Integration Extreme Learning Machine with ARIMA Model for Forecasting Electricity Purchasing and Distribution Data in Thailand

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***Abstract*—Whole countries of the world needed electrical energy to use in our daily life that have to control about purchasing and distribution for people and organization. In Thailand, Provincial Electricity Authority is the organization about provided and managed purchasing and distribution of electrical energy to people. If the balance of purchasing and distribution of electrical energy were out of controlled, other risk factors would be consequences. In this research, the control of purchasing and distribution of Provincial Electricity Authority was studied to forecasting electrical energy for finding the best of demand and supply by using ARIMA model integrated with Extreme Learning Machine model to find the best solution of forecasting. Experiment results show that Root Mean Square Error of the proposed model compared with real data of purchasing and distribution in November 2017 were 1.9799e-05 and 3.8798e-03 respectively.**

***Index Terms*—Forecasting, ARIMA model, extreme learning machine model.**

I. Introduction

Nowadays, electrical energy is one type of utility energy that whole countries of the world needed. In many countries, electrical energy was produced and generated by own generator and distributed to both of national and international. Thailand was the one mentioned above that managed about electrical energy. Three major companies that process and provide electrical energy to all areas in Thailand, Electricity Generating Authority of Thailand (EGAT) focused to generate and distributed electricity in Thailand, Metropolitan Electricity Authority (MEA) focused to provide electricity to 3 provinces which the main of economics fundamentals that all we know, Bangkok. Finally, Provincial Electricity Authority (PEA) provided and managed electricity to another 74 provinces around in Thailand and that researcher used raw data and shared experience about purchasing and distribution of electricity.

The main mission of PEA is managing and controlling electrical energy for people to whole area in Thailand. PEA purchased electrical energy from EGAT, VSPP and so on then distributed electrical energy to people. In addition, PEA was controlled and managed the balance of purchasing and distribution of electrical energy. If the balance of purchasing and distribution of electrical energy were out of controlled, risk factors, for instance, uncontrolled of cost, loss of electricity and so on which would be consequences.

In this research, the control of purchasing and distribution of PEA was studied to forecasting electrical energy for finding the best of demand and supply. The forecasting model in this research was used ARIMA model [1] integrated with Extreme Learning Machine (ELM) [2] model to improve the best solution of forecasting. Data of purchasing and distribution gathered from Power Economic Division of PEA [3] likewise experiment results show that Root Mean Square Error (RMSE) of the proposed model compared with real data of purchasing and distribution in November 2017 were 1.9799e-05 and 3.8798e-03 respectively.

II. Literature Review

This part describe about literature review that used to experiment in this paper. The main idea of this work is integrated Extreme Learning Machine model with ARIMA model [1], [4] for find the best solution.

A. Forecasting Techniques with ARIMA Model

Forecasting is the process to learn data from past and present then predict to the future. Many algorithms of forecasting where proposed in many research, for instance, Naïve approach, Exponential Smoothing and so on [5]-[7]. ARIMA was proposed by Box and Jenkins [8] which one of forecasting algorithm in type of time series that used historical data to estimate future data. The conceptual of ARIMA [4], [9] is combination of 3 method to forecast outcome as follows:

- AR–Auto Regressive using a linear combination of past values of the variable to predict data from equation 1.

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \tag{1}$$

where c is constant, φ_i is order of auto regressive in term of i, X_{t-i} is time series in term of t-i and ε_t is error of model

- I–Integrated data to make stationary data from raw data, for instance, differencing raw data.
- MA–Moving Average learned data from historical data and predict data (method liked to Auto Regressive but used error instead) from equation 2.

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2}$$

where μ is constant, ε_t is error of model, θ_i is order of

Manuscript received August 16, 2018; revised October 2, 2018. This research was supported by Provincial Electricity Authority that provided insight and expertise that greatly assisted the research.

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doi: 10.18178/ijmlc.2018.8.6.745

moving average in term of i and ε_{t-i} is error in term of t-i.

If solution of ARIMA model is found, ARIMA model exported output weight and residuals to predict data from dataset that to adjust with ELM for find the best solution.

B. Extreme Learning Machine

Extreme Learning Machine (ELM) [2], [10] model was proposed by Guang-Bin Huang *et al.* which train and test data very fast when compared with another artificial neural network model. The concept of this Single Layer Feed Forward Network (SLFN) type is trained by input data (x) and target data (t) in terms of $(x_i, t_j) \in R^n \times R^m$ from dataset then calculate to input neurons from equation 3.

$$\sum_{i=1}^{L} \beta_i g_i(x) = \sum_{i=1}^{L} \beta_i G_i(w_i, b_i, x_j) = t_j \tag{3}$$

where randomized input weight (w), hidden nodes (L), bias (b), $g_i(x)$ is activation function, β_i is output nodes, i=1, 2,…, n and j=1, 2, …, m . Then calculate to hidden neurons from linear equation 4.

$$H\beta = T \tag{4}$$

where H is the hidden matrix, β is output weight and T is target vector those parameters can described to

$$\mathrm{H} = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} G(w_1, b_1, x_1) & \cdots & G(w_n, b_m, x_1) \\ \vdots & \ddots & \vdots \\ G(w_1, b_1, x_m) & \cdots & G(w_n, b_m, x_m) \end{bmatrix}_{m \times n}$$

$$, \beta = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_n \end{bmatrix}_{n \times 1} , T = \begin{bmatrix} t_1 \\ \vdots \\ t_m \end{bmatrix}_{m \times 1}$$

Finally, output neurons were calculated by inverse H to find the output weight from equation 5.

$$\beta = H^{\dagger} T \tag{5}$$

where $H^{\dagger}$ is Moore-Penrose matrix of H. When ELM model was completely trained data and get the solution of output weight, ELM model compile test data with output weight from training to perform the best solution.

III. Research Methodology

In this phase, methodology of this research described to preparation of data and model to forecast in this experiment.

A. Data of Purchasing and Distribution Preparation

In this phase, data of purchasing and distribution collected from Power Economic Division of PEA in Thailand [3] to experiment with proposed model. This dataset collected from January 2008 and latest in November 2017 that show details about purchasing (pur) and distribution (dis) in Table I.

According to Table I, datasets were divided into training and testing datasets where datasets in 2008-2016 as training data and dataset in 2017 as testing data. After completely prepared dataset of training and testing, datasets proceed to reduce noise of data, for instance, white noise, non-stationary and so on by using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) [11] to analyze data.

According to Fig. 1 and Fig. 2 are data of purchasing and distribution respectively where Fig. 1(a) and Fig. 2(a) are raw data contain non-stationary, trend and seasonality and Fig. 1(b) and Fig. 2(b) are stationary data.

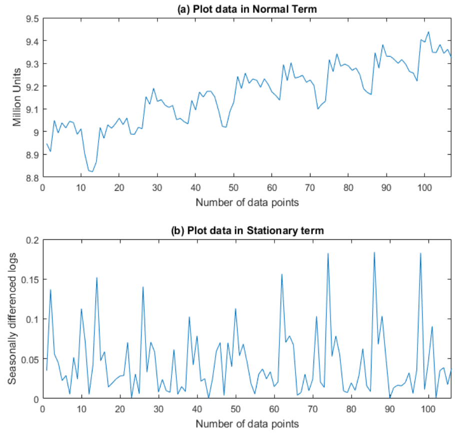

Fig. 1. Purchasing graph data comparison between raw data (a) and stationary data (b).

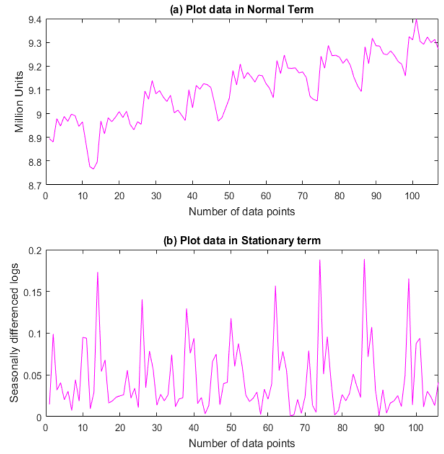

Fig. 2. Distribution graph data comparison between raw data (a) and stationary data (b).

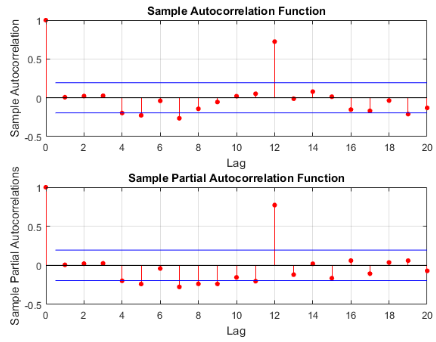

Fig. 3. ACF and PACF of purchasing stationary data.

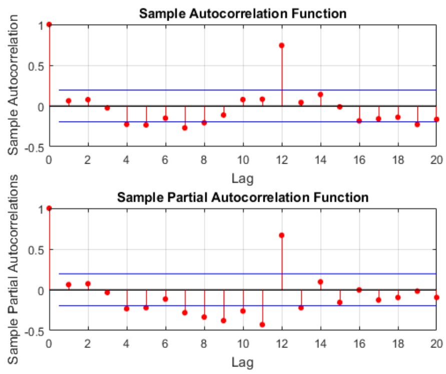

Fig. 4. ACF and PACF of distribution stationary data.

In this research, we converted from raw data to stationary data. As a result of ACF and PACF Algorithm in Fig. 3 and Fig. 4 were acceptable to proceed in ARIMA, ELM and proposed model due to more of data points in Fig. 3 and Fig. 4 are into bound of data.

TABLE I: DETAILS OF RAW PURCHASING AND DISTRIBUTION DATASET

Month \ Year	Type	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
JAN	Pur	7,687.96	6,792.37	8,258.25	8,460.49	8,860.1	9,497.39	9,133.12	9,621.13	10,481.78	10,722.29
	Dis	7,291.96	6,415.93	7,830.84	8,050.91	8,285.51	9,008.61	8,595.92	9,099.21	9,973.76	10,160.16
FEB	Pur	7,422.71	7,086.46	8,207.39	8,385.65	9,222.67	9,301.6	9,262.28	9,536.37	10,109.51	10,369.14
	Dis	7,186.07	6,604.96	7,746.17	7,871.87	8,631.66	8,662.49	8,551.52	8,892.26	9,495.62	9,723.38
MAR	Pur	8,512.95	8,252.18	9,445.28	9,293.76	10,328.3	10,876.49	11,117.88	11,462.04	12,138.23	12,426.49
	Dis	7,933.4	7,855.13	8,914.26	8,960.58	9,711.98	10,130.92	10,319.78	10,739.96	11,203.13	11,613.46
APR	Pur	8,051.32	7,869.04	9,136.82	8,908.74	9,788.3	10,136.65	10,545.05	10,705.6	12,001.51	11,635.51
	Dis	7,685.23	7,440.38	8,608.75	8,306.24	9,144.29	9,586.81	9,807.24	9,999.29	11,046.55	10,871.61
MAY	Pur	8,422.31	8,346.56	9,807.51	9,638.44	10,481.45	10,966.57	11,407.48	11,874.61	12,571.22	12,380.53
	Dis	8,003.78	7,962.85	9,311.98	9,122.92	9,980.7	10,365.82	10,792.83	11,131.02	12,058.96	11,814.34
JUN	Pur	8,234.28	8,225.03	9,249.99	9,430.81	10,019.9	10,252.03	10,795.78	11,283.61	11,480.96	11,915.97
	Dis	7,844	7,833.54	8,804.66	8,980.42	9,388.55	9,809.88	10,338.51	10,780.13	10,978.88	11,270.13
JUL	Pur	8,476.68	8,386.57	9,324.97	9,669.75	10,209.37	10,294.98	10,899.29	11,277.84	11,470.17	11,826.22
	Dis	8,085.79	7,983.33	8,926.24	9,187.75	9,633.43	9,800.2	10,357.8	10,765.3	10,852.18	11,305.53
AUG	Pur	8,430.35	8,595.88	9,102.88	9,673.96	10,150.98	10,376.53	10,817.38	11,125.27	11,880.48	12,315.52
	Dis	8,025.2	8,171.75	8,690.6	9,156.52	9,460.28	9,821.42	10,282.89	10,424.55	11,186.74	11,641.39
SEP	Pur	8,005.07	8,356.17	9,013.22	9,440.6	9,845.84	10,063.66	10,605.14	10,940.13	11,428.34	12,100.41
	Dis	7,679.06	7,971.38	8,527.55	9,036.78	9,253.8	9,620.97	10,014.88	10,380.79	10,926.36	11,481.05
OCT	Pur	8,203.55	8,601.85	9,085.18	8,897.34	10,219.95	10,163.62	10,715.27	11,116.48	11,631.34	11,763.28
	Dis	7,822.98	8,181.9	8,752.45	8,459.73	9,530.31	9,659.37	10,207.65	10,549.84	11,072.79	11,236.47
NOV	Pur	7,327.75	8,015.83	8,541.9	8,294.08	9,969.87	9,920.56	10,408.61	10,896.95	11,202.84	11,297.5
	Dis	7,113.89	7,739.08	8,126.95	7,850.5	9,506.56	9,429.48	9,928.5	10,353.74	10,626.95	10,820.25
DEC	Pur	6,828.47	8,007.99	8,588.89	8,261.45	9,641.02	8,945.68	9,776.77	10,549.6	10,681.38	N/A
	Dis	6,476.55	7,568.89	8,223.72	7,963.17	9,199.11	8,713.12	9,434.45	10,096.35	10,251.73	N/A

TABLE II: DETAILS OF STATIONARY PURCHASING AND DISTRIBUTION DATASET

Month \ Year	Type	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
JAN	Pur	NaN	NaN	0.005301	0.030773	0.015062	0.069958	0.01501	0.020737	0.016047	0.006449
	Dis	NaN	NaN	0.009404	0.034023	0.021238	0.039681	0.020926	0.013542	0.03618	0.012216
FEB	Pur	NaN	0.035111	0.042386	0.006178	0.008885	0.040107	0.020831	0.014043	0.008849	0.036162
	Dis	NaN	0.014628	0.029037	0.010871	0.022489	0.040929	0.039179	0.005179	0.023006	0.049127
MAR	Pur	NaN	0.137044	0.152291	0.14048	0.102821	0.113223	0.156417	0.182604	0.183928	0.182883
	Dis	NaN	0.098937	0.173346	0.140454	0.129539	0.117923	0.15659	0.187953	0.18879	0.165363
APR	Pur	NaN	0.055752	0.047541	0.033203	0.04231	0.0537	0.070446	0.052898	0.068274	0.011328
	Dis	NaN	0.031781	0.054245	0.034873	0.075828	0.060231	0.055204	0.050942	0.071457	0.014075
MAY	Pur	NaN	0.045048	0.058913	0.070836	0.078726	0.068419	0.078694	0.078613	0.103636	0.046378
	Dis	NaN	0.040614	0.067865	0.078523	0.093783	0.087524	0.078126	0.095761	0.107222	0.08769
JUN	Pur	NaN	0.022578	0.014668	0.058526	0.021777	0.045034	0.067376	0.055114	0.051051	0.09072
	Dis	NaN	0.020165	0.016372	0.056021	0.015743	0.061162	0.055124	0.043006	0.032031	0.093835
JUL	Pur	NaN	0.029013	0.01945	0.008073	0.02502	0.018733	0.004181	0.009542	0.000511	0.00094
	Dis	NaN	0.030359	0.018941	0.013714	0.022824	0.025748	0.000987	0.001864	0.001377	0.011607
AUG	Pur	NaN	0.005481	0.024651	0.024105	0.000435	0.005736	0.00789	0.007544	0.013621	0.035147
	Dis	NaN	0.007522	0.023327	0.026753	0.003405	0.018137	0.002163	0.007259	0.032164	0.030363
SEP	Pur	NaN	0.051763	0.028283	0.009898	0.024418	0.030521	0.030616	0.019815	0.016781	0.0388
	Dis	NaN	0.044089	0.024825	0.01894	0.013163	0.022068	0.020621	0.026409	0.004207	0.023551
OCT	Pur	NaN	0.024492	0.028977	0.007952	0.059267	0.037293	0.009884	0.010331	0.015991	0.017607
	Dis	NaN	0.018568	0.026067	0.026032	0.065986	0.029443	0.003983	0.019065	0.016154	0.013313
NOV	Pur	NaN	0.112898	0.070559	0.061661	0.07021	0.024774	0.024205	0.029036	0.019946	0.037536
	Dis	NaN	0.095016	0.055642	0.074148	0.07474	0.002495	0.024087	0.027728	0.018763	0.041098
DEC	Pur	NaN	0.070568	0.000979	0.005486	0.003942	0.033541	0.103439	0.062624	0.032395	NaN
	Dis	NaN	0.093861	0.022236	0.011837	0.01425	0.032875	0.079011	0.051042	0.025174	NaN

B. Raw Data to Stationary Data Conversion

According to Table I that was described about raw data of purchasing and distribution dataset from 2008 to 2017. This dataset cannot be used to experiment due to instability of data follow to Fig. 1(a) and Fig. 2(a). To make datasets to stability, we handled raw data to stationary data by taking common logarithm (also known as logarithm to base 10) and differencing the data one time [9], [12]. Follow to Table II, when convert to stationary data was completed. The stationary data point was shift to the right and data points were between 0 and 1.

Data from January 2008 to January 2009 was be NaN (Not-A-Number) due to the effect of differencing process (include ACF and PACF with 15 of lags value) that the data point shift to the right and we cannot used this data point to experiment. We used the data from March 2009 to November 2017 instead to experiment and forecasting.

C. Integration ARIMA Model with Extreme Learning Machine Model

The conceptual to integration ARIMA Model with ELM model is merged by using residuals from ARIMA Model [9], [12], [13] to input weight of ELM Model for calculated suitable output weight and then forecasting the data [14]. Algorithm of purposed model was described in Table III.

Both of ARIMA and proposed model were defined in type of ARIMA(p,D,q) that can described to

- p = Degree of Auto Regressive model
- D = Degree of Integrated
- q = Degree of Moving Average model

In this research, ARIMA and proposed models type were set to

- ARIMA(1,0,0) that means used only one degree of Auto Regressive.
- ARIMA(1,1,0) that means used combination one degree of Auto Regressive and Integrated.
- ARIMA(0,0,1) that means used only one degree of Moving Average.
- ARIMA(0,1,1) that means used combination one degree of Moving Average and Integrated.
- ARIMA(1,1,1) that means used combination one degree of Auto Regressive, Integrated and Moving Average.

All models type were experiment to find the best performance of forecasting and then evaluated to use and compare with Real-World dataset.

TABLE III: PROPOSED ALGORITHM.

Proposed algorithm.
Step 1) ARIMA Processing -Import input stationary data to ARIMA Model and get residuals data. Step 2) ELM Processing -Import input data with residuals data to adjusted input weight. -Calculate hidden matrix with Sigmoidal activation function. -Calculate last output weight by Moore Penrose of hidden matrix. Step 3) Forecasting -Forecasting by using last output weight from ELM model to predict target data.

D. Actual and Expected Target Comparison

Actual and expected target of purchasing and distribution were analyzed and compared to evaluate the solution to forecast and use in Real-World. Root Mean Square Error (RMSE) was defined to compare both of actual and expected target in equation

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - T_i)^2}{n}} \quad (6)$$

where Y_i is actual target and T_i is expected target.

The result of RMSE near to zero, the better of expected target solution which to use in Real-World forecasting.

IV. EXPERIMENTAL RESULTS

In this research and experiment, ARIMA model, ELM model and proposed model was used to predict data for finding the best solution. We defined ARIMA model into (1,0,0), (1,1,0), (0,0,1), (0,1,1) and (1,1,1) [12] and setting up of ELM model follow to paper [15] by 3 sets follow to Table IV.

TABLE IV: CONFIGURATION OF ELM AND PROPOSED MODEL.

Experimental Sets	Number of Hidden nodes	Iteration	Activation Function
1	100	100	Sigmoidal
2	500		
3	1000		

The detail of computer to experiment is CPU Intel Core i7-7700HQ up to 3.80 GHz, RAM 8 GB and MATLAB r2017a software. Run without using GPU Technique.

TABLE V: EXPERIMENTAL (1ST SET) RESULTS OF ALL MODELS COMPARED WITH RMSE IN PURCHASING DATA

Model	Purchasing data	
	RMSE of Training	RMSE of Testing
ARIMA (1,0,0)	5.3484e-05 ±2.4486e-05	1.0856e-02 ±0.00
ARIMA (1,1,0)	2.8109e-03 ±2.6506e-04	5.8146e-10 ±0.00
ARIMA (0,0,1)	8.6754e-05 ±1.1903e-04	6.15024e-02 ±0.00
ARIMA (0,1,1)	2.3946e-03 ±2.8799e-17	3.5258e-11 ±0.00
ARIMA (1,1,1)	2.5119e-03 ±2.6059e-04	9.5184e-11 ±0.00
ELM	1.8698e-01 ±0.00	6.4343e-01 ±0.00
ARIMA-ELM (1,0,0)	1.3435e-04 ±2.4722e-06	1.9504e+06 ±0.00
ARIMA-ELM (1,1,0)	1.2553e-03 ±1.0719e-03	2.2241e-01 ±0.00
ARIMA-ELM (0,0,1)	**1.7714e-33 ±0.00**	**3.07932e-12 ±0.00**
ARIMA-ELM (0,1,1)	6.4953e-05 ±4.1708-18	1.2824e-01 ±0.00
ARIMA-ELM (1,1,1)	1.7609 ±9.2805e-01	6.4538e-12 ±0.00

TABLE VI: EXPERIMENTAL (1ST SET) RESULTS OF ALL MODELS COMPARED WITH RMSE IN DISTRIBUTION DATA

Model	Distribution data	
	RMSE of Training	RMSE of Testing
ARIMA (1,0,0)	4.3562e-05 ±3.5277e-05	3.4985e-10 ±0.00
ARIMA (1,1,0)	2.9512e-03 ±8.6175e-05	2.6286-09 ±0.00
ARIMA (0,0,1)	1.6052e-05 ±2.7039e-05	5.4825e-02 ±0.00
ARIMA (0,1,1)	1.9121e-03 ±9.6985e-18	2.2005e-10 ±0.00
ARIMA (1,1,1)	2.8725e-03 ±5.9222e-05	1.8956e-11 ±0.00
ELM	1.8133e-01 ±0.00	5.6652e-01 ±0.00
ARIMA-ELM (1,0,0)	3.4168e-08 ±3.7548e-09	4.7924e-01 ±0.00
ARIMA-ELM (1,1,0)	2.3967e-08 ±9.7061e-09	8.4197e-01 ±0.00
ARIMA-ELM (0,0,1)	**1.6842e-32 ±7.7857e-34**	**4.1869e-12 ±0.00**
ARIMA-ELM (0,1,1)	2.7209e-05 ±1.7050e-09	2.3721 ±0.00
ARIMA-ELM (1,1,1)	7.3717e-07 ±4.2636e-08	9.3371e-12 ±0.00

According to Table V and Table VI described first set of experiment in term of minimum RMSE with Mean ± Standard Deviation **(Bold text is less RMSE which mean the best result)** of purchasing and distribution datasets respectively. The result shown that RMSE in training and testing phase of purchasing data as shown in Table V are 1.7714e-33 ± 0.00 in ARIMA-ELM (0,0,1) model and 3.07932e-12 ± 0.00 in ARIMA-ELM (0,0,1) model respectively and RMSE in training and testing phase of distribution data as shown in Table VI are 1.6842e-32 ± 7.7857e-34 in ARIMA-ELM (0,0,1) model and 4.1869e-12 ± 0.00 in ARIMA-ELM (0,0,1) model respectively. Proposed model was less RMSE in testing phase compared with other models.

According to Table VII and Table VIII described second of experiment in term of minimum RMSE with Mean ± Standard Deviation of purchasing and distribution datasets respectively. The result shown that RMSE in training and testing phase of purchasing data as shown in Table VII are 1.7714e-33 ± 0.00 in ARIMA-ELM (0,0,1) model and 3.0213e-12 ± 0.00 in ARIMA-ELM (0,0,1) model respectively and RMSE in training and testing phase of distribution data as shown in Table VI are 1.6842e-32 ± 7.7857e-34 in ARIMA-ELM (0,0,1) model and 4.1421e-12 ± 0.00 in ARIMA-ELM (0,0,1) model respectively. Proposed model was less RMSE in testing phase compared with other models.

TABLE VII: EXPERIMENTAL (2ND SET) RESULTS OF ALL MODELS COMPARED WITH RMSE IN PURCHASING DATA

Model	Purchasing data	
	RMSE of Training	**RMSE of Testing**
ARIMA (1,0,0)	5.3484e-05 ±2.4486e-05	1.0856e-02 ±0.00
ARIMA (1,1,0)	2.8109e-03 ±2.6506e-04	5.8146e-10 ±0.00
ARIMA (0,0,1)	8.6754e-05 ±1.1903e-04	6.15024e-02 ±0.00
ARIMA (0,1,1)	2.3946e-03 ±2.8799e-17	3.5258e-11 ±0.00
ARIMA (1,1,1)	2.5119e-03 ±2.6059e-04	9.5184e-11 ±0.00
ELM	4.6981e-13 ±0.00	2.5412 ±0.00
ARIMA-ELM (1,0,0)	1.3435e-04 ±2.4722e-06	1.9770e+06 ±0.00
ARIMA-ELM (1,1,0)	1.2553e-03 ±1.0719e-03	2.8638e-01 ±0.00
ARIMA-ELM (0,0,1)	**1.7714e-33 ±0.00**	**3.0213e-12 ±0.00**
ARIMA-ELM (0,1,1)	6.4953e-05 ±4.1708-18	1.5588e-01 ±0.00
ARIMA-ELM (1,1,1)	1.7609 ±9.2805e-01	4.2723e-12 ±0.00

TABLE VIII: EXPERIMENTAL (2ND SET) RESULTS OF ALL MODELS COMPARED WITH RMSE IN DISTRIBUTION DATA

Model	Distribution data	
	RMSE of Training	**RMSE of Testing**
ARIMA (1,0,0)	4.3562e-05 ±3.5277e-05	3.4985e-10 ±0.00
ARIMA (1,1,0)	2.9512e-03 ±8.6175e-05	2.6286-09 ±0.00
ARIMA (0,0,1)	1.6052e-05 ±2.7039e-05	5.4825e-02 ±0.00
ARIMA (0,1,1)	1.9121e-03 ±9.6985e-18	2.2005e-10 ±0.00
ARIMA (1,1,1)	2.8725e-03 ±5.9222e-05	1.8956e-11 ±0.00
ELM	4.4343-13 ±0.00	23.0998 ±0.00
ARIMA-ELM (1,0,0)	3.4168e-08 ±3.7548e-09	3.7224e-01 ±0.00
ARIMA-ELM (1,1,0)	2.3967e-08 ±9.7061e-09	1.0092 ±0.00
ARIMA-ELM (0,0,1)	**1.6842e-32 ±7.7857e-34**	**4.1421e-12 ±0.00**
ARIMA-ELM (0,1,1)	2.7209e-05 ±1.7050e-09	1.4867 ±0.00
ARIMA-ELM (1,1,1)	7.3717e-07 ±4.2636e-08	9.3393e-12 ±0.00

According to Table IX and Table X described third of experiment in term of minimum RMSE with Mean ± Standard Deviation of purchasing and distribution datasets respectively. The result shown that RMSE in training and testing phase of purchasing data as shown in Table VIII are 3.5749e-13 ± 5.6627e-04 in ELM model and 3.0055e-12 ± 0.00 in ARIMA-ELM (0,0,1) model respectively and RMSE in training and testing phase of distribution data as shown in Table IX are 3.0677e-13 ± 0.00 in ELM model and 4.1293e-12 ± 0.00 in ARIMA-ELM (0,0,1) model respectively. Proposed model was less RMSE in testing phase compared with other models.

TABLE IX: EXPERIMENTAL (3RD SET) RESULTS OF ALL MODELS COMPARED WITH RMSE IN PURCHASING DATA

Model	Purchasing data	
	RMSE of Training	**RMSE of Testing**
ARIMA (1,0,0)	5.3484e-05 ±2.4486e-05	1.0856e-02 ±0.00
ARIMA (1,1,0)	2.8109e-03 ±2.6506e-04	5.8146e-10 ±0.00
ARIMA (0,0,1)	8.6754e-05 ±1.1903e-04	6.15024e-02 ±0.00
ARIMA (0,1,1)	2.3946e-03 ±2.8799e-17	3.5258e-11 ±0.00
ARIMA (1,1,1)	2.5119e-03 ±2.6059e-04	9.5184e-11 ±0.00
ELM	**3.5749e-13 ±5.6627e-04**	4.7079 ±0.00
ARIMA-ELM (1,0,0)	1.3435e-04 ±2.4721e-06	1.9799e-05 ±0.00
ARIMA-ELM (1,1,0)	1.2553e-03 ±1.0719e-03	2.8165e-01 ±0.00
ARIMA-ELM (0,0,1)	8.6754e-05 ±1.1903e-04	**3.0055e-12 ±0.00**
ARIMA-ELM (0,1,1)	2.3946e-03 ±2.8799e-17	1.4564e-01 ±0.00
ARIMA-ELM (1,1,1)	2.5119e-03 ±2.6059e-04	5.6827e-12 ±0.00

TABLE X: EXPERIMENTAL (3RD SET) RESULTS OF ALL MODELS COMPARED WITH RMSE IN DISTRIBUTION DATA

Model	Distribution data	
	RMSE of Training	**RMSE of Testing**
ARIMA (1,0,0)	4.3562e-05 ±3.5277e-05	3.4985e-10 ±0.00
ARIMA (1,1,0)	2.9512e-03 ±8.6175e-05	2.6286-09 ±0.00
ARIMA (0,0,1)	1.6052e-05 ±2.7039e-05	5.4825e-02 ±0.00
ARIMA (0,1,1)	1.9121e-03 ±9.6985e-18	2.2005e-10 ±0.00
ARIMA (1,1,1)	2.8725e-03 ±5.9222e-05	1.8956e-11 ±0.00
ELM	**3.0677e-13 ±0.00**	4.9679 ±0.00
ARIMA-ELM (1,0,0)	3.4167e-08 ±3.7548e-09	3.8798e-03 ±0.00
ARIMA-ELM (1,1,0)	2.3967e-08 ±9.7061e-09	9.4151e-02 ±0.00
ARIMA-ELM (0,0,1)	1.6052e-05 ±2.7039e-05	**4.1293e-12 ±0.00**
ARIMA-ELM (0,1,1)	1.9121e-03 ±9.6985e-18	1.5882 ±0.00
ARIMA-ELM (1,1,1)	2.8722e-03 ±5.9223e-05	9.3385e-12 ±0.00

V. CONCLUSIONS AND FUTURE WORKS

Focused at testing phase in Purchasing dataset, RMSE in the first, the second and the third sets of experiment were 3.07932e-12 ± 0.00, 3.0213e-12 ± 0.00 and 3.0055e-12 ± 0.00 respectively and completed by ARIMA-ELM(0,0,1) model. Focused at testing phase in Distribution dataset, RMSE in the first, the second and the third sets of experiment were 4.1869e-12 ± 0.00, 4.1421e-12 ± 0.00 and 4.1293e-12 ± 0.00 respectively and completed by ARIMA-ELM(0,0,1) model. Both of error solution of datasets in the third set of experiment which contain 1,000 number of hidden nodes was minimum than other sets of experiment.

Furthermore, the forecast solution near to zero error margin that was used to predict in real world purchasing and distribution dataset. However, the proposed model which used in this experiment may be improve and adjust due to the overfitting in training phase that cause the problem in testing phase.

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