The 7th International Symposium on Innovative Materials and Processes in Energy Systems, IMPRES2025, 27–30 October, 2025, Sendai, Japan

A Data-Driven Model for Forecasting Thermal Load in District Energy Networks

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1. Introduction

District energy networks (DENs) play a significant role in decarbonizing commercial and residential buildings by centralizing the distribution of heating and cooling for multiple buildings [1]. DENs must handle peak demand fluctuations, necessitating accurate predictive modeling. Data-driven models offer significant advantages over traditional physical simulations in predicting thermal loads in DENs. While physical models depend on detailed knowledge of building characteristics and often struggle to incorporate dynamic operational schedules, occupant behavior, and external factors like weather variability, data-driven approaches can learn directly from historical operational data [2]. This enables them to capture complex, nonlinear relationships among numerous variables, leading to more accurate and adaptive thermal load forecasting. For the first time, this research develops an Attention-based Convolutional Recurrent Neural Network (ACRNN) to improve forecasting accuracy, optimize resource allocation, and enhance energy efficiency in DENs.

2. Data description

This study uses historical thermal load data from the City of Surrey, British Columbia, Canada s district energy network (2018-2019) and weather data from the Canadian Centre for Climate Services. The dataset includes multiple features (independent variables) related to weather conditions and a label, single dependent variable, which represents energy consumption in kilowatt-hours (kWh), listed in Table 1. The dataset has been preprocessed to handle missing values, remove outliers, and normalize features for optimal model performance.

Table 1- Data Description for thermal load data from and weather data.

Feature/Lable Name	Description
datetime	Combined date and time
Pressure_station	Atmospheric pressure at the station
pressure_sea	Atmospheric pressure at sea level
wind_dir	Wind direction
wind_speed	Wind speed [m/s]
relative_humidity	Relative humidity at the station
dew_point	The temperature at which air becomes saturated with moisture
temperature	Ambient air temperature at the station
cloud_cover_8	Cloud coverage on a scale of 0-8
max_air_temp_pst1hr	Maximum recorded air temperature in the past hour
min_air_temp_pst1hr	Minimum recorded air temperature in the past hour
Consumption (kWh) [Label]	Total energy consumption

3. Model development

Figure 1 shows the flow chart for the present ACRNN model implementation. The ACRNN model is implemented in Python, utilizing TensorFlow, a widely adopted deep learning framework known for its flexibility, scalability, and optimization capabilities. A critical component of model performance is hyperparameter tuning, which is performed using Bayesian Optimization [3].

For effective model evaluation, the dataset is split into training and testing subsets. Specifically, 80% of the data from the year is allocated for training and validation, allowing the model to learn complex patterns in historical thermal load and weather conditions. The remaining 20% (corresponding to the last few months of the year) is reserved for testing, ensuring that the model is evaluated on previously unseen data. This chronological split preserves the temporal integrity of the dataset, preventing data leakage and ensuring that the model generalizes effectively to real-world forecasting scenarios.

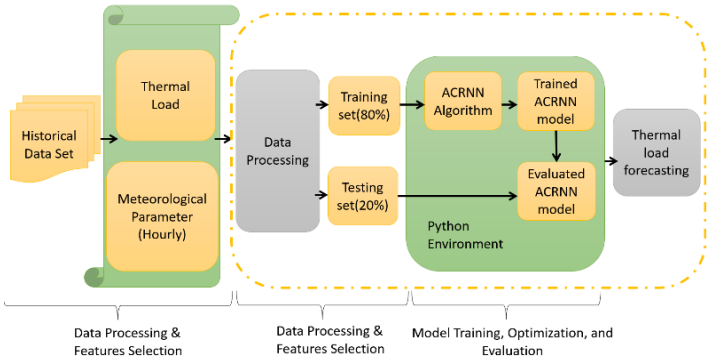


Fig. 1. Flow chart for the present ACRNN mode

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4. Results and discussion

The model was trained and evaluated using Google Colab with a Tesla T4 GPU. The total computation time was approximately 4 minutes for training and around 2 seconds for testing. Figure 2 shows the energy consumption patterns recorded over time, with the dataset divided into 80% for training and validation and 20% for testing to assess the model's generalization ability. The ACRNN model effectively captures both overall trends and periodic fluctuations in energy consumption, which may correspond to seasonal effects, operational schedules, or external factors. This ability to learn and predict complex consumption patterns highlights the model's accuracy in energy forecasting of complex and large systems such as DENs.

Figure 3 shows energy consumption trends at different temporal resolutions: (a) hourly moving-averaged energy consumption and (b) daily moving-averaged energy consumption. The ACRNN model effectively captures both trends and fluctuations at these levels, accurately reflecting short-term variations in hourly consumption as well as broader patterns in daily energy demand. This demonstrates the model's capability to adapt to different time scales, making it a reliable tool for energy forecasting.

Figure 4 shows the comparison between the ACRNN model's predicted energy consumption and the actual recorded values. The alignment confirms ACRNN's effectiveness in capturing consumption trends. Its predictions closely match actual values, with most within ±10% of actual consumption, demonstrating high accuracy and robustness.

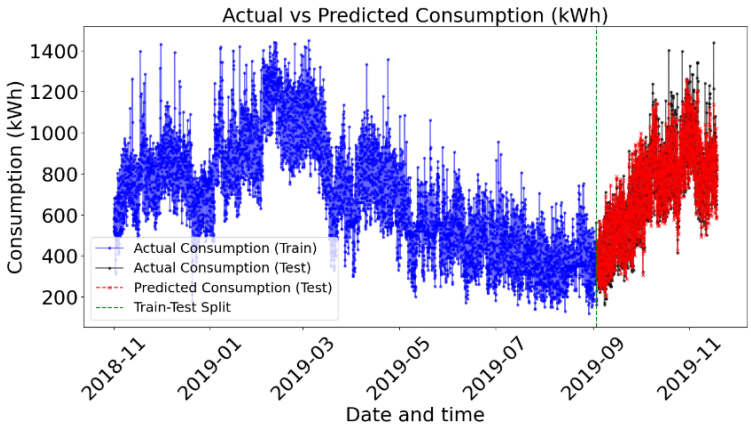


Fig. 2. Energy consumption vs date and time; First 80 percent of data is used for training and validation and the last 20% is used for testing.

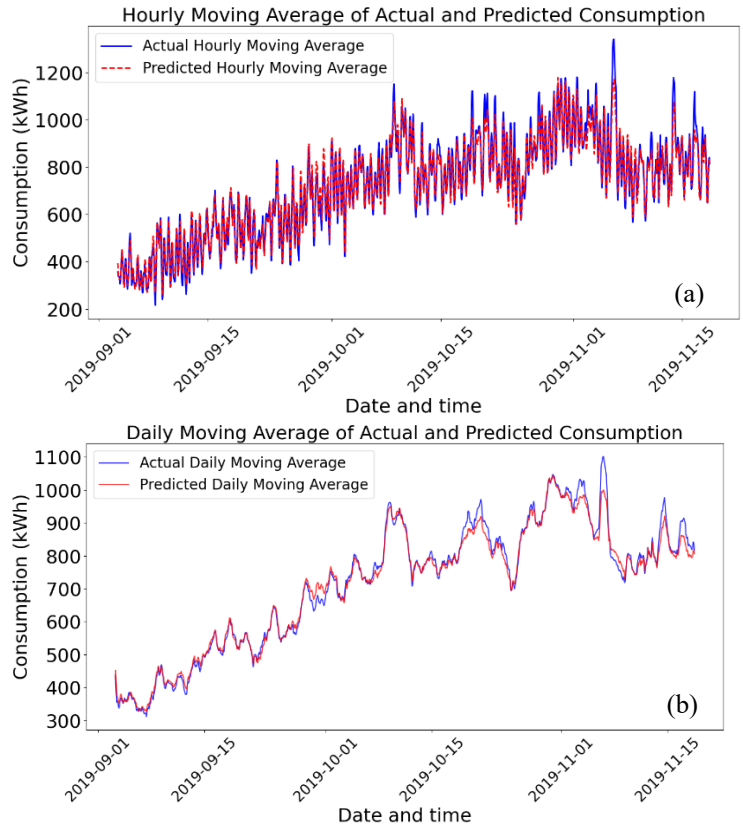


Fig. 3. Energy consumption vs date and time; a) hourly moving average, and b) daily moving average.

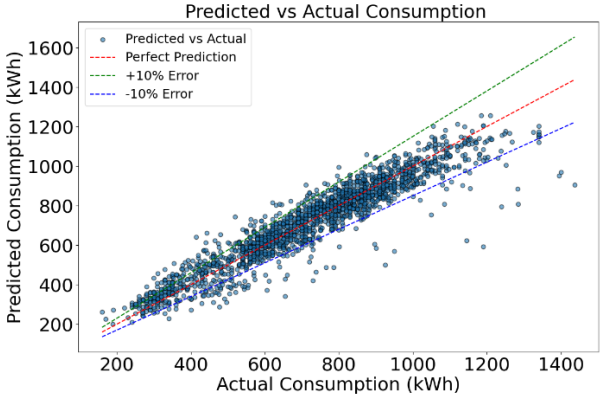


Fig 4. Predicted energy consumption vs actual consumption.

References

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[3] P.I. Frazier, INFORMS Tutorials in Operations Research (2018) 255–278.