# Auto-Regressive and Neural Network Models for Weather-Informed Load Forecasts

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***Abstract*—In this paper, we propose auto-regressive and neural network models to forecast load profiles based on weather measurements without a need for manual calibration. The accuracy of the auto-regressive model is compared to the accuracy of the predictions of the neural network model with optimized parameters. The methods are compared using a test set of thirteen loads, each with hourly load time-series data and an additional data-set containing twenty weather features also sampled hourly. The results of the study show an average of a ten percent increase in accuracy when using the proposed auto-regressive model compared to the optimized neural network strategy.**

***Index Terms*—Auto-regression, load forecasting, neural network, weather measurements**

## I. Introduction

Accurate load forecasting is still a challenge for power system utilities and is required for decision-making in power systems including short-term planning and electricity markets, as well as long-term planning to improve the reliability and resiliency of the power systems. [1] There are different types of load forecasting including long-term load forecasting (LTLF), medium-term load forecasting (MTLF), short-term load forecasting (STLF), and extremely short-term load forecasting (VSTLF). Several forecasting techniques have been used for a variety of time domains, including knowledge base expert systems, some statistical techniques, and artificial intelligence (AI) techniques.

The Independent System Operator (ISO) creates thorough long-term projections of the demand for energy to improve power system planning, reliability of the grid, and operation procedures [2]. The ISO also projects the long-term increase of resources like distributed generation and energy efficiency, which impacts the planning. ISO forecasts the electricity grid conditions for that day-ahead and the week-ahead periods. The power system is impacted by weather, generation capacity, and peak demand over the course of the next seven days, according to a summary that ISOs release daily. The load forecast is required to identify capacity gaps, and it prompts the commitment of generators with start times longer than 24 hours. The 10-year forecasts for seasonal peak demand for electricity are included in the long-term load forecast. Forecasts are created by the ISO for the area, the state, and various zones. The forecast's several iterations consider peak demand and energy both before and after the effects of state-sponsored energy-efficiency initiatives predicted by the Energy-Efficiency Forecast and behind-the-meter photovoltaic (PV) predicted by the Distributed Generation Forecast.



As renewable energy becomes more prevalent in the grid, weather measurements have a larger impact on the grid's actual generation capacity. Therefore it is important to include weather measurements in load forecasting algorithms. In our previous work [3] we proposed a strategy for direct inclusion of weather measurements such as wind speed, cloud coverage, and temperatures in AC optimal power flow (OPF) mainly to consider the availability of renewable energy resources and their available capacities at each hour. In work [4] a strategy is proposed to identify wind and solar resource droughts in the United States and the renewable generation dispatch is validated in [5].

A neural network-based short-term load forecasting technique for power grids that takes into consideration the features of weather perception is proposed in [6]. A neural network model is created for load forecasting, which increases the precision and speed of load forecasting, using the comprehensive weather perception index and load data as input in [7], where the neural network framework fits various backpropagation training algorithms and a variety of activation functions to predict both short- and long-term power burden for the New York Independent System Operator (NYISO) power load forecasting.

Weather conditions such as radiation intensity and cloud coverage are features that closely relate to the output power of a PV system. The advancement of PV power station monitoring systems makes it possible to obtain a large amount of meteorological data and train an ultra-short-term power model based on meteorological data. The authors of [8] proposed an ultra-short-term power forecasting model based on auto-regressive moving average (ARIMA) and support vector regression (SVR) using actual monitoring data of the PV system. The results illustrate that in the forecasting of irradiance and temperature leads to a reasonable prediction and tracking effectiveness. In [8], four weather conditions were used to verify the accuracy of the ARIMA-SVR model.

Minimizing the forecast error is one of the ways utilities minimize revenue loss [9]. A large array of time series, statistical, expert systems, and artificial intelligence techniques have been developed in [10] to solve the load forecast problem. Reference [9] proposes a method of auto-regressive (AR) Burg in solving short-term load forecasting where the tested method is based on historical load data where the AR model burg is tested and compared with Durbin's Auto-regressive Moving Average (ARMA) for getting better performance. [11] In order to anticipate day-ahead electric load, autoregressive integrated moving average (ARIMA) and artificial neural networks (ANN) models were implemented as forecasting models for a dataset from a power utility to address the linear and nonlinear characteristics of electric load data. In [12], day-ahead and week-ahead load forecasting is made using a stacked bidirectional long short-term memory recurrent neural network technique that takes into consideration weather data.

In this paper, we propose auto-regressive and neural network models to forecast load profiles based on weather measurements without a need for manual calibration. The accuracy of the auto-regressive model is compared to the accuracy of the predictions of the neural network model with optimized parameters. The methods are compared using a test set of thirteen loads, each with hourly load time-series data and an additional data-set containing twenty weather features also sampled hourly.

## II. Data Analysis Model Description

### A. *Auto-regressive Modeling*

The auto-regressive load prediction model first takes steps to detrend and then normalize the input data. An example of the detrended data is shown in Fig. 1. Once the general trend of the data is known it is compared to the trends of various similar load profile types available for various types of residential, commercial, and industrial loads to find the closest approximation to the input load's profile. One of the load profiles that the input is compared to is shown in Fig. 2.

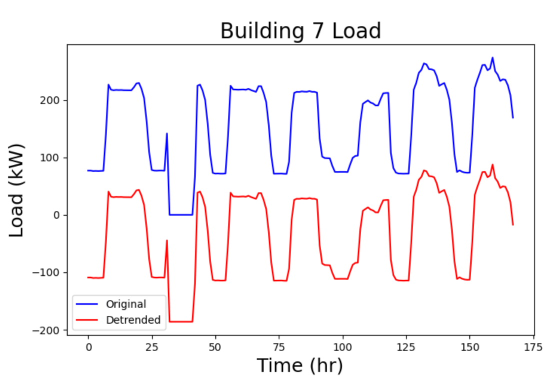


Fig. 1: Load profile of building 7 before and after detrending

If no reasonable match for the profile type is in the data-set the normalized detrended input is added as a profile and

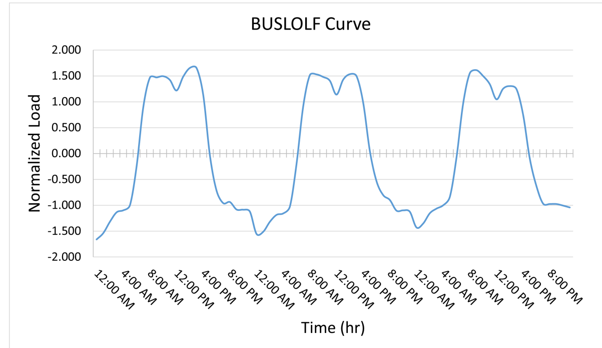


Fig. 2: Example of Load Profile Type used in Classification Business Low Load Factor Profile (BUSLOLF)

the values for the new profile are saved to the data-set. Once the input loads general profile is obtained the model is then loaded with the most appropriate batch size, window, and lag parameters to produce the most accurate results for the given profile type based on the available load data and the window of predicted data that is being generated. This process is outlined in its entirety in Fig. 3.

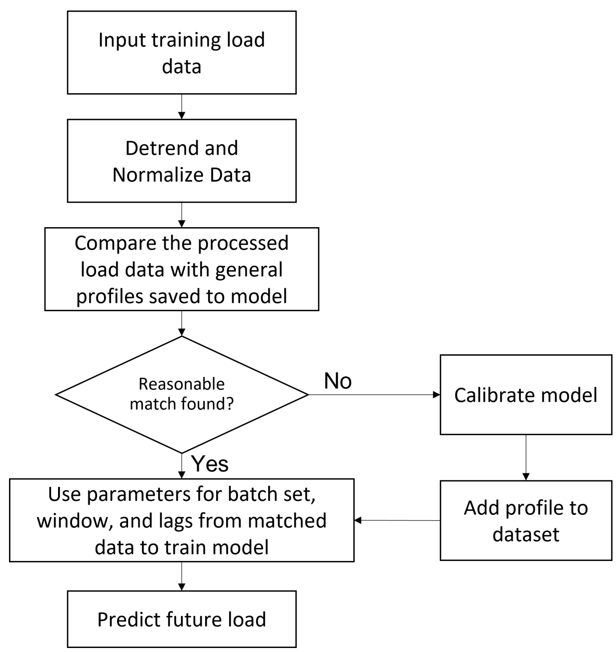


Fig. 3: Diagram of Auto-Regressive Prediction Process

Future loads are predicted using coefficients found by training the auto-regressive-model algorithm in the equation Eq. 1. Where $y_h$ is the predicted load, $x_i$ are the coefficients retrieved from the model, and $y_{N-i-1}$ is the historical load used based off of the window and lag parameters found from the general profile optimization step.

$$y_h = x_0 + \sum_{i=1}^{N} x_i * y_{N-i-1} \tag{1}$$

### B. Neural Network Modeling

The neural network methodology developed for this study begins with the twenty weather features from the original data-set the program then restricts the data-set to the weather features that most effect the eventual load prediction based on the general trends of the individual features. Once the most relevant features are ascertained the five layer neural network is then trained using the restricted data-set and the predictive load forecast is ascertained. The process is outlined by the diagram shown in Fig. 4

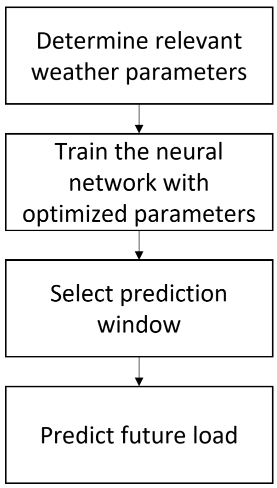


Fig. 4: Diagram of Neural Network Based Prediction Process

## III. Case Study

The input data-set for the case study included thirteen two year load profiles located in the Dallas area provided by the University of Texas at Dallas [13]. The two year profile period was from 01/01/2014-12/31/2015. For the case study load was predicted for a period of one year into the future for the thirteen buildings. Fig. 5 shows one week of the load profiles for the thirteen buildings used in the case study.

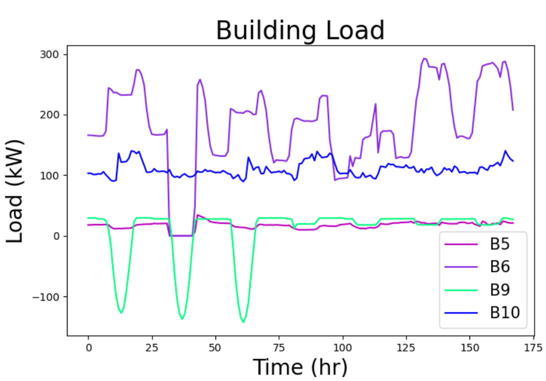


Fig. 5: Hourly Load for a few buildings used in the study

### A. Auto-regression

For the auto-regressive model the thirteen profiles were detrended and normalized as shown in Fig. 6

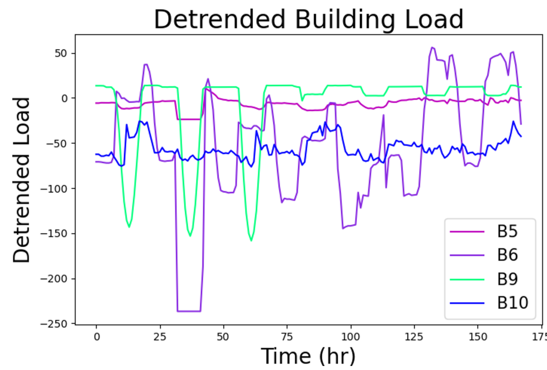


Fig. 6: Detrended Hourly Load for a few buildings used in the study

### B. Neural Network

For use in the Neural Network prediction algorithm the input data-set also contains weather data collected by the National Solar Radiation Database [14] for the same time period [13]. The weather data consisted of twenty features that could be used to predict the load for given weather conditions for the loads. The algorithm first sorts the available weather features to determine the most relevant when predicting load and then uses those most relevant features to train the neural network.

## IV. Results and Discussion

### A. Auto-regression

The augmented auto-regressive prediction algorithm was able to predict the load profile of each building in the study for a full year with a maximum RMSE of fifteen and a minimum RMSE of one. A chart showing the predicted and actual load profiles for one of the buildings in the study, for a one week period, is shown in Fig. 7. A chart tracking how the RMSE is effected by the batch size of the sampling for the same building referenced in Fig. 7 is shown in Fig. 8. The RMSE values for all thirteen load profile predictions in the study can be seen in Table I.

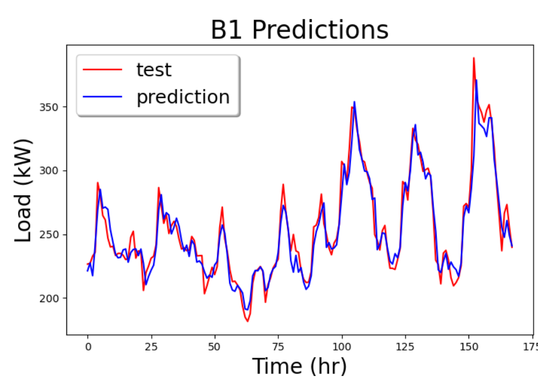


Fig. 7: Auto-regressive prediction for building B1

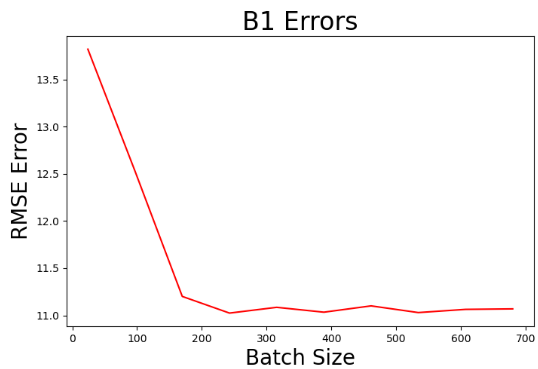


Fig. 8: RMSE Error for auto-regressive prediction at varied batch sizes

TABLE I: Error Rate Comparisons for Case Study

| | AutoReg RSME | Neural Network RSME | | AutoReg RSME | Neural Network RSME |
|---|---|---|---|---|---|
| B1 | 50.12 | 70.02 | B8 | 19.97 | 45.50 |
| B2 | 11.01 | 31.61 | B9 | 78.25 | 48.26 |
| B3 | 14.13 | 75.82 | B10 | 18.54 | 100.17 |
| B4 | 11.01 | 50.59 | B11 | 15.60 | 52.42 |
| B5 | 1.59 | 23.83 | B12 | 15.52 | 72.93 |
| B6 | 40.07 | 66.13 | B13 | 22.13 | 249.96 |
| B7 | 19.52 | 89.81 | | | |

The auto-regressive load prediction model shows an average of a ten percent decrease in RMSE when compared to an auto-regressive model that is not adapted for each input.

### B. Neural Network

The neural network algorithm first narrows down the list of features used in the network to those with the highest probability of being used to most accurately predict load. For the loads used in the case study four features were found to have the best accuracy for predictions. These features included temperature, humidity, pressure, and dew point.Once the appropriate features were isolated the neural network was trained and tested. The resulting predicted future load and loss function for one of the building is displayed in Figures 9 and 10.

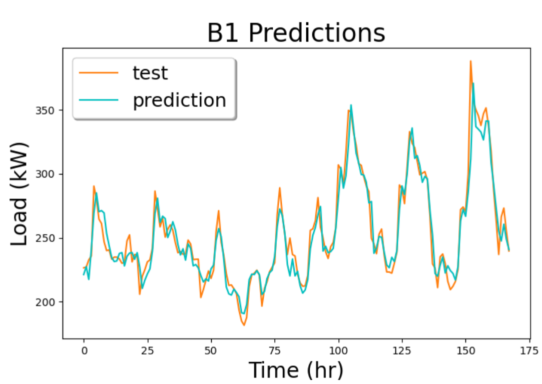


Fig. 9: Neural Network prediction for building B1

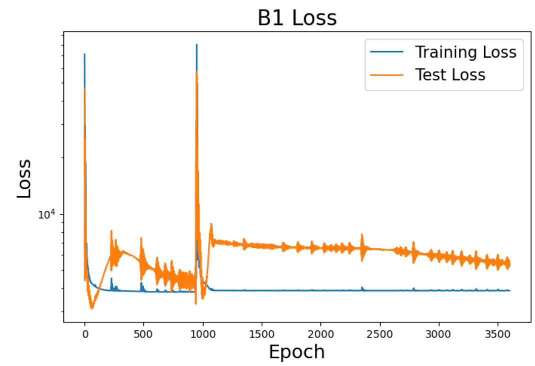


Fig. 10: Neural Network prediction for building B1

As shown in I the proposed auto-regressive model performs better than the neural network in a majority of cases.

## V. Conclusions

In this paper, we present auto-regressive and neural network models that are used to forecast load profiles using weather measurements without the need for manual calibration of the models. The proposed auto-regressive method for calibrating the neural network finds the minimum number of features required to have similar accuracy to the auto-regressive algorithm. The Auto-regressive model calibrates model parameters based on the building's load type. The accuracy of the models was then tested, using thirteen building load profiles and weather data containing twenty features, all with hourly data. The proposed auto-regressive load prediction model showed an average of a ten percent decrease in RMSE when compared to an auto-regressive model that is not adapted for each input. The improved auto-regressive model was able to adapt itself to a variety of different load types and create realistic predictions for future loads in both short and long-term planning. The optimized auto-regressive model also showed improvement when compared to the neural network model utilizing four of the twenty available weather features to train the network. The average difference in the RMSE is 50.73. Computationally the auto-regressive model also, performs faster than the neural network, allowing for larger system loads to be generated more quickly and accurately.

In future works, these models will be used to develop realistic load scenarios for studies of system reliability and resilience under a variety of predicted load and weather scenarios.

## References


[1] A. Azeem, I. Ismail, S. M. Jameel, and V. R. Harindran, "Electrical load forecasting models for different generation modalities: a review," *IEEE Access*, vol. 9, pp. 142 239–142 263, 2021.

[2] "ISO new england: System forecasting and load forecast". [Online]. Available: https://www.iso-ne.com/system-planning/system-forecasting

[3] T. J. Overbye, F. Safdarian, W. Trinh, Z. Mao, J. Snodgrass, and J. Yeo, "An approach for the direct inclusion of weather information in the power flow," in *Proc. 56th Hawaii International Conference on System Sciences (HICSS)*, 2023.

[4] J. L. Wert, F. Safdarian, A. Gonce, T. Chen, D. Cyr, and T. J. Overbye, “Wind resource drought identification methodology for improving electric grid resiliency,” 2023.

[5] J. L. Wert, T. Chen, F. Safdarian, J. Snodgrass, and T. J. Overbye, “Calculation and validation of weather-informed renewable generator capacities in the identification of renewable resource droughts,” 2023.

[6] F. Xu, W. Xu, Y. Qiu, M. Wu, R. Wang, Y. Li, P. Fan, and J. Yang, “A short-term load forecasting model based on neural network considering weather features,” in *2021 IEEE 4th International Conference on Automation, Electronics and Electrical Engineering (AUTEEE)*. IEEE, 2021, pp. 24–27.

[7] A. Nyandwi and D. Kumar, “Neural network approach to short and long term load forecasting using weather conditioning,” in *2020 International Conference on Electrical and Electronics Engineering (ICE3)*. IEEE, 2020, pp. 258–263.

[8] L. Zhou, H. Wu, T. Xu, F. Mei, Y. Li, X. Yuan, and H. Liu, “Ultra-short term hybrid power forecasting model for photovoltaic power station with meteorological monitoring data,” in *2017 32nd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, 2017, pp. 452–456.

[9] N. Kamel and Z. Baharudin, “Short term load forecast using burg autoregressive technique,” in *2007 International Conference on Intelligent and Advanced Systems*, 2007, pp. 912–916.

[10] S. A.-h. Soliman and A. M. Al-Kandari, *Electrical load forecasting: modeling and model construction*. Elsevier, 2010.

[11] L. C. P. Velasco, D. L. L. Polestico, G. P. O. Macasieb, M. B. V. Reyes, and F. B. Vasquez Jr, “Load forecasting using autoregressive integrated moving average and artificial neural network,” *International Journal of Advanced Computer Science and Applications*, vol. 9, no. 7, 2018.

[12] M. Zou, D. Fang, G. Harrison, and S. Djokic, “Weather based day-ahead and week-ahead load forecasting using deep recurrent neural network,” in *2019 IEEE 5th International forum on Research and Technology for Society and Industry (RTSI)*. IEEE, 2019, pp. 341–346.

[13] [Online]. Available: https://ieee-dataport.org/documents/short-term-load-forecasting-data-hierarchical-advanced-metering-infrastructure-and-weather

[14] “NSRDB: National Solar Radiation Database”. [Online]. Available: https://nsrdb.nrel.gov/data-viewer/