WIND ENERGY FORECASTS IN CALCULATION OF EXPECTED ENERGY NOT SERVED

By

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AUTHOR'S DECLARATION FOR ELECTRONIC SUBMISSION OF A THESIS

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ABSTRACT

The stochastic nature of wind energy generation introduces uncertainties and risk in generation schedules computed using optimal power flow (OPF). This risk is quantified as expected energy not served (EENS) and computed via an error distribution found for each hourly forecast. This thesis produces an accurate method of estimating EENS that is also suitable for real-time OPF calculation.

This thesis examines two statistical predictive models used to forecast hourly production of wind energy generators (WEGs), Markov chain model, and auto-regressive moving-average (ARMA) model, and their effects on EENS. Persistence model is used as a benchmark for comparison. For persistence and ARMA models, both Gaussian and Cauchy error distributions are used to compute EENS via a closed-form solution that reduces computational complexity..

Markov chain and ARMA both provide accurate forecasts of WEG power generation though Markov Chain model performs significantly better. The Markov chain model also produces the most accurate EENS estimate of the three models.

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General Terminology

$\hat{X}_t$: a time series of the forecasted wind energy generation.

X_t: a time series of the actual wind energy generation.

PG_t: A random variable that describes WEG generation at time t.

n: the number of elements within the training data.

m: the number of elements within the validation data.

$PG_{nominal}$: nominal wind power. For this case it is the maximum wind power a generator is capable of outputting.

$\overline{\overline{PG_t}}$: the forecasted power generation of a WEG at time t.

β: the PDF scale parameter in the general case.

PG_{sched}: the power generation scheduled for a given point of time.

Δt: the time interval used between forecasts. For this case it is one hour.

Markov Chain Model Terminology
N: the number of states used in the Markov chain model

S_i: the i^{th} state of a Markov chain

P_i: the amount of power generation that corresponds to the i^{th} state of a Markov chain

$\mathbf{P}(t_h)$: the first-order Markov chain transition matrix

$\hat{\boldsymbol{P}}(t_h)$: the estimate of the first-order Markov chain transition matrix

$p_{ij}(t_h)$: the generic element of $\mathbf{P}(t_h)$

$p_i(t_h)$: the generic column of $\mathbf{P}(t_h)$

$p_j(t_h)$: the generic row of $\mathbf{P}(t_h)$

ARMA Model Terminology
$ARMA(p,q)$: an ARMA process with orders p and q

p: the order of the auto-regressive part of an ARMA process

q: the order of the moving-average part of an ARMA process

a_j: the coefficients of the auto-regressive part of an ARMA process

b_k: the coefficients of the moving-average part of an ARMA process

List of Abbreviations

WEG: Wind Energy Generator

OPF: Optimal Power Flow

AENS: Actual Energy Not Served

EENS: Expected Energy Not Served

PDF: Probability Distribution Function

ARMA: Autoregressive-moving average

ANN: Artificial Neural Network

NRMSE: Normalized Root-Mean-Square

1. INTRODUCTION

1.1. Introduction

When wind energy generators (WEGs) are incorporated into the power supply mix, the uncertainties associated with wind energy increases the risk of power shortages and failure to supply a contracted load. This risk is also carried into determining optimal power flow (OPF) and is quantified by expected energy not served (EENS). EENS is an estimate of actual energy not served (AENS) which is the actual energy shortfall of a WEG at a given point in time. At any given time, a certain amount of power generation is scheduled from every WEG which is denoted here as PG_{sched}. EENS is the expected energy shortfall from the scheduled power. This shortfall is probabilistic because of the stochastic nature of wind energy and the uncertainties of the wind energy forecast.

Having an accurate forecast of WEG output and being able to calculate EENS in a timely fashion is very important for estimating the costs associated with uncertainties from WEGs as they become a larger part of the power grid.

1.2. Survey of Recent Work in WEG Forecasting and EENS

In the past, Monte Carlo simulation has been used to stochastically model WEG integration to the grid and to estimate the costs associated with the uncertainty introduced by the WEGs as in [1]. Ref. [2] uses Monte Carlo simulation in conjunction with OPF to maximize social welfare as it pertains to uncertainties in WEG generation. Ref. [3] uses Monte Carlo simulation to stochastically model locational marginal prices (LMP) and examine the effect that the introduction of WEG has on LMP. Monte Carlo simulation however, can be very taxing computationally, especially in systems with large numbers of WEGs as it scales exponentially with the number of buses in the system. Alternative ways of quantifying EENS have been developed for OPF as a result. Ref. [4] introduces a triangular-approximation for modeling WEG for OPF. Approximating the probability distribution of WEG generation effectively linearizes it, making it readily usable with OPF and does not require time-consuming Monte Carlo simulation. Thus, the method introduced in [4] is suitable for real-time OPF applications where the methods using Monte Carlo simulation are not. One shortcoming of this method however is that it uses an estimate of the WEG forecast's PDF and thus the accuracy of EENS estimation will suffer.

1.3. Objective

The main motivation of this thesis is to develop a methodology to estimate EENS from a predictive model that is suitable for real-time OPF. The relative accuracy of two statistical-only predictive models, autoregressive-moving-average (ARMA), and Markov chain as well as their effect on EENS calculations will also be examined. The effects of using Gaussian error distributions and Cauchy distributions to calculate EENS will also be analyzed.

This thesis will develop a way of estimating EENS using closed-form or pseudo-closed-form equations for EENS calculations. This will produce a more accurate estimate of EENS than in [4] because it dispenses with the approximation and will also be suited for real-time OPF applications.

1.4. Chapter-wise Introduction

Chapter 2:

Chapter 2 discusses the background of WEG forecasting and introduces the two models that are to be studied, Markov chain and ARMA as well as persistence model which is to be used as a benchmark. Background and calculation of EENS is discussed in the general case. For each model, the forecasting mechanism is explored in detail as well as the method by which a PDF is derived for EENS calculation. Finally, calculation of EENS is discussed for each model.

Chapter 3:

Chapter 3 presents the simulation results for each model. The accuracy of the forecast produced by each model is evaluated. The EENS estimated by each model is also examined and evaluated. Three case studies are considered: Amaranth wind farm, Wolfe Island wind farm, and ERCOT system-wide.

Chapter 4:

Chapter 4 presents the conclusions that can be drawn from this work. Recommendations for which model and PDF should be used for EENS estimation are given based on the results presented in chapter 3. The main contributions and relevance of this work are also discussed.

1.5. Chapter Summary

This chapter presents an introduction to the topic, motivation and objective of this thesis. It is followed by a chapter-wise summary.

2. THEORY

EENS is calculated from a probability distribution of the error in the forecasted WEG output. Thus, in order to determine EENS, two things are required: a forecast for wind energy output, and an error distribution of the forecast. The forecast for wind energy output at time *t* is denoted by $\hat{X}_t$. X_t is the actual wind energy generation of the next time step at time *t* and is used to determine the accuracy of the forecast. This thesis will explore three different predictive models for forecasting WEG output as well as methods of deriving a probability distribution of the error so that EENS can be calculated.

There are two main categories of predictive models for wind power generation: physical and statistical. Physical models consider physical variables such as wind speed, temperature, atmospheric conditions, etc. Statistical models do not consider any physical variables and instead use time-series analysis of historical wind power generation data. Statistical models have the advantage of being computationally simpler as well as being easier to implement than physical models.

Two predictive models will be explored, Markov chain, and ARMA. Markov chain and ARMA model were chosen for their accuracy on shorter time horizons as well as the advantages afforded by the fact that they are purely statistical models[5][6]. The Markov chain model in particular produces a very accurate probability density function for the forecasting error which is very useful in calculating EENS[6]. These two models will be used to generate forecasts for WEG outputs on the one-hour-ahead timescale. A third model, persistence model, will also be used as a benchmark for the first two. ARMA and Markov chain models have been compared and evaluated in the past for their forecasting ability but their respective effects on EENS have not [7].

An artificial neural network (ANN) is another statistical-only model that as become an increasingly popular method of forecasting WEG generation. ANNs are models that are so-named because they attempt to mimic the structure and functionality of animal brains. Adaptive weights are used to conceptualize the relative strengths of the connections within the network. They are trained by a training data set and used in prediction.

ANNs can be generally classified as feed-forward or feedback [8]. Feed-forward ANNs are more common in WEG forecasting and include backpropagation and radial bases function [9]. Backpropagation refers to the error of the ANN which is backpropagated through the network so that the weights can be updated in order to minimize future errors [10].

ANNs are capable of producing a point-forecast and associated probability distribution that is suitable for EENS estimation but will not be discussed in detail within this work. However, the method of estimating EENS from a forecasting model established in this work can be used with ANNs as well as other statistical models.

The next step in calculating EENS is to generate a probability distribution for these forecasts. In the case of the Markov chain model, a probability distribution will be created by the model itself for each forecast. In the case of persistence and ARMA, the probability distribution is modeled by a Gaussian or a Cauchy distribution. The scale parameters for each distribution will be determined by historical data.

There are several statistical distributions that can be used to model the error distribution of wind power generation point forecasts. As discussed previously, the forecast must be able to generate a probability distribution for a given time in order for EENS to be calculated. [11] provides a method for calculating EENS using a Weibull distribution for wind speed. Gaussian and Cauchy distributions will be utilized in this thesis and they will be fitted to WEG output generation as opposed to wind speed. For shorter time-steps, on the order of 1 hour, a Cauchy distribution will often provide a better fit than Gaussian distribution. This is a result of the excess kurtosis exhibited by the observed error distribution of wind energy forecasts. The observed error distributions have higher peaks and shorter tails than the fitted Gaussian has and are closer in appearance to Cauchy distributions. In many instances however, the central-limit theorem can be invoked to justify the use of a Gaussian distribution.

2.1. EENS Overview

The EENS of the WEG is the amount of energy that is expected to be less than the scheduled generation PG_{sched} based on the probability distribution of the forecast error. In the general case, EENS can be calculated from:

$$EENS = \int_0^{PG_{sched}} (PG_{sched} - PG) \cdot PDF(\overline{\overline{PG}}, \beta) dPG \tag{2.3.1}$$

$PDF(\overline{\overline{PG}}, \beta)$ in equation (2.3.1) above differs depending on the PDF being used. The Gaussian and Cauchy distributions each have a location parameter and a scale parameter which are denoted in the general case by $\overline{\overline{PG}}$ and β, respectively. In both Gaussian and Cauchy distributions the location parameter is $\overline{\overline{PG}}$. The scale parameter for the Gaussian distribution is σ^2 and the scale parameter for the Cauchy distribution is γ. The location parameter $\overline{\overline{PG}}$ is the point forecast produced by the forecasting model. The scale parameters are produced by the forecasting model using the training data. These two parameters are required for EENS to be calculated. The specifics of determining the location and scale parameters and calculating EENS from it in the case of Gaussian and Cauchy distributions will be described in detail in section 2.2.3, and 2.2.4, respectively.

In the case of the Markov chain model, the model produces a discrete PDF which is immediately suitable for EENS calculation. The specifics of producing the PDF in the this case and calculating EENS from it will be described in detail in sections 2.3.3, and 2.3.4, respectively.

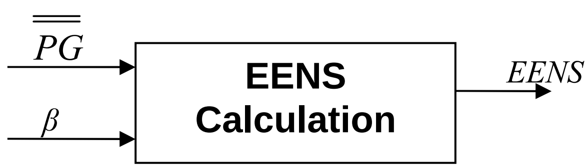

Figure 2.1.1: Diagram of the EENS calculator

Figure 2.1.1 shows a visual representation of the method outlined in this section. The "EENS Calculation" box represents equation 2.3.1. It can be seen from figure 2.1.1 that EENS is a function of $\overline{\overline{PG}}$ and β both of which are produced by the forecasting model.

2.2. Persistence Model (Used as a benchmark)

2.2.1. Theoretical Background

The persistence model assumes that the wind generation at the next hour is equal to the generation at the current hour. The forecasted generation at the next time step can be given by [12]:

$$\hat{X}_t = X_{t-1} \tag{2.2.1.1}$$

For very short time-steps (on the order of minutes) persistence provides a very accurate forecast and is in fact difficult to improve upon. For short time-steps (on the order of an hour) it still provides an adequate forecast. This is because there is high correlation between wind speeds[3], that is, wind speed does not change much from hour to hour and even less so from minute to minute.

Because persistence is very simple and easy to implement, it is often used as a benchmark to compare with other forecasting models. Other forecasting models must be able to outperform persistence to be viable.

2.2.2. Methodology

As seen in equation (2.2.1.1), the forecasted generation $\hat{X}_t$ at time t is given by the actual generation of the previous time step, X_{t-1}. The probability density function (PDF) of the forecasting error gives the probability distribution of forecasted power generation $\hat{X}_t$ at the next time step.

2.2.3. Probability Density Function

As noted previously, a probability distribution of a given point forecast's error (error PDF) is required for EENS calculation. In the case of the persistence and ARMA model, the error PDF is assumed to be either a Gaussian distribution or a Cauchy distribution.

Two parameters must be determined to construct the error PDF: a location parameter, and a scale parameter. The location parameter is the forecast at the current time step in both cases. The scale parameter is σ^2 for the Gaussian distribution and γ is the scale parameter for the Cauchy distribution. EENS is a calculated as a function of this location parameter, and scale parameter.

Gaussian: For a Gaussian distribution, the PDF is given by:

$$PDF_G(PG_t) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(PG_t - \overline{\overline{PG_t}})}{2\sigma^2} \right) \qquad (2.2.3.1)$$

PG_t ranges from 0 to $PG_{nominal}$. $\overline{\overline{PG_t}}$ is the forecasted generation of the current time step. It is the mean of the Gaussian distribution and the location parameter of the Cauchy distribution. Thus, it is given by:

$$\overline{\overline{PG_t}} = \hat{X}_t \qquad (2.2.3.2)$$

$\hat{X}_t$ can be found from equation (2.2.1.1).

σ^2 is the scale parameter of the Gaussian distribution and also the variance of the difference between the forecasted generation and the actual generation at each time step during the training data period. σ^2 is given by:

$$\sigma^2 \frac{1}{n} \sum_{t=1}^{n} \left(Y_t - \hat{\hat{Y}}_t \right)^2 \qquad (2.2.3.3)$$

Where n is the number of elements in the training data, Y_t is a time series of training data and $\hat{Y}_t$ is a time series of the prediction of the training data.

Cauchy: In the case of a Cauchy distribution, the PDF is given by:

$$PDF_C(PG_t) = \frac{1}{\pi\gamma \left[1 + \left(\frac{PG_t - \overline{\overline{PG_t}}}{\gamma} \right)^2 \right]} \qquad (2.2.3.4)$$

γ is selected to be half of the interquartile range of the Gaussian distribution and is thus given by:

$$\gamma = 0.6745\sigma \qquad (2.2.3.5)$$

With the location parameter $\overline{\overline{PG_t}}$, and the scale parameters σ^2 and γ for Gaussian and Cauchy respectively, EENS can be calculated.

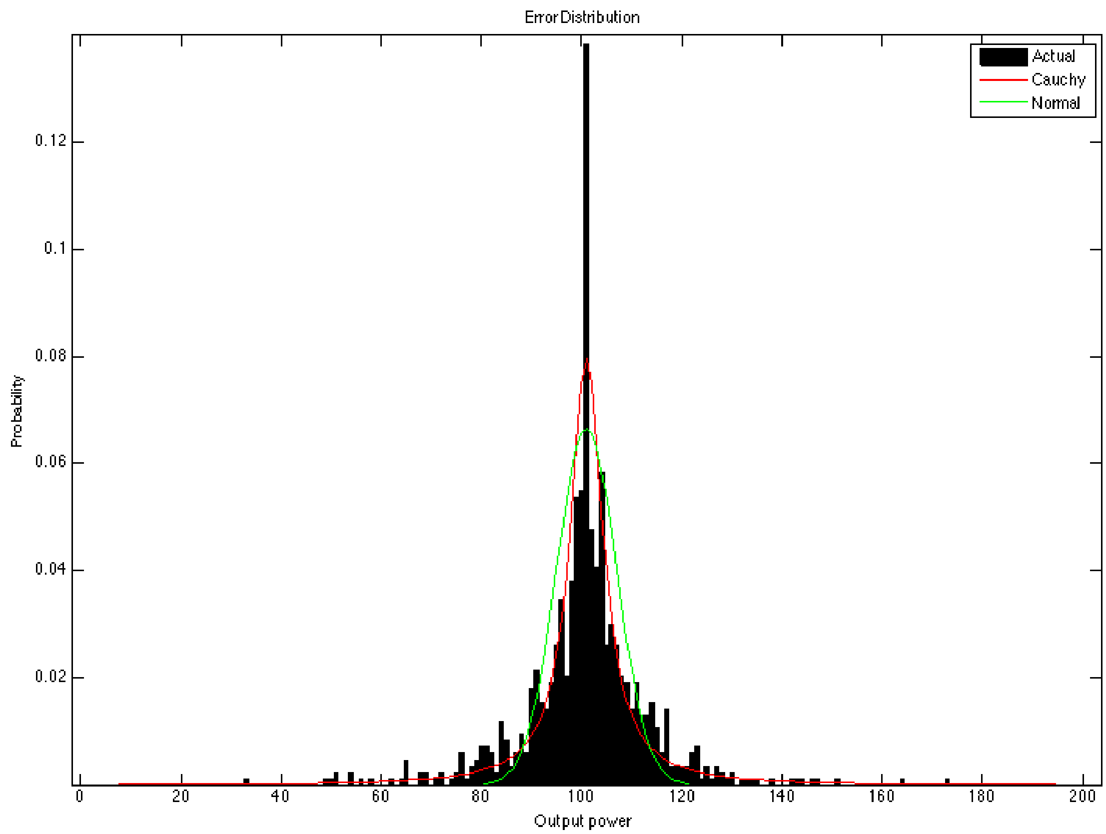

Figure 2.2.3.1: Forecasting Error Probability Density Function

Figure 1 shows the actual error distribution determined from a persistence model over the training data period. A Gaussian and Cauchy distribution based on a forecast of $\overline{\overline{PG_t}}$ at 100MW is overlayed on it. A bin size is chosen such that the number of bins is larger than the minimum prescribed by Scott's normal reference rule. The data comes from 3960 hours of wind generation data from the Amaranth wind farm.

2.2.4. Calculating EENS

As discussed previously, in the case of persistence and ARMA models, Gaussian and Cauchy distributions are used to fit the probability density functions of the forecast and to calculate EENS.

Gaussian: A solution for EENS calculated with a Gaussian distribution at a given PG_{sched} is derived below:

$$EENS_G = \frac{1}{\sqrt{2\pi\sigma^2}} \int_0^{PG_{sched}} \left(PG_{sched} - \overline{\overline{PG}} \right) e^{-\frac{(PG-\overline{\overline{PG}})^2}{2\sigma^2}} dPG$$

$$EENS_G = \frac{PG_{sched}}{\sqrt{2\pi\sigma^2}} \int_0^{PG_{sched}} e^{-\frac{(PG-\overline{\overline{PG}})^2}{2\sigma^2}} dPG - \tag{2.2.4.1}$$

$$\frac{1}{\sqrt{2\pi\sigma^2}} \int_0^{PG_{sched}} PG \cdot e^{-\frac{(PG-\overline{\overline{PG}})^2}{2\sigma^2}} dPG \tag{2.2.4.2}$$

Solving equation (2.2.4.1):

$$\frac{PG_{sched}}{2} \left[1 + erf \frac{\left(PG - \overline{\overline{PG}} \right)}{2\sigma^2} \right] \tag{2.2.4.3}$$

Where

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t} dx$$

Solving equation (2.2.4.2) with integration by parts:

let $a = \dfrac{1}{2\sigma^2}$, and $c = \dfrac{1}{\sqrt{2\pi\sigma^2}}$

$$u = ce^{-a\overline{\overline{PG}}^2} e^{-aPG^2}, \quad du = 2ac\overline{\overline{PG}}e^{-a\overline{\overline{PG}}^2}$$

$$dv = xe^{-aPG^2}, \qquad v = -\frac{1}{2a}e^{-aPG^2}$$

$$(2.2.4.2) = uv - \int v \cdot dv$$

$$(2.2.4.2) = -ce^{-a\left(PG_{sched} - \overline{\overline{PG}}\right)^2} - \overline{\overline{PG}}\int_0^{PG_{sched}} e^{-aPG^2} e^{2a\overline{\overline{PGPG}}} e^{-a\overline{\overline{PG}}^2} dPG$$

$$(2.2.4.2) = -ce^{-a\left(PG_{sched} - \overline{\overline{PG}}\right)^2} + a\overline{\overline{PG}}\left[1 + erf\left(aPG_{sched} - \overline{\overline{PG}}\right)\right] \qquad (2.2.4.4)$$

Thus, EENS is given by:

$$EENS_G = \frac{1}{\sqrt{2\pi\sigma^2}} \frac{e^{-\left(PG_{sched} - \overline{\overline{PG}}\right)^2}}{2\sigma^2} + \left(\frac{PG_{sched}}{2} - \frac{\overline{\overline{PG}}}{2\sigma^2}\right)$$

$$erf\left(\frac{PG_{sched} - \overline{\overline{PG}}}{2}\sigma^2\right) + \frac{PG_{sched}}{2} - \frac{\overline{\overline{PG}}}{2}\sigma^2 \qquad (2.2.4.5)$$

Here, $\overline{\overline{PG}}$, and σ^2 are given by equations (2.2.3.2), and (2.2.3.3), respectively.

A closed-form solution does not exist for the Gaussian because of the presence of the error function in the formulation as seen in equation (2.2.1.1). However, a number of closed-form approximations of the error function exist and a suitable one can be utilized. Numerical methods and look-up tables are also available.

Cauchy: A solution for EENS calculated with a Cauchy distribution at a given PG_{sched} is derived below:

$$EEENS_C = \int_0^{PG_{sched}} \left(PG_{sched} - PG\right) \frac{1}{\pi\gamma\left[1 + \frac{PG - \overline{\overline{PG}}}{\gamma}\right]} dPG$$

$$EENS_C = \frac{PG_{sched}}{\pi\gamma} \int_0^{PG_{sched}} \frac{1}{1 + \frac{PG - \overline{\overline{PG}}}{\gamma}} dPG - \tag{2.2.4.6}$$

$$\frac{1}{\sqrt{2\pi\sigma^2}} \int_0^{PG_{sched}} \frac{PG}{1 + \frac{PG - \overline{\overline{PG}}}{\gamma}} dPG \tag{2.2.4.7}$$

Solving equation (2.2.4.6):

$$(2.2.4.6) = PG_{sched}\left[\frac{1}{\pi}\tan^{-1}\left(\frac{PG - \overline{\overline{PG}}}{\gamma}\right) + \frac{1}{2}\right] \tag{2.2.4.8}$$

Solving equation (2.2.4.7) with integration by parts:

Finding the integration constant C. At $PG_{sched} = 0$, $EENS = 0$.

$$0 = -\frac{\overline{\overline{PG}}}{\pi}\tan^{-1}\left(-\frac{\overline{\overline{PG}}}{\gamma}\right) - \ln\left|\overline{\overline{PG^2}} + \gamma^2\right| - C$$

$$C = -\frac{\overline{\overline{PG}}}{\pi}\tan^{-1}\left(-\frac{\overline{\overline{PG}}}{\gamma}\right) - \ln\left|\overline{\overline{PG^2}} + \gamma^2\right|$$

Thus, EENS is given by:

$$E_C = \frac{PG_{sched} - \overline{\overline{PG}}}{\pi}\tan^{-1}\left(PG_{sched} - \overline{\overline{PG}}\right) - \frac{\gamma}{2\pi}\ln\left|\left(\frac{PG_{sched} - \overline{\overline{PG}}}{\gamma}\right)^2\right| +$$

$$\frac{PG_{sched}}{2} + \frac{\overline{\overline{PG}}}{\pi}\tan^{-1}\left(\frac{-\overline{\overline{PG}}}{\gamma}\right) + \ln\left|\overline{\overline{PG^2}}\right| + \gamma^2 \tag{2.2.4.10}$$

Here, $\overline{\overline{PG}}$, is again given by equation (2.2.3.2). γ is given by equation (2.2.3.5). It should be noted that EENS is a closed-form equation when using the Cauchy distribution. Equations (2.2.4.5) and (2.2.4.10) form two of the major contributions of this work. The closed form solutions (pseudo-closed form in the case of Gaussian) for EENS provide an accurate and easily calculable estimate for EENS that did not previously exist.

2.3. Markov Chain Model

2.3.1. Theoretical Background

A Markov chain is a stochastic process with the Markov property on a finite or countable state space, that is, if the conditional probability distribution of future states depends only on the current state. Thus, future states of a Markov chain do not depend on past states.

The state variable for power generation is divided into N bins, equally spaced intervals from 0 to $PG_{nominal}$ of length $PG_{nominal}/N$. These states are defined as [5]:

$$S = \{S_1, S_2 ... S_N\} \tag{2.3.1.1}$$

Every state S_i corresponds to an amount of power generation which is defined as:

$$S_i = \left(\frac{i \cdot PG_{nominal}}{N}\right) + \frac{PG_{nominal}}{2N} \tag{2.3.1.2}$$

The parameter N gives the size of the bins and is selected to accommodate the tradeoffs between precision and noise from sampling randomness. The $PG_{nominal}/2N$ term results from the fact that each state S_i is chosen to be the middle of the bin.

Changes from time t to t+1 are defined by a one-step transition probabilities matrix **P**. **P** is a symmetrical NxN matrix.

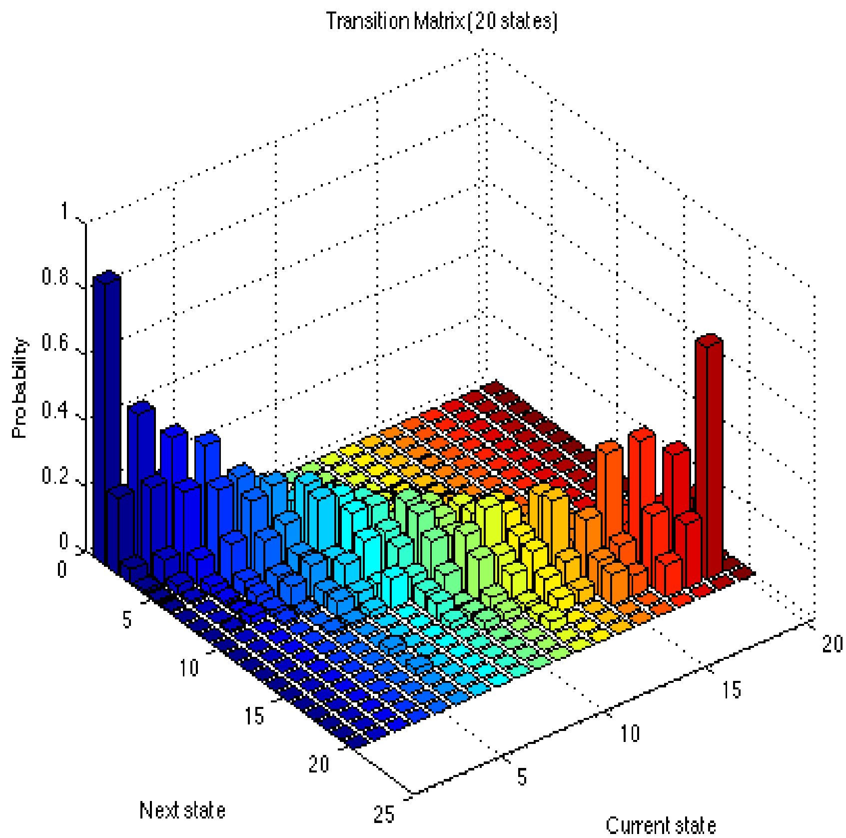

Figure 2.3.1.1: Example of a transition matrix created by a Markov chain model with N = 20

Figure 2.3.1.1 shows the highest probability clusters are centred around N = 0, and N = 20. This agrees with the assumption made previously that the WEG is most often operating at 0MW or at full power ($PG_{nominal}$). The above figure also shows that most transitions are centred around a diagonal from (0,0) to (N,N) which agrees with the assumption that WEG generation does not change very much hour to hour and the most probable transition is generally to the same state.

The estimate of the transition probabilities matrix **P** is determined based on the historical data and denoted as $\hat{\boldsymbol{P}}$. The columns of $\hat{\boldsymbol{P}}$ correspond to the current state of the process and the rows correspond to the state at the next time step. The generic element of $\hat{\boldsymbol{P}}$ is defined as $p_{ij}(t)$ and the generic row of $\hat{\boldsymbol{P}}$ is defined as $P_i(t)$ at time t. Each element of the transition matrix $\hat{\boldsymbol{P}}$ corresponds to a possible state of the process. Figure 3 shows an example of a transition matrix $\hat{\boldsymbol{P}}$ with 20 states.

An estimate for $p_{ij}(t)$ is given in [5] and shown below:

$$\hat{p}_{ij} = \frac{n_{ij}(t)}{\sum_{j} n_{ij}(t)} \forall i, j, \sum_{j=1}^{N} \hat{p}_{ij}(t) = 1 \forall i \tag{2.3.1.3}$$

nij is the number of transitions from state S_i to state S_j observed in the training data series.

Thus, P_i at time t can be defined as:

$$P_i(t) = \{\hat{p}_{i1}(t), \hat{p}_{i2}(t) \ldots \hat{p}_{iN}(t)\} \tag{2.3.1.4}$$

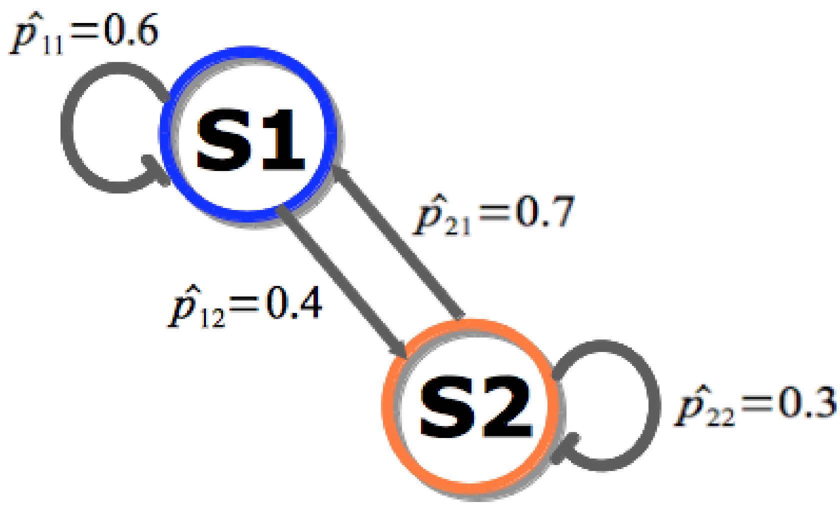

Figure 2.3.1.2: Sample two state Markov chain model

Figure 2.3.1.2 shows a simple Markov chain with two states. The numbers indicate the probability that the given state transition will occur. Note that they add up to 1 for each state. It can also be observed that a Markov chain with one state is equivalent to the persistence model as seen from equation (2.1.1.1) since every state transition is from the current state to itself.

Given that the generation at time t corresponds to state S_i, each element of row $P_i(t)$ of the estimated transition matrix $\hat{\boldsymbol{P}}$ gives the probability of the state of the next time step. Thus, $P_i(t)$ is a discrete probability distribution of the WEG output at the next time step. A point forecast can be obtained by using the state with the highest probability given by the previous time step. At time t, the largest element of $P_i(t)$ gives the most probable state at the next time step which is defined as $S_{max}(t)$.

$$S_{\max}(t) = \underset{i}{MAX}\,\hat{P}_{ij}(t-1) \qquad (2.3.1.5)$$

In the case where multiple states are equally likely, $S_{max}(t)$ is the average of those states. $S_{max}(t)$ corresponds to the forecasted WEG generation at time $\hat{X}_t$ which is expressed in MW. Thus, $\hat{X}_t$ is given by:

$$\hat{X}_t = N \cdot S_{\max}(t) + \frac{PG_{no\min al}}{2N} \tag{2.3.1.6}$$

2.3.2. Methodology

Equation (2.3.1.3) is applied to all elements of the transition matrix $\hat{\boldsymbol{P}}$. The result can be visualized by Figure 3. The point forecast of time t is given by equation (2.3.1.6).

2.3.3. Probability Density Function

As discussed previously, the Markov chain model differs from the persistence model in that the forecasted generation PG is given not as a point forecast but rather as a probability distribution. Therefore, in the case of the Markov chain model, the probability density function of the forecast does not need to be fit to a Gaussian nor a Cauchy distribution.

Given the state is S_i at time $t-1$, The vector $P_i(t)$ of the estimated transition matrix $\hat{\boldsymbol{P}}$ can immediately be used in EENS calculation. The PDF is thus given by:

$$PDF_M(PG_t) = P_i(t-1) \tag{2.3.3.1}$$

2.3.4. Calculating EENS

The probability distribution given in the Markov chain forecast is the probability density function of the forecast error used to calculate EENS. This is a discrete probability density function and at time t when the current generation is in state S_i, is given by $P_i(t)$. equation (2.1.1) can be reformulated as:

$$EENS_M = \sum_{k=1}^{PG_{sched}} p_{ik}(t)\cdot\left(PG_{sched} - PG\right)\cdot\frac{P_{no\min al}}{N} \tag{2.3.4.1}$$

2.4. ARMA Model

2.4.1. Theoretical Background

An autoregressive-moving-average (ARMA) model is a tool used for the analysis of time series composed of two polynomials and is used for modeling and predicting future values of both deterministic and stochastic processes. It is assumed that WEG generation exhibits short memory since WEG generation tends not to change very much over short time scales.

An ARMA model is composed of two parts: an auto-regressive (AR) part, and a moving-average (MA) part. An ARMA(p,q) process is defined as an ARMA model where the AR portion has an order of p and the MA portion has an order of q. The model is characterized as such [6]:

$$\hat{X}_t = \sum_{j=1}^{p} a_j X_{t-j} + \sum_{k=0}^{q} b_k e_{t-k} \tag{2.4.1.1}$$

The first term in equation (2.4.1.1) represents the auto-regressive component and the second term represents the moving average component. It shows that $\hat{X}_t$ is a linear combination of p past observations at time t (auto-regressive part) and a white-noise process with a mean of zero and a constant variance (moving-average part).

The simplest ARMA(p,q) process is one where p is 1 and q is 0. Similarly to the Markov chain model, this reduces to the persistence model in equation (2.2.1.1) since the model only uses the WEG generation of the previous time step.

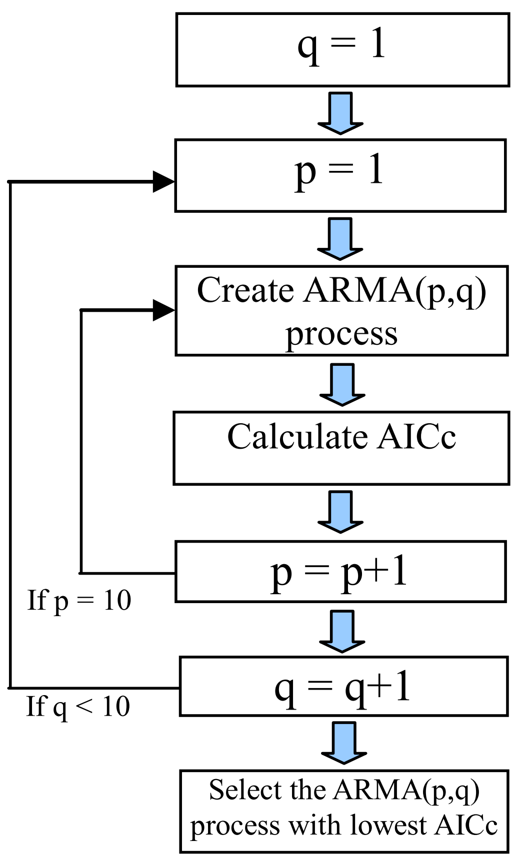

Figure 2.4.1.1: Flowchart depicting the process of determining

$\hat{X}_t$ is an ARMA(p,q) process where p, and q are the orders of the auto-regressive part and moving average parts respectively. Two tasks remain: the first is to select the orders p, and q of the model and the second is to select the coefficients a_j and b_k. Matlab's System Identification toolbox has tools that can be used for both tasks.

2.4.2. Model Order

The Akaike information criterion (AIC) is a tool used for model selection. It evaluates statistical models used for a given data set relative to each other. It compares the trade-off between the goodness of the fit and the number of parameters used in the model. One caveat of its use however is that because it only provides a relative measure, it is unable to tell if none of the models compared are good fits. AIC is given below[13].

$$AIC = 2k - 2\ln(L) \qquad (2.4.2.1)$$

Here, k is the number of parameters in the statistical model and L is the maximized value of the likelihood function of the estimated model which is assumed to be Gaussian and is given by equation (2.1.3.1). ln(L) is the log-likelihood of the likelihood function L and is given by:

$$\ln(L) = \ln\left(\frac{1}{\sqrt{2\pi\sigma_2}}\right) - \left(\frac{\overline{\overline{PG}} - PG}{2\sigma_2}\right) \qquad (2.4.2.2)$$

$\overline{\overline{PG}}$ Is given by equation (2.2.3.2), and σ^2 is given by equation (2.2.3.3).

The preferred model is the one with the lowest AIC. The first term in equation (2.4.2.1) penalizes a model for over-fitting and the second term rewards the goodness of the fit.

AICc is a modification on AIC that corrects for finite sample sizes. It is given below[14].

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \quad (2.4.2.3)$$

AICc is similar to AIC but carries a greater penalty for models with extra parameters. AICc will be used as the main criterion for order selection in ARMA models.

2.4.3. Coefficient Determination

A number of methods can be used for determining the *p* and *q* coefficients of an ARMA process such as Burg and Shanks, and Yule-Walker, or least-squares estimation. Least-squares estimation is used.

2.4.4. Methodology

The first step is to determine the model order. An ARMA(p,q) process is created with the training data as the input for each p, q = {1, 2,... 10}. Matlab's internal least-squares estimation method is used in determining p, and q[15].Therefore, 100 ARMA(p,q) processes will be created and AICc is calculated for each of them. The one with the lowest AICc is used to determine p and q. Figure 4 below illustrates the method of model order selection.

Once the orders of the model have been selected, equation (2.4.1.1) can be used to predict each future time-step. This can be used to either model the training data or to predict future values.

2.4.5. Probability Density Function

As noted previously, a probability distribution of a given point forecast's error is required for EENS calculation.

The method of producing a probability density function for the ARMA model forecast is the same as in persistence model and is described in section 2.2.3. The one difference in the case of ARMA model is that $\overline{\overline{PG_t}}$ is given by equation (2.4.1.1). σ^2 and γ are given by equations 2.2.3.3 and 2.2.3.5 for Gaussian and Cauchy distributions, respectively. With these two sets of parameters, EENS can be calculated.

2.4.6. Calculating EENS

EENS for the ARMA model is calculated in the same manner as persistence model. Using the Gaussian distribution, EENS is given by equation 2.2.4.5 and by 2.2.4.10 when using the Cauchy distribution. Again, $\overline{\overline{PG_t}}$ is given by equation (2.4.1.1).

3. RESULTS AND DISCUSSION

3.1. Data

Historical hourly power generation data for every wind generator/farm in Ontario was collected from the Independent Electricity System Operator (IESO) web-site from March 3, 2013 to October 2, 2013. In the models and calculations that follow, data from the Amaranth wind farm is used. Because WEGs often operate at maximum capacity or not at all, the nominal power generation $PG_{nominal}$ is defined as the maximum generation of the WEG.

Two sets of data are used: a training data set, and validation data set. The training data is used to construct the Markov chain and ARMA models (persistence does not require training) The validation data follows the training data immediately in time and is used to verify the accuracy of each model. The training data contains 165 days of data (3960 hours) and the validation data contains 35 days (840 hours).

Data from March 3, 2013 to August 27, 2013 is used as train-ing data and data from August 28, 2013 to October 2, 2013 is used for the validation data.

3.2. Amaranth Wind Farm

3.2.1. Comparing Forecast Error

The three models are trained on the hourly training data based on 3960 hours of the Amaranth Wind Farm's wind energy output with a nominal power output, $PG_{nominal}$, of 200MW.

Each of the three models is used to generate a one-hour-ahead forecast for the duration of the validation data (840 hours). They are plotted against the actual wind generation of the Amaranth Wind Farm during that time period.

In the Markov chain model used, N is chosen to be 200. In the ARMA model used, p and q are chosen to be 2. Plots of each predictive model between the 200th and 300th hours of the validation data are shown below.

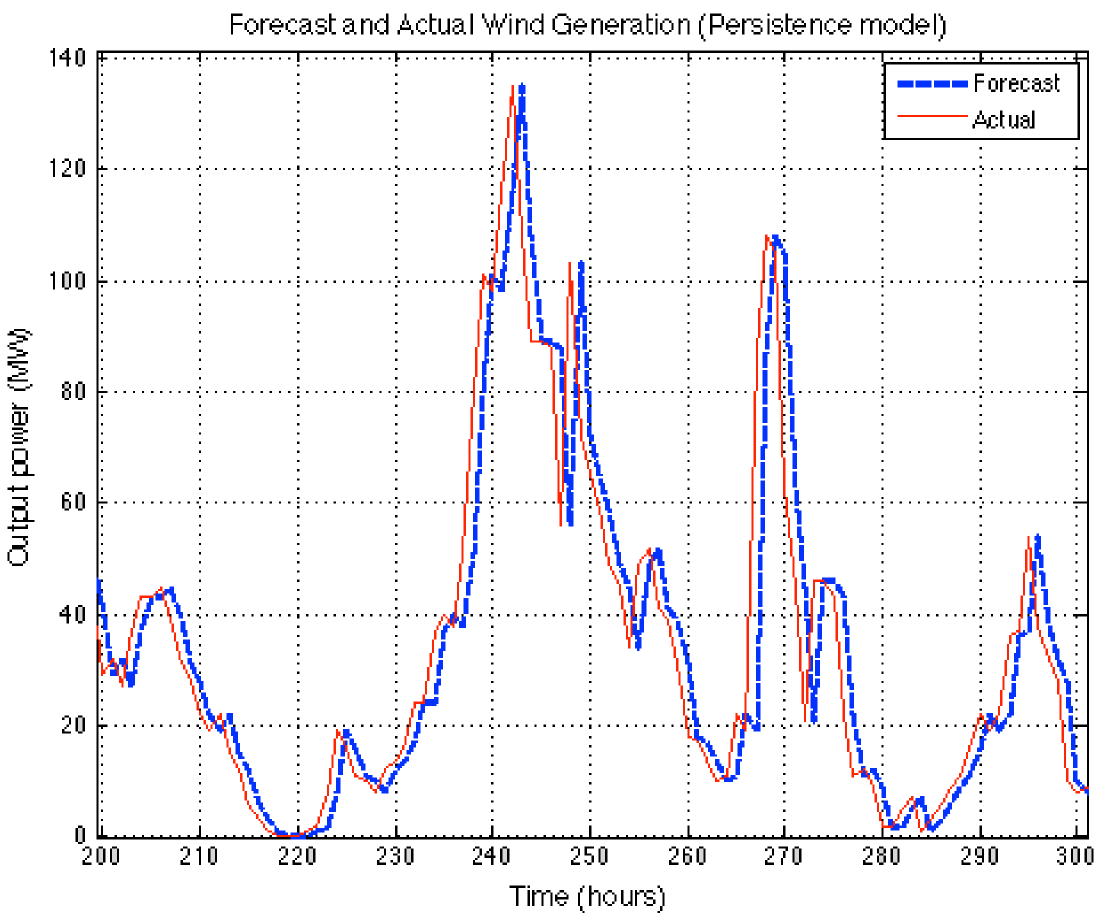

Figure 3.2.1.1: Persistence model wind energy generation forecast compared to actual generation for Amaranth wind farm

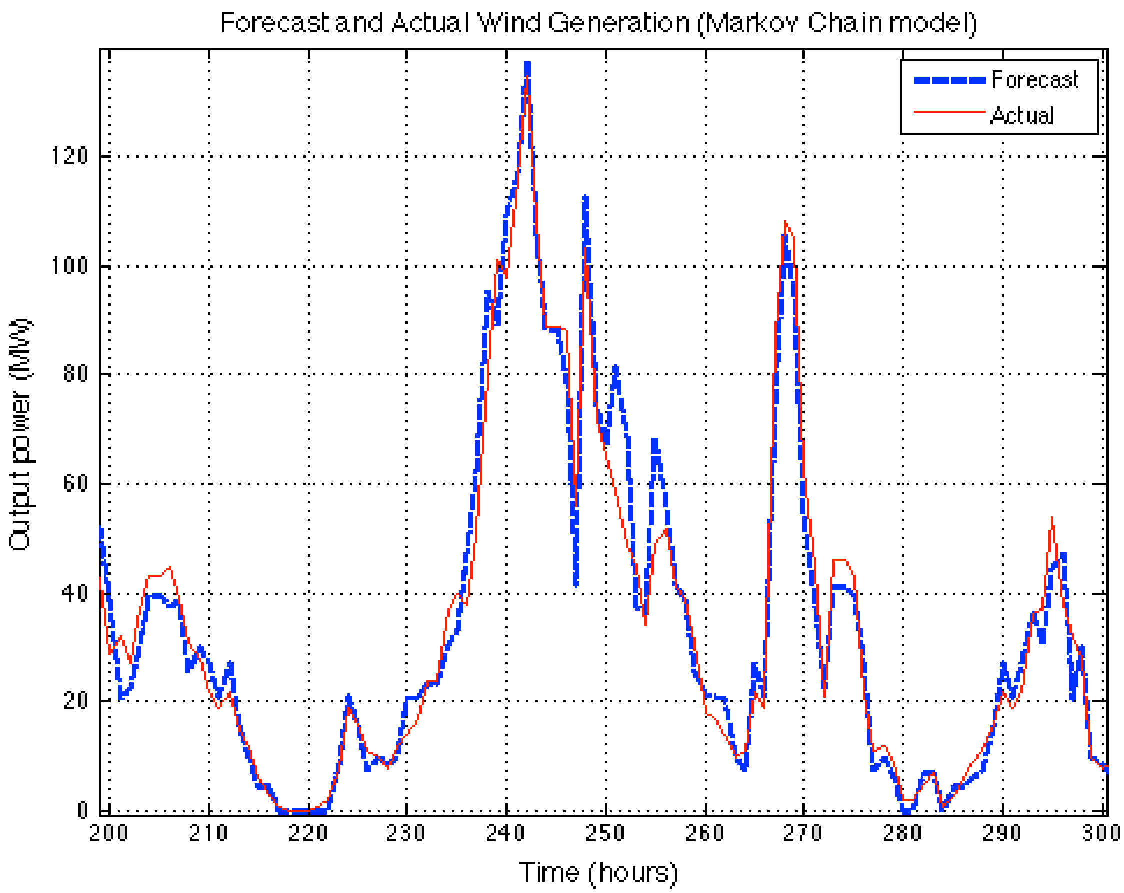

Figure 3.2.1.2: Markov chain model wind energy generation forecast compared to actual generation for Amaranth wind farm

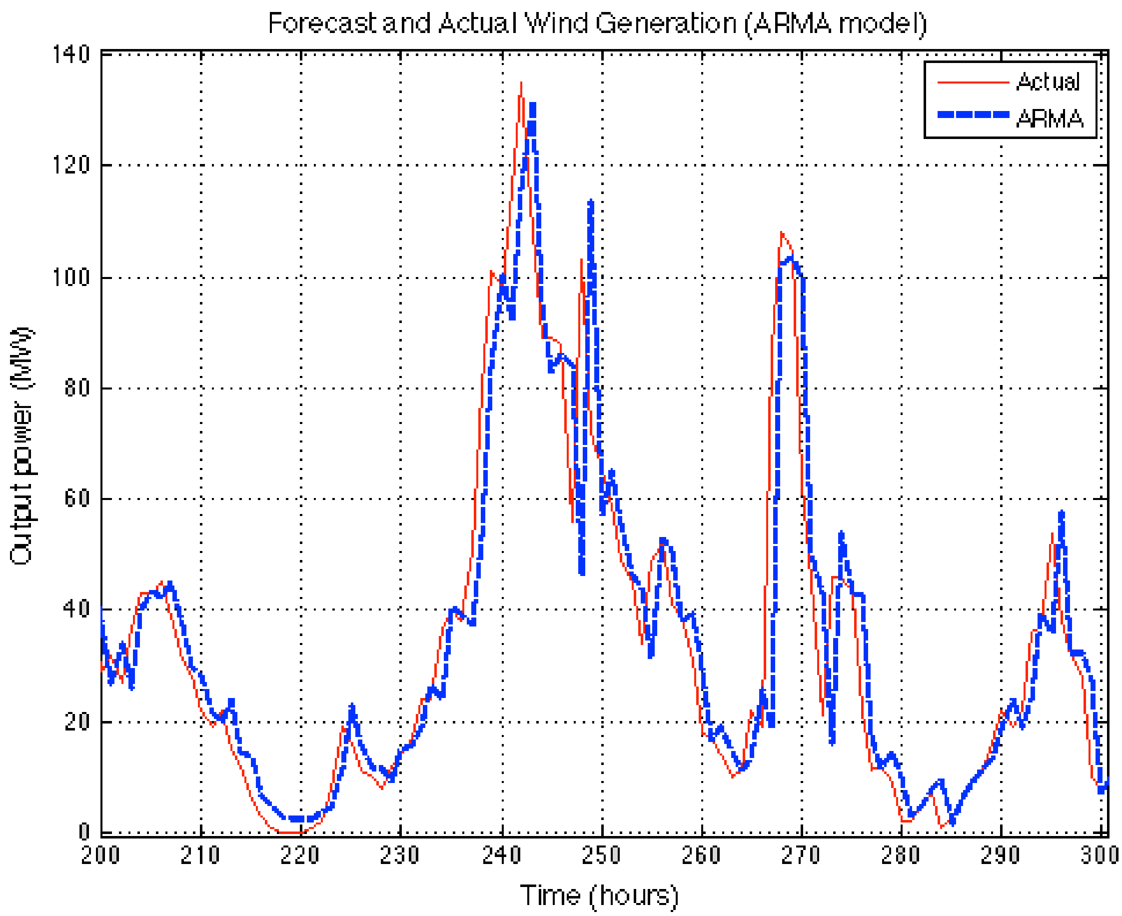

Figure 3.2.1.3: ARMA model wind energy generation forecast compared to actual generation for Amaranth wind farm

Figures 5 through 7 show that all three models are capable of producing an accurate forecast for the one-hour-ahead horizon. The persistence model produces a forecast that is delayed by one hour based on the actual generation. Qualitatively, they show that Markov chain and ARMA model provide a more accurate forecast of than persistence model.

The forecasts generated by each model is evaluated quantitatively by comparing their normalized root mean square error (NRMSE) which is calculated using the difference between forecasted generation and the actual generation over the duration, *m*, of the validation data period. It is expressed as a percentage of nominal power output of the WEG. NRMSE is defined by:

$$NRMSE = \frac{1}{PG_{nominal}} \sqrt{\frac{1}{m} \sum_{t=1}^{m} \left(X_t - \hat{X}_t \right)^2} \times 100\% \qquad (3.2.1.1)$$

The size of the validation period, *m*, is 840 elements. The results are summarized in the table below:

Table 3.2.1.1: NRMSE of forecast for each predictive model (Amaranth)

Model	**NRMSE (% of $PG_{nominal}$)**
Persistence	6.3302
Markov	2.6622
ARMA	5.2277

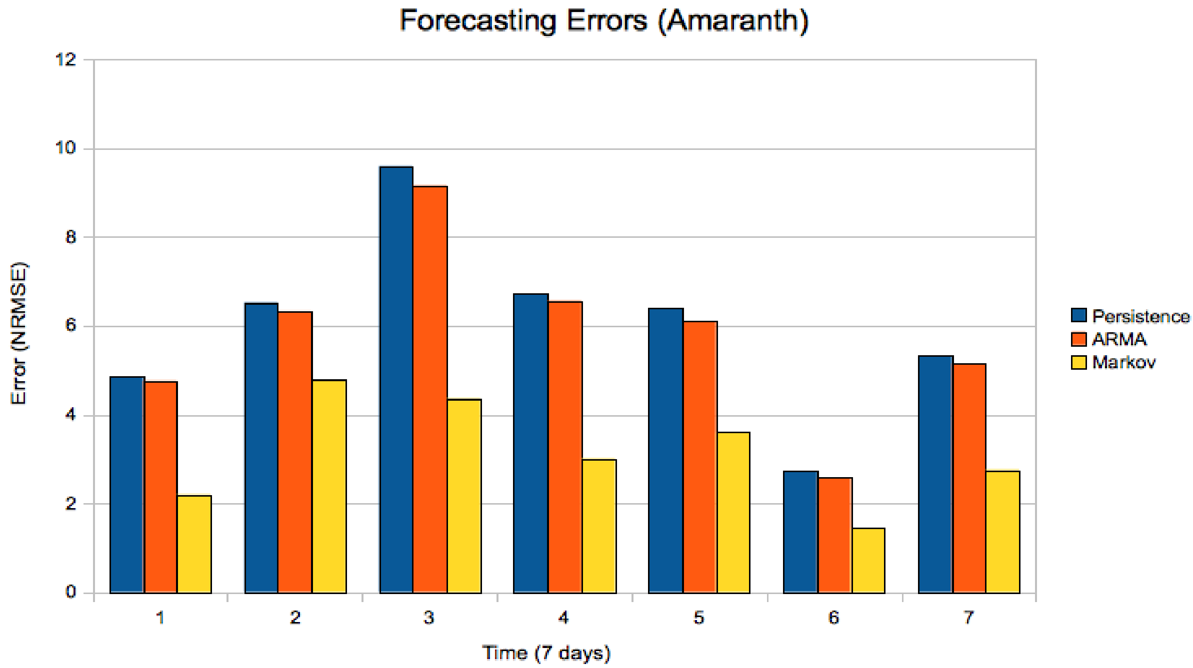

Figure 3.2.1.4: Forecast errors of all three predictive models plotted together for Amaranth wind farm

Figure 8 shows the NRMSE of each predictive model side by side during windows of 168 hours (7 days). Both Markov chain and ARMA models performed better than the persistence model. Markov chain performed significantly better than persistence and ARMA. Markov chain should be expected to work best in cases where the training data provides an accurate assessment of the wind generation of the wind farm at all times.

3.2.2. Comparing EENS

EENS was calculated using the error distributions of persistence, Markov chain, and ARMA model forecasts on the one-hour-ahead horizon. Gaussian and Cauchy distributions were used for persistence and ARMA models and their effects on EENS compared. The distribution generated by the Markov chain model's forecast was used for EENS calculation. EENS is also compared to AENS in order to evaluate the adequacy of the calculated EENS.

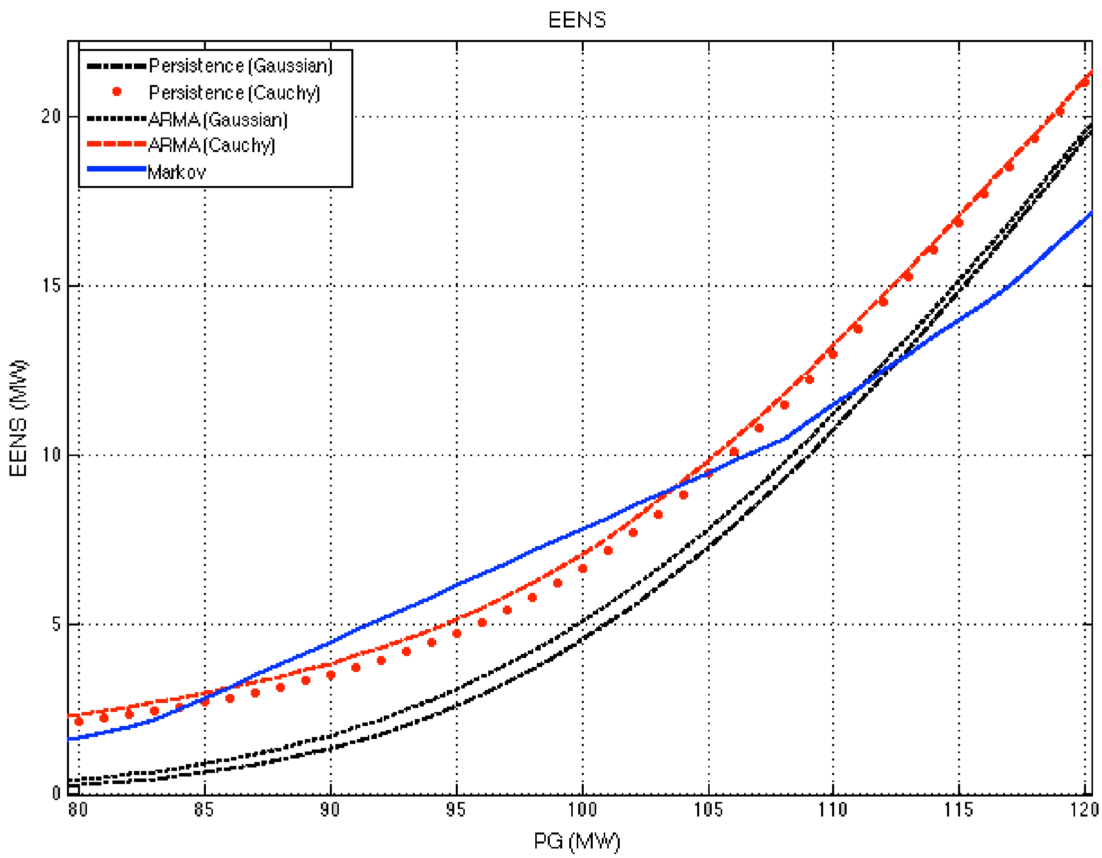

Figure 3.2.2.1: EENS calculated from persistence, Markov Chain, and ARMA models for Amaranth wind farm

The plot in figure 3.2.2.1 uses a forecasted generation $\overline{\overline{PG}}$, of 100MW. It compares EENS estimations for the three models with Gaussian and Cauchy distributions used for persistence and ARMA. The scheduled generation PG_{sched} is not necessarily known at the time of the forecast. For this reason, EENS is shown here as a function of PG_{sched}. The X-axis of the plot gives the EENS for a given PG_{sched}.

In all cases at this forecasted generation, EENS is very small when the expected generation PG_{sched} is less than 80 MW. This is explained by the fact that if the forecasted generation is at 100 MW, and PG_{sched} is much less than 100 MW, there is a high probability that the expected generation will be met. Thus, EENS will be small. As PG_{sched} increases, EENS increases as well.

Figure 3.2.2.1 shows that ARMA model using Gaussian distribution gives the smallest EENS and ARMA model using Cauchy distribution gives the greatest EENS. This difference is explained by the shorter tail of the Cauchy distribution relative to the Gaussian distribution. Markov Chain model gives the most moderate EENS estimation of the five scenarios shown in Figure 3.2.2.1.

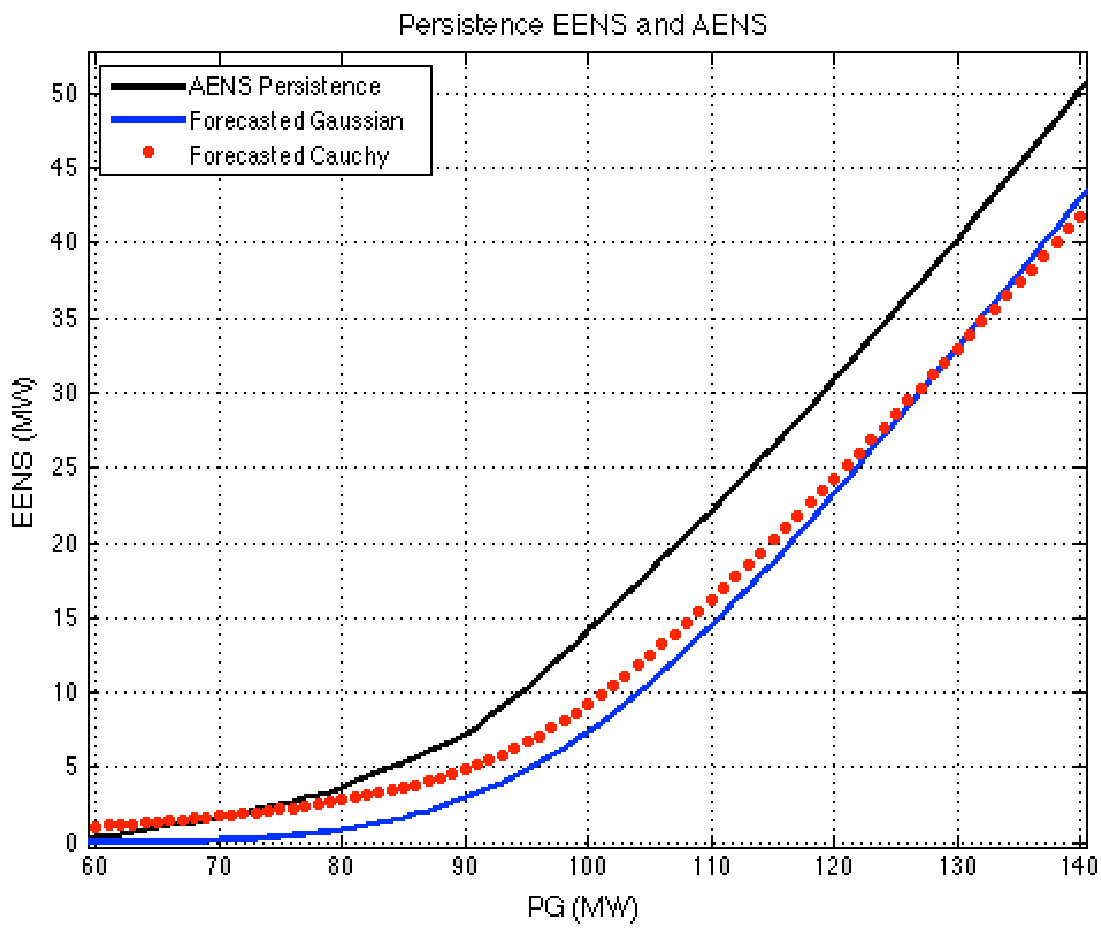

Figure 3.2.2.2: EENS plotted with AENS for persistence model with $\overline{\overline{PG}}$ *at 96MW for Amaranth Island wind farm.*

Figure 3.2.2.2 shows EENS plotted with actual energy not served (AENS) for persistence model using Gaussian and Cauchy distributions with $\overline{\overline{PG}}$ at 96MW. AENS is the actual energy shortfall for a given amount of PG_{sched}. AENS in figure 3.2.2.2 is determined as such:

1. Find all instances in the training data where 96MW is forecasted by the model.
2. Calculate the AENS for the actual generation at that time for all possible PG_{sched}.

3. Calculate the mean of each instance.

It can be seen from the plot in figure 3.2.2.2 that the Cauchy distribution provides a better estimate of EENS than the Gaussian distribution.

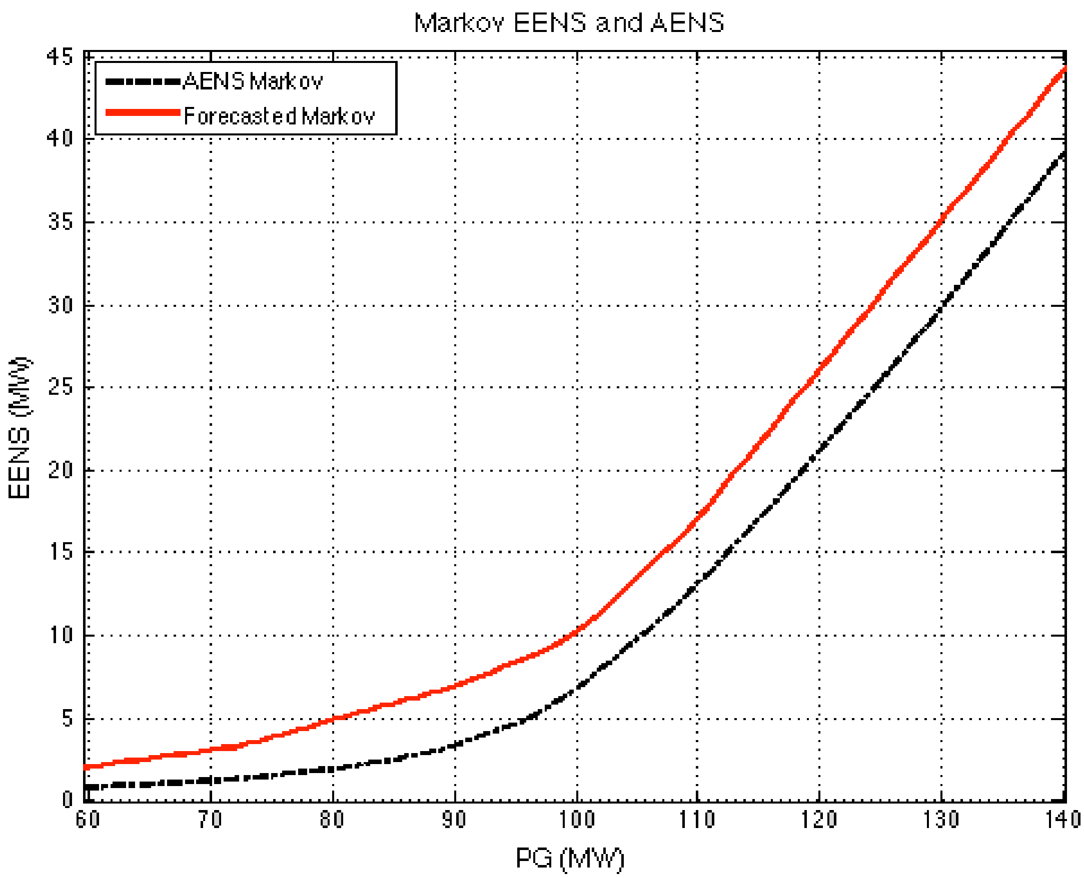

Figure 3.2.2.3: EENS plotted with AENS for Markov chain model with $\overline{\overline{PG}}$ *at 96MW for Amaranth wind farm.*

Figure 3.2.2.3 shows EENS plotted with AENS for Markov chain model with $\overline{PG}$ at 96MW. AENS in figure 3.2.2.3 is determined in the same way as in figure 3.2.2.2. The plot in figure 3.2.2.3 shows that Markov chain model provides a better estimate of EENS than the persistence model.

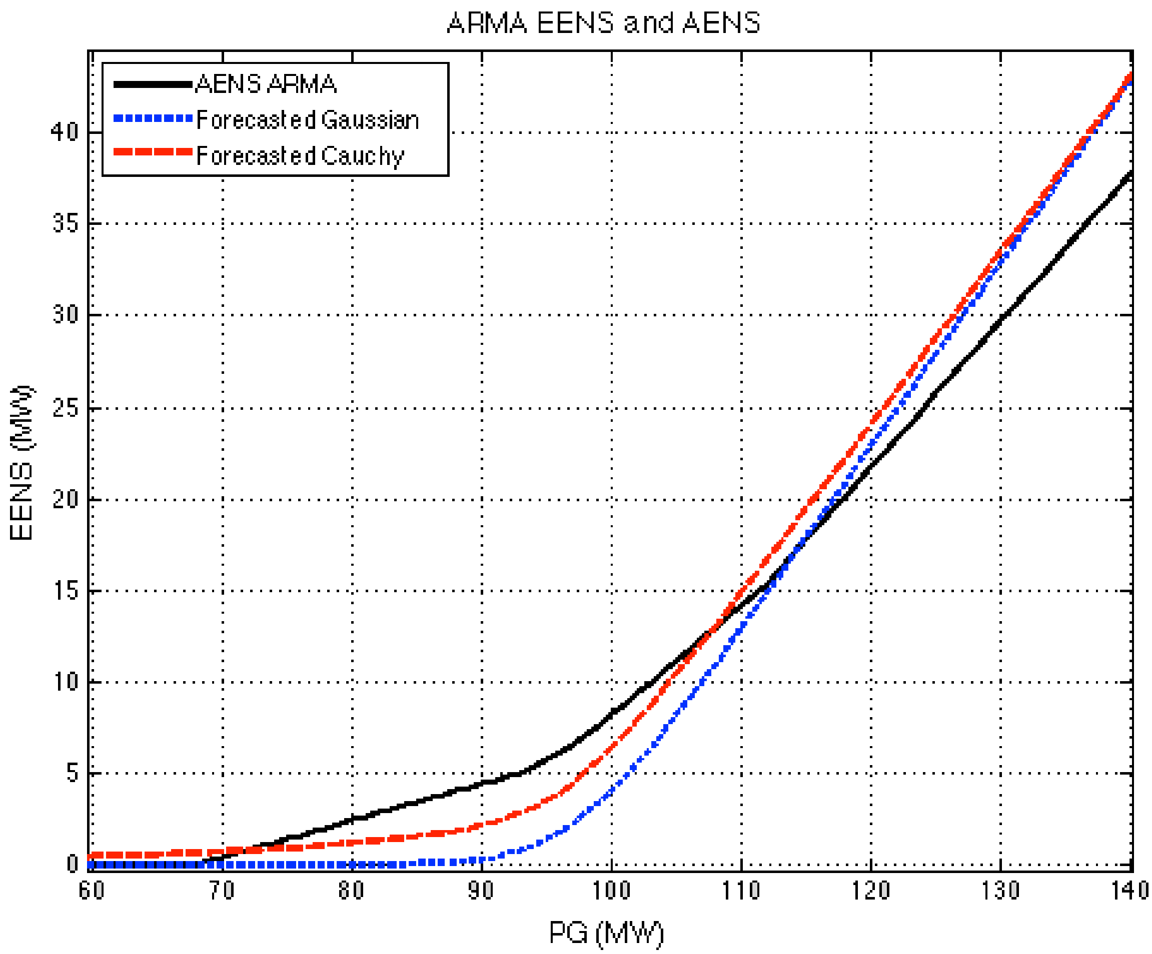

Figure 3.2.2.4: EENS plotted with AENS for ARMA model with $\overline{PG}$ at 96MW for Amaranth wind farm.

Figure 3.2.2.4 shows EENS plotted with AENS for ARMA model with $\overline{\overline{PG}}$ at 96MW. AENS in figure 3.2.2.4 is determined in the same way as in figure 3.2.2.2. The plot in figure 3.2.2.4 shows that ARMA model provides a better estimate of EENS than the persistence model however it is difficult to determine qualitatively if it provides a better estimate than the Markov chain model.

Table 3.2.2.1: NRMSE of EENS vs. AENS for each predictive model and distribution (Amaranth)

Model	NRMSE (% of $PG_{nominal}$)
Persistence (Gaussian)	9.91
Persistence (Cauchy)	12.48
Markov Chain	5.23
ARMA (Gaussian)	12.41
ARMA (Cauchy)	10.70

Table 3.2.2.1 gives the NRMSE (as defined in section 3.2.1) between EENS and AENS for each model and distribution with PG_{sched}. It can be seen that the Markov chain model provides the best estimate of the five scenarios but ARMA model using the Cauchy distribution also outperforms persistence model. In both persistence and ARMA models, Cauchy outperforms Gaussian.

3.3. Wolfe Island Wind Farm

3.3.1. Comparing Forecast Error

The three models are trained on the hourly training data based on 4800 hours of the Wolfe Island Wind Farm's wind energy output with a nominal power output, $PG_{nominal}$, of 197 MW.

Each of the three models is used to generate a one-hour-ahead forecast for the duration of the validation data (840 hours). They are plotted against the actual wind generation of the Wolfe Island Wind Farm during that time period.

In the Markov chain model used, N is chosen to be 200. In the ARMA model used, p and q are chosen to be 2. Plots of each predictive model between the 200^{th} and 300^{th} hours of the validation data are shown below.

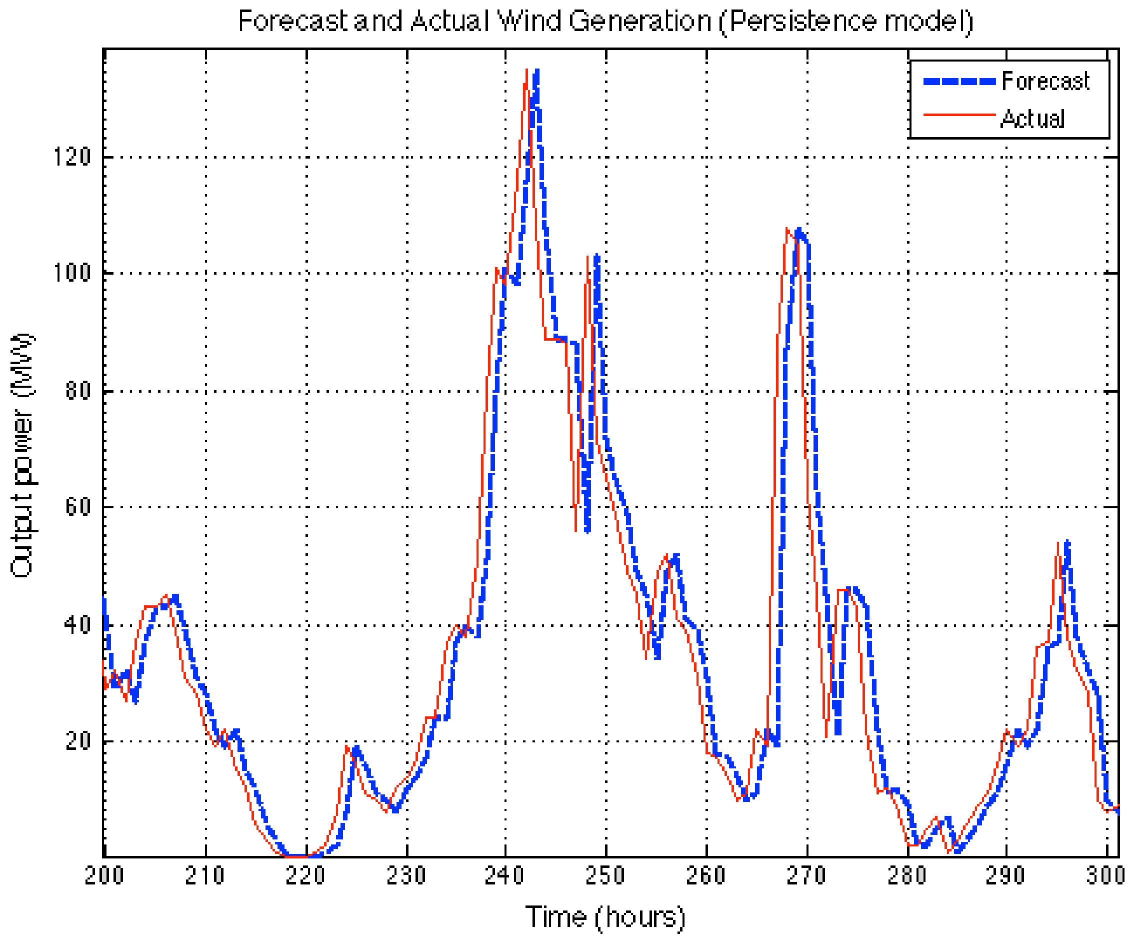

Figure 3.3.1.1: Persistence model wind energy generation forecast compared to actual generation for Wolfe Island wind farm

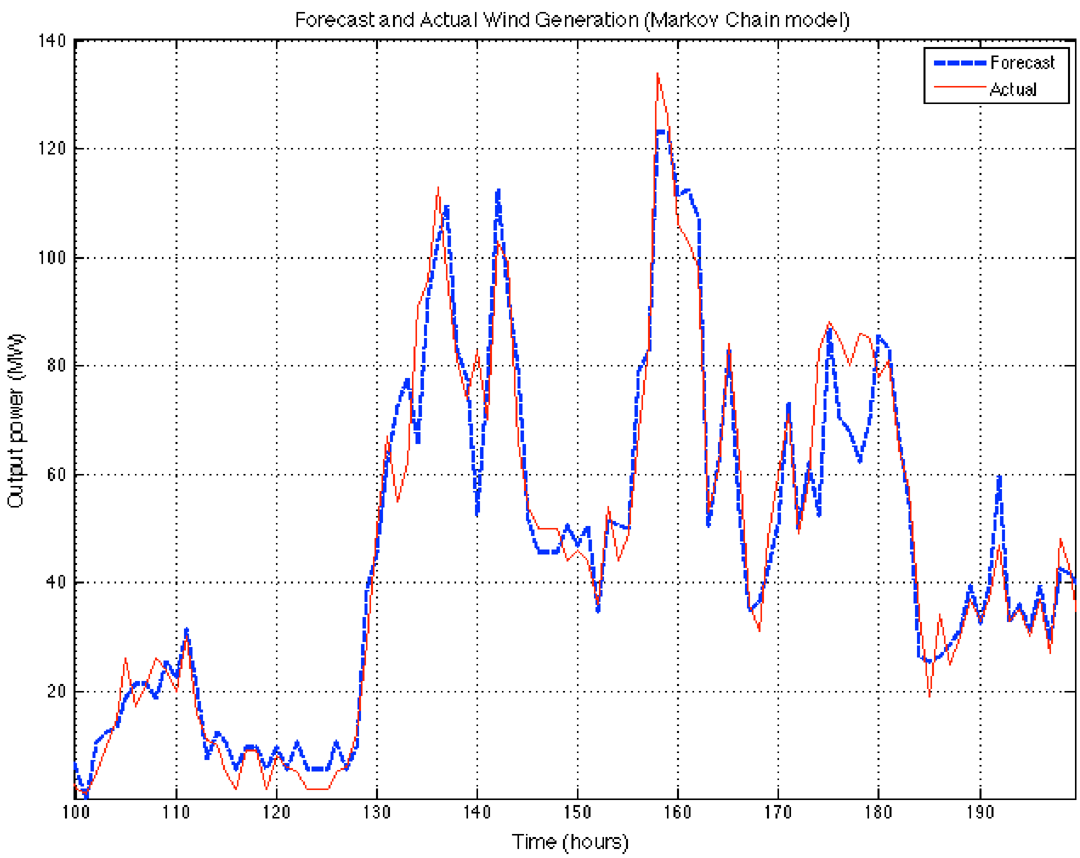

Figure 3.3.1.2: Persistence model wind energy generation forecast compared to actual generation for Wolfe Island wind farm

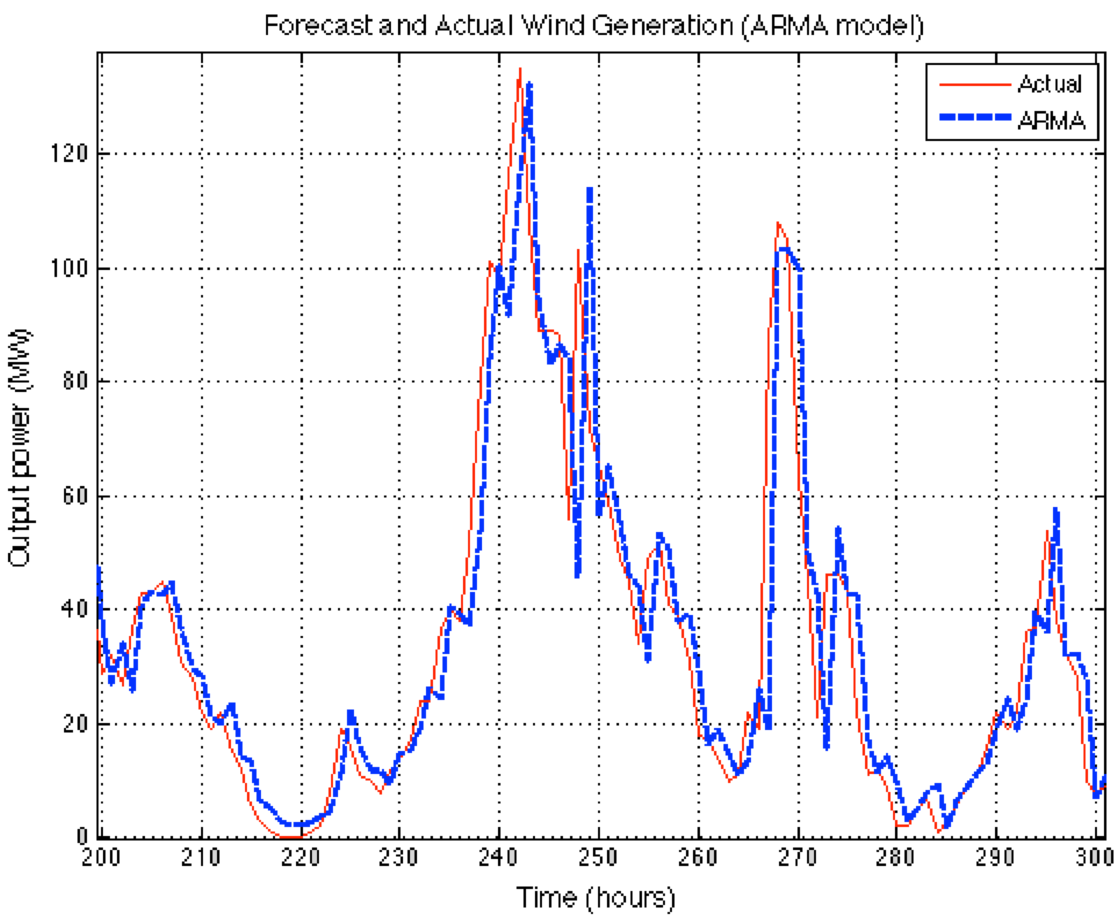

Figure 3.3.1.3: Persistence model wind energy generation forecast compared to actual generation for Wolfe Island wind farm

Figures 10 through 12 show qualitatively that the three models provide good estimates of WEG generation for the Wolfe Island wind farm.

As in table 3.2.1.1, table 3.3.1.1 shows the NRMSE of each model and its predictive accuracy using the data from the Wolfe Island wind farm. The sample size, *m*, is 840. The results are similar to the results from the Amaranth wind farm. The accuracy of each model is slightly worse in the case of Wolfe Island.

Table 3.3.1.1: NRMSE of forecast for each predictive model (Wolfe Island)

Model	**NRMSE (% of $PG_{nominal}$)**
Persistence	6.4271
Markov	2.8568
ARMA	6.2634

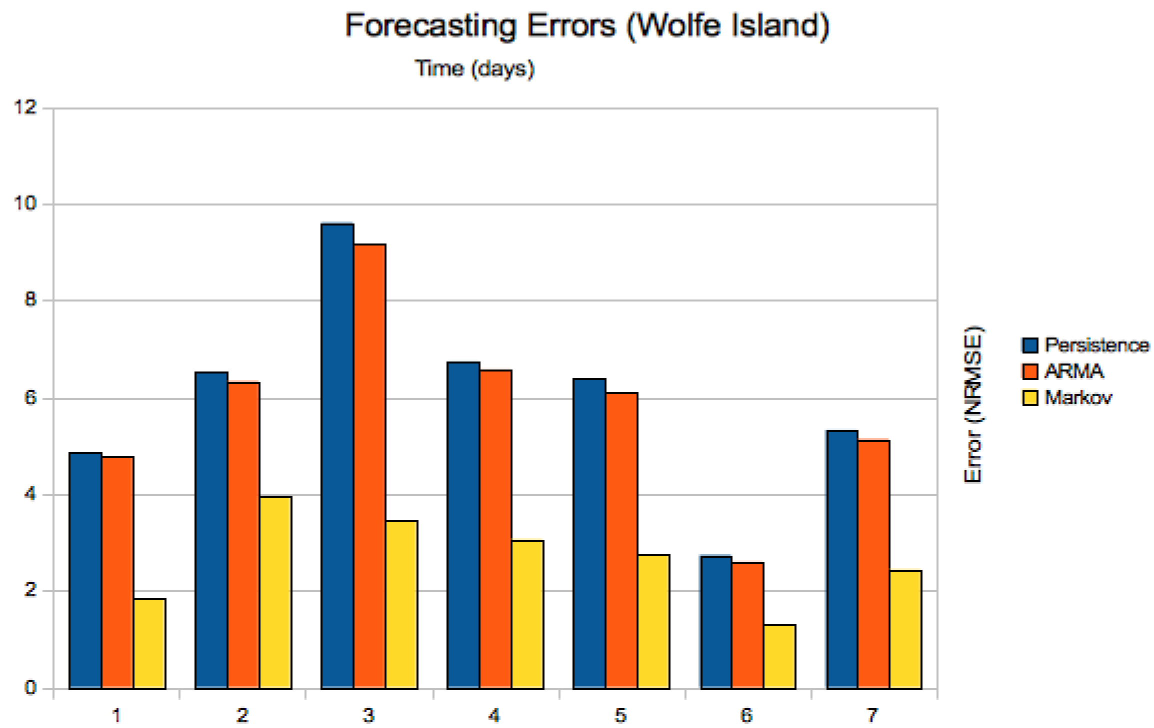

Figure 3.3.1.4: Forecast errors of all three predictive models plotted together for Wolfe Island wind farm

As in figure 3.2.1.4, figure 3.3.1.4 shows the NRMSE of each predictive model side by side during windows of 168 hours (7 days). Again, both Markov chain and ARMA models performed better than the persistence model and Markov chain performed the best of the three.

3.3.2. Comparing EENS

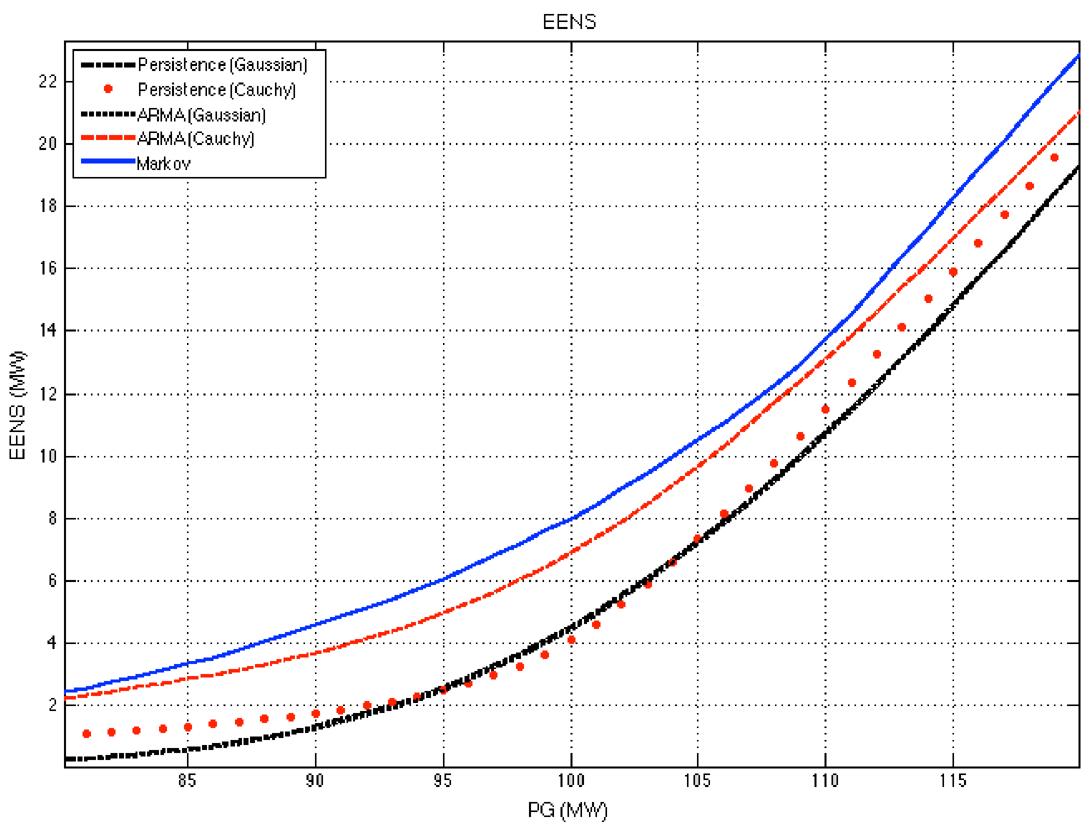

Figure 3.3.2.1: EENS calculated from persistence, Markov Chain, and ARMA models for Wolfe Island wind farm

The plot in figure 14 use a forecasted generation, $\overline{\overline{PG}}$, of 100 MW. It compares EENS estimations for the three models with Gaussian and Cauchy distributions used for persistence and ARMA. The results are similar to those in figure 9. For Wolfe Island, the ARMA and persistence EENS is much closer than that of Amaranth. The Markov chain EENS is vertically shifted upward compared to the Amaranth case because a $\overline{\overline{PG}}$ of 93 MW is used for Markov chain as a result of the discrete nature of the Markov chain model. In all cases, the EENS is slightly higher than the Amaranth case because of the accuracy of each forecast in the Wolfe Island case is slightly worse.

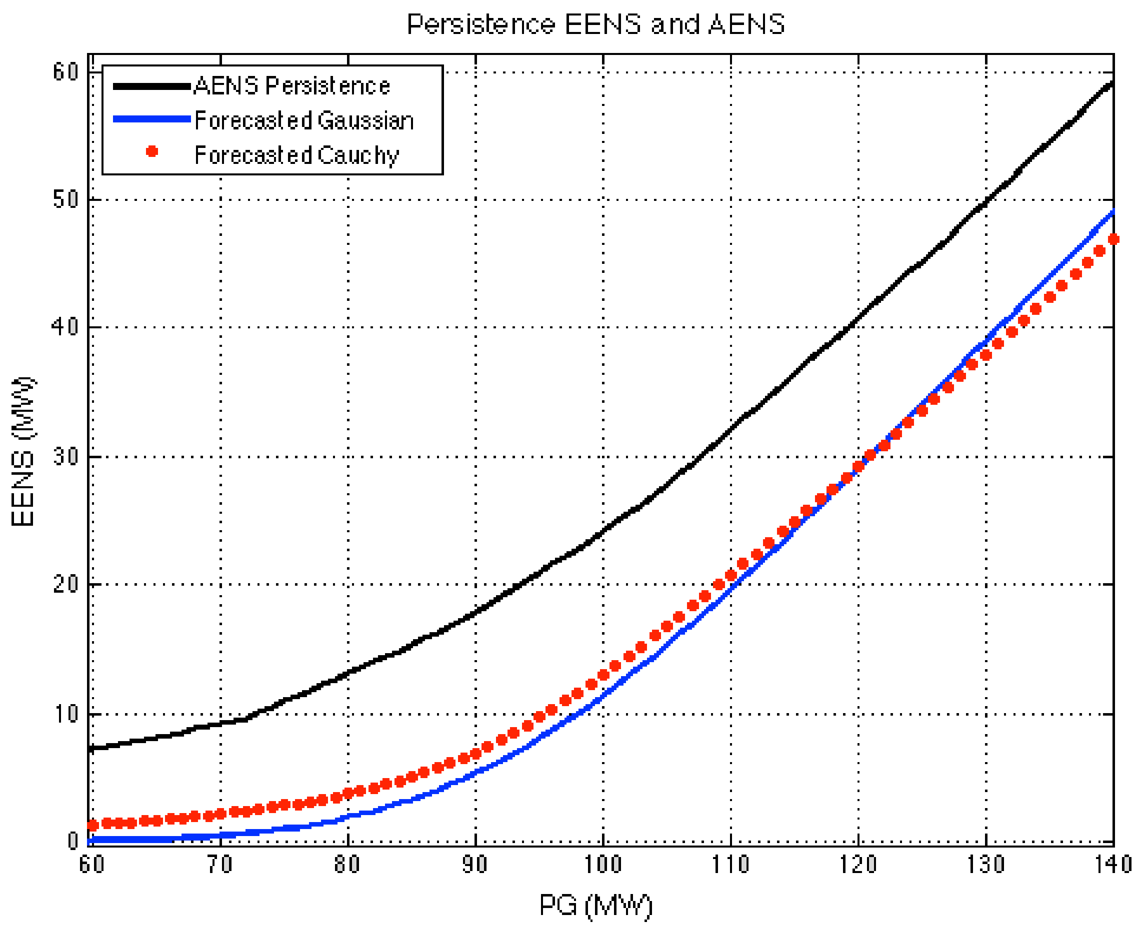

Figure 3.3.2.2: EENS plotted with AENS for persistence model with $\overline{\overline{PG}}$ *at 90MW for Wolfe Island wind farm.*

Figure 3.3.2.2 shows EENS plotted with AENS for persistence model for $\overline{\overline{PG}}$ at 90MW. AENS is determined in the same way as in figure 3.2.2.2

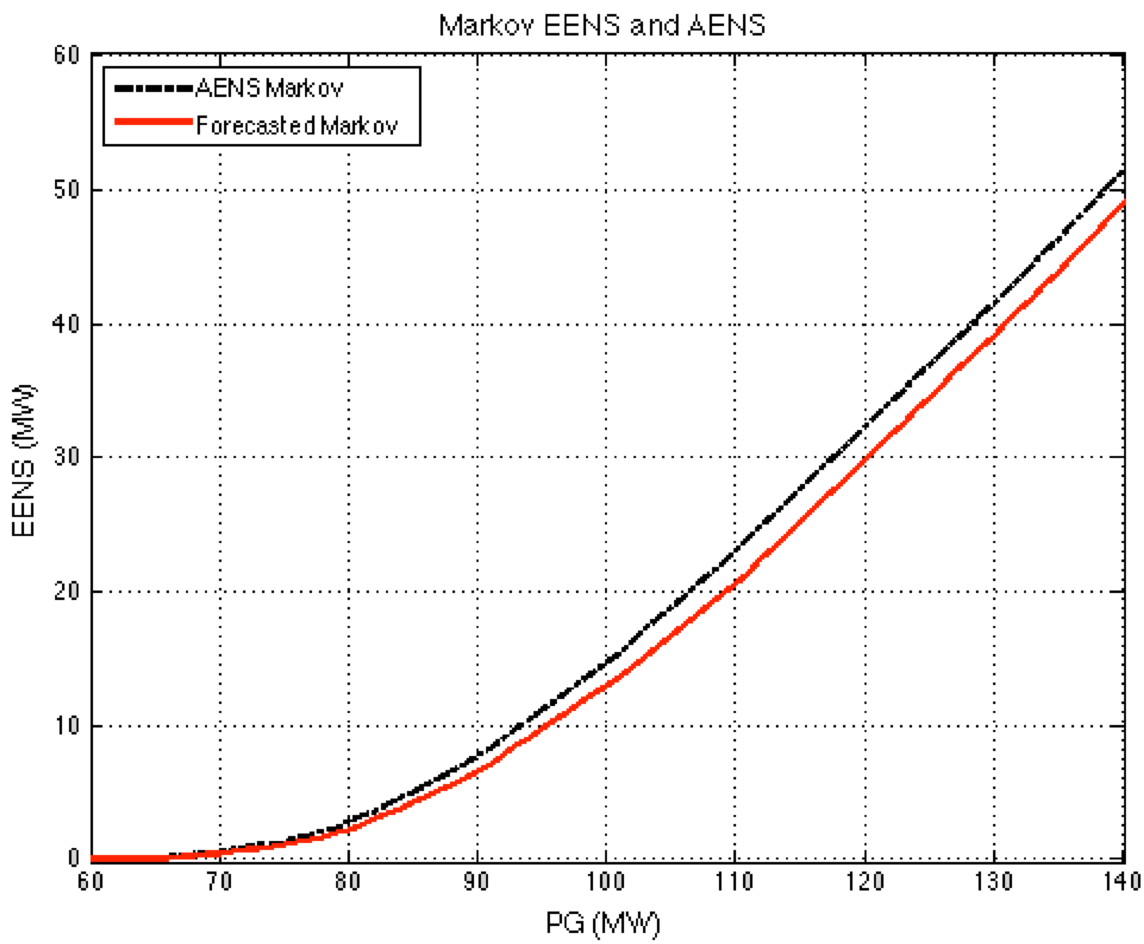

Figure 3.3.2.3: EENS plotted with AENS for Markov chain model with $\overline{\overline{PG}}$ *at 90MW for Wolfe Island wind farm*

Figure 3.3.2.3 shows EENS plotted with AENS for persistence model for $\overline{\overline{PG}}$ at 90MW. AENS is determined in the same way as in figure 3.2.2.2. A comparison between figure 3.3.2.2 and 3.3.2.3 shows qualitatively that Markov chain model again provides a more accurate EENS estimate than persistence model.

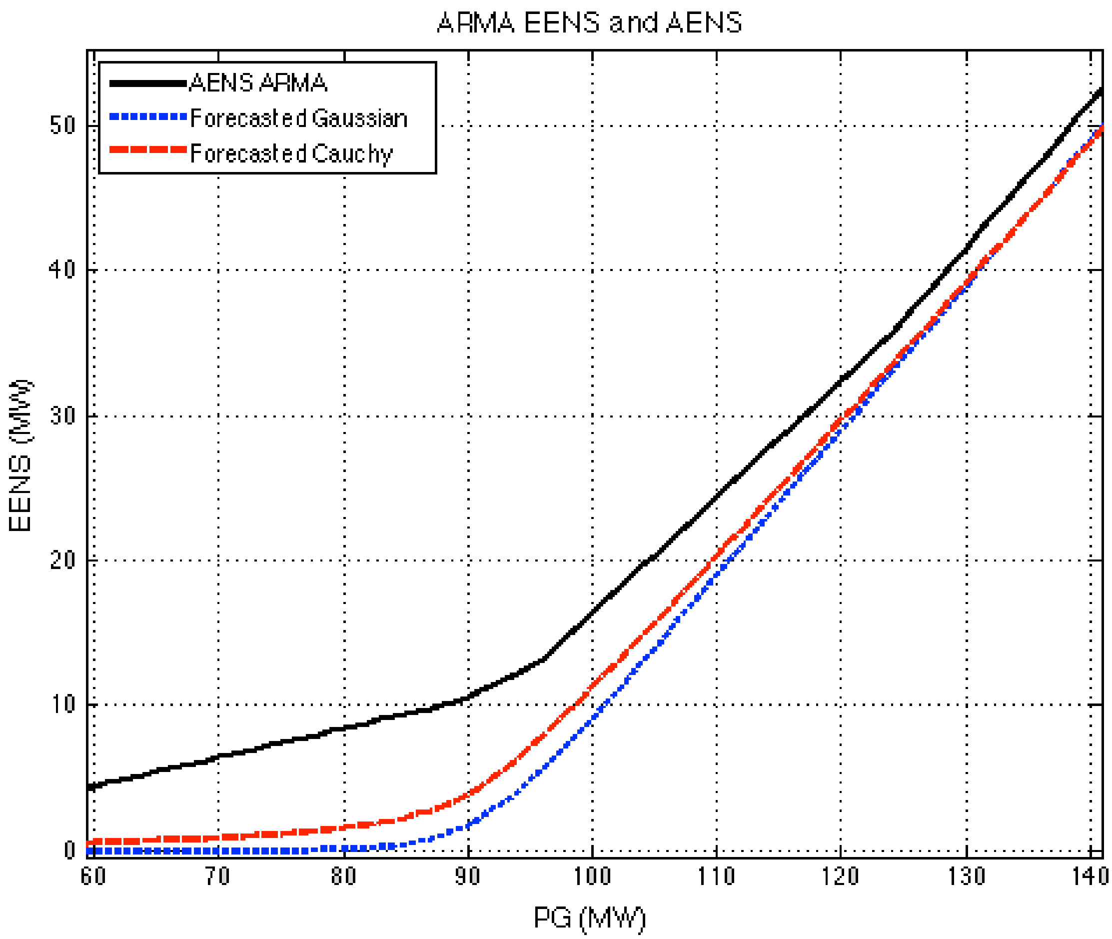

Figure 3.3.2.4: EENS plotted with AENS for ARMA model with $\overline{\overline{PG}}$ *at 90MW for Wolfe Island wind farm.*

Figure 3.3.2.4 shows EENS plotted with AENS for ARMA model with $\overline{\overline{PG}}$ at 90MW. AENS in figure 3.3.2.4 is determined in the same way as in figure 3.2.2.2. The plot in figure 3.3.2.4 shows that Cauchy distribution provides a better EENS estimate than Gaussian distribution for ARMA model.

Table 3.3.2.1: NRMSE of EENS vs. AENS for each predictive model and distribution (Amaranth)

Model	**NRMSE (% of $PG_{nominal}$)**
Persistence (Gaussian)	6.15
Persistence (Cauchy)	9.98
Markov Chain	1.34
ARMA (Gaussian)	4.58
ARMA (Cauchy)	4.46

Table 3.3.2.1 gives the NRMSE (as defined in section 3.2.1) between EENS and AENS for each model and distribution with PG_{sched} ranging between 60MW and 140MW. It can be seen that the Markov chain model again provides the best estimate of the five scenarios and ARMA also provides a more accurate estimate than persistence model. As with Amaranth wind farm, Cauchy distribution outperforms Gaussian for both persistence and ARMA models.

3.4. ERCOT System-wide

3.4.1. Comparing Forecast Error

The three models are trained on the hourly training data based on 240 hours of ERCOT's (Electric Reliability Council of Texas) system-wide wind energy output with a nominal power output, $PG_{nominal}$, of 12212 MW.

Each of the three models is used to generate a one-hour-ahead forecast for the duration of the validation data (48 hours). They are plotted against the actual wind generation of the Wolfe Island Wind Farm during that time period.

In the Markov chain model used, N is chosen to be 100. In the ARMA model used, p and q are chosen to be 2, and 1 respectively. Plots of each predictive model using the validation data are shown below.

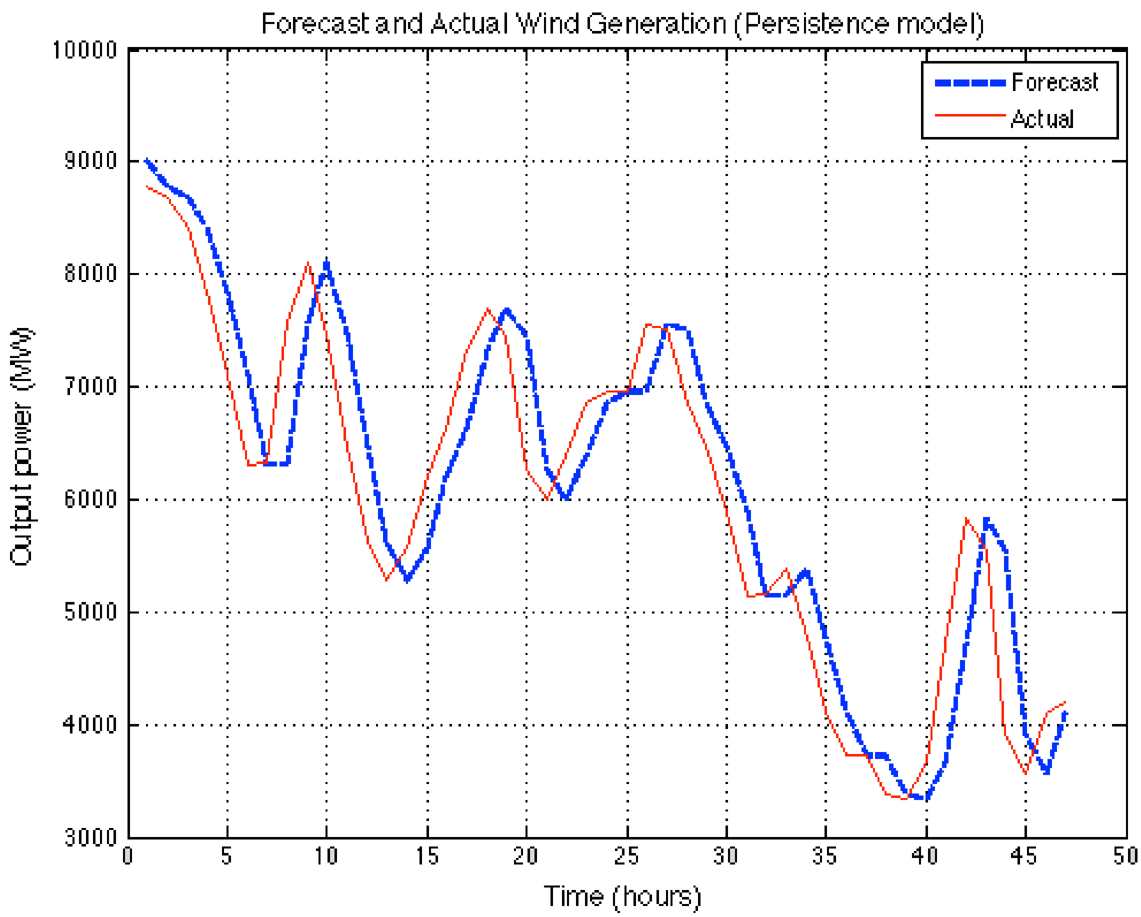

Figure 3.4.1.1: Persistence model wind energy generation forecast compared to actual generation for ERCOT system-wide

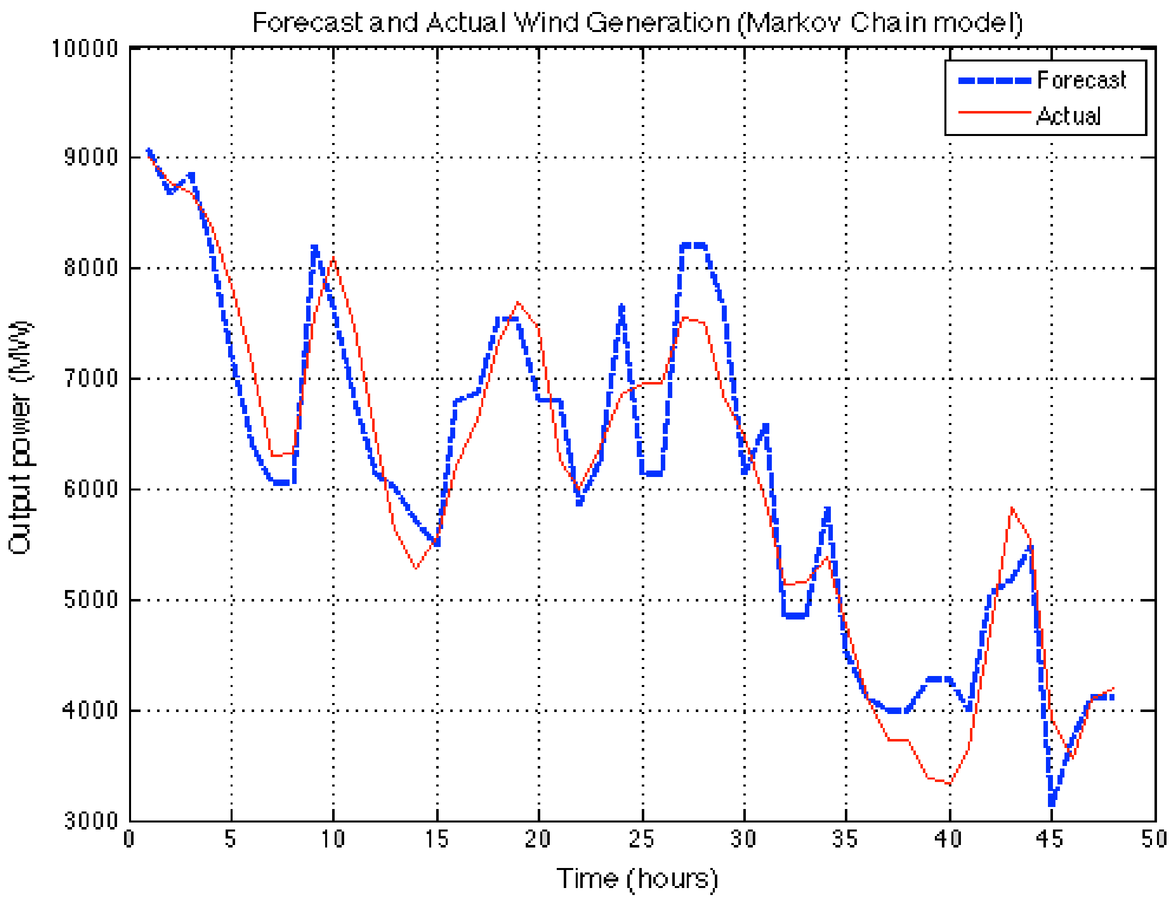

Figure 3.4.1.2: Markov chain model wind energy generation forecast compared to actual generation for ERCOT system-wide

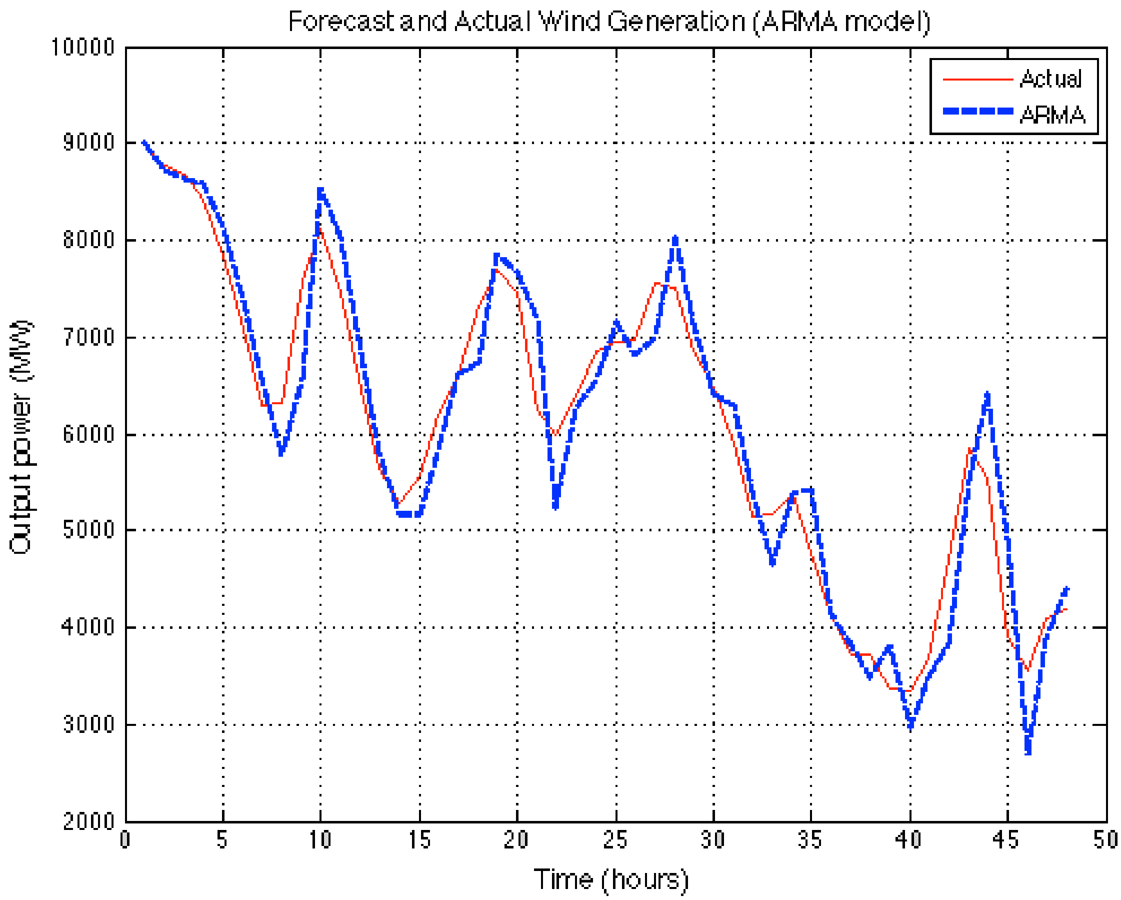

Figure 3.4.1.3: ARMA model wind energy generation forecast compared to actual generation for ERCOT system-wide

As in table 3.2.1.1, table 3.4.1.1 shows the NRMSE of each model and its predictive accuracy using the data from ERCOT system-wide. The sample size, *m*, is 48.

Table 3.4.1.1: NRMSE of forecast for each predictive model

Model	**NRMSE**
Persistence	5.0167
Markov	3.961
ARMA	3.7641

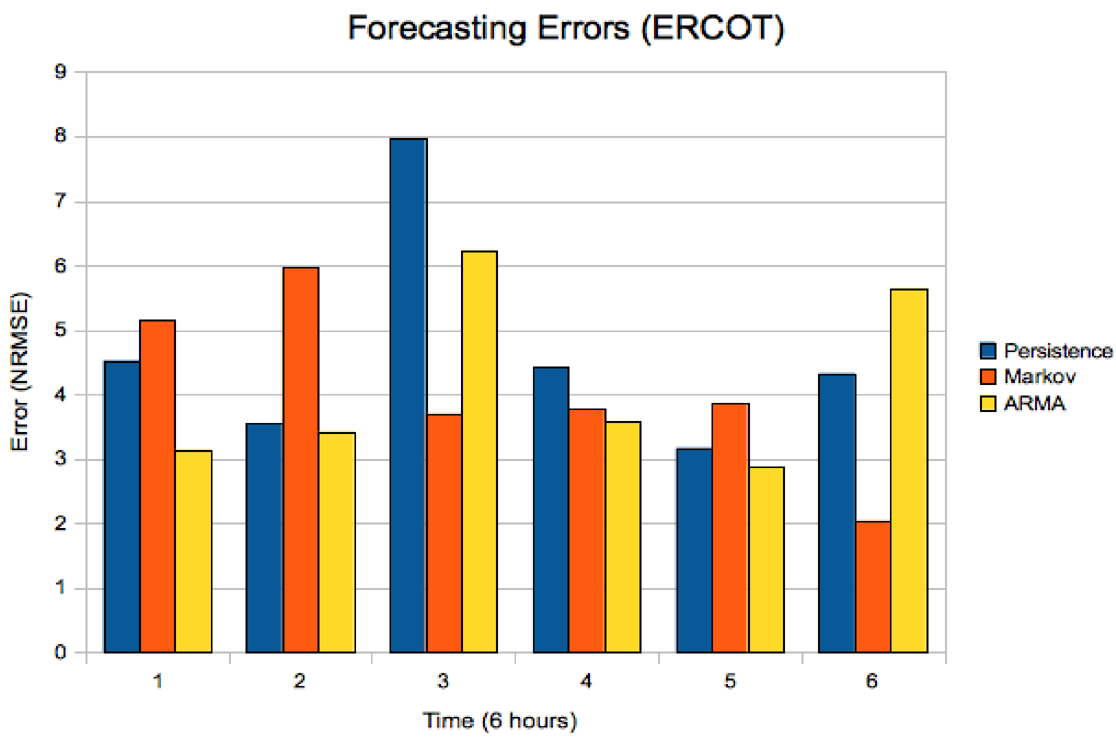

Figure 3.4.1.4: Forecast errors of all three predictive models plotted together for ERCOT system-wide

As in figure 3.2.1.4, figure 3.4.1.4 shows the NRMSE of each predictive model side by side during windows of 6 hours. Unlike figure 3.2.1.4, and figure 3.3.1.4 however, it is not immediately clear which model performs best. Table 3.4.1.1 shows numerically however that Markov chain and ARMA outperform persistence and ARMA performs best overall.

3.4.2. Comparing EENS

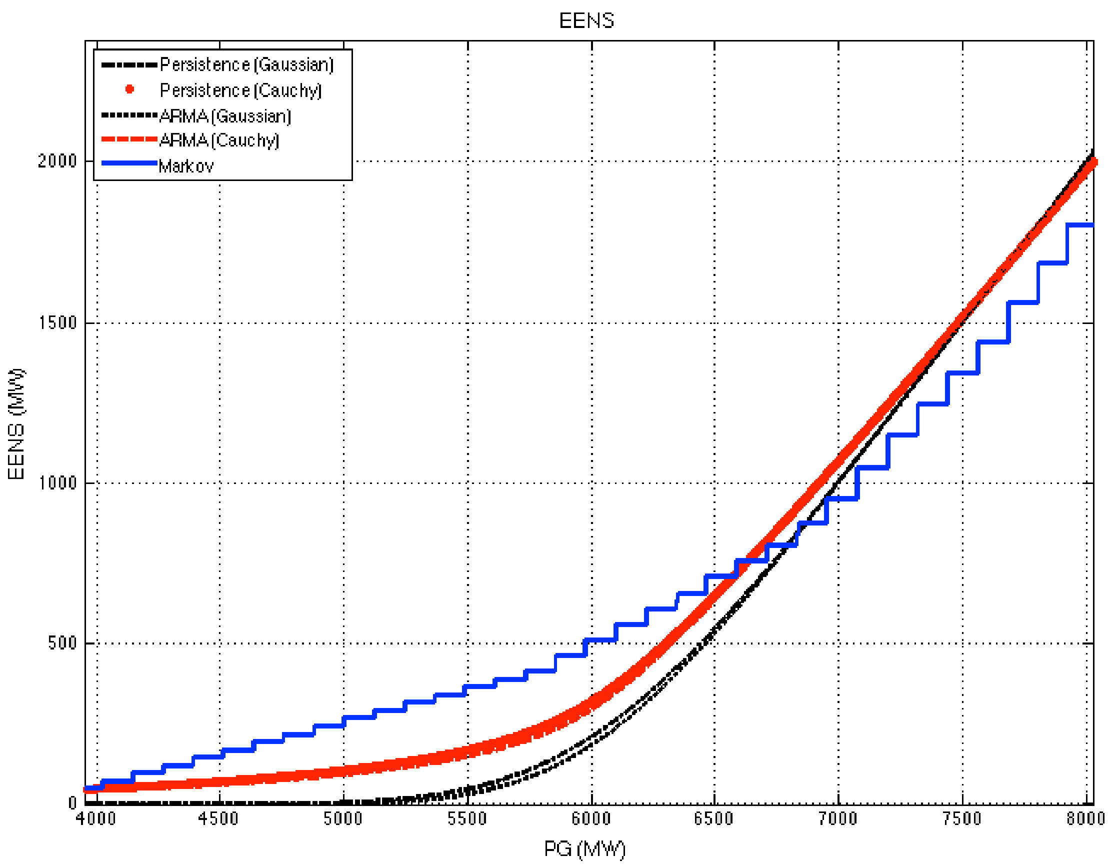

Figure 3.4.2.1: EENS calculated from persistence, Markov Chain, and ARMA models for ERCOT system-wide

The plot in figure 14 use a forecasted generation, $\overline{\overline{PG}}$, of 6000 MW. It compares EENS estimations for the three models with Gaussian and Cauchy distributions used for persistence and ARMA. In this scenario, The persistence and ARMA models using Gaussian distributions have lower EENS estimates than with Cauchy distributions for smaller values of *PG*. The Gaussian distribution exhibits greater slope in the linear portion starting around 6500 MW and the intersection point is near 7600 MW. The Markov chain model exhibits smaller EENS estimates compared to the other two models for values of PG smaller than 6700 MW, and higher EENS estimates for higher values of PG. It should be noted that the Markov chain plot exhibits a staircase pattern because the number of bins, N, is small relative to the nominal output power.

No comparisons between AENS and EENS are generated for the ERCOT system-wide case study because the training data is not sufficiently large for accurate results and conclusions to be drawn from it.

3.4.3. Comparison with Previous Work

The previously referenced paper [11] studied the use of ARMA models on Texas' ERCOT wind energy generators. In that paper, accuracy of the model was defined as "the number of forecasts made by the model that carry an error less than a preset value, expressed as a percentage of the total number of forecasts made. For example, if 100 hour-ahead forecasts are made with the number of counts of the error less than 25% being equal to 90; the accuracy of the forecast is said to 90% in the 25% error limit. [11]" This definition was used for persistence, Markov chain, and ARMA models to evaluate their performance relative to the results shown in [11].

Table 3.4.3.1: Accuracy with 25% error limit for one hour ahead forecast in [11].

January	April	July	October
83.888	82.491	73.032	82.253

Table 3.4.3.2: Accuracy with 25% error limit for one hour ahead forecast in for persistence, Markov chain, and ARMA models.

Model	Accuracy
Persistence	99.792
Markov chain	95.833
ARMA	99.792

The results in table 3.4.3.1 and table 3.4.3.2 show that the three models examined here provided good estimates of WEG generation for the ERCOT system. There are however, a few caveats about the results shown in table 3.4.3.2. The size of the training data and the validation data used is significantly smaller than was used in [11]. Also, the data used for table 3.4.3.1 is from 2006 while the data used for table 3.4.3.2 is from 2014. The ERCOT grid has changed significantly since then and the total WEG capacity has increased since then.

4. CONCLUSIONS

The ability to accurately forecast wind energy generator power generation as well as the expected energy not served of a wind energy generator is very important in quantifying the risks associated with wind energy. Expected energy not served calculation requires an error distribution for the forecasted wind energy generator power generation. To this end, various predictive models can be used to produce this error distribution. Although much work has been done on evaluating and comparing predictive models for wind energy generator power forecasting, their effects on expected energy not served has been thus far unexplored.

In this thesis, Markov chain model, and ARMA models are used to produce a point forecast for the one-hour-ahead horizon as well as an error distribution that could be used for expected energy not served calculation considering a wind farm data from Ontario, Canada. These two models were compared to persistence model which was used to establish a benchmark.

Of the two predictive models examined, Markov chain model provided the better forecast, defined here as least normalized root-mean-square error. Both Markov chain and ARMA models outperformed persistence model and produce an accurate forecast. As evidenced by tables 3.2.2.1, and 3.3.2.1, Markov chain also provides the best estimation of expected energy not served as compared to actual energy not served, again as defined as least normalized root-mean-square error. Again, Markov chain and ARMA models both outperform persistence model. Markov chain model in particular gives a very accurate error distribution which is useful in producing accurate expected energy not served calculations.

Two other case studies were examined. The first involved data from Ontario's Wolfe Island wind farm. The results from that were similar to those of the Amaranth wind farm though slightly less accurate. As a result, the estimated expected energy not served skewed higher. The second involved data from Texas' ERCOT system. These results were also compared to the results from [11] which used older data from the ERCOT system. In most cases, Markov chain model is recommended in order to produce the best expected energy not served estimate based on the case studies examined. It should be noted however, that the most suitable model can differ depending on the specific application or location. This thesis provides a methodology by which the best model for estimating expected energy not served can be determined for any given situation or models.

A closed-form solution was found for expected energy not served when using a Cauchy distribution. A solution for expected energy not served was also found when using a Gaussian distribution. It is not fully closed-form because of the presence of the error function within the solution but look-up tables can be used for efficient calculation. Both solutions aid in reducing the computational complexity of calculating expected energy not served which is important in solving for OPF.

5. APPENDIX

5.1. Simulation Data

5.1.1. Amaranth Wind Farm Raw Data

5.1.1.1. Training Data

The data below is the hourly training data from Amaranth wind farm used to create the Markov chain and ARMA models. It is used to generate the plots and tables section 3.2.

Hour																							
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
16	23	12	10	8	8	9	12	12	8	6	1	0	0	2	4	13	10	5	2	11	30	33	61
67	41	40	30	22	28	27	24	7	17	33	17	4	1	1	0	0	2	2	3	9	4	5	19
34	54	78	118	124	135	155	155	165	169	175	181	183	182	181	182	182	179	181	168	146	128	93	79
64	75	116	111	91	61	59	80	119	108	117	125	133	107	95	115	104	114	117	129	155	158	144	132
131	130	120	111	116	123	109	119	128	135	145	131	106	115	115	122	104	85	74	64	58	82	83	83
75	72	83	78	68	70	69	82	82	79	74	50	58	56	40	58	72	100	97	71	83	51	36	32
40	50	56	59	72	77	66	57	85	124	118	116	119	125	133	132	136	131	114	74	76	92	79	90
56	40	36	19	12	21	22	20	36	47	63	52	50	62	82	95	92	61	31	29	33	25	27	21
19	14	13	8	1	8	26	19	1	2	3	9	12	16	21	33	37	31	23	25	24	40	57	77
73	84	72	80	94	110	87	73	87	74	71	89	135	128	111	79	42	27	17	21	24	17	17	18
30	37	39	45	39	37	37	35	43	38	33	38	38	29	35	62	68	63	58	47	47	38	32	26
33	49	53	56	46	38	33	31	25	15	26	63	110	117	98	80	67	48	34	28	32	29	32	21
12	6	4	4	7	8	10	13	9	6	8	8	7	2	10	21	27	35	27	23	21	16	14	17
22	28	47	49	54	50	45	22	17	20	20	22	17	14	15	11	9	7	9	10	23	16	20	24
18	20	31	23	19	15	11	15	5	0	1	3	10	17	22	36	35	31	36	63	71	94	101	87
85	92	104	96	91	81	82	93	89	75	82	51	74	101	94	89	69	48	46	52	59	69	62	72
72	100	121	146	164	144	170	169	183	182	180	182	182	182	175	144	124	146	113	105	99	119	123	120
124	101	54	54	50	38	46	33	34	47	53	97	139	163	176	177	176	156	124	90	85	113	108	95
90	71	54	65	84	46	24	24	48	121	121	98	108	138	150	153	150	141	81	56	33	49	67	69
62	63	127	131	133	104	146	160	155	139	144	135	114	112	126	123	121	119	99	69	67	68	78	35

44	47	48	56	59	48	46	67	46	96	79	79	120	114	96	89	84	76	67	56	40	24	18	13
13	11	16	13	3	0	1	2	10	23	34	45	50	63	68	73	61	80	75	67	128	168	171	143
136	138	142	164	156	94	90	91	90	89	87	91	92	91	89	87	80	86	112	77	34	21	19	8
1	0	0	0	0	2	4	14	25	29	37	52	79	103	55	46	116	148	113	41	54	43	64	102
97	101	86	54	54	14	7	1	0	0	1	2	4	2	3	3	2	3	28	32	39	17	38	29
17	36	25	24	29	37	27	55	22	83	70	50	33	35	51	88	15	16	23	34	26	83	93	73
43	54	88	112	96	129	98	110	108	113	89	98	100	146	145	157	150	153	143	162	152	146	97	38
10	5	3	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	54	51	29	36	106	143	127	87	79	104	95	91	79	86	104	103	111
97	89	57	57	55	40	27	39	56	52	26	18	28	17	15	4	0	2	4	15	42	52	60	68
76	96	119	145	141	130	117	92	62	45	31	43	38	56	86	82	31	38	50	81	109	135	161	162
161	161	160	169	170	169	167	134	80	45	55	51	59	109	111	122	118	98	60	34	31	44	37	22
37	31	20	17	20	16	19	16	32	29	12	5	5	9	14	28	53	44	49	38	47	33	147	135
152	160	166	158	140	135	137	181	166	121	156	171	176	182	180	182	175	180	167	120	126	124	117	138
118	87	74	63	84	134	182	184	184	184	180	167	177	184	182	183	184	184	175	175	175	174	174	162
146	138	126	142	117	125	142	155	156	162	163	162	164	164	159	135	131	116	93	84	55	25	18	20
20	16	7	2	1	0	0	0	0	0	0	0	1	1	0	0	1	6	41	69	62	59	62	76
68	67	74	88	86	78	50	35	19	13	20	34	43	41	47	51	72	66	59	59	82	101	115	107
82	104	129	130	124	109	113	78	62	65	99	122	113	100	96	110	123	101	89	81	86	114	115	68
86	93	60	95	103	111	80	23	10	11	18	19	23	51	97	108	126	122	122	114	119	126	143	105
51	47	52	38	20	14	19	22	26	30	56	127	156	180	179	113	51	63	32	38	56	45	26	35
62	71	84	67	45	32	25	5	2	6	7	3	11	14	24	30	38	39	40	54	56	47	50	63
86	61	61	69	44	21	35	53	40	28	20	21	31	29	28	35	34	35	26	17	20	31	35	57
104	126	121	109	68	51	58	35	31	34	31	57	109	146	153	153	143	133	126	108	103	104	88	75
64	50	46	53	52	48	42	43	38	40	32	26	23	19	21	21	21	18	14	17	20	31	24	28
20	15	15	22	33	26	21	22	20	28	43	66	72	86	139	167	152	125	80	57	72	70	92	124
125	120	114	121	118	101	68	74	60	36	31	35	35	25	21	18	17	17	19	34	47	65	71	90
71	46	29	20	50	64	54	37	40	16	14	24	58	77	68	60	47	36	33	47	58	90	107	112
90	72	71	57	54	43	56	51	52	62	57	64	63	75	82	87	89	52	36	48	66	78	80	89
85	65	55	71	70	71	53	39	24	7	19	52	78	87	73	59	44	30	19	12	18	32	52	59
56	53	43	28	32	42	39	16	10	10	2	4	5	8	10	10	6	24	28	17	9	37	38	32
24	27	34	25	17	24	22	4	0	2	3	10	16	16	12	7	9	19	24	19	3	1	2	4
12	16	14	9	9	2	2	1	2	4	12	9	5	6	4	9	7	9	9	5	7	11	12	29
21	26	33	34	23	24	20	9	1	2	5	11	12	9	14	16	22	15	9	4	3	1	1	1
0	0	3	6	8	4	7	3	1	1	3	9	10	22	8	11	37	22	16	15	15	26	32	45

37	49	58	69	66	50	31	43	63	105	151	105	54	28	11	2	4	3	3	5	5	5	14	22
26	22	38	55	59	56	64	71	47	36	32	23	10	3	22	34	48	81	73	67	100	157	170	153
162	140	114	118	129	164	167	177	179	181	183	180	174	178	178	180	181	181	181	177	166	173	166	143
101	80	70	76	93	90	72	68	85	126	128	118	137	149	150	150	155	135	102	59	37	29	23	10
2	3	15	31	36	34	38	35	56	47	58	71	72	76	64	53	53	51	59	65	72	82	97	109
104	105	107	103	148	155	155	123	114	134	169	181	181	182	183	186	177	161	131	86	75	45	38	47
58	49	72	79	61	38	28	16	32	79	115	122	126	117	109	81	40	33	30	20	21	33	37	25
13	8	17	31	40	33	17	11	14	11	4	0	0	0	0	0	2	4	10	7	9	5	5	8
14	22	46	52	37	29	21	11	16	32	46	40	35	33	22	20	20	17	18	20	28	35	34	34
46	50	44	40	34	34	37	21	20	22	18	30	35	26	25	28	21	21	21	22	33	34	33	46
55	61	65	63	54	35	16	4	2	2	2	7	18	32	48	62	82	83	51	48	117	72	55	34
33	33	42	67	62	46	25	8	9	8	35	65	95	46	1	4	52	68	23	22	19	13	13	26
25	15	19	25	23	19	13	7	8	6	17	26	44	51	62	69	137	129	85	43	54	35	23	45
42	31	26	37	54	43	55	65	101	81	33	58	74	102	125	141	135	143	145	151	147	138	128	111
111	136	108	95	121	93	106	116	131	133	117	97	96	89	87	83	79	75	63	48	33	31	35	44
49	42	32	32	42	38	23	25	62	62	71	69	77	79	67	60	70	72	66	45	44	41	40	42
53	53	41	42	50	35	17	19	57	60	59	61	72	75	72	63	49	31	19	14	19	24	30	39
41	41	43	26	17	13	10	3	0	0	0	0	0	0	0	1	1	3	3	3	3	2	6	20
50	56	52	50	45	55	44	31	43	57	46	39	39	32	24	12	8	51	16	27	19	34	40	34
21	64	94	75	67	67	79	89	136	129	103	106	82	65	84	119	109	74	61	44	32	51	63	64
54	40	45	50	46	30	27	38	28	27	38	46	56	63	64	81	100	100	68	39	60	80	90	104
96	95	103	105	78	58	40	29	27	44	90	98	95	108	149	160	111	75	80	93	59	65	82	40
64	114	75	36	33	31	56	57	35	39	62	96	91	64	49	63	78	46	26	34	25	27	36	32
33	42	43	44	45	46	65	124	156	153	112	82	79	79	106	130	150	151	138	141	144	121	84	67
61	45	36	35	42	62	57	53	58	95	98	108	109	108	113	130	130	122	104	81	43	34	49	67
63	52	34	34	26	20	11	15	28	30	26	22	23	19	21	17	14	19	15	12	5	7	5	9
18	24	23	37	43	37	34	21	12	7	10	18	18	13	17	19	20	20	32	49	62	62	64	72
55	65	67	73	80	94	77	78	113	135	146	155	150	157	146	120	104	117	124	111	68	49	71	53
30	30	21	8	8	6	11	11	13	13	12	8	11	10	15	10	10	11	11	15	20	12	6	3
2	2	5	9	12	13	9	6	10	6	4	6	7	11	6	5	8	3	2	1	3	4	10	9
8	12	16	14	16	12	3	3	4	2	0	0	0	0	1	2	4	22	38	30	30	35	42	48
48	73	88	83	101	96	56	34	16	32	23	40	36	30	33	43	59	80	60	71	49	35	19	11
9	11	8	14	17	14	20	24	17	24	45	60	54	52	48	45	45	38	27	20	8	1	0	0
0	0	0	0	0	0	0	0	0	0	2	4	13	20	19	29	36	18	0	0	3	4	9	21
25	23	23	25	26	38	47	42	40	53	53	56	56	54	74	109	139	107	94	70	51	42	54	41

58	58	59	45	35	43	35	37	16	17	13	19	23	22	36	34	25	15	14	11	12	9	19	33
38	36	28	15	17	10	6	3	3	6	15	17	9	10	11	30	39	49	45	9	1	3	13	22
48	55	42	57	60	59	45	43	37	28	57	65	47	44	67	78	70	68	57	46	60	59	30	38
29	29	16	11	17	15	17	6	8	24	22	28	17	23	17	15	10	7	4	6	6	16	14	14
8	22	17	18	23	20	16	27	35	39	37	29	34	29	22	16	25	40	41	29	41	71	84	72
45	36	34	34	27	14	6	0	2	4	8	8	5	3	1	0	0	2	5	16	9	2	1	3
8	23	20	43	33	38	27	7	5	4	4	1	1	1	2	1	1	1	1	1	2	2	1	2
13	38	32	17	11	9	9	2	3	6	6	9	16	18	22	26	24	22	38	46	54	50	45	43
68	93	96	99	116	107	90	84	105	75	58	43	49	43	39	29	23	13	9	2	4	8	5	8
3	9	8	9	14	26	21	4	6	16	40	53	69	72	89	98	112	82	48	31	29	50	64	77
75	64	69	77	84	56	63	46	48	57	88	101	100	94	85	72	70	56	36	35	31	44	49	67
64	46	40	30	32	9	21	32	28	47	85	81	40	58	63	49	18	25	18	19	23	14	17	28
48	46	37	30	21	19	15	10	7	13	11	17	19	17	13	12	6	3	0	0	0	1	1	1
1	2	2	3	5	7	10	5	4	3	2	3	3	1	1	3	5	10	8	3	2	2	4	5
19	2	4	14	7	7	3	1	1	1	1	4	11	21	8	8	11	15	12	9	4	1	1	1
1	1	1	2	2	2	2	3	11	6	2	8	12	41	59	31	41	40	26	20	15	21	14	5
20	44	19	25	34	28	38	46	34	16	9	2	3	5	9	13	22	22	26	24	45	67	86	96
79	66	79	76	77	67	63	60	71	70	79	66	57	68	69	66	66	63	45	48	30	35	50	56
71	60	81	56	20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	5	21	24	22
16	14	9	14	19	18	22	23	11	6	10	19	27	44	38	30	19	17	11	20	29	16	31	27
28	24	10	7	2	2	1	1	1	1	1	1	2	2	1	0	0	0	2	3	10	12	32	40
46	45	47	47	42	48	28	8	6	6	3	4	11	17	17	16	26	21	22	8	5	2	2	4
13	9	3	7	3	3	1	1	1	1	3	3	1	1	2	12	1	2	4	9	5	4	13	17
18	14	11	10	16	18	3	3	3	7	12	19	30	22	17	47	18	21	5	6	2	9	8	9
16	7	6	9	7	6	1	0	2	2	5	5	9	18	26	10	6	6	3	9	15	20	33	45
35	59	53	63	83	73	85	111	138	139	109	101	99	107	83	105	90	102	102	70	43	65	96	90
56	31	24	20	19	28	23	16	3	7	21	24	22	22	20	15	21	28	31	19	17	29	44	58
53	49	44	41	46	39	16	8	3	1	1	1	0	1	0	0	2	4	8	7	9	6	10	11
8	4	2	1	0	0	3	6	14	7	2	1	1	1	1	1	1	3	4	11	21	24	20	10
3	4	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
0	1	2	3	8	8	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	1	1	0	1	0	0	0	0	0	0	0	1	0	0	2	4	5	1	0	0	0	2
7	39	51	61	52	32	9	2	3	13	21	29	42	74	107	109	82	50	36	18	29	35	28	26
26	36	28	25	31	27	12	2	6	8	6	7	16	1	27	108	84	28	26	38	50	74	82	84

93	106	109	114	115	101	90	111	141	160	166	170	174	174	143	59	134	87	69	53	9	6	3	13
25	24	22	25	30	38	33	27	30	52	55	65	75	97	98	96	71	57	32	14	14	13	16	25
26	16	25	48	37	27	26	16	6	0	0	0	0	0	0	0	1	3	7	8	2	4	6	15
20	10	20	27	38	41	17	7	13	11	9	14	12	11	6	0	0	3	4	17	23	18	16	21
26	30	43	46	44	54	43	36	35	24	66	107	110	112	98	124	109	116	122	99	82	65	119	93
98	69	60	95	90	81	98	109	69	107	96	59	49	42	30	24	24	16	9	7	6	6	9	12
17	19	13	14	12	8	7	1	0	0	0	0	0	0	0	0	0	3	7	22	38	46	41	36
35	21	10	6	3	5	4	3	2	2	2	5	11	12	15	13	21	15	11	25	39	57	69	71
73	73	38	27	26	36	33	19	18	23	15	34	36	71	20	60	27	20	32	31	39	33	29	28
38	41	42	48	52	60	55	105	121	130	138	116	88	66	46	21	51	64	31	21	46	39	37	39
33	40	32	37	26	18	18	22	27	21	23	18	12	16	32	25	23	34	44	21	23	23	27	21
17	15	17	24	13	19	22	27	47	33	19	7	5	4	5	13	14	3	0	0	0	0	0	2
4	7	2	7	9	5	1	2	4	9	10	5	1	5	12	13	15	25	20	15	4	4	5	8
3	5	7	0	1	1	3	7	31	36	37	52	46	64	47	41	38	31	24	20	18	10	10	11
10	10	8	10	17	21	21	4	3	11	35	41	31	107	114	94	81	78	73	42	20	10	36	46
45	33	29	37	32	32	34	40	43	41	35	41	59	74	89	110	118	117	105	73	65	43	34	36
36	33	35	38	27	21	27	22	35	41	50	65	71	97	100	104	91	66	33	33	36	30	27	28
33	33	28	34	36	29	25	13	7	4	2	2	3	1	3	3	3	9	20	20	21	16	12	15
20	11	8	10	12	14	19	17	12	19	34	36	38	42	53	54	40	32	39	41	49	56	49	44
59	68	66	60	59	80	61	60	82	121	109	125	131	135	107	92	60	54	44	31	10	3	2	3
12	4	1	2	3	7	1	0	0	0	2	2	1	2	3	4	4	11	5	8	15	11	17	15
22	25	27	32	46	50	35	20	19	15	4	0	1	2	11	33	54	55	44	41	57	69	41	44
47	60	47	43	30	31	21	13	32	29	26	18	17	16	16	14	15	19	19	18	9	9	12	13
17	24	29	29	24	9	7	5	2	8	13	21	17	22	28	38	48	15	5	5	14	15	17	23
45	47	37	33	25	12	9	1	1	2	2	5	12	41	44	44	48	38	23	19	33	41	29	30
16	2	5	22	23	40	43	59	79	114	104	98	125	135	141	120	104	110	112	76	74	75	81	84
71	58	70	62	58	57	59	76	105	123	114	95	78	82	58	37	40	108	63	48	52	69	73	62
75	89	76	39	15	11	13	6	15	44	50	44	37	32	30	27	26	24	18	18	27	32	38	34
44	50	50	47	50	31	24	9	0	1	1	2	5	7	3	2	2	2	5	7	12	11	6	3
1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	3	15	21	40	32	9	6
9	7	4	2	0	0	0	0	0	0	0	0	1	1	1	1	1	0	2	4	15	6	1	0
0	0	0	13	20	22	25	27	15	16	11	7	8	10	14	18	21	26	27	25	26	36	60	62
53	49	55	62	62	46	47	25	12	29	33	35	45	36	37	28	27	24	14	16	27	42	66	73
65	62	62	62	75	65	43	17	9	26	65	61	52	58	61	57	59	53	43	58	70	85	111	110
78	66	62	60	76	77	81	89	26	35	43	42	53	42	36	30	36	23	12	17	24	19	10	7

10	15	34	33	36	34	38	19	18	12	8	1	2	2	3	2	3	2	4	7	10	18	26	25
15	10	9	5	2	1	0	0	0	0	1	1	1	2	1	1	1	2	3	6	7	17	31	47
42	31	31	33	37	46	40	27	17	29	40	53	51	45	13	11	14	61	118	130	91	69	115	145
149	139	135	144	163	172	167	167	167	167	167	167	167	50	44	76	61	32	17	20	22	45	32	33
7	2	2	2	5	2	0	0	0	0	0	2	2	0	2	11	4	1	1	5	1	0	0	2

5.1.1.2. Validation Data

The data below is the hourly validation data from Amaranth wind farm used to verify the accuracy of the three models. It is used to generate the plots and tables in section 3.2

Hour																							
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
4	6	3	6	12	22	14	9	11	10	19	21	20	19	23	13	14	15	17	23	39	50	38	27
14	6	4	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	5	6	0	0
2	2	13	43	50	53	54	44	29	36	56	70	107	94	94	94	94	94	31	33	38	38	38	38
38	38	38	38	38	38	38	38	4	1	0	0	0	0	0	0	0	9	10	11	11	10	12	18
8	5	5	2	1	5	10	15	26	17	21	26	24	20	30	16	11	10	5	2	9	9	2	8
6	5	2	2	2	5	6	12	29	50	67	55	62	91	96	113	97	81	74	83	70	103	99	66
54	50	50	50	44	46	44	36	54	44	49	68	84	134	126	106	103	98	53	61	84	63	36	31
48	60	71	49	59	83	88	85	80	86	85	78	81	65	57	34	19	34	25	30	37	33	37	47
33	35	30	37	27	48	42	29	32	27	37	43	43	45	39	31	28	22	19	22	15	12	6	3
1	0	0	0	1	2	8	19	16	11	10	8	12	14	17	24	24	37	40	38	51	80	101	98
116	135	108	89	89	88	56	103	72	65	59	49	45	34	49	52	41	39	31	18	17	14	10	11
22	19	87	108	105	63	45	21	46	46	43	22	11	12	9	2	2	5	7	1	3	6	9	11
16	22	19	22	36	37	54	38	32	28	10	8	9	6	4	14	16	19	33	69	91	83	54	44
66	113	136	129	57	35	71	88	89	80	103	105	97	101	111	100	94	99	112	123	131	132	142	99
102	112	109	92	79	50	30	20	27	70	102	56	62	87	81	61	35	23	20	23	7	6	31	15
18	38	31	35	28	27	18	23	40	45	95	89	101	115	103	128	136	95	74	61	51	37	43	68
62	64	61	53	55	57	45	45	45	45	45	45	45	59	72	64	53	40	27	21	24	13	3	3
5	5	5	10	17	16	11	8	4	13	14	9	8	6	12	19	24	28	29	34	34	39	66	111
97	47	73	73	71	71	71	57	35	51	35	56	69	57	33	37	34	39	48	53	35	26	31	23
15	9	12	48	49	55	33	28	44	46	38	28	24	31	29	21	28	25	16	12	10	16	19	16
18	25	40	39	33	38	27	30	13	10	6	8	6	3	3	6	6	10	21	26	25	25	27	32
38	47	47	48	56	57	56	41	13	9	11	6	10	11	16	17	19	15	18	37	57	53	50	60
68	58	74	53	46	40	37	13	12	20	25	27	18	15	13	24	24	21	25	32	37	32	43	56
53	39	39	49	52	52	59	80	90	94	89	128	112	111	95	111	95	69	47	73	69	48	35	20
10	22	6	8	25	33	32	16	16	14	26	26	35	46	98	134	137	128	109	102	95	115	102	65

40	25	23	32	34	22	31	39	61	57	57	58	48	43	41	38	39	25	11	9	9	8	9	8
2	0	0	0	0	0	0	1	6	14	9	6	4	4	4	2	1	3	11	11	20	21	18	14
13	3	0	2	3	3	0	0	0	0	0	0	0	0	0	0	1	2	6	8	4	2	3	12
10	16	7	9	15	10	9	5	0	0	0	1	2	2	0	0	2	4	5	10	12	9	15	21
28	25	18	11	6	3	4	1	0	1	2	2	1	1	0	0	0	3	4	4	1	0	2	14
17	15	13	8	5	7	13	8	1	0	0	0	1	1	0	0	2	3	16	17	18	37	25	26
34	45	55	53	53	51	37	18	11	11	10	10	12	15	17	27	36	32	54	62	61	71	66	86
119	106	99	89	84	84	87	65	39	36	27	23	33	39	30	24	23	12	10	10	21	27	25	35
27	18	15	9	7	7	8	9	8	7	7	1	5	14	33	35	23	18	19	2	0	0	0	3
6	22	35	46	48	47	36	24	13	9	19	39	56	73	105	116	113	100	105	156	156	160	165	159

5.1.2. Wolfe Island Wind Farm Raw Data

5.1.2.1. Training Data

The data below is the hourly training data from Wolfe Island wind farm used to create the Markov chain and ARMA models. It is used to generate the plots and tables section 3.3.

Hour																							
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
16	23	12	10	8	8	9	12	12	8	6	1	0	0	2	4	13	10	5	2	11	30	33	61
67	41	40	30	22	28	27	24	7	17	33	17	4	1	1	0	0	2	2	3	9	4	5	19
34	54	78	118	124	135	155	155	165	169	175	181	183	182	181	182	182	179	181	168	146	128	93	79
64	75	116	111	91	61	59	80	119	108	117	125	133	107	95	115	104	114	117	129	155	158	144	132
131	130	120	111	116	123	109	119	128	135	145	131	106	115	115	122	104	85	74	64	58	82	83	83
75	72	83	78	68	70	69	82	82	79	74	50	58	56	40	58	72	100	97	71	83	51	36	32
40	50	56	59	72	77	66	57	85	124	118	116	119	125	133	132	136	131	114	74	76	92	79	90
56	40	36	19	12	21	22	20	36	47	63	52	50	62	82	95	92	61	31	29	33	25	27	21
19	14	13	8	1	8	26	19	1	2	3	9	12	16	21	33	37	31	23	25	24	40	57	77
73	84	72	80	94	110	87	73	87	74	71	89	135	128	111	79	42	27	17	21	24	17	17	18
30	37	39	45	39	37	37	35	43	38	33	38	38	29	35	62	68	63	58	47	47	38	32	26
33	49	53	56	46	38	33	31	25	15	26	63	110	117	98	80	67	48	34	28	32	29	32	21
12	6	4	4	7	8	10	13	9	6	8	8	7	2	10	21	27	35	27	23	21	16	14	17
22	28	47	49	54	50	45	22	17	20	20	22	17	14	15	11	9	7	9	10	23	16	20	24
18	20	31	23	19	15	11	15	5	0	1	3	10	17	22	36	35	31	36	63	71	94	101	87
85	92	104	96	91	81	82	93	89	75	82	51	74	101	94	89	69	48	46	52	59	69	62	72
72	100	121	146	164	144	170	169	183	182	180	182	182	182	175	144	124	146	113	105	99	119	123	120
124	101	54	54	50	38	46	33	34	47	53	97	139	163	176	177	176	156	124	90	85	113	108	95
90	71	54	65	84	46	24	24	48	121	121	98	108	138	150	153	150	141	81	56	33	49	67	69
62	63	127	131	133	104	146	160	155	139	144	135	114	112	126	123	121	119	99	69	67	68	78	35
44	47	48	56	59	48	46	67	46	96	79	79	120	114	96	89	84	76	67	56	40	24	18	13

13	11	16	13	3	0	1	2	10	23	34	45	50	63	68	73	61	80	75	67	128	168	171	143
136	138	142	164	156	94	90	91	90	89	87	91	92	91	89	87	80	86	112	77	34	21	19	8
1	0	0	0	0	2	4	14	25	29	37	52	79	103	55	46	116	148	113	41	54	43	64	102
97	101	86	54	54	14	7	1	0	0	1	2	4	2	3	3	2	3	28	32	39	17	38	29
17	36	25	24	29	37	27	55	22	83	70	50	33	35	51	88	15	16	23	34	26	83	93	73
43	54	88	112	96	129	98	110	108	113	89	98	100	146	145	157	150	153	143	162	152	146	97	38
10	5	3	2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	54	51	29	36	106	143	127	87	79	104	95	91	79	86	104	103	111
97	89	57	57	55	40	27	39	56	52	26	18	28	17	15	4	0	2	4	15	42	52	60	68
76	96	119	145	141	130	117	92	62	45	31	43	38	56	86	82	31	38	50	81	109	135	161	162
161	161	160	169	170	169	167	134	80	45	55	51	59	109	111	122	118	98	60	34	31	44	37	22
37	31	20	17	20	16	19	16	32	29	12	5	5	9	14	28	53	44	49	38	47	33	147	135
152	160	166	158	140	135	137	181	166	121	156	171	176	182	180	182	175	180	167	120	126	124	117	138
118	87	74	63	84	134	182	184	184	184	180	167	177	184	182	183	184	184	175	175	175	174	174	162
146	138	126	142	117	125	142	155	156	162	163	162	164	164	159	135	131	116	93	84	55	25	18	20
20	16	7	2	1	0	0	0	0	0	0	0	1	1	0	0	1	6	41	69	62	59	62	76
68	67	74	88	86	78	50	35	19	13	20	34	43	41	47	51	72	66	59	59	82	101	115	107
82	104	129	130	124	109	113	78	62	65	99	122	113	100	96	110	123	101	89	81	86	114	115	68
86	93	60	95	103	111	80	23	10	11	18	19	23	51	97	108	126	122	122	114	119	126	143	105
51	47	52	38	20	14	19	22	26	30	56	127	156	180	179	113	51	63	32	38	56	45	26	35
62	71	84	67	45	32	25	5	2	6	7	3	11	14	24	30	38	39	40	54	56	47	50	63
86	61	61	69	44	21	35	53	40	28	20	21	31	29	28	35	34	35	26	17	20	31	35	57
104	126	121	109	68	51	58	35	31	34	31	57	109	146	153	153	143	133	126	108	103	104	88	75
64	50	46	53	52	48	42	43	38	40	32	26	23	19	21	21	21	18	14	17	20	31	24	28
20	15	15	22	33	26	21	22	20	28	43	66	72	86	139	167	152	125	80	57	72	70	92	124
125	120	114	121	118	101	68	74	60	36	31	35	35	25	21	18	17	17	19	34	47	65	71	90
71	46	29	20	50	64	54	37	40	16	14	24	58	77	68	60	47	36	33	47	58	90	107	112
90	72	71	57	54	43	56	51	52	62	57	64	63	75	82	87	89	52	36	48	66	78	80	89
85	65	55	71	70	71	53	39	24	7	19	52	78	87	73	59	44	30	19	12	18	32	52	59
56	53	43	28	32	42	39	16	10	10	2	4	5	8	10	10	6	24	28	17	9	37	38	32
24	27	34	25	17	24	22	4	0	2	3	10	16	16	12	7	9	19	24	19	3	1	2	4
12	16	14	9	9	2	2	1	2	4	12	9	5	6	4	9	7	9	9	5	7	11	12	29

21	26	33	34	23	24	20	9	1	2	5	11	12	9	14	16	22	15	9	4	3	1	1	1
0	0	3	6	8	4	7	3	1	1	3	9	10	22	8	11	37	22	16	15	15	26	32	45
37	49	58	69	66	50	31	43	63	105	151	105	54	28	11	2	4	3	3	5	5	5	14	22
26	22	38	55	59	56	64	71	47	36	32	23	10	3	22	34	48	81	73	67	100	157	170	153
162	140	114	118	129	164	167	177	179	181	183	180	174	178	178	180	181	181	181	177	166	173	166	143
101	80	70	76	93	90	72	68	85	126	128	118	137	149	150	150	155	135	102	59	37	29	23	10
2	3	15	31	36	34	38	35	56	47	58	71	72	76	64	53	53	51	59	65	72	82	97	109
104	105	107	103	148	155	155	123	114	134	169	181	181	182	183	186	177	161	131	86	75	45	38	47
58	49	72	79	61	38	28	16	32	79	115	122	126	117	109	81	40	33	30	20	21	33	37	25
13	8	17	31	40	33	17	11	14	11	4	0	0	0	0	0	2	4	10	7	9	5	5	8
14	22	46	52	37	29	21	11	16	32	46	40	35	33	22	20	20	17	18	20	28	35	34	34
46	50	44	40	34	34	37	21	20	22	18	30	35	26	25	28	21	21	21	22	33	34	33	46
55	61	65	63	54	35	16	4	2	2	2	7	18	32	48	62	82	83	51	48	117	72	55	34
33	33	42	67	62	46	25	8	9	8	35	65	95	46	1	4	52	68	23	22	19	13	13	26
25	15	19	25	23	19	13	7	8	6	17	26	44	51	62	69	137	129	85	43	54	35	23	45
42	31	26	37	54	43	55	65	101	81	33	58	74	102	125	141	135	143	145	151	147	138	128	111
111	136	108	95	121	93	106	116	131	133	117	97	96	89	87	83	79	75	63	48	33	31	35	44
49	42	32	32	42	38	23	25	62	62	71	69	77	79	67	60	70	72	66	45	44	41	40	42
53	53	41	42	50	35	17	19	57	60	59	61	72	75	72	63	49	31	19	14	19	24	30	39
41	41	43	26	17	13	10	3	0	0	0	0	0	0	0	1	1	3	3	3	3	2	6	20
50	56	52	50	45	55	44	31	43	57	46	39	39	32	24	12	8	51	16	27	19	34	40	34
21	64	94	75	67	67	79	89	136	129	103	106	82	65	84	119	109	74	61	44	32	51	63	64
54	40	45	50	46	30	27	38	28	27	38	46	56	63	64	81	100	100	68	39	60	80	90	104
96	95	103	105	78	58	40	29	27	44	90	98	95	108	149	160	111	75	80	93	59	65	82	40
64	114	75	36	33	31	56	57	35	39	62	96	91	64	49	63	78	46	26	34	25	27	36	32
33	42	43	44	45	46	65	124	156	153	112	82	79	79	106	130	150	151	138	141	144	121	84	67
61	45	36	35	42	62	57	53	58	95	98	108	109	108	113	130	130	122	104	81	43	34	49	67
63	52	34	34	26	20	11	15	28	30	26	22	23	19	21	17	14	19	15	12	5	7	5	9
18	24	23	37	43	37	34	21	12	7	10	18	18	13	17	19	20	20	32	49	62	62	64	72
55	65	67	73	80	94	77	78	113	135	146	155	150	157	146	120	104	117	124	111	68	49	71	53
30	30	21	8	8	6	11	11	13	13	12	8	11	10	15	10	10	11	11	15	20	12	6	3
2	2	5	9	12	13	9	6	10	6	4	6	7	11	6	5	8	3	2	1	3	4	10	9

8	12	16	14	16	12	3	3	4	2	0	0	0	0	1	2	4	22	38	30	30	35	42	48
48	73	88	83	101	96	56	34	16	32	23	40	36	30	33	43	59	80	60	71	49	35	19	11
9	11	8	14	17	14	20	24	17	24	45	60	54	52	48	45	45	38	27	20	8	1	0	0
0	0	0	0	0	0	0	0	0	0	2	4	13	20	19	29	36	18	0	0	3	4	9	21
46	36	35	49	51	80	63	46	55	55	67	37	38	41	42	28	14	8	8	3	0	0	1	2
3	11	37	43	86	76	56	92	74	41	31	47	58	56	34	29	24	24	24	27	35	27	44	49
52	95	138	154	157	158	160	158	159	160	160	159	158	157	157	160	159	151	95	112	160	160	159	158
143	139	159	160	156	158	159	159	159	159	159	160	160	158	159	160	160	156	145	149	155	155	149	116
89	63	40	40	31	18	29	19	33	55	55	38	32	14	36	40	75	97	105	94	100	93	94	63
45	40	36	40	49	54	66	65	63	61	56	65	79	103	117	87	79	104	112	104	93	96	107	111
82	84	88	96	91	74	93	86	63	56	30	17	21	37	43	29	23	10	1	1	3	10	7	3
0	0	0	0	1	2	5	9	11	8	2	1	2	4	9	6	1	1	1	11	34	22	24	33
31	11	3	4	6	14	14	10	16	17	82	67	113	128	100	104	130	122	133	95	73	126	138	135
128	139	138	145	154	134	114	103	99	107	127	135	123	118	116	114	121	130	136	133	101	87	75	71
89	84	83	95	96	82	67	69	74	78	71	65	52	44	33	33	21	5	16	55	39	23	34	55
61	61	66	86	96	82	75	65	77	65	55	64	69	65	72	91	64	43	43	70	68	59	58	44
33	39	59	52	53	48	37	31	30	23	20	24	30	20	15	5	1	2	3	4	5	7	4	3
16	38	44	41	34	33	36	32	18	16	15	12	7	8	7	6	7	7	12	7	1	0	0	1
1	2	6	4	0	0	1	2	5	4	7	18	36	54	46	54	37	22	29	54	77	81	98	85
74	85	115	129	124	132	122	80	60	42	42	47	75	102	107	106	92	60	47	64	130	53	54	86
121	149	147	134	123	126	125	133	117	119	116	108	108	111	115	110	126	131	124	126	133	108	77	70
57	52	49	65	70	72	66	49	43	44	78	84	96	97	88	85	90	75	78	84	96	114	134	116
65	42	23	36	45	44	28	63	98	105	109	117	85	61	42	18	3	1	4	11	27	35	24	36
38	26	30	61	74	65	34	23	15	12	22	36	29	37	57	61	48	34	36	57	69	64	59	49
38	46	52	50	68	92	59	56	66	88	93	85	80	95	109	83	64	61	46	28	21	6	1	1
3	5	9	9	19	24	30	41	58	59	77	72	67	35	52	72	104	112	126	126	99	154	158	160
161	161	161	161	161	161	161	160	160	160	160	157	151	120	107	93	79	67	61	57	52	35	17	12
13	17	30	52	83	90	121	130	118	81	96	109	123	98	62	60	107	157	160	148	158	154	134	72
82	80	45	22	1	2	8	11	10	23	12	10	11	9	11	5	6	21	5	12	16	41	28	28
27	17	17	4	5	6	14	55	43	30	27	80	53	52	55	80	139	107	55	53	29	13	14	35
55	69	94	79	108	105	146	149	146	125	156	160	159	158	158	158	158	157	158	155	154	151	151	158
160	134	119	73	16	26	26	11	5	27	76	124	156	159	152	157	148	126	106	107	109	132	131	147

148	125	142	141	126	82	70	69	100	140	154	125	143	124	138	148	141	125	94	69	48	35	55	33
20	28	25	22	16	18	16	6	1	0	4	2	0	1	5	13	35	43	52	70	90	135	156	158
159	155	153	147	127	78	67	49	36	30	37	54	64	75	71	119	131	102	71	79	76	97	138	154
158	159	156	137	85	63	52	18	26	9	3	3	3	3	3	3	6	4	1	1	11	50	43	42
45	72	89	95	99	85	64	49	56	55	37	26	38	34	76	73	96	121	155	156	133	87	37	38
111	155	155	146	149	151	159	161	158	156	159	159	159	158	156	136	83	38	56	118	128	99	23	4
68	136	115	151	156	155	156	158	153	154	158	158	159	159	159	159	158	158	159	158	156	156	156	155
156	149	101	119	125	116	108	151	150	132	116	87	66	69	87	79	67	59	41	26	30	36	29	23
12	9	12	11	6	7	9	8	11	13	16	18	16	29	43	52	33	38	59	43	40	56	70	97
100	82	58	56	52	52	52	26	17	9	7	8	9	14	19	17	16	37	78	117	107	113	122	112
140	152	154	150	150	149	141	114	111	69	67	50	52	52	50	44	54	66	78	77	33	12	8	25
124	154	154	154	115	140	135	135	127	118	61	100	108	114	95	100	124	99	54	54	50	96	113	114
89	88	76	88	92	74	74	51	98	150	156	155	118	100	145	85	75	36	70	68	38	36	43	40
32	31	30	17	7	0	0	0	0	4	11	13	13	25	34	24	22	11	9	45	47	70	76	67
66	41	22	17	11	6	17	23	11	5	5	9	11	12	8	6	6	9	17	42	73	92	107	121
115	63	50	25	15	20	55	74	82	95	112	98	107	96	94	86	66	48	36	33	55	56	52	67
85	64	33	15	7	1	3	5	2	1	6	5	0	3	7	3	16	12	14	29	38	70	68	50
49	54	45	51	36	47	52	29	27	24	23	11	6	89	101	76	52	42	32	36	37	49	56	82
112	142	130	98	92	91	67	46	41	34	25	14	10	14	16	13	22	13	25	54	63	102	102	104
86	90	103	99	93	97	92	52	54	50	34	25	28	19	25	32	47	58	65	86	124	141	114	83
122	137	127	122	118	85	52	46	46	53	64	83	106	112	105	100	93	77	80	97	108	148	156	153
146	145	134	117	113	111	116	108	110	77	68	85	76	75	65	53	60	52	49	69	111	144	135	115
110	76	82	90	81	87	86	61	41	37	46	64	76	77	76	59	55	43	33	36	58	57	42	35
54	57	54	63	57	56	52	20	25	18	11	15	23	29	26	33	38	28	20	18	34	45	69	88
78	36	30	37	20	15	15	7	9	23	27	28	51	60	67	66	43	29	10	3	7	3	1	4
6	2	10	17	9	8	11	2	0	0	1	0	0	2	2	5	86	9	2	13	13	8	18	28
29	22	18	10	0	0	0	0	0	0	0	0	1	2	11	22	10	11	16	32	52	64	73	68
62	37	2	4	16	36	102	122	129	97	111	134	136	115	110	73	87	79	100	106	114	104	106	76
50	35	25	21	19	17	12	11	5	3	3	5	7	23	73	88	88	108	136	153	160	148	102	53
55	83	82	115	117	109	115	145	155	155	148	145	146	147	151	158	159	159	156	140	147	116	65	40
55	74	87	79	75	50	43	69	36	25	38	18	14	10	5	1	1	1	3	11	28	52	55	58
70	74	70	52	42	35	41	70	82	66	84	107	114	135	134	94	81	78	98	110	120	130	100	69

56	28	64	81	147	152	159	157	135	147	139	133	146	145	123	97	72	40	27	21	36	29	60	79
84	32	19	12	7	8	20	12	8	9	23	37	38	28	6	6	15	10	19	43	64	57	38	32
43	24	27	22	19	17	15	26	26	17	22	35	45	34	30	40	39	61	52	32	30	56	46	47
59	105	90	55	26	12	23	18	25	27	23	31	35	41	50	52	63	62	59	62	76	103	103	93
77	51	36	38	40	62	49	30	26	15	6	9	22	27	16	12	19	42	37	58	72	103	77	83
63	54	45	42	41	31	27	16	17	20	28	27	64	92	118	145	151	140	76	67	71	82	96	95
89	82	82	59	67	61	55	57	96	149	119	103	111	86	106	135	142	112	34	9	24	65	11	14
56	65	62	88	92	52	81	95	103	79	118	127	121	106	151	158	156	152	89	89	50	44	39	58
73	66	42	42	39	26	21	25	27	18	25	144	150	157	159	160	161	161	160	160	160	160	160	158
153	151	145	142	145	143	133	144	139	127	123	116	121	104	103	98	100	84	34	11	17	15	10	4
4	5	1	0	0	0	0	6	9	9	14	28	32	34	45	43	34	65	65	44	52	36	26	20
15	11	11	8	5	2	1	1	6	10	13	23	28	17	15	10	6	14	24	25	16	6	4	2
0	1	3	7	9	10	12	6	9	19	24	43	47	27	21	10	19	31	62	82	96	134	137	101
71	58	32	17	2	2	0	2	1	22	10	8	31	57	39	23	72	51	83	76	88	102	144	158
159	158	158	138	77	43	84	113	112	112	94	132	151	139	87	70	61	43	16	3	0	10	21	28
43	53	69	80	73	59	49	43	47	49	53	66	64	72	80	61	64	42	20	74	15	40	64	118
127	108	103	120	87	69	79	94	109	118	125	139	139	137	116	130	53	43	82	102	57	65	54	108
159	160	154	102	69	49	35	77	116	128	121	133	141	114	129	122	106	56	36	11	13	9	8	29
33	23	87	117	108	122	142	154	151	145	140	139	136	124	93	90	71	73	95	100	70	76	71	30
30	48	41	27	14	10	6	5	6	6	3	3	5	8	6	3	1	1	1	7	13	15	28	33
31	26	19	11	40	54	34	15	4	5	3	4	3	4	9	8	13	22	32	41	36	24	23	24
17	12	20	21	23	23	24	8	4	5	17	23	29	31	40	43	48	48	28	9	11	45	51	50
44	45	39	32	47	46	39	45	33	27	15	8	31	44	47	42	42	49	59	37	15	17	13	8
7	2	10	16	14	20	21	19	15	12	15	12	14	15	22	20	18	14	13	12	10	12	8	6
4	3	2	4	4	2	1	0	1	2	1	1	2	0	1	8	8	3	4	2	4	12	12	17
14	21	27	22	25	35	45	38	35	59	92	88	88	76	92	112	116	118	116	135	135	139	125	117
61	57	49	33	34	47	48	41	36	26	15	4	5	2	3	4	6	1	1	2	5	6	1	2
9	12	14	34	41	64	33	29	45	45	45	29	19	11	13	14	17	10	1	1	2	6	3	5
10	48	26	3	0	1	1	0	0	1	2	4	38	9	0	1	5	1	5	15	23	54	54	66
12	13	14	30	30	35	42	45	36	48	53	48	34	22	18	14	9	7	10	0	0	0	0	0
0	1	9	20	51	24	18	25	21	11	6	19	24	19	11	6	5	4	8	8	10	16	27	33
55	71	74	75	76	76	76	76	76	76	77	77	77	76	74	76	76	75	70	55	72	74	76	75

75	64	68	77	77	75	76	77	77	77	77	76	77	77	76	76	75	75	75	76	77	77	77	76
69	58	51	46	29	37	30	30	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
24	24	24	24	24	24	24	24	24	24	24	24	24	24	67	67	48	48	61	60	56	55	60	65
60	49	43	47	59	63	61	50	47	49	34	29	23	18	13	16	15	5	0	3	1	0	0	0
0	0	1	1	2	3	2	0	0	0	0	0	0	1	0	0	0	0	1	1	3	4	5	12
19	5	1	3	3	5	4	6	2	5	33	39	50	51	40	30	39	50	42	43	56	64	70	76
76	77	77	77	75	71	72	69	59	35	21	17	11	6	8	1	4	28	60	52	36	27	28	34
42	35	40	40	42	37	33	33	37	36	44	49	39	21	11	29	10	5	9	2	1	2	13	17
23	31	36	40	52	50	47	41	45	50	52	44	46	54	50	42	19	19	22	27	27	8	23	11
3	0	4	26	41	39	28	19	16	11	11	9	6	5	1	1	1	0	8	8	7	5	9	8
11	10	13	20	18	16	12	13	9	7	8	12	16	19	14	7	10	11	6	0	0	0	0	1
1	2	5	7	3	0	0	1	2	3	6	13	16	20	31	22	18	13	14	19	34	42	49	42
47	46	51	64	66	71	73	65	45	24	20	21	28	38	53	63	57	43	50	44	50	32	19	49
22	55	71	60	58	63	65	57	73	72	70	65	64	67	64	61	61	68	66	51	55	52	44	46
39	33	26	29	37	23	18	23	34	32	43	57	59	61	59	55	47	46	31	39	28	40	47	53
23	16	13	28	34	20	18	24	43	59	65	65	52	42	29	15	5	2	0	1	12	20	14	23
28	22	20	37	49	46	25	14	11	8	20	23	15	19	24	17	13	9	23	30	30	28	32	37
28	29	36	33	33	35	27	27	25	32	33	36	35	36	50	45	37	38	27	15	11	8	4	0
1	0	0	2	7	10	15	16	29	26	31	22	13	12	18	24	40	63	68	70	62	71	76	77

5.1.2.2. Validation Data

The data below is the hourly validation data from Wolfe Island wind farm used to verify the accuracy of the three models. It is used to generate the plots and tables in section 3.3

												Hour											
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
4	6	3	6	12	22	14	9	11	10	19	21	20	19	23	13	14	15	17	23	39	50	38	27
14	6	4	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	5	6	0	0
2	2	13	43	50	53	54	44	29	36	56	70	107	94	94	94	94	94	31	33	38	38	38	38
38	38	38	38	38	38	38	38	4	1	0	0	0	0	0	0	0	9	10	11	11	10	12	18
8	5	5	2	1	5	10	15	26	17	21	26	24	20	30	16	11	10	5	2	9	9	2	8
6	5	2	2	2	5	6	12	29	50	67	55	62	91	96	113	97	81	74	83	70	103	99	66
54	50	50	50	44	46	44	36	54	44	49	68	84	134	126	106	103	98	53	61	84	63	36	31
48	60	71	49	59	83	88	85	80	86	85	78	81	65	57	34	19	34	25	30	37	33	37	47
33	35	30	37	27	48	42	29	32	27	37	43	43	45	39	31	28	22	19	22	15	12	6	3
1	0	0	0	1	2	8	19	16	11	10	8	12	14	17	24	24	37	40	38	51	80	101	98
116	135	108	89	89	88	56	103	72	65	59	49	45	34	49	52	41	39	31	18	17	14	10	11
22	19	87	108	105	63	45	21	46	46	43	22	11	12	9	2	2	5	7	1	3	6	9	11
16	22	19	22	36	37	54	38	32	28	10	8	9	6	4	14	16	19	33	69	91	83	54	44
66	113	136	129	57	35	71	88	89	80	103	105	97	101	111	100	94	99	112	123	131	132	142	99
102	112	109	92	79	50	30	20	27	70	102	56	62	87	81	61	35	23	20	23	7	6	31	15
18	38	31	35	28	27	18	23	40	45	95	89	101	115	103	128	136	95	74	61	51	37	43	68
62	64	61	53	55	57	45	45	45	45	45	45	45	59	72	64	53	40	27	21	24	13	3	3
5	5	5	10	17	16	11	8	4	13	14	9	8	6	12	19	24	28	29	34	34	39	66	111
97	47	73	73	71	71	71	57	35	51	35	56	69	57	33	37	34	39	48	53	35	26	31	23
15	9	12	48	49	55	33	28	44	46	38	28	24	31	29	21	28	25	16	12	10	16	19	16
18	25	40	39	33	38	27	30	13	10	6	8	6	3	3	6	6	10	21	26	25	25	27	32
38	47	47	48	56	57	56	41	13	9	11	6	10	11	16	17	19	15	18	37	57	53	50	60
68	58	74	53	46	40	37	13	12	20	25	27	18	15	13	24	24	21	25	32	37	32	43	56
53	39	39	49	52	52	59	80	90	94	89	128	112	111	95	111	95	69	47	73	69	48	35	20

10	22	6	8	25	33	32	16	16	14	26	26	35	46	98	134	137	128	109	102	95	115	102	65
40	25	23	32	34	22	31	39	61	57	57	58	48	43	41	38	39	25	11	9	9	8	9	8
2	0	0	0	0	0	0	1	6	14	9	6	4	4	4	2	1	3	11	11	20	21	18	14
13	3	0	2	3	3	0	0	0	0	0	0	0	0	0	0	1	2	6	8	4	2	3	12
10	16	7	9	15	10	9	5	0	0	0	1	2	2	0	0	2	4	5	10	12	9	15	21
28	25	18	11	6	3	4	1	0	1	2	2	1	1	0	0	0	3	4	4	1	0	2	14
17	15	13	8	5	7	13	8	1	0	0	0	1	1	0	0	2	3	16	17	18	37	25	26
34	45	55	53	53	51	37	18	11	11	10	10	12	15	17	27	36	32	54	62	61	71	66	86
119	106	99	89	84	84	87	65	39	36	27	23	33	39	30	24	23	12	10	10	21	27	25	35
27	18	15	9	7	7	8	9	8	7	7	1	5	14	33	35	23	18	19	2	0	0	0	3
6	22	35	46	48	47	36	24	13	9	19	39	56	73	105	116	113	100	105	156	156	160	165	159

5.1.3. ERCOT System-wide Raw Data

5.1.3.1. Training Data

The data below is the hourly training data from the ERCOT system-wide used to create the Markov chain and ARMA models.

It is used to generate the plots and tables section 3.4.

					Hour						
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
9554.8	9362.31	8327	7099.26	6338.87	6003.01	5602.71	5447.11	6474.38	6166.71	5731.21	5305.24
8727.32	8613.33	8397.51	8040.86	7461.66	7040.15	6351.71	6588.31	7970.88	8545.73	8566.86	8166.12
1820.8	1976.87	2128.83	2752.86	3436.34	3979.16	4114.92	3830.86	2558.99	2248.96	3501.81	4220.43
679.34	781.32	1027.15	1550.42	2030	2155.8	2110.45	1974.87	1342.18	1181.71	1778.51	1932.04
6629.28	6385.92	5860.43	5103.72	4372.51	3969.99	3975.78	3674.02	2983.4	3418.6	4185.37	4046
9288.2	9275.83	9089.71	8604.97	8054.47	6099.93	4061.01	3097.43	2555.08	2484.02	2177.27	2169.81
4829.18	4937.51	4716.93	3969.75	4111.1	4153.23	4254.91	4455.27	4650.85	5703.12	6271.63	6016.5
9119.13	9064.24	8994.01	8980.39	8968.66	8772.8	8607.35	8645.82	8745.09	8958.45	8812.39	8507.42

9244.11	9105.43	8956.52	8498.43	8306.01	8207.26	8030.05	7624.55	7392.86	7213.8	6502.64	6386.37
9002.65	8776.63	8679.92	8421.33	7844.11	7095.24	6296.18	6318.25	7571.28	8112.22	7463.71	6459.29

Hour											
13	14	15	16	17	18	19	20	21	22	23	24
5037.53	4873.38	5139.43	4736.39	4476.55	5263.51	5873.18	6341.34	6914.51	7340.4	7754.27	8311.37
7359.39	6355.34	5695.04	5884.06	6697.3	7183.5	7627.75	6149.3	3612.71	2223.3	1813.93	1684.56
3808.84	3424.41	3466.09	3681.33	3829.01	3566.18	3162.03	2165.47	1083.86	741.22	723.69	769.66
1879.01	1470.85	1467.26	1587.05	1790.54	2076.53	2250.42	2405.44	2586.07	4060.31	5656.85	6599.23
4338.01	4510.5	4517.47	4556.46	4588.09	4671.75	5224.44	5398.41	6219.67	7551	8480.46	9150.56
2008.73	2025.26	2011.15	2091.31	2225.86	2442.32	2710.15	3194.65	3733.71	4949.77	5551.06	5382.94
5767.31	6053.74	6593.25	7380.02	8147.7	8783.21	9183.78	9226	8984.95	9024.83	9147.5	9181.73
8132.72	7728.79	7452.51	7230.17	7112.94	7392.17	7561.07	7749.76	8018.77	8645.5	9171.22	9284.34
6008.76	5452.68	5084.97	5448.39	6110.5	6842.59	7765.66	8351.67	8443.56	8532.28	8794.49	9017.56
5632.05	5289.15	5560.6	6210.07	6630.9	7332.79	7696.59	7458.72	6256.91	5999.42	6387.87	6865.02

5.1.3.2. Validation Data

The data below is the hourly validation data from ERCOT system-wide used to verify the accuracy of the three models. It is used to generate the plots and tables in section 3.4

Hour											
1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
6953.88	6964.82	7560.1	7505.61	6859.51	6468.97	5894.84	5142.95	5158.75	5382.66	4778.69	4119.7
4629.46	4816.23	5215.44	5214.61	4434.27	3892.21	3425.81	2940.78	3084.9	3718.1	4074.4	4180.54

Hour											
13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
3718.63	3719.3	3374.31	3338.69	3664.04	4704.71	5844.89	5544.6	3903.39	3566.71	4104.15	4187.59
4038.94	3762.79	3454.73	3840.56	4904.17	5146.76	5249.03	5245.77	5607.97	5158.31	5275.15	4921.21

5.2. Forecasted Data

5.2.1. Amaranth Wind Farm Forecasted Data

The data below gives the forecasts produced by each model over the period of the validation data for Amaranth Wind Farm. It is used to generate the plots and tables in section 3.2.

Actual	Persistence	Markov	ARMA
4	0	4.83	3.80
6	4	4.50	7.04
3	6	4.50	8.49
6	3	4.50	4.45
12	6	10.00	9.20
22	12	27.30	15.03
14	22	20.50	25.36
9	14	6.17	12.75
11	9	7.50	10.36
10	11	10.00	13.44
19	10	20.90	11.34
21	19	22.50	22.75
20	21	21.50	21.86
19	20	20.90	20.90
23	19	20.50	19.97
13	23	11.50	25.04
14	13	20.50	11.55
15	14	15.50	16.63
17	15	21.00	16.35
23	17	20.50	18.82
39	23	38.50	25.32
50	39	46.50	42.67
38	50	47.50	50.89
27	38	22.50	34.10
14	27	20.50	25.72
6	14	4.50	12.50
4	6	4.83	6.69
6	4	4.50	5.94
0	6	0.00	8.55
0	0	0.00	0.57
0	0	0.00	2.85
0	0	0.00	2.17
0	0	0.00	2.35
0	0	0.00	2.28
0	0	0.00	2.29
0	0	0.00	2.27
0	0	0.00	2.26
0	0	0.00	2.24
0	0	0.00	2.23
0	0	0.00	2.22
0	0	0.00	2.20
0	0	0.00	2.19
0	0	0.00	2.18
2	0	0.00	2.17
5	2	7.00	4.56
6	5	4.50	7.46
0	6	0.00	7.81
0	0	0.00	0.48
2	0	0.00	2.58
2	2	0.00	4.36
13	2	11.50	3.83
43	13	39.50	17.20
50	43	46.50	49.40
53	50	54.50	48.53
54	53	44.50	52.40
44	54	46.50	52.50
29	44	38.50	40.46
36	29	36.50	25.90
56	36	41.50	38.51
70	56	68.73	58.92
107	70	99.83	69.88
94	107	87.94	111.22
94	94	87.94	83.70
94	94	87.94	91.67
94	94	87.94	89.40
94	94	87.94	90.08
31	94	25.50	89.91
33	31	36.17	14.25
38	33	47.50	38.47
38	38	47.50	37.50

38	38	47.50	37.78	5	10	7.00	11.05
38	38	47.50	37.70	2	5	0.00	5.37
38	38	47.50	37.72	9	2	6.17	3.39
38	38	47.50	37.72	9	9	6.17	12.37
38	38	47.50	37.72	2	9	0.00	9.77
38	38	47.50	37.72	8	2	8.50	2.09
38	38	47.50	37.72	6	8	4.50	11.50
38	38	47.50	37.72	5	6	7.00	6.38
38	38	47.50	37.73	2	5	0.00	6.64
38	38	47.50	37.73	2	2	0.00	2.95
4	38	4.83	37.73	2	2	0.00	4.00
1	4	0.00	3.14	5	2	7.00	3.68
0	1	0.00	5.02	6	5	4.50	7.37
0	0	0.00	1.45	12	6	10.00	7.49
0	0	0.00	2.46	29	12	38.50	14.66
0	0	0.00	2.15	50	29	46.50	33.02
0	0	0.00	2.22	67	50	64.50	52.97
0	0	0.00	2.19	55	67	66.50	67.67
0	0	0.00	2.18	62	55	63.50	49.02
9	0	6.17	2.17	91	62	78.28	62.83
10	9	10.00	12.97	96	91	87.83	93.72
11	10	7.50	11.05	113	96	94.50	90.85
11	11	7.50	12.79	97	113	96.40	112.15
10	11	10.00	12.28	81	97	49.50	86.81
12	10	10.00	11.21	74	81	81.37	74.92
18	12	21.50	13.91	83	74	52.50	69.96
8	18	8.50	20.34	70	83	68.73	82.23
5	8	7.00	6.46	103	70	112.50	63.09
5	5	7.00	6.84	99	103	104.00	108.30
2	5	0.00	6.72	66	99	58.50	90.48
1	2	0.00	3.13	54	66	44.50	55.98
5	1	7.00	2.95	50	54	46.50	51.52
10	5	10.00	7.80	50	50	46.50	48.01
15	10	15.50	12.40	50	50	46.50	49.03
26	15	26.30	17.07	44	50	46.50	48.74
17	26	21.00	28.94	46	44	41.00	41.62
21	17	22.50	14.69	44	46	46.50	46.08
26	21	26.30	23.60	36	44	36.50	42.40
24	26	23.50	27.04	54	36	44.50	33.85
20	24	21.50	23.64	44	54	46.50	57.95
30	20	34.83	19.81	49	44	68.50	38.99
16	30	15.50	32.93	68	49	67.00	50.47
11	16	7.50	12.32	84	68	71.00	70.01
10	11	10.00	12.24	134	84	131.00	83.63

126	134	126.83	139.83	37	27	30.50	25.96
106	126	117.33	114.06	43	37	39.50	40.27
103	106	112.50	97.49	43	43	39.50	43.36
98	103	109.50	98.70	45	43	37.50	42.47
53	98	54.50	92.37	39	45	38.50	45.13
61	53	53.50	40.13	31	39	25.50	37.15
84	61	71.00	64.82	28	31	30.00	29.84
63	84	54.75	85.36	22	28	27.30	28.33
36	63	36.50	54.21	19	22	20.90	21.55
31	36	25.50	30.75	22	19	27.30	19.89
48	31	47.50	31.50	15	22	15.50	23.97
60	48	60.50	51.72	12	15	10.00	14.37
71	60	67.50	60.32	6	12	4.50	13.52
49	71	68.50	71.07	3	6	4.50	6.54
59	49	81.50	41.54	1	3	0.00	4.93
83	59	52.50	62.08	0	1	0.00	2.97
88	83	78.36	85.02	0	0	0.00	2.31
85	88	112.50	84.44	0	0	0.00	2.48
80	85	95.50	81.03	1	0	0.00	2.42
86	80	93.14	76.02	2	1	0.00	3.62
85	86	112.50	84.70	8	2	8.50	4.46
78	85	73.50	81.02	19	8	20.90	11.41
81	78	49.50	73.69	16	19	15.50	22.62
65	81	67.50	79.42	11	16	7.50	15.77
57	65	60.00	58.55	10	11	10.00	11.72
34	57	36.50	54.97	8	10	8.50	11.67
19	34	20.90	28.36	12	8	10.00	9.27
34	19	36.50	18.00	14	12	20.50	14.76
25	34	22.50	39.01	17	14	21.00	15.57
30	25	34.83	22.13	24	17	23.50	18.93
37	30	30.50	33.00	24	24	23.50	26.37
33	37	36.17	38.27	37	24	30.50	24.22
37	33	30.50	31.94	40	37	33.50	40.46
47	37	51.50	38.57	38	40	47.50	39.38
33	47	36.17	48.68	51	38	62.50	37.29
35	33	39.83	28.94	80	51	95.50	53.52
30	35	34.83	37.03	101	80	89.12	83.71
37	30	30.50	28.69	98	101	109.50	100.28
27	37	22.50	39.50	116	98	117.28	91.92
48	27	47.50	24.36	135	116	137.64	116.00
42	48	52.00	53.97	108	135	105.50	131.94
29	42	38.50	38.22	89	108	88.50	94.93
32	29	20.50	27.13	89	89	88.50	82.79
27	32	22.50	33.93	88	89	78.36	86.32

56	88	41.50	84.12
103	56	112.50	46.31
72	103	74.25	113.72
65	72	67.50	57.05
59	65	81.50	64.99
49	59	68.50	55.50
45	49	37.50	46.23
34	45	36.50	44.10
49	34	68.50	31.49
52	49	55.75	53.15
41	52	41.50	50.52
39	41	38.50	38.06
31	39	25.50	39.25
18	31	21.50	29.29
17	18	21.00	16.53
14	17	20.50	18.99
10	14	10.00	14.66
11	10	7.50	11.09
22	11	27.30	13.31
19	22	20.90	25.88
87	19	75.00	18.64
108	87	105.50	102.46
105	108	94.41	103.56
63	105	54.75	99.67
45	63	37.50	50.33
21	45	22.50	42.93
46	21	41.00	16.22
46	46	41.00	53.97
43	46	39.50	43.08
22	43	27.30	42.62
11	22	7.50	17.51
12	11	10.00	11.52
9	12	6.17	14.43
2	9	0.00	9.97
2	2	0.00	2.83
5	2	7.00	4.87
7	5	7.00	7.87
1	7	0.00	9.39
3	1	4.50	1.72
6	3	4.50	6.32
9	6	6.17	8.58
11	9	7.50	11.52
16	11	15.50	13.06
22	16	27.30	18.62

19	22	20.90	24.22
22	19	27.30	18.99
36	22	36.50	24.09
37	36	30.50	39.44
54	37	44.50	36.22
38	54	47.50	57.59
32	38	20.50	32.20
28	32	30.00	32.31
10	28	10.00	27.46
8	10	8.50	7.22
9	8	6.17	10.64
6	9	4.50	10.84
4	6	4.83	7.16
14	4	20.50	5.80
16	14	15.50	18.20
19	16	20.90	17.02
33	19	36.17	20.95
69	33	63.50	36.64
91	69	78.28	75.39
83	91	52.50	90.68
54	83	44.50	76.68
44	54	46.50	45.88
66	44	58.50	42.75
113	66	94.50	70.10
136	113	128.00	118.73
129	136	124.00	132.39
57	129	60.00	120.09
35	57	39.83	37.12
71	35	67.50	34.61
88	71	78.36	78.61
89	88	88.50	86.37
80	89	95.50	85.36
103	80	112.50	74.86
105	103	94.41	105.55
97	105	96.40	99.14
101	97	89.12	91.40
111	101	106.42	98.47
100	111	110.72	108.48
94	100	87.94	92.40
99	94	104.00	89.85
112	99	83.50	96.63
123	112	115.50	110.33
131	123	134.50	119.63
132	131	135.00	126.61

142	132	146.83	125.84	74	95	81.37	80.75
99	142	104.00	138.13	61	74	53.50	69.69
102	99	92.10	82.94	51	61	62.50	57.27
112	102	83.50	102.48	37	51	30.50	48.83
109	112	107.68	108.90	43	37	39.50	34.44
92	109	84.50	103.47	68	43	67.00	45.79
79	92	74.00	84.63	62	68	63.50	72.57
50	79	46.50	74.46	64	62	55.50	57.65
30	50	34.83	42.54	61	64	53.50	64.36
20	30	21.50	27.70	53	61	54.50	58.82
27	20	22.50	19.95	55	53	66.50	50.81
70	27	68.73	30.59	57	55	60.00	55.53
102	70	92.10	79.21	45	57	37.50	56.57
56	102	41.50	103.67	45	45	37.50	41.85
62	56	63.50	41.34	45	45	37.50	46.09
87	62	75.00	66.53	45	45	37.50	44.87
81	87	49.50	89.33	45	45	37.50	45.22
61	81	53.50	75.56	45	45	37.50	45.12
35	61	39.83	55.50	45	45	37.50	45.14
23	35	20.50	30.04	59	45	81.50	45.13
20	23	21.50	22.95	72	59	74.25	61.96
23	20	20.50	21.37	64	72	55.50	72.74
7	23	7.00	25.42	53	64	54.50	60.03
6	7	4.50	5.01	40	53	33.50	50.48
31	6	25.50	9.67	27	40	22.50	37.61
15	31	15.50	38.36	21	27	22.50	25.69
18	15	21.50	10.85	24	21	23.50	21.90
38	18	47.50	22.37	13	24	11.50	26.58
31	38	25.50	43.08	3	13	4.50	12.00
35	31	39.83	28.69	3	3	4.50	4.17
28	35	30.00	37.64	5	3	7.00	6.40
27	28	22.50	26.64	5	5	7.00	8.14
18	27	21.50	28.60	5	5	7.00	7.62
23	18	20.50	17.20	10	5	10.00	7.75
40	23	33.50	26.49	17	10	21.00	13.70
45	40	37.50	44.23	16	17	15.50	20.38
95	45	98.00	45.12	11	16	7.50	17.24
89	95	88.50	104.98	8	11	8.50	12.12
101	89	89.12	80.53	4	8	4.83	9.97
115	101	123.50	102.02	13	4	11.50	5.76
103	115	112.50	112.68	14	13	20.50	17.78
128	103	112.50	95.22	9	14	6.17	15.50
136	128	128.00	130.33	8	9	8.50	10.13
95	136	98.00	129.86	6	8	4.50	10.46

12	6	10.00	7.94	38	46	47.50	45.14
19	12	20.90	15.86	28	38	30.00	36.37
24	19	23.50	21.97	24	28	23.50	26.88
28	24	30.00	26.21	31	24	25.50	24.80
29	28	38.50	29.79	29	31	38.50	33.80
34	29	36.50	29.95	21	29	22.50	28.79
34	34	36.50	35.91	28	21	30.00	20.61
39	34	38.50	34.18	25	28	22.50	31.38
66	39	58.50	40.69	16	25	15.50	24.66
111	66	106.42	71.27	12	16	10.00	15.77
97	111	96.40	116.56	10	12	10.00	13.51
47	97	51.50	86.70	16	10	15.50	11.74
73	47	66.50	35.23	19	16	20.90	19.45
73	73	66.50	81.33	16	19	15.50	20.82
71	73	67.50	68.05	18	16	21.50	16.80
71	71	67.50	69.48	25	18	22.50	20.35
71	71	67.50	69.08	40	25	33.50	27.73
57	71	60.00	69.21	39	40	38.50	43.63
35	57	39.83	52.36	33	39	36.17	37.84
51	35	62.50	30.77	38	33	47.50	32.30
35	51	39.83	56.23	27	38	22.50	39.90
56	35	41.50	29.65	30	27	34.83	24.48
69	56	63.50	62.56	13	30	11.50	32.53
57	69	60.00	68.70	10	13	10.00	9.76
33	57	36.17	52.52	6	10	4.50	12.71
37	33	30.50	28.34	8	6	8.50	7.03
34	37	36.50	40.11	6	8	4.50	11.06
39	34	38.50	33.10	3	6	4.50	7.48
48	39	47.50	41.13	3	3	4.50	4.88
53	48	54.50	49.63	6	3	4.50	5.61
35	53	39.83	53.19	6	6	4.50	8.99
26	35	26.30	30.53	10	6	10.00	8.00
31	26	25.50	26.24	21	10	22.50	13.08
23	31	20.50	33.48	26	21	26.30	24.82
15	23	15.50	21.77	25	26	22.50	27.44
9	15	6.17	15.52	25	25	22.50	25.47
12	9	10.00	10.09	27	25	22.50	26.03
48	12	47.50	15.24	32	27	20.50	28.27
49	48	68.50	57.02	38	32	47.50	33.63
55	49	66.50	46.18	47	38	51.50	39.29
33	55	36.17	56.52	47	47	51.50	48.48
28	33	30.00	27.09	48	47	47.50	45.83
44	28	46.50	29.56	56	48	41.50	47.80
46	44	41.00	48.08	57	56	60.00	56.85

56	57	41.50	55.45	39	39	38.50	35.53
41	56	41.50	54.66	49	39	68.50	39.82
13	41	11.50	36.87	52	49	55.75	50.60
9	13	6.17	8.34	52	52	55.75	51.11
11	9	7.50	11.74	59	52	81.50	50.97
6	11	4.50	13.15	80	59	95.50	59.43
10	6	10.00	6.72	90	80	67.83	82.24
11	10	7.50	13.37	94	90	87.94	87.71
16	11	15.50	12.64	89	94	88.50	90.96
17	16	21.00	18.84	128	89	112.50	84.04
19	17	20.90	18.25	112	128	83.50	132.95
15	19	15.50	20.81	111	112	106.42	99.65
18	15	21.50	15.25	95	111	98.00	108.08
37	18	30.50	20.45	111	95	106.42	86.45
57	37	60.00	41.78	95	111	98.00	111.95
53	57	54.50	59.67	69	95	63.50	85.40
50	53	46.50	49.72	47	69	51.50	61.82
60	50	60.50	48.99	73	47	66.50	42.19
68	60	67.00	61.22	69	73	63.50	79.11
58	68	71.50	67.32	48	69	47.50	63.67
74	58	81.37	53.56	35	48	39.83	42.89
53	74	54.50	76.77	20	35	21.50	33.25
46	53	41.00	44.85	10	20	10.00	17.99
40	46	33.50	45.64	22	10	27.30	10.36
37	40	30.50	38.20	6	22	4.50	26.97
13	37	11.50	36.74	8	6	8.50	2.94
12	13	10.00	8.31	25	8	22.50	12.26
20	12	21.50	15.30	33	25	36.17	29.99
25	20	22.50	22.89	32	33	20.50	34.48
27	25	22.50	26.70	16	32	15.50	31.98
18	27	21.50	28.00	16	16	15.50	13.46
15	18	15.50	16.80	14	16	20.50	18.79
13	15	11.50	16.41	26	14	26.30	14.84
24	13	23.50	14.11	26	26	26.30	30.39
24	24	23.50	27.98	35	26	39.83	25.90
21	24	22.50	23.97	46	35	41.00	38.01
25	21	22.50	21.52	98	46	109.50	47.74
32	25	20.50	27.02	134	98	131.00	107.45
37	32	30.50	33.84	137	134	154.50	133.53
32	37	20.50	37.89	128	137	112.50	129.66
43	32	39.50	30.71	109	128	107.68	120.00
56	43	41.50	46.00	102	109	92.10	99.99
53	56	54.50	57.22	95	102	98.00	97.38
39	53	38.50	50.39	115	95	123.50	89.74

102	115	92.10	116.01	11	3	7.50	5.90
65	102	67.50	92.84	11	11	7.50	14.76
40	65	33.50	55.07	20	11	21.50	12.19
25	40	22.50	35.92	21	20	22.50	23.74
23	25	20.50	23.41	18	21	21.50	21.60
32	23	20.50	24.60	14	18	20.50	18.60
34	32	36.50	35.07	13	14	11.50	14.65
22	34	27.30	34.45	3	13	4.50	14.58
31	22	25.50	20.20	0	3	0.00	2.56
39	31	38.50	35.11	2	0	0.00	2.40
61	39	53.50	40.42	3	2	4.50	4.84
57	61	60.00	65.34	3	3	4.50	5.32
57	57	60.00	53.35	0	3	0.00	5.16
58	57	71.50	56.81	0	0	0.00	1.59
48	58	47.50	57.02	0	0	0.00	2.60
43	48	39.50	44.95	0	0	0.00	2.29
41	43	41.50	42.42	0	0	0.00	2.36
38	41	47.50	40.74	0	0	0.00	2.32
39	38	38.50	37.62	0	0	0.00	2.32
25	39	22.50	39.72	0	0	0.00	2.30
11	25	7.50	22.28	0	0	0.00	2.29
9	11	6.17	10.47	0	0	0.00	2.27
9	9	6.17	11.46	1	0	0.00	2.26
8	9	8.50	11.15	2	1	0.00	3.45
9	8	6.17	10.02	6	2	4.50	4.29
8	9	8.50	11.53	8	6	8.50	8.84
2	8	0.00	9.88	4	8	4.83	9.92
0	2	0.00	3.13	2	4	0.00	4.79
0	0	0.00	2.65	3	2	4.50	3.85
0	0	0.00	2.77	12	3	10.00	5.31
0	0	0.00	2.71	10	12	10.00	15.69
0	0	0.00	2.71	16	10	15.50	10.28
0	0	0.00	2.69	7	16	7.00	19.04
1	0	0.00	2.67	9	7	6.17	5.69
6	1	4.50	3.86	15	9	15.50	11.93
14	6	20.50	9.51	10	15	10.00	17.33
9	14	6.17	17.48	9	10	6.17	9.76
6	9	4.50	9.16	5	9	7.00	10.73
4	6	4.83	7.94	0	5	0.00	5.63
4	4	4.83	5.87	0	0	0.00	1.07
4	4	4.83	6.45	0	0	0.00	2.37
2	4	0.00	6.26	1	0	0.00	1.98
1	2	0.00	3.89	2	1	0.00	3.28
3	1	4.50	3.36	2	2	0.00	4.09

0	2	0.00	3.84	0	0	0.00	1.80
0	0	0.00	1.50	0	0	0.00	1.62
2	0	0.00	2.16	1	0	0.00	1.66
4	2	4.83	4.36	1	1	0.00	2.84
5	4	7.00	6.11	0	1	0.00	2.49
10	5	10.00	6.80	0	0	0.00	1.37
12	10	10.00	12.60	2	0	0.00	1.68
9	12	6.17	13.32	3	2	4.50	3.99
15	9	15.50	9.50	16	3	15.50	4.51
21	15	22.50	17.80	17	16	21.00	19.98
28	21	30.00	22.61	18	17	21.50	16.72
25	28	22.50	29.63	37	18	30.50	18.86
18	25	21.50	24.00	25	37	22.50	41.08
11	18	7.50	17.21	26	25	26.30	20.25
6	11	4.50	10.75	34	26	36.50	27.46
3	6	4.50	6.59	45	34	37.50	35.00
4	3	4.83	4.17	55	45	66.50	46.05
1	4	0.00	6.06	53	55	54.50	54.89
0	1	0.00	1.89	53	53	54.50	49.95
1	0	0.00	1.88	51	53	62.50	51.39
2	1	0.00	3.07	37	51	30.50	48.59
2	2	0.00	3.92	18	37	21.50	32.58
1	2	0.00	3.66	11	18	7.50	14.36
1	1	0.00	2.52	11	11	7.50	11.19
0	1	0.00	2.83	10	11	10.00	12.10
0	0	0.00	1.53	10	10	10.00	10.63
0	0	0.00	1.89	12	10	10.00	11.05
3	0	4.50	1.77	15	12	15.50	13.32
4	3	4.83	5.40	17	15	21.00	16.27
4	4	4.83	5.54	27	17	22.50	17.82
1	4	0.00	5.49	36	27	36.50	29.39
0	1	0.00	1.89	32	36	20.50	36.87
2	0	0.00	1.71	54	32	44.50	29.91
14	2	20.50	4.15	62	54	63.50	58.37
17	14	21.00	17.86	61	62	53.50	59.79
15	17	15.50	17.51	71	61	67.50	58.20
13	15	11.50	15.20	66	71	58.50	70.70
8	13	8.50	13.46	86	66	93.14	61.10
5	8	7.00	7.94	119	86	118.83	87.93
7	5	7.00	5.92	106	119	117.33	119.90
13	7	11.50	8.90	99	106	104.00	95.10
8	13	8.50	15.24	89	99	88.50	93.87
1	8	0.00	7.39	84	89	71.00	82.24
0	1	0.00	1.23	84	84	71.00	79.61

87	84	75.00	80.39
65	87	67.50	83.80
39	65	38.50	56.40
36	39	36.50	33.06
27	36	22.50	36.19
23	27	20.50	24.47
33	23	36.17	23.04
39	33	38.50	35.47
30	39	34.83	39.10
24	30	23.50	27.24
23	24	20.50	23.45
12	23	10.00	23.34
10	12	10.00	10.14
10	10	10.00	11.53
21	10	22.50	11.12
27	21	22.50	24.46
25	27	22.50	27.82
35	25	39.83	24.44
27	35	22.50	37.44
18	27	21.50	24.08
15	18	15.50	17.11
9	15	6.17	15.51
7	9	7.00	8.75
7	7	7.00	8.28
8	7	8.50	8.41
9	8	6.17	9.56
8	9	8.50	10.42
7	8	7.00	8.96
7	7	7.00	8.17
1	7	0.00	8.39
5	1	7.00	1.10
14	5	20.50	8.00
33	14	36.17	16.82
35	33	39.83	37.11
23	35	20.50	33.67
18	23	21.50	20.24
19	18	20.90	18.10
2	19	0.00	19.91
0	2	0.00	1.05
0	0	0.00	2.57
0	0	0.00	1.52
3	0	4.50	1.81
6	3	4.50	5.32
22	6	27.30	7.90
35	22	39.83	26.38
46	35	41.00	36.68
48	46	47.50	46.94
47	48	51.50	46.39
36	47	36.50	45.36
24	36	23.50	32.44
13	24	11.50	21.74
9	13	6.17	11.60
19	9	20.90	9.71
39	19	38.50	22.27
56	39	41.50	42.69
73	56	66.50	57.24
105	73	94.41	73.50
116	105	117.28	107.30
113	116	94.50	110.81
100	113	110.72	106.24
105	100	94.41	91.97
156	105	148.83	102.13
156	156	148.83	160.55
160	156	167.50	143.76
165	160	170.50	153.47
159	165	136.50	156.75

5.2.2. Wolfe Island Wind Farm Forecasted Data

The data below gives the forecasts produced by each model over the period of the validation data for Wolfe Island wind farm. It is used to generate the plots and tables in section 3.3.

Actual	Persistence	Markov	ARMA
4	0	6.50	3.79
6	4	5.50	7.13
3	6	4.50	8.54
6	3	5.50	4.46
12	6	9.50	9.31
22	12	21.50	15.11
14	22	20.50	25.48
9	14	9.50	12.66
11	9	7.50	10.44
10	11	12.50	13.52
19	10	25.50	11.37
21	19	21.50	22.92
20	21	22.50	21.86
19	20	25.50	20.96
23	19	22.50	20.01
13	23	12.50	25.14
14	13	20.50	11.47
15	14	13.50	16.78
17	15	21.50	16.38
23	17	22.50	18.92
39	23	37.10	25.42
50	39	45.50	42.86
38	50	31.50	50.96
27	38	29.50	33.98
14	27	20.50	25.75
6	14	5.50	12.45
4	6	6.50	6.74
6	4	5.50	6.02
0	6	0.00	8.65
0	0	0.00	0.57
0	0	0.00	2.99
0	0	0.00	2.24
0	0	0.00	2.45
0	0	0.00	2.38
0	0	0.00	2.38
0	0	0.00	2.37
0	0	0.00	2.36
0	0	0.00	2.35
0	0	0.00	2.33
0	0	0.00	2.32
0	0	0.00	2.31
0	0	0.00	2.30
0	0	0.00	2.29
2	0	5.50	2.28
5	2	10.50	4.69
6	5	5.50	7.59
0	6	0.00	7.92
0	0	0.00	0.54
2	0	5.50	2.74
2	2	5.50	4.49
13	2	12.50	3.95
43	13	44.00	17.44
50	43	45.50	49.75
53	50	50.50	48.52
54	53	51.50	52.54
44	54	50.50	52.55
29	44	38.50	40.43
36	29	34.83	25.89
56	36	53.50	38.75
70	56	77.50	59.13
107	70	107.77	69.99
94	107	91.57	111.60
94	94	91.57	83.35
94	94	91.57	91.87
94	94	91.57	89.33
94	94	91.57	90.12
31	94	36.50	89.91
33	31	32.50	13.61
38	33	31.50	38.98
38	38	31.50	37.41
38	38	31.50	37.88
38	38	31.50	37.74
38	38	31.50	37.79
38	38	31.50	37.77
38	38	31.50	37.78
38	38	31.50	37.78
38	38	31.50	37.78
38	38	31.50	37.78
38	38	31.50	37.78

38	38	31.50	37.78	12	6	9.50	7.62
4	38	6.50	37.78	29	12	38.50	14.86
1	4	0.00	-3.44	50	29	45.50	33.29
0	1	0.00	5.30	67	50	62.50	53.21
0	0	0.00	1.45	55	67	72.50	67.84
0	0	0.00	2.59	62	55	78.00	48.90
0	0	0.00	2.23	91	62	65.50	63.09
0	0	0.00	2.33	96	91	92.50	94.00
0	0	0.00	2.28	113	96	103.21	90.79
0	0	0.00	2.28	97	113	109.50	112.40
9	0	9.50	2.27	81	97	83.03	86.53
10	9	12.50	13.17	74	81	77.50	74.94
11	10	7.50	11.10	83	74	52.50	69.96
11	11	7.50	12.92	70	83	77.50	82.39
10	11	12.50	12.36	103	70	112.50	62.91
12	10	9.50	11.31	99	103	93.28	108.79
18	12	15.83	14.04	66	99	79.50	90.17
8	18	9.50	20.49	54	66	51.50	55.79
5	8	10.50	6.42	50	54	45.50	51.59
5	5	10.50	7.00	50	50	45.50	48.01
2	5	5.50	6.81	50	50	45.50	49.09
1	2	0.00	3.22	44	50	50.50	48.77
5	1	10.50	3.08	46	44	47.00	41.60
10	5	12.50	7.96	44	46	50.50	46.19
15	10	13.50	12.54	36	44	34.83	42.39
26	15	18.50	17.21	54	36	51.50	33.84
17	26	21.50	29.14	44	54	50.50	58.23
21	17	21.50	14.64	49	44	50.00	38.78
26	21	18.50	23.84	68	49	79.00	50.70
24	26	25.50	27.13	84	68	83.00	70.16
20	24	22.50	23.72	134	84	123.08	83.72
30	20	31.50	19.89	126	134	123.15	140.28
16	30	20.83	33.16	106	126	111.42	113.61
11	16	7.50	12.19	103	106	112.50	97.42
10	11	12.50	12.43	98	103	107.50	98.68
5	10	10.50	11.14	53	98	50.50	92.27
2	5	5.50	5.45	61	53	62.50	39.66
9	2	9.50	3.51	84	61	83.00	65.19
9	9	9.50	12.57	63	84	53.50	85.41
2	9	5.50	9.84	36	63	34.83	53.88
8	2	9.50	2.17	31	36	36.50	30.64
6	8	5.50	11.74	48	31	42.50	31.57
5	6	10.50	6.42	60	48	51.00	51.90
2	5	5.50	6.80	71	60	73.25	60.34
2	2	5.50	3.04	49	71	50.00	71.14
2	2	5.50	4.16	59	49	62.00	41.23
5	2	10.50	3.81	83	59	52.50	62.36
6	5	5.50	7.54	88	83	86.83	85.11

85	88	70.50	84.35	19	8	25.50	11.53
80	85	67.83	80.96	16	19	20.83	22.74
86	80	62.50	75.94	11	16	7.50	15.73
85	86	70.50	84.74	10	11	12.50	11.77
78	85	85.50	80.90	8	10	9.50	11.73
81	78	83.03	73.59	12	8	9.50	9.31
65	81	66.67	79.44	14	12	20.50	14.88
57	65	54.50	58.30	17	14	21.50	15.62
34	57	26.50	54.97	24	17	25.50	19.02
19	34	25.50	28.09	24	24	25.50	26.48
34	19	26.50	17.98	37	24	39.50	24.23
25	34	28.50	39.20	40	37	37.50	40.66
30	25	31.50	21.91	38	40	31.50	39.36
37	30	39.50	33.16	51	38	37.50	37.33
33	37	32.50	38.26	80	51	67.83	53.70
37	33	39.50	31.88	101	80	88.50	83.95
47	37	59.50	38.64	98	101	107.50	100.33
33	47	32.50	48.73	116	98	109.50	91.79
35	33	36.00	28.73	135	116	133.00	116.21
30	35	31.50	37.17	108	135	105.17	131.94
37	30	39.50	28.56	89	108	88.50	94.51
27	37	29.50	39.63	89	89	88.50	82.76
48	27	42.50	24.18	88	89	86.83	86.31
42	48	41.50	54.28	56	88	53.50	84.05
29	42	38.50	37.96	103	56	112.50	45.95
32	29	35.30	27.11	72	103	67.50	114.40
27	32	29.50	34.00	65	72	66.67	56.26
37	27	39.50	25.87	59	65	62.00	65.27
43	37	44.00	40.43	49	59	50.00	55.30
43	43	44.00	43.33	45	49	45.83	46.18
45	43	45.83	42.46	34	45	26.50	44.07
39	45	37.10	45.15	49	34	50.00	31.37
31	39	36.50	37.07	52	49	51.50	53.38
28	31	33.50	29.80	41	52	38.10	50.40
22	28	21.50	28.34	39	41	37.10	37.96
19	22	25.50	21.50	31	39	36.50	39.28
22	19	21.50	19.91	18	31	15.83	29.18
15	22	13.50	24.02	17	18	21.50	16.45
12	15	9.50	14.29	14	17	20.50	19.06
6	12	5.50	13.57	10	14	12.50	14.63
3	6	4.50	6.50	11	10	7.50	11.10
1	3	0.00	4.97	22	11	21.50	13.36
0	1	0.00	2.99	19	22	25.50	26.01
0	0	0.00	2.36	87	19	80.50	18.56
0	0	0.00	2.54	108	87	105.17	103.24
1	0	0.00	2.47	105	108	99.59	103.26
2	1	5.50	3.69	63	105	53.50	99.64
8	2	9.50	4.52	45	63	45.83	49.83

21	45	21.50	43.00	88	71	86.83	78.94
46	21	47.00	15.96	89	88	88.50	86.30
46	46	47.00	54.39	80	89	67.83	85.32
43	46	44.00	42.84	103	80	112.50	74.72
22	43	21.50	42.68	105	103	99.59	105.81
11	22	7.50	17.26	97	105	109.50	98.91
12	11	9.50	11.56	101	97	88.50	91.32
9	12	9.50	14.48	111	101	117.50	98.47
2	9	5.50	9.95	100	111	94.50	108.47
2	2	5.50	2.81	94	100	91.57	92.16
5	2	10.50	4.94	99	94	93.28	89.81
7	5	10.50	7.92	112	99	127.50	96.60
1	7	0.00	9.44	123	112	113.50	110.34
3	1	4.50	1.70	131	123	134.50	119.58
6	3	5.50	6.43	132	131	132.50	126.53
9	6	9.50	8.63	142	132	141.25	125.69
11	9	7.50	11.60	99	142	93.28	138.11
16	11	20.83	13.12	102	99	94.00	82.28
22	16	21.50	18.71	112	102	127.50	102.72
19	22	25.50	24.29	109	112	110.69	108.72
22	19	21.50	18.97	92	109	73.83	103.31
36	22	34.83	24.20	79	92	68.50	84.35
37	36	39.50	39.60	50	79	45.50	74.31
54	37	51.50	36.18	30	50	31.50	42.18
38	54	31.50	57.82	20	30	22.50	27.60
32	38	35.30	31.92	27	20	29.50	19.85
28	32	33.50	32.43	70	27	77.50	30.66
10	28	12.50	27.43	102	70	94.00	79.54
8	10	9.50	7.10	56	102	53.50	103.65
9	8	9.50	10.78	62	56	78.00	40.65
6	9	5.50	10.87	87	62	80.50	66.87
4	6	6.50	7.20	81	87	83.03	89.30
14	4	20.50	5.86	61	81	62.50	75.30
16	14	20.83	18.38	35	61	36.00	55.28
19	16	25.50	17.03	23	35	22.50	29.78
33	19	32.50	21.06	20	23	22.50	22.89
69	33	63.50	36.82	23	20	22.50	21.32
91	69	65.50	75.73	7	23	10.50	25.42
83	91	52.50	90.71	6	7	5.50	4.77
54	83	51.50	76.53	31	6	36.50	9.75
44	54	50.50	45.65	15	31	13.50	38.55
66	44	79.50	42.82	18	15	15.83	10.49
113	66	103.21	70.35	38	18	31.50	22.55
136	113	116.50	119.07	31	38	36.50	43.16
129	136	121.28	132.34	35	31	36.00	28.47
57	129	54.50	119.90	28	35	33.50	37.73
35	57	36.00	36.38	27	28	29.50	26.46
71	35	73.25	34.83	18	27	15.83	28.63

23	18	22.50	17.06	8	11	9.50	12.09
40	23	37.50	26.59	4	8	6.50	9.97
45	40	45.83	44.33	13	4	12.50	5.74
95	45	104.50	45.05	14	13	20.50	17.91
89	95	88.50	105.46	9	14	9.50	15.45
101	89	88.50	80.04	8	9	9.50	10.11
115	101	111.50	102.25	6	8	5.50	10.49
103	115	112.50	112.57	12	6	9.50	7.94
128	103	112.50	94.94	19	12	25.50	15.96
136	128	116.50	130.58	24	19	25.50	22.02
95	136	104.50	129.60	28	24	33.50	26.25
74	95	77.50	80.22	29	28	38.50	29.82
61	74	62.50	69.62	34	29	26.50	29.96
51	61	37.50	57.06	34	34	26.50	35.97
37	51	39.50	48.72	39	34	37.10	34.16
43	37	44.00	34.25	66	39	79.50	40.76
68	43	79.00	45.87	111	66	117.50	71.51
62	68	78.00	72.69	97	111	109.50	116.84
64	62	62.21	57.36	47	97	59.50	86.26
61	64	62.50	64.40	73	47	79.50	34.85
53	61	50.50	58.65	73	73	79.50	81.84
55	53	72.50	50.69	71	73	73.25	67.72
57	55	54.50	55.51	71	71	73.25	69.55
45	57	45.83	56.49	71	71	73.25	69.01
45	45	45.83	41.65	57	71	54.50	69.18
45	45	45.83	46.11	35	57	36.00	52.17
45	45	45.83	44.77	51	35	37.50	30.62
45	45	45.83	45.17	35	51	36.00	56.49
45	45	45.83	45.05	56	35	53.50	29.31
45	45	45.83	45.08	69	56	63.50	62.94
59	45	62.00	45.07	57	69	54.50	68.60
72	59	67.50	62.05	33	57	32.50	52.36
64	72	62.21	72.71	37	33	39.50	28.15
53	64	50.50	59.81	34	37	26.50	40.27
40	53	37.50	50.36	39	34	37.10	32.99
27	40	29.50	37.44	48	39	42.50	41.23
21	27	21.50	25.56	53	48	50.50	49.66
24	21	25.50	21.85	35	53	36.00	53.19
13	24	12.50	26.60	26	35	18.50	30.31
3	13	4.50	11.82	31	26	36.50	26.28
3	3	4.50	4.13	23	31	22.50	33.54
5	3	10.50	6.42	15	23	13.50	21.65
5	5	10.50	8.14	9	15	9.50	15.52
5	5	10.50	7.61	12	9	9.50	10.08
10	5	12.50	7.75	48	12	42.50	15.34
17	10	21.50	13.75	49	48	50.00	57.39
16	17	20.83	20.42	55	49	72.50	45.96
11	16	7.50	17.19	33	55	32.50	56.67

28	33	33.50	26.78	41	56	38.10	54.71
44	28	50.50	29.70	13	41	12.50	36.75
46	44	47.00	48.22	9	13	9.50	8.20
38	46	31.50	45.07	11	9	7.50	11.93
28	38	33.50	36.32	6	11	5.50	13.22
24	28	25.50	26.83	10	6	12.50	6.76
31	24	36.50	24.82	11	10	7.50	13.53
29	31	38.50	33.90	16	11	20.83	12.70
21	29	21.50	28.74	17	16	21.50	19.00
28	21	33.50	20.59	19	17	25.50	18.31
25	28	28.50	31.52	15	19	13.50	20.93
16	25	20.83	24.59	18	15	15.83	15.28
12	16	9.50	15.75	37	18	39.50	20.61
10	12	12.50	13.55	57	37	54.50	42.04
16	10	20.83	11.77	53	57	50.50	59.84
19	16	25.50	19.57	50	53	45.50	49.64
16	19	20.83	20.85	60	50	51.00	49.08
18	16	15.83	16.82	68	60	79.00	61.38
25	18	28.50	20.45	58	68	57.50	67.39
40	25	37.50	27.83	74	58	77.50	53.47
39	40	37.10	43.79	53	74	50.50	77.06
33	39	32.50	37.78	46	53	47.00	44.52
38	33	31.50	32.31	40	46	37.50	45.82
27	38	29.50	40.01	37	40	39.50	38.16
30	27	31.50	24.36	13	37	12.50	36.82
13	30	12.50	32.70	12	13	9.50	8.12
10	13	12.50	9.57	20	12	22.50	15.53
6	10	5.50	12.88	25	20	28.50	22.99
8	6	9.50	7.02	27	25	29.50	26.80
6	8	5.50	11.19	18	27	15.83	28.08
3	6	4.50	7.50	15	18	13.50	16.78
3	3	4.50	4.96	13	15	12.50	16.53
6	3	5.50	5.70	24	13	25.50	14.17
6	6	5.50	9.10	24	24	25.50	28.20
10	6	12.50	8.06	21	24	21.50	23.98
21	10	21.50	13.21	25	21	28.50	21.60
26	21	18.50	24.99	32	25	35.30	27.16
25	26	28.50	27.50	37	32	39.50	33.97
25	25	28.50	25.53	32	37	35.30	37.98
27	25	29.50	26.11	43	32	44.00	30.71
32	27	35.30	28.36	56	43	53.50	46.23
38	32	31.50	33.74	53	56	50.50	57.33
47	38	59.50	39.39	39	53	37.10	50.36
47	47	59.50	48.60	39	39	37.10	35.49
48	47	42.50	45.84	49	39	50.00	39.96
56	48	53.50	47.88	52	49	51.50	50.74
57	56	54.50	56.97	52	52	51.50	51.14
56	57	53.50	55.46	59	52	62.00	51.03

80	59	67.83	59.55	39	31	37.10	35.31
90	80	72.50	82.46	61	39	62.50	40.43
94	90	91.57	87.71	57	61	54.50	65.56
89	94	88.50	91.00	57	57	54.50	53.16
128	89	112.50	83.97	58	57	57.50	56.89
112	128	127.50	133.39	48	58	42.50	56.99
111	112	117.50	99.17	43	48	44.00	44.84
95	111	104.50	108.28	41	43	38.10	42.43
111	95	117.50	86.17	38	41	31.50	40.73
95	111	104.50	112.24	39	38	37.10	37.61
69	95	63.50	85.03	25	39	28.50	39.76
47	69	59.50	61.71	11	25	7.50	22.13
73	47	79.50	42.06	9	11	9.50	10.45
69	73	63.50	79.49	9	9	9.50	11.52
48	69	42.50	63.40	8	9	9.50	11.19
35	48	36.00	42.79	9	8	9.50	10.06
20	35	22.50	33.22	8	9	9.50	11.60
10	20	12.50	17.91	2	8	5.50	9.91
22	10	21.50	10.38	0	2	0.00	3.13
6	22	5.50	27.18	0	0	0.00	2.73
8	6	9.50	2.72	0	0	0.00	2.83
25	8	28.50	12.49	0	0	0.00	2.78
33	25	32.50	30.15	0	0	0.00	2.78
32	33	35.30	34.53	0	0	0.00	2.76
16	32	20.83	32.00	1	0	0.00	2.75
16	16	20.83	13.35	6	1	5.50	3.95
14	16	20.50	18.95	14	6	20.50	9.63
26	14	18.50	14.83	9	14	9.50	17.61
26	26	18.50	30.61	6	9	5.50	9.14
35	26	36.00	25.86	4	6	6.50	8.04
46	35	47.00	38.19	4	4	6.50	5.93
98	46	107.50	47.82	4	4	6.50	6.55
134	98	123.08	107.97	2	4	5.50	6.35
137	134	128.36	133.56	1	2	0.00	3.97
128	137	112.50	129.54	3	1	4.50	3.45
109	128	110.69	119.87	11	3	7.50	6.02
102	109	94.00	99.78	11	11	7.50	14.93
95	102	104.50	97.36	20	11	22.50	12.24
115	95	111.50	89.63	21	20	21.50	23.95
102	115	94.00	116.22	18	21	15.83	21.63
65	102	66.67	92.49	14	18	20.50	18.68
40	65	37.50	54.79	13	14	12.50	14.71
25	40	28.50	35.82	3	13	4.50	14.68
23	25	22.50	23.34	0	3	0.00	2.56
32	23	35.30	24.66	2	0	5.50	2.55
34	32	26.50	35.17	3	2	4.50	4.96
22	34	21.50	34.43	3	3	4.50	5.43
31	22	36.50	20.10	0	3	0.00	5.28

0	0	0.00	1.67	1	4	0.00	6.25
0	0	0.00	2.74	0	1	0.00	2.03
0	0	0.00	2.41	1	0	0.00	2.07
0	0	0.00	2.49	2	1	5.50	3.26
0	0	0.00	2.45	2	2	5.50	4.10
0	0	0.00	2.45	1	2	0.00	3.84
0	0	0.00	2.43	1	1	0.00	2.69
0	0	0.00	2.42	0	1	0.00	3.02
0	0	0.00	2.41	0	0	0.00	1.70
1	0	0.00	2.40	0	0	0.00	2.09
2	1	5.50	3.60	3	0	4.50	1.96
6	2	5.50	4.44	4	3	6.50	5.62
8	6	9.50	9.02	4	4	6.50	5.72
4	8	6.50	10.06	1	4	0.00	5.68
2	4	5.50	4.88	0	1	0.00	2.04
3	2	4.50	4.00	2	0	5.50	1.91
12	3	9.50	5.46	14	2	20.50	4.37
10	12	12.50	15.92	17	14	21.50	18.17
16	10	20.83	10.34	15	17	13.50	17.65
7	16	10.50	19.29	13	15	12.50	15.37
9	7	9.50	5.68	8	13	9.50	13.63
15	9	13.50	12.18	5	8	10.50	8.08
10	15	12.50	17.49	7	5	10.50	6.10
9	10	9.50	9.82	13	7	12.50	9.11
5	9	10.50	10.91	8	13	9.50	15.48
0	5	0.00	5.72	1	8	0.00	7.49
0	0	0.00	1.21	0	1	0.00	1.40
0	0	0.00	2.55	0	0	0.00	2.01
1	0	0.00	2.13	0	0	0.00	1.81
2	1	5.50	3.46	1	0	0.00	1.86
2	2	5.50	4.26	1	1	0.00	3.05
0	2	0.00	4.00	0	1	0.00	2.68
0	0	0.00	1.64	0	0	0.00	1.57
2	0	5.50	2.34	2	0	5.50	1.89
4	2	6.50	4.54	3	2	4.50	4.21
5	4	10.50	6.29	16	3	20.83	4.71
10	5	12.50	6.97	17	16	21.50	20.31
12	10	9.50	12.81	18	17	15.83	16.83
9	12	9.50	13.47	37	18	39.50	19.08
15	9	13.50	9.63	25	37	28.50	41.44
21	15	21.50	18.05	26	25	18.50	20.17
28	21	33.50	22.78	34	26	26.50	27.78
25	28	28.50	29.84	45	34	45.83	35.19
18	25	15.83	24.08	55	45	72.50	46.30
11	18	7.50	17.32	53	55	50.50	55.09
6	11	5.50	10.86	53	53	50.50	50.04
3	6	4.50	6.74	51	53	37.50	51.57
4	3	6.50	4.33	37	51	39.50	48.69

18	37	15.83	32.59
11	18	7.50	14.40
11	11	7.50	11.38
10	11	12.50	12.28
10	10	12.50	10.79
12	10	9.50	11.23
15	12	13.50	13.52
17	15	21.50	16.46
27	17	29.50	17.99
36	27	34.83	29.65
32	36	35.30	37.06
54	32	51.50	29.99
62	54	78.00	58.79
61	62	62.50	59.84
71	61	73.25	58.33
66	71	79.50	70.92
86	66	62.50	61.09
119	86	126.50	88.31
106	119	111.42	120.16
99	106	93.28	94.86
89	99	88.50	94.01
84	89	83.00	82.17
84	84	83.00	79.69
87	84	80.50	80.46
65	87	66.67	83.89
39	65	37.10	56.20
36	39	34.83	33.02
27	36	29.50	36.36
23	27	22.50	24.44
33	23	32.50	23.17
39	33	37.10	35.68
30	39	31.50	39.19
24	30	25.50	27.23
23	24	22.50	23.55
12	23	9.50	23.44
10	12	12.50	10.13
10	10	12.50	11.70
21	10	21.50	11.22
27	21	29.50	24.70
25	27	28.50	27.91
35	25	36.00	24.52
27	35	29.50	37.66
18	27	15.83	24.01
15	18	13.50	17.20
9	15	9.50	15.61
7	9	10.50	8.81
7	7	10.50	8.42
8	7	9.50	8.53

9	8	9.50	9.70
8	9	9.50	10.55
7	8	10.50	9.07
7	7	10.50	8.30
1	7	0.00	8.52
5	1	10.50	1.17
14	5	20.50	8.22
33	14	32.50	17.00
35	33	36.00	37.39
23	35	22.50	33.68
18	23	15.83	20.25
19	18	25.50	18.23
2	19	5.50	20.04
0	2	0.00	-1.12
0	0	0.00	2.81
0	0	0.00	1.62
3	0	4.50	1.96
6	3	5.50	5.48
22	6	21.50	8.05
35	22	36.00	26.67
46	35	47.00	36.83
48	46	42.50	47.12
47	48	59.50	46.46
36	47	34.83	45.45
24	36	25.50	32.42
13	24	12.50	21.79
9	13	9.50	11.65
19	9	25.50	9.84
39	19	37.10	22.50
56	39	53.50	42.94
73	56	79.50	57.41
105	73	99.59	73.69
116	105	109.50	107.61
113	116	103.21	110.78
100	113	94.50	106.22
105	100	99.59	91.86
156	105	158.00	102.27
156	156	158.00	161.01
160	156	161.50	143.40
165	160	170.50	153.60
159	165	160.50	156.64

5.2.3. ERCOT System-wide Forecasted Data

The data below gives the forecasts produced by each model over the period of the validation data for ERCOT system-wide. It is used to generate the plots and tables in section 3.4.

Actual	Persistence	Markov	ARMA
6953.88	6865.02	7693.56	6953.90
6964.82	6953.88	6533.42	6630.00
7560.1	6964.82	7458.04	7086.10
7505.61	7560.1	7458.04	7977.70
6859.51	7505.61	7693.56	7155.30
6468.97	6859.51	5800.70	6383.00
5894.84	6468.97	6594.48	6303.70
5142.95	5894.84	5190.10	5393.50
5158.75	5142.95	5190.10	4666.60
5382.66	5158.75	6289.18	5385.00
4778.69	5382.66	5190.10	5416.90
4119.7	4778.69	4359.68	4151.00
3718.63	4119.7	4050.31	3808.80
3719.3	3718.63	4050.31	3479.10
3374.31	3719.3	4335.26	3815.60
3338.69	3374.31	4335.26	2967.70
3664.04	3338.69	4050.31	3496.10
4704.71	3664.04	4945.86	3846.90
5844.89	4704.71	5678.58	5531.30
5544.6	5844.89	5556.46	6401.60
3903.39	5544.6	3317.59	4907.50
3566.71	3903.39	2808.76	2683.10
4104.15	3566.71	4359.68	3885.80
4187.59	4104.15	4274.20	4392.40
4629.46	4187.59	4762.68	4068.20
4816.23	4629.46	5190.10	5063.20
5215.44	4816.23	5190.10	4707.80
5214.61	5215.44	5190.10	5597.90
4434.27	5214.61	4884.80	4955.40
3892.21	4434.27	3317.59	3805.80
3425.81	3892.21	3968.90	3693.10
2940.78	3425.81	3480.42	3067.00
3084.9	2940.78	2442.40	2656.40
3718.1	3084.9	4050.31	3345.60
4074.4	3718.1	4359.68	4131.30
4180.54	4074.4	4274.20	4142.40
4038.94	4180.54	4359.68	4202.80
3762.79	4038.94	4050.31	3856.40
3454.73	3762.79	3968.90	3569.20
3840.56	3454.73	3317.59	3240.30
4904.17	3840.56	5251.16	4281.40
5146.76	4904.17	5190.10	5609.30
5249.03	5146.76	5190.10	4938.90
5245.77	5249.03	5190.10	5408.40
5607.97	5245.77	5556.46	5105.90
5158.31	5607.97	5190.10	5969.30
5275.15	5158.31	5637.87	4492.30
4921.21	5275.15	5251.16	5698.30

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