AN INTEGRATED DEEP-LEARNING MODEL-BASED PRECISE FORECASTING MODEL FOR SUSTAINABLE ENERGY SYSTEMS

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Highlights

The article presents an Integrated Deep Learning Model with a Combined Forecasting framework for SES Prediction in energy systems.

Abstract

Worldwide, Sustainable Energy Systems (SES) and regulations have been advocated to shift from fossil fuel sources to ecologically SES, including Wind Power (WP), Solar Power (SP), and Fuel Cells (FC). WP and SP sources must be more consistent and accessible when integrated into SES; hence, caution is required in their implementation and associated legislation. This paper formulates an energy forecasting model incorporating SES, serving as a basis for policy, utilizing the Korean model. Deep Learning (DL) predicts variable changes in power needs and generations, that is essential for SES and which traditional models cannot do. The gated recurrent unit has a higher forecasting ability than the other forecasting methods. Hence, it is chosen as the foundational model to analyze four distinct SES. The possibilities are assessed based on financial-ecological cost evaluation. The ideal situation employs an integrated gasified paired cycle, onshores and offshores wind turbines, SP locations, and FC facilities; this situation exhibits minimal economic-environmental expenses, produces reliable power to meet demand, and attains a 100% SE policy. The ideal scenario is evaluated by studying strengths, shortcomings, possibilities, and threats, examining domestic and global techno-economic and ecological power conditions.

Keywords

sustainable energy systems; renewable energy sources; deep learning; forecasting.

Introduction

Energy is essential for industrialization, urbanization, and a nation's economic progress in contemporary society [1]. Global energy consumption is increasing at an approximate rate of 2.3% annually. The study estimates that a worldwide fuel scarcity will occur imminently. Fossil fuels (FF) primarily contribute to ecological pollution, encompassing air and water contamination [2]. Sustainable Energy (SE) sources such as geothermal, wind, sun, and biomass have garnered significant interest as alternate development for energy options [22].

Sustainable Energy Sources (SES) are plentiful, sustainable, and environmentally benign [4]. FFs, comprising oils, coals, and natural gas, serve as dependable energy sources, fulfilling nearly 82% of the world's energy needs. Sustainable growth and global environmental degradation are critical challenges concerning energy in the 21st century. Energy consumption is rising at a rate of 3% annually, and the existing energy production relies on FFs. Anthropogenic Greenhouse Gas (GHG) emissions from FF consumption significantly increase, resulting in abnormal climatic patterns worldwide, including droughts and intense precipitation [5]. GHG emissions will rise 35% over the next 15 years without legislative constraints on FF utilization. International initiatives concerning SES and regulations, including managing energy, are being implemented to reduce reliance on FF-powered plants and alleviate environmental issues and the adverse ecological impacts of FF [3].

The Korean power system relies significantly on FFs, including coal, oil, and compressed natural gas, constituting 62.1% of its energy resources. Korea placed first on the list for rising GHG levels from 1995 to 2020 and GHG pollutants among countries in 2021. In response to Korea's power challenges, the Korean agencies have endeavored to diminish GHG pollutants while enhancing and advancing the utilization of SES.[6]. A notable SES in Korea is implementing 100% SE on Jeju Island. It has been certified as a 100% SES by establishing wind farms, Solar Power (SP) locations, and Fuel Cell (FC) facilities [22].

The research created a forecasting algorithm for seven-day-ahead power consumption and SE generation utilizing Deep Learning (DL) methods and domain expertise [7]. These findings are used to advocate for and inform viable SES and policies.[8]. This study assesses and contrasts DL algorithms with traditional statistical frameworks.[29]. The DL models encompass Deep Neural Networking (DNN) [24], Long Short-Term Memories (LSTM) [23], and Gating Recurrent Units (GRU) [10], effectively addressing the limitations of traditional methods like Multiple Linear Regression (MLR) [26] and Seasoned Autoregressive Integrating Moved Averages (SARIMA) [30]. The assessment of predictive techniques is crucial, as DL algorithms exhibit varying performance based on the features of the information. The efficacy of DL models varies based on forecasting time, training period, target dataset, and whether the model employs a basic or ensemble architecture. Other factors must be evaluated while choosing a suitable forecasting model.[11][12].

The research meticulously analyzes the forecasting models with precise numerical assessors and trust intervals, ultimately selecting the optimal forecasting approach for future power demand and SE output.[9][27]. The study employs the provided model for SE scenarios in the policy formulation for Jeju Island to realize its energy strategy.

Background

Energy forecasting involves estimating energy production from various sources. The increasing recognition of improved technologies has rendered energy forecasting a prevalent activity in contemporary power systems. Two distinct methodologies exist for energy prediction. The initial method is the top-down strategy, in which predictions are made at the top of the chain. The process is represented by the bottoming-up or building-up technique, wherein forecasts are generated from lower levels and aggregated to tiers of the predicting structures. In a mixed model, a bottoming-up method is more relevant and appropriate for determining the score of the forecasted elements. This section evaluates the energy forecasts of several prevalent SES, including wind, solar, hydro, and biomass powers.

2.1 SP Prediction

SP is an SES directly harnesses the sun's power as electricity (SP) or heat (photo-thermal). Unlike FF-based energy, photovoltaic energy is non-polluting and does not emit GHG. Predicting solar irradiance is challenging due to its dependence on environmental factors, including temperatures and sunshine duration.[25]. Owing to the unpredictable characteristics of these characteristics, the Machine Learning (ML) methodology is predominantly employed to forecast universal irradiation [21].

2.2 Wind Power (WP) Forecasting

The principal usage of WP is to harness the kinetic power of air and turn it into power on a big scale. Renewable and sustainable WP depends on solar irradiance, wind velocity, and other ambient circumstances. Due to the intermittency and unpredictability of WP, prediction is essential for its utilization. Like SP, WP forecasting is categorized into predictions based on time zones. The methodologies for forecasting WP range from mechanical (deterministic) approaches to statistical or ML strategies that utilize historical and time-series data analyses [13]. The precise forecast of WP is tricky owing to the temporal variability of the gusts. Numerous dynamic Artificial Neural Network (ANN)-based approaches [14], including Convolutional Neural Networking (CNN) [15] and Recurrent Neural Networking (RNN) [16], utilizing innumerable factors such as wind orientation, wind velocity, the outside temperature, solar radiation, environmental moisture, and atmospheric pressure, have been presented to improve predictability in both the long and short term.

2.3 Hydro Power Forecasting

It is an energy source that utilizes the kinetic power of water to produce power. It is often constructed in the course of a river. It has several benefits compared to most other energy sources, including exceptional reliability, superior performance, minimal maintenance costs, and the capacity to adapt to fluctuations in demand. Hydropower depends on the water volume that flows through the blades and the turbine's dimensions. During rainy times, hydropower turbines can generate increased energy due to abundant water, while more giant turbines yield higher output. Water scarcity renders smaller rotors more advantageous during other times of the year.

Optimizing and forecasting hydropower rotor dimensions is crucial in this context. The connection between turbine capacity and the water flow rate is non-linear and highly complicated. Optimization can be achieved by ML techniques, including Support Vector Machines (SVM) [17], Genetic Algorithms (GA) [18], and ANN. Similar to other forecasts, the prediction of hydropower is a process necessitating continual upgrades of meteorological information and historical power data to provide management.

2.4 Biomass Power Forecasting

It is an additional form of SE derived from biological materials. Biomass is an integral component of the carbon cycles, transitioning from the environment to crops, from crops to soils, and ultimately returning to the environment via the decomposition of plant matter.

Bio-energy is employed in several applications, including transportation as bio-diesel, power generation, and heating. Rural agricultural areas, wastelands, and woods generate the most pertinent biomass. The biomass forecast process is inherently precise, employing many approaches for biomass power calculation [28]. Research indicates that the precision of predictions for biomass power is notably higher when using linear methods. Employing these approaches in experiments presents significant challenges due to varying environmental factors and circumstances and insufficient data sets for estimate.[19].

The research suggests that SP and WP are probable future supplies for power plants. Due to their fluctuating output power, prediction approaches can enhance their effectiveness. Forecasting the energy production of photovoltaic panels and wind turbines presents some complications [20]. The primary difficulty is inadequate data sets and measuring devices in certain areas. Another problem is the need for standardized procedures that users readily follow to get the necessary information for assessing SP or WP generation under varying atmospheric conditions.

DL-based Forecasting Model for SES

The suggested structure of this study for projecting electricity consumption and SE output, as well as assessing SES, is illustrated in Figure 1. The initial phase involves executing a forecasting model to anticipate fluctuations in power consumption and SE output. Electricity consumption and SES generation from wind and solar electricity were recorded on Jeju Island from 2013 to 2017, as seen in Figure 1 (a). The results are further deconstructed using Empirical Mode Decompositions (EMD), as seen in Figure 1 (b), to improve the efficacy of prediction programs by generating Intrinsic Mode Functions (IMFs). Figure 1 (c) illustrates a model employed in the prediction framework. The predictive models utilize the decomposed information, whereas the algorithm predicts the original, non-decomposed electrical values. The forecasting algorithms employ a moving window technique incorporating 21 days of data to learn and predict power consumption for a week. The movement strategy improves the temporal forecasting efficacy of the methods. The research employs two statistical predicting methods—MLR and SARIMA—alongside three DL-based predicting methods: GRU, LSTM, and DNN.

The power needed and produced SE exhibit significant fluctuations, posing challenges for accurately predicting future power consumption and production alone through the predicting approach. Uncovering concealed structures in the information is essential by employing area expertise.

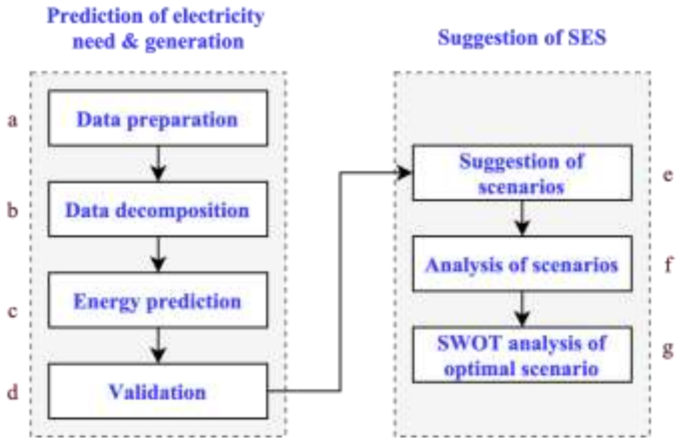


Figure 1. Workflow of the proposed model

The retrieved domain knowledge enhances prediction accuracy while minimizing unnecessary data in forecasting systems. Deconstructed data from the preceding 21 days are used as domain expertise to predict weekly power consumption. Figure 1 (d) illustrates that the projected electrical structure is corroborated against the empirical data set for the Mean Absolute Scaled Errors (MASE) and Mean Absolute Errors (MAE). The MASE is appropriate for assessing prediction results across multiple scales, while the MAE is typically employed as a model evaluation metric, quantifying discrepancies between projected and observed results. The MASE and MAE are delineated as follows:

$$MASE = \frac{1}{N}\sum_{x=0}^{N-1}\left(\frac{|i_x - \hat{\imath}_x|}{\frac{1}{N-1}\sum_{x=1}^{N}|i_x - \hat{\imath}_{x-1}|}\right) \quad (1)$$

$$MAE = \frac{\sum_{x=1}^{N}|i_x - \hat{\imath}_x|}{N} \quad (2)$$

Where i_x and $\hat{\imath}_x$ represent the observed and projected values at time x, accordingly.

The subsequent phase involves proposing and examining a renewable energy system for Jeju Island. To the projected electricity demand and SES in 2020, four SES are proposed to exclusively generate electricity utilizing SES, including WP, SP, FC, and Integrated Gasification Combined Cycle (IGCC). The SES is shown in Figure 1 (e). The various scenarios provide a viable amalgamation of SES capacity to meet fluctuating demand for power at minimal cost. As depicted in Figure 1 (f), the analytical parameters for the situations include economic expenses related to building, running, and administration and ecological costs arising from pollution emissions from energy plants. The scenario with the lowest total economic and environmental expenses is ideal for developing SE policy. The perfect situation is evaluated by utilizing a SWOT assessment to address vulnerabilities and risks while maximizing advantages and possibilities. The techno-financial-ecological SWOT evaluation encompasses local and global assessment, as seen in Figure 1 (g). The regional review delineates the positive and negative aspects of the best case in light of Korea's energy conditions. At the same time, the outside inspection elucidates the possibilities and risks by evaluating the global energy system and market situation.

3.1. Current Condition
The prevailing energy-generating model predominantly relies on FF rather than SES. Profound insights and deliberations are essential to attain complete future power generation by SES. This work proposes a precise forecasting methodology for a viable SES tailored to the features.

3.2. Method for Predicting Power Needs and SE
Jeju Island's SE generation and overall electricity consumption are anticipated by modeling techniques integrating data deconstruction methods with traditional statistical and DL prediction approaches. This amalgamation of approaches yields superior performance in feature extraction and prediction. The

decomposition method enhances the model's predicting capability by supplying broken-down, flexible sub-data derived from discontinuous, unprocessed information.

- ***EMD***

EMD is a commonly employed deconstruction method. EMD is entirely data-driven and adaptable and does not require preordained transformations reliant on choosing a particular structure. EMD disaggregates non-linear and irregular information into IMFs that meet two criteria: the count of extremes and zero-crossings equals or differs by one, and the average of the bands formed by the local minimums and maximums approximates zero. This work employs EMD, as seen in Figure 1 (b), to improve the predicting system's efficiency, with the calculated IMFs and residual fed into the algorithm.

- ***Traditional Statistical Forecasting Methods***

The data deconstructed by EMD in the sub-series serves as input for the statistics and DL forecasting algorithms. This research employs traditional statistical forecasting theories, including MLR, SARIMA, and DL models, as seen in Figure 1 (c). MLR forecasts are dependent on many factors through linear matching. SARIMA is an enhanced framework version that improves forecasting accuracy by accounting for seasonal variations through differencing.

- ***DL-based Forecasting Models***

DL models are contemporary ML techniques, although they have yet to be applied in energy prediction. This work employs these models alongside EMD for power prediction to address the limitations of traditional predictive methods. This work uses DNN as the primary DL method to account for the temporal peculiarities of the information. DNN employs a multiple-layer architecture with one input level, output level, and multiple concealed ones organized in an orderly manner. The Rectified Linearized Units (ReLU) and dropouts address the disappearing gradient issue and mitigate overfitting. The ReLU mitigates the gradient disappearing by transforming the harmful sources to null. In contrast, dropout omits elements from the concealed levels during activating computation in the forwarding motion and weight adjustment in the return.

LSTMs and GRUs are advanced iterations of traditional deep RNNs. Deep RNNs exhibit three primary drawbacks: prolonged training duration, inability to capture long-term dependencies, and the progressive attenuation of information about the initial input. LSTMs and GRUs were engineered to address these issues in their architectures, akin to Natural Language Processors (NLP) utilization. Even with the benefits of DL, its application in energy predictions is very recent, and research in this domain remains in its nascent phases.

3.3. SE Technologies

This study employs Wind Farms (WF), SP plants, and FC based on the suggested policy that excludes FF and other carbon dioxide-emitting technologies. The present research employs additional SE methods, such as IGCC, to evaluate SE possibilities for providing constant power unaffected by meteorological or seasonal fluctuations.

3.4. Description of the SE Scenarios

The present research presents four situations to aid in formulating SES and choices (Figure 1 (e)). The developed situations are:

Scenario 1: offshore WF, onshore WF, SP stations, and FC facilities; a foundational scenario derived from Jeju Island's existing SE strategy.

Scenario 2: offshore WF, onshore WF, SP stations, FC facilities, and IGCC technologies for reliable energy.

Scenario 3: offshore WF, onshore WF, SP stations, FC facilities, and storage; use of the supplementary storage for excess produced electricity and the provision of stored power.

Scenario 4: offshore WF, onshore WF, SP stations, FC plants, IGCC, and hydrogen storage systems; implementation of supplementary SES and a storing device.

The ability of SES in every model is established based on the presumptions:

The power deficit SE should provide is determined by subtracting the projected electricity output from SE techniques (wind and solar) from the anticipated total electricity consumption.

The requisite capacity of SE plants is 120% of the projected demand, reflecting the energy bandwidth.

The energy outputs of wind and solar electricity are variable and influenced by weather and seasonal factors. The energy production from WF and SP plants is assessed by accounting for fluctuations in power over 5 years.

The operational lifespan of power plants is 35 years for IGCC, 25 years for FCs, 28 years for WF, and 18 years for SP plants. The proposed financial and ecological expenses associated with each SES are utilized. Cost analysis, including construction expenditures and Operations and Maintenance (O&M) expenses relative to the output of the energy servers. Airborne pollutants from all nuclear plants are recommended. The ecological costs refer to the marginal damage expenses associated with global warming impacts. All fees are adjusted to their 2017 dollar equivalent utilizing the customer price index.

Results

This section discusses data comparing the efficacy of traditional forecasting algorithms to DL models. The experimental procedure and outcomes are given below. Initially, it is utilized to break down the SP generation into different distinct methods. Single branch rebuilding is applied to each deconstructed series to generate four sub-series (SS). The rebuilt sub-series are labeled SS-1, SS-2, SS-3, and SS-4. The suggested model demonstrates superior results than the proposed method without employing the combination of the linear approach. The findings ensure the efficacy of the suggested paradigm.

The proposed model's effectiveness is comprehensively validated by comparison with LSTM networks, SVM, and MLP. Photovoltaic electricity is contingent upon seasonal variables. Evaluations were performed for every season to elucidate the efficacy of the suggested paradigm. According to the Australian Times, the testing set is divided into 4 subsets: winter, spring, summer, and fall. Figure 2 presents the Mean Biasing Errors (MBE), Mean Absolute Percentage Errors (MAPE), and Root Mean Squared Errors (RMSE) coefficients for every model throughout all seasons.

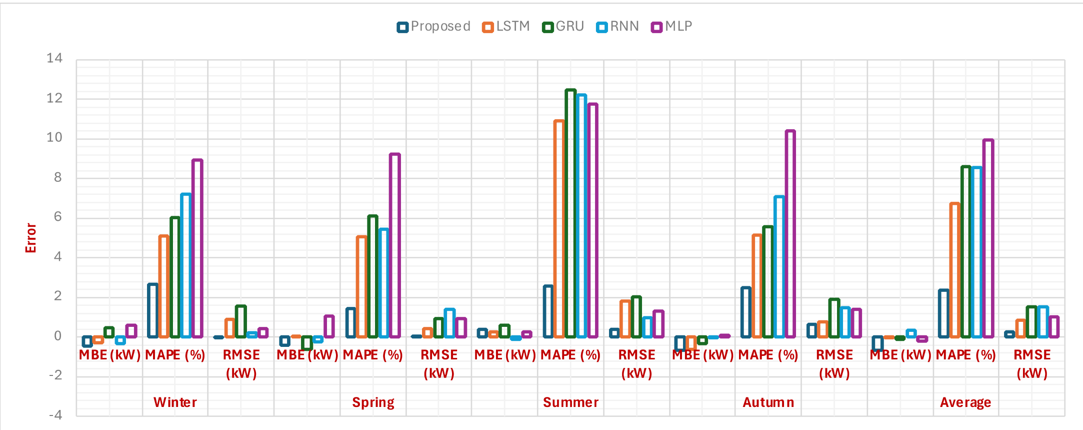
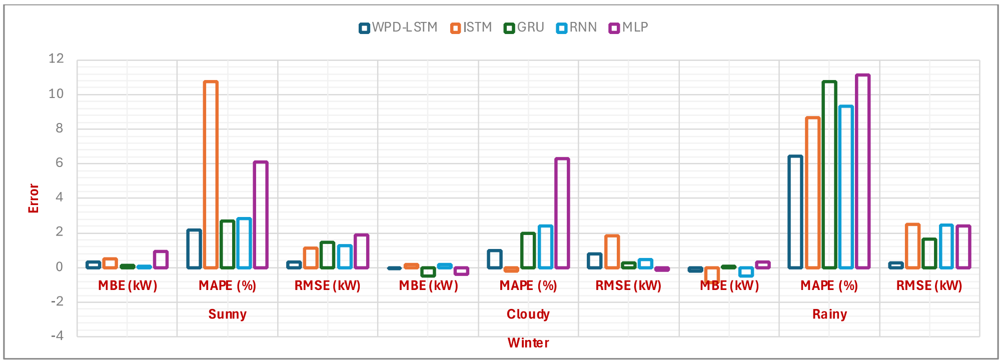


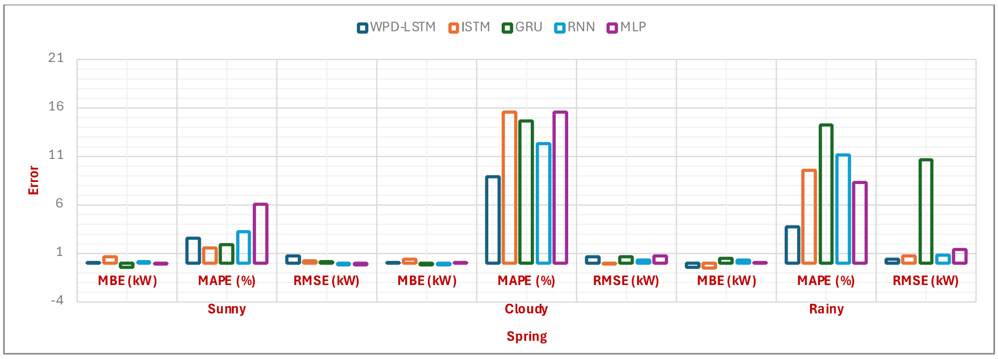
Figure 2. Error analysis of different DL models

The data indicate that the suggested forecasting system surpasses traditional approaches for short-term photovoltaic power predictions. Throughout every season, the suggested method’s MBEs, MAPEs, and RMSEs values are inferior to those of the other predicting methods. The suggested model's MBE is 0.0071, which correspondingly outperforms the values of -0.072, 0.1352, -0.1621, and 0.203 for LSTMs, GRUs RNNs, and MLPs. The MAPEs and RMSEs of the suggested method are satisfactory. In all instances save one, the MBEs of the suggested approach exceeded that of the other variants. The suggested model is superior to LSTMs, GRUs, RNNs, and MLPs for 1-hr-ahead photovoltaic energy prediction across all seasons. The MBE index derived from the suggested forecasting approach for the complete test database ranges from -0.0732 to 0.0432, with a mean of 0.0053. Compared to LSTMs, GRUs, RNNs, and MLPs, the mean of the MBE indicator has shown an average enhancement.

A day from every season was chosen at random for additional examination. All models demonstrate adequate predicting efficacy. The forecasting outcomes of the suggested hybrid DL method surpass those of LSTMs, GRUs, RNNs, and MLPs in accuracy. The anticipated outcomes of the suggested technique are more aligned with the score compared to LSTMs, GRUs, RNNs, and MLPs. The exact curvature and the suggested model curve exhibit the most significant similarity. Figure 3 presents the contrasting one-hour-ahead performance outcomes for three categories of days (randomly chosen bright, overcast, and raining days) throughout every season. Figure 3 presents the assessment findings with the output information for LSTMs, GRUs, RNNs, and MLPs. The suggested DL method performs better than all forecasting techniques.



(a)



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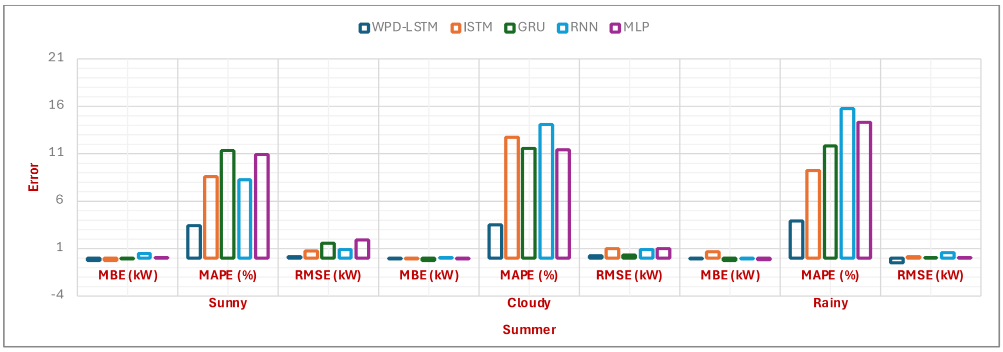
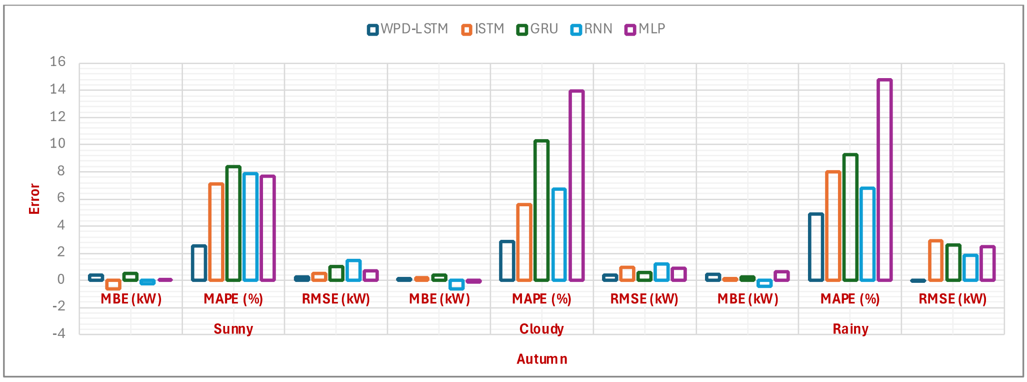


(c)



(d)

Figure 3. Forecasting error analysis

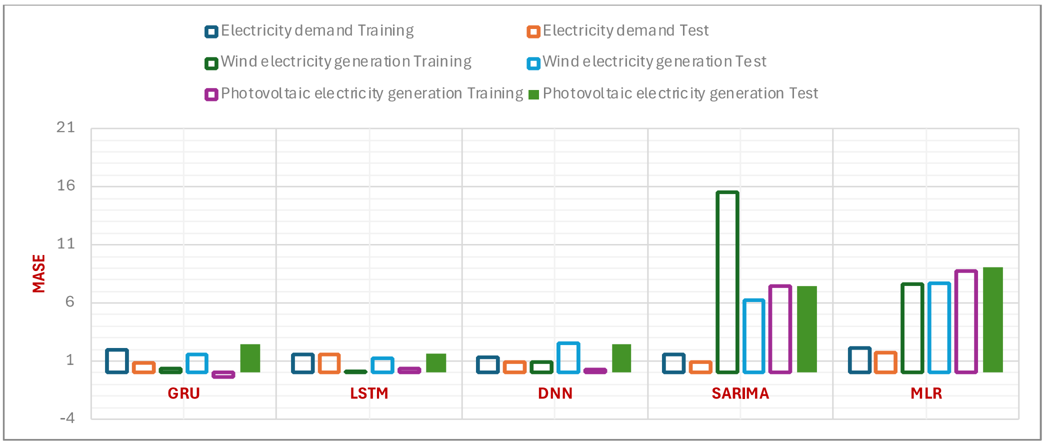
The suggested technique produces predicting results with minimal MBEs, MAPEs, and RMSEs on most days. The findings demonstrate the resilience of the suggested DL method. The enhanced accuracy of the suggested method is mainly attributable to the DL architecture consisting of four distinct LSTM systems, which effectively simulate intrinsic invariant characteristics and patterns. The lower- and higher-frequency elements included in the SP records are more effectively retrieved. Every LSTM system elucidates the linear and nonlinear correlations among climatic factors and photovoltaic energy output.

Figure 3 indicates that throughout all conditions, the precision of the suggested method is diminished on wet and gloomy dates compared to bright dates. Meteorological circumstances are more erratic on damp and overcast dates, that impedes precision. Enhancing prediction precision during overcast and precipitation events has emerged as a significant study objective in recent years and is one of our study's reasons. The suggested model demonstrates superior forecasting performance compared to some standard approaches, with a significant enhancement in accuracy in forecasting. The forecasted values of photovoltaic energy generation align with the actual measurements on bright days, and the outcomes are equally satisfactory for overcast and wet dates.

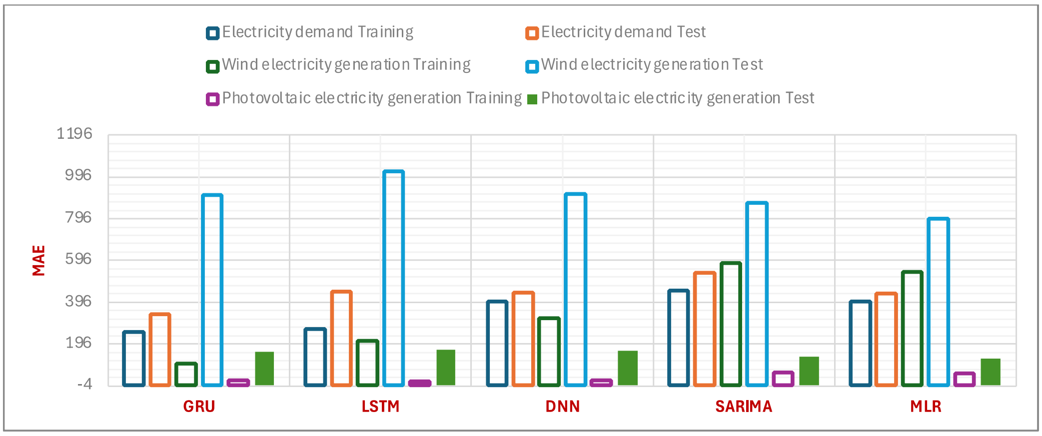
The RMSE of the suggested method is significantly lower, indicating satisfactory performance. The proposed method surpasses elements within a signal. The RMSE of the suggested model, excluding the linear combination approach, is minimal compared to the other four methods. Compared to the proposed model, which does not utilize the linear mixture approach, the RMSE of the suggested method is lower. This is due to the linear strategy employed in the suggested method, which enhanced predicting accuracy.

The efficacy of each prediction approach is observed more understandably. When meteorological conditions abruptly shift on a foggy day, the suggested hybrid DL model can detect the trend and adapt with high precision. The predicting outcomes of LSTMs, GRUs, RNNs, and MLPs are inferior to those of the suggested model. The suggested model has a lower error range than existing techniques across all meteorological situations. The proposed model is utilized for deterministic photovoltaic power forecasting in diverse settings.

In reality, enhanced forecasting accuracy signifies reduced uncertainties and variations in photovoltaic power output. Accuracy is essential for planning and executing electrical networks with significant integration of photovoltaic power. The predictive accuracy of the proposed model appears highly dependable across all seasons and meteorological circumstances compared to alternative models. The suggested model is more adept at meeting short-term photovoltaic power prediction requirements with higher accuracy than prior standards. The proposed DL model can mitigate operational and planning uncertainty in SES solutions.



(a)



(b)

Figure 4. Demand and generation forecasting error analysis (a). MASE (b) MAE analysis

Figure 4 presents the power demand and SE generation forecasting outcomes of the statistical systems and DL models evaluated using MASE and MAE metrics. GRU demonstrates superior predicting accuracy for power need, WP generation, and SP production as assessed by the MASE. Statistical models provide superior predicting ability compared to the DL models about the MAEs. The attributes of the model assessors elucidate this outcome. The MAE is typically employed to assess the efficacy of a prediction model and is an appropriate performance metric when both anticipated and actual information exhibits an even dispersion. The creation of power from WF and photovoltaic sources has a consistent upward trend due to Jeju Island's proactive development of WF and SP plants, aiming to achieve 100% energy production from sources that are renewable. The information's decomposition phase findings indicate that weather and seasonal factors disrupt the productiveness of SE generation, leading to highly variable data.

Conclusion

The research proposed and examined many SE scenarios to align with Jeju Island's goal of achieving 100% SE production and to guide policy development. The research created a DL-based prediction approach, seldom employed for energy projections, to address the accuracy constraints of traditional prediction models and improve overall model efficacy. The GRU prediction system has been shown to perform better for the MASE than other DL and statistical approaches. Unlike different models, the GRU can analyze and predict data that experiences fast temporal fluctuations. The proposed forecasting model offers a viable basis for formulating SE strategies. Effective regulations grounded in a precise energy prediction system can mitigate blackouts resulting from inadequate power generation and excess electricity, which arise when production surpasses system capacity.

The SWOT analysis elucidates the techno-economic and environmental conditions necessary for advancing the proposed SES. It is expanded to evaluate scenarios considering many system dimensions, including effective reductions in GHG emissions. This technique evaluates and deploys further SE-related systems and policies. This study offers guidelines for developing SES and legislation by employing sequential projections, SES analysis, and SWOT evaluation, considering time-varying energy patterns and unique features of SES methods, and assessing techno-economic-environmental energy developments domestically and globally.

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