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# Enhanced Load Forecasting in Distribution Networks Using LSTM Integrated with Quadratic Regression Model

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**Abstract:** This Research presents a hybrid load forecasting model that combines successfully Long Short Term Memory (LSTM) neural networks with a Quadratic Regression Model (QRM) for better optimization of short term load prediction of the power distribution systems. The LSTM and the QRM model are combined to take advantage of the sequential learning ability of LSTM and the analytical acumen of QRM, thereby increasing accuracy and reliability in dynamic energy demand environments. Practical relevance and reliability in the real-world electrical load data from distribution networks was ensured for model development, training and validation. The model's performance was compared to the traditional forecasting approaches. Experiments suggest a 2.5% decrease in Mean Absolute Error (MAE), a four-point-zero percent reduction in Root Mean Square Error (RMSE), and an R-squared ($R^2$) of 0.85, which means high forecasting capability. The accuracy of the predicting model is 97% better than the exitsing methods. The recommended approach helps to facilitate timely and informed decision making for utility providers with regard to load management, optimization of resources and planning of infrastructures. It also assists in minimizing energy wastages and increasing the power system's stability through the reduction of forecasting errors. Furthermore, the combination of the LSTM and QRM is consistent with the globally oriented strategy of advancement towards digitization and sustainability at the energy system level. The study further provides development of intelligent forecasting techniques and emphasizes the significance of hybrid models in modern grid-based activities. It is a scalable and responsive solution for utilities that are looking to meet the challenges presented by fluctuating demand and progress toward more resilient and environmental-friendly energy infrastructures.

**Keywords:** distribution networks; load forecasting; LSTM neural networks; quadratic regression model; smart energy

## 1 INTRODUCTION

The increasing global demand for energy and the growing complexity of energy supply networks necessitate advanced solutions to optimize electricity generation and distribution [1]. Conventional approaches to load forecasting often fail to account for the volatile and dynamic nature of modern energy demands. To address these challenges, this paper proposes a novel methodology integrating Machine Learning, specifically Long Short-Term Memory (LSTM) Neural Networks, with a Quadratic Regression Model (QRM) to enhance grid energy management [2, 3].

The energy system is rapidly transitioning toward more sustainable and intelligent distribution networks. With the global shift from conventional energy sources to renewable energy systems, precise load forecasting becomes increasingly critical [4]. Accurate load estimation is essential for optimizing energy generation and distribution, reducing carbon emissions, and ensuring the reliability and stability of power grids.

Energy distribution networks play a vital role in ensuring a consistent energy supply to consumers [5]. Traditional stochastic models often struggle to capture the dynamic nature of energy consumption, particularly as demand fluctuates rapidly in modern distribution systems. LSTM neural networks have revolutionized load forecasting by addressing temporal data complexities and demonstrating an exceptional ability to retain persistent patterns [6]. However, relying solely on LSTM models may introduce limitations, prompting the integration of QRM.

The proposed hybrid approach combines the strengths of LSTM in long-term analysis with the capabilities of QRM in refining remote sensing data. This integration results in a superior solution for energy distribution network forecasting, advancing the field of sustainable and adaptive energy systems [7, 8]. Our methodology not only improves forecasting accuracy but also contributes to environmentally responsible energy practices by enhancing grid stability and reliability.

The results of the proposed LSTM-QRM hybrid model highlight its efficiency compared to conventional methods. By achieving higher accuracy and reliability, this approach represents a significant step forward in energy management, aligning with global trends toward sustainable and intelligent energy networks [9, 10].

The novelty of this research lies in the adoption of Long Short-Term Memory (LSTM) neural networks combined with the Quadratic Regression Model (QRM). This integration provides a robust and realistic application for learning from diverse energy usage patterns. LSTM effectively captures temporal dependencies essential for energy prediction, while QRM enhances the accuracy of energy patterns, making forecasts more transparent and reliable [11]. By leveraging historical energy values for training and validation, the proposed model ensures precise energy demand predictions. This approach improves forecast credibility, empowering utility providers to allocate resources efficiently, mitigate risks, and reduce losses in distribution networks. Consequently, the research significantly contributes to the operational enhancement of energy delivery systems [12].

Existing energy management frameworks face challenges in accurately forecasting load demands due to their inability to fully account for dynamic variations in energy consumption patterns. Traditional methods often fail to adapt to temporal dependencies and fluctuating energy demands, leading to inefficiencies in resource allocation and higher operational costs [13]. While renewable energy integration has gained momentum, there is still a lack of effective models to handle variability and ensure grid stability [14]. This study addresses these gaps by integrating LSTM neural networks and QRM, creating a hybrid solution that combines the strengths of both models. Unlike single-model approaches, this hybrid model optimizes accuracy and efficiency, offering utility providers actionable insights for resource planning and sustainable energy distribution. Furthermore, by aligning with global sustainable development goals, the research bridges the gap between environmental responsibility and operational efficiency [15].

The LSTM-QRM model turns uncertain energy forecasting into a precise tool for decision-making. Accurate load forecasts help utility providers optimize resource distribution, minimize operational costs, and enhance the reliability of power supply. By reducing risks of overloads or shortages, the model contributes to grid stability and sustainability. Additionally, this model has broader implications for integrating renewable energy resources with utility grids. By decreasing reliance on fossil fuels, the approach supports global sustainability goals, such as the United Nations Sustainable Development Goals (SDG 7 and SDG 13) on affordable, clean energy and climate action, respectively.

## 2 ENERGY MANAGEMENT IN DISTRIBUTION NETWORKS

The distribution network is a critical link between energy generation and consumption. Energy consumption patterns are characterized by constant fluctuations and evolving trends, which challenge traditional energy management systems. These legacy systems often fail to adapt quickly, resulting in inefficiencies, increased costs, and adverse environmental impacts . The integration of renewable energy sources introduces further variability into generation patterns. Addressing these challenges requires innovative solutions that can manage fluctuating energy demands in real time, ensuring grid stability and reliability. Real-time voltage management and power quality maintenance are crucial for efficient distribution. Voltage levels, typically 230 V for single-phase residential and 400 V for three-phase industrial applications, must be consistently maintained.

The transition from conventional to renewable energy sources presents significant challenges for grid operators. By 2050, renewable energy is projected to account for 92% of global energy production, up from 47% in 2021. This increased penetration of variable renewables necessitates sophisticated forecasting models. Machine learning techniques, particularly LSTM, can enhance prediction accuracy by incorporating weather conditions and dynamic demand patterns. Smart energy management systems, combined with battery storage and Quadratic Regression Models, ensure an appropriate demand-to-supply ratio, preserving grid integrity. Distributed energy generation technologies, such as rooftop solar panels and small wind turbines powered by machine learning, offer consumers the opportunity to produce their own electricity, reducing reliance on traditional grids.

Severe weather conditions and outdated electric supply chains further exacerbate challenges, frequently causing power failures that disrupt commercial activities and damage appliances. To address these issues, grid operators must collaborate with policymakers to establish regulatory frameworks that support innovative infrastructure and intelligent algorithms.

Energy storage systems are also needed to deal with variability, to help maintain the stability and reliability of the grid. Energy management is not purely an Issue of efficiency, but, with good correlation to global sustainable development especially on limiting carbon emissions where distribution networks are instrumental. That is, greater efficiency and sustainability can go hand in hand as key elements of integrated energy policy. Ideas such as demand response programs help consumers participate in load balancing making power distribution innovative and sustainable [16]. They also include policy and societal aspect where government and other regulatory authority promote the adoption of technologies, and societal awareness and involvement in other measures such as demand-side management. The task of managing such issues involves timely utilizing innovative and progressive ideas to address the coordinated latent and optimum functionality of energy resource management.

With the shift from conventional sources of energy to renewable sources, numerous challenges arise to electricity grid operators. The issue also arises with the increased penetration of variable renewables, the share of which by 2050 is projected at 92%, up from 47% in 2021, causing problems of controlling the power and balancing the demand. To that end, further sophisticated models of renewable generation based on the weather condition by incorporating the Machine Learning techniques, namely Long Short Term Memory (LSTM) can help enhance the accuracy of predictions [17]. Further, the implementation of smart energy management systems, battery storage and employing Quadratic Regression assures appropriate demand to supply ratio for maintaining the integrity of the grid. The other issue is the deteriorating global transmission and distribution network and the requirement of new stations in the places, where renewable sources are being installed. An opportunity here is to consider the use of distributed electricity generation technologies like roof-top solar and small wind turbines powered by Machine Learning algorithms which enables consumers to produce their own electricity so as to minimize the reliance on standard grids. Intensive cooperation between grid operators and the policymakers applying intelligent algorithms is needed to create the necessary regulatory environment for new infrastructure's creation. Last but not least, severe weather conditions and obsolete electric supply chains cause power failures frequently unsettling commercial activities and harming electrical appliances.

## 3 ENABLING INTEGRATION AND PREDICTION FOR RENEWABLE ENERGY INCLUSION IN POWER DISTRIBUTION

The current engineering challenge lies in integrating renewable energy sources (RES) into electrical grids through a distribution system that incorporates the Main Power Distribution Unit (MPDU). This challenge is centered on optimizing the effective distribution of power originating from both conventional and renewable sources [18]. Essential to understanding and improving the operation of a distribution system, particularly one that incorporates an MPDU system with renewable energy, is the examination of power flow.

"Ensuring Equilibrium in Real and Reactive Power for Main Power Distribution":

$$\overrightarrow{P_i}^{\overline{\mathrm{DN}}} = \overrightarrow{V_I}^{\overline{(\mathrm{DN})}} \cdot \left( \vec{V}_j^{\overline{\mathrm{DN}}} \left( \overline{G_{ij}}^{\overline{\mathrm{DN}}} \cdot \ddot{\cos}\left(\vec{\theta}_i - \vec{\theta}_j\right) + \right.\right.$$
$$\left.\left. + \left( B_{ij}^{\overline{\mathrm{DN}}} \ddot{\sin}\left(\vec{\theta}_i - \vec{\theta}_j\right)\right)\right)\right) \tag{1}$$

$$\overrightarrow{Q_i}^{\overline{\mathrm{DN}}} = \overrightarrow{V_I}^{\overline{(\mathrm{DN})}} \cdot \left( \vec{V}_j^{\overline{\mathrm{DN}}} \left( \overline{G_{ij}}^{\overline{\mathrm{DN}}} \cdot \ddot{\sin}\left(\vec{\theta}_i - \vec{\theta}_j\right) + \right.\right.$$
$$\left.\left. + \left( B_{ij}^{\overline{\mathrm{DN}}} \ddot{\cos}\left(\vec{\theta}_i - \vec{\theta}_j\right)\right)\right)\right) \tag{2}$$

In the domain of predicting renewable energy, the symbols $\vec{P}_i^{\overline{\mathrm{DN}}}$ and $\vec{Q}_i^{\overline{\mathrm{DN}}}$ represent the injections of real and reactive power at the $\vec{P}_i^{\overline{\mathrm{DN}}}$ bus. $\vec{V}_I^{\overline{\mathrm{DN}}}$ indicates the voltage magnitude at the $\vec{V}_I^{\overline{\mathrm{DN}}}$ bus, while $\vec{\theta}_i$ and $\vec{\theta}_j$ depict the voltage angles at the $\vec{P}_i^{\overline{\mathrm{DN}}}$ and $\vec{Q}_i^{\overline{\mathrm{DN}}}$ buses, respectively. The symbols $\overrightarrow{G_{ij}}^{\overline{\mathrm{DN}}}$ and $\overrightarrow{B_{ij}}^{\overline{\mathrm{DN}}}$ denote the conductance and susceptance between buses, and the summation encompasses all neighboring buses. The proposed primary power distribution system is a specialized electrical distribution network crafted to anticipate and provide renewable energy to residential, commercial, and industrial areas. Operating as a closed-loop system, it introduces redundancy and heightened reliability when compared to radial distribution systems. The calculation of the grid reliability index remains an integral component within this forecasting framework.

### 3.1 Distribution Switchgear Module (DSM)

In the ever-evolving landscape of power distribution, the Distribution Switchgear Module (DSM) stands as a cutting-edge solution. Serving as a unified entity, the DSM goes beyond traditional roles, offering advanced features for the intelligent management and protection of the ring main power distribution network. They incorporate some of the modern developments such as smart sensors, real time analysis and remote control of operations to increase performance and flexibility.

Amid the paradigm shift toward smarter grids, the concept of ring networks within the ring main system has gained prominence. These smart ring networks not only form closed loops for bidirectional electricity flow but also leverage advanced communication protocols. This integration facilitates real-time data exchange, enabling predictive maintenance, fault detection, and optimal load balancing. The dataset was subjected to several necessary data pre-processing steps before reliable model training. The first step was identifying and handling missing values using linear interpolation to maintain the continuity of hourly energy consumption data. The second step consisted of normalizing all input features through Min-Max scaling to a [0, 1] range as it improves model convergence and the absence of characteristics that could bias the model (e.g. large-place numbers). After that, the input time series data was structured as sequences to be used in the LSTM model with an overlap sliding window. Each input sequence consisted of the past 24-hourly values forecasting the next hour's load demand. To keep the temporal integrity followed a chronological split of dataset for training and validating its performance. Finally, the various pre-processing steps for this dataset will allow the model to learn the temporal dependencies and generalize on unseen data. In the context of modern energy demands, the term "Ring Power Voltage" encapsulates the integration of renewable energy sources. Today's ring main systems are designed to efficiently handle diverse voltage levels, adapting seamlessly to the shifting of renewable energy inputs. Technologies like voltage regulators and power electronics play a pivotal role in maintaining stability amidst fluctuations inherent in renewable energy generation. In our transition to the new world of distributed generation or microgrids therefore, the Short-Circuit Capacity presents a different perspective. Since now power systems are incorporated into distributed energy resources such as solar photovoltaics and energy storage systems, the short-circuit capacity considerations relate to microgrids as well. Intelligent inverters, fault-tolerant systems, and grid-edge technologies contribute to enhancing short-circuit resilience, ensuring a robust and secure distributed energy landscape [19].

### 3.2 Voltage Drop and Grid Voltage Regulation

Within the distribution system, the emergence of voltage drop is a consequence of the inherent resistance present in the conductors . The determination of voltage drop ($V_d$) within a ring main distribution system employs a specific formula.

$$V_{\mathrm{DN}}^{\mathrm{RES(DN)}} d_{\mathrm{Grid}1-\infty} = I_{\mathrm{DN}}^{\mathrm{RES(DN)}} d_{\mathrm{Grid}1-\infty} \cdot$$
$$\cdot \left( R_{\mathrm{DN}}^{\mathrm{RES(DN)}} d_{\mathrm{Grid}1-\infty} . L_{\mathrm{DN}}^{\mathrm{RES(DN)}} d_{\mathrm{Grid}1-\infty} \right) \tag{3}$$

Representing the voltage decline (in volts) from the 1st primary grid to $N$ interconnected grids at an infinite distance in a ring main distribution network is denoted as $V_{\mathrm{DN}}^{\mathrm{RES}^{\mathrm{DN}}}{}_{d_{\mathrm{Grid}}1-\infty}$. Concurrently, $.^{\mathrm{RES}^{\mathrm{DN}}}{}_{d_{\mathrm{Grid}}1-\infty}$ signifies the current (in amperes) along the same path, and $.^{\mathrm{RES}^{\mathrm{DN}}}{}_{d_{\mathrm{Grid}}1-\infty}$ represents the conductor's resistance (in ohms per unit length). Additionally, $R_{\mathrm{DN}}^{\mathrm{RES}}{}_{\mathrm{grid}_{1-\infty}}$ indicates the conductor's length (in meters) for the same stretch. The imperative for maintaining stable power quality necessitates Grid Voltage Regulation. Typically, this is achieved through the adjustment of tap settings on distribution transformers. The computation of voltage regulation involves a specific formula.

$$\vec{V}_{\mathrm{DN}}^{\mathrm{RES(DN)}} R_{\mathrm{Grid}}^{\mathrm{DN}} = \frac{\vec{V}_{\mathrm{No\text{-}Load(Grid)}}^{\mathrm{RES}} - \vec{V}_{\mathrm{full\text{-}Load(Grid)}}^{\mathrm{RES}}}{\vec{V}_{\mathrm{full\text{-}Load(Grid)}}^{\mathrm{RES}}} \cdot 100 \tag{4}$$

Within power distribution systems that leverage RMUs, there are commonly integrated apparatuses designed for the regulation of voltage, including devices like voltage regulators and capacitors. The sustenance of grid stability is significantly contingent on the efficient regulation of voltage. To determine the requisite infusion of reactive power to achieve voltage regulation, one can utilize the ensuing equation:

$$\vec{Q}_{\text{reg}}^{\text{DNRES}} = \frac{\vec{V}_i^{\text{DN}^{\text{RES}}}\left(\vec{V}_{\text{set}}^{\text{DN}^{\text{RES}}} - \vec{V}_i^{\text{RES}}\right)}{\vec{X}_{\text{reg}}^{\text{RES}}} \tag{5}$$

Forecasting Renewable Energy involves applying load flow analysis to determine voltage and current levels at different points in the ring main distribution system, accounting for various operational conditions. This analytical process involves solving a series of power flow equations. To uphold the reliability of the ring main distribution system, precise protection coordination is essential. This coordination involves configuring protective components, including circuit breakers and fuses, to operate seamlessly in isolating faults effectively. The effectiveness of a Renewable Energy Forecasting-centric ring main distribution system is evaluated by its capacity to deliver electricity to consumers with minimal losses, a metric assessable through a specific calculation.

$$\overline{\eta_{\text{DN}}^{\text{RES}}}_{\text{PowerGrid}_i} = \frac{\overrightarrow{\varpi}_{\text{DN}}^{\text{RES}} \; \text{TotalPowerDelievered}}{\overrightarrow{\psi}_{\text{DN}}^{\text{RES}} \; \text{TotalPowerSupplied}} \cdot 100 \tag{6}$$

Typically, principle and formulas associated with Ring Main Distribution Systems include a broad range of ideas. It should be mentioned that specific values of the given parameters depend on the selected topology of the distribution network and its requirements.

Theoretically, in the context of changing landscape of renewable energy with renewable energy technologies where load forecasting proposed a critical feature in utilizing available resource effectively, in this envisaged system emphasis is given to forecast precise electricity demand with relation to RES capability. The center of this framework is load forecasting, a sophisticated activity in predicting and meeting the energy demand of consumers [20]. In this large and integrated system, a wide variety of RES technologies including PV arrays and wind turbines is systematically integrated to improve the accuracy of load forecasting shown in Fig. 1.

The effects of renewable technologies on load forecasting depend on the voltage levels at which these technologies generate electricity; solar photovoltaic (PV) arrays and wind turbines generating power at different voltage levels. These fluctuations are reflected in the load forecasting system and contribute to enhance the reliability of forecasting energy demand especially with respect to the intermittent nature of renewable sources. To reduce fluctuation in renewable energy production and improve the reliability of forecasts, energy storage systems including batteries are connected so that the excess energy produced in high generation periods can be stored for use during high demand duration. Moreover, smart load forecasting involves the application of both superior algorithms as well as real-time data, shifting prediction factors such as weather conditions and others. Thus, integrating actual data with Optimal Load Forecasting (OLF) enhances predictions, thus enhancing the effectiveness of energy control. Interconnection points allow for the integration of renewable energy source into the load forecasting network and simultaneously provide the voltage regulation and enhance the power quality. Of course, this also improves load predictions with clean energy sources in mind as well as contributes to environmental responsibility, with less demand for non-renewable resources.

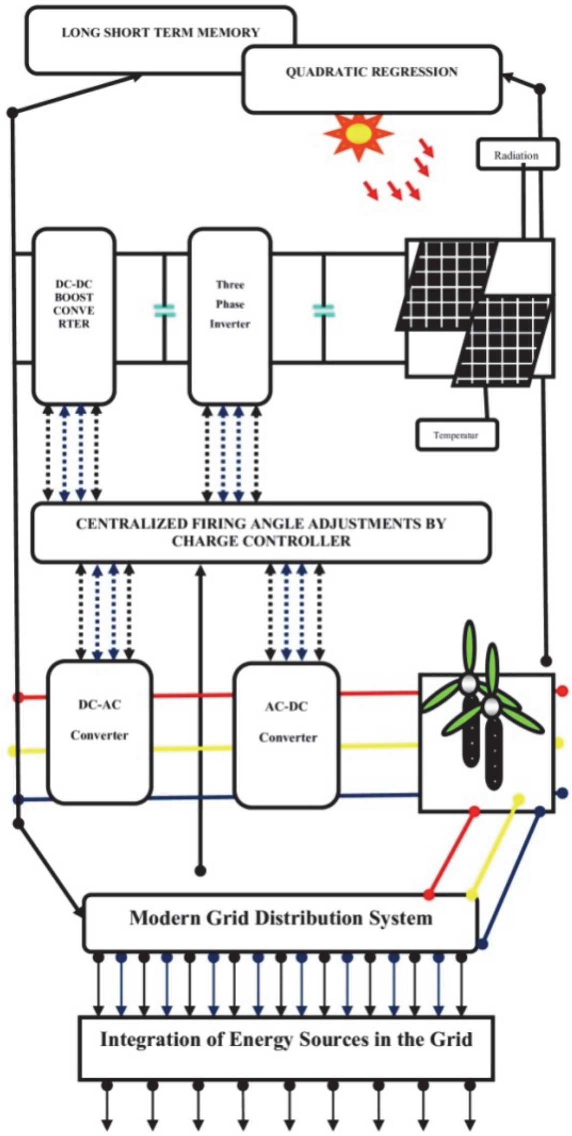


**Figure 1** Integrating RES into main power grid with LSTM and QRM utilities

In an endeavor to increase load transmission from one point to another, congestion is managed and energy delivery improved, which in turn leads to better load forecasting. Keeping the AC voltage and frequency stable is crucial to providing accurate load forecasting for good energy management shown in Fig. 2. Storing off-peak loads in more efficient and optimal storage systems strengthens the storage capability of the system for excess energy storage, dedicated to transition from fossil energy sources to non-conventional energy and better load prediction.

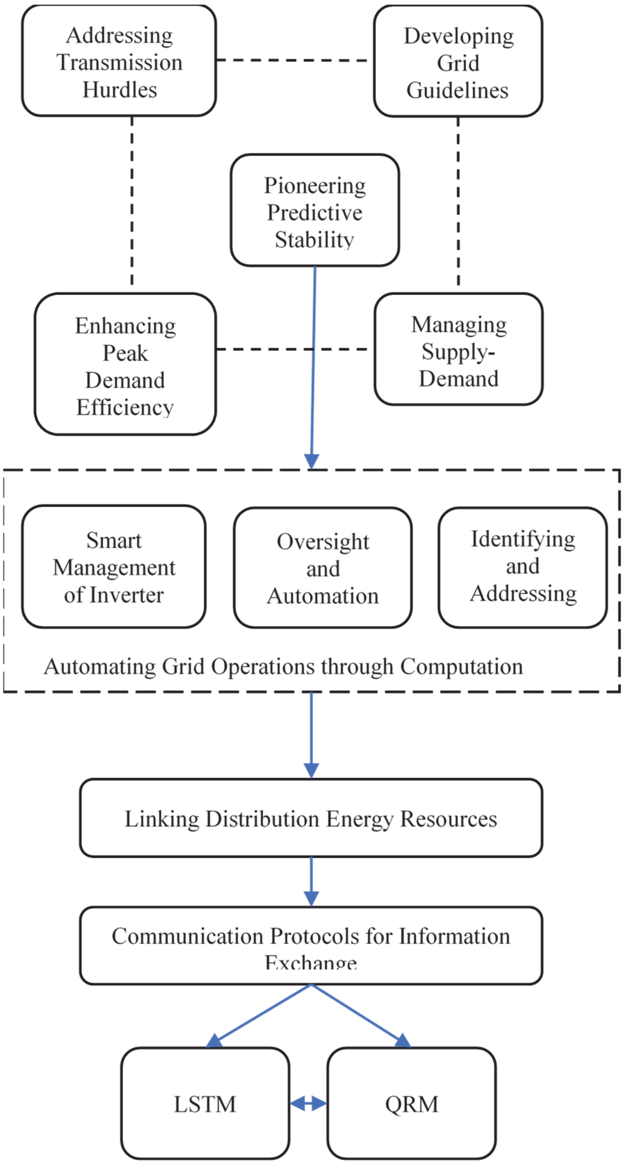


**Figure 2** Incorporation of RES forecasting stabilities of proposed systems

### 3.3 Transforming Energy Oversight: Eco-Prescriptive Load Prediction and Sustainable Concern

The conceptualized system for renewable energy load forecasting works with interactive elements involving advanced technologies, effective energy storage solutions, and superior load forecasting. As the primary feature, this system also minimizes the overall burden on the grid regarding sustainability, supported by load forecasting for renewable energy needs. Accuracy of real time data and the communication systems are the key to increasing efficiency in the handling of grid operations by grid operators due to effective forecasting. Such a model based on flexible legislation and politics encourages change and cooperation among the involved parties, which stimulates the development of the energy platform.

Intelligent load forecasting discusses the application of Artificial intelligence and data analysis which has developed the field by improving load forecasting accuracy. Therefore, as the energy system develops over time, it is essential to enhance these models in order to strengthen the structure of the power system. This assessment also brings in inductive load demand estimation which is a power required in circuits which contain inductive elements. Such methods embrace proper determination of the demand to help in the determination of the energy consumption as well as proper size of the required systems so as to improve both energy and efficiency and the prices that are charged.

The principle of total demand calculation based on consumption changes guarantees the corresponding configuration of the grids and the perspectives for transitioning towards a more sustainable energy system, based on the shares of renewable and non-renewable energy sources. Such an approach promotes a very effective energy network which is capable of catering for the needs of society. Improving grid energy management, its emphasis is directed towards the application methodology of ML together with resources within distribution networks to meet current difficulties within modern energy systems. Load pattern forecasts are made possible by the Long Short-Term Memory (LSTM) algorithms, with the Quadratic Regression Model giving further improvements in prediction by determining nonlinear load patterns. Such models facilitate complex revenue models through adaptive costs derived from historical data and other external influences, which results in effective utilization as well as control of demand. Learned algorithms also enhance demand response, energy storage, real-time grid stability monitoring and so on. Besides, predictive maintenance algorithms enhance infrastructure reliability. Moreover, machine learning predicts renewable energy generation and hence the proper functioning of grids and resources.

The use of ML integration is indispensable to transform decision-making for the sustainable distribution of energy since oscillating energy systems present many difficulties that can be mitigated with appropriate data interpretation for more precise determinations. An important use case is load forecasting for which ML techniques, particularly LSTM neural networks, offer accuracy in predicting the fluctuation in loads. It advances this process using Quadratic Regression Models (QRM) thus optimizing resource allocation. It also improves the management of sustainable energy for distribution networks in cases where it transforms real time options, balances the voltage strength in renewable energy systems, and scales down the use of backup equipment. Thus, ML assists in accurate load forecasting and resources allocation avoiding overload and providing the grid operational efficiency. LSTM and QRM are the advances enabling the development of a reliable and sustainable energy system, which is required to address variability and intermittency of REs.

## 4 RESULTS AND DISCUSSIONS

Integrating LSTM neural networks with a Quadratic Regression Model (QRM) proved to be very effective in the field of grid energy management. This dataset includes hourly energy consumption data for 746 days (or a total of 17904 data points (746 days × 24 hours), provides a detailed view of the time dimension of demand in the Greek national grid. With this dataset, we split the data set into 80% training and 20% validation for development of the model, we aimed to hold the order unchanged so that we can accurately forecast time-series demand. Hyperparameter tuning was done using grid search focused on determining the number of layers in the LSTM, number of units per layer, learning rate, batch size, and dropout. The best performing LSTM had two hidden layers made up of different units, 64 and 32. Batch size was 64, learning rate was 0.001 and dropout was 0.2 to prevent over-fitting. The model was trained over 100 epochs and had early stopping based on the validation loss. Finally, for QRM, a polynomial degree of 2 was used in order to balance bias and variance without overshooting.

Mean Absolute Error (MAE): forecasted values and the actual observed values and the Mean Absolute Error (MAE) is the standard measure to compare the forecast and the observation.

$$\vec{\mathrm{MAE}}_{\mathrm{RES}}^{\mathrm{PG}} = \frac{\left|\sum_{(n=1)}^{\dot{m}} \left(\vec{A}_n - \vec{P}_n\right)^2 \right|}{\ddot{N}} \tag{7}$$

Using the MAE, the obtained result represents the average deviation of the load forecasting predictions from the implemented values of approximately 2.5%. Due to this, the LSTM-QRM model presents a low MAE enabling accurate load forecasts.

Root Mean Squared Error (RMSE): RMSE which is also one of the most important performance metrics, looks for the square root of the mean of the squared differences between the predicted and observed values.

$$\overrightarrow{\mathrm{RMSE}}_{\mathrm{RES}}^{\mathrm{PG}} = \sqrt{\frac{\sum_{n=1}^{\dot{m}} \left(\vec{A}_{\dot{n}} - \overrightarrow{P_{\dot{n}}}\right)^2}{\ddot{N}}} \tag{8}$$

An RMSE of 4.0% here means that the model holds capability of estimating the load fluctuations with relatively smaller gaps. RMSE is usually scaled to show the best fitness of the model across actual data, and it is evident that a smaller RMSE has been obtained in this analysis.

R-squared ($R^2$) Value: The R-Squared or $R^2$ achieves the dependent variable (load in this case) with variance that is due to explanation by the independent variables (features used in the model).

$$R_{\mathrm{DN}}^2 = 1 - \frac{\sum_{i=1}^{n} \left[ y_i^{\mathrm{DN}} - \hat{y}_{\boldsymbol{i}}^{\mathrm{DN}} \right]^2}{\sum_{i=1}^{n} \left[ y_i^{\mathrm{DN}} - \vec{y}_i^{\mathrm{DN}} \right]^2} \tag{9}$$

where $N$ is the number of observations. $y_i^{\mathrm{DN}}$ is the actual observed value of the dependent variable for observation $i$, $\hat{y}_i^{\mathrm{DN}}$ the predicted value of the dependent variable for observation $i$. $\hat{y}_i^{\mathrm{DN}}$ is the mean of the observed values of the dependent variable. When applied to the load forecasting model LSTM-QRM, summation would be done for all observations, where $y_i^{\mathrm{DN}}$ refers to the actual load, $\hat{y}_i^{\mathrm{DN}}$ concerns the predicted load, and $\hat{y}_i^{\mathrm{DN}}$ -mediated the mean of the actual load data. In statistics, it indicates to what extent the model is capable of explaining the variance of the observed data and the closer the $R^2$ […] The obtained $R^2$ value equals 0.85, which means that 85% of the variation in the load data observed can be explained by using the LSTM-QRM model. This high $R^2$ value further supports the high reliability of the model in accounting for the variability of the given data, Fig. 3. The results presented by the graph showing the Stability in the RES System Distribution Grid Output Voltage allow inferring certain findings regarding the system in question. Therefore, the RES system has embraced massive reliability and minimal voltage-level fluctuation within the distribution grid, Fig. 4.

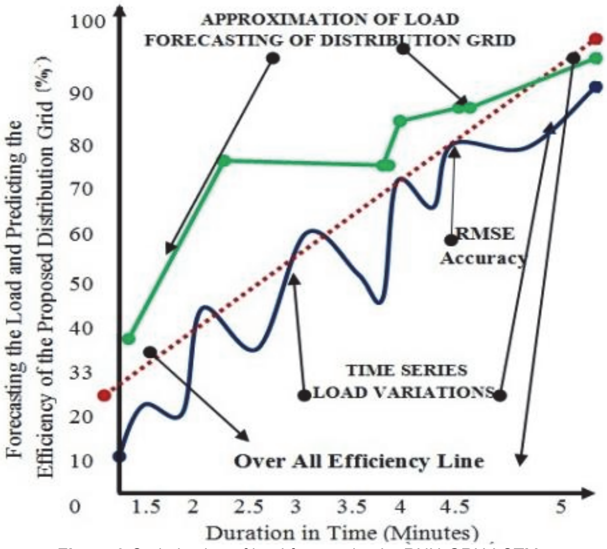


**Figure 3** Optimization of load forecasting by RNN-GRU-LSTM

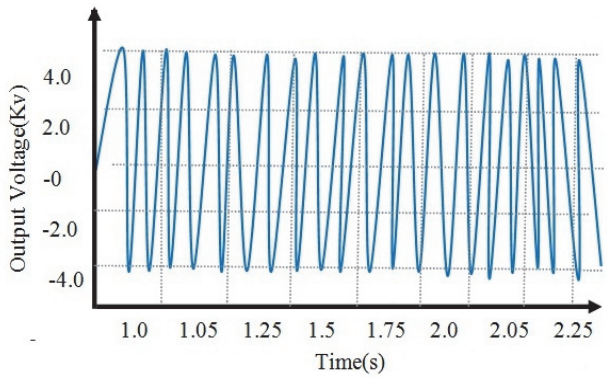


**Figure 4** Stability in the RES system distribution grid output voltage

LSTM in combination with QRM features as the new benchmark for energy management and offers the utility providers a tool that will help to increase grid resilience and foster the transition toward sustainable energy systems. The adaptive nature of distribution grid forecasts and the qualitative simulation of changed patterns in energy consumption make it a highly useful resource in the changes and improvements of Distribution Grids and energy-efficient supply networks.

Comparative assessment of models presented in Tab. 1 provides evidence of an overall superiority with the

Hybrid LSTM + QRM model which showed prediction credibility of 97.0%, MAE of 2.5, RMSE of 4.0, and a $R^2$ standard of 0.85. All of these metrics indicate considerable accuracy and reliability for forecasting accuracy and model reliability. The best performing of the traditional models was provided by XGBoost with an accuracy of 96.4% and MAE (2.8) and reasonably low RMSE (4.3) errors making it a reasonable baseline. The two models above do not count for the LSTM but they both had similar MAE and RMSE errors, although worse $R^2$ scores of 0.79 and 0.82 respectively. Also, considering that QRM is merely a regression method (against totally new neural network architecture like the LSTM), it shows better accuracy compared with Random Forests (92.1 %), lower RMSE, and $R^2$. Finally, Random Forests had better performance metrics overall, but it had the highest values of errors (MAE, RMSE), and the worst $R^2$ (0.75)), which means it clearly will not provide a very good prediction model for load forecasting tasks. Overall the hybrid model was well above the other models across all metrics standards of performance indicating it will significantly contribute to a reliable, data-driven output of energies load forecasting potential for smart grid applications.

**Table 1** Performance analysis

| Model | Prediction Accuracy / % | MAE | RMSE | $R^2$ Score |
|---|---|---|---|---|
| Random Forests | 89.5 | 4.5 | 6.1 | 0.75 |
| Neural Networks | 93.5 | 3.6 | 5.1 | 0.79 |
| XGBoost | 96.4 | 2.8 | 4.3 | 0.84 |
| LSTM | 94.8 | 3.2 | 4.8 | 0.82 |
| QRM | 92.1 | 3.7 | 5.3 | 0.79 |
| LSTM + QRM (Hybrid) | 97.0 | 2.5 | 4.0 | 0.85 |

Although the hybrid LSTM + QRM model produces a high degree of accuracy, it still has some limitations. The primary limitation is scalability. Training LSTM networks, and indeed all machine learning methods, is computationally expensive, especially when the input is large-scale, high-frequency data from large business utility grids. Second, the model is only as good as the historical data, and in areas where there is a minimum level or inconsistency in historical data, it is possible that an LSTM would be less accurate. Third, model generalization is always a potential problem with LSTMs; if the model learns to include noise or outliers from the training data rather than general trends, it could overfit. Hybridization helps mitigate this to some extent, but a failure to tune the model, together with inadequate validation of initial training, could lead to overfitting. Similarly, the model would also be limited in any response to sudden changes in consumption levels as a result of unexpected events (e.g., pandemics, policy decision). Thus, it is crucial that regular retraining with new data, rigorous cross-validation and real-time feedback methods are all incorporated into any ongoing development. Overall, while the hybrid model is promising, the limitations outlined above require caution in deployment and to continually monitor the reliability and adaptability of the model to different grid configurations. The proposed hybrid model can be applied in other regions or utilities if the model is trained with local historical load and weather data so that it can learn local consumption patterns. The flexibility of the model's architecture allows it to be adopted across diverse grid configurations and a variety of levels of renewable energy penetration. Furthermore, the model can also be adjusted with only a small number of model parameters to accommodate differences in grid topology and variability in demand. This flexibility allows for the potential for widespread use in utility networks that are geographically and operationally diverse.

## 5 CONCLUSIONS

The hybrid of Long Short-Term Memory (LSTM) neural networks and a Quadratic Regression Model (QRM) represents a promising approach to improving load forecasting, along with, ultimately, grid energy control. Based on prediction accuracy with a decrease in MAE (2.5%) and RMSE (4.0%) along with an $R^2$ value of 0.85 suggests the model held strong performance in prediction accuracy. While the measurements of MAE (2.5%), RMSE (4.0%), and $R^2$ (0.85) are positive measures for the tests completed, further testing is needed to adequately assess the robustness of the model for alternate geographical areas and energy systems and intermittent renewable energy conditions. Furthermore, although the model can theoretically support sustainable energy management, tangible environmental and economic benefits (e.g., reduced $CO_2$ emissions, operational cost reductions, or more favorable integration of renewable energy) were not explicitly evaluated. Including these kinds of indicators could demonstrate a sustainable outcome. Scalability is still a possible challenge, especially in areas with little data and limited infrastructure where real-time data quality and availability could affect performance. More to the point, the computational burden required to train LSTM networks with larger datasets may be beyond the reach of smaller utilities with limited resources. While better understanding the risk of overfitting will be important, it is worthwhile to note that understanding the model's ability to adapt to sudden demand shifts or non-repeating consumption behaviors has yet to be rigorously assessed. Although the LSTM-QRM model may provide baseline support to greener and more efficient energy systems in the future, future studies must include comparative studies across different climate, energy mix, and socioeconomic contexts. Finding the measure of real-world impacts on energy savings, emissions reductions, and cost-effectiveness will also be a priority in positioning as a truly sustainable and scalable option in the global transformation of smart grids.

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