Hybrid CNN-LSTM and Domain Modeling in Climate-Energy Analysis for a Smart Environment

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***Abstract*—This study aims to model the effect of local climate on energy generation in power plants in the United States. It considers climate change as well as the ever-growing electricity demand, contributing to greenhouse gas emissions. We propose an integration of AI-based and domain-specific paradigms via a hybrid approach of convolutional neural networks (CNN) & long short-term memory (LSTM) coupled with environmental models. Erstwhile studies focus mainly on specific energy sources, e.g. solar/wind power. There is a need for more comprehensive examination, e.g. temperature effects across various energy generation types at the macro level of states and micro level of power plants. This forms the major focus and novelty of our study. Fathoming the factors driving temperature-energy correlations, and assessing power plant vulnerability to changing climate patterns, are both essential to promote energy infrastructure resilience and sustainability. Our study offers novel insights into the complex interplay of temperature, energy generation, sustainability and related aspects to enable enhanced macro & micro level decision-making in energy sector. It therefore makes contributions to smart environment goals for smart cities and a smart planet.**

Keywords*— *CNN, Climate Studies, Electricity, Energy, LSTM, Predictive Modeling, Smart Environment, Smart Cities

I. INTRODUCTION

Energy consumption is a major driver of economic growth & environmental impact. Studying patterns in energy usage holds tremendous importance for addressing challenges in sustainable energy management. AI can play a role here.

Background: Global energy use is affected by climatic factors, e.g. temperature, socio-economic variables such as population demographics etc. Adequate climate-energy analysis is crucial in effectively planning the distribution and hence optimizing energy usage [1]. Due to climate change and drastic fluctuations in global temperature, there is more demand for electricity. As energy usage increases, greenhouse gas (GHG) emissions rise substantially. In the U.S., the electric power sector contributes to 31% of carbon dioxide (CO_2) emissions [2]. Global energy demands are rising, along with related emissions, and are expected to rise further due to greater urbanization, unless proactive measures are taken soon [3]. Climatic factors, particularly temperature, have much impact on energy demand-supply [4]. Energy use is closely tied to the weather, where energy consumption rises with a peak in increase/decrease of temperature [2]. Changes in energy demand will inevitably affect GHG emissions, but overall effects depend on energy sources for electricity/heating, including alternative ones.

Motivation: Most power companies lack consideration of climate impacts in development strategies today, which can lead to overestimation of capacity for future demands, causing electricity shortages [5]. As much as the energy sector contributes towards climate change, it is impacted by the effects of climate change. Generation of electricity can be affected, e.g. climate change can cause droughts. It can affect hydroelectricity depending on streamflow, impact thermal power plants requiring cooling water to generate electricity at full capacity [6,7] etc. Climate change can severely compromise resilience and reliability of current energy systems. Yet, analyzing comprehensive effects of temperature and climate change on electric power systems is limited in existing studies [8-14], leaving many gaps due to which authorities have very few options to assess the infrastructure reliability (primarily relying on historical climate conditions). Local weather conditions are vital in influencing power generation [7]. Fathoming the macro and micro dynamics of power generation and demand can thus assist stakeholders (e.g. grid operators, policymakers) to make macro & micro level decisions in the energy sector.

Problem Definition: Motivated by this background, our work in this paper has the following main goals.
1. Investigate existing correlations between local plant power generation, local temperature, and state-level power demand, to analyze trends, and identify interdependencies.
2. Assist stakeholders to make better decisions to optimize generation & distribution of energy resources, contributing to the complex macro & micro dynamics of energy.

Approach & Contributions: Environmental modeling entails mathematical or computational models to simulate behavior and interactions of energy systems. These models can capture complexities of energy generation, distribution & consumption to fathom system behavior under different scenarios. Machine learning methods, e.g. convolutional neural networks (CNN), can play important roles here from the AI perspective. Yet, AI-based modeling alone can often face problems due to lack of adequate domain knowledge, limited interpretability and other issues. *In this work, an amalgamation of AI-based and domain-specific paradigms is proposed via a hybrid approach of CNN-LSTM modeling integrated with environmental modeling for comprehensive energy analysis at a macro & micro level.* It entails various factors encompassing power generation and temperature measurements. Our major contributions are as follows.

- Comprehensive study of *multiple energy sources* from environmental data repositories with a strong emphasis on *climatic* factors
- Use of *macro & micro* level dynamics, scalable with modification to other research on applied AI
- Amalgamation of *AI-based and domain-specific modeling* for climate-energy analysis
- Hybrid *CNN & LSTM adaptation*, leveraging their best features for exemplification in further work

II. LITERATURE REVIEW

Traditional forecasting models often rely on time-series analysis, and autoregressive integrated moving average (ARIMA), mostly showing linear relationships. Machine learning models are better for nonlinear relationships and complex patterns. Studies show high accuracy of neural networks to capture nonlinear dynamics of the system [9].

Monitoring energy use, e.g. load monitoring of appliances, or of buildings as a whole, can lead to reduced energy consumption [10]. Neural network capability to incorporate diverse and dynamic inputs (weather data, market prices, consumer behavior etc.) into energy forecasting models helps find intricate relationships between such variables and energy, offering accurate predictions to guide decisions for a more sustainable energy management future. In a recent study [11], a model incorporated climate data and building characteristics for improved pre-design of heating and cooling of buildings. Lim et al. [12] used a CNN-LSTM model for stable solar power generation forecasting (CNN to categorize weather conditions, LSTM to learn solar power generation patterns based on them). Zhang et al. [13] deployed an ultra-short-term load forecast model based on temperature factor weight and LSTM to analyze power consumption and temperature by using a feedback temperature factor weight. Their results helped to reduce prediction error, to reduce operating costs.

In smart cities, where energy systems are interconnected and complex, such models can help reduce GHG emissions [14]. It is noted that 64% of the total emission from the electric power sector in the US comes from residential areas with over 100 million urban households, consuming over 7,500 trillion BTU energy in 2020 alone (more than half of the total energy consumed). However, the per capita consumption rates of cities are the lowest per household [2]. This offers the scope for being more efficient. Many studies reveal that machine learning can help in reduction of energy usage in buildings via adaptive usage patterns, and more automation in devices and systems [1]. Machine learning methods can predict cost savings for consumers while reducing carbon footprint of buildings. As real-time data is used in smart cities, CNN-LSTM models can be used to help optimize energy use, reduce peak loads, and enhance overall system efficiency [14].

Although numerous studies have explored relationships between temperature and energy generation, there are many research gaps. Most studies focus on temperature impacts over energy generation from specific sources, e.g. solar / wind power [12]. There are gaps on comprehensive effects of temperature on various types of energy generation as a whole. Moreover, while the influence of temperature on energy generation has been acknowledged [12], there is a need for investigation into the underlying factors that drive this relationship, and how it can affect the supply chain of energy. These and other aspects motivate further research. Our work in this paper can offer valuable insights into the interplay of temperature, energy generation, sustainability, and related aspects via AI-based modeling merged with environmental modeling, at a macro & micro level.

III. Proposed Methodology: Hybrid CNN-LSTM

We propose a methodology for energy analysis by climate based on an amalgamation of environmental and AI-based paradigms. This entails environmental modeling coupled with CNN and LSTM thus constituting a hybrid CNN-LSTM model. It is described in the next subsections.

A. *Environmental Modeling and Data Harvesting*

Datasets on temperature and energy generation in local power plants in the 48 states of the continental United States (excluding Hawaii and Alaska) are harvested in this work. Historical weather data entails local temperature averages, from models in NOAA (National Oceanic and Atmospheric Administration) NCEI (National Center for Environmental Information). The models leverage domain knowledge in environmental science and management. Data on the aforementioned sources is harvested from local climate stations. This helps to collate useful information on monthly and daily temperature averages, longitude, and latitude. Likewise, energy generation datasets are harvested from multiple energy sources of different models in the U.S. EIA (Energy Information Administration) as follows.
1. Inventory of Operable Generators [EIA-860M]
2. Monthly Generation by Plant [EIA-923]
3. Monthly Electric Power Industry Report [EIA-861M]
4. Electric Power Operations (Daily and Hourly): Daily Demand by Subregion [EIA-930]

These datasets model information on the type of fuel, energy statistics, location of the powerplant (longitude, latitude, state), consumers, price, revenue etc. The data is collated for January 2018 to December 2022.The dataset with combined energy generation data has 200,526 rows of data and the temperature dataset has 169,932 rows. Table I and Fig. 1 provide relevant snapshots of the data.

TABLE I. Data harvested by environmental modeling

Attr.	**Net Generation (MWh)**	**Fuel Consumption (BTUs)**	**Total Consumption (BTUs)**	**Temperature (°C)**		
				Mean	*Min.*	*Max.*
mean	83,728.4	774,151.40	832,123.60	10.6	16.4	4.7
std	232,162.7	2,269,354.00	2,279,946.00	9.9	10.6	9.6
min	-20,897.0	1.00	1.00	-21.8	-16.4	-28.9
med	4,621.5	43,643.00	55,599.50	10.6	16.7	4.4
max	2,987,699.0	31,197,000.00	31,197,000.00	37.4	45.8	31.8

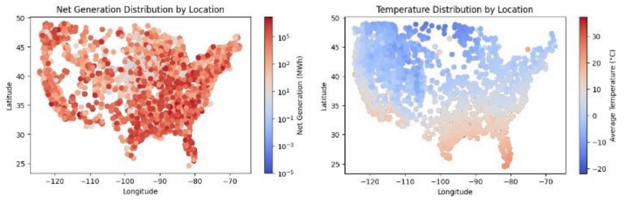

Fig. 1 Map of the US with distribution of average monthly net energy generation (Left), Distribution of average monthly temperatures (Right)

The environmentally modeled data is pre-processed using machine learning methods. This is to ensure that the data is consistent, accurate, and suitable for analysis by the CNN-LSTM model. In the powerplant dataset obtained by the concerned environmental models, the pre-processing steps are as follows: (1) remove missing values; (2) drop rows with numerical cells equal to zero; (3) exclude rows where the fuel type is not "ALL"; (4) sort data by datetime; (5) select relevant attributes (timestamp, latitude, longitude, generation, total-consumption-btu, consumption-for-eg-btu); (6) drop rows located outside the US48 range. In the temperature dataset, the following pre-processing steps are executed: (1) remove missing values; (2) sort data based on datetime; (3) select relevant attributes (timestamp, latitude, longitude, max, min, mean temperature); (4) drop rows that fall outside the US48 range. Thereafter, the environmental datasets are merged by longitude, latitude. In the process of merging datasets, our algorithm begins by looping through the energy records in chronological order. The temperature data is utilized to construct a search tree, which is rebuilt whenever a change in period data is detected. This ensures that the search trees only contain records for a specific timestamp (YYYY-MM). Each energy record is compared against temperature records stored in the search tree. The best match(es) can be determined using Euclidean distance, incorporating latitude, longitude. Here *''i''* depicts number of temperature readings around the powerplant to create the average temperature *(T)* for a given plant. The number of readings can be initialized using domain knowledge, and further refined in our approach (as revealed in experimental results). For more than one match (*Ti>1*), temperatures are combined to calculate an average temperature, each value being weighted based on its respective distance from the plant using a linear weighting approach. This is guided by domain knowledge in environmental science. Additionally, the timestamp feature is split into year and month, and the distances of temperatures for a given plant are combined to calculate an average distance. As a next step, statistical analysis with z-score normalization occurs. The average distance is used to establish a lower & upper fence, and any outliers beyond these fences are eliminated. Following the outlier detection and removal, the data is thus normalized. Numerical attributes are normalized by a MinMaxScaler, and categorical attributes using a OneHotEncoder.

B. AI-Based Modeling with CNN-LSTM

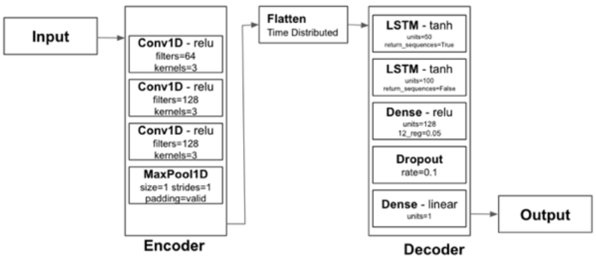

Fig. 2 CNN-LSTM Proposed Framework

In the AI-based modeling, the proposed method is a hybrid CNN-LSTM model. This is harnessed for modeling the effect of local temperature averages on energy generation in local power plants in the U.S. Fig. 2 illustrates the structure of the proposed hybrid CNN-LSTM model in our work. This model combines the strengths of both CNN and LSTM to capture spatial and temporal correlations within the environmental datasets as follows. The CNN model has three CNN layers and a max-pooling layer. After the first convolutional layer analyzes the data, it shows the discovered feature map. Thereafter, the second later repeats this process, and finally the third later amplifies the features. The max-pooling layer simplifies the feature maps by retaining the highest signals, preserving one-quarter of the original values and reduces the complexity of feature maps by retaining the highest signals. The flattened feature maps are then transformed into a long vector, and the repeat vector layer connects the input and output sequences by repeating the internal representation each step again. The extended short-term memory decoder has three LSTM layers to generate values for each forecasted interval. Time-distributed layers are employed before the final output layer to explain each step. The dense layer uses learned weights to make complex decisions based on the extracted features, ultimately producing the output. Dropout is a regularization technique that prevents overfitting by randomly dropping out layer outputs during training. This improves robustness of the model and reduces reliance on specific neurons.

Algorithm 1: Hybrid CNN-LSTM Modeling

1. Input: Data Δ // Environmentally modeled climate-energy data
2.Curate Δ with domain knowledge
    i. Merge Δ by latitude, longitude as (ψ, θ)
    ii. Normalize {Δ_N} by Min-Max Scaling // Numeric data
    iii. Modify{Δ_C} by One-Hot encoding // Categorical data
    iv. Return derived data as Δ (X, Y) attribute-values
3. Remodel X_{SHAPE} [0] to X_{SHAPE} [1], Reshape Y as η lists, 1 value each
4. Create model μ with inputs:
    i. Convolutional Layers in CNN: CL = 3
    ii. MaxPool Layers: ML = 1, Flatten Layers: FL =1
    iii. LSTM Layers: LL = 3 (tanh activation)
    iv. Dense Layer: DE = 1 (128 neurons), Dropout Layer: DO = 1
    v. Output Layer: OL = 1
5. Set Filters γ = 64, Kernel-size κ = 3, Activation α = ReLU
6. Set LSTM_units: υ = 50
7. Set Dropout_rate: δ = 1%, Learning_rate: λ = 0.1%
8. Compile μ with:
    i. Root Mean Squared Error RMSE, Adam optimizer AO
9. Set early callback value = ε**,** patience ρ = 5, restore-best-wgt ω = True
10. Initiate step decay function σ:
    i. $\sigma = 0.001$
    ii. $\sigma = 0.9 * \sigma$ ^ [FLOOR $(1 + \tau)$] // τ: number of epochs
11. If plateau with factor Φ = 0.5, ρ = 1, then reduce λ
12. Fit μ with Δ (X_{TRAIN}, Y_{TRAIN})
    i. Batch-size = β, Epochs = τ
    ii. Validation-data = Δ (X_{VAL}, Y_{VAL})
    iii. Set ε with reduced λ
13. Evaluate μ on remaining Δ(X_{TEST}, Y_{TEST})
14. Output: Return output Ω via OL // Learned hypothesis on model

Algorithm 1 presents the pseudocode to demonstrate the hybrid CNN-LSTM model adapted for our climate-energy analysis. Combining convolutional and LSTM layers has the effect of diversification. This creates a dynamic setup to predict energy generation encompassing environmental modeling features. It aims to merge the best of both worlds.

C. Model Training and Evaluation

The CNN-LSTM model executes on curated environmental data to conduct energy analysis. Python's Scikit Learn is used for programming in the overall implementation. The model is then subjected to evaluation. For this purpose, the data is split into training, validation, and test sets of varying sizes. The training set is used to train the model, validation set for tuning hyperparameters & model selection, and test set for evaluating final performance of the trained model on unseen data. Performance is evaluated by measuring error, which is calculated as validation loss here. Validation loss can indicate how well our CNN-LSTM model predicts net energy generation. In this paper, the following metrics are used: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE). Table II shows validation loss (val_loss) of the model with *Ti*. The model is optimized for *Ti = 1*; the temperature reading closest to a given power plant calculated using Euclidean distance.

IV. Experimental Results and Discussion

In this study, the optimization of the model is aimed at considering different average temperature ranges, depicted by *Ti.* Fig. 3 synopsizes our experimental results. Table II displays validation loss for different temperature readings.

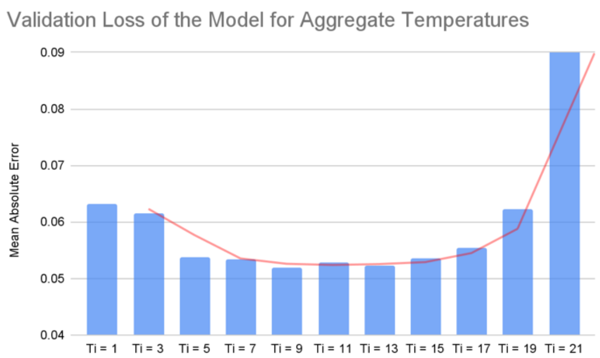

Fig 3. Mean Absolute Error (MAE) of the model for different aggregate temperatures (Ti, where 'i' is number of temperature readings on the powerplant to create the average temperature (T) for a given plant.

TABLE II. Validation Loss with Temperature Measurements

Ti	MAE	MSE	RMSE
Ti = 1	0.0631	0.0259	0.1392
Ti = 3	0.0616	0.0243	0.1297
Ti = 5	0.0538	0.0228	0.1279
Ti = 7	0.0533	0.0222	0.1282
Ti = 9	0.0519	0.0221	0.1272
Ti = 11	0.0529	0.0293	0.1315
Ti = 13	0.0522	0.0224	0.1279
Ti = 15	0.0536	0.0248	0.1284
Ti = 17	0.0554	0.0261	0.1373
Ti = 19	0.0622	0.0258	0.1389
Ti = 21	0.0927	0.0346	0.1423

It is observed that as the value of *Ti* increases (indicating a larger average temperature range around the power plant), an improvement in the model's performance is noticed (as per the loss metric). It can be initially recommended that the model becomes more proficient in predicting energy generation patterns by considering a broader range of temperature data along with the constant factors of time and fuel consumption. However, as *Ti* is further increased and reaches around *Ti=15*, a deterioration in the model's performance is observed. It shows that the model gets overly generalized. Consequently, an increase in loss is observed, indicating a decline in the model's predictive capability. In the experiments shown here, *Ti=9* and *Ti=13* exhibit better performance across all evaluation metrics compared to *Ti=11*. While this is a correlation and not essentially a causality, it indicates that these specific ranges can improve predictive accuracy, giving closer alignment with actual energy generation patterns. More inferences can be drawn via domain knowledge (listed in Conclusions). The CNN-LSTM model reaffirms that temperature has a dual impact on energy-related processes. It is noticed that on a micro level (power plant), temperature affects the efficiency of converting fuel into energy; whereas on a macro level (state-wide), temperature influences energy demand directly. In our experiments *Ti = 9*, yields the best results in capturing micro-to-macro relationships, as the MAE, MSE and RMSE are comparably the lowest (0.0519, 0.0221, and 0.1272 respectively) indicating this to be a near optimal number. A possible explanation from a domain-specific angle is that *Ti=9* and *Ti=13* depict the average temperature ranges on the most notable variations in temperature relevant to energy generation. They can map to temperature thresholds / conditions having a more direct impact on the efficiency and performance of power plants. Indirect effects can be due to electricity demand affected by temperature. Additionally, *Ti=9* and *Ti=13* can be temperature variations more representative of certain geographical locations or climate conditions where power plants are situated. Different regions often tend to exhibit temperature patterns and sensitivities to energy generation. Hence, by considering average temperature ranges aligning closely with local climate characteristics, the model can better capture nuanced relationships between temperature and energy generation. It shows the importance of micro & macro scaled research for more comprehensive analysis of relationships in energy management. It helps in improving energy efficiency and heads towards optimization.

V. Impact on Smart Cities

The findings of this study have implications for smart cities and sustainability. Integrating real-time temperature data into smart city infrastructure allows dynamic adjustments in energy production and distribution, while maximizing resource utilization. For instance, Fig. 4 offers a visual depiction of prediction results for energy consumption using our hybrid modeling approach. It is seen that as *Ti* increases, the graph forms a narrower bell curve, implying greater stability or predictability in energy generation in response to temperature variations. It can be advantageous to stakeholders for planning and optimizing power plant operations. Moreover, accurate depiction of temperatures around each power plant tends to increase the precision of subsequent analyses. Here, left-most clusters (blue) show colder climatic conditions whereas right-most clusters (red) show warmer ones. It reveals that power generation is maximized when average monthly temperature around a power plant falls between -10°C, 10 °C. A general upward trend from -25°C to -5°C can be associated with increase in consumer-demand for electricity in colder temperatures; the downward trend from 10°C to 20°C can be associated with the lower capacity of power lines at high temperatures. Such inferences from our hybrid CNN-LSTM modeling for energy analysis can help in smart city planning and smart grid development. For example, it is evident that prediction results for energy consumption are better for *Ti=5* than for *Ti=1*, and further better for *Ti=13*, but almost similar for *Ti=13* and *Ti=21*. Hence, it could be more optimal to select *Ti=13* for smart grid layouts in smart cities.

Our work in this paper can be orthogonal to other studies [14, 15]. On a related note, regions with more alternative fuel vehicles (AFVs) are associated with regions having better air quality [16]. Hence, smart grids to optimize the charging and discharging of electric vehicles based on temperature conditions, can be suitably designed via results of studies such as ours. This is in order to improve energy efficiency and reduce carbon footprint in transportation.

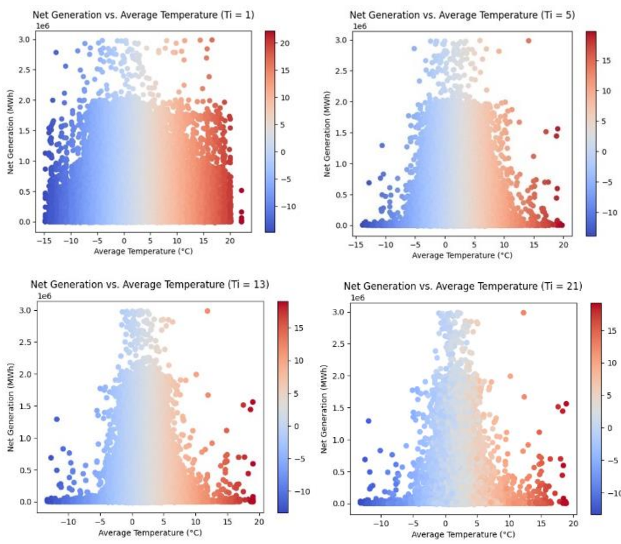

Fig 4. Prediction results for Net Energy Generation (MWh) for various Ti values where 'i' is the number of temperature readings surrounding the power plant to create the average temperature (T) for a given plant.

Likewise, adapting more sustainable AI with machine learning techniques to create strategies for electric vehicle ride-sharing can result in fuel-saving, and decarbonization analogous to other work [17]. By incorporating renewable energy and advanced energy management, via more well-informed decision-making with AI-based and domain-specific paradigms, integrated energy systems can help mitigate air pollution in smart cities. Our work in this paper can make modest contributions to such initiatives.

VI. Conclusions and Future Work

Our research emphasizes amalgamating AI-based models with domain-specific models for analysis. It is exemplified with climate-energy analysis via hybrid CNN-LSTM and environmental modeling. Our key findings are as follows.
1.Power generation is maximized when average monthly temperature surrounding a power plant is -10 °C to 10 °C.
2. Upward trend from -25°C to -5°C is associated with an increase in consumer demand for electricity or associated with climates in areas where people choose to live.
3. Downward trend from 10°C to 20°C is associated with the lower capacity of power lines at high temperatures.
4. At the micro level there is a strong correlation between the power each plant generates and temperature around it.
5. Correlations at the micro level are more complex than the macro level because of added layer of variables.

Stakeholders can make better decisions based on such findings to mitigate energy waste & CO_2 emissions. Smart city planners can use the discovered knowledge for energy conservation, load balancing, and smart grid layouts. While we identify macro / micro levels as state / power plant, other studies can use different mappings for macro & micro scales, with lessons learned from our study for more well-grounded decision-making. To the best of our knowledge our study in this paper is among the first on *comprehensive climate-energy* analysis using *multiple source*s at *macro & micro levels* via integrating *AI-based and domain-specific methods* by *hybrid CNN-LSTM* & *environmental models.*

Future work can entail comparing seasonal differences, identifying gaps in demand and supply of power during various seasons, correlating states with residential sector / commercial sector, and analyzing demand of electricity by industry and geography. Questions can be raised as follows.
1. Does energy source of the power affect CO2 emissions?
2. How does it correlate with socio-economic conditions?
This can blend machine learning and predictive models into smart city infrastructure for proactive energy management and good demand-response mechanisms. Our study thus paves the way for more innovative solutions towards a smart environment in smart cities and a smart planet.

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