KARNATAKA ELECTRICITY DEMAND FORECASTING FY 17-22

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Karnataka Electricity Demand Forecasting FY17-22

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Abbreviations and Acronyms

ANN	Artificial Neural Network
ARIMA	Auto-Regressive Integrated Moving Average
AT&C	Aggregate Technical and Commercial
BEE	Bureau of Energy Efficiency
BESCOM	Bangalore Electricity Supply Company Limited
CAGR	Compound Annual Growth Rate
CEA	Central Electricity Authority
DISCOM	Distribution Company
EESL	Energy Efficiency Services Limited
EPS	Electric Power Survey
GDP	Gross Domestic Product
GSDP	Gross State Domestic Product
GW	Gigawatts
HVAC	Heating, Ventilation and Air Conditioning
IPMA	Indian Pump Manufacturers' Association
KERC	Karnataka Electricity Regulatory Commission
KPTCL	Karnataka Power Transmission Corporation Limited
KREDL	Karnataka Renewable Energy Development Limited
LED	Light-Emitting Diode
MNRE	Ministry of New and Renewable Energy
MoEFCC	Ministry of Environment, Forests and Climate Change
MU	Million Units
RE	Renewable Energy
RTPV	Rooftop Photovoltaic
SLDC	State Load Dispatch Centre
TRMM	Tropical Rainfall Measurement Mission
UJALA	Unnat Jyoti by Affordable LEDs and Appliances for All

Executive Summary

The Government of India has set ambitious targets for the electricity sector. These include 24X7 power for all by 2019; 175 Gigawatts (GW) of Renewable Energy (RE) capacity across India by 2022; and 40% of electricity generation capacity from non-fossil sources by 2030. Achieving these targets requires energy planning and investment at the state level. A significant challenge in energy planning is accurate forecasting of electricity consumption and demand. In this context, a study was conducted to forecast the electricity consumption and demand for Karnataka (as seen by the utilities) for 2017-2022.

The Central Electricity Authority (CEA) releases the Electric Power Survey (EPS) report, which covers year-wise electricity demand projection for Distribution Companies (DISCOMs), States/Union Territories, regions and for India as a whole. These projections have (at times) been overestimations of the actual consumption and demand (e.g., on average, the national energy requirement was overestimated by 12% and the peak load requirement by 18.6% for the years 2011-16). Further, the methodology for these projections is detailed at the national level, but not so at the state level.

CSTEP used a combination of methods for the energy and load forecasts (a time-series method for short-term forecasts and a quasi-econometric method for long-term forecasts). The impact of meteorological variables such as temperature, relative humidity, rainfall and wind speed was factored into short-term forecasts, whereas the impact of appliance usage [Air Conditioners (ACs), induction stoves, etc.], as well as that of major policy interventions such as Rooftop Photovoltaics (RTPVs), the Unnat Jyoti by Affordable LEDs and Appliances for All (UJALA) scheme, Energy Efficiency, etc., were considered in the quasi-econometric model for long-term forecasts. The short-term forecasts are on an hourly basis, whereas the energy estimation/long-term forecasts are on a yearly basis.

As of April 2017, Karnataka's annual (electrical) energy requirement was reported to be approximately 66,900 Million Units (MU) and the peak demand was approximately 10 GW. However, as per the KERC 17th Annual Report, the annual energy requirement in the state was only 50,894 MU. Further, the energy requirement in 2022 as per CEA estimates would be approximately 1,08,000 MU, whereas CSTEP estimates Karnataka's annual (electrical) energy requirement (as seen by the distribution utilities)[1] in 2022 to be 58,048 MU. Further, as per CEA estimates, the peak load requirement in Karnataka for 2022 would be 18.4 GW, whereas CSTEP estimates the peak load requirement in Karnataka in the same year to be approximately 10.4 GW. This difference is primarily due to the impact of the UJALA scheme [replacing incandescent and CFL bulbs with Light-Emitting Diodes (LEDs)] as well as the expected adoption of RTPV installations. The contribution of the agricultural sector to the total consumption in Karnataka is expected to shrink from approximately 37% today to 26% in 2022. The short-term forecasts (using the two previous hourly load data points) are observed to be within a 10% margin of error. Finally, rainfall, relative humidity and temperature were determined to have a strong correlation with load and their respective correlation coefficients were estimated.

[1] This is based on the assumption that the (expected) 2.3 GW of RTPV installations will lower the demand and load required to be serviced by the distribution utilities.

Table of Contents

List of Figures

List of Tables

1. Introduction

Energy providers (planners, transmission companies and power distribution utilities) regularly forecast consumption and electrical load to predict the amount of energy needed to supply reliable power to consumers. Load forecasting is determined by various factors such as historical load data, national Gross Domestic Product (GDP), sectoral growth and end-use consumer behaviour. This helps in determining key supply-side needs, including additional generation capacity, transmission and distribution infrastructure, and finance.

Load forecasts can be divided into short-term forecasts (from one hour to one week) and medium/long-term forecasts (from a week to more than a year). Decisions based on short-term load forecasts help respond to load sensitivities due to changes in weather conditions as well as in tariff setting [1]. Short-term load forecasts are also helpful for planning short-term power procurement for Distribution Companies (DISCOMs). Medium/long-term forecasts help in planning generation capacity, generation mix, technical infrastructure and investments required for strengthening/upgrading the infrastructure to meet the growing demand. The accuracy of these forecasts can, however, vary significantly. For example, it may be possible to forecast the next-day peak load with an accuracy of 1-3% [2], whereas it may be difficult to predict the load for the next year with similar accuracy, due to unavailability of weather and/or consumer behaviour data.

For the month of April 2017, India's electrical energy requirement was estimated to be 1,01,329 Million Units (MU) (with energy availability at 1,00,810 MU). The peak load required was 159.5 Gigawatts (GW), whereas the met peak load was 158.4 GW. The provisional Aggregate Technical and Commercial (AT&C) loss as reported for 2014-15 was approximately 25%. The national GDP has grown at a rate of 6% (on average) since 2012 and this has led to increased energy consumption. Also, the Government of India has announced various sector-specific initiatives, which have a direct effect on demand, namely, 40 GW of solar Rooftop Photovoltaic (RTPV) addition (which will increase the supply, thereby having a negative effect on the demand seen by utilities), LED-based UJALA (Unnat Jyoti by Affordable LEDs and Appliances for All) scheme (negative), electric vehicle mission (positive), adoption of energy-efficient appliances and solar pumps (negative), etc.

As of April 2017, Karnataka's annual (electrical) energy requirement was reported to be approximately 66,900 MU and the peak demand in the state was approximately 10 GW. The state reported 18% AT&C losses [3]. The installed capacity in the state was 21 GW, of which thermal accounted for 46% (9.6 GW), followed by Renewable Energy (RE) sources at 36% (7.5 GW) and large hydro at 18% (3.8 GW) [4]. Karnataka's population was 6.11 crore in 2011, and is estimated to be 6.72 crore in 2017 [5]. Per-capita electricity consumption in the state increased from 996 kWh in 2011-12 to 1,500 kWh in 2016-17, an increase of 51% in the last 5 years.

Keeping these statistics in mind, this study attempts to forecast the load and energy demand for Karnataka (as seen by the utilities) up to 2022. It uses a time-series method for short-term forecasts and a quasi-econometric method for long-term forecasts. The report is further organised as follows: relevant literature reviewed (including studies in the Indian context) are presented in the next section. The subsequent section presents the analysis, results and inferences for long-term demand forecasts. The methodology for hourly short-term forecasts is discussed next (with relevant mathematical analysis covered in the Appendix). The report concludes with a section on conclusions and policy recommendations.

2. Rationale and Literature Survey

Methodologies for demand forecasting can be classified into five categories, namely, Compound Annual Growth Rate (CAGR)/Trend Analysis, Partial end-use, Time-series, Econometrics and Artificial Intelligence (neural networks and machine learning techniques).

These are described briefly below:

(1) CAGR/Trend Analysis: In the CAGR method, the future demand is estimated using a constant growth rate. The growth rate variable can be the past growth of demand itself or the GDP. This method is known to give accurate results when the growth of demand is proportional to the growth of the economy or when the demand growth is monotonic. For developing countries such as India, this method might produce inaccurate results because it "…forecasts demand met and not actual demand besides ignoring the effect of changes in incomes, prices, consumer tastes and quality of supply." [1]

(2) Partial End-use: In the partial end-use method, demand is estimated based on public behaviour, utilising data such as appliance ownership, hours of usage, overall electricity consumption, etc. Though the method captures the existing electricity demand patterns (typically through end-user survey analysis), it is data-intensive and the results are difficult to analyse over a large, non-homogenous population. [2]

(3) Time-series: In the time-series method, the demand is estimated based on past demand. This method is simple, but it depends completely on past data and does not capture patterns arising from population growth, price changes, disruptive changes due to technology, policy changes, etc. [2]

(4) Econometrics: In econometric models, the load is forecast using multiple socioeconomic and other variables. These variables, including GDP, per capita income, population growth, price, etc., can be data-intensive and require multiple data sets over large time scales. [1]

(5) Artificial Intelligence: In Artificial Intelligence-based methods, such as neural networks, algorithms are developed to identify load patterns. These methods forecast load with high accuracy [6] but outputs are subject to the quality and accuracy of inputs.

In addition, the authors of [7] have investigated the effect of weather on energy demand. Most of these studies used models to forecast the load for either the day-ahead or week-ahead timeframe[2]. Studies have suggested a correlation between load and weather parameters such as temperature, humidity, hours of sunlight [8], [9], day of the week [7], etc. For example, the work in [10] examined the individual impact of rainfall, humidity and temperature, and derived correlations of 0.17, 0.24 and 0.34, respectively. The work in [7] quantified the error for every month for two different locations and the average error in the model ranged between 1.12% and 3% depending on the month and hour of forecast. Lastly, the work in [11] quantified the error in terms of forecast duration. The error was approximately 2.8% on the seventh day of forecast.

The research in [12] estimated demand comparison using 27 feeders (in different categories). It included the weather variables of temperature, relative humidity, wind speed and direction, and cloud cover. The outputs generated by Auto-Regressive Integrated Moving Average (ARIMA) and an Artificial Neural Network (ANN) were compared. The error was found to be uniform for ARIMA (1.5-3%) but had high variability for ANN (0.5-6%).

[2] The accuracy of prediction is generally defined in terms of the R-squared error and the moving average error.

2.1 Indian Landscape

In India, load forecasting is primarily done by the Central Electricity Authority (CEA) at the national level, with inputs from state agencies such as transmission and distribution utilities. The data are published in the Electric Power Survey (EPS). The 18th EPS projects both national- and state-level electricity demand till 2019 (at yearly intervals) and till 2032 (at 5-yearly intervals). It also provides load forecasts for states using the CAGR method primarily. The estimates provided by the 18th EPS for India are shown in Figure 1 (energy) and Figure 2 (load).

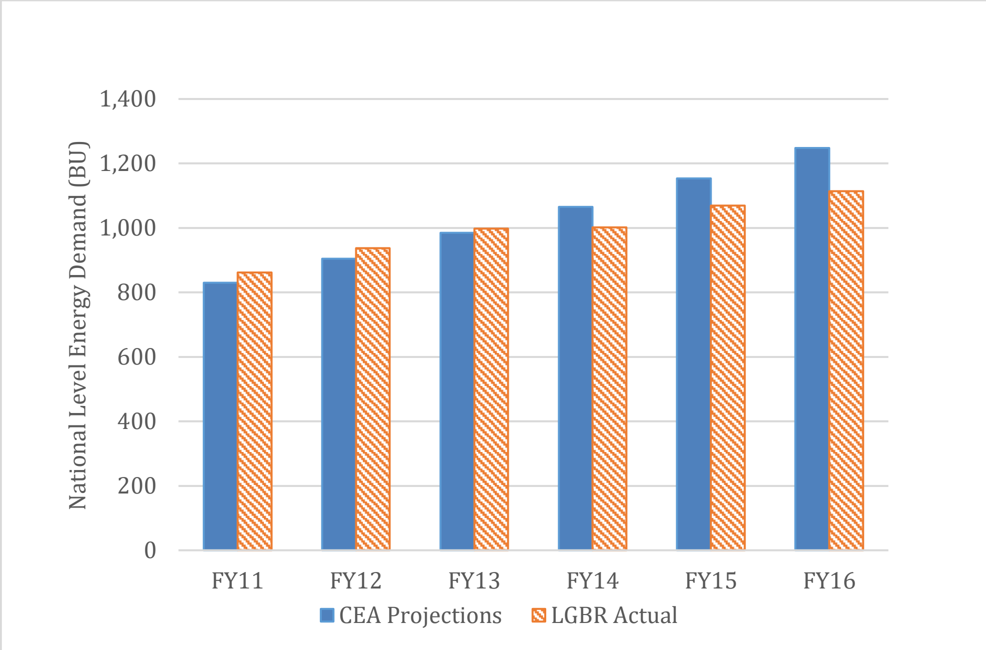

Figure 1: Comparison of Energy Demand: CEA Projection vs Actual (National)

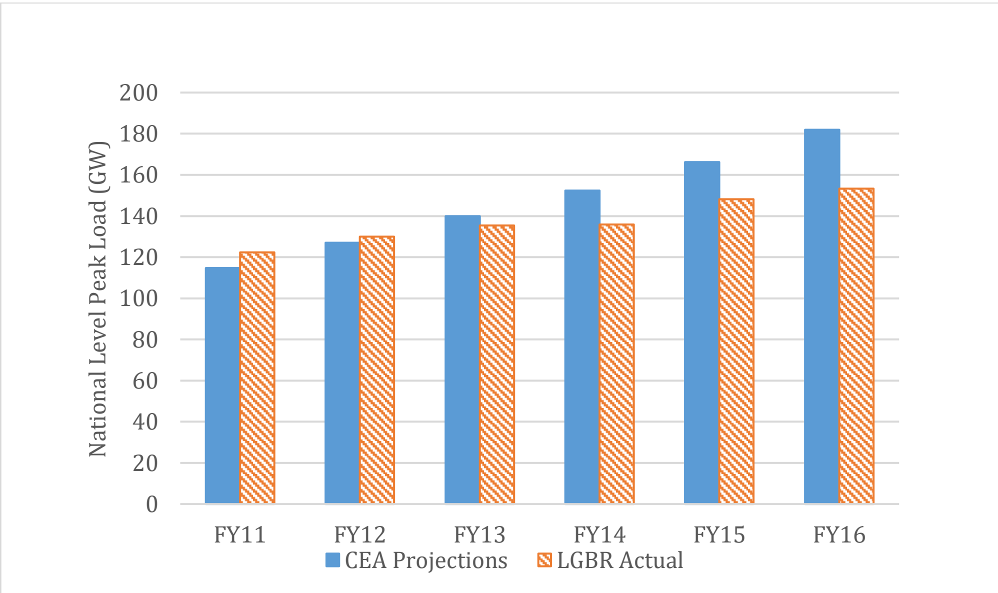

Figure 2: Comparison of Peak Load: CEA Projection vs Actual (National)

Lawrence Berkeley National Laboratory published a study on estimating energy demand due to appliances such as air conditioners (ACs), induction cooking stoves, fans, refrigerators, etc. [13]. The Planning Commission, on the other hand, used econometric analysis for estimating the demand, where they assumed GDP growth rates of 6.5%, 7.7% and 8.0%, respectively, for the 9th, 10th and 11th plan periods [1].

These studies provide insights for the electrical demand scenario at the national level. However, there is limited information available in the public domain for estimating demand at the state level. As each state has different demographics, land area, policies, per capita consumption, etc., it is essential to estimate demand at the state level to plan for power purchase, tariff determination and capacity additions. CEA has released state-wise demand projections in the 18th EPS. The estimates for Karnataka are shown in Figure 3 (energy) and Figure 4 (load).

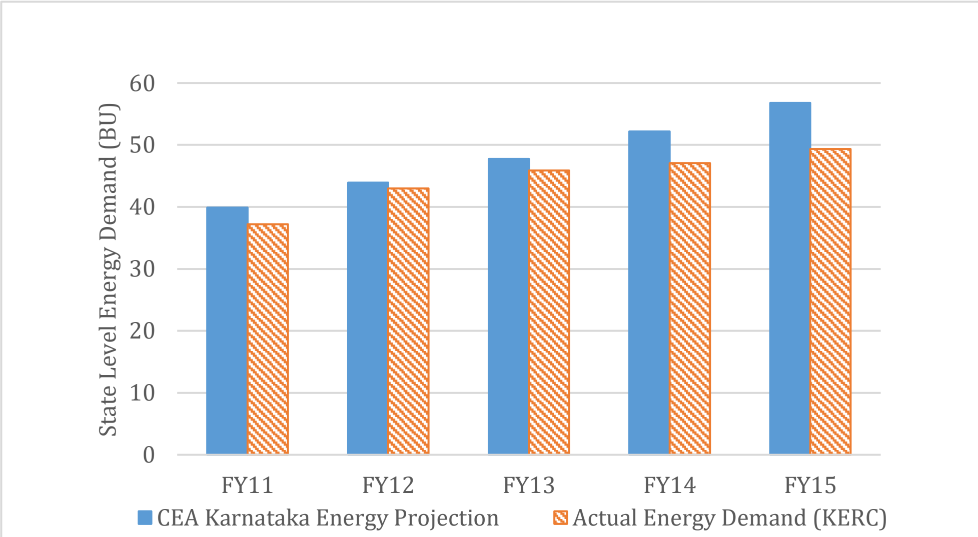

Figure 3: Comparison of Energy Demand: CEA Projection vs Actual (Karnataka)

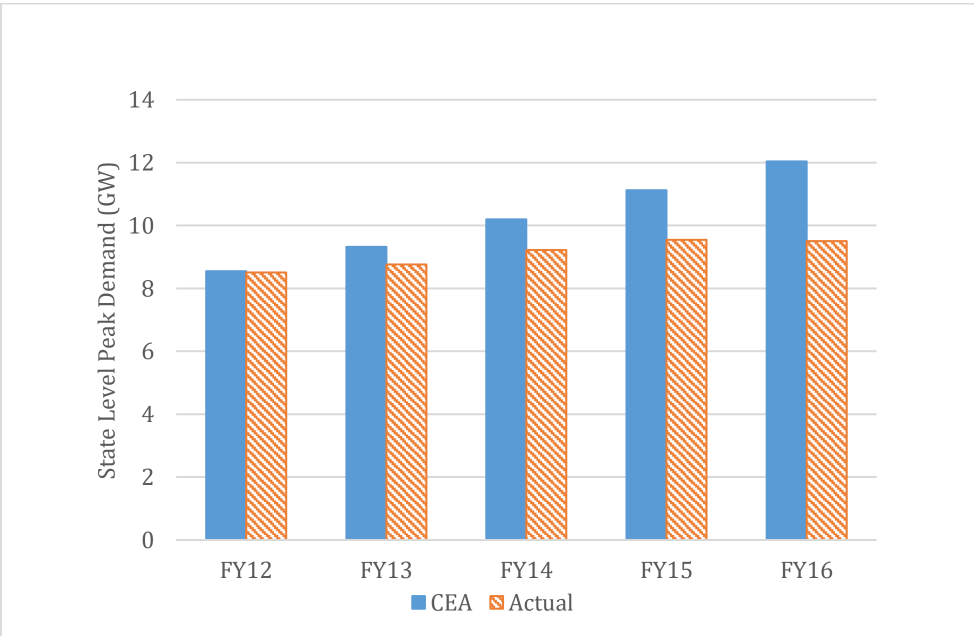

Figure 4: Comparison of Peak Load: CEA Projection vs Actual (Karnataka)

The graphs above suggest that CEA has overestimated the actual demand (in the case of energy by 12% and for peak load by 18.6%) for India. For Karnataka, the projection is in excess by 15% for energy and 26% for peak load. Thus, there is merit in undertaking an accurate energy and load forecasting, which is crucial for power sector planning.

In this study, a hybrid approach has been used for energy and load forecasting. It is a combination of a time-series method for short-term forecasts and a quasi-econometric method for long-term forecasts. The meteorological variables considered in the time-series model are temperature, relative humidity, rainfall and wind speed, whereas appliance ownership (ACs, induction stoves, etc.) and policy interventions such as RTPV, the UJALA scheme, Energy Efficiency, etc., are considered in the quasi-econometric model. The short-term forecasts are on an hourly basis, whereas a yearly basis is chosen for the energy estimation/long-term forecasts.

3. Methodology

Electricity demand depends on economic variables, public behaviour and local weather conditions. In addition, seasonality over larger geographic areas has an effect on demand. Key aspects of the methodology, along with associated data sets and assumptions, are described in the sections below.

3.1 Long-term Energy Forecast for Karnataka

State-level energy consumption data from 2011 to 2016 were collected from the annual reports of the Karnataka Electricity Regulatory Commission (KERC) [14]. 2016 was considered as the base year for analysis. Population data were collected from the 2011 national census report [15]. Other sources of input were based on stakeholder interactions with KERC, KPTCL and CEA. Appliance ownership data for induction stoves and ACs were obtained from the Census 2011 data set. Solar-related data (number of solar pumps used in the agriculture sector, installed capacity of private solar parks, rooftop solar panel installations and capacity) were obtained from the Ministry of New and Renewable Energy (MNRE) [16]. Karnataka's population and Gross State Domestic Product (GSDP) were obtained from the Directorate of Statistics, Government of Karnataka [17]. Data related to agricultural pumpsets (quantity, capacity and efficiency) were gathered from Energy Efficiency Services Limited (EESL). Efficiency data for other appliances (lights, fans, refrigerators, etc.) were gathered from various sources, such as reports of the Ministry of Environment, Forests and Climate Change (MoEFCC) [18]; Centre for Environmental Planning and Technology University; and Bureau of Energy Efficiency (BEE).

3.2 Estimated Effect of Air Conditioners

The net electricity consumption in Karnataka has increased over the last few years. Part of this can be directly attributed to the usage of ACs. The reasons behind the proliferation of ACs include (1) growth of the IT industry and commercial spaces in Bengaluru and Mysore, and (2) increasing summer temperatures [19]. According to the Census 2011 [15], the number of domestic ACs in Karnataka was approximately 2,16,000. As per market research, India will experience growth in total AC sales at a CAGR of 10% up to 2020 [20]. The same growth rate till 2022 is assumed in this study. In the commercial sector, Heating, Ventilation and Air Conditioning (HVAC) has been considered for estimating the cooling demand. It is assumed that each office/commercial floor has (on average) 2,000 sq. ft. of floor area and requires roughly a 6 tonne AC[3], which is assumed to run for 12 hours a day for the entire year. For the domestic sector, it is assumed that a 1 tonne AC will run for 4 hours a day in the months of April and May. The peak load scenarios are estimated assuming typical[4] public behaviour for those appliances [13].

[3] Based on interaction with local retailer.
[4] Consumer behaviour assumed as per consultation with commercial vendors.

3.3 Estimated Effect of Induction Stoves

As per Census 2011, the number of induction stoves sold in Karnataka was 17,000. A report by a leading market survey agency [21] quotes 10% growth in adoption of induction stoves throughout India till 2020. The same growth rate till 2022 is assumed in this study. Assuming a compounded growth rate for Karnataka, the number of induction stoves in the state is expected to increase to 48,500 by 2022. In this analysis, it is assumed that an average induction stove with 1.5 kW rating is used for 3 hours.

3.4 Estimated Effect of Rooftop Solar Photovoltaic (RTPV) Modules

MNRE has made RTPV installations mandatory for new constructions. Further, Karnataka has planned for 2.3 GW of RTPV by 2022 [16], of which 1.3 GW will be installed in the BESCOM jurisdiction. Stakeholder interactions in this context suggested that 60% of the installations could be on residential structures and the remaining 40% on commercial establishments. Generation from RTPV was calculated using the RTPV tool built using CSTEP's techno-economic model CSTEM [22].

3.5 Estimated Effect of Agricultural Pumps

The Government of Karnataka launched the "Surya Raitha" scheme in 2014. Under this scheme, existing irrigation pumps will be replaced with more efficient pumps and solar irrigation pumps will be installed. There are around 39 lakh irrigation pumps in Karnataka. It is expected that the pump market will witness growth at a CAGR of 6% for the next 5 years [23]. Further, according to the EESL-IPMA report [24], the average efficiency of an existing irrigation pump is 37%, whereas the average efficiency of a new pump is 73%. It is assumed that the share of agricultural load in the state load is approximately the same as the share of agricultural energy consumption (37%) in the state energy consumption. For growth in the number of irrigation pumpsets, it is assumed that 80% of the agricultural load is due to irrigation pumps, and 10% of pumps every year will be replaced with energy-efficient pumps.

3.6 Estimated Effect of Energy Efficiency

BEE and the state government promote various schemes to encourage the adoption of energy-efficient appliances, such as star-rated appliances, energy-efficient pumps, etc., in various sectors. It is estimated that about 0.5% of the total electricity consumption can be saved annually by adopting energy-efficient practices in the industrial [25] sector and 1% each in residential and commercial sectors [26].

3.7 Estimated Effect of UJALA Scheme

The UJALA scheme is an extension of the Domestic Efficient Lighting Programme (DELP) of the Government of India; it aims to convert existing incandescent lamps to LEDs [27]. It is estimated that lights account for 30-50% of the total household electricity consumption. Under the UJALA scheme, the government plans to further distribute 3.8 crore LEDs by 2019 [27], [28].

3.8 Estimated Effect of Private Solar Parks and Other Solar Initiatives

The present open-access strategy of the central government has allowed consumers to install RE power plants on private lands. These can supply power to any commercial consumer through the existing grid infrastructure available from the government. As per Karnataka Renewable Energy

Development Limited (KREDL), RE power plants worth 372 MW of capacity have been sanctioned, of which 41 MW has already been commissioned[5]. The annual output from the installation of a 1 MW solar plant is considered to be 1.7 MU.

4. Results of Energy Estimation

The state-level energy demand[6] can be calculated as a summation of demands (positive and negative) from various categories. The method is as follows: first, the demand is estimated using a 6.5% CAGR. This is termed "Business As Usual (BAU)". Next, the impact of usage of energy-intensive appliances, such as ACs and induction stoves, which is not subsumed into the BAU, is added to the demand. "Control" technologies like efficiency, RTPV, UJALA and private solar parks will lower the demand and are therefore subtracted from the demand. The results of the method and a comparison with the 18th EPS for Karnataka are given in Figure 5.

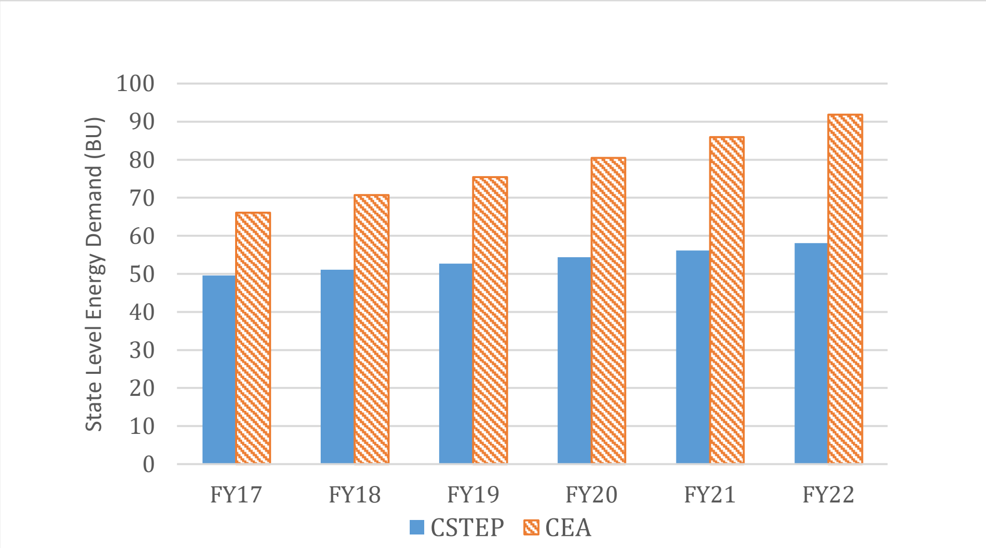

Figure 5: Comparison of Energy Demand Projection: CEA and CSTEP (Karnataka)

4.1 Share of Appliances and Policies over State-Level Load

Table 1 provides an estimate of the changes (and the direction of change) caused by each of the appliances and policy interventions mentioned in the previous section.

Table 1: Annual Contribution of Appliances and Policies in State-Level Energy Demand

Appliance/Policy	Addition to Annual Demand (MU)						Remarks
	2017	2018	2019	2020	2021	2022	
AC (domestic)	119	131	145	159	175	193	4 hours of usage in summer (1 tonne)
AC (commercial)	2,925	3,217	3,539	3,893	4,282	4,710	12 hours of usage daily (6

[5] As of November 2016.
[6] The method also adds an additional 4,000 MU under the "Other" category.

							tonne)
Induction stoves	49	54	60	66	72	79	3 hours of usage daily (1.5 kW)
RTPV	629	1,269	2,028	2,917	3,932	5,076	2.3 GW by 2022
Irrigation pumps	13,853	13,885	13,907	13,929	13,951	13,973	80% of agri load is due to pumps
UJALA (LED)	2,233	4,467	6,964	6,964	6,964	6,964	7 hours of usage daily
Private solar parks	58	93	148	238	382	614	

4.2 Change in Share of Categories over State-Level Load

Different categories of consumption will be subject to changes, and so there will be a change in the category-wise share in the state-level energy demand. Figure 6 and Figure 7 show the contribution of each category to the state energy demand in 2016 and 2022. Figure 7 shows that there could be an increase of 7% in the industrial share in the state-level energy demand. This may be because the state government is focused on growth in the industrial sector, and because of limited intervention of "control" technologies. For the domestic sector, although there is growth in consumption through ACs and induction stoves, the growth rate is curbed due to penetration of RTPV and due to energy savings resulting from the UJALA scheme. In the commercial sector, the growth in consumption is rapid because of HVAC penetration, which overshadows the reduction caused by RTPV and private solar parks. The agricultural sector, however, shows a decline in energy consumption due to the projected increased use of efficient irrigation pumps[7].

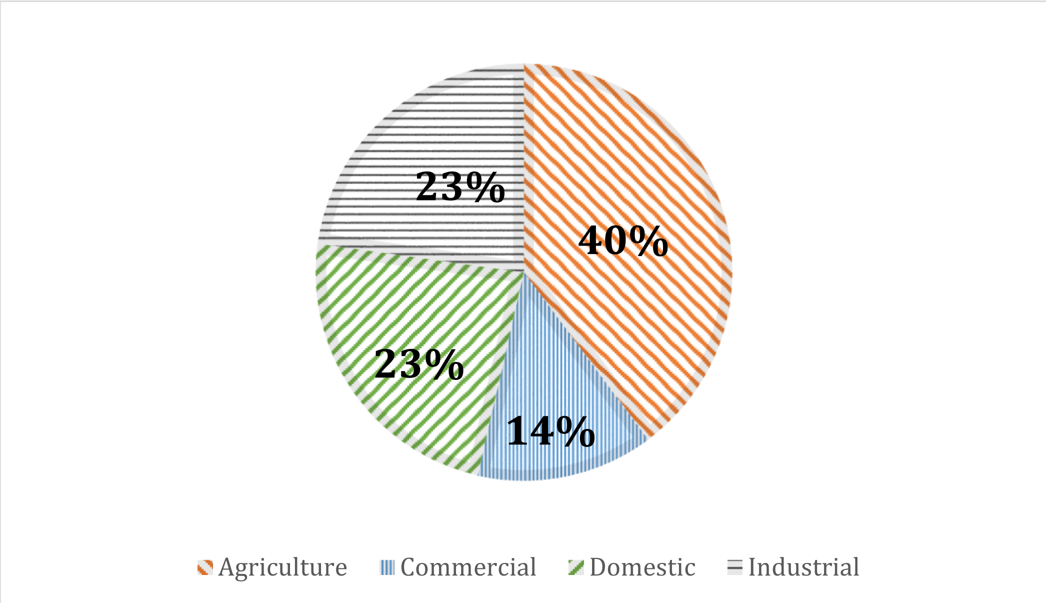

Figure 6: Contributions of Categories in State-Level Energy Demand for FY16 (Karnataka)

[7] This estimation does not include the effect of utility-scale solar parks.

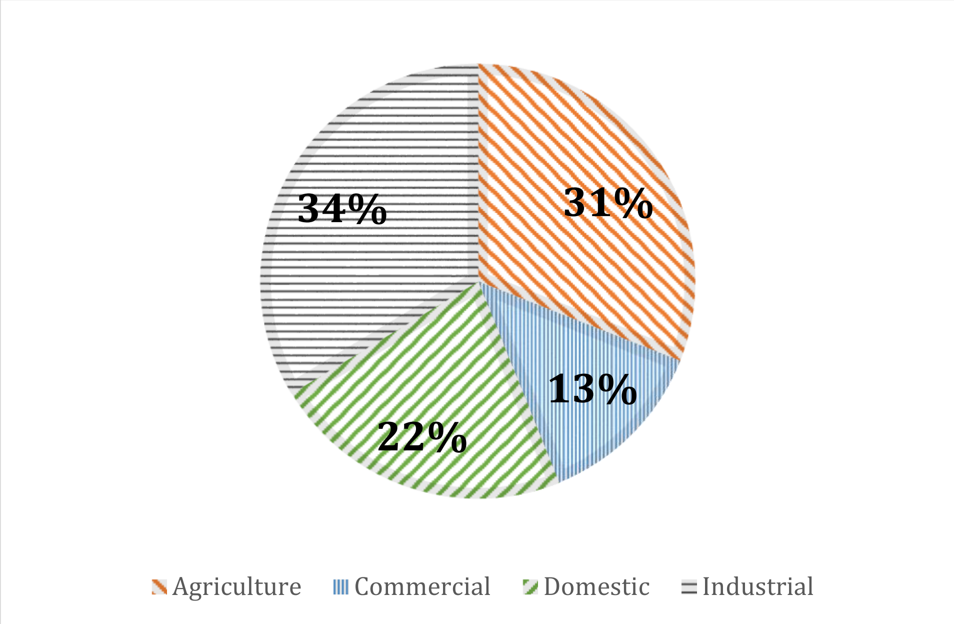

Figure 7: Estimated Contributions of Categories in State-Level Energy Demand for FY22 (Karnataka)

5. Day-ahead Load Forecasting for Karnataka

Meteorological variables such as temperature, rainfall, relative humidity and wind velocity, and seasonal variation have been used to estimate loads [8], [9] in the short term (including day-ahead forecasts). As weather-variable predictions are not accurate beyond two weeks [29], the model discussed below is not applicable for use in long-term forecasts. However, historical weather data give an estimate of weather patterns for particular days, months and seasons. The sensitivity of load to weather changes can assist utilities in estimating short-term loads for procurement and distribution.

To establish a load-forecasting equation, correlations between different meteorological variables and load were examined. A time-series graph was plotted for meteorological variables such as temperature, rainfall, relative humidity and wind speed for each year. Further, each meteorological variable was regressed with load. It was observed that temperature has a strong positive correlation of 0.6 (on average) with load, whereas rainfall and relative humidity have negative correlations (-0.15 and -0.55, respectively). The correlation for wind varies from -0.45 to 0.35 and is assumed to provide limited insight in estimating load.

For this study, temperature, relative humidity and wind speed data have been obtained from the re-analysis data server of the European Center for Medium Range Weather Forecasting. The data are available at 0.75*0.75 km spatial and 6 hourly temporal resolution [30]. Rainfall data at 25 km resolution every 3 hours have been obtained from the data server of the Tropical Rainfall Measurement Mission (TRMM) [31]. The load data are available at hourly resolution and the meteorological variables are assumed to remain unchanged for that particular period (e.g., rainfall data at 12:30 hours are considered constant for load output at 11:00 hours to 14:00 hours). Peak load data at hourly interval for 5 years (2011-15) are collected from the Karnataka State Load Dispatch Centre (SLDC) [32]. The SLDC also reports planned and unplanned outages for a 24 hour period. Planned outages and unscheduled load curtailments have been included in the hourly data to get an estimate of possible un-met load.

5.1 Formulation of Load-Forecasting Equation and Model

The linear regression formulation considering the meteorological variables and previous load lags is:

$$L_t = \alpha_1 L_{t-1} + \alpha_2 L_{t-2} + \alpha_3 R_t + \alpha_4 \alpha T_t + \alpha_5 H_t + \beta, \qquad (1)$$

where:

L_t is the load at time period t,

L_{t-1} and L_{t-2} are the loads at time periods t-1 and t-2, respectively,

R_t is the rainfall at time period t,

T_t is the temperature at time period t,

H_t is the relative humidity at time period t.

The statistical coefficients are represented by $\alpha_1, \alpha_2, \alpha_3,\ \alpha_4,\ \alpha_5$ and β. A detailed description of the model, its formulation and validation has been discussed in the Appendix. Applying empirical analysis, the values of the constants were determined as presented in Table 2 below.

Table 2: Linear Regression Model Summery without Wind as an Input

	L_{t-1}	L_{t-2}	R_t	T_t	H_t	**Constant**
Coefficient	1.04	-0.19	-0.29	2.77	-9.36	1,051.73
***p*-value**	0.000	0.000	0.000	0.000	0.006	0.016
Adjusted *R*-Squared	92.08%					

From the above results, the chosen variables are all significant at the 5% level (p-values less than 0.05). The regression equation can be written as:

$$L_t = 1.04 L_{t-1} - 0.19 L_{t-2} - 0.29 R_t + 2.77 T_t - 9.36 H_t + 1{,}051.73$$

5.2 Validation of the Model

The 2015 model equation was used to calculate the 2016 state-level hourly load patterns. Figure 8 shows that if the weather variables are estimated accurately, the calculated load forecast will be within 10% of the actual load.

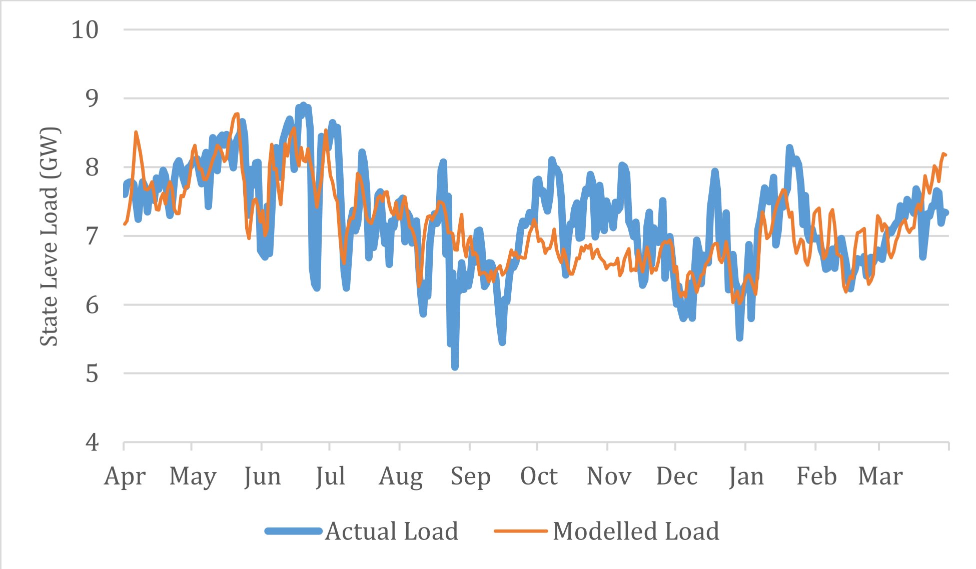

Figure 8: Comparison of Model-Predicted Load vs Actual Load for FY16 (Karnataka)

5.3 Weather Sensitivity Analysis

The results for equation (1) show that the weather variables are correlated to state demand. It is useful to also know the change in load due to a change in weather pattern. This can give estimates of upcoming demand, in advance, based on weather forecasts.

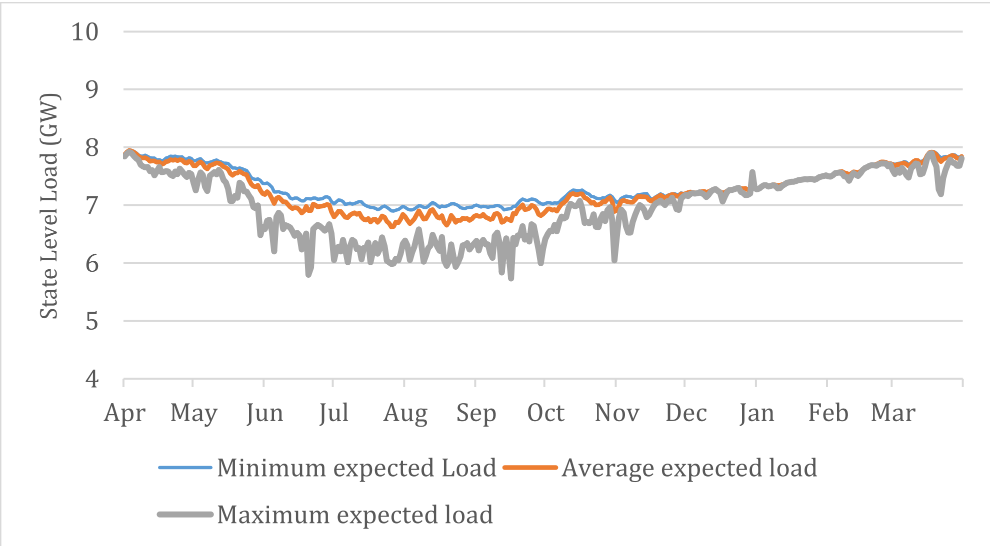

Figure 9: Impact of Rainfall over State-Level Load (Karnataka)

Figure 9 illustrates that, on average, rainfall alone can make a load difference of 362 MW at the state level[8]. This difference can increase up to 1,320 MW (contributing 18% to the state-level average load) on days of significant amount of rainfall.

[8] In the figure, the avg. expected load is calculated as follows: the observed rainfall for each day for 10 years (Jan 1, 2007, to Dec 31, 2016) is averaged by day and the value obtained is used in equation (1) to determine the estimated load for that day.

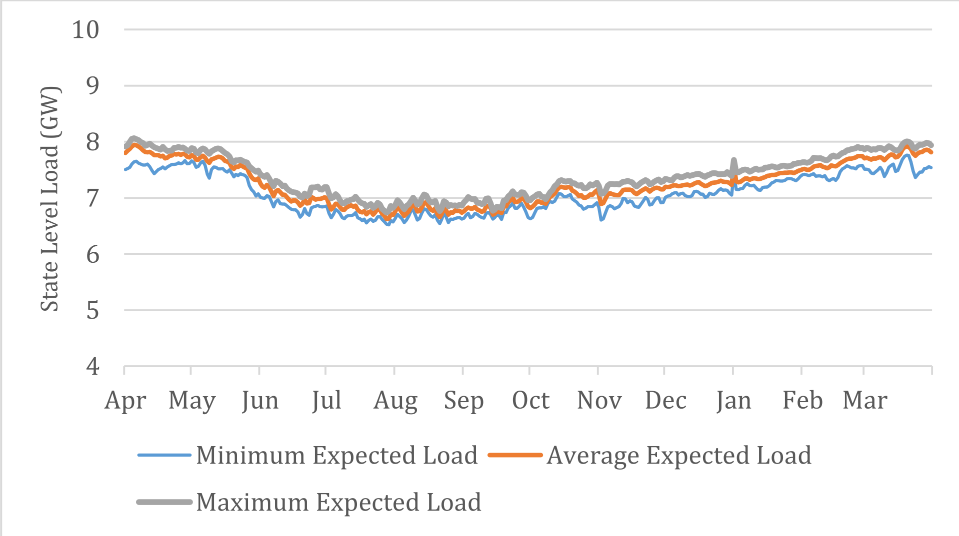

Figure 10: Impact of Temperature over State-Level Load (Karnataka)

Figure 10 shows that, on average, temperature alone can make a load difference of 307 MW at the state level. This difference can increase up to 516 MW (contributing 6.7% to the state-level average load).

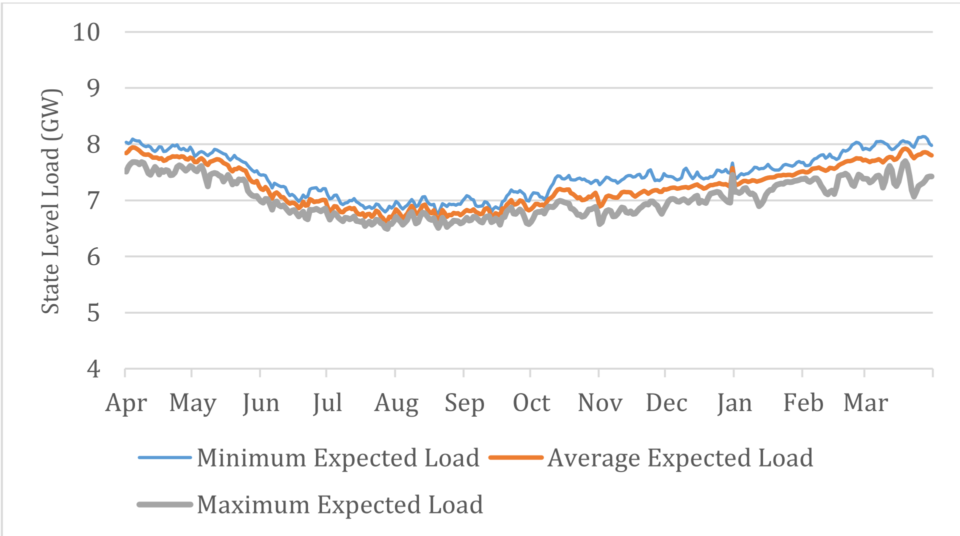

Figure 11: Impact of Relative Humidity over State-Level Load (Karnataka)

Further, relative humidity alone can make a load difference of 413 MW at the state level (Figure 11). This difference can increase up to 880 MW (contributing 11.5% to the state-level average load).

5.4 Peak Load Estimation

Appliances will not only affect the annual energy demand, but will also cause changes to the load patterns, particularly, peak load. The peak load estimation is given in Figure 12.

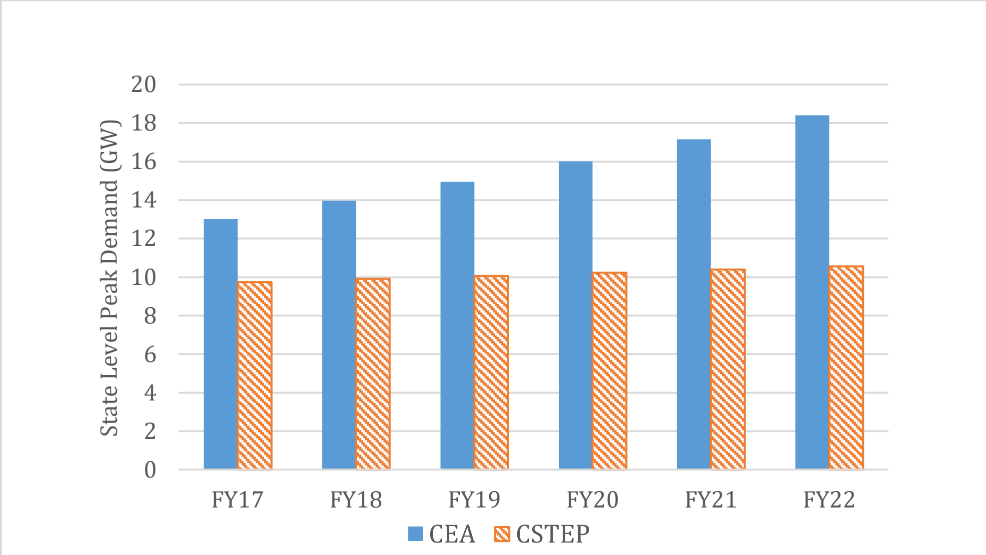

Figure 12: Comparison of Peak Load Projection between CEA and CSTEP (Karnataka)

5.5 Change in State-Level Load Pattern

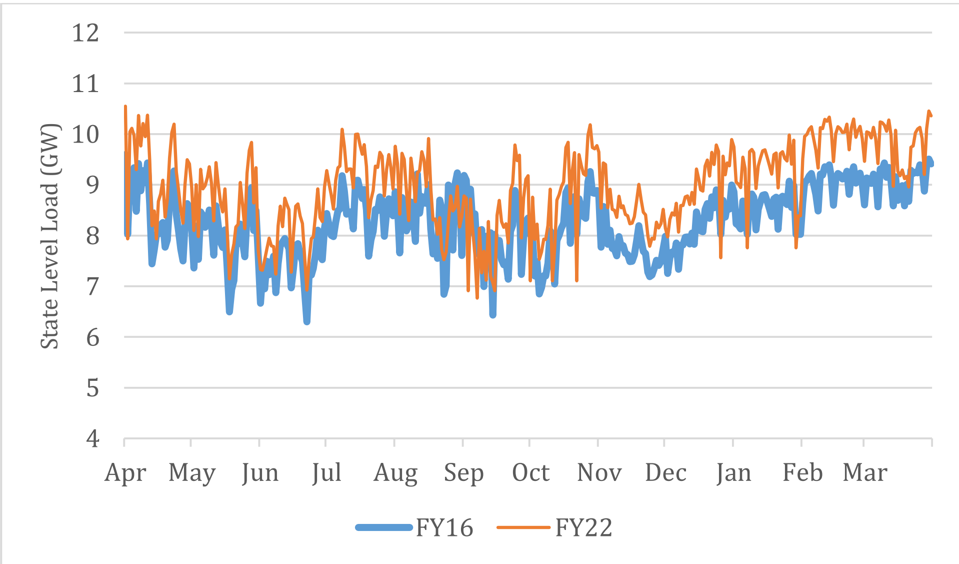

Figure 13: Projection of State-Level Load Pattern, FY16-FY22

Figure 13 shows a comparison of yearly load profile for FY16 and FY22. Although ACs are predominantly used in the summer months, their effect is not significant compared with the state-level load demand. With other interventions like UJALA, RTPV, induction stoves for cooking, etc., influencing the factors throughout the year, ACs are unlikely to make any changes in the state-level load pattern, except shifting the pattern because of growing demand. The average demand will increase from 8,289 MW in FY16 to 8,963 MW in FY22. The CAGR growth is projected to be in the region of 1.3% for 6 years.

6. Conclusions and Policy Recommendations

This study estimates the electricity consumption and demand for Karnataka from 2017-2022, and compares it with those estimated by the CEA in the 18th EPS. The estimation is broken down into two durations, namely, long term (from a week to a year) and short term (from a day to a week). The study has used a quasi-econometric method for long-term forecasts and a time-series method for short-term forecasts. The short-term forecasts were observed to be within a 10% margin of error and are useful when weather variables are present. Temperature, rainfall and relative humidity were determined to have a strong correlation with load and their respective correlation coefficients were estimated.

The study estimates Karnataka's energy requirement in 2022 to be 58,048 MU. Further, the peak load requirement in Karnataka in the same year is expected to be approximately 10.4 GW[9]. The primary reasons for the difference from the CEA estimates seem to be the impact of the UJALA scheme (replacing incandescent and CFL bulbs with LEDs) as well as the expected increase of RTPV installations throughout the state. The contribution of the agricultural sector to the total consumption in Karnataka is expected to shrink from approximately 37% today to 26% in 2022. However, the actual demand and peak load values in the future would be affected by the implementation of the assumed policies and the validity of the assumptions made during the course of this study.

[9] Assuming 2.3 GW of RTPV installation, the demand seen by the utilities will be reduced by 3,880 MU.

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8. Appendix

Appendix 1: Correlation Analysis

In order to establish a load-forecasting equation, we first need to establish a correlation between different meteorological variables and load individually. First, we plot a time-series graph of meteorological variables such as temperature, rainfall, relative humidity and wind speed for each year. We can clearly see similar trends for all the years. The correlation matrix between load and other weather variables is given in Table 3 below.

Table 3: Correlation Matrix

	Load	Temperature	Rainfall	Relative Humidity
Load	1	0.354	-0.369	-0.609
Temperature	0.354	1	0.679	-0.079
Rainfall	-0.369	0.679	1	0.318
Relative Humidity	-0.609	-0.079	0.318	1

Then we regress each meteorological variable with load and examine the correlation. Temperature has a strong positive correlation of 0.6 (on average) with load, whereas rainfall and relative humidity have negative effects (-0.15 and -0.55, respectively). Only wind has a mixed impact. Its correlation with load varies from -0.45 to 0.35. But we will see later that wind does not have an impact on load in terms of input variable. For better understanding, a correlation analysis was done by breaking the time series into different seasons. The results are given in Figure 14 and Figure 15.

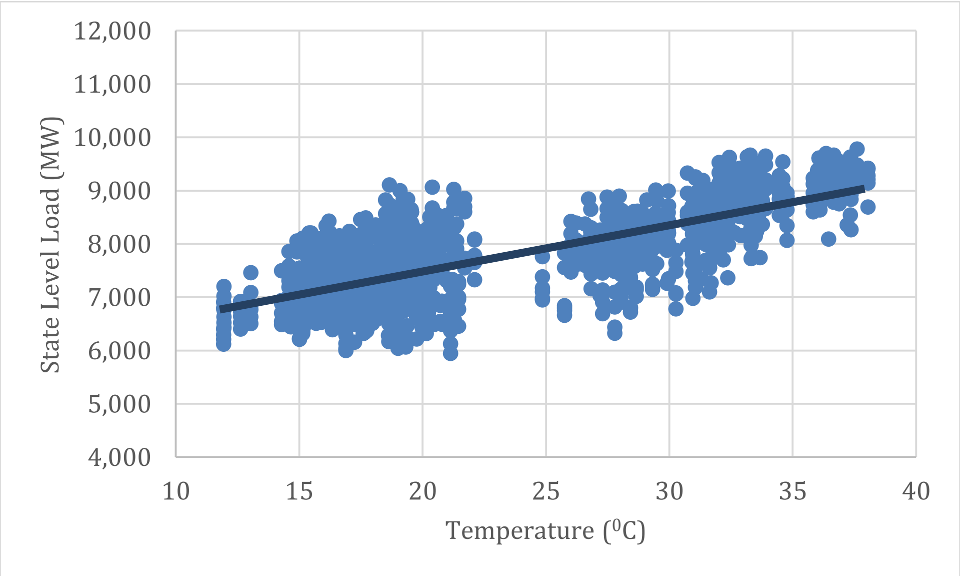

Figure 14: Dependency of State-Level Load over Temperature

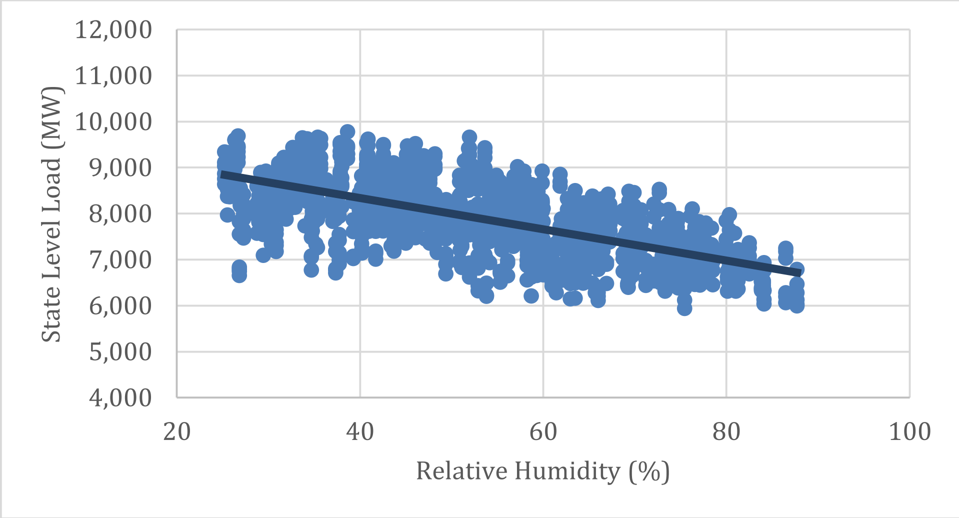

Figure 15: Dependency of State-Level Load over Relative Humidity

Appendix 2: Auto-correlation Analysis

Load demand at any time depends on not only the present weather variables, but also over past load. Thus, we have investigated the dependency of present load over past load. A high positive auto-correlation between lags of load was observed, which decreases with increasing time gaps. The auto-correlation shows clear statistical significance till 48 hours, but after three lags it really does not make any significant improvement in the model output. Thus, we consider the first lag and the second lag of load in our modelling equation (Figure 16).

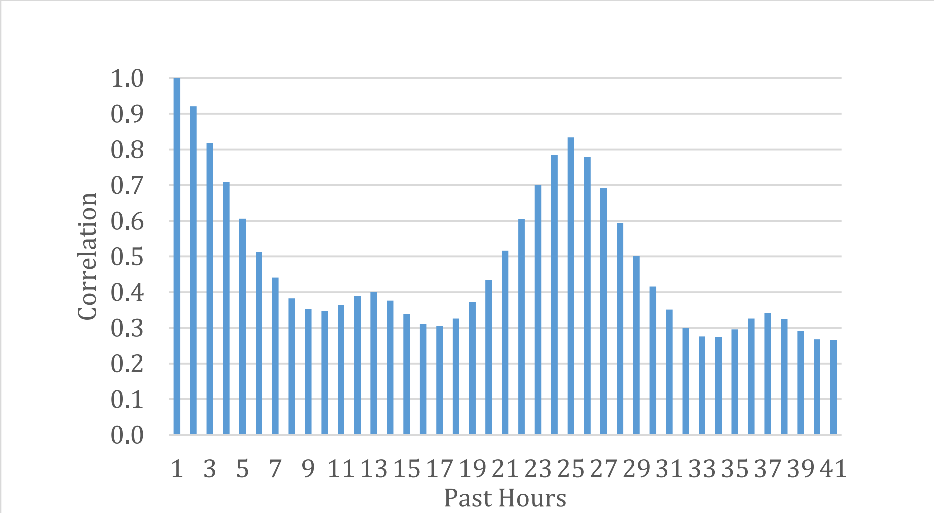

Figure 16: Auto-correlation Analysis of Past Load

Appendix 3: Test for Heteroscedasticity in the Model

Presence of heteroscedasticity indicates that the linear regression analysis might not be efficient[10]. A homoscedasticity assumption means that the variance around the regression line is the same for all values of the predicted load. Hence, we plot a scatter graph of the residuals and tried to fit a line through them. We observe that the residual terms are random and there is no trend line (as confirmed in Figure 17). Thus, the linear regression analysis used here is sufficient to build the model.

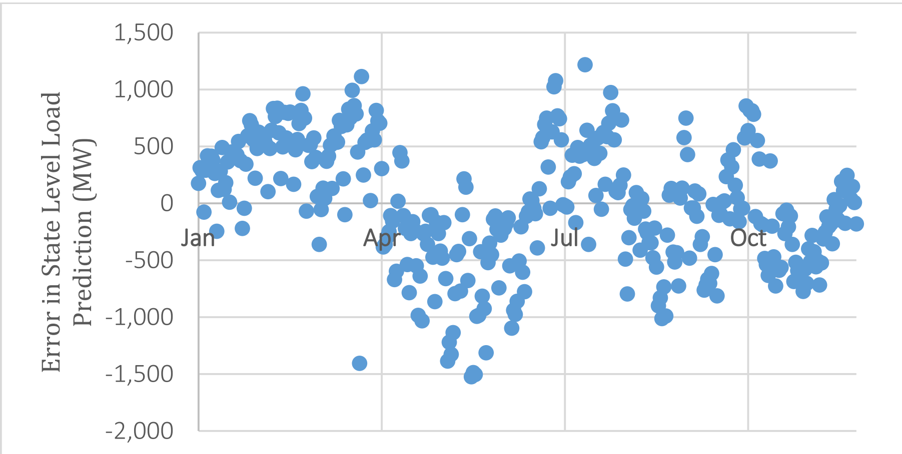

Figure 17: Model Error for 2016

[10] http://www.jstor.org/stable/1912559.

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