Artificial Intelligence Techniques for Energy Management in Smart Buildings.

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by

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Chapter 8

Conclusion and Future Directions

8.1 Conclusion

This thesis comprises machine learning and deep learning techniques that enable efficient energy modeling and optimization. The focus has been on using state-of-the-art machine learning and deep learning algorithms to design and forecast short-term energy for smart buildings and optimizing novel ones. Various machine and deep learning algorithms, like Linear Regression, ARIMA, LSTM, Bi-lSTM, etc., have been used, often in conjunction with several data sets. The methodologies that are used to build the proposed frameworks help tackle a multitude of computational challenges, like (i) decreasing the model training time, (ii) reducing the size of the model without compromising its performance to deploy it on real-world scenarios., (iii) Increasing better accuracy from models to models in terms of various evaluation metrics for different ML and deep learning algorithms. The major findings of the overall research are as follows:

(i) The first work demonstrated a mix of multiple approaches for time-series energy forecasting and outcomes from altering the types of input data. It was discovered that the best-case scenario for energy prediction involves using the current day/hour as a feature in multivariate modeling. While testing the models for various lags, it is discovered that the previous 8 hours' energy usage delivers the best value for the ninth hour. When the lag is measured in hours, CNN-LSTM and CNN-GRU models perform better in scenarios 1 and 2 for univariate and multivariate models, respectively.

(ii) The second work integrates CNN and BiLSTM architecture, which tackles the difficulties in precise energy prediction. In addition, it takes occupancy count into account as an extra feature for an accurate energy forecast. With CNN layers, the suggested model effectively captures the spatial properties of the data and aids in extracting significant energy-related feature sets. The following BiLSTM layers successfully capture long-term patterns in the data and simulate temporal dependencies. The suggested hybrid approach accurately and efficiently projects energy usage one day ahead of time. The suggested plan considerably raises the accuracy of energy prediction in terms of R-squared (R^2), MAE, and MSE. The low values of MAE and MSE indicate minimal deviation between the predicted and actual energy consumption values. In contrast, the high R^2 value signifies the model's ability to explain the variance in the data. The simulation results indicate that the proposed scheme outperforms the existing state-of-the-art algorithm.

(iii) In the third work, the occupancy-based plug load data is broken down into various subsequences Using VMD. The prediction difficulty is decreased using VMD to separate the initial complex plug data into distinct sub-sequences. Next, to predict the occupancy-based plug load data for other rooms in a building, LSTM is applied to each subsequence. Compared to other machine learning models and deep learning model methodologies, the accuracy result produced after employing VMD-LSTM is superior. The suggested model achieves 95% accuracy for a 5-minute forecast, 95% accuracy for a 15-minute forecast, 94% accuracy for 30-minute forecasts, and 95% accuracy for hour-wise occupancy-based plug load prediction. The proposed model provides more accurate results as VMD separates data into sub-sequences. It can forecast energy for smart buildings with a 12 and 24-hour lag ahead.

(iv) The fourth work presents a novel energy prediction mechanism for smart buildings based on extreme weather events using the BERT model. The BERT model uses self-attention processes to extract complex patterns and connections from the data and make exact energy forecasts. To improve the model's predictive power, include multivariate variables like temperature, dew point, humidity, timestamps, and energy use. The model provides accurate projections for one, eight, and twenty-four hours, effectively capturing the intricate links between weather and energy consumption. The model's improved performance and accuracy in energy prediction are shown by the low values of MAE, MSE, and MAPE that BERT attained together with high R-squared (R^2) values. The outcomes show that the BERT model performs better than state-of-the-art algorithms. The model's precise predictions help to cut down on energy waste, boost energy efficiency, and eventually minimize expenses and environmental effects. Moreover, the model's temporal flexibility indicates its generalizability and dependability in real-world contexts.

(v) Heat load energy demand is important in energy storage management systems. Heat load prediction for smart buildings is in significant demand today, but it faces numerous problems, including temporal-spatial correlations in multivariate information. Therefore, the fifth work presented revolutionary intelligent modeling and predicting heat energy consumption in smart buildings using smart heat meter data. The suggested model was tested on the real-time Danish Residential Building dataset. The proposed hybrid deep learning model combines parallel CNN and LSTM; CNN extracts high-level features from the given data, while LSTM extracts the temporal link between local characteristics. The proposed model made accurate heat load estimates by combining real and created features. Aside from heat energy, other factors such as volume flow, intake flow energy, backflow energy, hour, day, and month are incorporated while developing multivariate models. The exhaustive experimental findings were examined over 24 hours, 168 hours, one day, and seven days, respectively. The model generates promising R_2 results with lower error measures such as MAE and RMSE.

In overall the brief findings of the conclusion are

(i) The first work explored combining different methods for time-series energy forecasting and found that using the current day/hour as a feature in multivariate models yields the best results. Testing with time lags showed that energy use from the previous 8 hours predicts the ninth hour best. CNN-LSTM performed well for univariate models, while CNN-GRU excelled in multivariate scenarios. (ii) The second work uses VMD to break down complex plug load data into simpler parts, then applies LSTM to predict occupancy-based energy use in other rooms. This VMD-LSTM model achieves high accuracy, with 95% for 5, 15-minute, and hour-wise forecasts, and 94% for 30-minute forecasts, outperforming other methods. It can also predict energy use with a 12 to 24-hour lag. (iii) The next work uses VMD to break down complex plug load data into simpler parts, then applies LSTM to predict occupancy-based energy use in other rooms. This VMD-LSTM model achieves high accuracy, with 95% for 5, 15-minute, and hour-wise forecasts, and 94% for 30-minute forecasts, outperforming other methods. It can also predict energy use with a 12 to 24-hour lag. (iv) The fourth work introduces a BERT-based energy prediction model for smart buildings during extreme weather. Using self-attention, it captures complex weather-energy patterns with features like temperature, humidity, and energy use. It predicts energy use for 1, 8, and 24 hours with high accuracy, outperforming other models and reducing energy waste, costs, and environmental impact. (v) The fifth work focuses on predicting heat load for smart buildings, which is crucial for energy storage management. Using smart heat meter data, a hybrid deep learning model combining CNN and LSTM was developed. CNN extracts high-level features, while LSTM captures time-based patterns. Tested on a real Danish Residential dataset, the model accurately predicts heat load using factors like flow energy, hour, and day. It shows strong performance over 24 hours to 7 days with high R-squared and low MAE and RMSE.

8.2 Future Directions

The present thesis could be investigated further under various conditions, such as longer predicting horizons and with different kinds of energy data. Some promising future directions are as follows:

1. The study mainly focused on multivariate modeling with a limited number of features. Therefore, more research may be done to identify the most compelling feature combination for accurate energy forecasting. It would be beneficial to investigate the potential advantages of utilizing external input data by combining multiple datasets to enhance energy prediction further. Future studies could examine the application of comparable models for longer-term forecasting, even though the current thesis concentrated on short-term heat load prediction.
2. The creation of real-time heat load prediction models that might be applied to dynamic energy management in smart buildings is another potential topic of future research direction. Supporting more responsive energy management systems and improving model predictions will require integration with more real-time sensor data.
3. The current thesis explicitly focused on smart buildings of apartment, single-family, and terraced types. However the proposed model will be extended for other types of buildings and multiple families.
4. This study can be extended for better decisions by introducing generative AI in future work.
5. Future studies should examine how well this strategy works in other contexts by considering price with other multivariate features.

This work can be used for industry building automation, smart city development, administrative building automation, and residential building automation.