ARIMA Time Series Modelling for Energy Forecasting in Wireless Sensor Networks

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***Abstract*— Energy conservation is critical in wireless sensor networks since it affects the sensor's lifespan. Reducing the frequency of transmission is one way to reduce expenses, but it must not compromise the accuracy of the data that is being received. Hence, this paper has developed an autoregressive integrated moving average (ARIMA) time-series-based model to improve the prediction approach. The proposed ARIMA-based model assures the characteristics of the nodes that remain idle for extended times to conserve energy during inactive periods. It forecasts a building's energy usage based on the data gathered (e.g., day of the week, light energy, temperature, humidity, etc.). The proposed methodology efficiently preserves the constrained battery power of wireless sensor nodes while maintaining the predicted data values within the application-defined error bounds. Through experiments, it has been shown that these predicted data values closely match the actual observed data values and requires less communication between sensor nodes and aggregators than the actual data aggregation method. The proposed methodology enhanced the prediction accuracy as compared with existing approaches. This approach produces the mean absolute error (MAE) as 45.06.**

Keywords*— *Energy forecasting, ARIMA, Time series analysis, Wireless sensor networks, Machine learning

I. Introduction

The widespread use and development of Wireless Sensor Networks (WSNs) have the potential to impact every aspect of our lives, including home automation, health care, military services, energy management, and many other applications. These applications are the results of the continuous development of technologies like the miniaturization of devices and wireless technology. WSN comprises several tiny, inexpensive sensor nodes that may actively interact with one another over shorter ranges [1]. These sensor nodes of a WSN are geographically dispersed sensors that collaboratively transmit their data to a central location while monitoring environmental conditions or concerning activities.

Recent developments in computing and communication have influenced sensor network research significantly. WSNs are networks of tiny sensor nodes working together to collect, process and transmit data on specific physical phenomena across wireless channels. These self-organizing, energy-efficient, extremely reliable networks can serve as ideal sentinels for supervising bridges, animals, buildings, pipelines, and underground mining operations. The advancement of WSNs evolves in three different technologies such as communication, sensing, and computing. Therefore, separate and combined developments in each of these technologies have motivated research in wireless sensor networks [2]. The need for reduced energy consumption is one of the most significant constraints for sensors. The power sources carried by sensor nodes are limited and typically irreplaceable. As a result, whereas conventional networks strive to provide good quality of service, sensor network protocols must place a massive emphasis on power savings. They must include built-in trade-off mechanisms that provide the user with the choice to extend the network lifetime at the expense of a longer transmission latency or lower throughput [3].

The deployment of cutting-edge machine learning methods has increased significantly during the past decade in WSNs [4]. It has been discussed how artificial learning methods are used in WSNs to process information and enhance network performance [5]. Similarly, a survey summarizes the uses of intelligent learning models in wireless ad hoc network layers. The authors examined the use of three well-known machine learning models, neural networks, reinforcement learning, and decision trees for WSN communication levels [6]. The work in [7] has explored computational intelligence techniques for overcoming difficulties in WSNs, such as aggregation, task scheduling, data fusion, routing, and localization [7]. In this context, computational intelligence focuses on biologically inspired techniques like evolutionary algorithms, neural networks, and fuzzy systems [8].

Optimization methods and deep learning models have been used to build several energy-efficient solutions for WSNs. The deployment of a WSN includes a delay-aware data-gathering network. The primary objective is to decrease the latency in the WSN data collection process, which tends to extend the network lifetime [9]. It is expected that additional relay nodes have been used to reduce network vulnerability and that the Particle Swarm Optimization model has been used to set an optimum sink position for relay nodes to address the lifetime problem [10].

WSN is made up of several sensor nodes therefore, the ability to compute data has been limited using fusion centre technology, which is complicated to upgrade regularly. Data communication hence consumes more energy, especially for wireless relaying nodes. In the last ten years, data mining approaches have been used to extract relevant information from a variety of data sets, and they are seen to be a more effective tool for forecasting bigger data sets. Logistic regression, support vector machine, and boosting are examples of data mining approaches that have been developed during the past few decades [11]. Additionally, using these data mining models tends to improve the operation of the fusion centre, but the problem with energy consumption remains the same. The author devised the Deep Neural Network to reduce the dimensionality of data and retrieve the underlying representation [12].

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Due to the large number of sensor nodes, the data of WSN has expanded quickly, and a centralized data mining solution is used to reduce the overall energy consumption. To improve the load balancing and energy efficiency at the fusion centre of WSNs, the author introduced a deep-learning-based distributed-data-mining model with long short-term memory [13]. A long-short-memory with a recurrent neural network model separates the network into several layers and places them into the sensor nodes. The overhead of the fusion centre in WSN is significantly decreased by employing a deep-learning-based long-short-term memory distributed-data-mining model. The long-short-memory with the recurrent-neural-network model is subjected to an extensive range of experiments with variable numbers of hidden layer nodes and signaling intervals as well compared to other approaches, the long-short-memory with recurrent-neural-network model increases throughput while minimizing energy usage, average latency, and signaling overhead [14]. The contribution of the paper follows. This work develops time series based ARIMA model for the energy forecasting in WSN. Model stationery estimation and model parameter estimation are derived from statistical analysis and optimal ARIMA model developed for the futuristic energy prediction in WSN. The organization of the paper is follows. The recent relevant literatures are summarized in section II. Section III describes the proposed methodology of the work. The experimental results and its analysis are discussed in section IV. Section V concludes the paper.

II. Related work

A method based on Multilayer Perceptron (MLP) was suggested by Michel Chammas et al. (2019) [1] to forecast the consumption of various types of energy such as the day of the week, light energy, the temperature of a building, humidity using data gathered from a Wireless Sensor (WSN).

A correlation least mean square prediction model that incorporates the correlation component of weather variations was proposed by Dongchao Ma et al. in 2020 [2]. The algorithm can solve it rapidly and efficiently, increasing the accuracy of short-term prediction due to its low complexity and degree of flexibility. According to experimental findings, the Correlation Least Mean Square prediction algorithm's error rate is decreased by roughly 15% when compared to the Least Mean Square model, and the forecast accuracy is greatly increased while dealing with weather variation.

The Combinational Data Prediction Model (CDPM) created by Khushboo Jain et al. (2022) [3] may build past data to regulate delays and forecast future data to decrease unnecessary data transmission. Two methods are implemented to apply this hypothesis in WSN applications. The initial approach builds sensor node models that are gradually optimum (SNs). The second forecasts and recreates the data observed by the base stations. Using a real data set and a WSN-based simulation, the performance of the proposed Combinational Data Prediction Model data-prediction approach is compared with the existing algorithms.

Mahdi Lotfinezhad et al. (2008) [4] provided a framework for analysis to assess the performance of wireless sensor networks in terms of energy consumption, as well as a novel mechanism for data collection for fast sink access. The clustered architecture uses a simple, minimal-overhead medium access control of the data sink access in the design. Packet arrival cannot be described by a continuous random process since data is only collected sporadically. Hence a transient analysis is used as the foundation rather than a stable-state analysis. The tests are used to evaluate how, under the proposed MAC, the energy saving alters the dependency on the amount of data correlation in the network. It was done using techniques from random geometry.

R. Velmani et al. (2014) [5], An effective solution to the concerns of mobility, coverage distances, traffic, delay, end-to-end connection, and tree intensity is provided in the form of the energy-efficient velocity and cluster tree link-aware strategy for data collection in WSNs. The developed energy-efficient velocity and cluster tree link-aware strategy effectively use the data-collection tree to limit energy utilization, reduce collision in group heads, and decrease the latency in WSNs. The energy-efficient velocity and cluster tree link-aware strategy is its ability to build a straightforward data-collection tree, which reduces the energy utilization of the head and avoids repeated cluster creation. According to the findings of simulations, energy efficient velocity and cluster tree link aware strategy offer a higher quality of service for mobility-based WSNs, namely, energy consumption, end-to-end latency, network lifespan, and throughput.

Yang Zhang et al. (2018) [6] employed an integration to accomplish low power capacity and a double-stage capacitor construction to ensure node synchronization in the circumstances without harvested energy. This study elaborates on the energy management mechanism from the perspectives of saving energy, energy measurements, and energy predictions. It also discusses the general layout of the Intermittent-Energy-Aware platform. In addition, the authors were able to synchronize nodes in a variety of temporal and energy contexts, measure actual energy, and provide a technique for calculating light energy based on solar energy measurements. Experiments are carried out to confirm the strong performance of Intermittent-Energy-Aware in terms of reliability and validity in real contexts. The Intermittent-Energy-Aware framework has been demonstrated to have extremely great accuracy and low power consumption for energy monitoring and forecasting.

Guorui Li et al. (2018) [7] offer a Denoising Autoencoder (DCDA)-based Data Collection strategy for sensor data. Using the historical sensed information, a De-noising Auto-encoder is learned to generate the data reconstruction matrices and data measurement matrices. The whole network's sensor information is then gathered via a data-collection tree during the data-collection phase. Finally, its data transmission and data reconstruction performances are assessed concerning those of other systems using real-world sensor information. The investigational findings demonstrate that, in comparison to its rivals, the suggested system produces lower energy usage, greater data compression rates, faster data reconstruction speed and more accurate data reconstruction.

In this study [8], Tongxin et al. (2019) implemented a dual-prediction system using a least-mean-square filter. The dual-prediction system is data quality-based, enabling simultaneous data prediction by the sensor nodes and gateway. The sensor nodes will only transmit sensed data to the gateway or another node and, as a result, update the filter coefficients if the difference between the expected data and the actual sensed data is greater than a predetermined threshold. It has been noted that this approach successfully reduces both the overall number of transmissions and their time, allowing for additional energy savings. The suggested approaches may save at least 62.3 percent of the total energy used for data transmission while producing predictions that are 93.1 percent accurate.

To acquire real-time data from a WSN, Shalini Rani et al. (2017) [9] suggested a big-data efficient gathering method for WSNs. Based on a received signal indication and the remaining energy of the sensor devices, clustered communications are created. Due to the load-balancing strategy, experimental simulations demonstrate that big-data efficient gathering is consistent with data transmission time and network lifetime. Numerical outcomes derived in MATLAB.

Walaa M. Elsayed et al. (2019) [10] suggested a prediction model that was based on a distributive clustering model for reducing the quantity of sent data to minimize the energy utilization in WSN nodes. The outcomes showed that distributed-data-predictive decreased the rate of data transfer to 20%. Furthermore, it reduced the energy usage throughout the whole dataset sample to 95 percent. The sensory network's lifespan was effectively extended using DDPM, which improved its performance by roughly 19 percent. Yanjun Yao et al. (2014) [11] presented distributed heuristics to help the method scale for large-scale network operations as well as a centralized heuristic to decrease the computing cost of WSNs. Using simulations and a hardware testbed, we thoroughly assess EDAL to compare its performance to that of comparable protocols.

In demanding circumstances where all network nodes are mobile and while reducing energy consumption and end-to-end latency, German A. Montoya et al. (2021) [12] introduced a multi-objective optimization model for determining the best communication path between a sink node and a source node. Additionally, to discover a communication channel between a source node and a sink as quickly as possible while using the least amount of energy, the author offers a predictive distributed routing method based on Markov Chains that takes into consideration network mobility. Additionally, the author suggested using deep learning to estimate future node distances in a mobile network to see if path-based communication may be disrupted by node migrations in the future. Finally, the author compared the prediction algorithms to common routing algorithms to examine them in the context of real-time situations. This yielded encouraging results in terms of energy usage and latency across all mobile node scenarios.

An unmanned aerial vehicle is used as a data mule in Nazib et al. (2021) [13] designed an energy-efficient and quick data-collecting method for mountainous terrain in unmanned aerial vehicle-aided WSNs. With the generated data collecting places, the author created the traveling salesperson problem and used a modified genetic algorithm to solve it to accomplish quick data gathering. In terms of control overhead, scalability, latency, energy consumption, and load balancing, the suggested energy-efficient and quick data-collecting system performs better than the traditional ones based on the results of our simulations.

A unique adaptive sensor selection framework is provided in this research as an improvement to Sushmita Ghosh et al. (2021) [14] strategy for such sensor hubs to maximize energy sustainability. According to the cross-correlation between the features, energy available at the node, and the energy used by the sensors, a Confidence-Bound learning-based optimization approach is designed to choose the best effective sensor set in a measurement cycle. The parametric values of inactive sensors are also predicted using a Gaussian-process regression-based prediction model using the cross-correlation parameters of effective sensors. The suggested approach has a complexity of O(2P) for P sensor nodes and uses 54% less energy than the state-of-the-art while retaining a reasonable range of sensing error.

Hongju Cheng et al. (2019) [15] offer a unique paradigm for multiple-step sensor data forecast in WSN. LSTM has beeen introduced to find the feature characteristics of various qualities through the pre-processed sensor input. Following that, one-step prediction is obtained using these abstract attributes. The multiple-step prediction is finally created by iteratively using the preceding step's prediction outcomes and the historical data. The result of the experiments indicates that the suggested multiple-step predictive model can predict multi-step sensor data after choosing optimal node patterns in which the spatial and temporal correlation is emphasized and that its performance is superior to that of other relevant approaches [15-24].

To handle several significant technological issues, Chong Liu et al. (2007) created a general framework. These challenges were how to divide the sensor nodes into clusters, dynamically maintain the clusters in response to environmental changes, schedule parameters for a cluster of sensor nodes, examine temporal correlation, and accurately recover the data in the sink node. The author experimentally evaluated the technique using a real testbed system and a big synthetic data set [25-31].

III. Proposed Methodology

In this paper, an optimal auto-regressive model based on the aggregate method of data is proposed that makes use of time series models to forecast data for the future at both the common sensor node and aggregator. With the recently sensed data, the sensor nodes will develop a suitable time series model and automatically communicate the model's parameters to the aggregator. The sensor nodes will rebuild the model when the predicted error exceeds the application-stated error value and send the predicted value with the new model to the aggregator. The predicted values of our suggested scheme substantially resemble the actual sensor values and contribute to saving energy between the sensor nodes and aggregators, as demonstrated in this paper.

A model for forecasting future data values is created using historical data using time series analysis. A common prediction model for univariate time series is the ARIMA model, often known as the Box-Jenkin model [31]. Moving-average (MA), Auto-Regressive (AR), and one-step differencing are the three parts of an ARIMA model. The MA module tracks relationships between prediction errors, the one-step different module records relationships between nearby samples, and the AR module calculates the current sample as a linearly weighted sum of earlier samples. The ARIMA(a,b,c) model of time series {t1, t2, ….} is defined as in Equation (1)

$$\phi_a\,(K)\Delta^b t_n = \Theta_c(K)\varepsilon_n \qquad (1)$$

Where Δ^b is the difference of backward, K is the backward-shift operator, differencing order is t_n, ϕ_a and Θ_c are the polynomials of order. To prevent the creation of unbounded processes, the parameters ϕ and Θ are selected in such a way that 0s of both polynomials lie outside the unit circle. Figure 1 depicts the proposed optimal ARIMA model.

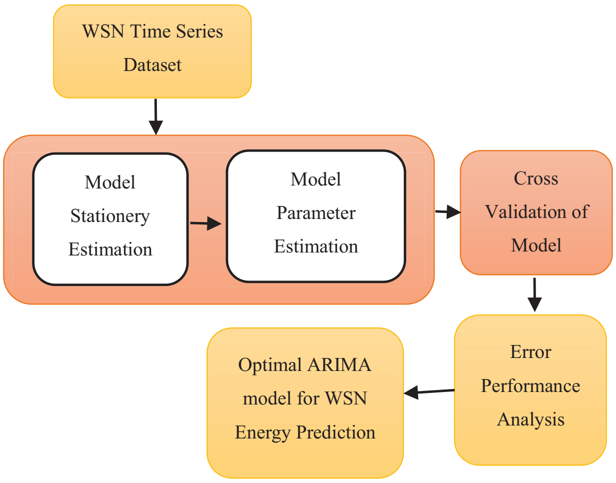

Figure.1 Schematic diagram of the proposed model

The WSN time series data is being examined, and its stationary distribution is approximated. The WSN time series data is analyzed for the estimation of ARIMA model parameters. The time series data will be divided into k subsets of data for cross-validation. The machine learning model was applied to all subsets (k-1), and then the subset model was evaluated using cross-validation. The performance error is analyzed with respect to the proposed optimal ARIMA model for WSN energy prediction. Figure.2 illustrates the flow diagram for evaluating the optimal ARIMA model parameters.

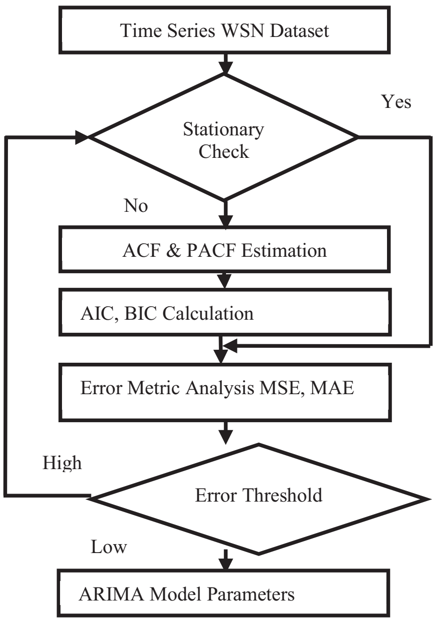

Figure. 2 Workflow of the proposed Model

The stationary distribution is approximated for the time series WSN data. To make the WSN time series data stationary when the variance is non-stationary, the data must be changed by differencing the original data. The data series should be repeatedly differenced until the WSN time series becomes stationary if it indicates a pattern over time, periodicity, or any other non-stationary pattern. When the WSN time series data becomes stationary, then the optimal ARIMA models are identified. Multiple ARIMA models adequately represent the time series data that can be identified after getting the partial autocorrelation function (PACF) and autocorrelation function (ACF). It gives the auto-correlation values between the WSN time series data and its lag values. The n-order autocorrelation coefficient of time series {t1, t2, ….} is defined as in Equation (2).

$$\gamma_k = \frac{\sum_{r=n+1}^{R}(y_r-\bar{y})(y_{r-n}-\bar{y})}{\sum_{r=1}^{R}(y_r-\bar{y})^2} \qquad (2)$$

The n-order partial autocorrelation coefficient of time series {t1, t2, ….} is defined as in Equation (3)

$$\phi_t = \begin{cases} \gamma_1 & m = 1 \\ \dfrac{\gamma_m - \sum_{n=1}^{m-1}\phi_j\,\gamma_{m-n}}{1-\sum_{n=1}^{m-1}\phi_j\,\gamma_{m-n}} & m > 1 \end{cases} \qquad (3)$$

A. *Estimation of optimal ARIMA model parameters*

The time series is examined, and the model parameters are estimated after determining an optimal ARIMA model. If the lag one autocorrelation is positive and the PACF of the differenced time series exhibits a rapid cutoff, then one or more AR terms should be included in the model. The stated number of MA terms is the lag after which the PACF terminates. Consider an MA component in the model if the lag one autocorrelation is negative and the ACF of the differenced time series exhibits a rapid cutoff. The stated number of MA terms is the lag after which the ACF terminates. The most appropriate ARIMA model for analysis is the one with the least Bayesian Information Criterion (BIC) indicator and Akaike Information Criterion (AIC) indicator. The BIC and AIC indicators are calculated using Equations (4) and (5), respectively.

$$BIC = 2j/R + (n\log R)/R \qquad (4)$$

$$AIC = -2j/R + 2n/R \qquad (5)$$

Where 'j' is the likelihood log, 'n' is the number of the regressor, and 'R' is the number of observations. Thus, the appropriate optimal ARIMA model is chosen for the WSN time series data.

IV. Results and Discussions

This section summarizes the energy forecasting results using the ARIMA time series machine learning algorithm. Figure 3 illustrates the energy consumption by lights and appliances over the dates 22-01-2016 to 22-05-2016 every 10 minutes. It can be seen that the appliances have very high energy consumption compared to lights. The appliances have an energy consumption of up to 1100 Watts. In Figure 4, the light's energy consumption has been depicted over the same period. The lights have an energy consumption of up to 70 Watts, and the average energy consumption is about 20 Watts.

Figure 5 illustrates the ARIMA model-based energy consumption forecasting of appliances over the dates 22-01-2016 to 22-05-2016 every 10 minutes. Actual energy consumption and the ARIMA model predicted energy consumptions are the same at most ranges. Table 1 gives the statistical summary of ARIMA model-based energy forecasting for the appliances. It summarizes the AR, MA, Coefficient, Standard error, z-score, P>|z| value, and [0.025 0.975] values. Further, it summarizes the Ljung-Box (L1), Jarque-Bera (JB), Prob(Q), Prob(JB), Heteroskedasticity (H), Skew, Prob(H) (two-sided), Kurtosis values. Its values are 0, 405915.70, 0.98, 0, 0.77, 2.94, 0, and 24.43, respectively.

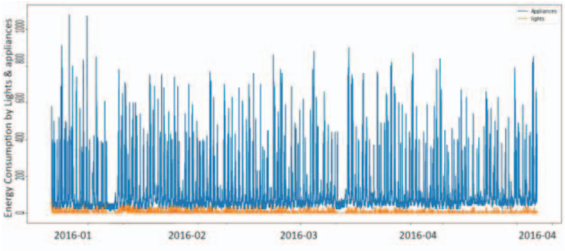

Figure.3 Energy Consumption by Lights & appliances

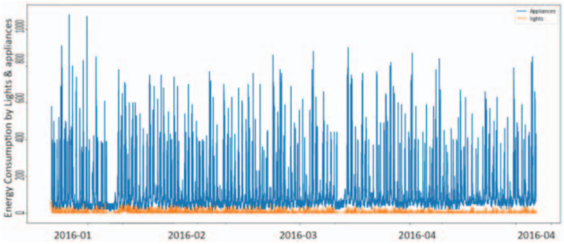

Figure.4 Energy Consumption by Lights

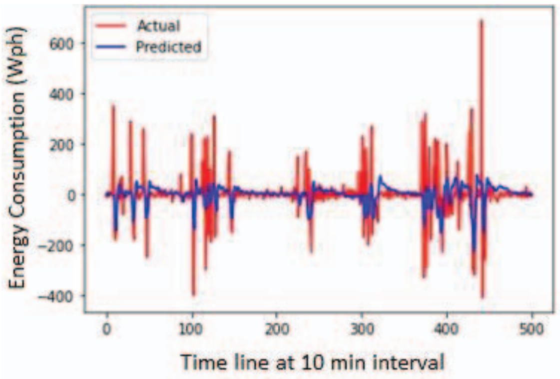

Figure.5 Appliances Energy prediction using ARIMA

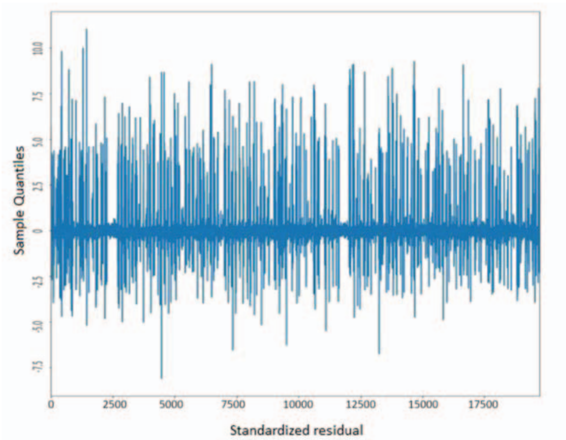

Figure.6 Standardized residual for Energy Consumption

These statistical values suggest that the ARIMA time series model is producing better results for the energy

Table.2 Error Evaluation for ARIMA

Metric	MAE	MSE	RMSE	MedAE	R2
Proposed	45.646	7364.991	85.819	19.218	-4.32
Paper [32]	66.95	-	56.84	-	-

Table.1 Statistical summary of ARIMA Forecasting

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	0.0011	0.117	0.010	0.992	-0.227	0.229
ar.L1	0.8671	0.077	11.290	0.000	0.717	1.018
ar.L2	-0.8739	0.086	-10.154	0.000	-1.043	-0.705
ar.L3	0.2082	0.063	3.308	0.001	0.085	0.331
ar.L4	0.1037	0.029	3.540	0.000	0.046	0.161
ma.L1	-1.0554	0.077	-13.780	0.000	-1.206	-0.905
ma.L2	0.6998	0.100	7.017	0.000	0.504	0.895
ma.L3	-0.2253	0.057	-3.919	0.000	-0.338	-0.113
ma.L4	-0.2800	0.032	-8.736	0.000	-0.343	-0.217
sigma2	4410.092	18.308	240.888	0.000	4374.2	4445.98

Ljung-Box (L1) (Q) :0.00	Jarque-Bera (JB):405915.70
Prob(Q) :0.98	Prob(JB) :0.00
Heteroskedasticity (H):0.77	Skew :2.94
Prob(H) (two-sided) :0.00	Kurtosis :24.43

consumption of appliances. Table.2 gives the error metrics for the ARIMA time series model based forecasting. The error metrics such as Mean Absolute Error (MAE), Median Absolute Error (MedAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and R2 values are evaluated; the error values are 45.646, 7364.991, 85.819, 19.218, and -4.320 respectively. Figure 6 shows the standardized residual for 'y' for ARIMA model-based forecasting of energy consumption over the sample quantiles. Figure.7 shows the comparison chart of theoretical quantiles and sample quantiles. The

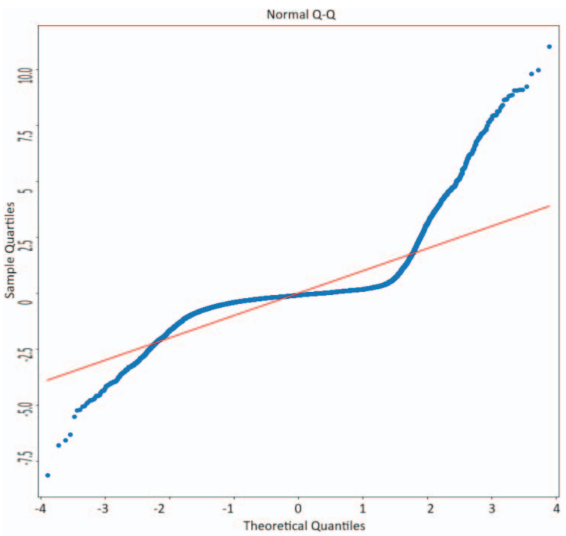

Figure.7 Normal Q-Q

autocorrelation function with a 95 % of confidence level is shown in Figure.8.

V. Conclusion

The ability to save energy is one of the most crucial criteria for integrating systems and enhancing smart homes and communities. In order to reduce power usage, energy forecast is crucial. In this research, we proposed an ARIMA model to simulate a time series-based energy prediction system. Data

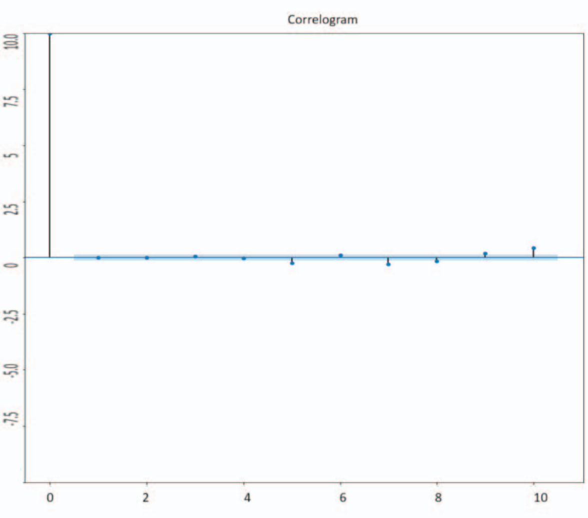

Figure.8 ACF

from a WSN put in a two-story structure, including temperature, day of the week, light energy, humidity, etc., have been used in a variety of data categories. We evaluated the significance of light energy and temporal data as additional characteristics for the prediction model. While the lights' energy lowered performance, the temporal aspects somewhat enhanced it for all systems. It can be seen a reduction in relative predicting error performance for our technique. In every case, our system performed better than others. We conclude that weather parameters would be sufficient to forecast energy usage based on the trials performed. This makes low-cost energy forecasting methods possible. To verify our findings, more research on various datasets should be conducted.

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