Analysis of RTG Crane Load Demand and Short-term Load Forecasting

Feras Alasali [1], Stephen Haben[2], Victor Becerra [3], William Holderbaum[4]

***Abstract*—** The increasing numbers of international trading ports around the world are facing significant energy and environmental challenges such as rising energy consumption and greenhouse emissions. To understand the energy demand behaviour of ports or cranes, several simulation studies have been carried out using data from the Port of Felixstowe in the UK. The aim of this paper is to propose a 24-hours active power forecast model and analysis tools for a single electrified RTG crane. This model could be a potential solution to these energy consumption and management problems. The crane data has been collected for 30 days and analysed in terms of the daily demand usage, the number of crane moves and the weight of containers. Two different forecast methods, ARIMAX and Artificial Neural Network have been used to forecast highly stochastic, non-smooth and very volatile active crane power demand. The results indicate that the ANN forecast model is more accurate according to the mean absolute percentage error (MAPE) results during the testing period.

***Keywords*---**ARIMAX; Neural Network; load forecasting; Rubber Tyred Gantry Cranes.

I. Introduction

The electrical energy demand in ports has been rising as a result of the shift from diesel RTG cranes to electrified RTG cranes, which are connected to low and medium voltage grids, to reduce gas emissions and fuel consumption. According to [1] and [2] the volume of container traffic in the United Kingdom may increase by around 54% in the next 15 years. Furthermore, this may increase the total power consumption and peak demand at port substations. Ports may need a new substation or to upgrade the port infrastructure to cover this rise in demand. However, there is a lack of understating of the energy demand behaviour at port substations and electrified RTG cranes. This understating, is vital for developing strategies and solutions to reduce the environmental effects of emissions and peak demand problems [3] [4]. Electrical load forecasting is key for developing an efficient energy management system and accurate load forecast models are required for energy planning and substation operations. Load forecasting provides the necessary information for making decisions on generating power, load shifting and electrical infrastructure development. Generally, electric load forecasting with lead time can be divided into four categories:

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TABLE I: THE LOAD FORECASTING CATEGORIES

Load forecast type	Prediction target
Very short term	Few minutes - one hour
Short term	One hour - several days
Medium term	One week - one year
Long term	One year or more

Short-term load forecasting deals with intervals of one hour to several weeks [5]. The accuracy of short-term load forecasting has a significant effect on the operating efficiency of any utility, especially for the interval forecast time from one hour to one week. Some utility decisions such as the scheduling of power generation and scheduling of energy purchases are based on the short-term forecast results [4][5].

A large variety of statistical methods and intelligence techniques have been used in short-term forecasting. The statistical methods developed built on input data have a specific structure such as being based on seasonal trends or autocorrelation patterns. The methods below are commonly used in time series techniques [6]:

- ARMA: Autoregressive moving average.
- ARIMA: Autoregressive integrated moving average.
- ARIMAX: ARIMA with exogenous variables.

Fuzzy Inference Systems, expert systems and Artificial Neural Networks (ANN) are intelligence methods that can be used for short-term forecasting.

Many techniques have been developed for forecasting electrical energy demand and several research studies in the literature have used ANNs and ARIMAX. However, very few studies are directly related to investigating electrified RTG cranes or substation port loads [5][6][7][9]. As shown in figure 1 the stochastic and volatile nature of the active power demand of cranes creates a significant challenge in predicating or forecasting this demand. A novel short-term load forecast models using ARIMAX and ANN have been developed in this paper. The aim is to generate an hourly active power forecast for 24 hours ahead for a single RTG crane.

II. Analysis of RTG Crane Load Demand

A. Data

In this paper, the electrified RTG crane data was collected for 30 days from the 11th of April 2016 to the 11th of May 2016 from the Port of Felixstowe in the UK. The record of data includes hourly three-phase active power; number of crane moves and gross container weights. The consumption of three-phase active

power by the electrified RTG crane has been analysed in terms of daily, weekly and hourly usage. Figure 1 shows that the hourly three-phase active power curve does not exhibit clear seasonality, which make finding a weekly or daily pattern difficult. In addition, an hourly three-phase active power usage at the same hour for 30 days displayed highly stochastic, non-smooth and very volatile behaviour from 0 KW on some days to around 800 KW on others as shown in figure 2.

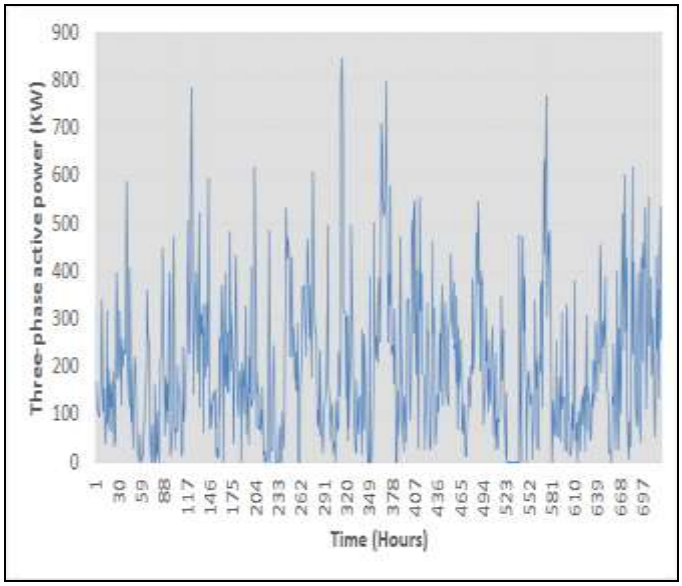

Fig. 1. 30 days 24 hourly active power profile.

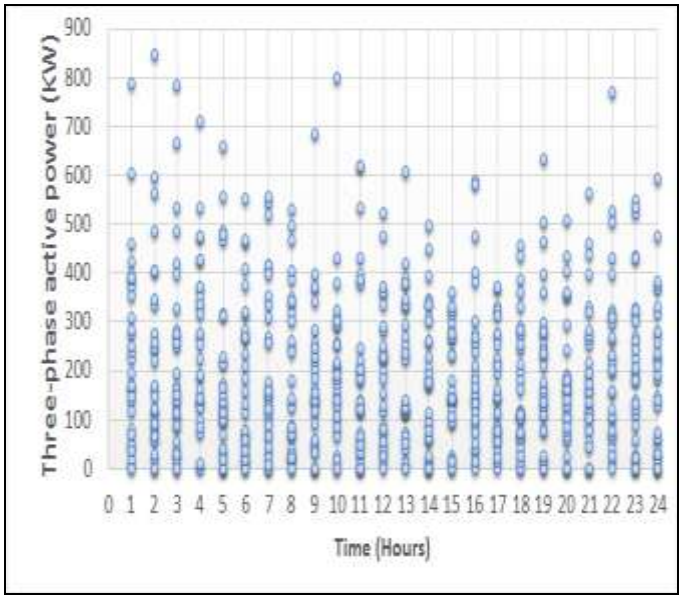

Fig. 2. Hourly active power usage.

The three-phase active power usage in weekly terms is shown in figure 3. In figures 3 and 4, it seems to be difficult to find weekly or daily patterns that can be used for a forecast model. In addition, as shown in figure 4, the three-phase active power is also highly volatile on the same day over the three weeks. Furthermore, it reached around 550 KW on Monday (week two) and around 40 KW on Monday (week three) at the same hour (3 am), which makes load forecasting complex and challenging.

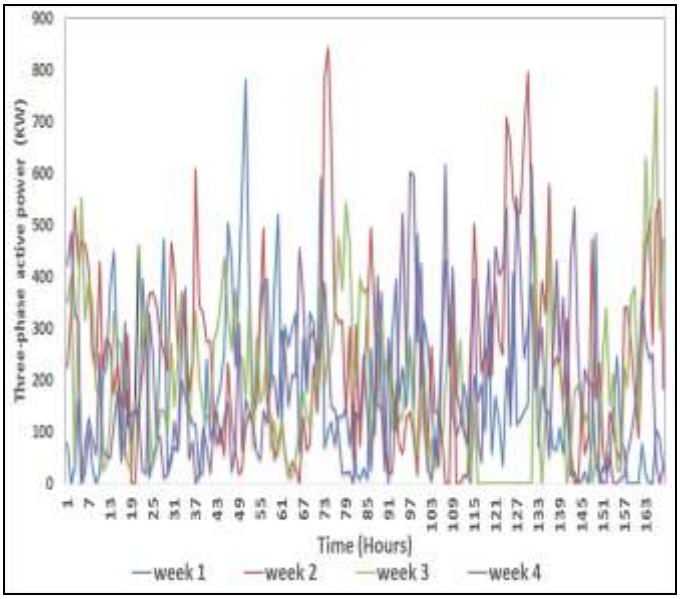

Fig. 3. Weekly active power profile.

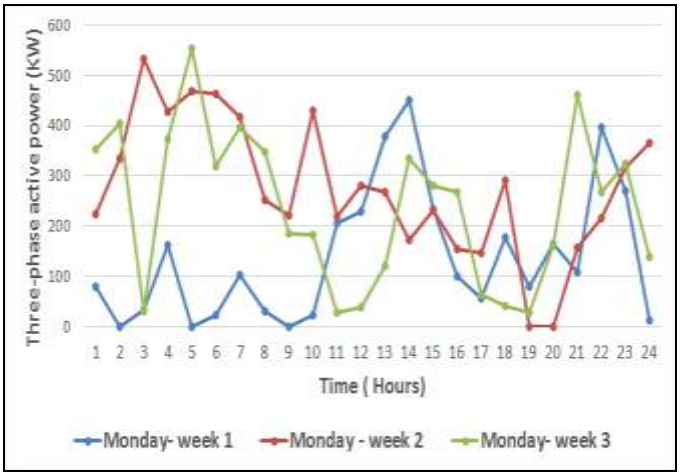

Fig. 4. Mondays' active power profile during three weeks

The active power consumption of the electric RTG crane displayed random behaviour because of the increasing effect of environmental and human behavior. Port work activity mainly depends on the trends or the movement of shipments [3]. For example, there may be many ships at the same time on certain days and this is may increase the activity of cranes and increase the demand for power. The human factor is part of the port's work, for example the crane driver may move a container before others and they do not usually have a specific order for crane movement [3][4]. Therefore, the three-phase active power pattern for the electric RTG crane has become more stochastic.

B. Data correlation analysis

Due to the highly non-smooth and stochastic behaviour of the crane active power demand curve, correlation analysis between the number of crane moves, container gross weight and three phase active power data is strongly recommended to create a more accurate forecast model. Generally, active power demand in a crane increases when the number of crane moves or container weight increases. Therefore, due to the unrecognisable and complex active power curve with the

unpredictable human factor, the number of crane moves and container weight should be introduced as an input for a forecast model to achieve a satisfactory forecast percentage error [7][8]. Figures 5 and 6 show the relationship between the number of crane moves and container gross weight with three phase active power.

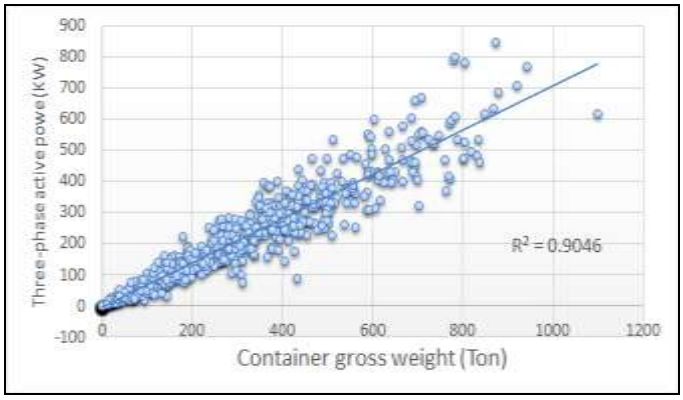

Fig. 5. The relationship between three-phase active load and container gross load weight.

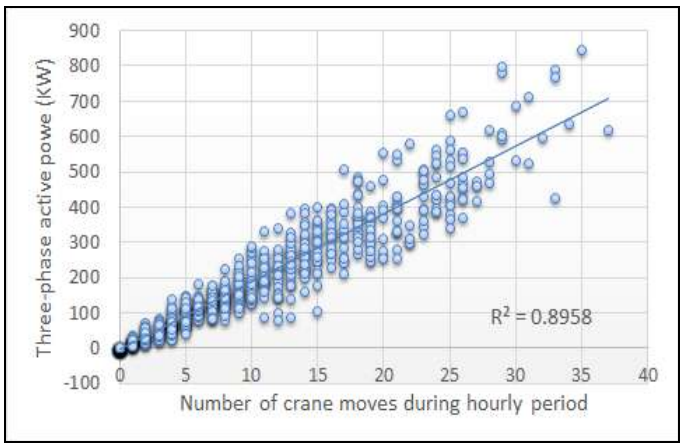

Fig. 6. The relationship between three-phase active load and number of crane moves.

III. Load Forecast Methods

From the data correlation analysis, there is a strong relation between container weight or number of moves during hourly period and three-phase active power demand. Figure 5 shows that the regression line with the below equation fits around 0.9046 of the data:

$$Y_t = 0.7079 X_t - 1.2745 \quad (1)$$

Where X_t is the value of gross of container weight per (Ton) at time t and Y_t is the forecast value for three-phase active power per (KW) at time t.

This relationship can be used to create a predictor input for ARIMAX and ANN to increase the accuracy of the forecasting model especially with the difficulty of finding a seasonality or time pattern on the RTG power curve. In this paper, the container weight and number of moves for 24 hours a-head is an assumption for the ARIMAX and ANN forecast models' inputs.

A. ARIMAX

Time series methods introduce the data as a function of time based on the historical data with seasonal trends or stationary patterns. These methods detect and explore the time structure using historical data. Time series methods have been developed based on previous historical data to predict and forecast the future in many fields such as economics, electric loads and price forecasting. There are several time series models that have been used in all types of electrical load forecasting and the most often used are below [6] [10]:

- ARIMA (autoregressive integrated moving average): is targeted at the non-stationary processes such as seasonality by adding integrated parts for the extension of ARMA.
- ARIMAX (autoregressive integrated moving average with exogenous variables): Due to the output data or forecast possibly depending on other factors or predictors, the ARIMA model has been extended into the ARIMA model with an illustrative variable [10].

ARIMAX is the most classical time series model used for load forecasting. It works by simply adding a covariate element on the ARIMA equation. The equation below describes the non-seasonal ARIMA model with (*p*,*d*,*q*) parameters, where [11]:

$$\tilde{Y}_t = C + \Phi_1 \tilde{Y}_{t-1} + \ldots + \Phi_p \tilde{Y}_{t-p} + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} + e_t \quad (2)$$

Where $\tilde{Y}_t$ is the differenced series, Φ_p is non-seasonal operator of autoregressive terms AR(*p*), θ_q is non-seasonal operator of moving average MA(*q*), C *is a* constant term and e_t is white noise.

Furthermore, the parameter d in ARIMA model is the non-seasonal orders of differencing of the input data. The first order differencing for the time series is:

$$\tilde{Y}_t = Y_t - Y_{t-1} \quad (3)$$

A.1 ARIMAX Model identification and Modeling Steps.

The modeling procedure of the ARIMAX model involves an iterative six stage process as follows [10] [11]:

1- Preparation of data including plotting the load curve and splitting data into training and test data sets.
2- Checking the stationarity of logarithmic transformation sequences and differencing. There is different test to check whether the data is stationary such as the Augmented Dickey-Fuller test, Phillips-Perron test and KPSS test for stationary trends.
3- If the data are stationary, we can move to the next step; otherwise, we should first take the differences and test the stationarity again; then the second order of differential operations until the data are stationary.
4- Identifying a suitable model by computing the autocorrelations function (ACF) and the partial

autocorrelations function (PACF) of stationary series. However, there are many useful methods that can be used to determine the ARIMA parameters such as Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC).

5- Examining the residuals by checking the ACF plot of the residual and checking to see if it looks like white noise or not.

6- Trying a modified a model until residuals are obtained similar to white noise, then generating the forecast model of the data based on the final (*p,d,q*) parameters.

B. Artificial Neural Networks (ANN)

ANN models have been widely used and studied in electrical load forecasting where there is a complex relationship between customer load and factors such as holiday and weather conditions that require a long calculation time. The ability to make decisions and analyse the complex relationship makes ANN an appropriate choice and a powerful technique for the study of short term electrical load forecasting [12][14][13].

An ANN is basically a non-linear circuit and data processing system, that has a large number of processing elements called neurons. A neuron is a highly interconnected element that has the capability of processing non-linear and linear mathematical functions to operate the neural network. The three main components of the nonlinear model of a neuron are shown in figure 7. Firstly, the input (x_j)is multiplied by a positive or negative weight (W_{Kj}). Then the weighted inputs are added together. Finally, the output of the neuron is limited through the activation function [7][13].

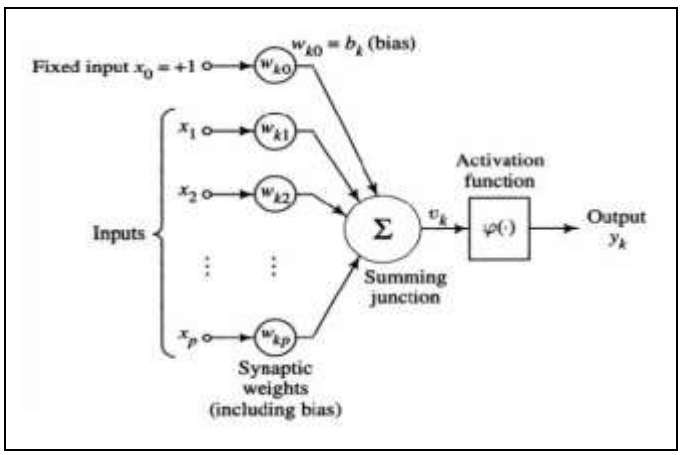

Fig. 7. Nonlinear model of a neuron [13]

The ANN modelling procedure involves an iterative four steps process as follows [14] [15][16]:

1- Collecting and pre-processing data including plotting the load curve and normalising the data.

2- Building the network by:
- Dividing the data into two groups: training and testing data.
- Selecting the input and output.
- Selecting the number of hidden layer and neurons.

3- Training the model by using a suitable training algorithm and the training data set. The Levenberg -Marquardt Algorithm that has been selected for this work is a fast and efficient algorithm.

4- Testing the model's performance by using the test data set.

IV. FORECASTING MODELS

The target of this paper is to forecast the hourly active power for a single electrified RTG crane for 24 hours ahead by using the ARIMAX and ANN models and testing forecast models for seven days. Matlab program has been used to create both models and analyse the models performance. Furthermore, the mean absolute percentage error (MAPE) has been used to evaluate the ARIMAX and ANN models' performance. The mean absolute percentage error (MAPE) is defined in the equation [10][17]:

$$\text{MAPE} = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{x_i - \tilde{x}_i}{x_i} \right| \tag{5}$$

Where x_i is the actual time series data, $\tilde{x}_i$ is the forecasted time series data and N is the number of non-missing observations points.

A. ARIMAX forecast model

The ARIMAX technique has been applied in the area of electrical load forecasting due to it having the ability to connect the time series with other factors such as weather or the human factor [11]. The load data used for a single crane was 30 days of an hourly three-phase active power demand measured in Kilowatts (KW) from April the 15th, 2016 to May the 14th, 2016 and the data was obtained from the Port of Felixstowe in the UK. The forecast input data included the following information: date, three- phase active power to create the data time series, number of crane moves and the container gross weight as variable factors to improve the forecast accuracy. The input data was divided into main two sets: the training set from the 11th of April 2016 to the 3rd of May 2016, while the data from the 4th of May 2016 to the 11th of May 2016 was used to create the test set.

In order to create the ARIMAX model, the stationarity of the RTG crane three-phase active demand was checked by the Augmented Dickey-Fuller test and it showed that the input data is stationary. In addition, to identify the suitable ARIMAX parameters (*p, d, q*) the autocorrelations ACF and the partial autocorrelations PACF of stationary series for 120 lag are plotted in figure 8 and 9. The figures show clearly that there is difficulty in finding seasonal patterns and determining the parameters by using these plots. The Bayesian Information Criterion (BIC) was used in this paper to determine the order of an ARIMAX model [10]. The best ARMIAX models are obtained from the minimum BIC value. The BIC and AIC can be written as the equation below [18]:

$$BIC = AIC + (\log(T) - 2)(p + q + k + 1) \tag{6}$$

$$AIC = -2\log(L) + 2(p + q + k + 1) \tag{7}$$

Where AIC is Akaike's Information Criterion as per the equation 7, L is the likelihood of the data, T is number of observations and $k=1$ if $C \neq 0$ and $k=0$ if $C=0$ (C is refer to equation 2).

In this model, the BIC matrix calculated and tested for the following (*p,d,q*) parameter values:

- *p*: from 0 to 9.
- *d*: from 0,1 and 2.
- *q:* from 1 to 9.

The matrix showed that the best model parameters (*p, d, q*) for the electric RTG crane input data had the minimum BIC and are equal (1, 0, 2). This model has been designed to generate a 24-hour active power forecast by using the ARIMAX model with the number of crane moves and the container gross weight as predictive factors. The forecasting model results for the ARIMAX model showed MAPE was around 19.37 % for the test set period (seven days) as shown figure 10. The lower or non-active hours on the RTG crane with zero active power demand during the day led to an increase in the MAPE due to the forecast model not being able to predict this period accurately.

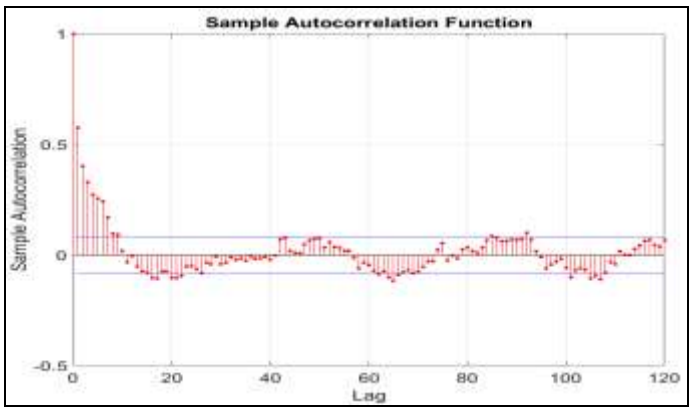

Fig. 8. Autocorrelation Function (ACF).

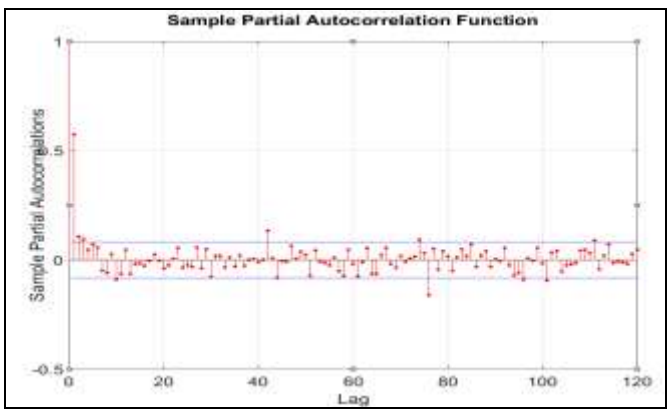

Fig. 9. Partial Autocorrelation Function (PACF).

B. *ANN Forecast model*

The Artificial Neural Network (ANN) method has been developed to forecast electric RTG crane daily active power consumption on an hourly basis. Generally, the majority of load forecasting methods or models in the electrical market have found difficulties in including some factors such as temperature and human activity as an input instead of only using the past historical load demand values and hours of the day. The objective is to forecast a 24-hour active power and test the model during a seven day period by using ANN for a single electrified RTG crane [13][19].

The data input and the training and testing sets in ANN are the same data that were used for the ARIMAX model. The inputs matrix of the ANN model in this paper is given below to forecast the active power of crane for the following week:

1. Min/Max/ Average daily active power.
2. Average daily container gross weight.
3. Average for previous 2 hours' active power.
4. Average for previous 2 hours' container gross weights.
5. Container gross weight.
6. Number of crane moves.
7. Hour of day.

Furthermore, the three-layer feed forward ANN with sigmoid neurons was used to predict hourly three-phase active power for the following day. The network was trained with the Levenbreg-Marquardt backpropgation algorithm and the number of neurons in one hidden layer was 20. The ANN forecast model output was the hourly three-phase active power for 24 hours. The ANN model performed well in predicting the active power curve shape as shown in figure 12. In addition, figure 11 shows that the MAPE value during the test period was around 13%.

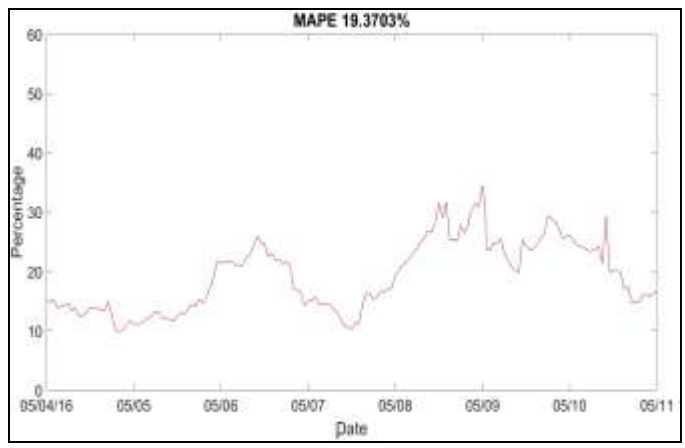

Fig. 10. MAPE for 7 days (test period) - ARIMAX model.

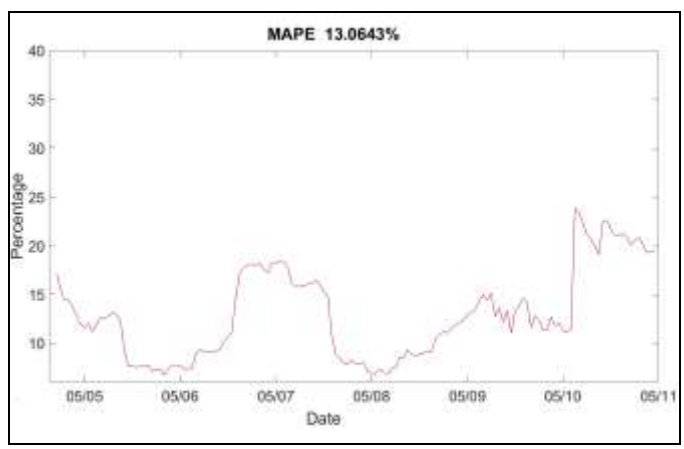

Fig. 11. MAPE for 7 days (test period) - ANN model.

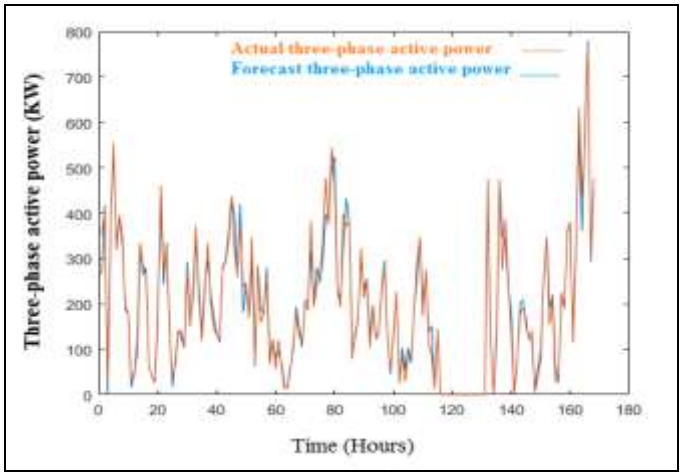

Fig. 12. Actual and forecast three-phase active power (test period).

V. Result Analysis

The forecast model produced different results depending on the forecast method used. The ANN forecast model showed a better performance than the ARIMAX model for the RTG data set. The MAPE calculations for the test set period showed that the MAPE values in the ANN model were less than 6.3% of the ARIMAX model. Figures 13 and 15 show the histogram distribution for MAPE using the ANN and ARIMAX models. The distribution showed that the highest frequency for the MAPE values in the ANN model was seven for the 7% value compared to a frequency of eight for MAPE values of 15%, 17% and 24% in the ARIMAX model. Furthermore, the highest value of MAPE was 24% using the ANN model and 37% using the ARIMAX model. In addition, the minimum value of MAPE in the ARIMAX model was 10% and 7% for the ANN forecast model

In figure 16, the hourly breakdown forecast statistical analysis for the ARIMAX model showed that the mean of MAPE was almost stable at around 20 % during the time from 3am to 3pm, around 15% for the rest of the day and the highest MAPE for the ARIMAX forecast model was 37% at 11 pm. Figure 14 shows that the mean MAPE for the ANN model during daytime hours was usually between 11% to 14% and the highest MAPE was 24% at 4 am.

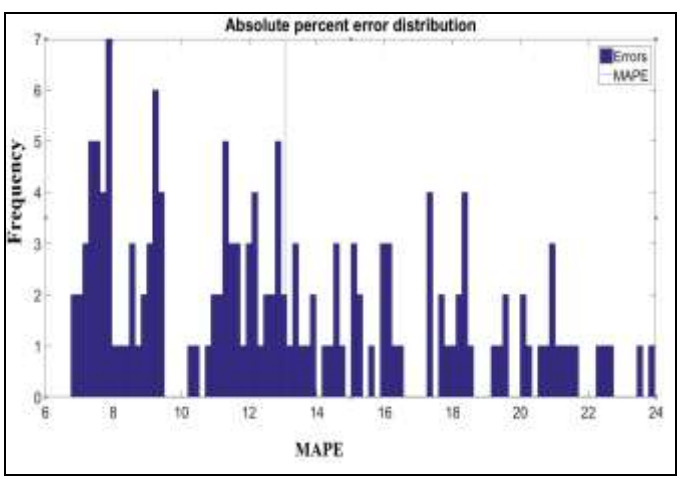

Fig. 13. Histogram analysis for MAPE - ANN model

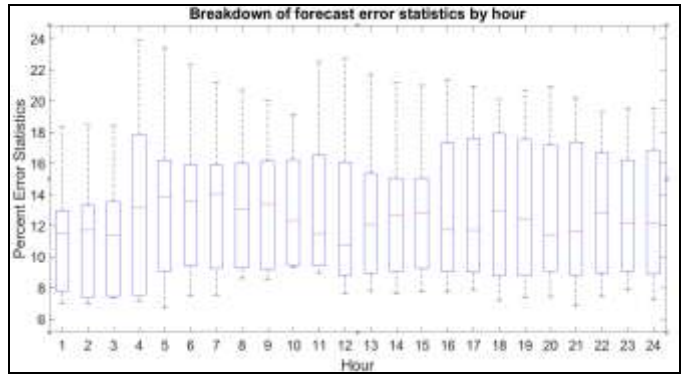

Fig. 14. Breakdown of MAPE statistics by hour (ANN model)

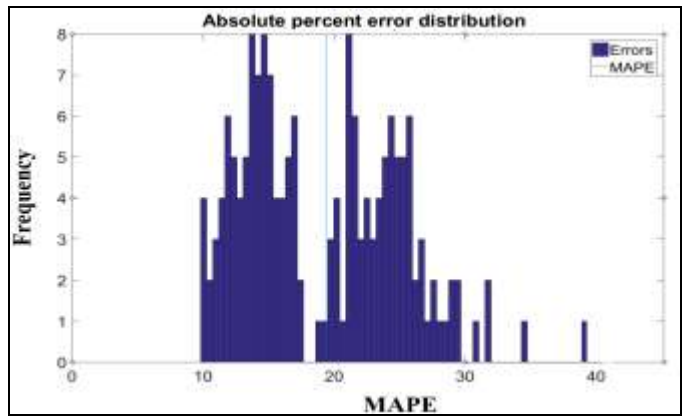

Fig. 15. Histogram analysis for MAPE - ARIMAX model

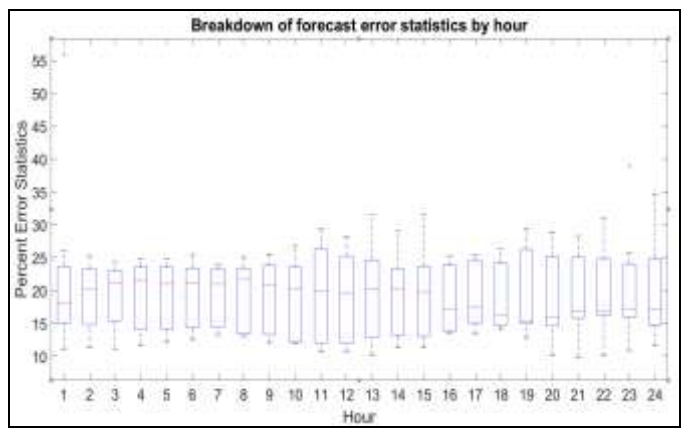

Fig. 16. Breakdown of MAPE statistics by hour (ARIMAX model)

VI. Conclusion

This paper introduced two forecast models to generate a 24-hour three-phase active power forecast for a single electrical RTG crane by using ARIMAX and ANN methods. It also aimed to study and analysis the three-phase active power and find the relationship between the active power, container gross weight and the number of moves of an RTG crane during one hour. This analysis was used to create the input matrix for the ANN and ARIMAX models. Comparing ANN and ARIMAX models, we can conclude that the ANN more accurate according to the MAPE results. In future studies, pre-processing and filtration data methods can be used to increase the models' accuracy. Furthermore, load forecasting models maybe used to control the energy storage system for RTG cranes or create a work schedule to operate cranes.

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