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The effect of electricity consumption determinants in household load forecasting models

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Abstract

Usually, household electricity consumption fluctuates, often driven by several electrical consumption determinants such as income, household size, and price. Recently, research studies on the investigation of predictor variables in household electricity consumption have increased especially in the developing and newly industrialized countries. However, the studies just focus on identifying the predictor variables of household electricity consumption that influence load forecasting models. In Tanzania, for instance, scholars found that using the "income" determinant improves the performance of a forecasting model. The scholars suggest without any empirical bases that adding more predictor variables would have improved the accuracy of the model. This study aims to analyze the effect of the number of predictor variables on household load forecasting performance based on Tanzania's data. Nonlinear regression based on a Weibull function and multivariate adaptive regression splines approaches are used for this purpose. Our findings indicate that income, household size, and number of appliances are common predictor variables of household consumption in developing countries. The measured forecasting root-mean-square error (RMSE) when using income, household size, and the number of appliances is 0.8244, 1.2314, and 0.9868, respectively. Finally, we forecasted load using all three determinants and the RMSE dropped to 0.7031. Having obtained the smaller value of RMSE when all predictors are used reveals that the inclusion of all three predictor variables in load forecasting leads to a significant decrease in RMSE by 14.73%. Therefore, the study recommends using multiple predictor variables in load forecasting models to increase accuracy.

Keywords: Electricity consumption, Predictor variables, Load forecasting, Performance

Introduction

Before 2015, most suburban households in Tanzania did not have access to electricity from the national grid. The major sources of power were generators and solar panels. Recently, the national grid has electrified many suburban households. This electrification followed the Tanzania power system master plan of 2016 [1], which targeted connecting all off-grid suburban households to the national grid between 2035 and 2040 [1]. Compared to the previous years, this massive new household connection has increased electricity consumption by 90%. The rapid expansion of the suburban areas increases electricity household consumption. The information on the actual determinant of electricity household consumption in suburban areas, specifically for developing and newly industrialize countries (DNI) countries, remains speculated due to its growing complexity [2]. Household electrical consumption greatly affects the residential energy sector [3]. The estimation of electricity consumption in a specific household depends on different electricity consumption determinants (technically referred to as predictor variables) [4].

Following the above challenge, scholars conducted several research studies to examine the critical electricity household determinant in DNI countries [4]. In literature, the "income" factor is reported to be the primary driver of electricity consumption in the household, followed by household size and age of household dwellers, appliance ownership, education level of household head, floor area, and so on [5]. However, the determinants of electricity consumption are reported to vary from one context to another. It is therefore important to conduct the study on electricity consumption analysis on country basis.

For example, [6] uses advanced metering infrastructure (AMI) data to examine the difference between a household's actual and perceived electricity consumption. The results confirm that house and household size are the most critical determinants that affect actual household electricity consumption. Emerging artificial intelligent (AI) models for prediction call the study to address the issue of their performance in accessing the household electrical consumption determinant [7]. The artificial neural network (ANN) provides promising results, and determinants such as household income, house, and weather conditions showed a significant influence on household electricity consumption.

A recent study by [8] explores the influencing factor for urban household electricity consumption and found that household income, appliances, and per capita electricity consumption are the main determinants of urban household electricity consumption. Another study by [9] presents socioeconomic indicators such as age, gender, marital status, income, and background education as the critical electrical consumption determinants for Turkish households. The two studies conducted by [10, 11] indicate that household income and electricity price are the major determinants of household electricity consumption. Several other researchers from DNI countries presented the electricity determinants in their respective countries, such as Ghana [12], Turkey [9], Nigeria [13], and India [14], to mention a few.

Recently, there has been no visibility of the determinants that provide the best household consumption estimation in Tanzania. This invisibility makes it difficult to establish a robust forecasting model. A study to investigate the determinant that has a great effect on forecasting accuracy has been conducted [15]. In such a study, the authors confirm that the use of the "income" variable leads to attaining better accuracy than other factors. Furthermore, the authors recommend that the use of more than one predictor variable, such as house size and others, would increase the forecasting accuracy of the model [15]. To the best of our knowledge, there is no research study on Tanzania's context, attempted to confirm the claim stated by the authors in [15]. Therefore, the motivation of this research study is to analyze the effect of the number of predictor variables on household load forecasting performance based on Tanzania's data.

The findings from this study pave the way for the power utility companies in Tanzania and other DNI countries to efficiently align a power system master plan (PSMP) in an elegant way. The PSMP will include the electricity consumption determinants established in this research to forecast residential power consumption. In addition, researchers will use the findings from this study to identify the determinants to be included in the forecasting models to attain promising accuracy. The theoretical and practical contributions of this work are as follows:

(1) Establishment of critical electricity household consumption determinants in Tanzania suburban areas.
(2) Establishment of the impact of electricity household consumption determinants on the accuracy of load forecasting models.
(3) Recommends the best practice for using determinants in load forecasting models to increase accuracy. This paper is organized as follows; "Materials and methods" section describes general methodology undertaken to achieve the desired objectives. Furthermore, "Results and discussion" section presents and interprets the results of the study. The last section concludes the paper while highlighting some key issues such as the limitation, future work, and recommendation.

Materials and methods

This study involves qualitative methods in data collection. Data analysis and model implementation processes are achieved quantitatively using statistical methods. Thereafter, the paper surveys some literature to investigate household electricity consumption in developing countries through document review. Moreover, the impact of predictor variables on the accuracy of a load forecasting model is analyzed using both univariate and multivariate nonlinear regression methods. Finally, the result in each stage is evaluated quantitatively using the RMSE method. The overall research design process is shown in Fig. 1.

Study area

This study is based on a small suburban area in the Kigamboni district in Tanzania mainland. However, the focal point of this research is at Somangila ward in which two streets,

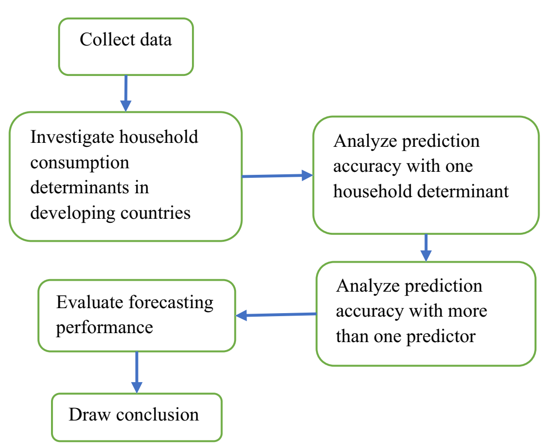

Fig. 1 Research design process

namely Minondo and Shirikisho, were surveyed. The two streets aforementioned comprise about 270 houses connected with electricity services. In addition, the Somangila ward has been recently connected with power services. The geographical location of the Somangila area is shown in Fig. 2.

Data collection

A questionnaire was used to collect the household electricity consumption data. The process of developing the questionnaire has considered three main aspects; first, consideration of the characteristics of the respondents in the research domain. The domain behavioral analysis process was achieved by probing a sample of 80 house owners. The domain behavioral analysis revealed that more than 65% of the residents have a basic level of education (primary and secondary education). Therefore, the questionnaire was designed in a basic English language. In addition to the basic education level of the respondents, survey questions were also provided in the Swahili language.

Second, due to the characteristics of the respondents described above, the study avoided the use of technical terms such as "load," and alternatively, the word "units" was used. In addition to the observed characteristics of the respondents, the questionnaire was designed to include closed-ended and short-answer questions. Third, the questions included in the questionnaire were formalized based on the related works identified, following the document review process. Fourth, the face validation technique was adopted in this work. The face validation technique is ideal for social science researches [16]. Furthermore, the expert assessment method was used in the validation process in which a sample questionnaire was shared with five psychology and five linguistic experts. The final questionnaire sheet used in this study is attached in "Appendix B."

The designed questionnaire was composed of eight questions of which four questions were picked up for this research. Moreover, the questionnaire was collected from 153 houses out of 270 houses. Thereafter, only 103 questionnaire data were used in the study because 50 questionnaires out of 153 were dropped after the observational analysis because they contained outliers. Furthermore, 100 houses (from the 270 houses) were not surveyed because they were not yet connected to the grid services. In addition, data

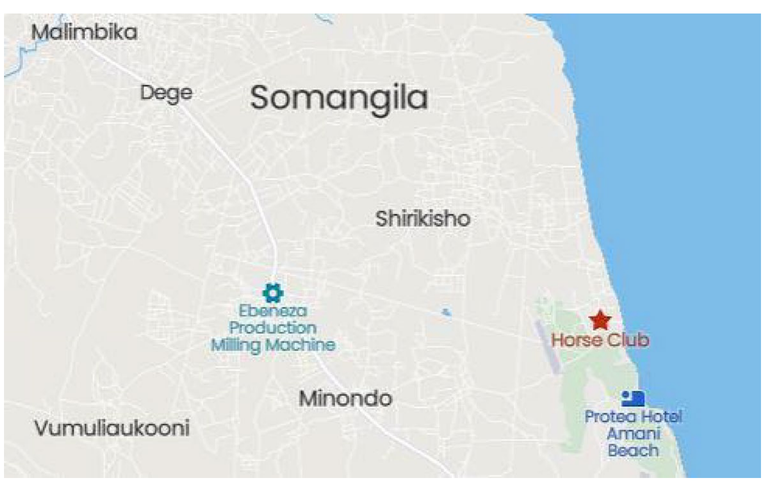

Fig. 2 Somangila map for the study area (source: google map, 11/5/2022)

from 17 houses were not obtained because the house owners were not available. Therefore, the data used in this work were 103 out of the 270 total houses in the two streets.

Investigating household consumption determinants in DNI Countries

Document review was used to investigate the determinants of household electricity consumption in developing countries, in which 20 articles were selected as shown in Table 2 ("Appendix A"). The document review methodology in this study was based on the systematic literature review procedures adopted from [17]. The procedures contained four stages, and each stage contain several steps to follow. Furthermore, the systematic review started with the identification of review protocols that were used for finding relevant articles.

The databases and library used in this study were Elsevier, Science Direct, Energies, IEEE Explore, and Springer as shown in Table 1. "Electricity consumption," "Household Determinants," "Load forecasting," "developing countries," and "Newly-industrialized countries" were used as a keyword in searching for the relevant papers. In this step, a total of 100 articles were obtained. The second step was the collection and selection of relevant documents based on the search fields. Through screening titles and abstracts, 60 articles were selected for further steps. The selected articles were then filtered based on inclusion criteria as seen in Table 1. Therefore, out of the 60 selected articles, 20 papers were qualified to proceed to the stage of critical review and analysis. The summary of the review protocol used is presented in Table 1.

Analyzing the effect of a univariate predictor variable

A nonlinear regression model using a Weibull function is used to analyze the effect of a single variable (daily income, household size, and number of appliances) on forecasting accuracy in the household context. Furthermore, the "Nonlinear Least Squares" (nls) was used to estimate model parameters. The "nls" method is shown in Eq. (1) [18]. The objective function of the "nls" is to minimize the sum of squared residuals.

$$S = \sum_{i=1}^{m} r_i^2 \tag{1}$$

The value of r_i in Eq. (1) is substituted by the one obtained from Eq. (2);

Table 1 Systematic review methods as per this study

Indicators	Description
Keyword	Electricity consumption, household determinants, load forecasting, and DNI countries
Search fields	Title, abstract, and keywords
Inclusion criteria	Paper that focused on electricity consumption determinants in households from the developing countries
Exclusion criteria	Reports, working papers, papers published in the predatory journals, short- and medium-term forecasting, and paper published before 2018
Language	English
Time window	From 2018 to 2021
Database and Library	Science Direct, Scopes, Energies, Web of Science, ACM, IEEE Explore, and others

$$r_i = y_i - f(x_i - \beta) \tag{2}$$

where $r_i =$ residual in prediction error, $\beta =$ model parameter, $x_i =$ independent variable and $y_i =$ dependent variable. Thus, the value of β can be estimated derivatively using Eqs. (1) and (2).

The use of a univariate nonlinear regression model is based on the fact that in this case, a single predictor variable is examined. The nonlinear regression model based on a Weibull function is shown in Eq. (3) [19].

$$y = a - b * e^{-(c*x)} \tag{3}$$

where y is a response variable; a, b, and c are model parameters to be estimated by Eq. (1) and Eq. (2). In addition, x is a predictor variable.

Analyzing the effect of multivariate predictor variables

Multivariate adaptive regression splines (MARS) model was used to determine an optimal predictive regression line using more than one predictor. MARS is a nonparametric regression technique that extends the capability of linear models to handle nonlinear cases. In addition, MARS attempts to establish a model of the following form [20]:

$$\widehat{f}(x) = \sum_{i=1}^{k} C_i B_i(x) \tag{4}$$

where $B_i(x)$ is a weighted basis function and C_i is a constant. Moreover, the values of $B_i(x)$ can be a constant "1" or, hinge function or product of two or more hinge functions. In addition, the hinge functions take the form of $max(0, x - c)$ or $\max(0, c - x)$ where c is constant.

This work used 80% of the data to train the MARS model and the rest 20% for testing purposes. Moreover, the "earth" function available in the "earth" package in the RStudio was used, in which the "degree" parameter was set to 4, and the "nprune" was initialized to 10. In addition, during the MARS training, the "train" available in the "caret" package was used, in which the method was set to "earth," and the metric parameter was initialized to "RMSE." Finally, after training the model in the R Studio package, the optimal model was obtained with nprune = 2 and degree = 3. Figure 3 shows the optimal regression line after executing the training code. The red regression line is then used for prediction.

Results and discussion

Results

Household electricity consumption determinants in DNI countries

The review process conducted to investigate driving factors of household electricity consumption from 20 published articles revealed that income, household characteristics (household size and house size), age of the head, employment, electricity price, and characteristics of electric appliances are some of the determinants that affect electricity usage. Table 2 in "Appendix A" shows the referenced articles and the corresponding findings.

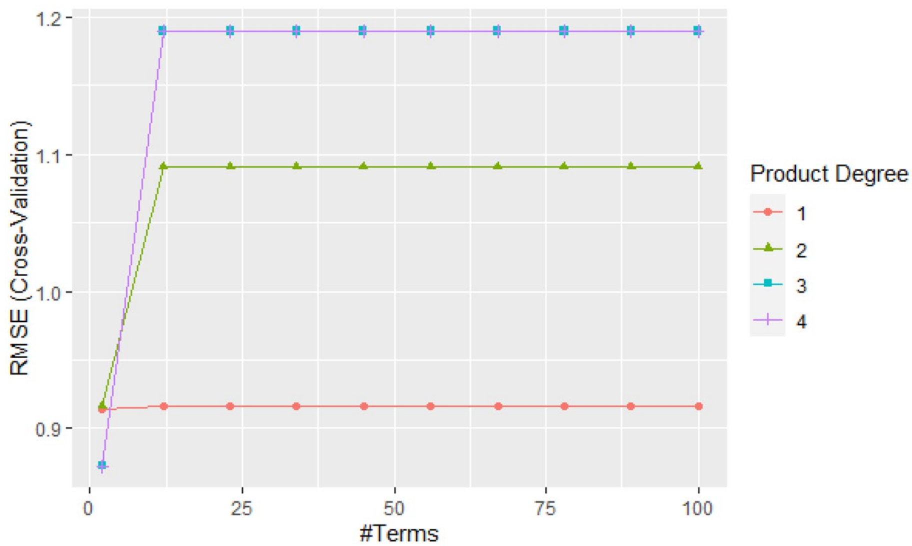

Fig. 3 MARS optimization results

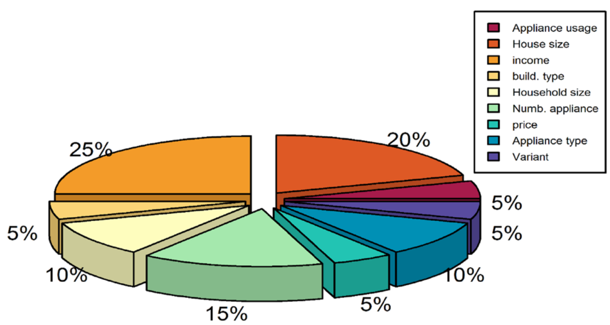

Fig. 4 Household electricity consumption analysis

The result after the analysis process indicated that income, electricity price, household size, appliances, house size, and building type are dominant factors affecting electricity consumption when it comes to household context. The pie chart presented in Fig. 4 shows that income is a leading determinant by 25%, followed by the house size (by 20%) and the third one is the number of appliances (by 15%). Following the observations stated above, income can be used in univariate models as a predictor variable when it comes to household forecasting.

Effect of the predictor variables on the performance of load forecasting

The "income" variable was used as a model predictor in the univariate nonlinear regression model shown in Eq. (3), and the results gave an RMSE value of 0.8244 KWh. The prediction trend for the 23-testing record set is shown using the graph in Fig. 5. As shown in Fig. 5, the income variable seems to render a significant effect on forecasting accuracy, especially from the 8th to the 23rd record.

The RMSE value of 0.9868 KWh was observed when the "number of appliances" variable was used as a model predictor. The RMSE value observed is a bit large

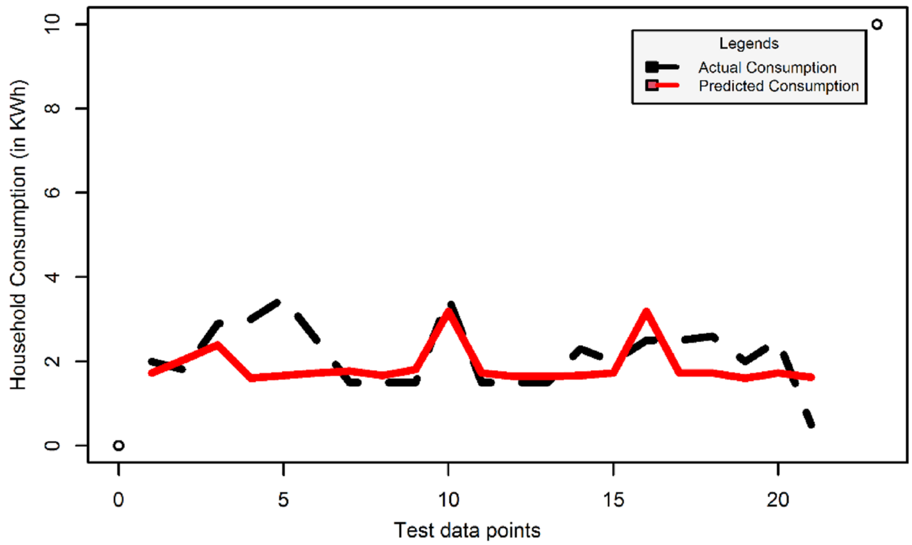

Fig. 5 Forecasting accuracy using the "income" variable

compared to the one obtained when the income variable was used (the RMSE difference being 0.1130 KWh). Our findings advocate that load forecasting modelers should rely on the income variable when subjected to the two choices of the variables (between income and appliance variable) when it comes to household consumption in Tanzania and other developing countries as a whole. The reason for obtaining better forecasting accuracy with the income than with the appliances is that house owners tend to occasional usage of power-consuming appliances to economize the electric bill. For example, people tend to use other means of ventilation in hot seasons such as leaving the house windows open rather than putting the fans on. Therefore, in most cases, the increase in the number of appliances may not have a significant impact in suburban areas. Figure 6 shows the forecasting trend for the 23-testing record set.

Another determinant variable used was household size (number of people). The RMSE value obtained in this case was 1.2314 KWh. Moreover, the value of RMSE obtained with household size is relatively large compared to the ones found when using income and appliance variables were used. The higher RMSE in this case implies that household size, in some contexts, does not guarantee a high consumption rate since the people living in a house might be non-demanding, such as elders and children. In addition to that a house might have been occupied by a large number of people but they can still be dormant to the use of electric appliances in a house. Figure 7 shows the forecasting trend for the 23-testing record set.

Finally, the MARS model shown in Eq. (4) was used to analyze the forecasting trend using income, household size, and number of electric appliances variables. With the MARS, the RMSE value of 0.7030 KWh was observed. The RMSE value in this case seems to be smaller compared to the use of either of the predictor variables mentioned above. Therefore, having obtained such a small RMSE value indicates that promising results are achieved with the use of more than one predictor. Figure 8 shows the forecasting trend for the 23-testing record set.

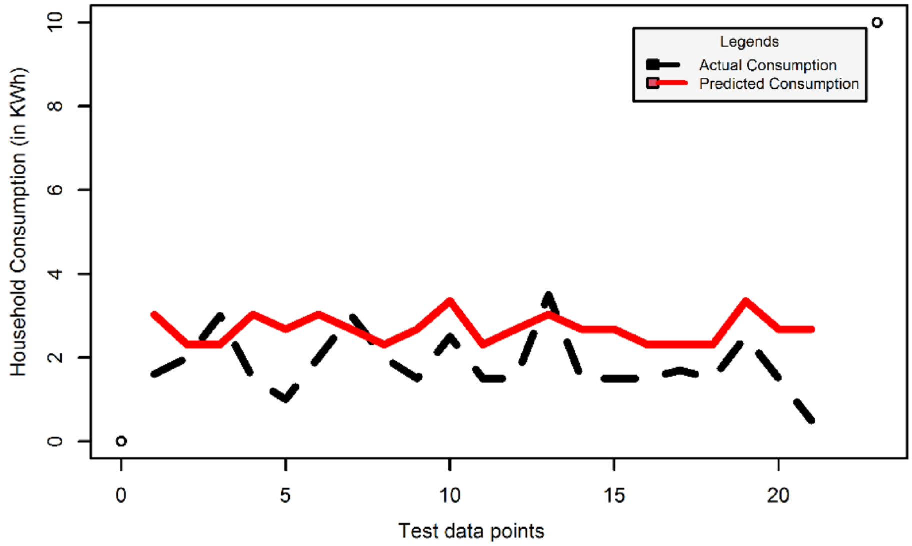

Fig. 6 Forecasting accuracy using "appliance" variable

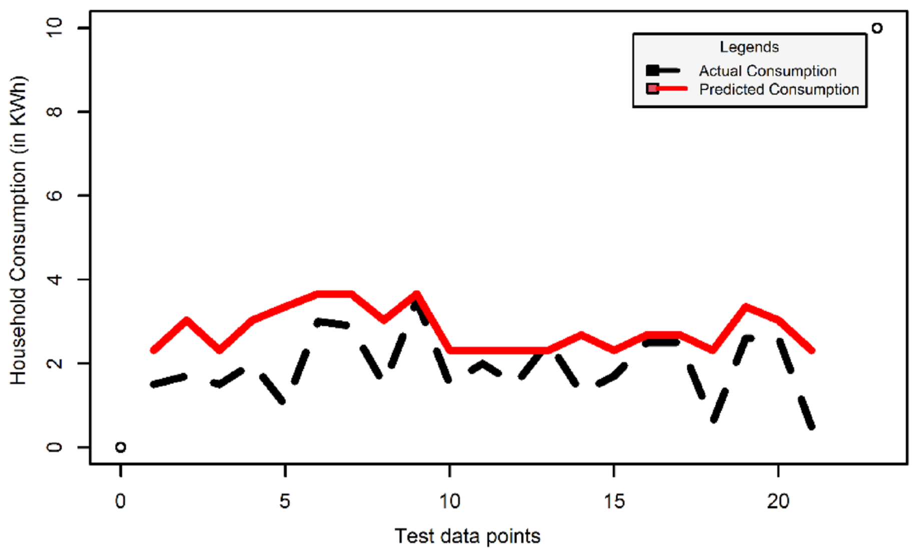

Fig. 7 Forecasting accuracy using the "household size" variable

Concerning results obtained when the three predictors were used, it is obvious that forecasting accuracy in household consumption can be optimized with the use of more than one variable. The finding in this work coincides with the claim advocated by [15, 21, 22] in which they recommend that future work should consider the use of more predictor variables to improve the accuracy. The prediction performance in all four cases described above is shown using bar charts in Figs. 9 and 10 using RMSE and MAPE values respectively.

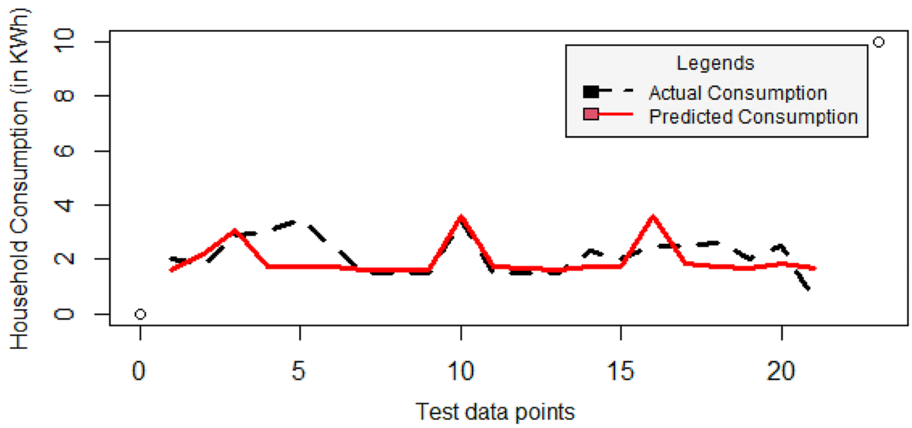

Fig. 8 Forecasting accuracy using more than one predictor variable

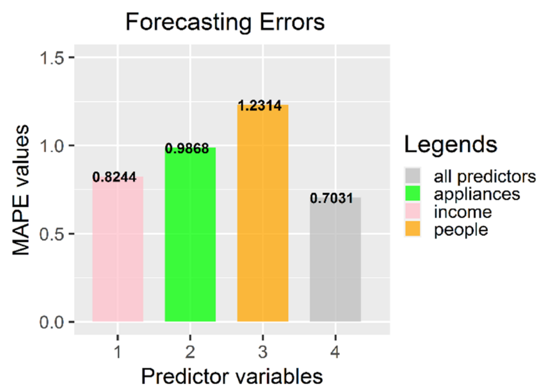

Fig. 9 Corresponding RMSE values

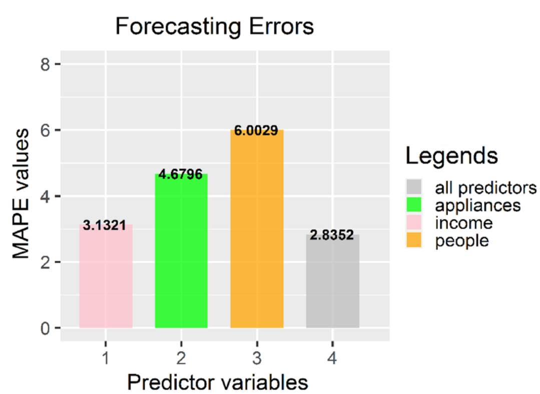

Fig. 10 Corresponding MAPE values

Discussion

First, among several determinants presented in the literature about the developing and newly industrialized (DNI) countries, the study identified that income, household size, and number of appliances are common factors used frequently to estimate household electricity consumption patterns. Our findings agree with the ones reported by [23–25] that income, household size, and number of appliances are common determinants of electricity consumption in DNI countries.

Second, the result of load forecasting based on a univariate predictor variable show that the income had the lowest RMSE (0.8244 KWh) compared to household size (1.2314 KWh) and the number of electrical appliances (0.9868 KWh). This result indicates that a load forecasting model can achieve better results with income variables rather than with house size and number of electric appliances in the context of using only one determinant. This finding agrees with the research results reported by [12, 15].

Finally, results indicate that the forecasting model achieves better accuracy when multiple predictor variables are used. The accuracy seems to outperform that of the univariate model. Using multiple predictor variables reduces the RMSE value by 14.73%. Our finding confirms the opinion suggested by [15, 21, 26] that the use of more than one predictor variable would have increased forecasting accuracy. Also, the finding conforms to the findings reported by [27].

Conclusion and future work

In this study, the effect of predictor variables on forecasting household electricity consumption has been investigated. The effect of both univariate and multivariate predictor variables on load forecasting performance has been analyzed using the Weibull and MARS methods, respectively. In addition, the study has explored the common leading predictor variables used in many developing and newly industrialized (DNI) countries using a document review approach.

The finding of this study paves the way to load modeling analysts to identify proper predictor variables to increase the performance of a forecasting model. The theoretical and practical contributions of this work are as follows: First, the study attempts to establish the critical electricity consumption determinants in residential suburban areas. Second, the study reveals how the number of predictor variables (determinants) affects the performance of a load forecasting model in household electricity consumption. Third, the study recommends the best practice for using determinants in load forecasting models to increase performance.

This research is limited to the survey conducted in one suburban area in Tanzania of which 153 houses among 270 in the two streets of Somangila were involved during data collection. However, we admit that a survey that is based on only one location might limit the generalizability of research findings. However, we believe that we have paved the way for further research on load forecasting issues, especially concerning the effect of the number of predictor variables. Therefore, we recommend further research that will involve a large number of surveyed areas. Furthermore, future research should attempt to consider other predictor variables such as house size. In addition to this, future research should also focus on exploring other domains such as urban areas.

Appendices

Appendix A

Table 2 Review findings on household determinants from 20 studies

SN	Author	Determinants investigated	Country	Findings
1	[2]	Social-demographic such as income, house size, and education level House characteristics Appliance characteristics and usage behavior	Malaysia	Appliance usage
2	[28]	Income Household size House size	Ethiopia	House characteristics-House size
3	[29]	Social-demographic factor Non-economic factors such as behavior and attitudinal Appliance usage and characteristics	Ethiopia	Income
4	[30]	Income Demographic House Characteristics-Building type Non-economic factors	China	House characteristics-Building type
5	[23]	Social-economic Appliance usage and characteristics House characteristics	Montenegro	House characteristics-house size
6	[31]	Social-economic factor Household characteristics Wind speed and number of frost-days	Netherlands	Varies from one place to another
7	[32]	Appliance House characteristics Education level	China	House size
8	[24]	Household Characteristics-Building type Household size Appliance	Botswana	Building type
9	[33]	Social-economic factors House characteristics Climate condition	Greece	House and household size
10	[22]	Social-demographic House characteristics Appliance usage	Korea	Number of appliances
11	[28]	Income Household size Location Education level	Southern Ethiopia	Income
12	[10]	Income Appliance usage Price	South Africa	Income
13	[11]	Income Price	Brazil	Price
14	[34]	Social-economic Household size House size	Ghana	Household size
15	[35]	Income Appliance usage House size Location Education level	Ghana	Appliances
16	[25]	Income Appliance usage Technology development	India	Income
17	[5]	Income Household size	Israel	Income
18	[13]	Income Appliance usage Household size House size	Nigeria	Appliances
19	[36]	Income House size Appliances	Taiwan	Appliance type
20	[26]	Appliance usage Social-demographic House size	Korea	Appliance usage

Appendix B: Sample Questionnaire used

Household Electricity Consumption Survey

(Tafiti kuhusu matumizi ya umeme majumbani)

Study area/ Eneo la utafiti: Kigamboni – Mbutu/Mwembe Mdogo

Introduction/Utangulizi

Please help us fill in the following questions and your anonymity is highly conserved/ Tafadhali tusaidie kujibu maswali yafuatayo usiri wako unazingatiwa na usiandike taarifa za utambulisho wako kama majina na kadhalika.

Your response is very important for the completion of this study in producing findings/ Majibu yako ni muhimu sana katika kukamilisha na kutoa mjumuisho katika utafiti huu.

A. Bibliographic information/Taarifa za Kiwasifu

1. Education level /Kiwango cha elimu (put a tick in the box/weka tiki katika sanduku).

Primary/ Msingi	
Secondary/upili	
University/chou kikuu	
None/Hakuna	

2. Umeajiriwa/are you employed? (put a tick in the box/weka tiki katika sanduku).

Unemployed/Sijaajiriwa	
Employed/nimeajiriwa	

3. Average daily income/wastani wa kipato chako kwa siku (fill in the box/jaza katika sanduku)

Tanzania Shillings/ Shilingi za Kitanzania

B. Household Electricity Consumption/ Matumizi ya umeme majumbani

4. Number of people in the house/ Idadi ya watu nyumbani (fill in the box/jaza katika sanduku).

5. Number of appliances in use (excluding lamps) /idadi ya vifaa vya umeme unavyovitumia (ukiacha taa). fill in the box/jaza katika sanduku.

6. Average daily electricity consumption (in KWh) / Wastani wa matumizi ya umeme kwa siku (Units). fill in the box/jaza katika sanduku.

7. Number of young people in the house / vijana wanaoishi nyumbani. fill in the box/jaza katika sanduku.

8. Alternative source of energy at home / matumizi mbadala ya nishati ukiacha umeme (kuni/wood, mkaa/charcoal, nishati wa jua/solar energy). Tick in the box/jaza katika sanduku.

YES/NDIYO		NO/HAPANA	

2

Abbreviations

DNI	Developing and newly industrialized
ESDN	Electric secondary distribution network
MAPE	Mean absolute percentage error
MARS	Multivariate adaptive regression splines
NLS	Nonlinear least squares
PSMP	Power system master plan
RMSE	Root-mean-square error
TANESCO	Tanzania electric supply company

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Author contributions
HAB involved in crafting the idea, research design, and implementation. On the other hand, HM involved in reviewing the literatures and proposing the research gap. Furthermore, both authors participated in content writing, rendering, and compilation from the first to the final draft of the manuscript.

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Data availability
The data used in this research are private and belong to the authors of this manuscript. Therefore, the data can be available on the request sent to the authors of this paper.

Declarations

Competing interests
The authors declare that they have no conflict of interest.

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Publisher's Note

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