Hybrid ARBS-Net Framework for Accurate Energy Forecasting in Smart Grid-Driven Electric Mobility Environments

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Abstract. The main objective of this study are to develop an intelligent forecasting for Electric Vehicle Charging Station (EVCS) and to significantly enhance the accuracy of energy consumption forecasting in renewable integrated smart grid environments. These objectives are achieved through solving the following tasks: implementing data preprocessing to handle missing values, remove outliers and eliminate inconsistent observations for improving dataset reliability; performing feature engineering for generating meaningful temporal and derived variables that strengthen model interpretability; and carrying out detailed Exploratory Data Analysis (EDA) for extracting statistical trends, recognize correlations and uncover hidden temporal dependencies in energy consuption behaviour. Structure on the preparatory stages, a hybrid Deep Learning (DL) approach using a Radial Basis Spiking Net (ARBS-Net) is developed by combining radial basis kernal (RBF) with temporal behavior of Spiking Neural Networks (SNN), enhanced with attention mechanisms for capturing non-linear fluctuations and time varying required pattern. The most important results obtained from Python based experiments highlight enhancement in forcasting performance, with the proposed model achieving a Mean Squared Error (MSE) of 0.1183, a Mean Absolute Error (MAE) of 0.2694, a Root Mean Squared Error (RMSE) of 0.3439, and an overall prediction accuracy reaching a $R^2\ score$ of 0.99. The significant of the results lies in their ability to support predictive energy allocation, optimize load balancing strategies and improve grid stability. By providing highly dependable demand forecasts for charging infrastructure, the proposed framework contributes to the sustainable integration of electric mobility within future smart energy systems.

Keywords: electric vehicles, electric vehicle charging stations, Deep Learning, data preprocessing, feature engineering, exploratory data analysis, and Attentive Radial Basis Spiking Net.

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Structura hibridă ARBS-Net pentru previziuni precise ale consumului de energie în mediile de electromobilitate bazate pe rețele inteligente

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Rezumat. Scopul principal al acestei cercetări constă în dezvoltarea unui sistem inteligent de prognoză pentru stațiile de încărcare pentru vehicule electrice (EVCS) și în îmbunătățirea semnificativă a preciziei de prognoză a consumului energetic în cadrul rețelelor inteligente integrate care utilizează surse regenerabile de energie. Aceste obiective sunt atinse prin rezolvarea următoarelor sarcini: implementarea preprocesării datelor pentru a gestiona valorile lipsă, a elimina valorile aberante și a elimina observațiile inconsistente pentru îmbunătățirea fiabilității setului de date; efectuarea ingineriei caracteristicilor pentru generarea de variabile temporale și derivate semnificative care consolidează interpretabilitatea modelului; și efectuarea unei analize exploratorii de date (EDA) detaliate pentru extragerea tendințelor statistice, recunoașterea corelațiilor și descoperirea dependențelor temporale ascunse în comportamentul de consum de energie. În etapele pregătitoare, este dezvoltată o abordare hibridă de Deep Learning (DL) utilizând o rețea Radial Basis Spiking Network (ARBS-Net) prin combinarea nucleului radial (RBF) cu comportamentul temporal al rețelelor neuronale Spiking Network (SNN), îmbunătățită cu mecanisme de atenție pentru captarea fluctuațiilor neliniare și a modelului necesar variabil în timp. Cele mai importante rezultate obținute din experimentele bazate pe Python evidențiază îmbunătățirea performanței de prognoză, modelul propus atingând o eroare medie pătratică (MSE) de 0.1183, o eroare medie absolută (MAE) de 0.2694, o eroare medie pătratică (RMSE) de 0.3439 și o precizie generală de predicție de 0.99. Semnificația rezultatelor constă în capacitatea lor de a susține alocarea predictivă a energiei, de a optimiza strategiile de echilibrare a sarcinii și de a îmbunătăți stabilitatea rețelei.

Cuvinte cheie: vehicule electrice, stații de încărcare pentru vehicule electrice, Deep Learning, preprocesare date, inginerie caracteristici, analiză exploratorie a datelor și aețea atentă de spiking radială pe bază.

Гибридная структура ARBS-Net для точного прогнозирования энергопотребления в средах электромобильности, основанных на интеллектуальных сетях

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Аннотация. Основная цель данного исследования заключается в разработке интеллектуальной системы прогнозирования для зарядных станций электромобилей (EVCS) и значительном повышении точности прогнозирования энергопотребления в интегрированных интеллектуальных сетях, использующих возобновляемые источники энергии. Эти цели достигаются путем решения следующих задач: реализация предварительной обработки данных для обработки отсутствующих значений, удаления выбросов и устранения несогласованных наблюдений для повышения надежности набора данных; выполнение инжиниринга признаков для генерации значимых временных и производных переменных, которые усиливают интерпретируемость модели; и проведение подробного эксплораторного анализа данных (EDA) для извлечения статистических тенденций, распознавания корреляций и выявления скрытых временных зависимостей в поведении энергопотребления. На подготовительных этапах разработан гибридный подход глубокого обучения (DL) с использованием радиальной базовой спайк-сети (ARBS-Net) путем объединения радиального базового ядра (RBF) с временным поведением спайк-нейронных сетей (SNN), усовершенствованных с помощью механизмов внимания для улавливания нелинейных колебаний и требуемых временных изменений. Наиболее важные результаты, полученные в ходе экспериментов на основе Python, подчеркивают улучшение прогнозирующей способности, при этом предлагаемая модель достигает среднеквадратичной ошибки (MSE) 0.1183, средней абсолютной ошибки (MAE) 0.2694, среднеквадратичной ошибки (RMSE) 0.3439 и общей точности прогнозирования, достигающей 0.99. Значимость результатов заключается в их способности

Ключевые слова: электромобили, зарядные станции для электромобилей, глубокое обучение, предварительная обработка данных, проектирование признаков, разведочный анализ данных и внимательная радиально-базисная импульсная сеть.

I. INTRODUCTION

Emissions from fossil-fuel-powered vehicles are a major cause of air pollution and have harmful effects on the environment. Meanwhile, as oil reserves continue to dwindle and extraction becomes increasingly difficult, the need for alternative energy sources in transportation is growing. Therefore, EVs produce zero emissions and are powered using RE, contributing to cleaner and sustainable energy transportation [1]. Today there are more EVs powered by Renewable Energy System (RES) such as solar Photovoltaic (PV) and wind are supporting the goal of peaking energy independence. Additionally, EVs have lower maintenance and fuel costs compared to traditional vehicles, making them financially attractive. Due to these environmental and financial benefits, the demand for EVs is rapidly increasing [2]. However, large-scale adoption of EVs creates considerable pressure on the electrical grid. As the demand for charging EVs increases, a large number of vehicles on the road causing stress to the distribution network. The growing EVs propulsion increases the load curve which in turn create additional stress on transformer and the entire distribution grid [3]. To mitigate this issue, RES based EVCS have been developed. These EVCS provides clean energy, while also avoiding transmission costs by generating power locally. However, with the influx of EVs into the energy sector, it becomes essential for Charging Station (CS) to effectively manage the simultaneous vehicle charging and power dispatch [4]. Moreover, the conventional power grid is composed of several interconnected components such as transformers, alternators, transmission lines and diverse electrical loads to deliver electricity from source of production to the consumer. Though, the process is much more complicated and the broader demand from EVs charging complicates its operation, thus the distribution grid requires robust and reliable management systems to operate effectively and reliably [5-6]. Fig. 1 illustrates graphical representation of energy consumption in EVCS.

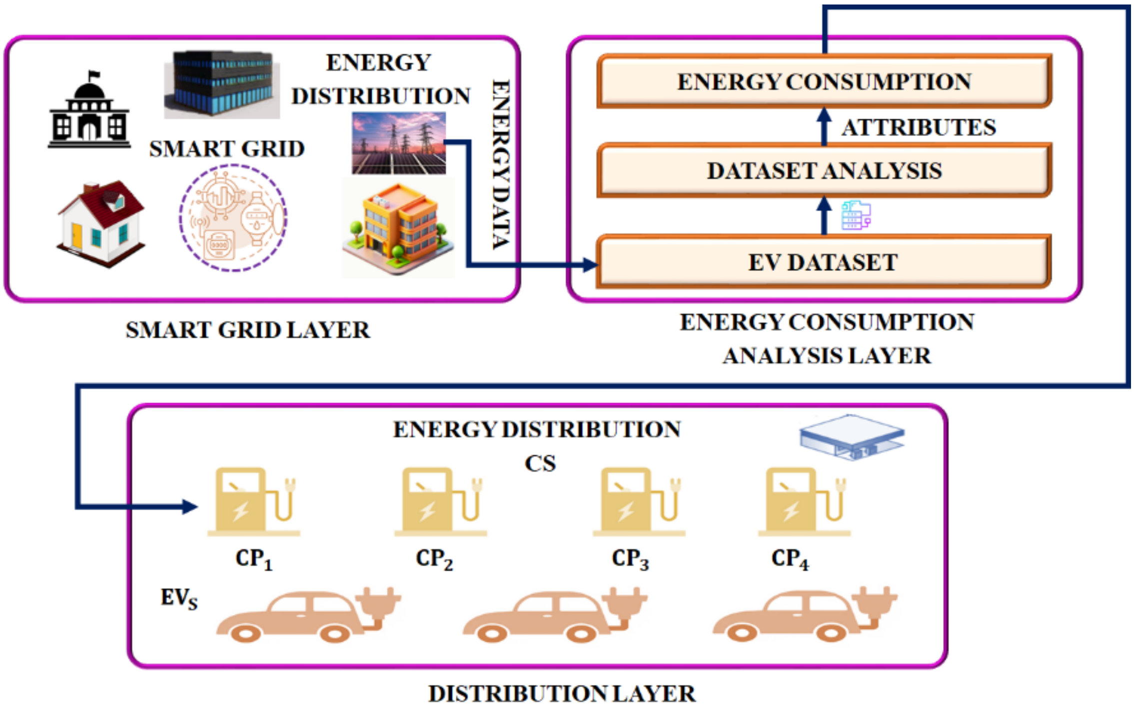

Fig. 1. Graphical diagram for EVCS energy consumption.

Consequently, the smart grid uses advanced technology to improve the efficiency of the power system. By integrating enhanced sensors, smart meters, and analytic software, it is collected and analyzed comprehensive data on EV energy consumption patterns. This capability enables more effective energy management, demand forecasting and load balancing [7]. A smart grid operates as a two-way communication power supply system between utilities and consumers, allowing electricity to be monitored and controlled more efficiently. Through this intelligent coordination, the smart grid aids address the challenges posed by large scale EVCS while ensuring sustainable power delivery [8]. The smart grid encompasses many electrical systems that utilize significant energy, including building Heating, Ventilation, and Air Conditioning (HVAC) systems, and Home Energy Management Systems (HEMS). It addresses the power supply issues by utilizing advanced communications technologies. Essentially, it consists of an intelligent network of interconnected devices and systems, often through wireless technology [9]. As part of this development of smart grid technologies, Internet of Things (IoT) generates and processes data from the devices in real time to support their decision-making process, living standard, and enhance sustainability. With the increasing adoption of EVs, smart grid technologies have been more essential, particularly in optimizing charging schedules to minimize the overall operating cost [10]. Along with the increasing number of EVCS in a smart grid, there is an increase opportunity for researchers to operate the CS effectively. As a result, the smart grid is able to manage EVs that arrive in a high-energy load to maintain reliable power supply and stable operation. Furthermore, the energy consumption behavior of EVs is dynamic and influenced by several factors including charging requirements, travel destination, and weather conditions [11]. The rapid acceleration of EVs has created a massive demand for reliable charging infrastructure. However, the operation and maintenance of EVCS consumes significant amounts of energy and led to operating costs. Thus, reliable power consumption forecasting is essential for the efficient utilization of CS and for reducing operating expenses [12].

Therefore, the EV charging consumption is examined with respect to two approaches: test set-based and analysis-based charging demand forecasting methods. In a test set-based approaches, which includes trial-and-error, prototype, or equipment-based methods are often expensive, time consuming and unsuitable for large EV charging analysis. Comparatively, analysis-based approaches employ Machine Learning (ML) and DL models, which led to more accurate predictive representation of EV energy consumption [13-14]. The ML models such as Random Forest (RF), XGBoost, Support Vector Regression (SVR), and Multi-Layer Perceptron (MLP) have been used to forecast EVCS energy demand by integrating historical charging data with weather variables. RF and XGBoost showed long term prediction, making practical for grid management and scheduling. However, its relied on short term datasets and lacked key factors such as vehicle type, public events, and environmental condition, limiting scalability. SVR and MLP achieved the best predictive performance, though weather inputs reduced accuracy in certain conditions [15-16]. The DL methods like Recurrent Neural Networks (RNN), and Gated Recurrent Unit (GRU) models to forecast energy consumption in EVCS. These models captured the charging demand patterns effectively for demand–supply balance and infrastructure planning. Nevertheless, the model's constrained by small datasets and high computational resource, reducing their feasibility for large-scale real-time applications [17].

A. Literature survey

Munseok Chang *et al* (2021) [18] have developed a Long-Short Term Memory (LSTM)-based forecasting model to predict aggregated fast-charging power demand across several EVCS. This model accounted for time series data with irregular and varying charging behaviours, making demand estimation useful for both grid planning and operational reliability. However, the model is limited to datasets from a single region, making it difficult of generalize results to different charging infrastructures. **Yining Hua *et al* (2022)** [19] have implemented a Fine-grained RNN (F-RNN) classifier for predicting the energy consumption by EVs. It improves predictions through segmenting trajectory data, incorporating environmental factors, and transferring knowledge from ICE/HEV datasets. Nonetheless, it depends heavily on pre-trained non-EV data and involves complex pre-processing which affect adaption to varying real driving conditions. **Dan Zhou *et al* (2022)** [20] have presented a day-ahead EVCS forecasting with the integration of LSTM with a Bayesian DL (BDL) approach. The approach incorporates uncertainty into prediction using binary probability theory and variational inference, which improved prediction accuracy and reliability. Nevertheless, the model required high computation cost and requires extensive data, which limit it's real-world applications. **Danlan Wu *et al* (2021)** [21] have developed a Generative Adversarial Network (GAN)-enhanced ensemble model for predicting energy consumption in large commercial buildings. The method achieves greater predictive robustness, resulting in more affluent, accurate training datasets. However, evaluate on a single dataset with limited set of GAN variants and ensemble methods, its generalizability to broader applications is limited. **Faisal Mohammad *et al* (2023)** [22] have introduced Convolutional LSTM (ConvLSTM) and Bidirectional ConvLSTM (BiConvLSTM)-based encoder-decoder structures for forecasting energy demand in EVCS. The approach enabled spatiotemporal representations from multi-location datasets and improved forecasting accuracy for intelligent energy management. However, the model required extensive computational resources and lacked with larger multivariate datasets, which limits their scalability in various real-world contexts.

Existing methods have several limitations in accurately forecasting energy consumption, therefore in this work implements the ARBS-Net classifier to overcome theses challenges and improve prediction performance. The contributions of the work are,

- Data preprocessing stage involves handling missing values and treating outliers to data quality, reduces inconsistence and reliability of energy consumption forecasting.
- Performed feature engineering by extracting date and creating new features to capture pattern in energy consumption, enhancing model interpretability.
- Conducted EDA using time series and statistical analysis methods to identify patterns, trends, and anomalies in energy consumption.
- Implemented an ARBS-Net to forecast accurate energy consumption, achieving lower error values, and improved temporal pattern recognition, thereby delivering superior forecasting performance.

II. PROPOSED SYSTEM DESCRIPTION

In the ARBS-Net based energy consumption system, data is gathered from dataset such as, PV system specifications, operational measurements from EVCS, microgrid load data, control strategies, and target outcomes as shown in Fig. 2. Before model development, the raw data pre-processed through handling missing values and outlier treatment. Handling missing values is necessary for addressing incomplete recorded data, which disrupts the learning process, while outlier treatment enhances the dataset by improving consistency, reducing noise. Once the data is cleaned, feature engineering is carried out to enhance the dataset by generating new variables. Temporal features such as dates and time are derived, along with additional context-based features that find hidden patterns. EDA is then performed using time-based and statistical data analysis methods to identify load trends, energy consumption, usage pattern and correlation between variables.

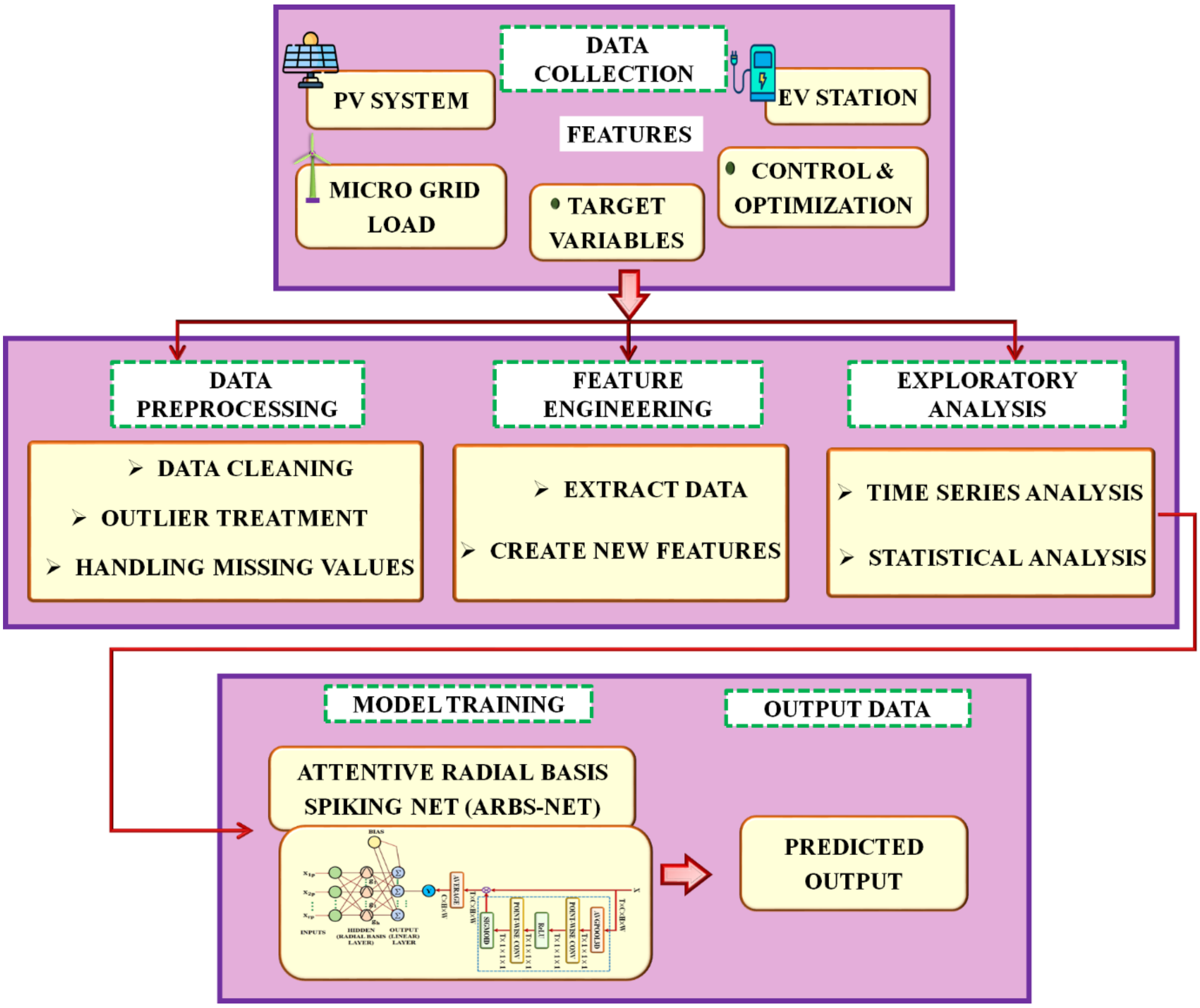

Fig. 2. Proposed block for DL based energy consumption forecasting.

The processed data is used to train the ARBS-Net model, to accurately forecast energy consumption and capture residential EV charging behaviour by combining RBF, SNN and attention mechanism. The predicted energy consumption patterns are analyzed to support demand forecasting, load scheduling and efficient utilization of renewable resources.

III. PROPOSED METHODOLOGY

A. Data Preprocessing

The first step in the experiment is data pre-processing, as time series data often contain missing values and duplicates during data collection. Data pre-processing is the process of identifying, and correcting incomplete, inaccurate or inconsistent records by either replacing, correcting, or deleting the data parts of the data. In this work data cleaning involves, handling missing values and outlier treatment.

Handling Missing Values

Missing values in DL are absent attributes in a dataset, often caused by data collection, faulty sensor readings, and sensor failure in CS. The voltage level, current, and power readings sometimes be missing. Thus, the missing value algorithm applied to check whether missing values are correlated with any observed variables in the dataset. Formally, let $X = (a, b)$ where a stands observed value and b stands missing value in X, and let Y be a random variable. The missingness mechanism characterized as:

$$P(Y \mid X, \varnothing) \tag{1}$$

where $\varnothing$ represents the missing aspect of the data. Following this formulation, consider three common mechanisms for handling missing values:

1. Missing Completely at Random (MCAR):

$$P\left(Y|X,\varnothing\right) = P\left(Y,\varnothing\right) \tag{2}$$

The missingness of the values is independent of the observed values and the unobserved values. Assuming a CS fails to record voltage readings due to a temporary communication failure. Such missed readings are classified as MCAR. MCAR values are typically handled by random deletion and simple imputation.

2. Missing at Random (MAR):

$$P\left(Y|X,\varnothing\right) = P(Y_a \mid \varnothing) \tag{3}$$

The missing values typically depends only on subset of the observed variables. If power consumption data is missing during fast-charging sessions, the pattern of missing values is related to the variable charging type. MAR often be addressed using regression-based or covariance-based imputation techniques.

3. Missing Not at Random (MNAR):

$$P\left(Y|X,\varnothing\right) = P(Y \mid a, b, \varnothing) \tag{4}$$

In this scenario, when missing values depend on the missing data itself or on unobserved covariates, the missing values is classified as MNAR. If high current flow values are systematically missing due to sensor limitations, the missing values are considered MNAR. Addressing MNAR typically require advanced DL based methods to model unobserved associations.

Missing values in the EV charging dataset are addressed using a combination of statistical imputation and predictive imputation methods, based on whether the missing data are MCAR, MAR, or MNAR.

These various methods utilized to address missing values allow for a complete and reliable dataset, which ultimately improve accuracy of energy forecasting and optimization within smart grid integrated EVCS.

Outlier Treatment

Outlier handling is essential to ensure the reliability of data. Outliers occur due to abnormal readings of voltage, current, power flow, and charging demand, which result from sensor malfunction, unusual load behaviour, and clerical error leading to erroneous entry of values. Outlier rejection, as part of the data cleaning process, eliminates or adjust abnormal readings to maintain consistency in system parameters. Conversely, outlier detection captures significant behaviours, such as unusual charging demand, irregular load fluctuation, or atypical RE generation which indicate potential grid stress and system fault. Proper handling of outliers improves the quality of economic and reliability assessment, and supports the analysis of optimal charging approach with EV’s and establishing grid stability.

B. Feature Engineering

This study applies feature engineering to enhance the utility of the proposed EVCS analysis. The raw dataset is refined by extracting date-related features, including day, month, and time of charging, which capture time-dependent variations in charging demand and grid behavior. These time features allow for the model to recognize seasonal cycles, charging demands during peak and off-peak charging pattern, and different sized variations in RE availabilities. In addition to date-based extraction, new features are created from existing variables to identify relationships that less apparent in the dataset. Thus, the model is specifically using indices like the power-to-current ratio, voltage fluctuation index, and energy efficiency ratio to better represent of CS performance. By embedding domain knowledge through these new features, the dataset more accurately reflects both the operational efficiency and reliability of the charging network. The integration of both new temporal and engineered features added depth to the learning process of the classification models, which increased accuracy and interpretability. With this approach, it ensured that the proposed system utilizes raw operational parameters, while also recognizing higher-level behaviours, enabling more effective analysis of EV-grid interactions.

C. Exploratory Data Analysis

The EV charging dataset using EDA to discover hidden features, usage trends and relationships in energy demand. Statistical analysis techniques including histograms, box plots and correlation plots are employed to examine the distribution of charging sessions, energy and charging time. The analysis is able to display differences in demand for various time intervals and revealed a dependency on State of Charge (SOC), time of connection and consumed energy. Subsequently, a time-series analysis captured the time-based features of charging behavior. This analysis considered as the characteristics of trend, seasonality, cyclicity, and irregularity representing the long-term growth in demand, periodic cycles of charging, medium term variations, and shorter-term fluctuations. These insights support accurate modeling, forecasting of charging demand while also facilitating higher integration of renewable energy sources.

D. Attentive Radial Basis Spiking Net (ARBS-Net)

The ARBS-Net is a hybrid DL model which combines the nonlinear generalization capacity of RBF kernels, SNNs, and the feature refinement capability of attention methods to accurately model EV charging demand and the variability in RE generation. The RBF kernel is the first layer to capture nonlinear dependencies in the input features. The RBF kernel is defined as:

$$K\left(x,x'\right)=e^{\frac{d\left(x,x'\right)^{2}}{2\sigma^{2}}} \tag{5}$$

Where $d\left(x,x'\right)$ is the Euclidean distance between feature vectors $x\,and\,x'$:

$$d\left(x,x'\right)=x-x'\sqrt{\sum_{i}\left(x_i-x_i^{'}\right)^{2}} \tag{6}$$

In this expression, σ is a parameter that controls the level of nonlinearity, with smaller values yielding smoother mappings and larger values enabling the model to capture more complicated variations in demand. The RBF is expressed in terms of the parameter $\gamma=\frac{1}{2\sigma^{2}}$, resulting in the equivalent expression,

$$K\left(x,x'\right)=e^{-\gamma x-x'^{2}} \tag{7}$$

The RBF mapping embodies a nonlinear transformation of the EV charging features, allowing for more effective representation of the flux of demand before transition into a network of spiking neurons. In order to represent fluctuation, the spiking component employs a Leaky Integrate-and-Fire (LIF) neuron model, which provides a balance between biological principles and computational efficiency. As part of that transformation, the pre-synaptic input represents the charging demand or renewable energy fluctuation which is predictable to the LIF neuron as a weighted signal. The membrane potential evolves over time and is based on the existing input and historical charging activity. The scaling of synaptic weights determines the significance of events and the membrane time constant controls the depth of memory. The discrete-time LIF neuron is represented, as follows,

$$H_t=V_{t-1}+\frac{1}{\tau}\left[-\left(V_{t-1}-V_{reset}\right)+X_t\right] \tag{8}$$

Where X_t refers to the input charging demand or renewable fluctuation at time t, V_{t-1} is the membrane potential corresponding to accumulated charging state, V_{reset} is the reset potential, and τ is the membrane time constant controlling the loss of previous load influences. The synaptic weight determines the magnitude of each charging event, while the time constant control the memory length, allowing the model to flexibly capture short term deviations and long-term variation in EV demand and renewable supply.

In ARBS-Net, temporal feature learning is further enhanced by incorporating a Temporal Attention (TA) module that emphasize the most important charging events over time.

The aim of this module is to predict the salience of a frame in the spiking neural sequence, which utilize the temporal statistics of the distribution at the selected frame while also integrating contextual information from adjacent frames.

For the spatial input tensor of the $n-th$ layer at time point t, denoted $X_{t,n-1}\in\mathbb{R}^{L\times B\times C}$, where C is the size of the channel, the TA module executes a squeeze operation to obtain a statistical descriptor of the distribution of events. To obtain the statistical vector at time frame t, consider,

$$s_t^{n-1}=\frac{1}{L\times B\times C}\sum_{k=1}^{C}\sum_{i=1}^{L}\sum_{j=1}^{B}X_{t,n-1}\left(k,i,j\right) \tag{9}$$

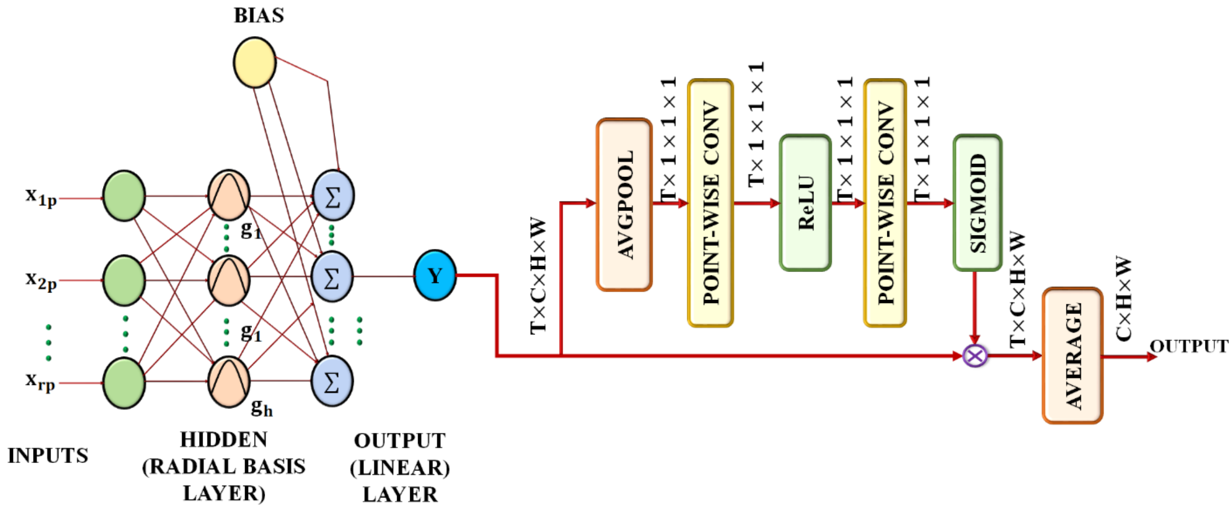

Fig. 3. Structure of ABRS-Net.

This accurately represents the total activity level of EV demand or renewable generation at that moment. In the excitation step, the statistical vector s_{n-1} is given to a two-layer fully connected network that finds correlations over frames, thereby producing TA scores. This operation is defined as,

$$d_{n+1} = \begin{cases} \sigma\left(W_{2n}\delta\left(W_{1n}s_{n-1}\right)\right) \\ f\left(\sigma\left(W_{2n}\delta\left(W_{1n}s_{n-1}\right)\right)-d_{th}\right) \end{cases} \tag{10}$$

Here δ *and* σ denote the ReLU and sigmoid functions respectively, $W_{1n} \in \mathbb{R}^{T_r \times T}$ and $W_{2n} \in \mathbb{R}^{T \times T_r}$ are trainable weight matrices, r controls model complexity, $f(\cdot)$ is the Heaviside step function, and d_{th} is the TA threshold. The final input at timestep t is achieved by applying the TA score to the input tensor as follows,

$$\tilde{X}_{t,n-1} = d_t^{n-1} \cdot X_{t,n-1} \tag{11}$$

Its amplify frames related to significant charging volatility or renewable generation variations. Then, the dynamics of the TA-LIF layer's membrane potential are represented as follows,

$$U_{t,n} = H_{t-1,n} + g\left(W_n, \tilde{X}_{t,n-1}\right) \tag{12}$$

Where $H_{t-1,n}$ represents historical membrane potential and $g(\cdot)$ is the weighted synaptic transformation of the attended input. As a result of combining nonlinear mapping from the RBF kernels, spiking dynamic and frame level refinement using TA, ARBS-Net is able to learn nonlinearities, temporal dependencies and salient patterns related to EV charging demand and renewable generation integration. The ABRS-Net structure as displays in Fig. 3. This hybrid architecture serves as a robust and biologically-inspired computational framework that leads to improvement in forecasting accuracy, robustness against volatility and increased interpretability within renewable-based EVCS.

IV. RESULT AND DISCUSSION

The developed work ABRS-Net to forecast energy consumption in EVCS. In this work, python software used to evaluate the model's performance through MSE. RMSE, MAE and R^2 *score* verifying its reliability in predicting charging demand. The EV Charging Grid Optimization Dataset acquired from Kaggle that has 1000 records containing relevant operational and infrastructure parameters of EVCS. The dataset includes station ID, station location, EV station charging type, number of chargers, voltage, current, power consumed, power loss, voltage variation, and EV identifiers. These parameters produce information on the technical and operational characteristics of the EV charging infrastructure and are useful for analyzing grid performance, charging efficiency, and energy utilization. The dataset is also useful for modeling and optimization as it contains variability for the various electrical parameters such as voltage, current, and power consumption. It also includes power loss and voltage variations to determine the reliability and stability of the grid based on variable charge demand. The data is divided into training and testing data, with 80% of the data as training data, and 20% of the data as the testing and validating data. This dataset has structured numerical and categorical data making it useful for DL studies to improve EVCS efficiency and grid stability.

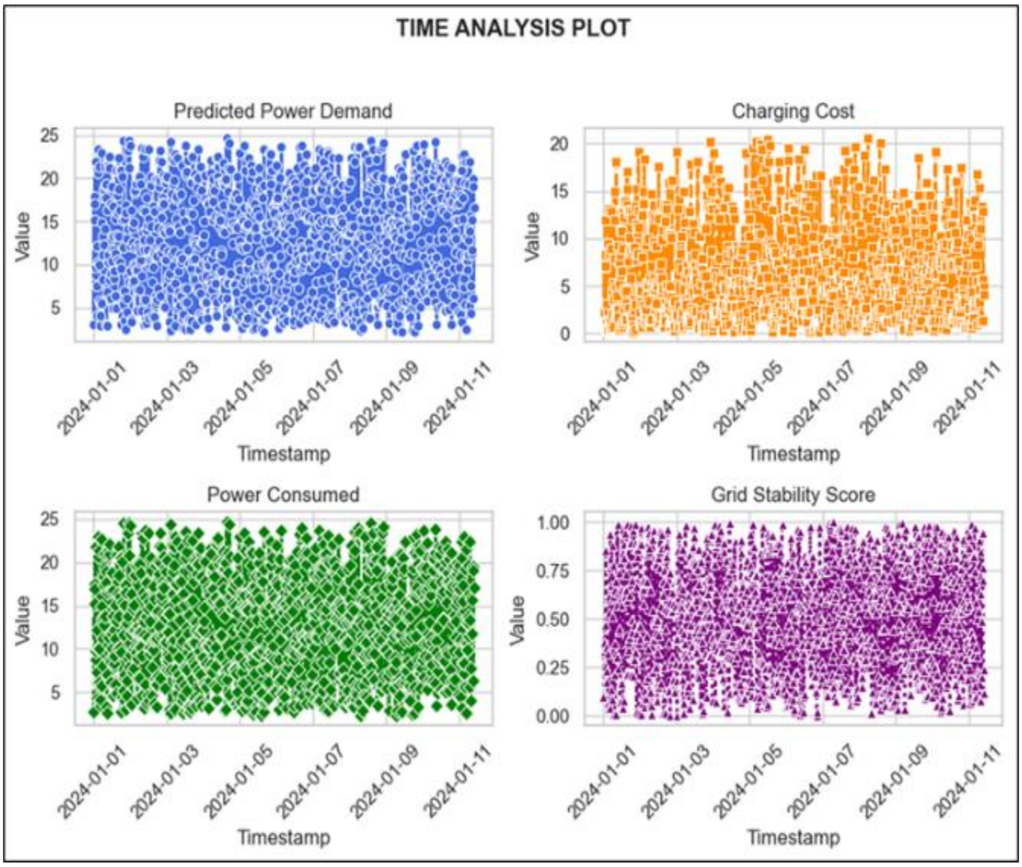

Fig. 4. Time series analysis of EV charging parameters.

Fig. 4 displays time-series analysis of smart grid-integrated EV charging parameter. It presents four elements is evaluated from 2024-01-01 to 2024-01-11. Predicted Power Demand: estimates the required level of load across each time stamp and Charging Cost shows the changing costs associated with charging over time. Power Consumed is the actual energy from the grid when charging any EVs, and Grid Stability Score indicates the grid's strength and balance are sustained under different load conditions.

Henceforth, understanding the interconnections and relationships between EV charging demands, price volatility, energy consumption, and grid stability will aid in effectively allocating energy in a smart grid-connected world.

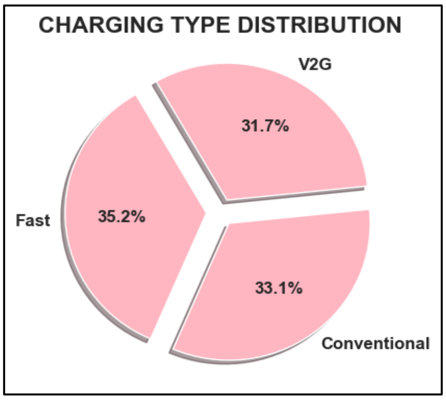

Fig. 5. Distribution pf charging types in the dataset.

Fig. 5 shows distribution of charging types in the dataset delivers the percentage of fast charging has 35.2%, conventional charging has 33.1%, and Vehicle-to-Grid (V2G) charging has 31.7%. the distribution charging types highlights a balanced representation of charging modes allowing for a comparative evaluation of each charging type in terms of energy demand and grid performance.

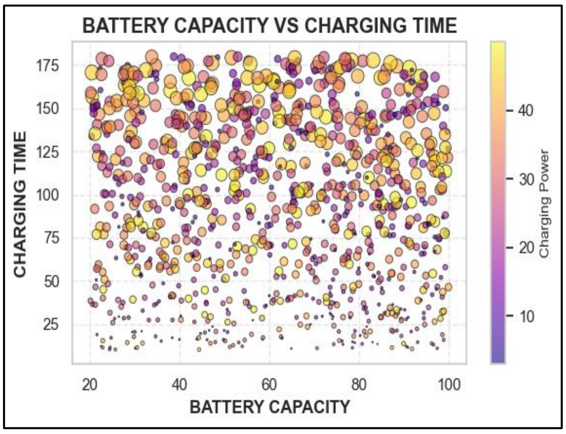

Fig. 6. Battery capacity vs charging time.

Fig. 6 shows the relationship between battery capacity and charging time for EVs, with the bubble size and colour indicate charging power. It illustrates as battery capacity increases charging times also tend to widely difference, due to the varying levels of charging power across the vehicles. It highlights the interaction between battery size, charging time, and charging power which is crucial connection for optimizing charging strategies and grid management.

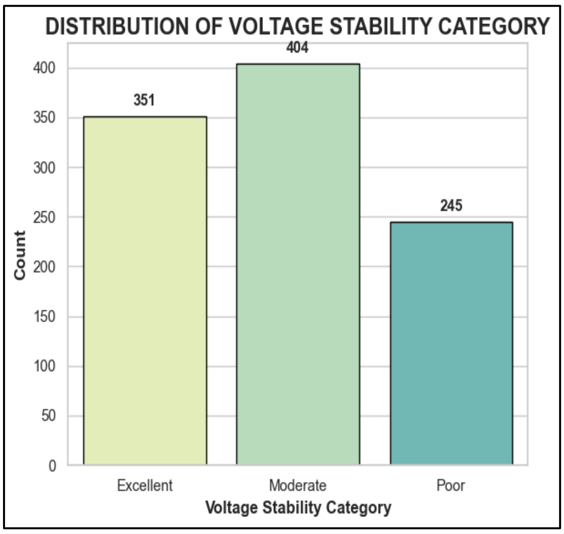

Fig. 7. Distribution of voltage stability category.

Fig. 7 represents distribution of voltage stability categories in the smart grid system, which shows the number of categories classified as Excellent (351), Moderate (404), and Poor (245). The results suggest that most cases are moderate stability, substantial number of cases with excellent voltage, while relatively few are categorized as poor stability, which demonstrates the variability of stability conditions with the integration of EVs.

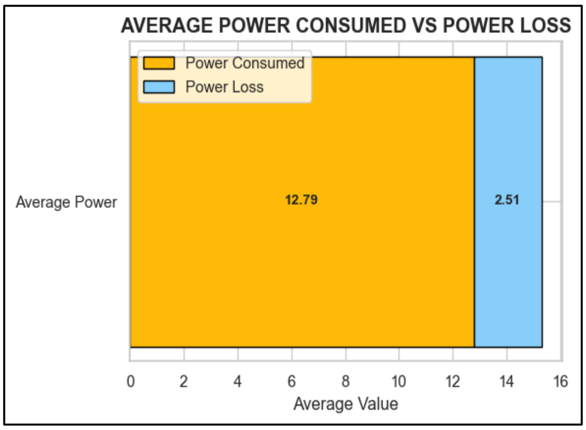

Fig. 8. Average Power consumed vs power loss.

Fig. 8 depicts Average power consumption and power loss illustrates that the system reports average power consumption of 12.79 units versus power loss of 2.51 units. This shows that a significant portion of the supplied energy is successfully utilized, with only a minor amount energy as losses. The relatively minimal loss range demonstrates the system's efficacy in handling EV charging and grid operation.

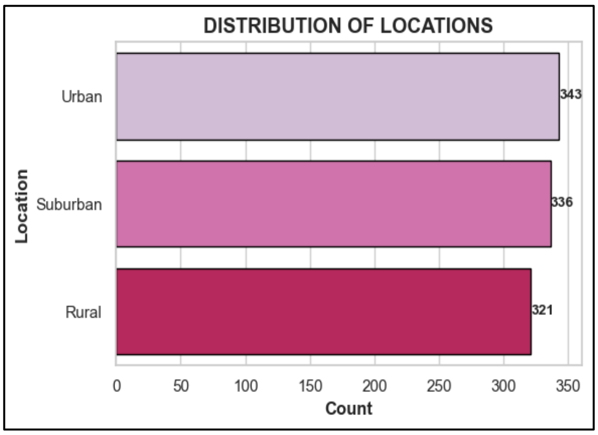

Fig. 9. Distribution of locations.

Fig. 9 depicts the distribution of CS, comparing their presence in urban (343), suburban (336), and rural (321) areas. The results show a rather equal deployment across regions, with urban areas having a slightly larger concentration. This balanced distribution promotes greater accessibility and ensures that EV adoption is unhindered to specific regions.

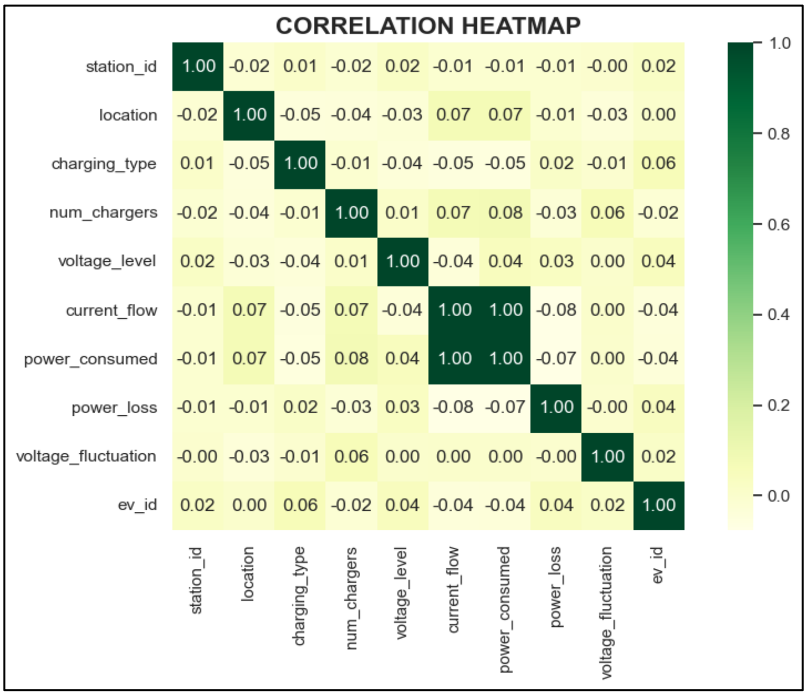

Fig. 10. Correlation heatmap of dataset features.

The heatmap in the Fig. 10 depicts the interrelationships between features including location, charging type, number of chargers, voltage level, current flow, power consumption, power loss, and voltage variations. Furthermore, the correlation coefficients between most features are low, demonstrating that non-electrical features remain linearly dependent on grid-related variables. The relationship between current flow and power consumption showed the largest positive association, which is probably due to their direct impact on the charging process and overall energy demand.

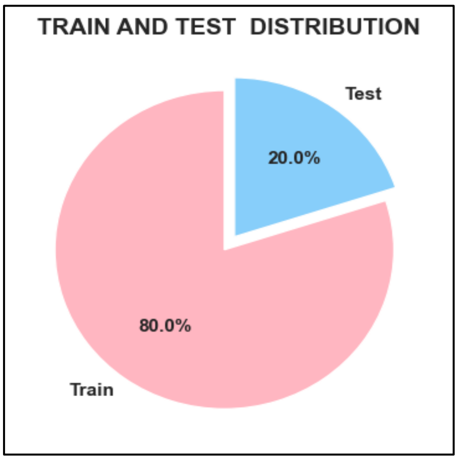

Fig. 12. Train and Test Distribution.

Fig. 12 displays data splitting technique used for developing models, with 80% of the dataset allocated for training and 20% for testing. The splitting process delivers sufficient information for learning while also preserving a strong assessment dataset. The distribution improves model generalization and delivers an accurate evaluation of performance.

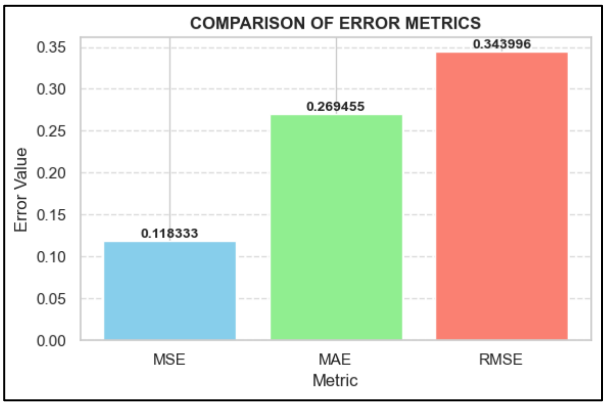

Fig. 13. Comparison of error metrics.

Fig. 13 illustrates an assessment of error metrics including the MSE, MAE, and RMSE, to evaluate the proposed model predictive accuracy. The MSE value of 0.1183 indicates better generalization properties, the MAE is 0.2694, which signifies the average absolute difference between predicted value and actual value and the RMSE is 0.3439, it’s more sensitive to deviation. Thus, the comparative assessment indicates that the model persists in minimizing error across a variety of performance metrics, demonstrating its dependability and accuracy.

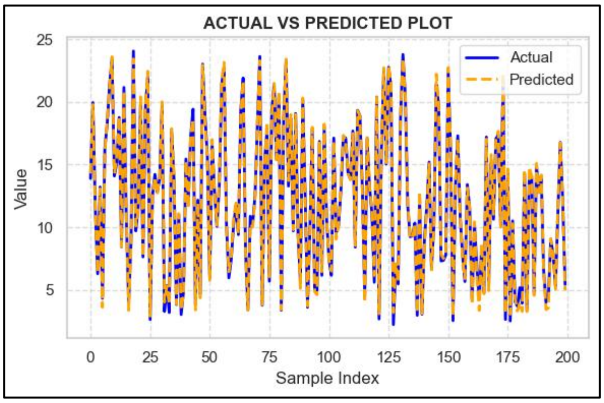

Fig. 14. Actual vs. predicted values plot.

Fig. 14 shows the model's performance by comparing actual dataset values to predicted results. The precise alignment of the actual and predicted curves demonstrates the model's stability for capturing dynamic variations in charging-related factors. The minimum difference between the two series shows that the proposed structure delivers accurate predictions for EV charging system analysis.

A. Comparison

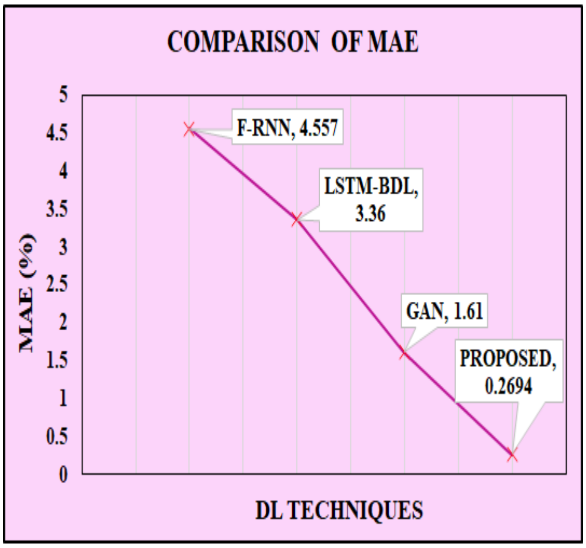

Fig. 15. Comparison of MAE.

Fig. 15 illustrates the MAE performance of various DL methods for energy consumption forecasting. The comparison involves F-RNN [19] has 4.557, LSTM-BDL [20] has 3.36, GAN [21] has 1.67 and the proposed ARBS-NET has 0.2694, its shows the proposed method achieves the lowest MAE, thus demonstrating superior prediction accuracy compared to other listed DL methods.

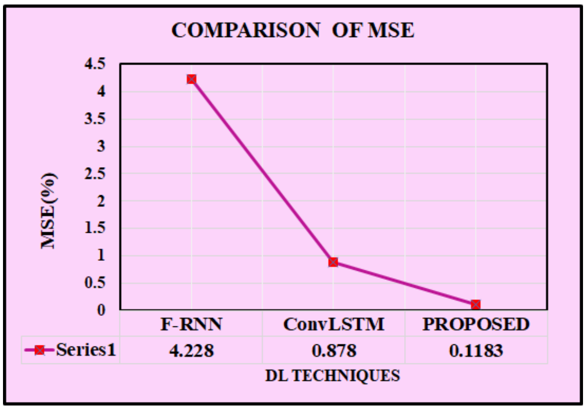

Fig. 16. Comparison of MSE.

Table 1

Comparison of RMSE

DL techniques	RMSE
F-RNN [19]	6.503
LSTM-BDL [20]	5.033
GAN [21]	4.83
ConvLSTM [22]	0.71
PROPOSED	0.3439

Fig. 16 illustrates the MSE value of various DL methods for energy consumption forecasting. The recorded MSE values are F-RNN [19] (4.228), ConvLSTM [22] (0.878) and the proposed ARBS-NET (0.1183), its shows that the proposed method is lowest MSE, highlighting its effectiveness in minimizing prediction error compared to other listed DL methods.

Table 1 presents RMSE values for various DL methods such as F-RNN, LSTM-BDL, GAN, ConvLSTM and proposed model. Among these techniques, proposed method achieves lowest RMSE, ensuring its superior predictive performance and robustness. Lower RMSE, MAE, and MSE values indicates that the model is more accurate and reliable. Reducing error rates illustrate the model's ability to accurately reflect actual energy usage patterns. This contains exact forecasting, facilitating the efficient operation, planning, and energy management of EVCS.

V. CONCLUSION

The proposed ABRS-Net based system effectively tackle the difficulty of predicting energy consumption in smart grid integrated EVCS. By combining RBF, SNN and attention mechanism, the model captures the temporal pattern and non-linear behaviour of EV charging demand. The extensive data preprocessing, feature engineering and EDA stages effectively achieves high quality inputs, improving model dependability and interpretability. From the python software, the proposed ARS-Net outperform traditional DL methods in terms of MSE of 0.1183, MAE of 0.2694, RMSE of 0.3439 and R^2 score of 0.99. The proposed system aids in pro-active energy distribution and efficient load balancing, as well as grid stability, therefore allowing for sustainable RE integration and facilitating optimal performance of EV charging infrastructure. Furthermore, this work illustrates the intelligent forecasting via ARBS-net enhance energy management methods, decrease operational losses, and contribute to a reliable, globally resilient, efficient EV charging systems in future smart grids.

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