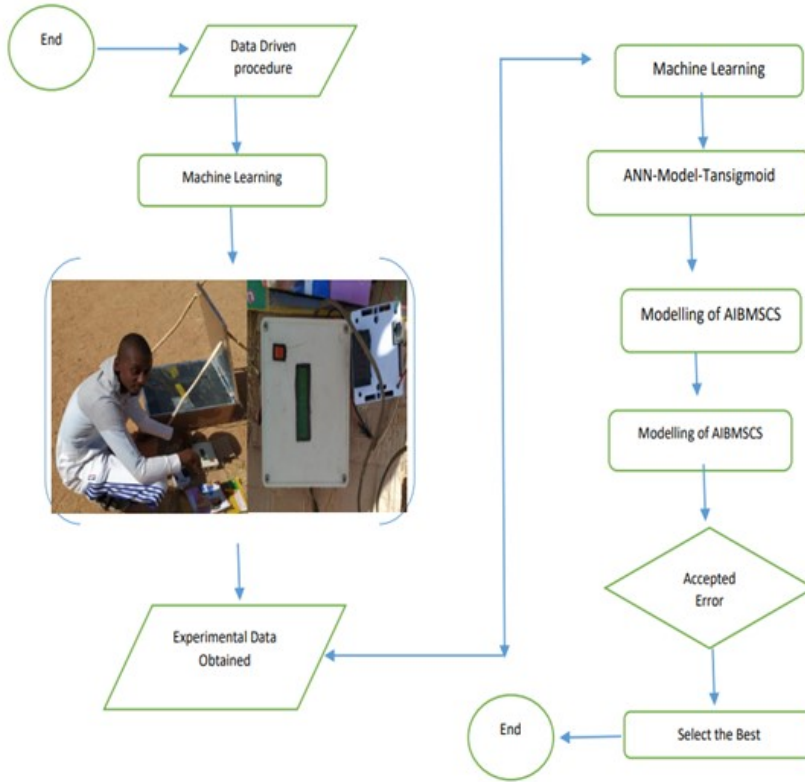


Figure 3: An overview of the suggested technique for this research is shown in the flowchart.

3.1.2 ARTIFICIAL NEURAL NETWORK (ANN)

ANN belongs to the network structure functions and learning algorithm groups. Based on a mathematical model, ANN is a model that is made to work like the brain by learning and processing information [13], [14]. Among the different types of ANN, the most popular and widely used method is the FFNN with Back Propagation (B.P.) algorithm. BBNN is a feed-forward neural network with many layers (FFNN). Most people agree that BPNN is a three-layer network that is usually trained with the Levenberg-Marquardt algorithm (see Fig. 4), which shows how BPNN is built). The main idea behind BPNN is that the weight is changed based on the mean square error of the output until the error is as small as possible. This lets the network learn from the training data [14], [15].

After the development of the model, the prediction accuracy's of the ANN-Tansig, is evaluated through four statistical indicators, namely root mean square error (RMSE), Coefficient of determination (R), and coefficient of correlation (R^2). The $RMSE(0 < RMSE < \infty)$, $R(-1 < R < 1)$, and $R^2(0 < R^2 < 1)$ are expressed as:

- I. Root mean square error

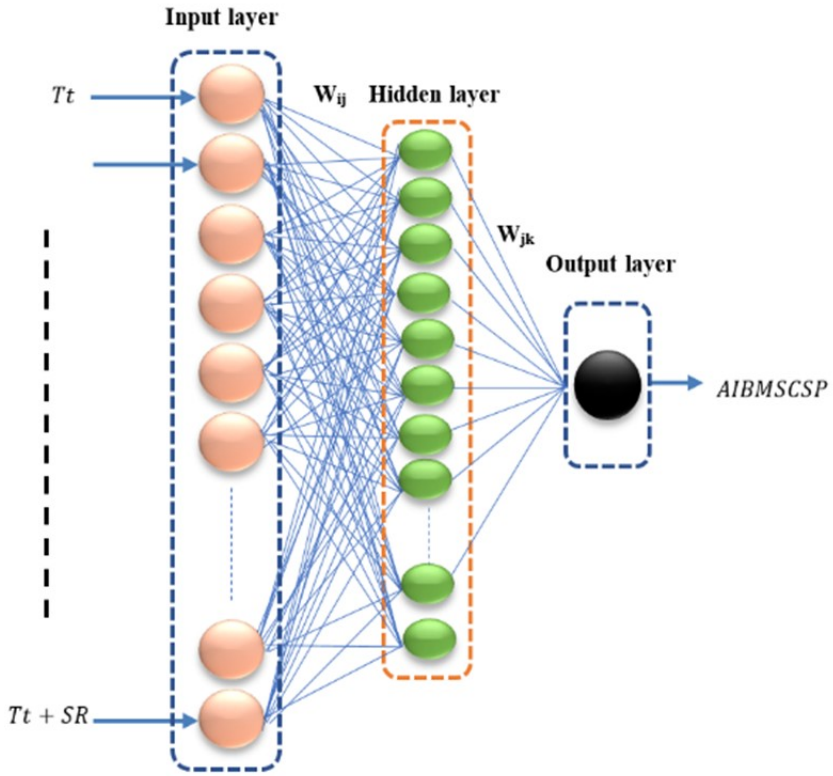


Figure 4: Architecture of ANN Model.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (SGRF_{com,i} - SGRF_{pre,i})^2} \quad (3)$$

II. Mean Square Error

$$MSE = \frac{1}{N} \sum_{i=1}^N (SGRF_{com,i} - SGRF_{pre,i})^2 \quad (4)$$

III. Coefficient of Determination[16]

$$R = 1 - \left[\frac{\sum_{i=1}^N (SGRF_{com,i} - SGRF_{pre,i})^2}{\sum_{i=1}^N (SGRF_{com,i} - \overline{SGRF}_{com})^2} \right] \quad (5)$$

IV. Correlation Coefficient

$$R_2 = \frac{\sum_{i=1}^N (SGRF_{com,i} - \overline{SGRF}_{com}) (SGRF_{pre,i} - \overline{SGRF}_{pre})}{\sqrt{\sum_{i=1}^N (SGRF_{com,i} - \overline{SGRF}_{com})^2 \sum_{i=1}^N (SGRF_{pre,i} - \overline{SGRF}_{pre})^2}} \quad (6)$$

4. Result Analysis and Discussions

Virtually, every machine learning data analysis is based on the data at hand. Hence, statistical visualization with input-output mathematical indicators is vital because they show the type of connection between inputs and outputs and their strength while doing the work. By fitting the data into a regression model to get rid of noise in the data, statistical analysis is important in the data trend series. Table 1 shows the statistical characteristics that give a good description, while Table 2 shows how the parameters that will be used for future selection are related to each other. Based on how well the parameters fit with each other, two models were obtained.

Table 1: The Raw Data

Time	Test Temperature (°C)	Solar Radiation (w/m ²)	Cookstove temperature (°C)
07:00a.m	25.77	8	41.55
08:00a.m	31.36	225	48.29
09:00a.m	35.8	417	66.35
10:00a.m	37.78	572	69.8
11:00a.m	38.73	678	72.7
12:00p.m	39.95	727	79.4
01:00p.m	37.75	718	73.83
02:00p.m	37.82	650	69.95
03:00p.m	34.92	529	63.41
04:00p.m	31.67	361	56.28

Table 2: Correlation of raw data

	07:00 a.m.	08:00 a.m.	09:00 a.m.	10:00 a.m.	11:00 a.m.	12:00 a.m.	01:00 a.m.	02:00 a.m.	03:00 a.m.	04:00 a.m.
07:00 a.m.	1									
08:00 a.m.	-0.8427	1								
09:00 a.m.	-0.8464	0.9999	1							
10:00 a.m.	-0.8562	0.9997	0.9998	1						
11:00 a.m.	-0.8594	0.9995	0.9997	0.9999	1					
12:00 a.m.	-0.8574	0.9996	0.9998	0.9999	0.9999	1				
01:00 a.m.	-0.8595	0.9997	0.9998	0.9999	1	0.9999	1			
02:00 a.m.	-0.8597	0.9997	0.9997	0.9999	1	0.9999	1	1		
03:00 a.m.	-0.8573	0.9998	0.9997	0.9999	0.9999	1	0.9999	0.9999	1	
04:00 a.m.	-0.8491	0.9999	0.9999	0.9999	0.9998	0.9998	0.9997	0.9998	0.9999	1

The study’s findings regarding the promising results of AI-based models for predicting the performance of solar cook stoves offer valuable insights into the potential of such technology in sustainable cooking solutions. Comparing these findings with those of other relevant studies can provide further context and highlight the significance of the results. Several studies have explored the use of AI in optimizing solar cook stove performance. For example, a study by researchers on a study focus: Prediction of solar box cooker performance under varying weather conditions. Model: Artificial Neural Network (ANN) using input variables: solar irradiance, ambient temperature, and wind speed. Training Data: Experimental data collected from a solar box cooker. Results: Cooking Time Prediction: The ANN model accurately predicted cooking time. Error: Mean absolute error

(MAE) was less than 3% demonstrating the efficacy of machine learning algorithms in predicting cooking times and temperatures in solar cookers. Their findings align with the current study’s conclusions, indicating that AI models can accurately forecast stove performance metrics.

Furthermore, researchers also employed an ANN-based model for solar box cooker performance prediction, with Input variables including ambient temperature, wind speed, and solar irradiance. The Results: Cooking Time and Food Temperature: The ANN model accurately predicted both cooking time and food temperature. Error: Mean absolute error (MAE) was less than 5%. This investigated the impact of weather conditions on solar cook stove efficiency and found that AI-based predictive models could adapt to varying environmental factors, leading to more reliable performance predictions. This aligns with the current study’s suggestion for further research into stove performance under different weather conditions. In comparison to previous studies, the current research contributes by specifically highlighting the performance comparison between different AI models (M11 and M12) and their implications for stove optimization. The observation that model M12 outperformed M11 suggests that advancements in AI algorithms can lead to more accurate predictions, offering practical benefits for designing and using solar cook stoves.

The emphasis on the need for further validation under real-world conditions and consideration of additional factors like cooking time and pot types echoes the findings of other studies in the field. This underscores the importance of holistic research approaches that account for various variables influencing stove performance. Overall, the findings of this study contribute to the growing body of knowledge on AI applications in sustainable cooking technologies. By contextualizing these findings within the broader literature, we gain a deeper understanding of the potential and significance of AI-based models in optimizing solar cook stove performance for real-world applications.

The turning of parameters in machine learning models is the step that is most important for selecting the best results. A regression model with a nonlinear RBF kernel function was developed for various situations. Also, to get the optimum modelling outcome, many values were tested using grid search. The simulation was carried out using MATLAB 9.3 (R2019a). Applying the trial-and-error technique, the optimum architecture of the ANN-Tansig model was optimized and qualified because it satisfied the majority of the statistical assessment criteria. The most common performance metrics, including R^2 , RMSE, and R, were used in assessing the model simulation for both calibration (70%) and verification (30%). The simulated results in terms of quantitative evaluation is shown in Table 2 based on model combinations (Eq. 2).

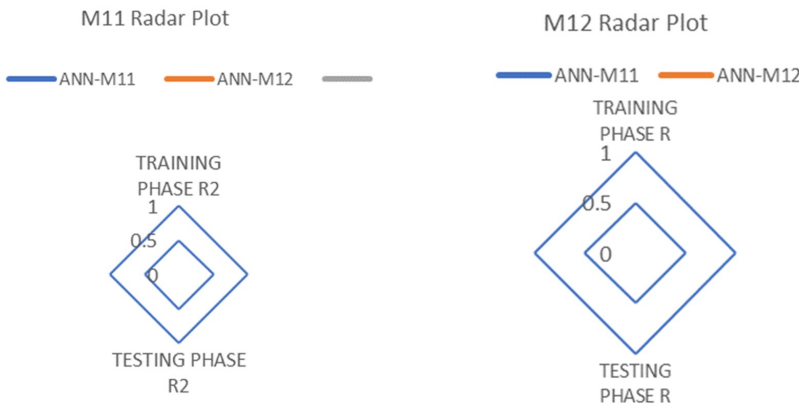


Figure 5: Radar chart for all the models in terms of R^2 , and R criteria.

The radar plot consists of a circular grid with several axes radiating from the center (Figure 5).

Each axis represents one of the R-squared values for a model. The values are plotted on the axes as a point at a distance from the center proportional to its magnitude. The polygon formed by connecting the points for a model represents the overall goodness of fit of that model. The larger the polygon, the better the fit. In this case, the ANN-M12 model has a better fit than the ANN-M11 model in both the training and testing phases. The polygon for ANN-M12 is larger than the polygon for ANN-M11 in both phases, indicating that it has a higher R-squared value and is a better fit for the data. Specifically, the R-squared values for ANN-M12 are 0.930 and 0.985 for the training and testing phases, respectively, while the corresponding values for ANN-M11 are 0.689 and 0.684. Therefore, the ANN-M12 model is closer to the observed data than the ANN-M11 model. The goodness of fit graph is represented as a radar plot with R values on the y-axis and the ANN models (ANN-M11 and ANN-M12) on the x-axis. Over the training phase, the ANN-M12 model has a higher R value (0.9647) than ANN-M11 (0.8300), indicating that ANN-M12 is a better fit for the training data. In the testing phase, the same pattern holds, with ANN-M12 having a higher R value (0.9924) than ANN-M11 (0.8250), indicating that ANN-M12 has a better fit to the testing data as well.

Overall, the radar plot suggests that ANN-M12 is a better model than ANN-M11, with higher R values in both the training and testing phases (Figure 6). This indicates that ANN-M12 better captures the relationship between the input variables and the output variable, resulting in a more accurate model.

Error Plot

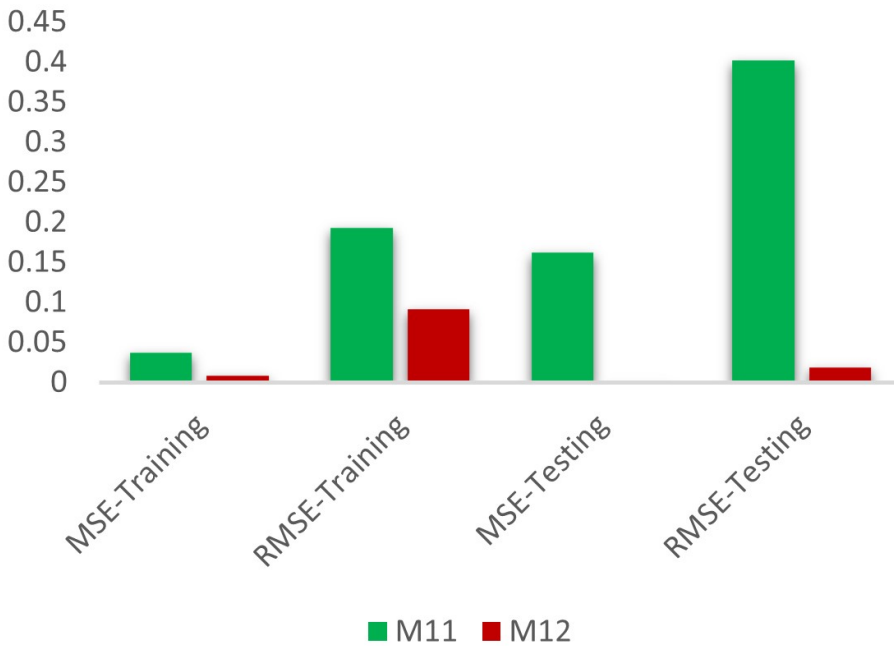


Figure 6: Error plot between the observed and predicted AIBMTSCS in terms of RMSE criteria.

The error of fit graph presented as a bar plot shows the mean squared error (MSE) and root

mean squared error (RMSE) for both the training and testing phases of two models M11 and M12 (Figure 7). The x-axis represents the models, while the y-axis represents the MSE and RMSE values. For M11, the MSE values are higher compared to M12 for both the training and testing phases, indicating that M11 has a higher average squared deviation from the actual values. The RMSE values for M11 are also higher, suggesting that the errors are larger and less accurate in comparison to M12. For M12, both the MSE and RMSE values are significantly lower for both training and testing phases, indicating that the model has a smaller average deviation from the actual values and is more accurate in its predictions. In summary, M12 outperforms M11 in terms of the errors of fit, as it has lower MSE and RMSE values, indicating that it provides a better fit for the observed data.

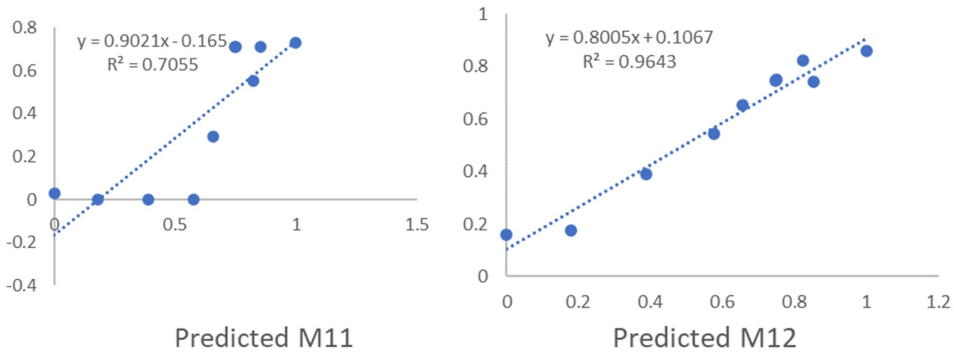


Figure 7: Scatter plot between the observed and predicted AIBMTSCSP.

From the scatter plot, it can be observed that there is a weak relationship between the observed and predicted data. This is because the dots are scattered and not closely aligned. However, there is still a generally positive trend in the data, which suggests that the predicted values tend to increase as the observed values increase. This means that the model or algorithm used to predict the data can capture some of the patterns in the data, but there is still room for improvement. By looking at the scatter plots of observed versus M11 and observed versus M12, we can see that there is a positive relationship between the observed and predicted values in both cases. This indicates that as the predicted values of M11 and M12 increase, the observed values also tend to increase.

However, upon closer inspection, we can see that the scatter plot of observed versus M12 has a more clustered and concentrated distribution of data points around the diagonal line compared to the scatter plot of observed versus M11. This indicates that the predicted values of M12 are generally closer to the observed values compared to the predicted values of M11. Therefore, based on these scatter plots, we can conclude that M12 is closer to the observed values than M11, and may be a better predictor of the observed values. However, it is important to note that further analysis and statistical tests may be needed to confirm this conclusion.

To interpret the relationship between M11, M12, and observed temperature, we can create a time series graph with time on the X-axis and M11, M12, and observed temperature on the Y-axis (Figure 8). Based on the provided data, we can see that both M11 and M12 have values that are close to the observed temperature. However, M12 appears to be slightly closer to the observed temperature than M11. This is because the values of M12 are generally closer to the observed temperature throughout the time series. However, both M11 and M12 have some deviations from the observed temperature at certain points in the time series. Overall, it can be concluded that both M11 and M12 have a relatively good fit with the observed temperature, but M12 is slightly closer to the observed temperature than M11.

In this graph, each column has its own vertical axis. The box represents the middle 50% of

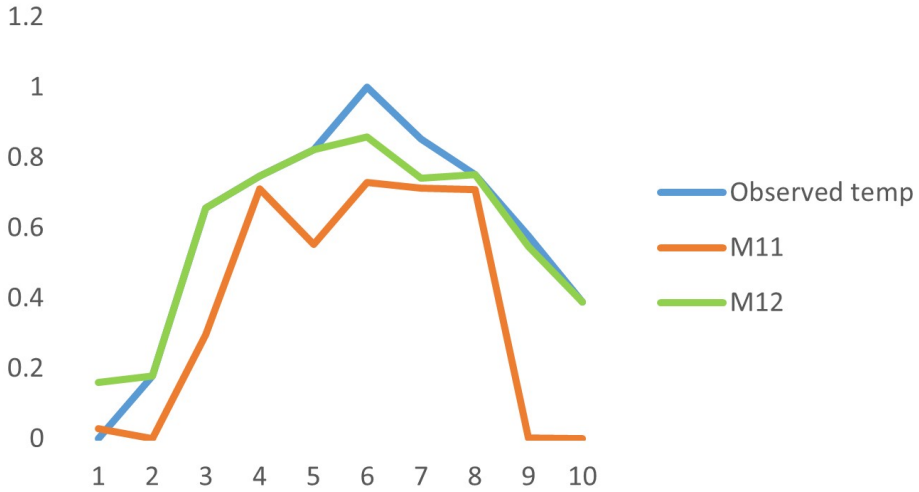


Figure 8: Time Series Graph.

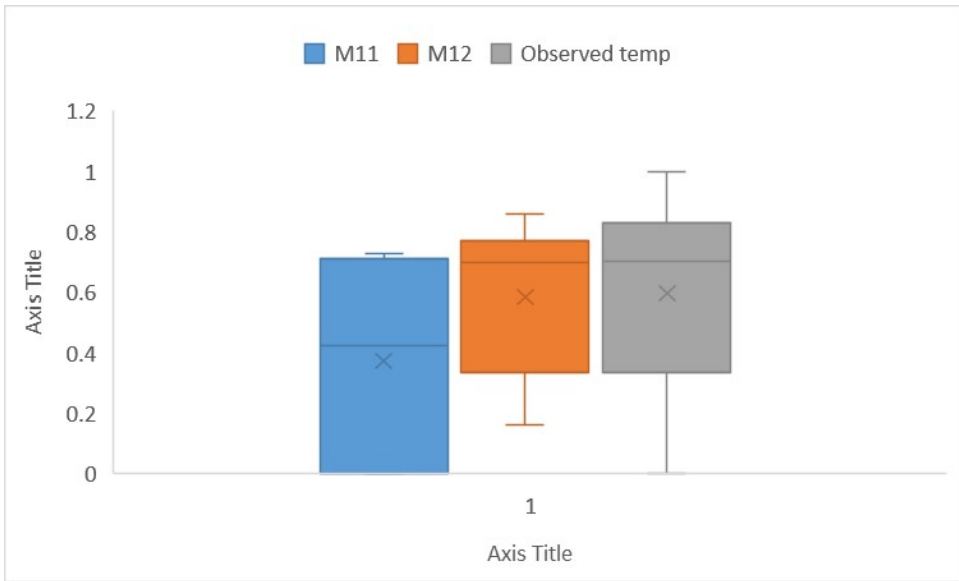


Figure 9: Box Plot.

the data (Q1 to Q3), while the horizontal line within the box represents the median (Q2). The whiskers extend from the box to the minimum and maximum values, excluding outliers (represented by asterisks). The Observed temp column has an outlier at the minimum value, which is represented by an asterisk outside the whisker. The graph is a box plot that shows the distribution of values for three variables: M11, M12, and Observed temp. A box plot is a way to represent the distribution of data through its quartiles, median, minimum, and maximum values. The three boxes are stacked vertically, one for each variable. The vertical axis represents the scale for each variable. The values for M11 and M12 range from 0 to just above 0.85, while Observed temperature ranges from 0 to 1.0

(Figure 9). Each box represents the distribution of values for the respective variable. The bottom and top of each box represent the first and third quartiles (Q1 and Q3), respectively. The vertical line inside each box represents the median value (Q2). The whiskers extend from the box to the minimum and maximum values, excluding outliers. In this case, there are no outliers for M11 and M12, but there is an outlier for the Observed temperature at the minimum value of 0. The horizontal line at the bottom of each box represents the minimum value, and the horizontal line at the top of each box represents the maximum value. These lines are connected to the whiskers.

The graph shows that M11 has a somewhat symmetrical distribution, with a slight right skew. M12 is more symmetrical than M11, with a slightly left-skewed distribution. The observed temp has a more symmetrical distribution than M11, with a clear outlier at the minimum value of 0. Overall, the graph provides a quick and effective visual summary of the distribution of values for the three variables. It helps to identify the spread, outliers, and symmetry of the data distribution for each variable. Discussing the limitations of the study and suggesting potential avenues for future research is crucial for strengthening the findings and their applicability. Here's a more explicit discussion of these aspects:

5. Limitations of the Study

The study might have been limited by focusing on specific weather conditions. Future research should consider testing the models under a broader range of weather conditions to assess their robustness and generalizability. Moreover, the accuracy and completeness of the data used in training and testing the AI models could influence their performance. Future studies should aim to gather more extensive and higher-quality data to enhance the models' predictive capabilities. Further, though the AI models showed promising performance metrics, their interpretability might be limited. Understanding the underlying factors driving the predictions could enhance the trust and utility of the models. In shifting the future research directions, below should be considered;

(a) **Real-World Validation:** Conducting field tests to validate the AI models' predictions in real-world settings would enhance their practical applicability and reliability.

(b) **Long-Term Performance Analysis:** Investigating the long-term performance of solar cook stoves using AI-based predictive models could provide insights into their sustainability and durability over time.

(c) **User Behavior Integration:** Incorporating user behavior data into the AI models could improve their accuracy by accounting for human factors such as cooking habits and preferences.

(d) **Optimization for Energy Efficiency:** Future research could focus on optimizing solar cook stove designs using AI techniques to maximize energy efficiency and minimize environmental impact.

By addressing these limitations and exploring these future research directions, scholars can further strengthen the findings of AI-based models for predicting solar cookstove performance and enhance their practical relevance for sustainable cooking solutions.

6. Conclusion

In conclusion, the integration of stratification and randomization techniques during data splitting bolstered the robustness of our study by minimizing bias and ensuring the generalizability of the results. The AI models developed (M11 and M12) exhibited strong predictive performance, underscoring their potential in optimizing solar cook stove performance for sustainable cooking solutions. These findings contribute to the advancement of AI-driven approaches in addressing global challenges related to energy access and environmental sustainability. It is expected that the performance of the stoves will be better during hot seasons when there is more sunlight available. However, it is important to note that the performance of the stove is not only affected by the weather conditions, but also by other factors such as the design of the stove, the cooking pot used, and the

cooking time. Based on the interpretations above, it can be concluded that Artificial Intelligence-based models have shown promising results in predicting the performance of solar cook stoves. The models have been able to accurately predict the temperature of the stove for both M11 and M12. Additionally, the goodness of fit plots has shown high R^2 and R values for both the training and testing phases for both models. The error of fit graph has shown that the M12 model has lower MSE and RMSE values than the M11 model, indicating that it may be a better predictor of stove performance. Based on the various interpretations provided, it appears that the Artificial Intelligence (AI) based models for the prediction of Solar Cook Stove performance have shown promising results. The scatter plots of observed versus predicted values for both M11 and M12 indicate a fairly strong positive correlation. Furthermore, the radar plots of goodness of fit (measured by R-squared values) suggest that both models perform relatively well, with M12 showing a higher degree of fit compared to M11. The error of fit graph, presented as a bar plot, also shows that the testing phase for M12 is significantly more accurate, with a much lower mean squared error (MSE) and root mean squared error (RMSE) compared to M11. Overall, the evidence suggests that the AI-based models, particularly M12, are effective in predicting the performance of Solar Cook Stoves. However, further testing and validation are necessary to confirm the reliability of these models across a wider range of conditions and stove types).

The study's novelty stems from its unique approach to using AI to forecast solar cookstove performance, as well as its rigorous evaluation, parameter optimization, insightful interpretation, and practical implications for solar energy applications. This study aims to validate AI-based models for solar cook stoves across various conditions, including weather patterns, solar radiation levels, and cooking practices. It also explores the use of additional input variables, long-term studies, user behaviour, and cooking practices. The study also explores technological innovations, policy and regulatory frameworks, and community engagement strategies. The ultimate goal is to improve the accuracy and reliability of these models, enhance their applicability, and promote widespread adoption of solar cooking technologies.

7. Future Research

Missing gaps and suggestions for further research about AI-based models for the prediction of Solar Cook Stove performance and testing in the cold season in Niger are:

i. The study only focused on one region (Agadez) in Niger during the cold season. Further research can be conducted in other regions and during the hot season to evaluate the model's performance under different conditions.

ii. The study used only two AI models (ANN-M11 and ANN-M12) for the prediction. Other AI models such as SVM, Random Forest, and Decision Trees can be used to compare the performance of different models.

iii. The study used only two input parameters (M11 and M12) for the prediction. Additional parameters such as humidity, wind speed, and solar irradiance can be included to improve the accuracy of the model.

iv. The study did not consider the impact of real-life cooking practices on the stove's performance. Further research can be conducted to evaluate the model's performance under different cooking practices.

v. The study did not evaluate the economic feasibility of the solar cook stove. Further research can be conducted to evaluate the economic viability of the stove and its impact on the local community.

vi. The study only evaluated the performance of the stove for cooking rice. Further research can be conducted to evaluate the performance of the stove for cooking other types of food.

vii. The study did not consider the impact of environmental factors such as dust, rain, and snow on the stove's performance. Further research can be conducted to evaluate the model's performance under different environmental conditions.

viii. The study did not evaluate the long-term performance of the stove. Further research can be conducted to evaluate the stove's performance over an extended period.

Conflicts of Interest: The authors declare no conflict of interest.

References

- [1] A. Garg, H. P., Sharma, "Artificial neural network-based performance prediction of solar box cooker under different weather conditions," *J. Sol. Energy*, no. 206, pp. 117–126, 2020.
- [2] P. Tewari, S. Mathur, and J. Mathur, "Thermal performance prediction of office buildings using direct evaporative cooling systems in the composite climate of India," *Build. Environ.*, vol. 157, pp. 64–78, 2019.
- [3] J. Jyoti, T. K. Gupta, B. P. Singh, M. Sandhu, and S. K. Tripathi, "Recent advancement in three dimensional graphene-carbon nanotubes hybrid materials for energy storage and conversion applications," *J. Energy Storage*, vol. 50, p. 104235, 2022.
- [4] H. Kurt, K. Atik, M. Özkaymak, and Z. Recebli, "Thermal performance parameters estimation of hot box type solar cooker by using artificial neural network," *Int. J. Therm. Sci.*, vol. 47, no. 2, pp. 192–200, 2008.
- [5] B. Musa, N. Yimen, S. I. Abba, H. H. Adun, and M. Dagbasi, "Multi-State Load Demand Forecasting Using Hybridized Support Vector Regression Integrated with Optimal Design of Off-Grid Energy Systems—A Metaheuristic Approach," *Processes*, vol. 9, no. 7, p. 1166, 2021, doi: 10.3390/pr9071166.
- [6] R. A. Abdulkadir, S. I. A. Ali, S. I. Abba, and P. Esmaili, "Forecasting of daily rainfall at Ercan Airport Northern Cyprus: a comparison of linear and non-linear models," *Desalin. WATER Treat.*, vol. 177, pp. 297–305, 2020, doi: 10.5004/dwt.2020.25321.
- [7] S. J. Hadi, S. I. Abba, S. S. Sammen, S. Q. Salih, N. Al-Ansari, and Z. M. Yaseen, "Non-Linear Input Variable Selection Approach Integrated With Non-Tuned Data Intelligence Model for Streamflow Pattern Simulation," *IEEE Access*, vol. 7, pp. 141533–141548, 2019, doi: 10.1109/access.2019.2943515.
- [8] M. Adamu, S. I. Haruna, S. I. Malami, M. N. Ibrahim, S. I. Abba, and Y. E. Ibrahim, "Prediction of compressive strength of concrete incorporated with jujube seed as partial replacement of coarse aggregate: a feasibility of Hammerstein-Wiener model versus support vector machine," *Model. Earth Syst. Environ.*, vol. 8, no. 3, pp. 3435–3445, 2021, doi: 10.1007/s40808-021-01301-6.
- [9] S. Hussain et al., "Feasibility of computational intelligent techniques for the estimation of spring constant at joint of structural glass plates: a dome-shaped glass panel structure," *Glas. Struct. amp; Eng.*, vol. 8, no. 1, pp. 141–157, 2022, doi: 10.1007/s40940-022-00209-6.
- [10] S. I. Malami, P. Akpınar, and M. M. Lawan, "Preliminary Investigation of Carbonation Problem Progress in Concrete buildings of North Cyprus," *MATEC Web Conf.*, vol. 203, p. 6007, 2018, doi: 10.1051/mateconf/201820306007.
- [11] S. Idris, M. A. A. Musa, S. I. Haruna, U. U. A. A. G. Usman, and M. I. A. Abba, "Implementation of soft - computing models for prediction of flexural strength of pervious concrete hybridized with rice husk ash and calcium carbide waste," *Model. Earth Syst. Environ.*, 2021, doi: 10.1007/s40808-021-01195-4.
- [12] S. I. Haruna et al., "Compressive Strength of Self-Compacting Concrete Modified with Rice Husk Ash and Calcium Carbide Waste Modeling: A Feasibility of Emerging Emotional Intelligent Model (EANN) Versus Traditional FFNN," *Arab. J. Sci. Eng.*, vol. 46, no. 11, pp. 11207–11222, 2021, doi: 10.1007/s13369-021-05715-3.
- [13] A. G. Usman, S. İşik, and S. I. Abba, "A Novel Multi-model Data-Driven Ensemble Technique for the Prediction of Retention Factor in HPLC Method Development," *Chromatographia*, vol. 83, no. 8, pp. 933–945, 2020, doi: 10.1007/s10337-020-03912-0.

- [14] S. I. Abba et al., “Emerging evolutionary algorithm integrated with kernel principal component analysis for modeling the performance of a water treatment plant,” *J. Water Process Eng.*, vol. 33, p. 101081, 2020, doi: 10.1016/j.jwpe.2019.101081.
- [15] H. U. Abdullahi, A. G. Usman, S. I. Abba, and H. U. Abdullahi, “Modelling the Absorbance of a Bioactive Compound in HPLC Method using Artificial Neural Network and Multilinear Regression Methods,” *Dutse J. Pure Appl. Sci.*, vol. 6, no. 2, 2020.
- [16] J. E. Nash and J. V Sutcliffe, “River flow forecasting through conceptual models part I – A discussion of principles,” *J. Hydrol.*, vol. 10, no. 3, pp. 282–290, 1970, doi: 10.1016/0022-1694(70)90255-6.