International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

A PSO-ANN Hybrid Model for Electric Vehicle Charging Demand Forecasting for EV Supply Chain

Pavan Vishwakarma[1], Prof. Manish Soni[2]
Department of Mechanical Engineering[1,2]
MIT, Ujjain, India.[1,2]

ABSTRACT: With the high frequency roll out of electric vehicles, simultaneous charging may pose a challenge in the near future, especially in peak hours. Hence it is mandatory to analyze previous data pertaining to charging demand for electric vehicles to meet the charging and infrastructure demands in the future. This will allow both the utility providers as well as the consumers to plan for peak charging times and associated congestion at EV charging stations. Several researchers have explored data driven machine learning models to predict EV charging demands as machine learning models can analyze complex patterns and relationships within the data to generate accurate predictions. This paper presents a Particle Swarm Optimization (PSO)-Neural network model for EV charging demand prediction. Contrary to conventional neural network models, the PSO is used to adaptively update the network weights. The results clearly indicate that the proposed approach outperforms existing baseline approaches in terms of prediction MAPE.

Keywords: Electric Vehicles, EV Charging Demand, Demand Forecasting, Particle Swarm Optimization (PSO), Deep Neural Networks.

I. Introduction

The supply-demand dynamics in automobile production is witnessing a paradigm shift with the rapid influx and phase in of electric vehicles, not only in developed countries but also in developing countries. Few areas in the world of clean energy are as dynamic as the electric car market [1]. Recent years have seen exponential growth in sales together with improved range, wider model availability and increased performance. Electric vehicles are the key technology to de-carbonise road transport, a sector that accounts for over 15% of global energy-related emissions. Recent years have seen exponential growth in the sale of electric vehicles together with improved range, wider model availability and increased performance. Passenger electric cars are surging in popularity – we estimate that 18% of new cars sold in 2023 will be electric. If the growth experienced in the past two years is sustained, CO_2 emissions from cars can by 2030 be put on a pathway aligned with the Net Zero Emissions by 2050 (NZE) Scenario. However, electric vehicles are not yet a global phenomenon. Sales in developing and emerging economies have been slow due to the relatively high purchase price of an electric vehicle and a lack of charging infrastructure availability. Still an exponential growth in the rise in sales of electric vehicles worldwide can be seen [2].

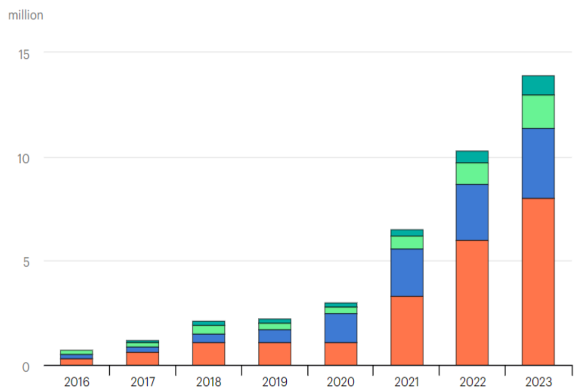

Fig.1 Rise in Electric Vehicle Sales (Source: https://www.iea.org/energy-system/transport/electric-vehicles)

Figure 1 depicts the rise in the sales of EVs globally. With this, a challenge in terms of EV charging would be imminent.

One of the primary challenges in the future of electric vehicle (EV) charging lies in the expansion of charging infrastructure [3]. As more individuals transition to EVs, the demand for charging stations will increase significantly. This necessitates substantial investments in installing charging points in public spaces, residential areas, and along highways to ensure convenient access for EV owners [4]. The cost and logistics involved in this expansion pose a significant challenge, especially in less populated or rural areas where the density of EVs might be lower. The charging station requirement for increasing EV sales is a challenge to be addressed as several countries lack the needed optimal charging infrastructure [5].

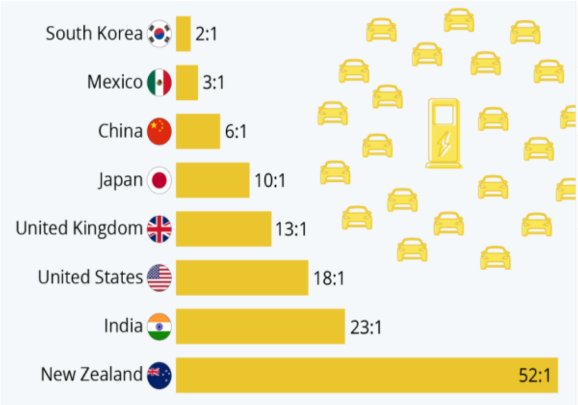

Fig.2 Ratio of EVs to public charging points across different countries (Source: https://www.statista.com/chart/26325/ratio-electric-vehicles-to-public-charging-points/)

Figure 2 depicts the ratio of number of EVs rolled out to the number of charging stations across various countries [6].

II. Challenges Associated with EV Charging

Some of the major challenges associated with the EV charging infrastructure are presented next:

Grid Capacity and Stability: The widespread adoption of EVs places additional strain on the electricity grid. Charging numerous vehicles simultaneously, particularly during peak hours, could overload local grids and lead to stability issues . Integrating smart charging solutions and advanced grid management technologies becomes crucial to distribute the load evenly and optimize charging schedules. Additionally, upgrading grid infrastructure to accommodate higher demand and incorporating renewable energy sources to power EV charging can help mitigate these challenges [7].

Charging Speed and Standards: Another challenge lies in improving charging speeds and establishing universal standards. While current EV charging technology has made significant advancements, fast-charging solutions are still not as widespread or as quick as refueling a conventional vehicle. Standardization of charging connectors and protocols is essential to ensure interoperability and convenience for EV users, regardless of their vehicle make or model. Moreover, advancements in battery technology and charging infrastructure are necessary to reduce charging times and enhance the overall EV ownership experience [8].

Range Anxiety: Range anxiety, the fear of running out of battery charge before reaching a destination, remains a concern for many prospective EV buyers. Despite improvements in battery technology, achieving longer driving ranges on a single charge is crucial to alleviate this anxiety and increase consumer confidence in EVs. Enhancing battery energy density, optimizing vehicle efficiency, and expanding the availability of fast-charging stations along major travel routes are essential strategies to address this challenge. Additionally, educating consumers about the practicality and benefits of EVs can help dispel misconceptions and alleviate range anxiety [9].

Cost and Affordability: The upfront cost of purchasing an EV, as well as the cost of installing home charging infrastructure, can be prohibitive for some consumers. While the total cost of ownership for EVs is often lower due to lower fuel and maintenance expenses, the initial investment remains a barrier for many potential buyers. Government incentives, subsidies, and tax breaks can help offset these costs and encourage more widespread adoption of EVs. Additionally, advancements in battery technology and economies of scale in manufacturing are expected to drive down the cost of EVs in the future, making them more accessible to a broader range of consumers [10].

Thus, the transition to electric vehicles offers numerous environmental and economic benefits, several challenges must be addressed to facilitate their widespread adoption [11]. These challenges include expanding charging infrastructure, ensuring grid capacity and stability, improving charging speed and standards, alleviating range anxiety, and addressing cost and affordability concerns. Collaboration between governments, industry stakeholders, and technology innovators will be crucial in overcoming these challenges and accelerating the transition to a sustainable transportation ecosystem powered by electric vehicles [12].

III. EV Charging Demand Prediction.

The need for EV charging demand prediction is paramount for optimizing infrastructure investment, managing grid stability, enhancing user experience, promoting energy efficiency, and supporting policy and planning initiatives. By leveraging predictive analytics and data-driven insights, stakeholders can address the challenges and opportunities associated with the widespread adoption of electric vehicles, ultimately advancing towards a more sustainable and resilient transportation ecosystem [13].
Accurate EV charging demand prediction is crucial for optimizing infrastructure investment. By forecasting future demand, stakeholders can strategically plan the placement and capacity of charging stations to meet the needs of EV owners efficiently. This helps prevent overbuilding or underbuilding of charging infrastructure, ensuring that resources are allocated effectively and cost-effectively. Additionally, it allows for the identification of high-demand areas where additional charging stations may be required to alleviate congestion and enhance accessibility. Moreover, EV charging demand prediction plays a vital role in grid management and stability. By anticipating when and where charging will occur, grid operators can better manage electricity distribution, prevent overloads, and minimize disruptions. This is particularly important during peak periods when a surge in charging activity could strain the grid and lead to voltage fluctuations or blackouts. Accurate predictions enable grid operators to implement demand response strategies, such as incentivizing off-peak charging or adjusting electricity prices dynamically, to balance supply and demand effectively [14].
Predicting EV charging demand contributes to enhancing the overall user experience for EV owners. By providing real-time information about charging availability and wait times, drivers can plan their trips more efficiently and avoid unnecessary delays. This improves convenience and satisfaction, encouraging more individuals to switch to electric vehicles. Additionally, predictive algorithms can suggest optimal charging locations based on factors such as proximity, availability, and charging speed, further streamlining the charging experience for users [15]. Effective EV charging demand prediction facilitates energy management and efficiency. By aligning charging schedules with periods of low electricity demand or high renewable energy generation, stakeholders can maximize the utilization of clean energy sources and minimize reliance on fossil fuels. This not only reduces carbon emissions associated with EV charging but also contributes to overall grid decarbonization efforts. Moreover, predictive analytics can help identify opportunities for load balancing and demand-side management, enabling more efficient use of resources and infrastructure [16].
Additionally, EV charging demand prediction supports policy development and urban planning initiatives aimed at promoting sustainable transportation. By providing insights into future charging patterns and trends, policymakers can design incentive programs, zoning regulations, and transportation policies that encourage EV adoption and support the deployment of charging infrastructure [17]. Furthermore, accurate demand forecasts inform long-term planning efforts, such as urban development projects and transportation infrastructure investments, ensuring that cities are equipped to accommodate the growing population of EVs and address associated challenges effectively [18]. Machine learning models are indispensable from EV charging demand prediction due to its ability to handle the complexity, dynamics, scalability, flexibility, feature engineering, model complexity, real-time decision-making, and adaptability to uncertainty inherent in charging data. By leveraging machine learning algorithms, stakeholders can develop accurate, scalable, and adaptive prediction models that support effective management of charging infrastructure, grid integration, and sustainable transportation planning in the era of electric mobility [19].

IV. Proposed Methodology

The method developed in this work combines the particle swarm optimization (PSO) and Artificial Neural Networks (ANN) for EV charging demand forecasting for the EV charging supply chain. The proposed methodology presents an amalgamation of the following two approaches:

1. Particle Swarm Optimization (PSO)
2. Artificial Neural Networks (ANN)

Each of the approaches are explained next [20].

The PSO:
The PSO algorithm is an evolutionary computing technique, modeled after the social behavior of a flock of birds. In the context of PSO, a swarm refers to a number of potential solutions to the optimization problem, where each potential solution is referred to as a particle. The aim of the PSO is to find the particle

position that results in the best evaluation of a given fitness function. In the initialization process of PSO, each particle is given initial parameters randomly and is 'flown' through the multi-dimensional search space. During each generation, each particle uses the information about its previous best individual position and global best position to maximize the probability of moving towards a better solution space that will result in a better fitness. When a fitness better than the individual best fitness is found, it will be used to replace the individual best fitness and update its candidate solution according to the following equations [21]:

$$\mathbf{v_{id}(t) = w \times v_{id}(t-1) + c_1 Ø_1(p_{id}\text{-}x_{id}(t\text{-}1)) + c_2 Ø_2(p_{gd}\text{-}x_{id}(t\text{-}1))} \quad \mathbf{(1)}$$

$$\mathbf{x_{id}(t) = x_{id}(t-1) + v_{id}(t)} \quad \mathbf{(2)}$$

Table. 1 List of variables used in PSO equations.

v	The particle velocity
x	The particle position
t	Time
c_1, c_2	Learning factors
Φ_1, Φ_2	Random numbers between 0 and 1
p_{id}	Particle's best position
p_{gd}	Global best position
w	Inertia weight

The PSO is used to adaptively update the weights of the neural network based on the minimization of the performance function.

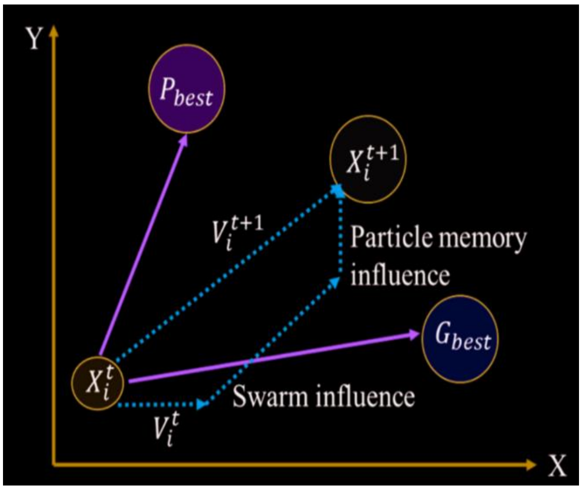

Fig.3 Visualization of PSO

While, traditional optimization focuses on a single objective function to be minimized or maximized. However, many real-world problems involve multiple conflicting objectives that cannot be optimized simultaneously without making trade-offs. Multi-objective optimization aims to find a set of solutions that represent the best trade-offs among these conflicting objectives, known as the Pareto front. PSO can be adapted to handle multi-objective optimization by incorporating mechanisms to guide the search towards discovering Pareto-optimal solutions efficiently. Several adaptations have been proposed to extend PSO for multi-objective optimization. One common approach is to modify the fitness evaluation mechanism to assess the quality of solutions based on their dominance relationship with respect to other solutions. This involves comparing solutions in terms of Pareto dominance, where one solution is considered better if it improves at least one objective without worsening any other. Additionally, strategies for maintaining diversity in the population are crucial to ensure thorough exploration of the Pareto front.

The ANN Model:

The ANN model is one of the most powerful regression models which has been used multiple times for traffic speed forecasting [22]. While,

The mathematical model of the ANN is depicted in figure 3.

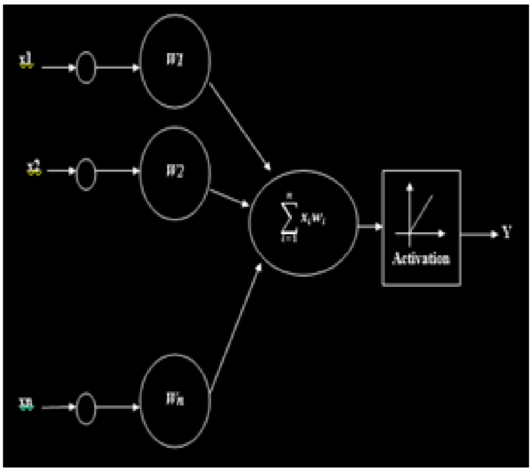

Fig.4 Mathematical Model of Neural Network

The output of the neural network is given by:

$$y = f(\sum_{i=1}^{n} \mathbf{XiWi} + \Theta) \quad (4)$$

Where,
Xi represents the signals arriving through various paths,
Wi represents the weight corresponding to the various paths and
Θ is the bias.

In this approach, the back propagation based neural network model has been used with weight updating mechanism through the PSO [23].

The training rule for the approach is given by the BFGS algo:

$$w_{i+1} = w_i - \mu[H]^{-1}\frac{\partial e}{\partial w} \quad (5)$$

Here,
w represents the weights.
i represents the iterations.
μ represents the learning rate.
H represents the Hessian Matrix.
e represents the forecasting error.

The training is stopped based on the mean square error or mse given by:

$$mse = \frac{\sum_{i=1}^{n} e_i^2}{n} \quad (6)$$

The final computation of the performance metric is the mean absolute percentage error given by:

$$MAPE = \frac{100}{M}\sum_{i=1}^{N}\frac{E-E_i|}{i} \quad (7)$$

The accuracy of prediction is computed as:

$$Ac = 100 - \frac{100}{M}\sum_{i=1}^{N}\frac{E-E_i|}{i}\ \% \quad (8)$$

Here,
n is the number of errors
i is the iteration number
E is the actual value
E_i is the predicted value

IV. RESULTS AND DISCUSSIONS

The proposed model is implemented on MATLAB due to the availability of in built mathematical functions for EV charging demand. The data parameters used are:

1. Day
2. Start Time
3. End Time
4. Charging Time
5. Total Charging Energy Consumption (kWh).

While other parameters such as ambient temperature, weather conditions etc. may also be taken into account, but due to the complexity in collecting data specific to a geographical location is tedious, the most important parameters which are applicable to global EV scenarios are considered.

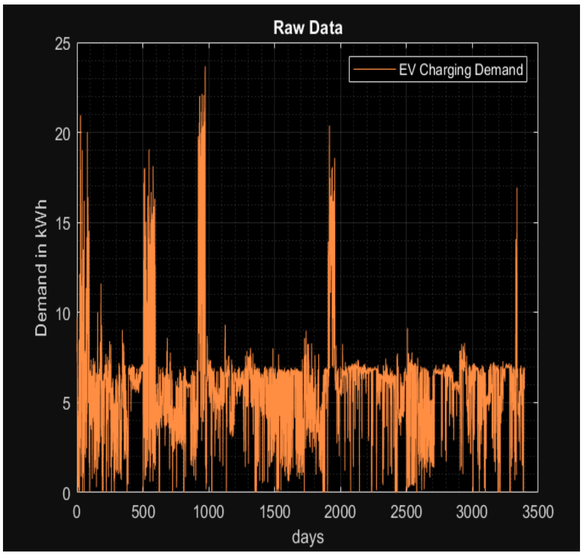

Fig.5. Raw Data

Figure 5 depicts the raw demand in kWh as a function of time (days).

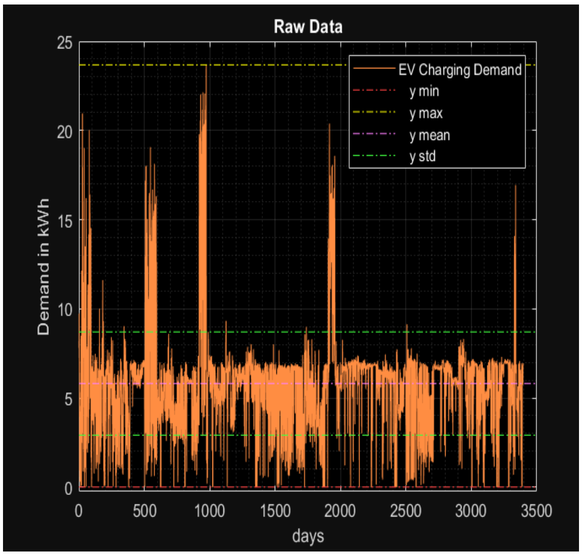

Fig.6 Statistical Data Parameters.

Figure 6 depicts the statistical markers of the raw data. The statistical parameters are presented in table 1.

Table.1 Statistical Parameters of Data

S.No.	Parameter	Value
1	Minimum	0
2	Maximum	23.68
3	Mean	5.81
4	Standard Deviation	2.893

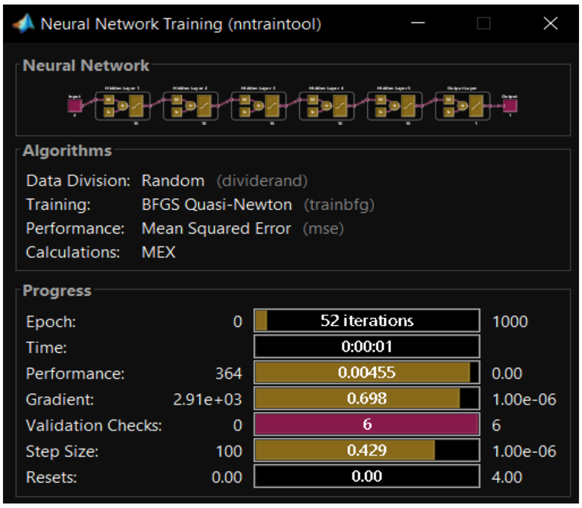

Fig.7 Model Design Parameters

The details of the training are depicted in the figure above, which clearly shows the designed neural network, the training function, the data division and the iterations.

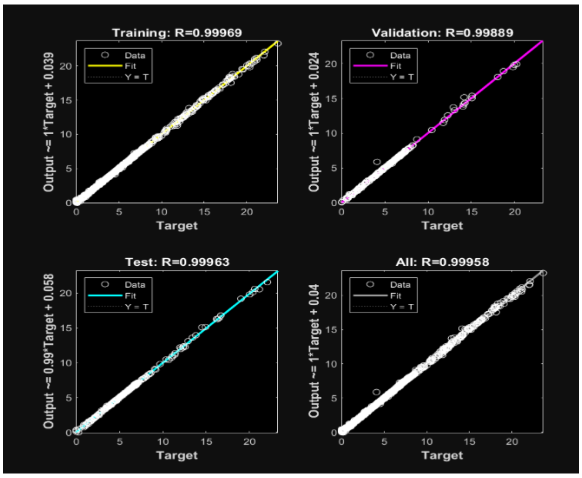

Fig.8 Regression

The figure above depicts the regression obtained in the proposed approach which is a sort of similarity among two random variables. The maximum allowable regression is unity depicting complete similarity.

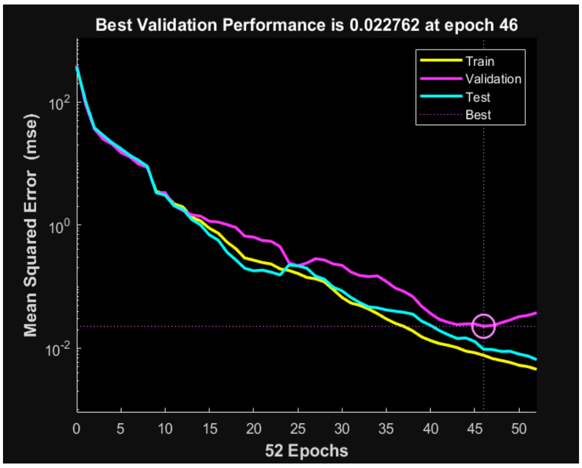

Fig.9 Performance Function

The performance function that decides the culmination of training is the mean squared error or mse.

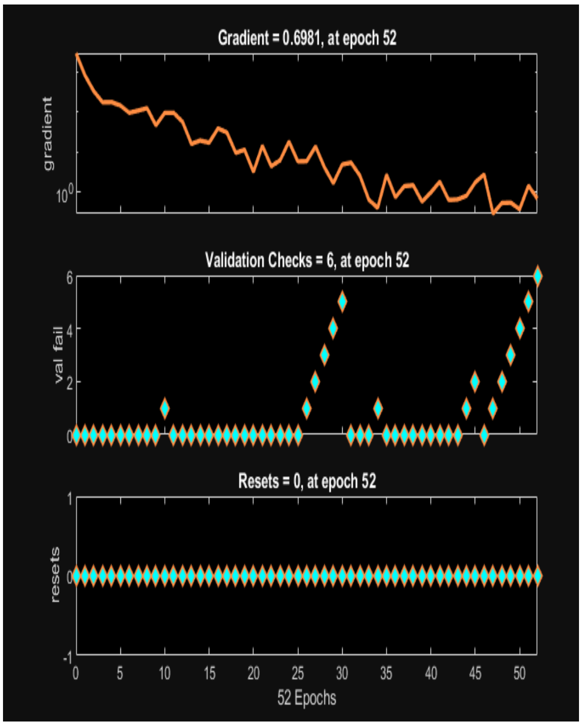

Fig.10 Training States

The training state parameters such as gradient, validations checks and resets are depicted in the figure above.

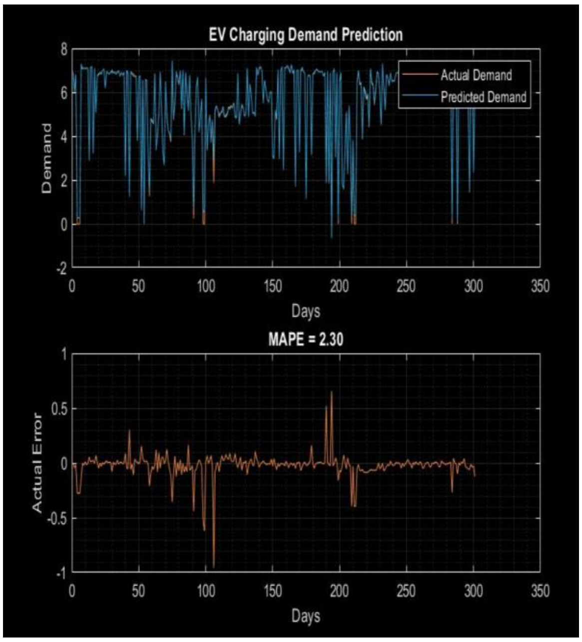

Fig.11 Actual and Modelled values

The above figure shows the MAPE of the proposed system which comes out to be 2.30%.

Table. 2 Summary of Results

S.No	PARAMETER	VALUE
1.	Samples	3395
2.	Proposed Model	PSO-ANN
3.	Iterations	52
4.	Regression	0.99958
5.	MAPE (Proposed Work)	2.30%
6.	MAPE (Previous Work)	5.9%
7.	Approach (Previous Work, [1])	Multi Task Learning (MTL)
8.	MAPE (Previous Work [6]	6.83 (LSTM)

The summary of results is presented in table 2. The performance of the proposed approach (MAPE of 2.3%) is found better compared to previously existing technique [1] which attains a MAPE of 5.9% using the multi task learning model, and also other benchmark models such as the LSTM [6].

V. CONCLUSION

It can be concluded that it is critically important to predict EV demand accurately especially in peak hours to avoid congestion and maintain grid stability. As the data is extremely sporadic in nature, pattern recognition has been explored through machine learning models. Machine learning facilitates advanced feature engineering and model complexity, enabling the incorporation of diverse input variables and the development of sophisticated prediction models. Additionally, machine learning algorithms, such as neural networks and ensemble methods, can capture complex relationships between features and output variables, resulting in more nuanced and accurate predictions.

The proposed work is a combination of the ANN-PSO algorithm and attains an MAPE of only 2.30% and outperforms previously existing approach (multi task learning or MTL) in terms of forecasting accuracy and MAPE, which is 5.9%. Thus, the model can be utilized to accurately forecast EV charging demand over both short and long periods of time with accuracy.

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