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Time-Series Estimation based AI Algorithm for Energy Management in a Virtual Power Plant System

Yeonwoo LEE[1]

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Abstract

This paper introduces a novel approach to time-series estimation for energy load forecasting within Virtual Power Plant (VPP) systems, leveraging advanced artificial intelligence (AI) algorithms, namely Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average (SARIMA). Virtual power plants, which integrate diverse microgrids managed by Energy Management Systems (EMS), require precise forecasting techniques to balance energy supply and demand efficiently. The paper introduces a hybrid-method forecasting model combining a parametric-based statistical technique and an AI algorithm. The LSTM algorithm is particularly employed to discern pattern correlations over fixed intervals, crucial for predicting accurate future energy loads. SARIMA is applied to generate time-series forecasts, accounting for non-stationary and seasonal variations. The forecasting model incorporates a broad spectrum of distributed energy resources, including renewable energy sources and conventional power plants. Data spanning a decade, sourced from the Korea Power Exchange (KPX) Electrical Power Statistical Information System (EPSIS), were utilized to validate the model. The proposed hybrid LSTM-SARIMA model with parameter sets (1, 1, 1, 12) and (2, 1, 1, 12) demonstrated a high fidelity to the actual observed data. Thus, it is concluded that the optimized system notably surpasses traditional forecasting methods, indicating that this model offers a viable solution for EMS to enhance short-term load forecasting.

Keywords : Virtual Power Plant, LSTM, SARIMA, energy management system, load forecast, microgrid, AI

Major Classification Code: Artificial Intelligence

1. Introduction

The virtual power plants (VPPs) lead to its emergent advent derived by the integration of renewable energy sources with conventional power systems, which will result in a paradigm shift in energy management and distribution. VPPs synergize the output of a network of microgrids (MGs), each with its own array of distributed energy resources (DERs), such as wind turbines, photovoltaic cells, and fuel cells. Managing such a complex system requires sophisticated Energy Management Systems (EMS) to optimize energy flow and ensure reliability. A cornerstone of effective EMS is the ability to forecast energy loads accurately over short-term periods. This is where the challenge of time-series estimation comes into play,

* This research was supported by Research Funds of Mokpo National University in 2023.
1 First & Corresponding Author. Professor, Dept. of Information and Communication Eng., Mokpo National University, Korea.
Email: ylee@mokpo.ac.kr

demanding advanced computational techniques capable of handling large datasets with intricate patterns. The concept of microgrid network (MG) which is well known as a promising way to guarantee a reliable energy supply and demand of users can be realized by aggregating conventional generators, renewable energy systems (RESs), and energy storage systems (ESS) along with different loads. One of most generally considered RESs is a photovoltaic (PV) prosumer utilizing solar power. A smart microgrid is defined as an energy production sources such as distributed energy resources (DERs), energy storage (battery) facilities, energy flow/distribution management. The virtual power plant (VPP) is believed to providing highly efficient power service to customers through virtually sharing of these dispersed DERs, and battery storage units in microgrids (MGs). An energy control system such as energy management system (EMS) has an important role in a MG in order to operate MG's components and DERs efficiently, and to achieve the goals of sustainability in the EMS are economic operation, reliability, and environmental impact.

For a successful forecasting of energy loads within VPPs, it is not merely a matter of algorithmic precision, but also it is about integrating DERs into a cohesive framework that can adapt to the highly dynamic nature of energy markets and consumption patterns. The EMS's capability to predict energy demand with high accuracy has profound implications for the operational efficiency of power systems, the integration of renewable energy, and the overall stability of the electric grid. For providing such capability, this paper presents a groundbreaking approach to short-term load forecasting by harnessing the power of artificial intelligence (AI). Specifically, it explores the efficacy of long short-term memory (LSTM) networks, a type of recurrent neural network that is particularly well-suited to recognizing and predicting temporal patterns in time-series data. Complementing this is the application of the seasonal autoregressive integrated moving average (SARIMA) model, a renowned statistical method for analyzing and forecasting seasonal time-series.

The methodology detailed herein is based on the real-data set retrieved by Korea Power Exchange (KPX). A decade's worth of data from the KPX's Electrical Power Statistical Information System (EPSIS) provides the training data set for the LSTM-SARIMA algorithm foundation. Throughout the testing based on these real-dataset, the proposed time series-based load estimation and forecasting model is a feasible solution to energy load forecasting. By providing a robust forecasting model, the research supports EMS in minimizing imbalances between energy supply and demand, accommodating the variable nature of renewable energy sources, and contributing to the overall sustainability and resilience of power systems.

2. Theoretical Background

Various load forecasting methods into two primary approaches: parametric-based and AI-based methods ass shown in Fig. 1. Under the parametric umbrella, the methods are further classified into statistical methods and Kalman filter techniques. For AI-based methods, the classification splits into Fuzzy systems and machine Learning (ML) algorithms. In addressing the multifaceted challenge of load forecasting, researchers have delineated methods into two primary frameworks: parametric-based and AI-based methodologies. Each framework comprises several distinct approaches with unique characteristics and applications.

Within the parametric-based category, statistical methods are foundational to load forecasting. Linear Regression (LR), for instance, posits a direct, linear correlation between independent variables and the forecasted load, simplifying the predictive process through a straightforward equation. Brockwell and Davis (2002) offer a comprehensive introduction to such time series forecasting techniques. Alternatively, the Moving Average (MA) approach, as elucidated by Box, Jenkins, and Reinsel (2015), mitigates short-term volatility by averaging past data points, thus revealing underlying trends. Extending this concept, the Autoregressive Moving Average (ARMA) model, discussed by Hamilton (2020), integrates the autocorrelation of time series with the moving average of forecast errors to enhance predictive accuracy.

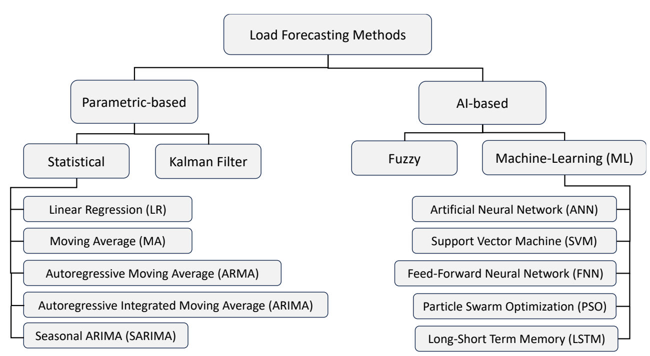

Figure 1: Load Forecasting Methods

The Autoregressive Integrated Moving Average (ARIMA) model, also expounded upon by Box and colleagues (2015), further refines the ARMA approach by accommodating non-stationary data through differencing, allowing for the analysis of data with trends or seasonal patterns. The Seasonal ARIMA (SARIMA) model, a subset of ARIMA, specifically targets seasonal fluctuations within time-series data, making it particularly relevant for load forecasting in energy sectors with pronounced seasonal consumption patterns. The Kalman Filter represents another parametric-based method, distinguished by its recursive mechanism that processes a series of measurements over time, accounting for statistical noise and other inaccuracies. Kalman's seminal 1960 paper provides a profound insight into this filtering and prediction technique.

Shifting to AI-based methods, fuzzy systems, grounded in Zadeh's fuzzy set theory (1965), offer a stark contrast to the precision of statistical methods by modeling the imprecision inherent in human reasoning and decision-making processes. This method is particularly advantageous in scenarios where the data or the system behavior is too complex to be captured by conventional quantitative techniques.

Machine Learning (ML), a rapidly evolving domain within AI, encompasses a variety of algorithms and models, each with unique capabilities. Artificial Neural Networks (ANNs), as detailed by Goodfellow, Bengio, and Courville (2016), mimic the neural structure of the brain and are adept at recognizing complex patterns and performing predictive modeling. Support Vector Machines (SVMs), introduced by Cortes and Vapnik (1995), provide a powerful framework for classification and regression, especially beneficial in high-dimensional spaces.

Feedforward Neural Networks (FNNs), a specific type of ANN where the connections between nodes do not form cycles, are tailored for static pattern recognition, as expounded upon by Haykin (1998). Particle Swarm Optimization (PSO), a technique inspired by the social behavior of animals, is detailed by Kennedy and Eberhart (1995) and excels in optimizing problems by refining candidate solutions iteratively. Lastly, Long Short-Term Memory (LSTM) networks, a special class of ANNs designed by Hochreiter and Schmidhuber (1997), excel in identifying and predicting sequence patterns, making them particularly suited for time-series forecasting tasks.

The confluence of these methodologies presents a rich toolkit for researchers and practitioners to forecast loads with increasing precision, adapting to the growing complexities and demands of modern energy systems

3. LSTM-SARIMA Load Forecasting

The VPP can consist of separate DERs, traditional conventional heating power plant (CHP), energy storage facilities, and dispatchable loads and also, it can hierarchically aggregate MGs and DERs. The energy control system in VPP utilizing AI algorithm-based Energy Management System (EMS) is shown in Fig. 2.

In the (EMS) that oversees the microgrids forming a VPP, it is essential to predict energy demand for energy trading purposes, segregating into short-term and long-term forecasts. These predictions must efficiently allocate the generated renewable energy resources as they become available. Although not illustrated in Figure 2, the EMS is required to forecast the volume of energy trades, ranging from as short as 15-minute intervals to as long as daily intervals. The proposed system fulfills these functions using AI-based Long Short-Term Memory (LSTM) methods and parametric-based Seasonal Autoregressive Integrated Moving Average (SARIMA) models. The LSTM is utilized to learn patterned energy trade datasets and implement short-term time series predictions. Meanwhile, the SARIMA model employs seasonally adjusted automated regression averages for forecasting long-term trends in energy trading.

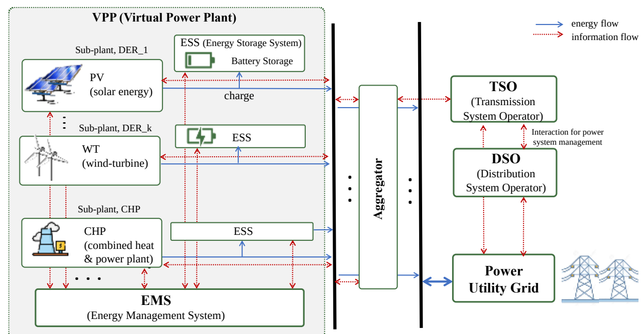

Figure 2: Conceptual Model of Virtual Power Plant with AI Algorithm based Energy Management System

3.1. LSTM Model

The LSTM model is a type of recurrent neural network (RNN) used for sequence prediction. It can be represented by the following equations:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (1)$$
$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (2)$$
$$g_t = tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g) \quad (3)$$
$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (4)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \quad (5)$$
$$h_t = o_t \odot \tanh(c_t) \quad (6)$$

where x_t represents the input at time (t). h_t is the hidden state at time (t). c_t is the cell state at time (t). i_t, f_t, g_t, and o_t are the input, forget, cell, and output gates, respectively. σ represents the sigmoid activation function. $tanh$ represents the hyperbolic tangent activation function. W and b are weight matrices and bias terms for the gates. The LSTM model uses these equations to process sequential data and capture long-term dependencies, making it suitable for time series forecasting.

3.1.1. LSTM Model Parameters

The key parameters of LSTM network are as follows. $N_{neurons}$ parameter specifies the number of neurons or units within the LSTM layer. The chosen number of neurons influences the model's ability to identify and learn patterns in the data, with a higher number typically providing a greater capacity for complexity but also requiring more computational power. Activation function (σ) is applied to the output of a neuron or unit in the LSTM layer. Generally, the ReLU (rectified linear unit) function is used due to its advantages in mitigating the vanishing gradient problem and accelerating the convergence of stochastic gradient descent. Input shape parameter (i_t) details the expected dimensions of the input data, encompassing both the sequence length and the number of features per sequence. The input shape must be carefully determined to match the structure of the input dataset, ensuring that the model can process the data effectively.

Incorporating these parameters, the LSTM model is constructed to provide the capability to discern both the short-term and long-term dependencies within time-series data. This is particularly beneficial for applications like power supply and demand forecasting, where temporal patterns and the influence of past events play a critical role in prediction accuracy. The proposed short-term energy trade forecasting model is shown in Fig. 3.

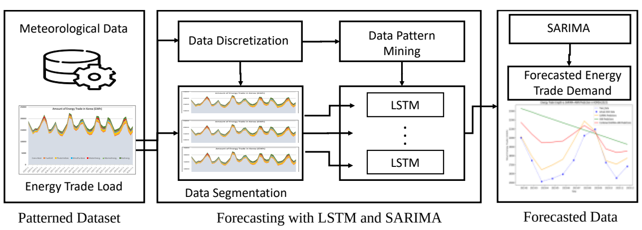

Figure 3: Proposed Short-term Energy Trade Forecasting Model

3.2. SARIMA Model

The SARIMA model is a type of time series forecasting method used to predict future points in the series. It's an extension of the ARIMA (Autoregressive Integrated Moving Average) model that also accounts for seasonality. SARIMA models are particularly useful when a time series is influenced by seasonal factors, such as sales data that peaks during the holiday season or electricity consumption that varies with the seasons.

3.2.1. Components of SARIMA Model

The components of a SARIMA model are as follows.

Seasonal Autoregressive (SAR): This part of the model captures the dependencies among observations at previous times that are separated by a number of periods equal to the season length. For example, if a monthly data is given with a yearly cycle, the season length would be 12.

Seasonal Integration (I): This involves differencing the series at the seasonal periods to make it stationary. In other words, it is the process of subtracting the observation from the same season, say a year or a month earlier.

Seasonal Moving Average (SMA): This part models the error of the series as a linear combination of error terms that occurred contemporaneously and at various times in the past.

Non-seasonal ARIMA Model: This is the underlying ARIMA model which may include non-seasonal autoregressive terms, non-seasonal differences, and non-seasonal moving average terms.

3.2.2. SARIMA Model Parameters

The SARIMA model is a time series forecasting model. It can be represented by the following equation:

$$Y_t = c + \phi_1 Y_{t-1} + \theta_1 \epsilon_{t-1} + \epsilon_t \tag{7}$$

where: Y_t represents the current time series data point. c is a constant term. ϕ_1 is the autoregressive (AR) coefficient, which represents the relationship between the current value and the previous value. Y_{t-1} is the previous time series data point. θ_1 is the moving average (MA) coefficient, representing the relationship between the current value and the previous error term ϵ_{t-1}. ϵ_t is the error term at the current time step.

SARIMA Model Parameters: The SARIMA model uses these parameters to capture the autoregressive, differencing, and moving average components of the time series, along with seasonal patterns. The parameters of the SARIMA model can be typically denoted as

$$SARIMA(p, d, q)(P, D, Q, S). \tag{8}$$

Where p is the number of autoregressive order, d is the number of non-seasonal differences needed for stationarity, q is the number of lagged forecast errors in the prediction equation (moving average order), P, D and Q are the seasonal equivalents of p, d and q, S is the length of the seasonal cycle. These models are fundamental in time series analysis and forecasting, with SARIMA focusing on statistical modeling, and LSTM focusing on deep learning-based sequential prediction. These model parameters define the structure and behavior of the SARIMA and LSTM models. SARIMA model parameters describe autoregressive, differencing, and seasonal patterns in time series data, while LSTM model parameters define the architecture and activation functions used in a recurrent neural network for time series prediction. These parameters should be adjusted based on the specific characteristics of the given data and problem.

The key parameters of a SARIMA model are as follows.

Auto-Regressive Order Parameter (p): this indicates how far back in the past the values influence future predictions. A higher value implies longer-term dependencies. Adjusting this parameter is important if long-term patterns in time series data are significant.

Differencing Parameter (d): This is used to stabilize the time series data. Setting the appropriate order of differencing for non-stationary time series data is crucial.

Moving Average Order Parameter (q): This focuses on adjusting the model using the prediction errors. It helps to better capture the noise or irregular fluctuations in the time series.

Seasonal Parameters (P, D, Q, S): For data with seasonality, these parameters are important. P, D, Q represent the seasonal AR, differencing, and MA parameters, respectively, and S denotes the seasonal period.

Figure 4 illustrates the overall architecture of the proposed hybrid SARIMA and LSTM network model. The SARIMA model extracts the autoregressive linear regression feature of energy trade data because in a short time historical data, for example 5 min. A linear model like SARIMA can forecast with high accuracy linearity that is intrinsic in the data. As can be seen from the overall architecture, the energy trade data forecasting model is designed from several LSTM network blocks as shown in Fig. 5.

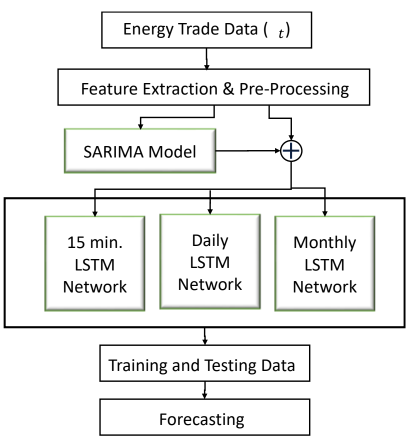

Figure 4: Overall Archtecture of Hybrid SARIMA-LSTM Network Model

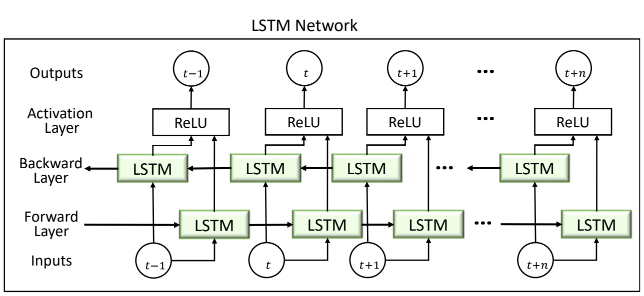

Figure 5: LSTM Network

4. Simulation and Discussion

4.1. Simulation Setup

The SARIMA model used in our simulation test above has the parameters set to (1, 1, 1)(1, 1, 1, 12), which indicates a simple model with one autoregressive term, one difference, and one moving average term, both for the non-seasonal and seasonal parts, with an annual seasonality. Adjusting the parameters of a SARIMA model can significantly impact the accuracy of time series forecasting. Understanding the impact of each parameter helps in determining which ones are most critical. Finding the optimal parameters usually requires several attempts, and each attempt should be evaluated through cross-validation.

In the proposed framework, an artificial neural network (ANN), specifically a multi-layer perceptron (MLP), is implemented to complement the SARIMA model's predictive capabilities. The ANN approach mirrors the structure of the human brain's neural network, capitalizing on its ability to discern complex patterns and relationships within vast datasets. This synergy facilitates a more nuanced understanding of the dynamics involved in real-time power supply and demand forecasting. Within this context, the ANN architecture selected is the MLPRegressor from the scikit-learn library, which is characterized by its layered structure of interconnected neurons. The configuration of the model is as follows: The `hidden_layer_sizes` parameter is set to (1, 0, 0), designating a single hidden layer consisting of 100 neurons, providing sufficient complexity to capture intricate patterns without overfitting. The `activation` function chosen is 'ReLU', favored for its efficiency and effectiveness in non-linear transformations within the network. For weight optimization, the `solver` employed is 'ADAM', renowned for its performance in large datasets and its adaptive learning rate capabilities. The `max_iter` parameter is fixed at 2000, ensuring ample iterations for the optimization algorithm to converge, reflecting a balance between computational efficiency and the accuracy of the model.

This ANN is adept at assimilating the intricate behavior of energy trade values, trained exhaustively on historical datasets to extrapolate future trends. The meticulous training process allows the model to internalize and generalize from the embedded patterns, thereby enhancing the fidelity of the forecasts generated for power supply and demand 15 minutes into the future. Both the LSTM-SARIMA and ANN models provide a forecast for the energy trade in GWh for 2023, and their combined forecast aims to leverage the strengths of both models to provide a more accurate prediction.

4.2. Simulation Results

4.2.1. Simulation Step of SARIMA Model

Forecasting with a SARIMA model involves the following steps.

Forecasting Step of SARIMA Model, $SARIMA(p, d, q)(P, D, Q, S)$
Step 1: Model Identification: Using autocorrelation and partial autocorrelation functions to estimate the initial values of p, d, q, P, D, and Q.
Step 2: Model Identification: Using autocorrelation and partial autocorrelation functions to estimate the initial values of p, d, q, P, D, and Q
Step 3: Parameter Estimation: Using statistical techniques like maximum likelihood estimation to estimate the parameters of the model.
Step 5: Model Checking: Using diagnostic tests to determine whether the residuals are white noise (indicating a good fit).
Step 4: Forecasting: Using the model to forecast future data points.

SARIMA models are powerful tools but also complex, requiring careful tuning and validation to ensure accurate forecasts. They are widely used in economic and financial time series analysis, among other fields.

4.2.2. Energy Trade Dataset

The dataset employed for the enhancement of the forecasting model encompasses a comprehensive range of distributed energy resources. This includes both renewable energy modalities and traditional power generation facilities. The dataset has been procured from the Korea Power Exchange (KPX) Electrical Power Statistical Information System (EPSIS), representing a longitudinal span of ten years. This extensive temporal dataset has been pivotal in substantiating the efficacy of the integrated Long Short-Term Memory (LSTM) and Seasonal Autoregressive Integrated Moving Average (SARIMA) model, as delineated in Figure 6.

In the proposed framework, an ANN, specifically a MLP, is implemented to complement the SARIMA model's predictive capabilities. The ANN approach mirrors the structure of the human brain's neural network, capitalizing on its ability to discern complex patterns and relationships within vast datasets. This synergy facilitates a more nuanced understanding of the dynamics involved in real-time power supply and demand forecasting.

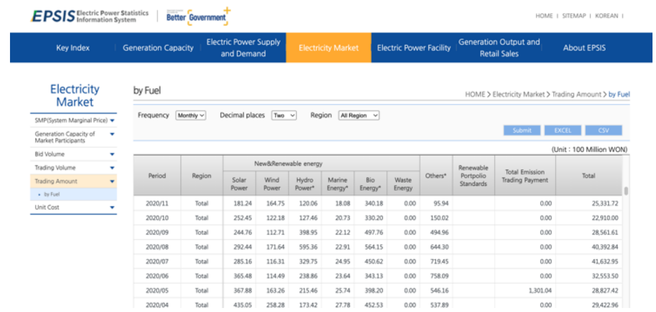

Figure 6: Real-dataset retrieved by Korea Power Exchange (KPX), Electrical Power Statistical Information System (EPSIS)

4.2.3. Results

Figure 7 delineates the dynamics of energy trade in Korea over the period 2022 to 2023, encompassing an array of energy resources including traditional thermal power plants, fuel cell technology, wind turbines, hydroelectric (water) power, biomass, and marine energy generation systems. The data indicate that a substantial portion of the nation's energy production is attributed to traditional thermal power plants. Concurrently, renewable energy sources are depicted as occupying a pivotal role in augmenting energy security and addressing imbalances and shortages. These renewable sources not only contribute to diversifying the energy mix but also play a critical role in supporting the transition towards a more sustainable and resilient energy system. The analysis underscores the strategic importance of enhancing the capacity and efficiency of renewable energy technologies to mitigate reliance on conventional fossil fuel-based power generation, thereby promoting environmental sustainability and energy independence

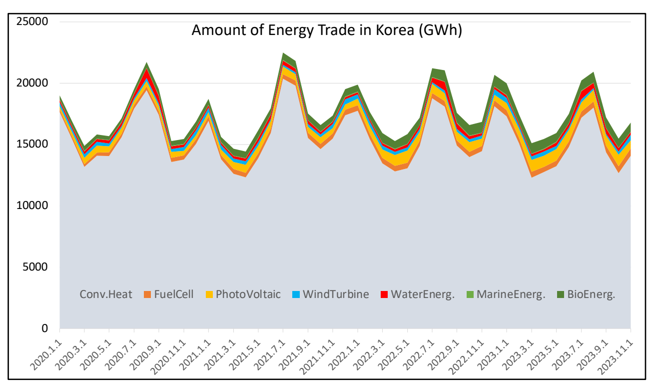

Figure 7: Amount of Energy Trade in Korea (GWh) over the period 2020 to 2023

Figure 8 presents the average volume of energy trade over the past decade. This longitudinal analysis encapsulates the aggregated transactions across various energy sectors, providing insights into trends and patterns in energy exchange during this period.

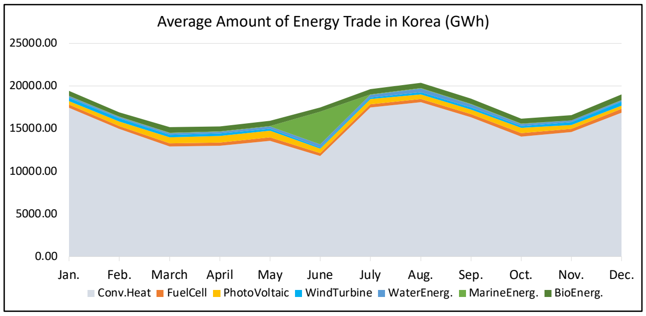

Figure 8: Average Amount of Energy Trade in Korea (GWh) over the past 10 years used for model training

The result graph of Figure 9 has been adjusted to reflect the SARIMA model's forecasts with the added constant to correct the direction of prediction relative to the actual data. Now the orange line for the SARIMA forecast should trend in a direction that is more consistent with the actual data trend, as should the red line for the adjusted hybrid LSTM-SARIMA forecast. The changes made aim to ensure that the models' forecasts are better aligned with the historical data, providing a more accurate representation for the year 2023.

To predict the real-time power supply and demand 15 minutes into the future, a forecasting model employing both the LSTM-SARIMA model and ANN can be constructed. Initially, the SARIMA model will be utilized to forecast. Considering the seasonality and trend of the time series data, followed by the construction of the ANN model to learn nonlinear relationships. The methodology encompasses the following steps: Data Preparation: Time series data will be transformed into a suitable format. SARIMA Model Construction: A SARIMA model will be established and trained for the time series data. ANN Model Construction: An ANN model will be built and trained using the same dataset. Forecast Execution: Future power supply and demand will be forecasted using both models.

Figure 10 demonstrates the energy trade forecasts generated by the proposed hybrid LSTM-SARIMA model augmented with an Artificial Neural Network (ANN) framework. Data preprocessing involved segmenting datasets into specified time intervals prior to the construction of the SARIMA model. Adjustments to the SARIMA parameters (P, D, Q, S) were deemed necessary to tailor the model to the unique size and attributes of the dataset. As depicted in Figure 10 and delineated in Eq. (8), the parameters were refined to configurations including (1, 1, 1, 12), (2, 1, 1, 12), (2, 2, 1, 12), and (2, 2, 2, 12). Forecasts produced with parameter sets (1, 1, 1, 12) and (2, 1, 1, 12) demonstrated a high fidelity to the actual observed data. The hybrid LSTM-SARIMA model exhibited proficiency in tracking the ascending trends while effectively averaging fluctuations in both ascending and descending trends. Consequently, it is asserted that meticulous selection of the SARIMA parameters, coupled with an optimal LSTM averaging interval, is crucial to enhance the precision of energy trade forecasting and prediction

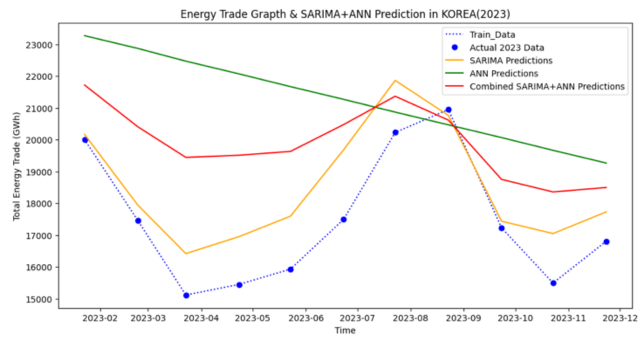

Figure 9: Energy Trade Forecasting Result based on SARIMA, ANN, and SARIMA+ANN model for the year 2023

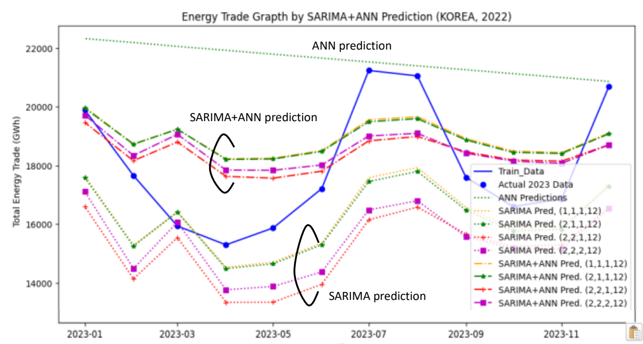

Figure 10: Average Amount of Energy Trade in Korea (GWh) over the period 2023

5. Conclusion

Our findings indicate that the model's capability to discern and leverage the inherent patterns and seasonality in energy usage data results in a significant enhancement in forecasting accuracy. The utilization of a broad spectrum of distributed energy resources within the model ensures its applicability to a diverse energy network, reflecting real-world complexities. The empirical validation, carried out with a decade of data from the KPX's EPSIS, confirms that the proposed model outstrips traditional forecasting methods. The implications of this research are twofold. Firstly, it offers a viable and improved method for EMS in virtual power plants, leading to better management of energy supply and demand. Secondly, it contributes to the body of knowledge in time-series forecasting, presenting a robust framework that can be adapted and extended to other domains requiring precise prediction capabilities.

In conclusion, this study has presented a comprehensive analysis of energy trade forecasting by deploying a cutting-edge hybrid LSTM-SARIMA model integrated with an ANN framework. The sequence of figures delineated throughout the paper has illuminated the efficacy of the forecasting model. The integrative approach of combining LSTM and SARIMA models, augmented by ANN, represents a promising direction for future forecasting methodologies in the energy sector. The proposed hybrid LSTM-SARIMA model with parameter sets (1, 1, 1, 12) and (2, 1, 1, 12) demonstrated a high fidelity to the actual observed data. Thus, it is concluded that the optimized system notably surpasses traditional forecasting methods, indicating that this model offers a viable solution for EMS to enhance short-term load forecasting. Further investigation into parameter optimization and model robustness is recommended to bolster the reliability of forecasts in fluctuating market conditions.

Reference

Ding, M., Guo, Y. & Zhang, J., et al. (2015). Node Vulnerability Assessment for Complex Power Grids Based on Effect Risk Entropy- weighted Fuzzy Comprehensive Evaluation. *Journal of Electrical Engineering Technology, 30*(3), 214-223.

Bonventi, W., & Godoy, E. P. (2023). Fuzzy logic for renewable energy recommendation and regional consumption forecast using SARIMA and LSTM. *Journal of Renewable and Sustainable Energy, 15*(2).

Box, G. E., Jenkins, G. M., & Reinsel, G. C. (2015). Time series analysis: Forecasting and control. *John Wiley & Sons*.

Brockwell, P. J., & Davis, R. A. (2002). Introduction to time series and forecasting. *Springer*.

Chaturvedi, S., Rajasekar, E., Natarajan, S., & McCullen, N. (2022). A comparative assessment of SARIMA, LSTM RNN and Fb Prophet models to forecast total and peak monthly energy demand for India. *Energy Policy, 168*, 113097.

Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273-297.

Dataset, Korea Power Exchange (KPX), Electrical Power Statistical Information System (EPSIS), http:// https://epsis.kpx.or.kr/epsisnew/selectEkmaPtdBftChart.do?menuId=040501

Dubey, A. K., Kumar, A., García-Díaz, V., Sharma, A. K., & Kanhaiya, K. (2021). Study and analysis of SARIMA and LSTM in forecasting time series data. *Sustainable Energy Technologies and Assessments, 47*, 101474.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. *MIT Press*.

Hamilton, J. D. (2020). Time series analysis. *Princeton University Press.*

Haykin, S. (1999). Neural networks: A comprehensive foundation (2nd ed.). *Prentice Hall.*

He, K., Ji, L., Wu, C. W. D., & Tso, K. F. G. (2021). Using SARIMA–CNN–LSTM approach to forecast daily tourism demand. *Journal of Hospitality and Tourism Management, 49,* 25-33.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735-1780.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. Transactions of the ASME, *Journal of Basic Engineering, 82*(D), 35-45.

Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In Proceedings of ICNN'95 - International Conference on Neural Networks (Vol. 4, pp. 1942-1948). *IEEE.*

Lee, Y. (2023). Importance Assessment of Multiple Microgrids Network Based on Modified PageRank Algorithm. *Korean Journal of Artificial Intelligence, 11*(2), 1-6.

Lee, Y. (2022). Energy Management System with Power Offering Strategy for a Microgrid Integrated VPP. Computers, *Materials and Continua, 75*(1), 2313-2329.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338-353.