Modelling Residential-Scale Consumer Demographics using Monthly Electricity Consumption Data

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***Abstract*—Electricity is one of the most widely used forms of energy that plays a significant part in sufficing the fundamental energy demand based on contemporary human needs. It is becoming highly tedious for the energy sector to manage and surveil the modern energy demands based on the constantly changing consumer demographics. In order to progress as a business, it has become pertinent for the distribution companies to evolve their development plans, tariffs, and business models according to the consumer requirements. This article proposes three different models to predict the attributes of a consumer household, namely the multivariate linear regression (MLR), the support vector regression (SVR), and the artificial neural network (ANN). The study uses the PRECON dataset, which is based on the monthly electricity consumption of households in Lahore, Pakistan. All of the proposed models play significant roles in predicting the required consumer demographics for forecasting. The linear model shows the ability to predict the number of people with very low MAPE of 3.57% as compared to other models. So far, ANN has shown the best results in predicting the number of fans, air conditioners, and rooms. However, the MAPE reports extracted from this study show the inability of the used models to explain the variation of property area confidently.**

***Index Terms*—energy prediction, residential building, machine learning algorithm, electricity consumption, demographics, consumer profile**

I. Introduction

Energy is integral to both life and its ability to perpetuate. A contemporary human life, marked by an amplified dependence on profuse, technologically oriented and advanced energy resources, calls for newer, sustainable and more sophisticated models of energy distribution. The efforts toward unearthing and utilizing sustainable energy sources to meet the modern energy requisites are not only paramount in sanctioning a sustainable and secure future for this planet but also play a vital role in the current social and economic capability and development of a country. In this context, electricity is one of the most widely used and exigent form of energy where human life has directly or indirectly become extensively dependent on it. It is predominantly generated through conventional power sources such as fossil fuels, nuclear power and hydro power and increasingly through solar power and several renewable sources of energy. The generated energy is then supplied to the consumers by the power grids and distribution companies. It is becoming highly tedious for the energy sector to manage the modern consumer demands based on the constantly changing consumer demographic. According to the Pakistan Economic Survey 2020–21, electrical power consumption per capita has increased by 23.5% [1] over the period of 2000 to 2020. It has therefore, become pertinent for the distribution companies (DISCOs) to handle the distribution load according to the changes and patterns of the consumer's electricity demand.

To ensure sustainable development for the energy sector of Pakistan, the DISCOs need to effectively start incorporating the consumer demographics and consumer-driven approach in their business models. The demographics and consumption patterns of consumers can prove to be a significant source of relevant insights needed for short and long term planning of energy optimization. The data extracted shall help distribution companies to manage revenue assessments, unit maintenance, scheduling, energy trading, expansion planning and to improve energy efficiency. Most importantly, the data will allow the companies to develop an optimized generation schedule to address demand accordingly. In addition, policy makers will also be able to review the current strategies to minimize the electricity supply and demand gap and develop future strategies that will ensure economical electricity with methodical generation, transmission and distribution though out Pakistan. The technique discussed in this paper can potentially bring huge impact to energy sector in all of the developing countries generally. Along with solving several of existing problem in energy sector such as, frequent power failures caused by heavy air conditioning loads in summer, power theft and long-term existing policy failures and implementation gaps, this technique can also provide a vital information for long term development plans.

The sufficient and accurate supply, availability and collection of the relevant data is one of the biggest hurdles in this process. The most typical methods of consumer demographics data collection include surveys, census, or simulations which are highly flawed, inefficient and very uneconomical. Our study offers the country-wide installation of smart meters as an alternate solution. When the idea was initially pitched in the early 2020, a capital expenditure of at least \$6 billion was estimated to cover the 90% of a 35 million electricity consumer base [2]. However, in comparison, a total cost of only \$1.3 billion was invested in New York to employ 4.7 million meters to its gas and electric customers [3]. Unfortunately, such huge figures are hindering the progress of the plan even before its start. Considering the economic condition of especially the developing countries, such as Pakistan, with meagre resources and none to spare, such resource hungry methods are not practicable. The proposed technique in this paper uses the readily available monthly electricity consumption data to predict the consumer demographics, which is much more pragmatic. This technique can serve as a blueprint for other developing countries as well.

To this end, this research proposes a novel consumer demographic prediction model from monthly electricity consumption data and evaluates its performance using mean absolute percentage error metric. The novelty lies in the introduction of this concept which has not yet been applied for a third world country like Pakistan. This research has been successful in achieving state-of-the-art accuracy in the model by applying data refinement techniques, followed by data training using three different machine learning algorithms. The knowledge of consumer demographics can play a vital role in sustainability and development of energy sector especially in developing countries.

The rest of the paper is organized as follows. Section II discusses the work previously done in this domain. Section III analyzes the characteristics of the data and proposes 3 different techniques. Implementation of forecasting techniques and results are discussed in Section IV. Lastly, conclusions are drawn in Section V.

II. Literature Review

It is pivotal to understand the role of energy sector and more specifically electricity in the economic development, technological advancement, and planning of a country. To monitor household power consumption non-intrusive load monitoring is used which not only gives an analysis of the consumer behavior but also explores energy conservation patterns. Biansoongnern et al. present an NLIM (non-intrusive load monitoring) model in [4] which measures the electricity consumption of some particular appliances without installing additional instruments which reduces cost and time and achieves significant saving in energy consumption by sampling the consumption at 1 Hz interval. In another paper Berges et al, discuss an NLIM approach that gives feedback about the energy consumed in a residential building along with the operational schedule of appliances [5]. Some NLIM methods use the steady state operations of the appliances for energy disaggregation. In [6], the authors use steady state energy used pattern to classify cases of step change by disaggregating energy usage at circuit level. The primary constraint of these techniques is that they require the availability of high granularity electricity load data which is available only through smart meters. Unfortunately, lack of resources impede the DISCOs in developing countries from rolling out smart meters for all its consumers [3]. Using the readily available monthly electricity consumption data is one of the novelty factors in our technique, thus reducing the required resources drastically.

A model is proposed [7] where household electricity consumption is forecasted using support vector regression. One of the most significant contributions to the present research and literature on load forecasting is related to the variable selection approach used in determining the best subset of consumption predictors used. It selects 18 of the 48 initial variables as the critical predictors. As the nature of algorithms progressed and a new era of artificial intelligence started, Singh et.al's study [8] proposed the use of ANN for load forecasting. Considering the different load profiles for weekends and weekdays, they use separate neural networks for each. As technology progressed into the deep learning era, Troung et.al [9] proposed the usage of deep neural networks for energy prediction to accurately forecast the day-ahead hourly energy consumption profile of a residential building using occupancy rate as an input. It gives a coefficient of determination of 97.5%. A hybrid approach that employs Convolution Neural Network (CNN) and Gated Recurrent Units (GRU) for accurate energy consumption prediction has also been proposed [10] which acts as an effective alternative to the previous models in terms of complexity as well prediction accuracy. Another recent paper by Theile et al. [11] focuses on predicting power consumption using two machine learning algorithms namely Support Vector Machine(SVM) and Recurrent Neural Network (RNN). The model incorporates time, day of the week, and the week number within the year to yields different results when either one of them is used for prediction. The RNN proposed the most substantial results with a mean error of 3.5227%, obtained using the features such as temperature, weekday, tempo, and holiday. The literature also provides a solution to the problem of limited data by using transfer learning techniques [12]. Firstly, CNN is used to capture the intraday, daily, and weekly cyclostationary patterns, trends and seasonality in energy assets time series. Then, transfer learning strategy is applied on the CNN model results to yield significant improvements. Huge amount of research has been done in this respect ranging from different forecasting models and techniques to economic indicators and electric loads on all domains (i.e., short, medium and long terms).

All the present literature proves to be invaluable in comprehending the role, significance and use of time series techniques for forecasting electricity demand however all the research has been limited to load prediction based on specific demographics and load disaggregation using high frequency data. While this an advantage for energy providers and utility companies but there is room for more open and unrestrained research. Predicting the demographics of people from their energy loads still requires a considerable amount of research. The modelling approach presented in this paper contributes towards introducing newer methods of demographics prediction. The proposed approach has not yet been addressed in any literature as of our knowledge.

III. Methodology

The engagement with consumer demographics not only transforms the distribution networks and the development sector but also paves the way for adoption of customer-based, profit-oriented strategic business plans and decisions by the DISCOs. Such reforms will facilitate progress, growth and profit for both the consumers and the distributors. In addition, serious problems such as the high rate of transmission and distribution network failures, power theft and load shedding faced by countries like Pakistan will also be dealt with [13]. By understanding the electricity consumer's requirements and usage patterns, the DISCOs can identify such electricity distribution inefficiencies [14]. Furthermore, DISCOs will be able to design customized tariff packages that will prove suitable for its customers. Being aware of the demographic parameters such as number of air conditioners, fans and refrigerators will enable the DISCOs to better handle the escalating issue of degrading power factor and overloading of local distribution network in all seasons especially summer. To contribute in this regard, our methodology is described below.

A. Dataset

The dataset used for this study is Pakistan Residential Electricity Consumption (PRECON). It includes the electricity consumption of 42 residential properties bearing varied demographics from June 2018 to May 2019 at minute interval [15]. This dataset can be regarded as an adequate representative sample of electricity consumption profiles of residential buildings in Pakistan and one of the pioneer datasets which covers information on a vast scale. It encompasses multiple consumption patterns ranging from different house sizes to different number of electrical appliances, and further appends details about the number of residents in the household. The selected residential properties are widely scattered all over the city of Lahore, Pakistan, allowing the data to engulf different types of households that vary not only in financial status, but in daily activities and usage patterns too.

1) Data Pre-processing: The challenges faced during the collection of this dataset resulted in some households with partly missing electricity consumption data. This made certain households unsuitable to be used in training or testing of the machine learning models. Hence, after the removal of the houses with missing data, 34 households were left to formulate the results. All the findings described below use the data related to these filtered households. Out of all the attributes presented and established in PRECON, the following six were selected:

- Number of people
- Number of fans
- Number of air conditioners
- Number of refrigerators
- Property area
- Number of rooms

These attributes were selected on the basis of their role and significance for the distribution companies. Being aware of the number of people, area of the property and information about other major home appliances, will help DISCOs manage the power system more strategically. For instance, data related to the number of installed air conditioners, fans and refrigerators in a particular household will give significant insights to predict and manage the degrading power factor during the summer season. Similarly, data on the number of people can help DISCOs predict short term residential load.

Aforementioned demographics will also enable the system operator to predict daily load patterns in addition to their weekly and seasonal variations. Having the knowledge of property area can further guide the distribution companies to manage and reallocate resources efficiently. For example, meter reading officials that traverse their allocated regions to gather electricity consumption data, require both manpower and further resources to cater these individuals. The hiring of such meter reading officials is necessary as Pakistan lacks the resources for the installation of smart meters [2]. In essence, information about property area can enable the DISCOs to manage their resources efficiently.

Figure 1 shows the distribution of the selected attributes of the households from the PRECON dataset. The box plot displaying the number of people indicates that the median number of people living in a house is 6 and it goes as high as 10. Similarly, the median number of installed air conditioners in a house is 4 with a highest number of 11. The diverse demographics observed in this dataset make it highly competent for training machine learning models [16].

Figure 2 shows the distribution of monthly energy consumption calculated by aggregating PRECON data to monthly intervals. The length of the box plots show the amount of variation in each month for the houses. In Pakistan, summer usually ranges from May till September which reflects as higher electricity consumption in those months [17]. For the rest of the year, the residential electricity consumption remains comparatively low because of absence of cooling load such as air conditioners, fans and refrigerators. All the gathered information is highly substantial for training the models.

B. Multivariate Linear Regression (MLR)

To predict the six attributes described above, the first statistical model used is MLR [18]. Monthly electricity consumption for the whole year creates twelve independent input variables. These input variables are used to construct one equation each

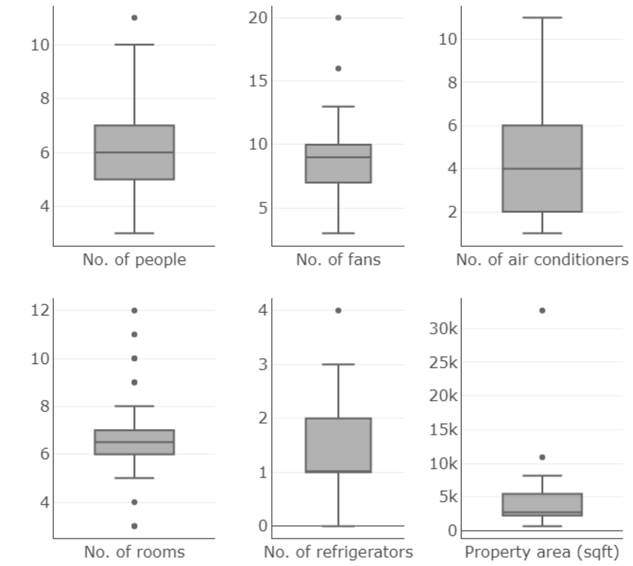

Fig. 1. Diversity in customer demographics data

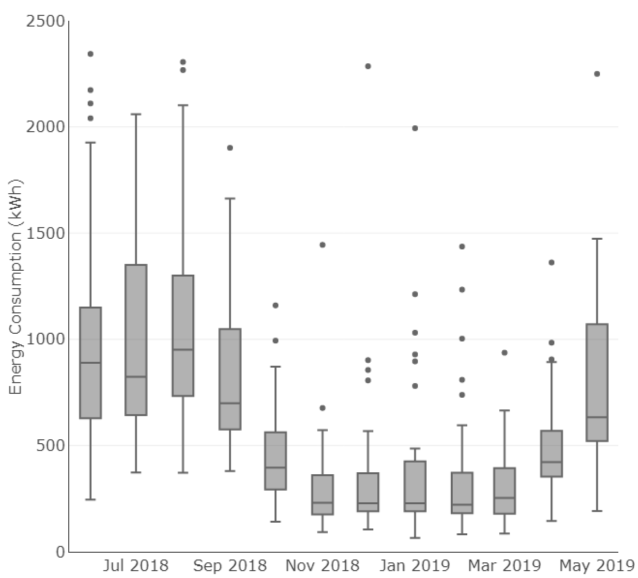

Fig. 2. Monthly electricity consumption distribution

for all six attributes. A generic form of the equation is given in 1.

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i \tag{1}$$

where X_i is the electricity consumption for a month and Y is the predictor variable. β_0 is the intercept. n is the total number of months. B_i represents the gradient coefficient of electricity consumption of each month. To achieve a better prediction, a minimum threshold for p-value was set and step-wise bi-directional selection [19] was used to eliminate predictor variables. The table II shows the gradient coefficients with their p-values. The coefficients of the rejected independent variables are neither included in the model nor shown in the table.

C. Support Vector Regression (SVR)

SVR is the second model adopted in this study. It uses the same principle as support vector machine, but is additionally modified for regression problems. It operates by finding a hyper-plane in an N-dimensional space in order to distinctly classify the data points whereas N is the number of features [20]. Radial Basis Function (RBF) kernel has been used which models the non-linearity between the independent variables and the predictors. It allows the tuning of gamma and cost hyperparameters which control the complexity of the model.

D. Artificial Neural Network (ANN)

ANNs are immensely popular owing to their ability in solving both classification and regression problems [21]. This study has used ANN for regression to predict the household demographics. The number of layers, number of neurons, activation functions, learning rates for each attribute are tuned to achieve minimum error. Initially, each node in ANN is randomly assigned a numerical weight which is tuned through back propagation. These weights then regulate the amplitude of the signal that passes between them. A sample of the ANN used in this study is shown in the figure 3.

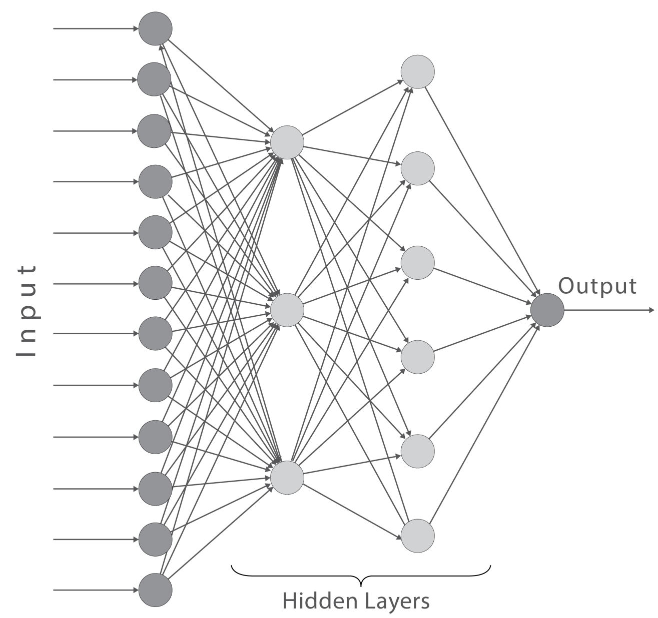

Fig. 3. Sample neural network

E. Evaluation Criteria

There are multiple evaluation techniques to assess the performance of regression models. The most commonly used error metrics include Mean Error (ME), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) [22]. Since ME takes the average of the difference between actual and predicted values, it also becomes prone to negation of over estimation with under estimation by the model. Consequently, it may create a false indication of better model performance. MAE addresses this problem by taking into account the absolute value of the calculated error. However, at the same time, it does not depict the significance of that error with respect to the actual value. Keeping in view the problems associated with ME and MAE, MAPE covers the above-mentioned issues and hence, is regarded as a better indicator for the evaluation and comparison of the three models used in this study. It gives an intuitive interpretation of relative error by considering actual and predicted values. MAPE can be calculated using the formula given in equation 2.

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - P_t}{A_t} \right| \tag{2}$$

where n is the number of test samples, A is the actual value and P is the value predicted by the model.

IV. Results and Discussion

The houses selected after cleaning and pre-processing of the data are divided into train and test subsets of 30 and 4 households respectively. The models are trained using the parameters mentioned above and the finalized models are used for predicting the test subset.

Table II shows the intercept and the gradient coefficients extracted from MLR models. In order to predict the property area using MLR, the electricity consumption of July, November and December 2018 is used with gradient coefficients of -5.28, 18.98 and 5.6 respectively. All three of the independent variables used show significance in explaining the variance in property area, as the p-value is less than 5% for all. Rest of the months are rejected by the stepwise bi-directional selection algorithm due to their p-value being higher than 10%. Table II also shows the accepted independent variables for the rest of the attributes as well as their p-values.

The performance of each model is then evaluated using MAPE as shown in table I. All of the three models play their significant roles in predicting the required consumer demographics. The linear model is able to predict the number of people with very low error relative to the other two models with MAPE of 3.57%, represented with a dark shaded cell in the table I. It is further complemented by table II which shows that the number of people primarily hold a strong linear relationship with the consumption of the month of June 2018 and August 2018. For the month of June 2018, the number of people has a negative linear relation with the electricity consumption while it has a positive linear relation with electricity consumption of August 2018 with a gradient coefficient of -0.002 and 0.004 respectively. However, the performance of all three models is not satisfactory for predicting property area with minimum MAPE of 141.31% reported by SVR. The cause of such a setback could be attributed to the limited size of the dataset. Number of refrigerators were predicted by both MLR and SVR with MAPE of 8.33%, outperforming the ANN. For the number of fans, air conditioners and rooms, ANN was able to give much lower MAPE than MLR and SVR.

TABLE I
Mean absolute percentage error obtained from the three prediction models

Parameter	MAPE		
	MLR	SVR	ANN
Number of people	3.57	21.07	9.12
Number of fans	59.17	65.00	10.00
Number of air conditioners	77.38	66.07	11.90
Number of rooms	44.04	40.48	10.71
Number of refrigerators	8.33	8.33	25.00
Property area (sqft)	226.90	141.31	189.80

The results presented in this study provide satisfactory outcomes for some attributes such as number of people and air conditioners. However, the crucial attribute of property area is not explained well by any of the three models, as evident from the reported MAPE. This problem can be dealt with by expanding the dataset or improving the models and tuning their various hyperparameters. Several other variants of MLR can be tested to achieve better results by using interactions between independent variables. In the same way, other kernels such as sigmoid and polynomial can be explored in future to improve performance for demographic attributes. In this study, the ANN employed resilient backpropagation with weight backtracking. For future, other algorithms such as semi-log regression can be applied to minimize error.

V. Conclusion

The motivation of this paper is based on the idea that knowledge of consumer demographics can substantially transform the business model of electricity distribution companies. This can help the distribution companies understand the needs of their customers better and provide customized tariff rates and better plans for all of their diverse consumer base. It can potentially solve the prevalent problem of power distribution in developing countries as well. This paper has successfully introduced a resource-efficient method to predict residential consumer demographics from monthly electricity consumption data into the bargain. The suggested techniques include multivariate linear regression, support vector regression, and artificial neural network. The results show significant findings that several parameters can be predicted with MAPE of less than 12%, and the number of people can be predicted with MAPE of approximately 4%. On the other hand, the prediction of property area shows MAPE in the order of hundreds. The results of this study are quite promising and can contribute to tackle considerable existing policy-implementation gaps. A significant amount of research and work is still called for to improve the models' reliability using different hyperparameters and a larger dataset. As the study progresses, the models used can be further extended to include commercial and industrial consumers allowing newer and better energy optimization methods in developing countries.

TABLE II
COEFFICIENT WITH THEIR P-VALUES IN PARENTHESIS OBTAINED USING MLR

	Property Area	Rooms	People	Air conditioners	Refrigerators	Fans
Intercept	2143.1(0.03)	4.24(0)	3.94(0)	2.2(0)	1.61(0)	5.36(0)
Jun 2018	-	-	-0.002(0.05)	-	-	-
Jul 2018	-5.28(0)	-	-	-	-	-
Aug 2018	-	-	0.004(0.009)	-	-	-
Sep 2018	-	-	-	-	-	-
Oct 2018	-	-	-	-	-	-
Nov 2018	18.98(0)	-	-	-	-	-
Dec 2018	5.6(0.03)	-	-	-	-	-
Jan 2019	-	-0.004(0)	-	-	-	-
Feb 2019	-	-	-	0.006(0)	-	-
Mar 2019	-	0.014(0)	-	-	0.004(0.03)	0.01(0)
Apr 2019	-	-	-	-	-	-
May 2019	-	-	-	-	-0.0015(0.04)	-

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