Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Short-Term Load Forecasting for a Campus Building: Regression with Residual Correction and Gaussian Smoothing versus a Feedforward Neural Network

Al Hoqe Monfaredul Islam

monfaredul.islam@gmail.com

City College of New York https://orcid.org/0009-0007-2007-8090

Mario Ortiz

mario.ortiz@ccny.cuny.edu

City College of New York

Nafiul Miah

City College of New York

Method Article

Keywords: Building energy, Gaussian smoothing, load forecasting, neural networks, regression

Posted Date: November 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11571815/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Short-Term Load Forecasting for a Campus Building: Regression with Residual Correction and Gaussian Smoothing versus a Feedforward Neural Network

Al Hoqe Monfaredul Islam, Mario Ortez, Nafiul Mia
Department of Electrical Engineering, Grove School of Engineering, The City College of New York (CUNY)
160 Convent Avenue, New York, NY 10031, USA
alhoqe.islam92@stu-mail.ccny.cuny.edu, mario.ortiz62@stu-mail.ccny.cuny.edu, nafiul.mia@cuny.edu

***Abstract*—Accurate short-term load forecasting supports efficient operation and energy planning for large buildings, yet many campus facilities lack the data volume and expertise needed for complex models. This paper compares two hourly forecasting approaches for Shepard Hall at The City College of New York using metered load data from 2022 to January 2026. The first is a multiple linear regression model with daily and weekly lag features, an hourly mean-load feature, and weekend indicators, enhanced by hour- and day-type residual correction and a five-point Gaussian smoothing filter. The second is a two-hidden-layer feedforward neural network with 14 engineered temporal, calendar, and academic-schedule features, trained with recency-weighted loss and the Adam optimizer. On the test week of February 1–7, 2026, Gaussian smoothing reduced the regression mean squared error (MSE) by 46%, from 91.68 to 49.26 kW^2 (RMSE 7.02 kW), while the neural network achieved an MSE of 219.53 kW^2 (RMSE 14.82 kW). The results show that a simple, interpretable regression with targeted post-processing can outperform a deeper neural network for single-building forecasting with limited data.**

***Index Terms*—Building energy, Gaussian smoothing, load forecasting, neural networks, regression.**

I. Introduction

Short-term load forecasting (STLF) is central to power system operation and has been studied for decades [1, 2]. At the building level, forecasts support energy management, demand response, procurement, and peak reduction, but building loads are noisier and more strongly shaped by occupancy than system-level demand [3, 4].

Regression models and artificial neural networks (ANNs) are the two most common approaches to electricity demand forecasting, each with distinct advantages [5, 6]. Regression models are simple, fast, and interpretable, and with good feature engineering they remain competitive [4, 7]. Neural networks can capture nonlinear relationships but need more data and tuning, and they can overfit when training data are limited [6].

University buildings add a further challenge: demand depends on the academic calendar, with large drops during holidays and breaks. This paper presents a case study for Shepard Hall at The City College of New York (CCNY) and makes three contributions:

1. A lag-based regression model enhanced with hour- and day-type residual correction and five-point Gaussian smoothing, which together reduce forecast error by 46%.
2. A feedforward neural network using 14 engineered features, including an academic-calendar indicator, cyclical time encodings, and recency-weighted training.
3. A direct comparison on the same test week, with an analysis of where each model fails, showing that the simpler model performs better in this limited-data setting.

II. Data

Hourly total electricity consumption for Shepard Hall was obtained by summing the building's metered circuits, with timestamps converted to a standard format. Data from 2021 were excluded because consumption that year deviated strongly from later years, likely due to reduced campus occupancy during the COVID-19 pandemic. Data from 2022 through January 2026 were used for training, and the week of February 1–7, 2026 was held out for testing. CCNY's academic calendar was added as an external dataset to mark instructional days, holidays, and breaks.

III. Regression Model

A. Model Structure

The multiple linear regression model predicts load $\hat{y}(t)$ from past load and calendar features:

$$\hat{y}(t) = b_0 + b_1 y(t-24) + b_2 y(t-48) + b_3 y(t-168) + b_4 x_{\text{hour}}(t) + b_5 I_{\text{Sat}}(t) + b_6 I_{\text{Sun}}(t), \quad (1)$$

where $y(t-24)$, $y(t-48)$ and $y(t-168)$ are the loads one day, two days, and one week earlier; $x_{\text{hour}}(t)$ is the historical mean load for that hour; and I_{Sat}, I_{Sun} are weekend indicators. Lag terms capture daily and weekly cycles, the hourly mean captures the typical daily shape, and the indicators capture weekend reductions.

B. Parameter Estimation

Coefficients are estimated by least squares, minimizing

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2. \quad (2)$$

C. Residual Correction

Regression leaves systematic errors at certain hours and day types. The residual $e(t) = y(t) - \hat{y}(t)$ is averaged for each hour h and day type (weekday, Saturday, Sunday), and the average r_h is added to the forecast:

$$\hat{y}_{\text{corr}}(t) = \hat{y}(t) + r_h. \quad (3)$$

D. Gaussian Smoothing

Linear regression produces small oscillations around peaks and transitions. A five-point Gaussian-weighted filter reduces this noise while preserving the daily trend:

$$\hat{y}_k^s = \frac{1}{16}\left(\hat{y}_{k-2} + 4\hat{y}_{k-1} + 6\hat{y}_k + 4\hat{y}_{k+1} + \hat{y}_{k+2}\right). \tag{4}$$

Because MSE penalizes large errors heavily, reducing a few large peak deviations lowers overall error substantially. For example, if a peak of 420 kW is predicted as 390 kW, the squared error is 900 kW^2; smoothing the neighborhood [370, 410, 390, 430, 405] gives 404.7 kW, reducing the squared error to about 234 kW^2.

IV. Feedforward Neural Network

A. Features and Preprocessing

Fourteen input features were engineered: hour of day and day of year; indicators for weekends, Fridays, and regular weekdays; sine and cosine encodings of time to represent cyclic behavior; interaction terms between selected features; and a binary *isClass* indicator from the academic calendar. All inputs were normalized with Z-score scaling.

B. Architecture and Training

The network has two hidden layers with 180 and 90 neurons using tanh activation, and one linear output neuron:

$$A^{(1)} = \tanh\left(W^{(1)}X + b^{(1)}\right), \quad A^{(2)} = \tanh\left(W^{(2)}A^{(1)} + b^{(2)}\right),$$
$$\hat{Y} = W^{(3)}A^{(2)} + b^{(3)}. \tag{5}$$

Training minimizes a weighted MSE that gives recent years more importance:

$$L = \frac{1}{N}\sum_{i=1}^{N} w_i\left(\hat{y}_i - y_i\right)^2. \tag{6}$$

Gradients are computed by backpropagation, and parameters are updated with the Adam optimizer [8] with a decaying learning rate.

V. Results and Discussion

A. Regression Results

Without smoothing, the regression model follows the daily and weekly pattern but deviates at peaks and transitions (Fig. 1), with an MSE of 91.68 kW^2. Adding residual correction and Gaussian smoothing reduces the MSE to 49.26 kW^2 (Fig. 2), a 46% improvement. Peaks are slightly underestimated after smoothing, a trade-off that is acceptable given the overall gain.

B. Neural Network Results

The neural network captures the overall daily and weekly shape (Fig. 3) but reaches an MSE of 219.53 kW^2. Its largest errors occur on weekends, where it overestimates the baseline load (for example, February 1 and 8), and at weekday peaks, which it tends to underestimate. Predictions for Monday through Thursday are also very similar, indicating that the features do not distinguish well among weekdays.

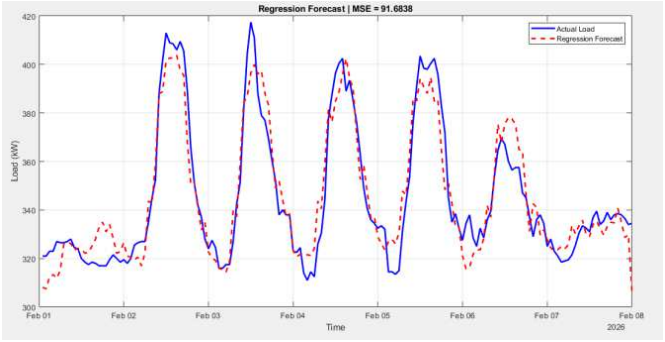


Figure 1. Regression forecast before Gaussian smoothing, February 1–7, 2026 (MSE = 91.68 kW^2).

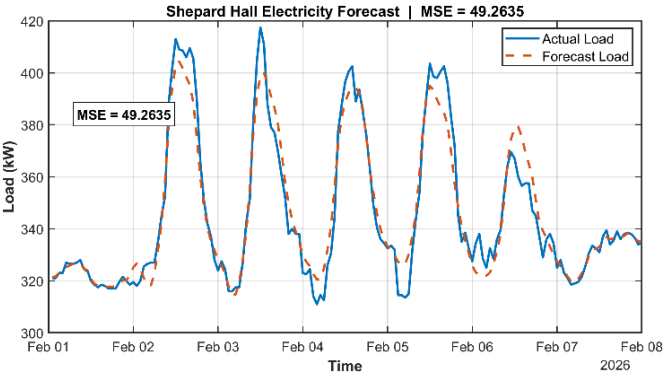


Figure 2. Regression forecast with residual correction and Gaussian smoothing (MSE = 49.26 kW^2).

C. Model Comparison

Table I summarizes performance on the same test week. RMSE is the square root of the reported MSE. The enhanced regression model achieves less than one quarter of the neural network's MSE. The lag features carry strong information about the building's repeating weekly pattern, and the residual correction removes systematic hour-of-day bias. The neural network, despite its flexibility, did not learn the weekend baseline accurately from the available data. These findings agree with earlier studies showing that well-engineered regression models remain competitive for building load forecasting [4].

D. Month-Ahead Forecast

The regression model was also used to forecast all of February 2026 recursively (Fig. 4). The forecast keeps clear daily and weekly cycles, but a gradual downward drift appears because each prediction feeds the next, so small errors accumulate over time.

E. Limitations

The evaluation covers one building and a single test week, and accuracy is reported as MSE and RMSE only. Weather and occupancy data were not included. Future work will test across multiple seasons, add percentage error metrics and a seasonal-naive baseline, and include temperature and occupancy inputs.

VI. Conclusion

This paper compared a regression model with residual correction and Gaussian smoothing against a feedforward neural net-

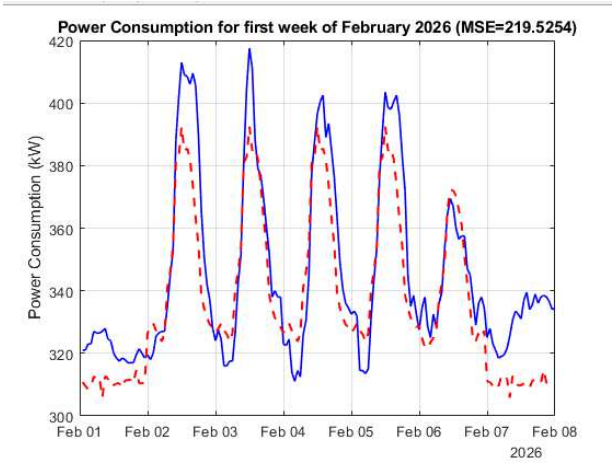


Figure 3. Neural network forecast versus measured load, February 1–7, 2026 (MSE = 219.53 kW^2).

Table I. Forecast Accuracy, February 1–7, 2026

Model	MSE (kW^2)	RMSE (kW)
Regression	91.68	9.58
Regression + correction + smoothing	**49.26**	**7.02**
Feedforward neural network	219.53	14.82

work for hourly load forecasting of a CCNY campus building. Smoothing and correction reduced regression error by 46%, to an RMSE of 7.02 kW, while the neural network reached 14.82 kW. For single buildings with limited data, a simple and interpretable model with targeted post-processing can outperform a more complex network. Future work will add weather and occupancy inputs, longer evaluation periods, and hybrid models that combine the strengths of both approaches.

Acknowledgment

The authors thank Professor Ahmed Mohammed of The City College of New York for his guidance and support throughout this work, and The City College of New York for providing Shepard Hall metering data.

References

[1] G. Gross and F. D. Galiana, "Short-term load forecasting," *Proc. IEEE*, vol. 75, no. 12, pp. 1558–1573, Dec. 1987.

[2] T. Hong and S. Fan, "Probabilistic electric load forecasting: A tutorial review," *Int. J. Forecasting*, vol. 32, no. 3, pp. 914–938, 2016.

[3] K. Amasyali and N. M. El-Gohary, "A review of data-driven building energy consumption prediction studies," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 1192–1205, 2018.

[4] B. Yildiz, J. I. Bilbao, and A. B. Sproul, "A review and analysis of regression and machine learning models on commercial building electricity load forecasting," *Renew. Sustain. Energy Rev.*, vol. 73, pp. 1104–1122, 2017.

[5] F. Kaytez, M. C. Taplamacioglu, E. Cam, and F. Hardalac, "Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines," *Int. J. Electr. Power Energy Syst.*, vol. 67, pp. 431–438, 2015.

[6] H. S. Hippert, C. E. Pedreira, and R. C. Souza, "Neural networks for short-term load forecasting: A review and evaluation," *IEEE Trans. Power Syst.*, vol. 16, no. 1, pp. 44–55, Feb. 2001.

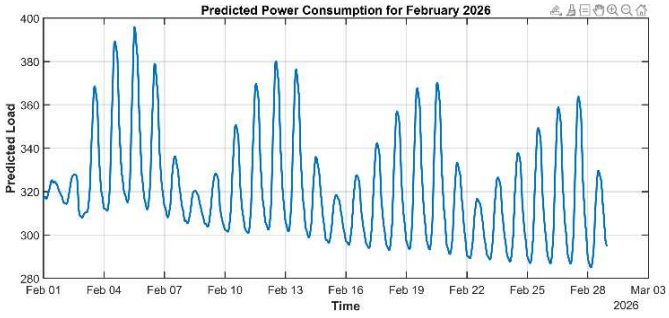


Figure 4. Recursive regression forecast for February 2026.

[7] R. Panigrahi, N. R. Patne, S. Pemmada, and A. D. Manchalwar, "Regression model-based hourly aggregated electricity demand prediction," *Energy Reports*, 2022.

[8] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015.