

Forecasting for smart energy: An accurate and efficient negative binomial additive model

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ABSTRACT

Smart energy requires accurate and efficient short-term electric load forecasting to enable efficient energy management and active real-time power control. Forecasting accuracy is influenced by the characteristics of electrical load particularly overdispersion, nonlinearity, autocorrelation and seasonal patterns. Although several fundamental forecasting methods have been proposed, accurate and efficient forecasting methods that can consider all electric load characteristics are still needed. Therefore, we propose a novel model for short-term electric load forecasting. The model adopts the negative binomial additive models (NBAM) for handling overdispersion and capturing the nonlinearity of electric load. To address the seasonality, the daily load pattern is classified into high, moderate, and low seasons, and the autocorrelation of load is modeled separately in each season. We also consider the efficiency of forecasting since the NBAM captures the behavior of predictors by smooth functions that are estimated via a scoring algorithm which has low computational demand. The proposed NBAM is applied to real-world data set from Jericho city, and its accuracy and efficiency outperform those of the other models used in this context.

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1. INTRODUCTION

Smart energy requires short-term forecasting for predicting the future load several hours ahead and for evaluating control strategies before putting them in use [1]. Thus, accurate and efficient forecasting is required to enable effective and timely decision making process. The accuracy of the load forecasting models is affected by electric load characteristics such as nonlinearity [2-5] high fluctuations [5, 6], autocorrelation and seasonal patterns [5, 7, 8]. The high fluctuation in electric load causes overdispersion expressed by a large variance value that is clearly larger than the mean [9]. Research states that electric load fluctuation depends on the life style, day time and location [10, 11]. Overdispersion reduces the accuracy if it is not handled properly, particularly in the short-term forecasting, because forecasting methods are sensitive to the fluctuation [12]. In the meantime, the efficiency of the forecasting methods is affected by the data size, and model's time complexity that determines the time needed for an algorithm to produce accurate results [9].

Although several short term forecasting models have been proposed, overdispersion has not been appropriately handled in these models. The statistical forecasting models such as regression based models and smoothing based models assume that the variance is equal to the mean [4, 7, 13], or they utilize distributions that ignore the high variations [14, 15]. In other models, the high variance in time series is treated to become homogeneous and stationary by Box-Cox and differentiating transformations which increase the computational demand [7]. In the artificial intelligence based models (e.g. [11, 16, 17]), considering the high variation costs

much computational time [18]. Therefore, this paper focuses on the problem of overdispersion, nonlinearity and temporal autocorrelation to increase the accuracy of forecasting models. Simultaneously, the paper aims to reduce the computational demand to increase the efficiency of the forecasting models.

This paper proposes a temporal Negative Binomial Additive Model (NBAM) to handle the overdispersion precisely. The temporal NBAM is nonparametric and capture nonlinearity via smoothing functions. To address the autocorrelation and seasonality, the daily load pattern is classified into low, moderate and high seasons in which the autocorrelation can be modeled separately. The proposed model is efficient because the method utilizes a low-complexity optimization technique to estimate the smoothing function. The proposed model is tested on real-world data set collected from Jericho city - Palestine, and its results are compared with other classical load forecasting models including ARIMA, ARMA, Holt-Winters (HW) and negative binomial linear model. The results show that the proposed temporal NBAM is more accurate than other models because its mean absolute percentage error (MAPE) is lower than the others. Also, the NBAM is more efficient because the computational time needed for training and forecasting is lower than the time of the other models. The negative binomial based models were successfully applied to forecasting traffic data that is autocorrelated, overdispersed and have seasonal patterns [19-22].

2. RESEARCH METHOD

This section proposes a method for forecasting electrical load which is nonlinear, overdispersed, and temporally autocorrelated. The proposed method adopts the Generalized Additive Models for handling nonlinearity and Negative Binomial for handling overdispersion, and then develops a temporal model for handling the temporal autocorrelation.

2.1. Generalized additive models (GAMs)

The GAMs focus on capturing the nonlinearity by permitting the correlating variables to have nonlinear relationship [23]. In GAMs, a response variable \mathbb{Y} has a mean value (μ) that is assumed dependent on predictors \mathbb{X} via a function which is nonlinear. The importance of the GAMs is generalizing the conventional additive models so that the response variable can fit into any distribution from the exponential family [23, 24]. Consequently, any GAM allows for more flexibility than parametric-based models. The mean μ of \mathbb{Y} , which is $\mu = E(\mathbb{Y} | \mathbb{X} = x)$ can be linked to some predictors by

$$G(\mu) = s_0 + s(x_i) + \varepsilon_i \quad (1)$$

where G indicates that the correlation is controlled by a link function, and s_0 is the overall mean or the intercept of \mathbb{Y} , x_i is the i^{th} records in a data set, $s(x_i)$ is a smooth function for the i^{th} record of the predictor \mathbb{X} , ε_i is the error which is independent of the predictors, and $\varepsilon_i \sim NID(0, \sigma^2)$, and σ^2 is the variance [23, 24]. The importance of the smooth function is that it can behave as the original data and it can catch nonlinearity. Smoothers estimate the smooth function by fitting the data of a predictor through developing a continuous curve that consists of multiple sections combined by knots [23]. Each curve contains a total number of sections z , and each section can have an equation such as the linear regression equation or the cubic polynomial equation. Each equation contains a base function and coefficients. The base function is used to generate the model matrix $\mathbf{X}_{n \times z}$, and the coefficients form the parameter matrix $\mathbf{M}_{z \times 1}$. Details on estimating the base functions and the model matrix \mathbf{X} are in [24]. The smooth function has a degree of smoothness parameter λ that decides the number of sections (z). λ is estimated in cross validation process such that the mean square error is minimized [23]. In GAMs, a local scoring algorithm is used to computationally estimate the smooth functions by maximizes a likelihood function as stated in [23, 24]. The scoring algorithm is chosen carefully so that the computational time is very low. Also, the generalized cross-sectional validation is used for avoiding overfitting of data [24].

2.2. Negative binomial additive model (NBAM)

The NBAM is a special case of the GAMs to overcome its main limitation which is only modeling data of exponential distribution [25]. Besides having nonlinear dependency, the response variable and the predictors may follow other distributions. For example, if overdispersion is found in the data, i.e. the variance $\sigma^2 > \mu$, the best distribution for describing that data will be the Negative Binomial [12]. In fact, a NBAM extends the GAM to treat the overdispersion by allowing \mathbb{Y} to have Negative Binomial distribution [25]. The Negative binomial distribution can accounts for the high fluctuations in the data by permitting the variance σ^2 of \mathbb{Y} to be

greater than the mean as $\sigma^2 = \mu + \varphi\mu^2$ where φ is the overdispersion parameter [12]. The negative binomial model for \mathbb{Y} given predictors \mathbb{X} is additively fit to data by choosing a natural log link function. The NBAM is written as

$$\log E(\mu) = s_0 + s(x_i) + \varepsilon_i \quad (2)$$

where a local scoring algorithm is used to train the smooth function iteratively by estimating φ and μ that maximize a log-likelihood function explained in [25].

2.3. Development of temporal NBAM

The NBAM can be applied to electric load by considering the temporal autocorrelation of the load. First, the electric load daily pattern is classified into three seasons, low, moderate and high seasons. In the data set shown in Figure 1, the seasons are: (1) a low load season from 02:00AM to 10:00AM (8 hours) and exists in the early morning when the load is less than the daily mean; (2) a high load season from 06:00PM to 01:00AM when the load is bigger than the daily mean (8 hours); (3) a moderate load season between 01:00AM-02:00AM and 10:00AM-06:00PM(9 hours) when the load is around the mean. Each season will have its own forecasting model. The benefit of this classification is allowing training each season individually, removing the outliers and decreasing the variability as the electric load is not fluctuating between the maximum load value and the minimum value during a single season.

Second, the temporal correlation is modelled for each season. We let $y_{i,t}$ be the response variable corresponding to the load measured from station i at time frame t . The temporal autocorrelation is considered by incorporating a one-step lag load of the dependent station as a predictor, i.e. $y_{i,t-1}$. Thus, the proposed temporal NBAM is expressed by

$$\ln y_{i,t} = \mu_i + s_i(y_{i,t-1}) + \varepsilon_t. \quad (3)$$

The lag values $y_{i,t-1}$ accounts for the electric load persistence, and it regularly updates the model with any change of the data trend. Equation 3 is for accommodating the smooth function to data based on the negative binomial distribution, and for computing the model matrix \mathbf{M} and the parameter matrix \mathbf{P} that are used in the forecasting process.

The estimation begins by selecting a dependent station, selecting the season based on the time, selecting the data belonging to the same season from historical data, and then starting the estimation of the smooth function of load for that station. The R *mgcv* package introduced in [24] is used for performing the analyses. This R package contains all libraries needed for smooth function estimation and forecast results generation. Forecasting by GAM models requires a data set (data for the season of interest), a model matrix \mathbf{M} and a model parameter matrix \mathbf{P} which are computed in the training stage [24].

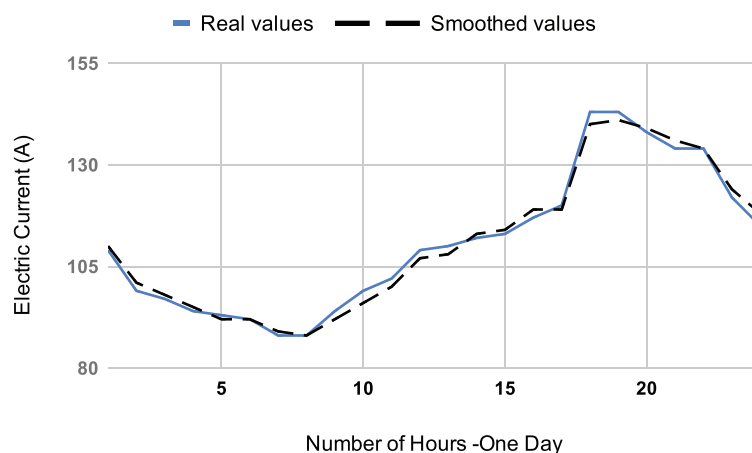


Figure 1. Single-day electric load and an example of the smooth function for the load in Aqabat Jaber station

2.4. Data set

A data set consisting of electrical current measured every hour from 15 stations was collected in Jericho city in the period between January to December in 2015. The total number of records collected from

each station is 4380 records. Figure 2 illustrates the electric load pattern for 17 consequent days. Before the analyses start, the invalid records such as missing values, negative values and zero values in the data set were treated. The number of the these records is less than (2%) per day which is very small and does not reduce the forecasting accuracy.

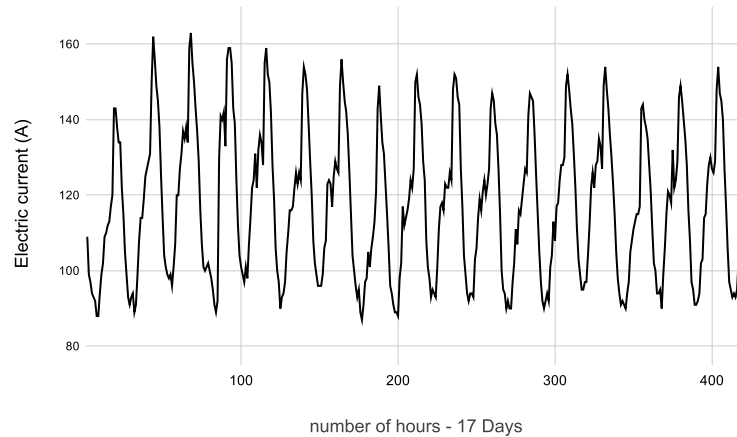


Figure 2. The load over 17 days from 13/Nov/2015 to 29/Nov/2015 in Aqabat Jaber station

The electric loads of the selected stations during 17 days are represented by time series. Figure 2 illustrates an example of the load time series during 17 days, while Figure 1 illustrates the load time series during a single day. The figures demonstrate that the load data have cyclic seasonal patterns that are repeated every day. Also, the electric load illustrated in Figure 2 and 1 is temporally autocorrelated, that is, the value of the load at any moment depends on the previous one.

The electric load has overdispersion because the variance of the load at each station is larger than the mean as shown in Table 1. The table shows the mean, the variance and the dispersion values for three stations during the low, moderate and high seasons. Overdispersion exists in the data if the dispersion value which is "the Pearson statistic (χ^2) divided by the degrees of freedom is larger than one" [12]. In the data set, all loads are overdispersed as the corresponding dispersion values shown in Table 1 are larger than one. The aforementioned characteristics are common among electrical networks locally and globally. The overdispersion of the load refers to the variations in the consumption of electric energy within the seasonal daily patterns. The variations depend on the place in the city (urban, industry, market), changing conditions of weather, time of the day, and life style.

Table 1. The statistical measures of four stations during the four load seasons

Area	Aqabat Jaber	Sea level 1	Sea level 2	Sea level 3
μ for high season	153.0	149.2	87.3	205.9
σ^2 for high season	168.1	181.4	127.7	327.5
dispersion for high season	2.4	2.3	2.5	2.8
μ for moderate season	125.7	127.6	68.3	189.3
σ^2 for moderate season	143.1	155.3	98.0	242.6
dispersion for moderate season	2.7	2.8	1.9	1.9
μ for low season	101.8	97.8	46.1	151.4
σ^2 for low season	117.2	152.6	77.3	197.0
dispersion for low season	1.9	2.5	1.7	2.0

3. RESULT AND DISCUSSION

This section shows the results of the proposed method which is the temporal NBAM. The section firstly shows how the method is trained, and then shows its accuracy and efficiency.

3.1. Training of the proposed temporal NBAM

The proposed NBAM is trained for the four stations in the data set, and ten-months data collected from January-2015 to October-2015 are used. The proposed model is trained separately for each load season such that the complete data set is divided to three data sets including a set for daily low season of eight hours length, a set for daily moderate season of seven hours length, and a set for daily high season of nine hours length. Therefore, each load season will have a different forecasting model. The result of the training process is described in Table 2 and Figure 1.

As shown in Table 2, the three load seasons have significant load autocorrelation because the P-value is smaller than the significance level. In our analyses, the statistical confidence interval is 95% and the significance level is 5%, similar to [10]. Table 2 shows the main statistical output of the NBAM when Aqabat Jaber is the response variable. The use of the Negative Binomial is justified because the values of φ are greater than zero as shown in Table 2. Also, the smooth function for the data in Aqabat Jaber station is plotted in Figure 1. The NBAM describes the real data with tiny differences which motivates us to use this model for forecasting.

Table 2. The main outputs of the NBAMs for the Aqabat Jaber station

	low season	Moderate season	high season
autocorrelation P-value	7×10^{-14}	2×10^{-14}	5×10^{-14}
Intercept (μ)	3.45	4.57	2.39
overdispersion φ	3.63	2.33	3.18
data size n	2432	2128	2736
z	41	38	33
size of M	2432×41	2128×38	2736×33

3.2. Forecasting accuracy

The NBAM utilizes the R *mgcv* package mainly the *predict* function. The proposed NBAM is evaluated during each load season using the models generated in the training stage. The smooth functions obtained from the training stage based on the coefficients shown in Table 2 is used to produce the Aqabat Jaber forecasts for multiple steps ahead, ranging from one hour to 24 hours.

The models used for comparison are trained as in [9]. These models are classical forecasting models and they are widely used in this field. The models are: the temporal NBLM [9], the Holt-Winters (HW) [26], Auto Regressive Integrated Moving Average (ARIMA) [14], and the Auto Regressive Moving Average (ARMA) method as in [7]. A single season for the HW, the ARMA and the ARIMA models is used because they are cyclic-based models and need a repeated pattern. The Mean Absolute Percentage Error (MAPE) is calculated to compare the accuracy of the models forecasting results, similar to [3, 10]. Table 3 shows the MAPE values of the five models for the selected stations during the three load seasons for a ten-hours horizon. To show the accuracy of the NBAM, the results of the models during the high load season are also presented in Figure 3.

Table 3. The MAPE values of different models for three electric stations during the three load seasons

load season	Method	MAPE % Aqabat Jaber	MAPE % sea level 1	MAPE % seas level 2
	NBAM	0.88	1.09	0.83
Low	Temporal NBLM	1.51	1.72	1.39
Load	HW	3.17	3.62	3.49
Season	ARMA	2.36	3.12	2.97
	ARIMA	6.27	5.09	4.24
	NBAM	2.38	1.97	2.11
Moderate	Temporal NBLM	3.57	1.95	2.77
Load	HW	5.24	3.29	4.33
Season	ARMA	4.77	2.83	3.91
	ARIMA	6.79	4.65	5.18
	NBAM	3.35	1.61	1.24
High	Temporal NBLM	4.62	2.12	2.61
Load	HW	5.87	3.68	4.36
Season	ARMA	5.29	3.63	3.61
	ARIMA	7.19	5.95	5.98

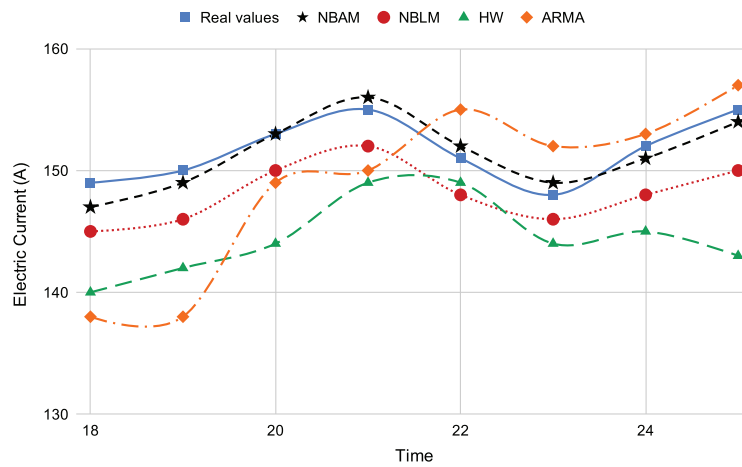


Figure 3. The forecasting of load for 10-hours horizon during the high load season in Aqabat Jaber station

The MAPE values of the NBAM are less than those of the temporal NBLM, the HW, the ARMA and the ARIMA which concludes that the NBAM is more accurate than the others. Also, Figure 3 emphasizes that the NBAM has better accuracy than the other models. The temporal NBLM handles the overdispersion but its structure contains a regression which incorporates few correlating hours from the recent past. On the contrary, the NBAM captures the entire trend and pattern because its structure contains a smooth function that behaves exactly the same as the real data. We find that the smooth function of the NBAM performs better than the temporal correlation with the previous five hours as in NBLM. Classifying the load into three different seasons, the variance is ensured to be lower than the variance of the entire daily season, as in Table 1. Thus, the forecast accuracy is increased.

3.3. Forecasting efficiency

To measure the efficiency of the proposed NBAM, the computational time during the training and forecasting stages is recorded. More focus is given to the high load season since this season has the largest data size which is 2736. As in [9], the model is tested on Intel CPU of 2.8 GHz, 64-bit operating system and 16GB RAM. The NBAM is found faster than the other models during training for producing the smooth functions, and during the forecasting, as presented in Table 4. The NBAM efficiency also outperforms the other models during the forecasting and the training stages. The reason behind the low computational time is that the smooth function is optimized using regression spline where each section coefficients are computed by minimizing the mean square error.

Table 4. The computation time of the models during the training and forecasting stages

Model	Training (sec)	Forecasting (sec)
NBAM	1.69	0.08
NBLM	2.124	0.26
ARMA	5.94	3.19
ARIMA	6.82	4.78
HW	6.38	0.86

4. CONCLUSION

Nonlinearity, overdispersion, temporal autocorrelation and seasonality are important characteristics of Electrical load. These characteristics have dramatic effect on the forecasting accuracy and efficiency, and they requires careful handling during developing a forecasting model. Therefore, this paper adopted the NBAM because of its ability to handle nonlinearity and overdispersion. A temporal NBAM was derived by allowing the current electrical load to autocorrelate with previous loads. Also, In the proposed model, the seasonal patterns of the electric load is classified into low, moderate and high load patterns. The future work will include applying the developed NBAM to a real time electrical load monitoring system in Palestine.

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