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Short-term electricity demand forecasting for Kathmandu Valley, Nepal

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Abstract

Accurate electricity demand forecasting for a short horizon is very relevant aspect for managing day-to-day operation control, scheduling, and planning. The deterministic variables such as type of days, and weather variables such as temperature are the major factors that affect the forecasting accuracy. Since the automation systems are continuously increased and implemented by smart meters and internet of things, static models computations are replacing accordingly by dynamic real time robust forecasting models. Therefore, time series, regression, machine learning, and deep learning models are designed and implemented on the electricity demand dataset of Kathmandu Valley, Nepal. Accuracy improvement is also considered during model design. The result shows that the deep learning model, long short term memory (LSTM) performs outstanding performance in-terms of mean absolute percentage error (MAPE) value 1.56%, and root mean square error (RMSE) value 3.12 MW. While analyzing the regression coefficients, electricity demand during Dashain shows the lowest variation while Tihar (Dipawali/Laxmi Puja) shows the highest (peak) demand variation.

Keywords: Deep learning; Impact analysis; LSTM; Short-term electricity demand; Temperature impact; Weather variables

1. Introduction

The electricity demand forecasting is indispensable procedure for energy planning in power industry. Based on lead hour of forecasting, it is classified as short term, medium term, and long term forecasting. Apadula et al. [1] classified the demand load forecast into four categories: very short-term forecasts (from a few minutes to 1 h ahead), short term forecasts (from 1 h–1 week ahead), medium-term forecasts (from one week to a year head) and long-term forecasts (longer than a year ahead). However, according to Zamo et.al. [2], energy prediction can be categorized into five types: Intra-hour predicting for next 15 min to 2h with a time step of 1 min; Hour-ahead predictions with hourly granularity with a maximum lead time of 6 h; Day-ahead prediction with one to three days ahead; Medium-term prediction from 1 week to 2 months ahead; and Long-term prediction with one to several years for monthly or annual production. Such lead time prediction influences the selection of models, methods and the choice of external parameters in the model. For example, long term forecasting model consist the socio-economic and population growth as the major factor, whereas we exclude these factors and include atmospheric, seasonal and other short-term dependencies [3]. However, this paper focuses on development of the short-term electricity demand model to predict the electricity demand for the capital city of Kathmandu, Nepal.

Kathmandu is the capital of Nepal, and the demand for electricity in this region ranging from 101.12 MW to 229 MW throughout the day [4]. This variation throughout the day is due to consumers' daily activities and their reactions to the effects of environmental and social factors. Understanding these effects allows the Nepal Electricity Authority to better plan and even implement demand response to manage it in the future [5]. For the electricity consumption, economic status of the people plays a significant role. Therefore, three different economic development scenarios such as (i) Low growth rate of 4.5% GDP, (ii) Normal growth rate of 7.2% GDP, and (iii) High growth rate of 9.2% are were considered while analyzing the demand. Regarding the consumption, [6] assumed that 100% of the cooking and 75% of water heating in urban areas by 2020, metro cities by 2025. This study concluded that there would be 30% rise in demand of electricity by 2020 compared to 2015's demand. This prediction made in 2015 is almost achieved by 2021-2022. In case of Nepal, people were facing the electricity crisis and power outage because of insufficient installed capacity, while these days Nepal Electricity Authority (NEA) is announcing different strategy to promote the electrical consumption.

Very few attempts have been done for short term load forecasting in context of Nepal[4, 7]. A method called artificial neural network (ANN) is used to anticipate the future load of Kathmandu Valley of Nepal. The Neural Network is build and trained with historical data along with seven different input variables. This trained model is then used for the day ahead prediction for 24 hours' load. Bhandari et al.[7] estimated the forecasting error significantly low, where mean square error (MSE), RMSE, and MAPE are found between 2.59 MW to 7.78 MW, 1.61 MW to 2.79 MW, and 1.61% to 5.07%, respectively. They concluded that the ANN technique was the best among all the techniques showing the robustness of the method for non-linear load data. However, they estimated accuracy only for one specific date, and hence obtained conclusion or recommendation may not have a strong validity. Yaju et al. [4] presented a study of electricity demand and its relation to the previous day's lags and temperature by examining the case of a consumer distribution center at Baneshwore grid. The effect of the temperature on load, load variation on weekends and weekdays,

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and the effect of load lags on the load demand were thoroughly discussed. Based on the analysis conducted on the data Yaju et al. [4], short-term load forecasting is conducted for weekdays and weekends by using the previous day's demand and temperature data for the whole year. Using the conventional time series model as a benchmark, an ANN model was developed to track the effect of the temperature and similar day patterns. The results show that the time series models with feed-forward neural networks (FF-ANNs), predicts with 0.34% MAPE on a weekday and 8.04% on a weekend. However, the experimental result was taken from a randomly picked less number of test results, therefore the conclusion could be biased. Therefore, we have focused to fill up a research gap by constructing a robust short-term electricity demand forecasting model.

1.1. Related Works

Several works have been published world-wide introducing different methods to tackle the short-term load forecasting (STLF) problems. These methods split into three large groups: artificial intelligence [8, 9], statistical [10, 3], and hybrid models[11, 12]. In statistical methods, traditional time series forecasting models especially auto-regressive integrated moving average (ARIMA) models [13], Seasonal ARIMA (SARIMA) [14], and exponential smoothing models [15] are considered as the baseline for many years. In such models lagged inputs of historically collected data predicts the future electricity demand.

Several modeling concepts for robust parameter estimation used prior to 1990 were discussed in [16, 17], and concluded that regression modeling concept was superior [17, 18, 19, 20, 21, 22, 23] for short term load forecasting. The main feature of this approach is the interpretative capability of explanatory variables so that impact of individual variables can be analysed. However, the characteristics of electricity demand are highly non-linear. The handling capability of non-linear dataset is found superior in artificial intelligence (AI) approach such as machine learning and deep learning approach. In these approach Ridge, SVM, recurrent neural network (RNN), LSTM, and gated recurrent unit (GRU) are the popular machine learning approach among the researchers. In [24], hourly electricity load forecasting state space model based on stochastic behavior in time-varying process were design and presented to account for changes in customer behavior and in utility production efficiency.

To tackle the non-linear and highly dynamic load fluctuations of residential customers, artificial intelligence techniques have become popular in load forecasting [25]. The main techniques include ANN [15], Ridge regression, and support vector machines (SVM) [25]. The Ridge regression allows to perform non-linear regression by constructing a linear regression function in a high dimensional feature space. While ANN model tends to provide slightly better forecast [26], this comes at a cost of longer computational times. The optimal number of layers and neurons in neural network model has to be determined empirically [14].

The presence of non-linearity on electricity demand is due to the unpredictable human behavior and the activities. In residential areas, electricity demand may rise to a peak during the morning and evening. According to the calendar, electricity demand behavior is changing for example, people set up the out-door roaming plan during long holidays. If they move out from home, electrical appliances may not be used properly. However, during the festival period people may gathered at home for the celebration. In such condition,electrical appliances may be in use. Therefore, the special days such as festivals and holidays show the special characteristics. Residential customers are very sensitive to weather fluctuations and calendar (weekday, weekend, and holiday). Retail stores, restaurants, hotels and educational institutes are commercial customers, and their demand is affected by business schedules and some weather behavior. This results in electricity demand dropping significantly during weekends or holidays. The issue on forecasting accuracy due to public holidays was discussed by Ziel et al [27]. They presented a state-of-the-art technique to handle the calendar impacts by removing them from the data set, treating them as weekend or introducing separate holiday dummies. They concluded that the incorporation of holiday effects can improve the forecasting accuracy during public holidays periods by more than 80%.

Similarly, weather condition often plays an important role in the forecasting accuracy. Short-term daily peak power load in summer or in winter fluctuates regularly, showing an obvious periodical characteristic. It is greatly affected by temperature, wind, precipitation, and other meteorological factors. Including such meteorological factors in the model, forecasting accuracy was significantly improved by 13% for Hokkaido Prefecture dataset in Japan [23]. However, among these meteorological factors, many research article include only temperature variable considering the most influencing factor. They suggest that if temperature factor is included in the model, the impact of wind, precipitation and other meteorological factors found negligible [3, 23]. In some study, the weather variables are excluded due to three major reasons: (i) they show lower impact on electricity demand [28]; (ii) it is expensive to install weather stations to collect all these data; and (iii) there are potential collinearity problems by employing several weather variables as explanatory variables [29].

Since our objective is concerned to the impact analysis of temperature, we have incorporate only temperature variable. The major contributions of this research work are as follows:

1. This research contributes as the pioneer literature for the interested researcher in short-term forecasting domain for Nepal
2. The marginal impact of temperature that leads to raising the demand for day hours and night hours is explored for Kathmandu Valley, which is quite useful for demand side management.
3. The utility company of Nepal (i.e NEA) and other private companies can implement this model to maintain grid stability and overcome black out.

2. Materials and Methods

2.1. Study Area Selection

Kathmandu is the capital and also the largest city $50\,\text{km}^2$ area with dense population of around 20 thousand people per square kilometer [30]. Kathmandu Valley is growing at 4% per year according to World Bank in 2010, one of the fastest-growing metropolitan areas in South Asia, and stand at the first city in Nepal to face the unprecedented challenges of rapid urbanization and modernization at a metropolitan scale. The population of Kathmandu in 2020 was about 2.5 million with 4.63% annual growth. This represents 9.3% population of the country. Since the metropolitan region is considered as the economic hub, the consumption of the metropolitan region alone is about 25% of the total consumption of Nepal. There are many factories, industrial parks, government offices and universities campus within this reason.

2.2. Electricity Demand Profile

In this study, hourly demand data provided by NEA from 1 May 2017 to 31 Jan 2019 are used. Since the samples of observations are hourly recorded, we have 15720 samples for entire time horizon. According to annual report of NEA [5], Kathmandu regional office

Figure 1: Location map of Kathmandu Valley, Nepal[30]

distributed the electricity to 674,047 consumers in Kathmandu Valley, which is 16% of total consumers of Nepal.

The pattern of electricity demand exhibits a trend, seasonal patterns, weekly and daily patterns, and holiday effects. The premise of effective load management becomes more reliable due to the accurate load forecasting [31]. Forecasting supports utility companies in their operations and supply management for their customers. Electric load forecasting is an important process that can increase the efficiency and revenues of electricity generation and distribution companies. It helps them to plan their capacity and manage their distributions to all the consumers with their required energy. The accuracy in forecasting is the key factor. The key factors that influence spot prices are mainly depends on the demand as well as the ability to respond to this demand by the available generating units. Therefore, possible errors in load forecasting could have significant cost implications for the market participants [23].

Fig. 2 shows the variation of load demand for 12 months of the year. Blue line shows the daily load variation from January 2018 to December 2018 and Orange line shows the load demand during the public holidays.

In Kathmandu city, the nightlife almost end at the mid-night which is reflecting in Fig. 3 where the demand is continuously decreasing after mid night until the morning hours. In the morning after 8 am, the demand is again becomes high because of people's movement, break-fast, office, and day hours.

In Fig. 4, blue dots indicate electricity demand during no holiday (Holiday=0) and orange dots indicate electricity demand during the holiday. It clearly describes the huge variation on electricity demand during the holiday as compared to non-holiday electricity demand data.

2.3. Temperature Impact

Overall peak demand in Nepal is observed during the Tihar festival, especially on the day of 'Dipawali/Laxmi puja' often reaches to 1300 MW. This peak demand is because of the celebration that day as the 'lightening day'. NEA faces the power supply management challenges especially on this day. However, there is huge swing on the electricity demand due to temperature. The micro-study of temperature for short term load forecasting and impact analysis of climate change was conducted by [32] using a simple regression model for Thai data.

3. Methodology

The overall methodology is presented in Fig. 5 . It consist three major blocks named as data-preparation, model-development, and selection of best model.

3.1. Data-Preparation

The raw electricity demand dataset and the temperature dataset hence collected was consist few missing values and outliers. The quality of data affects the data mining results. Raw data needs to be pre-processed so as to improve the efficiency. Therefore, the preprocessing of dataset is one of the most critical steps that deals with the preparation and transformation of the initial dataset. Data cleaning, data Integration, and the data Transformation were the major steps involved in this research works.

3.1.1. Stationarity test

Stationary series has constant mean and variance over a time. The Dickey-Fuller test is implemented to test presence of stationarity in dataset. The Null Hypothesis (H_0) suggests that the dataset is non-stationary while alternate Hypothesis (H_1) suggests dataset is stationary i.e it does not have time-dependent structure. In our experiment $p - value < 0.05$ and therefore reject the null hypothesis H0, that means the data does not have a unit root and is stationary.

3.1.2. Lagged load and temperature impact

The lag load or loads from the previous day or previous hour of the same hour can be highly related to future loads. Studies on lag load relation correlation [33] showed that first-day lag impact has a high contribution to the demand. Likewise, one study [34] discussed the repletion of weekdays such that the 7-day lag had a high contribution because of the same day and same hour relating similar effects each day. Fig. 6 reflects the order of moving average (MA) from autocorrelation function (ACF) and order of autoregressive (AR) from partial auto-correlation (PACF).

3.1.3. Data normalization

Normalization is a technique often applied as part of data preparation for machine learning. The goal of normalization is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values. It is used when features have different ranges. Min Max algorithm is used to normalize data within range of 0 to 1.

3.2. Model Development and Mathematics

There are several methods of model design in literature but the accuracy on electricity demand forecasting from traditional statistical modeling approaches to the modern DNN approaches to cope the non-linear characteristics of electricity demand.

In this study several experiments are conducted for the following methods, (i) Time-series model: ARIMA, (ii) Regression model: MLR, (iii) Machine learning model: RIDGE and SVM, and (iv) Deep learning model: RNN, LSTM, and GRU,

3.2.1. Time-series models

The ARIMA algorithm was integrated by autoregression (AR) and moving average (MA) method with an addition of integrative module. This model is characterized by three terms, respectively, p, d, and q. The general format of the model is $ARIMA(p, d, q)$. The term p is the order of the AR term, q is the order of the MA term, and d is the number of differencing required for obtaining a stationary time series. The forecasting equation of the $ARIMA(p, d, q)$

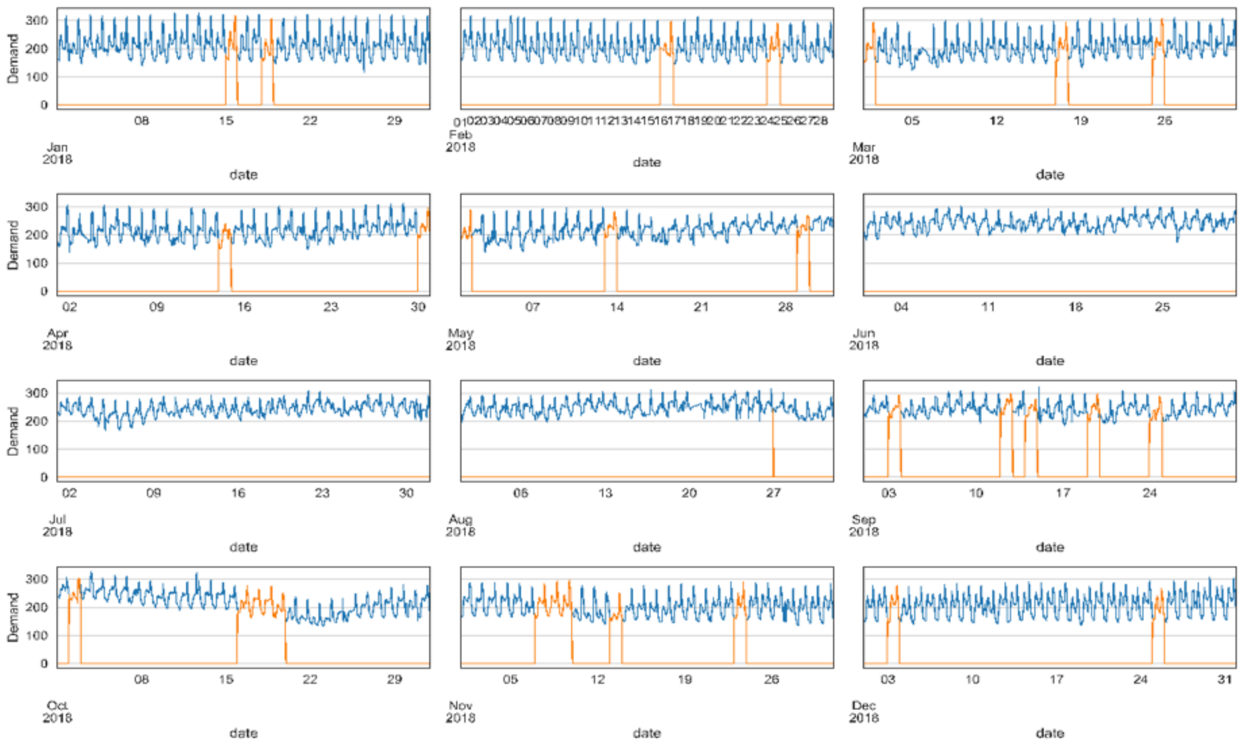


Figure 2: Overall electricity demand in Mega Watts.

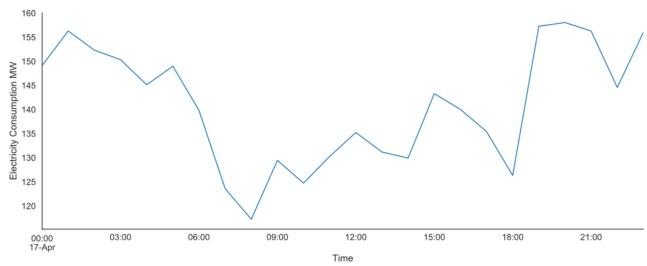


Figure 3: Hourly electricity demand pattern in Mega Watts.

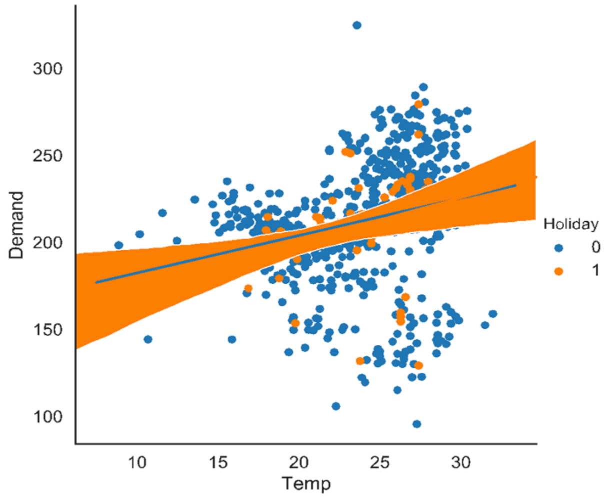


Figure 4: Variation of electricity demand on temperature change for working days

is expressed as,

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{p} \theta_i \epsilon_{t-j} + \epsilon_t \tag{1}$$

where c is the constant representing the intercept,ϕ_i and y_{t-i}, respectively, are the parameters and regressors for the AR part of the model, while θ_j and ϵ_{t-j}, respectively, represent the parameters and regressors of the MA part of the model, whereasϵ_t is the random error term. The selection of appropriate values for p, d, and q can be determined from ACF and PACF test where as the optimum values can be obtained from $auto\ arima$ functions in Python.

3.2.2. Multiple linear regression (MLR) models

In MLR response variable is depends on more than one explanatory or independent variables.

To estimate k parameters we need at least n equations, where $n >= k$, then the general equation can be represented as,

$$y = X\beta + \epsilon \tag{2}$$

where, $y = (y_1, y_2, ..., y_n)'$ is a $n \times 1$ vector of n observation and X consists of $n \times k$ matrix of n observations on each of the k explanatory variables, $\beta = (\beta_1, \beta_2, ..., \beta_k)'$ is a $k \times 1$ vector of regression coefficients and $\epsilon = (\epsilon_1, \epsilon_2, ..., \epsilon_n)'$ is $n \times 1$ vector of random error components. The estimation of these generic question is performed using ordinary least square (OLS) estimation methods.

The least square method recommends computing $\beta = \beta_0$ which minimizes,

$$L_T(\beta) = \sum_{t=1}^{T} (y_t - \beta x_t)^2 \tag{3}$$

The Ridge regression procedure is a slight modification on the least square method and replaces the objective function $L_T(w)$ by,

$$a||w|| + \sum_{t=1}^{T} (y_t - w x_t)^2 \tag{4}$$

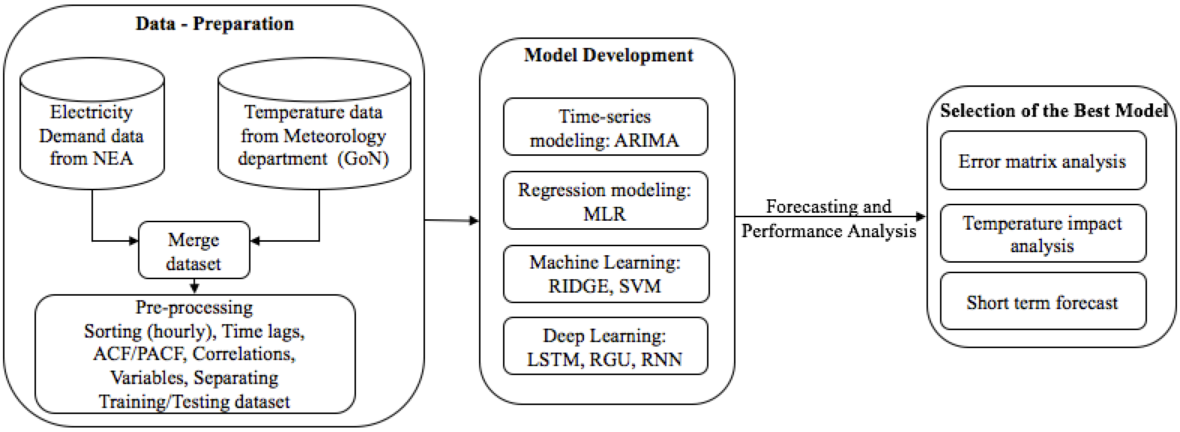
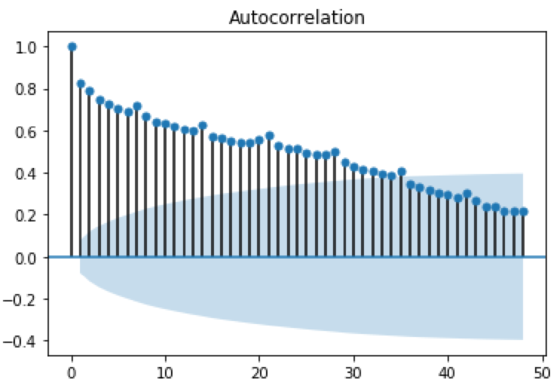
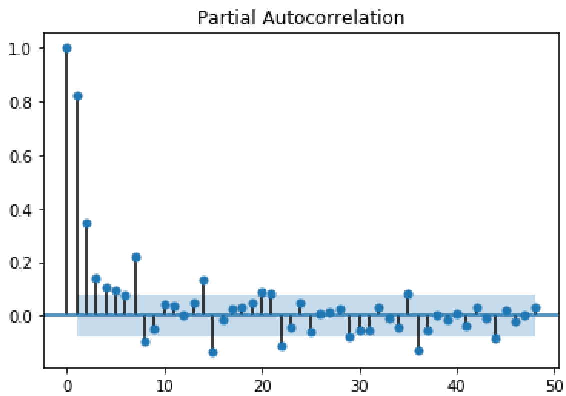


Figure 5: Methodology.



(a) ACF plot for electricity demand.



(b) PACF plot for electricity demand.

Figure 6: Determination of AR and MA order.

where a is a fixed positive constant, parameter β in ols is replaced by weight (w), and considering least square's special case, 4 can be re-expressed as minimum expression by,

$$a||w|| + \sum_{t=1}^{T} \xi^2 \tag{5}$$

where the constraints $y_t = wx_t = \xi_t, t = 1, ..., T$.

3.2.3. Machine learning models

SVM is a good choice to characterize the nonlinear statistical features which existed in the small-scale dataset. This algorithm is frequently applied by many researchers in recent years [35]. The fundamental principle of the model is mapping the input data into a high-dimensional space to explore the nonlinear relationship between the input data and output variables; the input dataset is assumed as $((x_1, y_1), ..., (x_n, y_n))$, and the optimization is described by the following formula:

$$\begin{aligned} min\frac{1}{2}w^T w + C\frac{1}{n}\sum_{i=1}^{n}(\xi_i - \xi_i^*) \\ w^T\phi(x_i) + b - y_i \leq \epsilon + \xi_i \\ y_i - w^T\phi(x_i) - b \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, 1, ..., n \end{aligned} \tag{6}$$

where w, b, ξ, and ξ^* are the decision variable parameters of the optimization problem; $w^T w$ is a regularized term, and $\xi$and ξ^* are the slack variables; C is the penalty parameter,ϵ is the insensitive loss coefficient.

3.2.4. Deep learning models

When the number of layers are increased, then such dense neural network is called deep neural network and such multilayer perceptions are the foundation to most of the deep learning models. The basic deep network moves forward in direction with feedback. Depending on the number of hidden layers precision of the output can be uplifted. The input is fed to the hidden layers by the weight, sum of the product of inputs $I_j$and weights Wij. The hidden layer is used sigmoid activation functions to limit the values within the range of 0 to 1. The RNN is computed as,

$$\begin{aligned} h_t &= f(h_{t-1}, x_t) \\ h_t &= tanh(w_{hh}h_{t-1} + w_{xh}x_t) \end{aligned} \tag{7}$$

The RNN is a special type of DNN with memory as their output which depends on the previous commutations. To overcome the limitation of RNN, LSTM is introduced. Unlike in RNN, LSTM allows the network to keep or forget the information relevant to the sequence.

where, i_t, f_t and o_t are the input, forget and output gates as shown in Fig. 7. These gates help to learn and store the sequence related information from previous cells. C_t and $\hat{C}$ are the new current cell state and new candidate value for cell state. Similarly, cell state acts as transport highway that transfers relative information way to the sequence chain. A memory to the network which carries out the information from earlier state to the last state which helps to reduce the effect of short-term memory. The computations of LSTM cells are stated as,

$$\begin{aligned} h_t &= f(h_{t-1}, x_1) \\ i_t &= \sigma(w_i(h_{t-1}, x_t) + b_i) \\ f_t &= \sigma(w_f(h_{t-1}, x_t) + b_f) \\ o_t &= \sigma(w_o(h_{t-1}, x_t) + b_o) \\ \hat{C} &= tanh(w_c(h_{t-1}, x_t) + b_c) \\ C_t &= f_t.C_{t-1} + i_t.\hat{C}_t \\ h_t &= o_t.tanh(C_t) \end{aligned} \tag{8}$$

As seen from equation 8, decisions to block the signal (0 output) or not block (1 output) are made depending on the outcome of the gates and updates the old cell state into the new cell state. Similarly, GRU is an another in deep neural network unit. This unit also adopts the feature of gates but here, it is limited to only 2 gates.

$$z_t = \sigma(w_z(h_{t-1}, x_t) + b_z) \tag{9}$$

Similarly, Reset get here decided what past information is to be processed further.

$$r_t = \sigma(w_r(h_{t-1}, x_t) + b_r) \tag{10}$$

As GRU used hidden state to transfer information, $\hat{h}_t$, here represent the current memory content. With reset gate apply 0 to 1 value the element wise product with previous hidden state determines the current memory content.

$$\hat{h}_t = tanh(w(rt \times rh_{t-1}, x_t)) \tag{11}$$

Final output is decided with the help of update gate, as information from precious state h_{t-1} and the current memory content $\hat{h}t$ are used to determine output.

$$h_t = (1 - z_t) \times h_{t-1} + z_t\hat{h}_t \tag{12}$$

4. Result and Discussion

There are several evaluation criteria to assess the performance of the different models. Most of the forecasting papers uses these three evaluation methods which are the MSE, RMSE, and MAPE; the formulations are detailed as follows,

$$\begin{aligned} RMSE &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|^2} \\ MAPE &= \sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times \frac{100}{n} \end{aligned} \tag{13}$$

Here, y_i is the observed data, $\hat{y}_i$ is the predicted value of the forecast model, and n is the number of the observed dataset. In this paper, we have considered only RMSE and MAPE values.

We have prepared a web-page which is lunched in the local server to display the visualization of demand and predictions. The individual model performances are as,

Fig. 8 shows the performances for different models. The training and testing performance for each models presented in Fig. 8. The performance of time-series model (ARIMA) predicted with MAPE 2.35% and RMSE value 4.51MW. Similarly the performance of MLR is much impressive compared to ARIMA with MAPE value 1.64% corresponding to RMSE value 3.17MW. The major advantage of MLR model is that impact of variables can be interpreted according to the forecasting model.

Performance of ML models RIDGE and SVM are two ML model that we have used to estimated using machine learning techniques. The SVM performs better than both time series and MLR model in terms of forecasting accuracy. The improvement on forecasting in SVM is due to the non-linearity handling capacity of machine learning models. However, the best forecasting performance in-terms of training and testing for Kathmandu Valley is given by the deep learning model, LSTM. Since the characteristics of long term dependencies can be handled by LSTM, it can ignore the un-related information to the demand while have a memory to consider related information. This helps the model for better performance.

The prediction error is evaluated as the deviation of predicted electricity demand from the true electricity demand. This deviation shows the amount of over forecasted value or the under-forecasted value. Normally, over-forecast cause the excess of resource while under-forecast may cause for the scarcity on the demand that may lead for load-shading. Fig. 9 describes the deviations from true value while predicting. Most of the variation occurs during day hours, because of more human activities.

The prediction error in terms of MAPE is expressed in Fig. 10. This plot shows the presence of outliers during the morning and day hours, indicating high volatile demand during these hours.

The major limitation of machine learning or deep learning models is their black box performance. They are good enough for accurate performance while the analysis of the individual variables and their impact is missing. For this purpose, MLR can be considered as the best option.

4.1. Impact of days, previous days, and special days

Using MLR models, the coefficients are analysed and plotted in Fig. 11 where the hourly demand variation for each days. There is huge fluctuations after 10 am to evening 8 pm and Wednesday shows the huge variation. Interestingly, Tuesday shows the least variation in demand.

Fig. 12a shows the hourly demand variation impact due to the previous days demand. The graph indicates that the impact of yesterday (Demand1D) has the highest impact for next day demand and that impact of two previous day (Demand2D), and seven previous day(Demand7D) going decrease in accordingly, this result is found as our expectation.

Fig. 12b also shows the hourly demand variation according to the special days such as, Gatasthapana, Dashain, Tihar, and the working day after the holiday. The graph indicates that Dashain has the lowest demand variation while Ghatasthapan has highest demand variation untill evening 7 pm, while after 7 pm Tihar (Dipawali/Laxmi Puja) shows the peak demand variation. The reason behind low demand variation in Dashain is because of shut down of all the industries and the peak variation during Tihar/Laxmi Puja is due to Lightening function at the home.

4.2. Impact of temperature

Fig. 13 describe the marginal increase or decrease of electricity demand per degree rise or fall in temperature for each months and days.

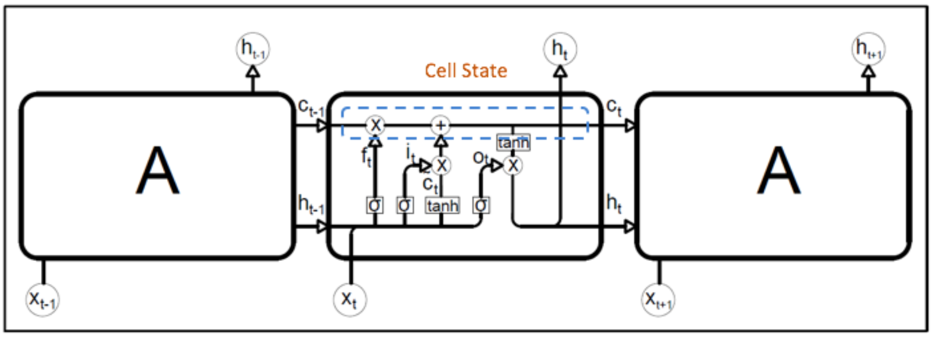


Figure 7: Repeating module of LSTM cell.

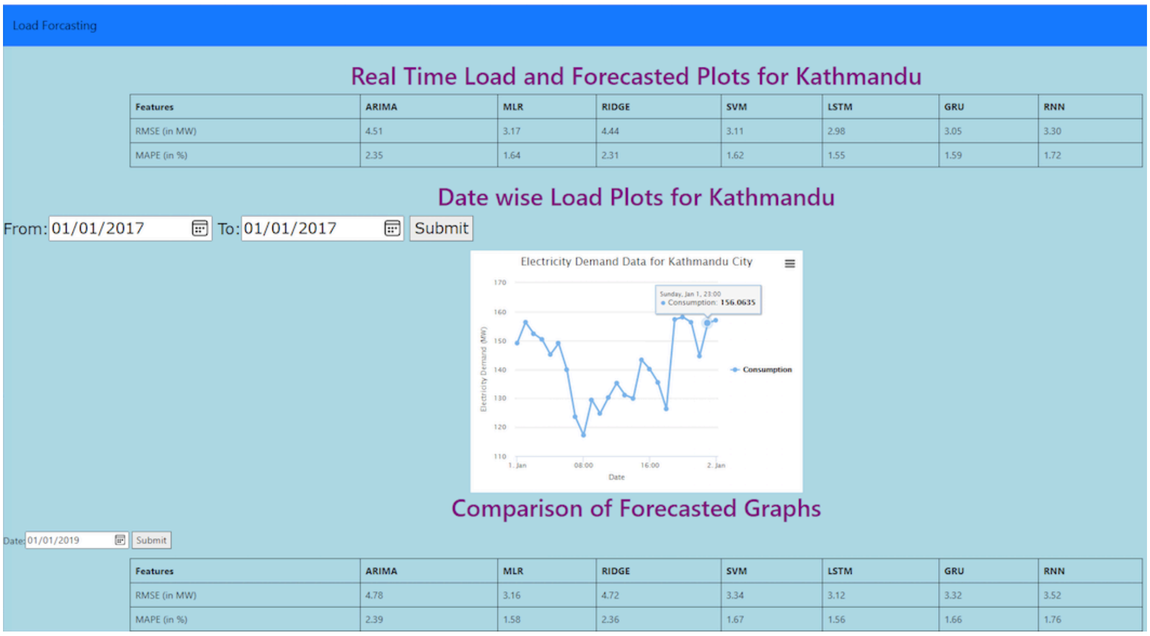


Figure 8: Visualization of demand and predictions in local server.

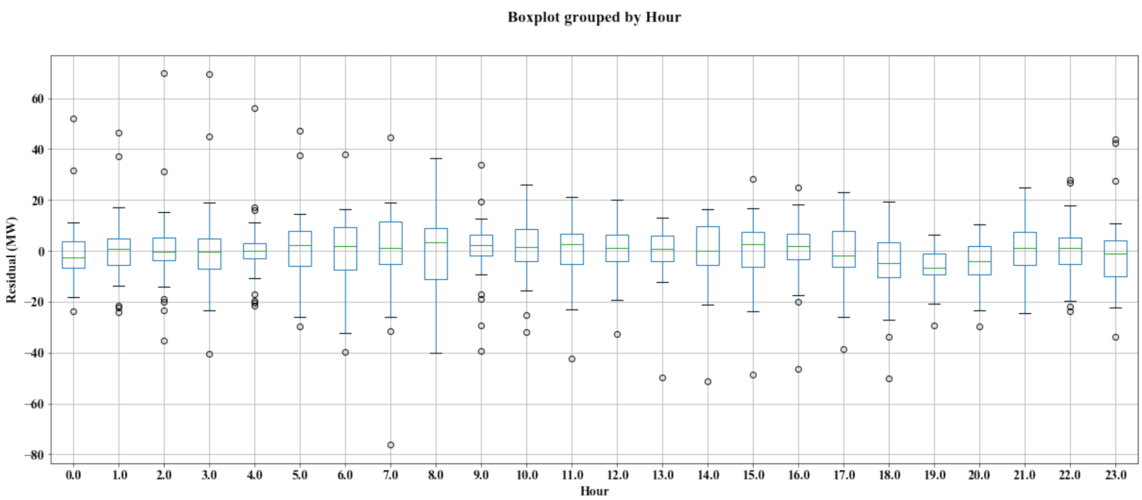


Figure 9: Deviation of electricity demand from the actual demand (LSTM model)

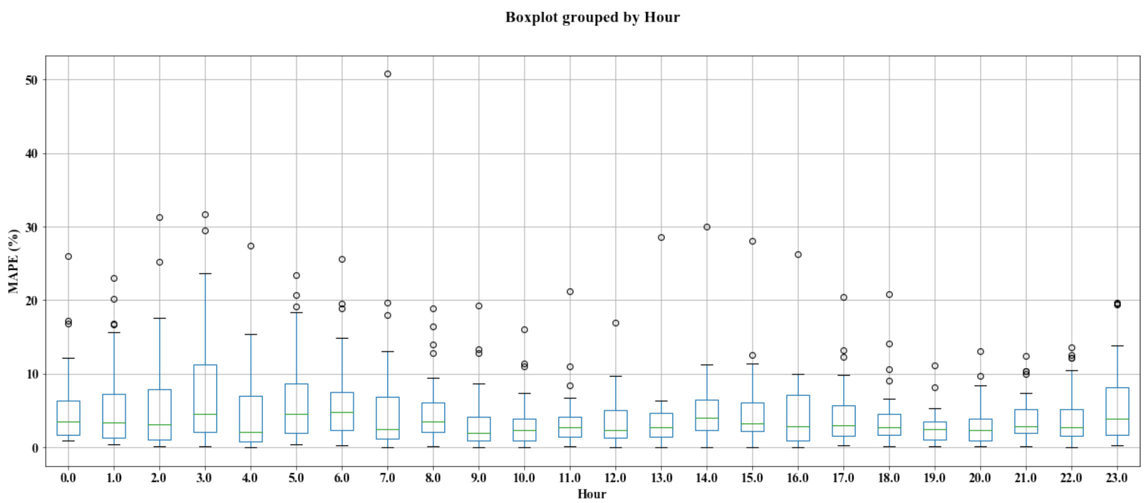


Figure 10: Hourly variation of MAPE for LSTM model.

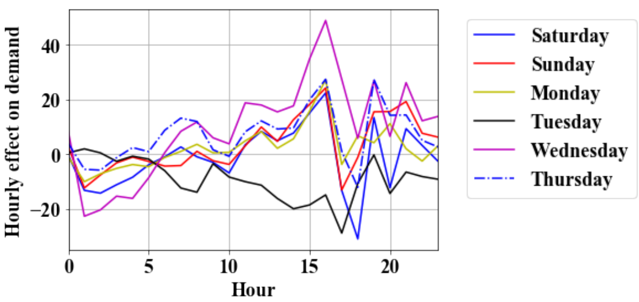
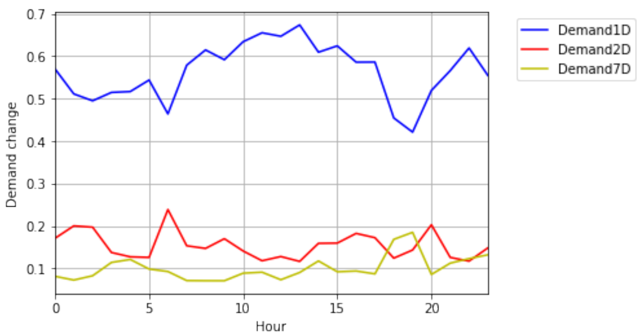
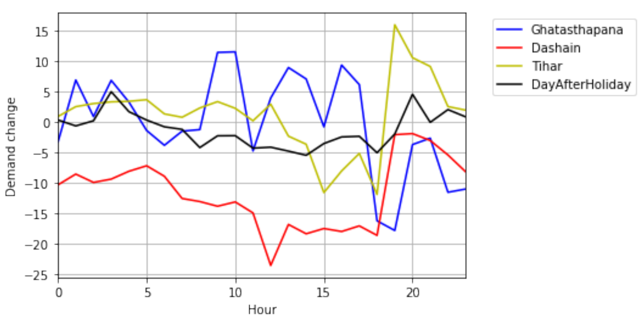


Figure 11: Impact of individual days for electricity demand.



(a) Impact of previous days.



(b) Impact of special days.

Figure 12: Impact analysis of calendar for electricity demand.

Fig. 13 shows that rate of change of demand during winter (November to March) is quite different deviations than the rest of months. Considering the April as the base months, demand is decreasing during day hours, especially after 8 am to 9 am. Because the people may turn off electrical appliances and move out for sun or move to office. Similarly, during the Summer months (May to September) people may use fans and cooler during the day or evening hours, so that electricity demand per degree rise/fall in temperature should be high compare to morning hours.

5. Conclusion

Accurate forecasting of electricity demand is the key factor for the management of load distribution and consumption. The dataset are continuously increasing because of smart meters and automation systems. Electricity demand data are continuously increased by smart meters and automation systems, static models computations are replacing accordingly by dynamic real time robust forecasting models. Therefore, time series, regression, machine learning, and deep learning models are constructed and implemented on historical dataset of Kathmandu Valley of Nepal. The result shows that deep learning model predict the with better accuracy compared to other models. The overall prediction on the test dataset is found that time series model predicted with MAPE 2.39% and RMSE value 4.78 MW. While the regression model is much impressive compared to time-series with MAPE value 1.58% corresponding to RMSE value 3.16 MW. The best performance among the models is obtained from deep learning model (LSTM) which is 1.56%. However, for the analysis of the impact of variables to the electricity demand is possible from regression model. As our expectations, impact of previous day, special days, and temperature is estimated.

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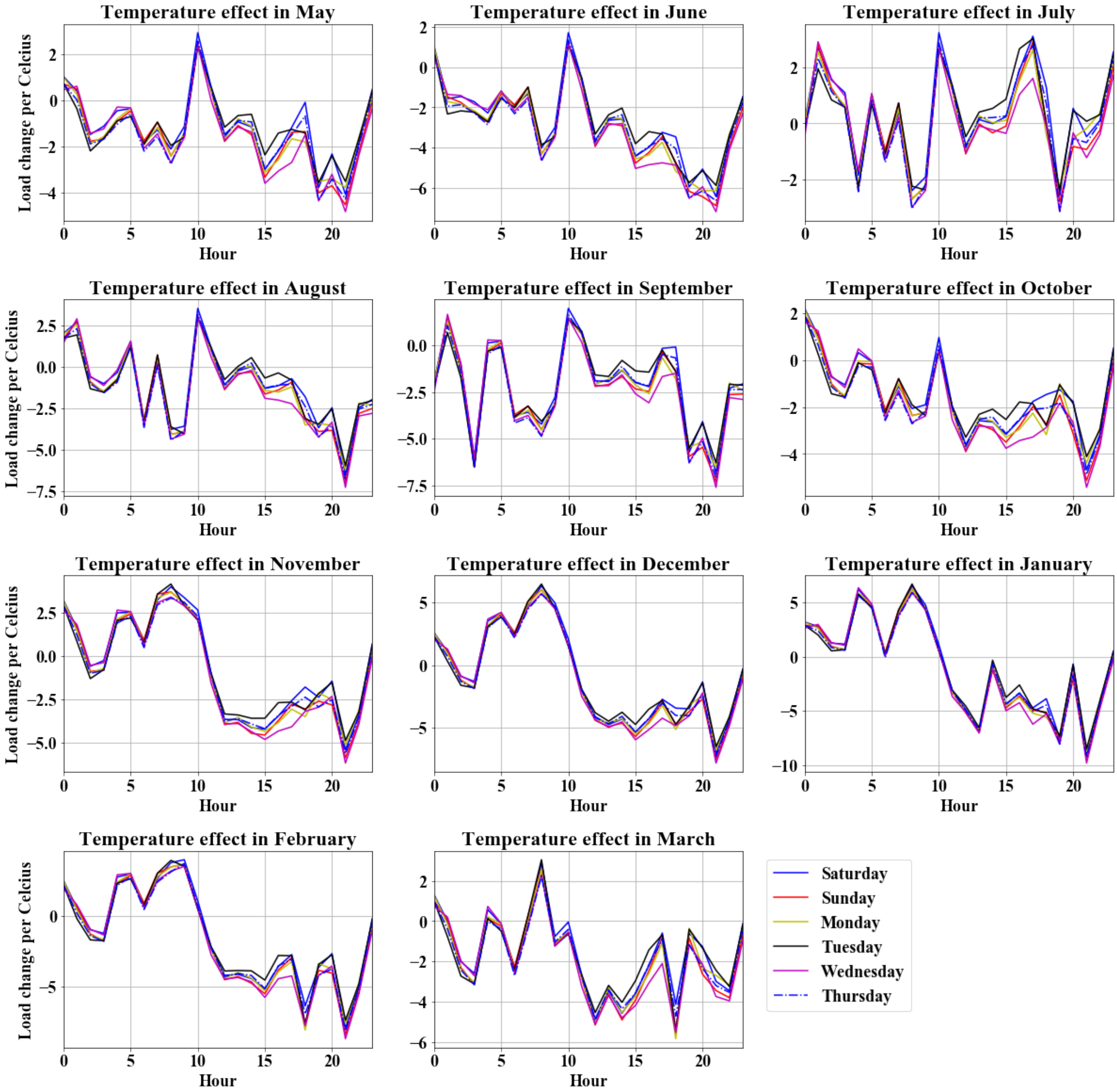

Figure 13: Change in electricity demand per degree rise/fall in temperature.

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