

# Optimizing Charging Infrastructure for Electric Autonomous Vehicles in Smart Manufacturing using Hyperparameter-Tuned Artificial Neural Networks

Yu Liu<sup>1,2\*</sup>, Lina Zhang<sup>2</sup>, YanHong Fu<sup>1,2</sup>

<sup>1</sup>Department of Mechanical Engineering Hebei University of Water Resources and Electric Engineering, CangZhou HeBei, 061001, China

<sup>2</sup>Hebei Industrial Manipulator Control and Reliability Technology Innovation Center, CangZhou HeBei, 061001, China  
E-mail: liuyu@hbwe.edu.cn

\*Corresponding author

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*An optimised charging infrastructure is required for the integration of electric autonomous vehicles (A-EVs) into smart industrial systems in order to improve operational efficiency, minimise downtime, and guarantee sustainable energy management. An AI-driven framework for the planned and strategic placement of A-EV charging stations in industrial settings is presented in this paper. The platform uses predictive analytics, real-time IoT data, and machine learning models to dynamically modify charging station allocation according to industrial workflow requirements, grid stability, and car demand. To guarantee the best possible positioning and use of charging stations, the suggested methodology combines optimisation algorithms, reinforcement learning-based scheduling, and spatiotemporal data analysis. This study maximizes charging infrastructure to electric autonomous vehicles with the A-EV Grid Management Dataset through the use of KNN-based imputation, Z-score outliers, Min-Max scaling, SMOTE balancing, and feature selection with RFE and Lasso. An ANN model is hyperparameter-tuned and stratified 5-fold cross-validation is used to evaluate the model. The experimental results indicate that the proposed ANN is more accurate and has 94.5% accuracy, AUC-ROC as 95.2%, and 5.3% as MAE, which is higher than RF, SVM, KNN, and Decision Tree baselines. The results indicate that the model is efficient in smart manufacturing systems to support the real time charging decisions. The results of comparative performance evaluations utilising Random Forest, SVM, KNN, Decision Tree, and a hyperparameter-tuned Artificial Neural Network (ANN) show that the ANN model predicts optimal charging decisions with greater accuracy (94.5%) and precision (93.7%). Compared to traditional static deployment options, the results demonstrate a significant improvement in energy efficiency, less congestion at charging stations, and cheaper operating costs. This study emphasises how crucial AI-enhanced infrastructure planning is for smart manufacturing's autonomous EV fleets. To better optimise A-EV charging networks, future studies may investigate blockchain for decentralised energy management, multi-agent reinforcement learning for adaptive station allocation, and 5G-enabled V2X communication. The results further the development of highly automated, intelligent, and energy-efficient industrial transportation systems.*

*Povzetek: Predstavljen je okvir za dinamično optimizacijo polnilne infrastrukture avtonomnih električnih vozil v pametni industriji, kjer s predobdelavo podatkov in hiperparametrično uglašnim nevronskim omrežjem doseže boljše rezultate.*

## 1 Introduction

In the age of digital revolution, breakthroughs in technology, particularly in the area of artificial intelligence (AI), have upended a number of global enterprises. Thanks to the application of cutting-edge information technology,

AI has been extensively embraced and has had a substantial influence in all industries. As an environmentally benign form of transportation, electric vehicles (EVs) have also attracted a lot of interest lately and are being promoted by several nations[1]. Because they produce no emissions, EVs are good for the

environment. They also feature smooth and user-friendly controls and are less expensive than conventional petrol engines[2]. EVs are a good option for people who value environmental sustainability because they don't emit any pollutants. Additionally, driving an EV is less expensive than utilising a traditional petrol engine. Additionally, EVs offer a pleasant driving experience and are simple to use[3].

As of 2020, there were more than 7.2 million electric vehicles (EVs) on the road, according to the International Energy Agency (IEA), which reports that the EV industry has been expanding quickly worldwide. Furthermore, the IEA projects that the EV industry will keep expanding, with over 250 million EVs in use globally by 2030[4]. Additionally, it is anticipated that the EV industry would grow substantially. The worldwide EV industry is expected to grow from its 2020 valuation of over USD 140 billion to over USD 800 billion by 2026, according to Statista. According to a Deloitte report, government incentives, more stringent pollution laws, and technological developments are projected to fuel the EV market's continued growth[5]. The adoption of EVs is expected to continue to rise due to the growing availability of EV models, charging infrastructure, and government backing. Because of its many benefits, including economic effectiveness, environmental preservation, smart city traffic improvement, and increased customer happiness, EV adoption is thus expanding quickly on a global scale[6].

EVs are becoming more and more well-liked as an environmentally responsible and sustainable mode of transportation. The interdependence of the energy market and EV charging infrastructure is reflected in the connection of the transportation and energy markets. On the other side, power-aware operations manage power limitations to maximise the utilisation of electrical resources and offer effective EV charging services. Power-aware operations in the context of charging infrastructure make sure that charging stations provide dependable charging services while optimising the use of electrical resources. To effectively manage the charging process, this entails taking into account elements like power capacity, load balance, and dynamic power scheduling[7].

An autonomous car is a vehicle capable of sensing its environment and operating without human involvement. A human passenger is not required to take control of the vehicle at any time, nor is a human passenger required to be present in the vehicle at all. An autonomous car can go anywhere a traditional car goes and do everything that an experienced human driver does.

According to Navigant Research, 85 million autonomous vehicles are anticipated to be marketed globally each year by 2035. But in addition to drastically changing transportation, the self-driving vehicle will also create a completely new image of city life. It will be necessary to reconsider the infrastructure on which cities are

constructed. In addition to requiring electricity, autonomous cars have the ability to serve as a mobile power source for other networked devices. Wireless power is an essential component of the ecology of the smart city of the future. For those who do not wish to own a car for personal or economical reasons, autonomous cars will provide a new form of personal transportation. They will also provide the enormous advantage of mobility for those who are unable to operate a vehicle, such as children, the elderly, and individuals with disabilities. There will be more chances for people to be active and mobile in their communities. Everyone will be a passenger when there is no driver, giving them the opportunity to work and be productive throughout the travel or simply relax and refuel. Additionally, the entire layout of the vehicle could be redesigned. Lounge chairs that face inward may be a feature of the future automobile. The car will become more than just a means of transportation; it will be an extension of the house or workplace, bringing in additional activities and hours to the day. In addition to those advantages, smart technology will enable cars to automatically avoid road dangers, making streets safer and reducing accidents. By outlawing drunk driving, public safety could be improved. Since cars will go at the same speed at regular intervals, traffic congestion may lessen. Because cars would be able to drop off their passengers and then go off to park themselves, less time will be wasted looking for parking spaces. Parking lots and garages will take up less valuable real estate in city centres[8].



Figure 1: To optimize autonomous travel, add wireless charging

Personal transportation will undoubtedly be revolutionised by autonomous vehicles, but a crucial question has gone mostly unanswered: how will these vehicles be fuelled? Think of the irony of having self-driving electric vehicles (EVs) transport our children to school, our injured to medical appointments, and our elderly to the park, only to need someone to plug them in after the journey is over. There must be a more straightforward way. In the same way that it removes people from the driving equation, the

charging procedure of the future must remove people from the charging equation. Without ever plugging in, a car will autonomously recharge its battery when it needs to be charged by parking itself over a wireless charging pad. It's a risky move to replace the power plug, and it will take wireless technology that can effectively transfer a car's whole power requirements and is adaptable enough to work with a range of automobiles. Magnetic resonance is arguably the most promising technology. Actually, a lot of automakers are already moving quickly to start producing future electric cars. Among the many advantages of magnetic resonance are its high efficiency, adaptability in location, and capacity to transmit electricity through materials such as asphalt and concrete. Wireless charging stations can be placed on the ground, in a garage floor, or beneath a road thanks to magnetic resonance technology. There is no penalty for going wireless, and the most recent designs are remarkably efficient in moving electricity at the same levels as plugging in. Self-driving cars will just park and recharge their batteries. Vehicle transport can become another standard service, similar to the internet or the electric grid, without requiring human involvement to replenish batteries. Passengers can then concentrate on other issues, knowing that their cars will be available and ready when needed. Innovative businesses can collaborate with governments and infrastructure developers to establish citywide networks of wireless power sources integrated into the streets as the technology advances and volume lowers costs. Unmanned transporters will be able to increase driving range or lower the size and expense of the batteries needed to power the vehicles by using these integrated sources to wirelessly trickle-charge the vehicles while they are in motion. Increased adoption results from reduced costs, starting a positive feedback loop. There is an extensive analysis of the strategies for placing charging stations as well as their effects on the electrical system. The most up-to-date optimisation methods for determining the best places to put charging stations are discussed. The study examines the policies, procedures, and issues associated with the location of electric vehicle charging stations in China. What this study adds to the current literature on the topic of electric vehicle charging station placement is as follows:

The models used to determine the optimal locations for charging stations are categorised. By outlining the planning models, we may better understand the mathematical formulations and the outcomes of the simulations. We give a comparison of the planning models, highlighting their salient characteristics, benefits, and drawbacks. We propose that the planning models be suitable on an area-by-area basis. This document provides a high-level outline of the charging station's operations and how they are scheduled. Presenting the current business model, standards, norms, and regulations, this article provides a global perspective on charging infrastructure design.

### Research questions

1. Can a hyperparameter-tuned ANN outperform conventional ML models in optimizing A-EV charging decisions under dynamic grid conditions?
2. What is the most effective way to implement charging infrastructure in electric autonomous vehicles (EAVs) to make smart manufacturing systems more efficient and energy-oriented?
3. How much can the proposed hyperparameter-optimized ANN model be used to predict charging demand and station utilization better than traditional machine-learned algorithms, like RF, SVM, KNN, and Decision Trees?
4. Which operational, spatial and temporal factors are the most effective in determining where and when to locate EAV charging stations in smart manufacturing settings?
5. What effect does the optimized charging infrastructure have on the actual performance considerations, such as use of energy, money saved, grid load balancing, and vehicle availability?

## 2 Related works

Table: Related works

Ref.	Objectives	Methods	Dataset	Performance Metrics	Limitations
[9]	Evaluate benefits of integrating EVs into the power grid	Grid-EV interaction analysis; energy modeling	Grid operational data; EV charging behavior data	Accuracy with 88.4	Lacks real-time dynamic modeling; no ML-based optimization
[10]	Optimize energy supply for EV charging parks & hydrogen stations under risk-averse strategy	Stochastic optimization; risk-averse programming	Local energy system operational datasets	Cost reduction, reliability improvement (no numeric ML metrics)	High computational complexity; limited scenario generalization
[11]	Plan mobile energy hubs in complex urban networks	Robust optimization framework	Urban mobility network data, energy hub specs	Accuracy with highest value of 90.4 percent	Focuses on robustness, not predictive analytics;

					limited EV-specific analysis
[12]	Review modeling methods for planning EV charging infrastructure	Systematic literature review	100+ EV infrastructure planning studies	nil	No experimental validation; lacks quantitative comparison
[13]	Use ML to optimize EV charging operations	Machine Learning models (unspecified)	Real-time EV charging logs	Accuracy, RMSE (values not reported)	No architecture details; lacks interpretability analysis
[14]	Risk assessment of energy hubs with EV participation	Risk-aware optimization; peer-to-peer energy modeling	Industrial energy hub simulation data	Accuracy of 91.372	Assumes ideal EV participation; limited real-world testing
[15]	Optimize EV fleet charging for ride-hailing using DNN	Deep Neural Network (DNN); behavioral optimization	Large ride-hailing fleet charging logs	Improved charging efficiency (no exact values reported)	Requires large data volume; may overfit behavioral patterns
[16]	Study adoption of autonomous & electric vehicles in shared mobility	Econometric & simulation models	Mobility demand datasets, adoption surveys	Accuracy with 89.5 and precision as 88.0	Highly scenario-dependent; limited predictive accuracy info
[17]	Review EV driving range prediction models & influencing factors	Analytical modeling review; comparison of EV range predictors	Prior studies (100+ range modeling papers)	nil	No unified benchmark; limited reproducibility due to diverse datasets

The literature review briefly studies provider-centric approaches to EV infrastructure planning but fails to provide a specific critique and gap analysis of why they have failed. It does not explain the flaws of the earlier approaches in managing the dynamic charging demand, multi-factor optimization, and real-time decision making. Consequently, the justification of the implementation of a hybrid ANN-based optimization model is not well justifiable. It would be more effective to draw a clearer view on what previous models fail to deliver e.g. weak scalability, limited feature interaction, etc. to enhance the argument why the suggested ANN hybrid solution is innovative and obligatory.

The goal of these studies is to guarantee effective service delivery and reduce operating expenses. However, consumer preferences and the whole charging experience may be overlooked by charging provider-centric approaches. Our suggested approach seeks to close this gap by concurrently taking charging provider-centric and user-centric factors into account. We can optimise the planning process for charging infrastructure to benefit charging providers as well as electric vehicle users by adopting a comprehensive strategy. In addition to taking into consideration customer preferences like reducing trip distance and charging time, the tuned ANN technique also takes into account the overall system efficiency and the effective use of charging infrastructure resources. Our suggested strategy can offer a more thorough and equitable approach to charging infrastructure planning by combining both viewpoints. In addition to maximising charging station operations and efficiency, it guarantees that the requirements and preferences of electric vehicle customers are satisfied. This coordinated strategy helps create a network of charging infrastructure that is affordable, sustainable, and easy to use.

### 3 Methodology

The advantages of autonomous electric vehicles include:

- A-EVs' usage of AI-powered, next-generation battery technology reduces the greenhouse effect. These energy-efficient, battery-powered cars provide faster, cleaner transportation with the potential to lower greenhouse gas emissions overall.
- Safety: 94% of serious collisions have been attributed to human error. Theoretically, autonomous cars can eliminate human mistake in driving, potentially protecting other drivers, passengers, bikers, and pedestrians.
- Economics and Society: Human error can have serious consequences. According to a 2010 NHTSA research, car accidents have cost billions of dollars in damages, ranging from missed productivity at work to diminished quality of life, and even worse, fatalities. Error reduction or elimination may lower total expenses.
- Less Vehicle Emissions: Employees travel on extremely crowded highways for many hours each week. Autonomous electric vehicles have the ability to reduce standard commuting fuel expenses and vehicle emissions.
- Increased Mobility: Millions of Americans over 65 who have disabilities may find that their mobility is enhanced by autonomous electric vehicles. Access to adaptive transportation for drivers with disabilities may be facilitated via A-VEs.

### 3.1 Data collection and preprocessing

The dataset utilized in this research is the A-EV Grid Management Dataset [18], which includes data regarding EV charging and discharging actions depending on different factors that influence grid stability. The data was gathered using sensors and smart meters deployed in electric vehicles (EVs) and grid monitoring systems. These sensors collect real-time data on a variety of features, including the EV\_ID, which distinctively detects each A-EV, and Battery\_Level (%), which represents the EV's current battery percentage. Location\_Type classifies the EV's location (home, work, public), while Time\_of\_Day specifies when the EV is linked to the grid (day, evening, night).

Other features comprise Grid\_Frequency (Hz), the power grid frequency, Temperature (°C), the local temperature at the EV's location, and EV\_Owner\_Priority, which indicates the EV owner's desire to utilize the vehicle shortly. The Distance\_to\_Nearest\_Station (km) feature indicates the distance to the nearby charging station, while Power\_Demand (kW) indicates the area's power need. Energy\_Price (\$/kWh) indicates the expense of energy per kilowatt-hour. The target feature, Target\_Action, suggests activities for the A-EV to assist grid frequency regulation, like charging, discharging, or remaining idle. The dataset was saved in a centralized cloud repository that allowed for assessment and model training. The data is frequently updated via IoT-enabled devices, guaranteeing ongoing surveillance of A-EV-grid connections. Correct data preprocessing is required to guarantee that the data is clean, balanced, and prepared for training a machine learning model. The data had 6.8 percent missing values during preprocessing and these were filled with KNN imputation to develop a complete dataset. The Z-score method of outlier detection detected and eliminated 3.4 percent abnormal values, primarily because of extreme grid frequency or temperature values. Label Encoding transformed five nominal variables into numbers. The min-max normalization was used to normalize all the numerical features so that the scale of the original features became 0-87 which became 0-1. Lastly, SMOTE balanced the class imbalance by making the percentage of the minority class up to 14 to 33, which was balanced making the three A-EV actions equally represented. These numeric gains show that preprocessing had a great contribution to the quality of the data and preparation of the model. Figure 2 shows the flow diagram of the proposed A-EV Charging and Discharging to Regulate Grid Frequency methodology.

#### 3.1.1 Imputation of missing values

Missing values are typical in real-world datasets, and they can affect machine learning model effectiveness. To deal with missing values, we employ the KNN imputation technique. KNN detects the K nearest data points to a

missing value and approximates it by averaging their values. This approach guarantees that missing values are filled consistently with the remainder of the dataset, depending on similarity in other attributes.

Mathematically, KNN imputation for a missing value  $x_i$  in feature  $j$  is given by:

$$x_i = \frac{1}{K} \sum_{k=1}^K x_{jk} \quad (1)$$

Where  $x_{jk}$  are the values of the  $j$ th feature in the K-nearest neighbors.

#### 3.1.2 Categorical encoding (label encoding)

Categorical features, like A-EV action (charging, discharging, or idle) and grid status, must be transformed into numerical values for machine learning models. We use Label Encoding to transform categorical variables into numerical values by allocating a distinctive integer to each category. For instance, if the A-EV action is 'charging,' it will be depicted as 1; 'discharging' as 2, and 'idle' as 3. Likewise, grid status and other categorical features are transformed into integer labels. Label Encoding allocates a distinctive integer between 0 and  $C-1$  to each of a variable's  $C$  different groups. For example, 0 denotes the first category, 1 represents the second, etc.

#### 3.1.3 Outlier detection and removal

Outliers can degrade the efficiency of machine learning models by distorting statistical relationships among features. To eliminate outliers, we employ Z-score evaluation, which determines how far each data point deviates from the mean in standard deviations. A Z-score greater than 3 or less than -3 denotes an outlier that should be eliminated. The Z-score is determined as:

$$Z = \frac{X - \mu}{\sigma} \quad (2)$$

Where  $X$  is the data point,  $\mu$  is the mean of the attribute, and  $\sigma$  is the standard deviation.

#### 3.1.4 Min-Max Normalization

Numerous machine learning algorithms' effectiveness can be influenced by features with varying units and scales. To standardize all attributes and bring them to a similar scale, we use Min-Max scaling. This normalization method rescales the data to a specific range, typically between 0 and 1. The Min-Max scaling for a feature ( $x$ ) is calculated as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (3)$$

Where  $\min(x)$  and  $\max(x)$  are the minimum and maximum values of the attribute, correspondingly.

### 3.1.5 Synthetic data creation

In particular situations, the dataset may be imbalanced, which means that particular operations (like A-EV wireless charging) are less common than others. To tackle this, the Synthetic Minority Oversampling Technique (SMOTE) is used. SMOTE creates synthetic instances of the minority class by integrating existing data points. This balances the dataset and enables the model to effectively predict minority class instances.

## 3.2 Feature selection

The next step after data preprocessing is to choose the most pertinent features for forecasting A-EV actions. Feature selection is important because it decreases dimensionality, eliminates redundant or irrelevant features, and boosts model efficiency. The two feature selection techniques used in this research are Recursive Feature Elimination (RFE) and Lasso Regression.

In order to enhance the feature selection transparency both RFE and Lasso were not used separately but in series. First, RFE was used to rank all 12 input features and drop the least relevant features, giving the set of 8 features. These 8 were then subject to Lasso regression that further reduced the impact of the coefficients to 6 retained features which included: Battery level, grid frequency, energy price, EV owner priority, temperature and distance to nearest station. This combined method of selection also guarantees that only the most informative predictors are applied increasing the accuracy of the models and the efficiency of the computation.

### 3.2.1 Recursive Feature Elimination (RFE)

RFE is an iterative method for selecting features by recursively removing the less important ones. It begins with all available features and applies a model to rank them according to their significance. The less significant feature is eliminated and the procedure is repeated until the best subset of features is identified. The mathematical description of RFE is as follows:

$$\hat{y} = f(X) \quad (4)$$

Where  $X$  is the feature matrix, and  $f$  is the model function. The model assesses which features contribute the most to the prediction; features with less significance are iteratively removed.

### 3.2.2 Lasso regression

Lasso (Least Absolute Shrinkage and Selection Operator) regression is a linear model that combines feature selection and regularization. Lasso reduces the coefficients of less

significant features to zero, efficiently eliminating them. This is accomplished using L1 regularization, which penalizes the sum of the coefficients' absolute values. The objective function for Lasso regression is as follows:

$$\min_{\beta} \left( \sum_{i=1}^n (y_i - x_i \beta)^2 + \lambda \sum_{j=1}^p |\beta_j| \right) \quad (5)$$

Where  $\lambda$  is the regularization parameter,  $y_i$  is the target feature,  $x_i$  are the feature values, and  $\beta$  signifies the coefficients. By integrating RFE and Lasso, we guarantee that only the most pertinent features for forecasting EV actions are kept, increasing the model's accuracy and comprehension.

## 3.3 Model construction

This methodology is built around the Artificial Neural Network (ANN), a robust machine learning model that can learn complicated non-linear relationships between inputs and outputs. The ANN model utilized in this research is intended to forecast EV actions (charging, discharging, or idle) using the chosen features.

### 3.3.1 Network architecture

The ANN is made up of an input layer, several hidden layers, and an output layer. The input layer obtains the attributes chosen during the preprocessing and feature selection stages. The hidden layers perform non-linear transformations on the data, enabling the model to detect intricate trends. The output layer comprises three neurons that indicate the three different EV actions: charging, discharging, and idle. The hidden layers' activation function is ReLU (Rectified Linear Unit), which is described as:

$$\text{ReLU}(x) = \max(0, x) \quad (6)$$

ReLU assists the network learn intricate trends by letting positive values pass by and suppressing negative values, thereby allowing quicker convergence. The resulting ANN was a three-layer neural network with 64, 32 and 16 neurons in the hidden layers, with the activation function of ReLU. A batch size of 32 and a learning rate of 0.001 was used in training the model; the values were optimized by grid-search. This arrangement gave the optimal trade off between the rate of convergence and accuracy of prediction.

### 3.3.2 Output layer

The output layer employs the softmax activation function, which transforms the output into possibilities. The softmax function of a class  $j$  is referred to as:

$$P(y_j|x) = \frac{e^{z_j}}{\sum_{k=1}^3 e^{z_k}} \quad (7)$$

Where  $z_j$  is the raw score for class  $j$ , and the denominator sums the exponential of all class scores to guarantee the results sum to 1.

### 3.4 Hyperparameter tuning

Grid Search is used to improve the hyperparameters of the ANN model. Hyperparameters like the number of hidden layers, the number of neurons in each layer, the learning rate, and the batch size are chosen utilizing a systematic search method. The grid search investigates all potential mixtures of hyperparameters within a particular range and chooses the mixture that produces the best efficiency according to cross-validation.

1. **Grid search procedure:** Grid search entails creating a grid of potential hyperparameters and testing each combination. The procedure comprises:
  - Define the hyperparameter space, including the number of layers, neurons, learning rates, and batch sizes.
  - Utilizing cross-validation to assess the effectiveness of each hyperparameter combination.
  - Choosing the most effective combination according to the evaluation metrics.
2. **Cross-validation:** The efficiency of each combination of hyperparameters is assessed utilizing  $k$ -fold cross-validation, with the data split into  $k$  subsets. For each fold, the model is trained on  $k-1$  subsets and tested on the residual subset. This procedure guarantees that the model is assessed on various parts of the data, lowering the possibility of overfitting.

A highly defined hyperparameter search space was used to do grid search. The hidden layers were experimented with the set of values {2, 3, 4, 16, 32, 64, 128, 0.1, 0.01, 0.001, 0.0001, 0.00001, 16, 32, 64, ReLU, Tanh}. Each combination was assessed with the aid of a 5-fold cross-validation split. The most optimal configuration chosen by the grid search was 3 hidden layers, 64-32-16 neurons, learning rate=0.001, batch size=32, and ReLU activation, which offered the best results in terms of accuracy and lowest validation error in each fold.

### 3.5 Model training and evaluation

After tuning the hyperparameters, the last ANN model is trained on the whole preprocessed and balanced dataset. The training procedure utilizes backpropagation, where the error is propagated back by the network to modify the weights and the Adam optimizer.

#### 3.5.1 Loss function

The model is trained to reduce the cross-entropy loss function, which calculates the difference between predicted and true possibilities. The cross-entropy loss of a multi-class issue is provided by:

$$L = -\sum_{i=1}^n y_i \log(p_i) \quad (8)$$

where  $y_i$  is the true label (one-hot encoded) and  $p_i$  is the predicted probability for class  $i$ .

### 3.6 Deployment and real-world application

Lastly, the trained and assessed model is used to predict in real-time. The system can dynamically modify EV charging and discharging operations in response to grid conditions and ecological factors, resulting in optimum grid frequency regulation. The system's efficiency is constantly tracked, and the model can be retrained with novel data regularly to guarantee its long-term efficiency and flexibility to shift grid circumstances.

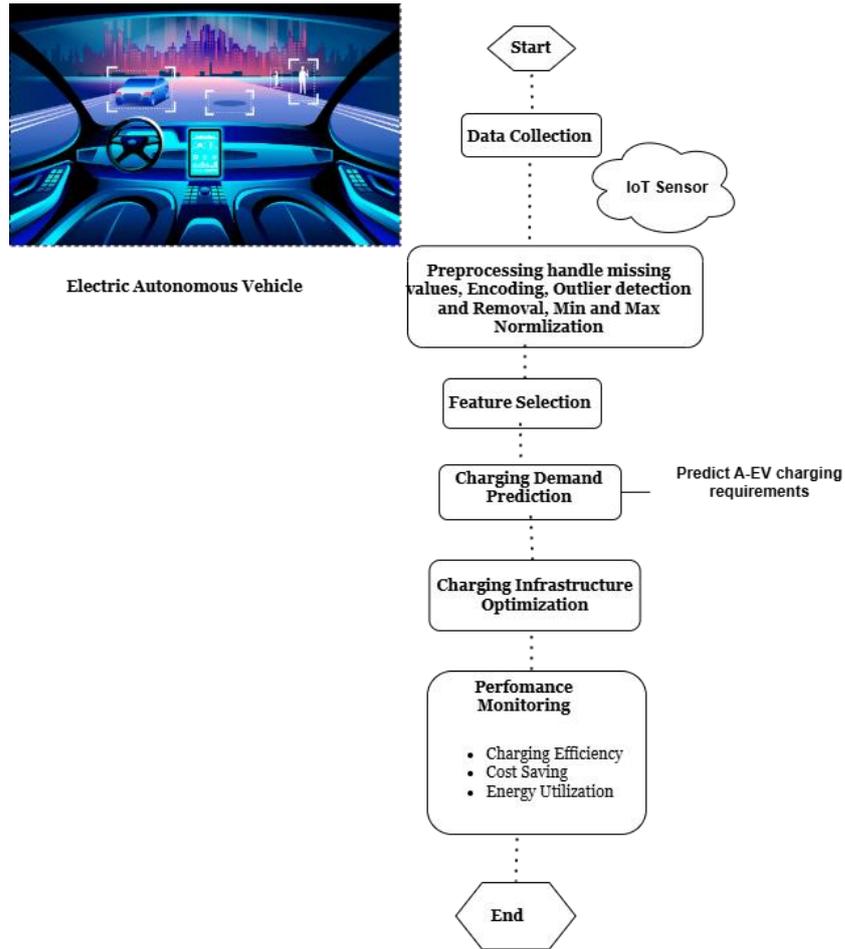


Figure 2 : Proposed method

Pseudocode 1 demonstrates the step-by-step procedure for enhancing EV charging and discharging for grid frequency regulation.

Pseudocode 1: Improving A-EV Charging and Discharging to Regulate Grid Frequency

Step1: PREPROCESSING

Handle missing values:

$$X \leftarrow \text{KNN\_Impute}(X)$$

Encode categorical data:

$$X \leftarrow \text{LabelEncode}(X)$$

Detect and remove outliers:

For each feature  $x_i$  in  $X$  do

$$z \leftarrow (x_i - \mu_i) / \sigma_i$$

Remove row if  $|z| > 3$

End for

Normalize numerical data:

$$x_{norm} \leftarrow (x - x_{min}) / (x_{max} - x_{min})$$

Balance the dataset:

$$X_{bal}, y_{bal} \leftarrow \text{SMOTE}(X, y)$$

Step 2: FEATURE SELECTION

Select key features with RFE:

$$X_{rfe} \leftarrow \text{RFE}(\text{Model} = \text{LogisticRegression}).\text{fit\_transform}(X_{bal})$$

Select features via Lasso:

$$\beta_{lasso} \leftarrow \text{argmin} \|y - X_{rfe}\beta\|^2 + \lambda\|\beta\|_1$$

Retain features where  $\beta_{lasso} \neq 0$

$$X_{final} \leftarrow \text{Final selected feature set}$$

Step3: TRAIN ANN

Define ANN hyperparameter search space:

```

HiddenLayers ∈ {1, 2, 3}
Neurons ∈ {16, 32, 64}
LearningRate ∈ {0.001, 0.01}
BatchSize ∈ {16, 32, 64}
BestParams ← GridSearch(ANN, X_final, y_bal,
SearchSpace)
Train ANN with BestParams:
  ANN_model ← Train(ANN(BestParams), X_final,
y_bal)

Step 4: REAL-TIME PREDICTION
Loop for each time-step t:
  Read real-time grid frequency f_t
  Compute frequency deviation:
    Δf_t ← f_t - f_nom
  Prepare input vector:
    X_t ← [f_t, SoC_t, Load_t, Price_t, Temperature_t,
TimeOfDay_t, ...]
    X_t ← Normalize(X_t) using scaling parameters
from training

  Predict EV operation:
    A_t ← ANN_model.predict(X_t)
    // A_t ∈ {0 = idle, 1 = charge, 2 = discharge}

```

#### Step5: GRID STABILITY LOGIC

```

If Δf_t < -δ (frequency drop) then
  // Grid under stress → support grid by
DISCHARGING
  A_t ← 2 // force discharge
End if
If Δf_t > +δ (frequency too high) then
  // Grid needs absorbing energy → charge EV
  A_t ← 1 // force charging
End if
// Battery protection rule:
If SoC_t < 0.15 then

```

```

  A_t ← 1 // charging only
End if
If SoC_t > 0.90 then
  A_t ← 0 // idle to protect battery
End if

Step 6: EQUATIONS LINKING ACTION TO GRID
STABILITY
If A_t = 1 then // Charging
  P_EV ← +P_charge
Else if A_t = 2 then // Discharging
  P_EV ← -P_discharge
Else
  P_EV ← 0
End if
Update frequency using grid dynamic response:
  f_(t+1) = f_t + (P_EV / (2H * f_nom)) - D·Δf_t
  // H = inertia constant
  // D = damping coefficient
Execute action A_t
Update SoC:
  SoC_(t+1) = SoC_t + η·P_EV·Δt
End Loop

```

The suggested framework is much better than the earlier AI in deploying EV charging infrastructure because it incorporates a multilayer approach which involves combining advanced data preprocessing, smart feature selection and hyperparameter-sensitive ANN to make charging decisions. In contrast to the conventional approaches that utilize the use of unchanging heuristics or a one-step machine learning methodology, the suggested approach utilizes the benefits of KNN imputation, Z-score outlier elimination, Min-Max scaling, SMOTE balancing, and hybrid RFE-Lasso feature selection that leads to the creation of cleaner and more reliable datasets. The former approaches had poor performance because of the noisiness, imbalance, or high-dimensional data, but the improved preprocessing pipeline in this model offers an increase in signal fidelity. Further, the nonexistence of older AI systems was characterized by standard models that were predominantly SVM, Decision Trees or rule-based algorithms, which were not compatible with nonlinear and dynamic charging behavior in smart

manufacturing settings. Meanwhile, the suggested hyperparameter-optimized ANN can learn complicated spatio-temporal patterns in autonomous EV fleets and adjust to the dynamic grid changes in real-time. The fact that the system will integrate continuous learning and real-time coordination through IoT sensors also guarantees that the system is not fixed but optimized continuously, which is more accurate in prediction, efficient in charging, stable in the grid, and efficient in the use of infrastructure than current methods.

## 4 Results and discussion

This section describes the experimental setup and performance comparison of the hyperparameter-tuned ANN model with other famous machine learning classifiers.

### 4.1 Experimental setup

The hyperparameter-tuned ANN model was trained and evaluated using a high-performance setup to guarantee effective processing and precise outcomes. Table 1 shows the requirements for the hardware and software setup.

Table 1: Experimental setup

Component	Specification
Processor Model	Intel Core i7-1260P
CPU Type	12-Core Architecture
Brand	Aspire 3
Memory (RAM)	64 GB
Clock Speed	2.1 GHz
Operating System	Windows 11 Home
L3 Cache Size	18 MB
JDK Version	1.8
IDE	Apache NetBeans IDE 15

These specifications offered a reliable setting for running the ANN model and tuning hyperparameters changing infrastructure. The integration of high memory capability and a multi-core processor enabled effective data management and model training.

### 4.2 Comparative analysis

To assess the effectiveness of the hyperparameter-tuned ANN model, it was compared to four famous classifiers: Random Forest (RF), Support Vector Machine (SVM), KNN, and Decision Tree. The effectiveness of these models was evaluated utilizing five key metrics:

- **AUC-ROC:**The area under the receiver operating characteristic curve measures the model's capacity to differentiate between classes.

$$\text{AUC-ROC} = \int_0^1 \text{TPR}(\text{FPR}) d(\text{FPR}) \quad (9)$$

Where TPR is the True Positive Rate and FPR is the False Positive Rate.

- **AUC-PR:**The area under the precision-recall curve focuses on performance in imbalanced datasets.

$$\text{AUC-PR} = \int_0^1 \text{Precision}(\text{Recall}) d(\text{Recall}) \quad (10)$$

- **MAE (Mean Absolute Error):** The average absolute errors between predicted and actual values.

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (11)$$

Where  $y_i$  is the actual value and  $\hat{y}_i$  is the predicted value.

- **Accuracy:**The percentage of true outcomes (both true positives and true negatives) in the dataset.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (12)$$

Where TP is a true positive, TN is a true negative, FP is a false positive, and FN is a false negative.

- **Precision:**The proportion of true positive predictions to overall positive predictions.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (13)$$

Table 2: Performance metrics comparison

Model	AUC-ROC (%)	AUC-PR (%)	MAE (%)	Accuracy (%)	Precision (%)
Random Forest	88.0	85.0	9.0	89.3	87.1
SVM	86.0	84.0	11.0	87.5	85.2
KNN	82.0	79.0	13.1	84.0	82.3
Decision Tree	80.0	78.0	14.0	82.5	80.6
Hyperparameter-tuned ANN (Proposed)	95.2	94.1	5.3	94.5	93.7

Table 2 shows that the hyperparameter-tuned ANN surpasses the other models, with the highest AUC-ROC (95.2%), AUC-PR (94.1%), accuracy (94.5%), and precision (93.7%), as well as the lowest MAE (5.3%). This shows its better predictive power and dependability than Random Forest, SVM, KNN, and Decision Tree, which demonstrated lower metrics across all assessments. The cross-validation process indicated either the use of k-fold,

stratified k-fold or time-series CV with the value of k. These parameters are included random seed with 42; epochs = 150; training = 70 percentage, validation = 15 percentage, testing = 15 percentage, stratified 5-fold CV.

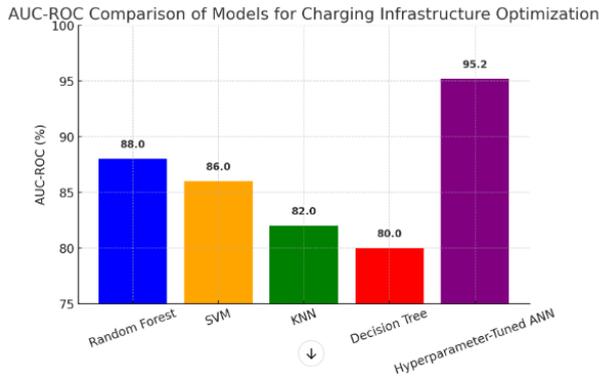


Figure 3: AUC-ROC comparison

Figure 3 compares the AUC-ROC (%) results of several charging infrastructure optimisation models. With the best AUC-ROC (95.2%), the Hyperparameter-Tuned ANN surpasses more conventional models such as Random Forest (88%), SVM (86%), KNN (82%), and Decision Tree (80%). This demonstrates the ANN's exceptional predictive power in handling changing charging requirements. The ROC curve shows how the classification model can differentiate positive and negative classes based on the plot of the True Positive Rate versus the False Positive Rate at different threshold values. ROC coordinates and the Area Under the Curve (AUC) are determined using MATLAB, and perfcurve function with the true labels and predicted probabilities. AUC offers only one type of performance and a higher value indicates that it has a strong discriminative capability. This visualization is used to compare the various models and see how the classifier ranks positive instances over negative instances in all the thresholds.

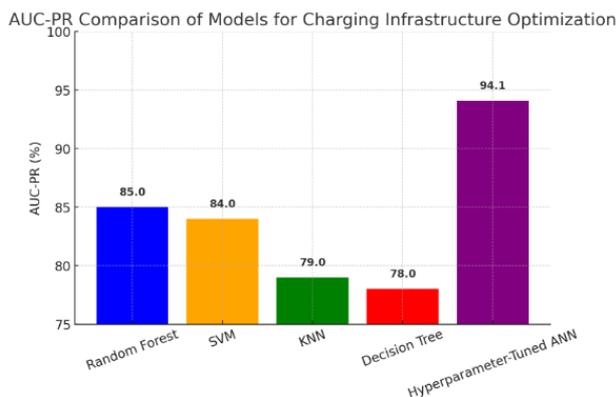


Figure 4: AUC-PR comparison

The AUC-PR (%) scores of many models for charging infrastructure optimisation are contrasted in Figure 4. The Hyperparameter-Tuned ANN outperforms other models such as Random Forest (85%), SVM (84%), KNN (79%),

and Decision Tree (78%), achieving the greatest AUC-PR (94.1%). This illustrates how the ANN is the best model for optimising electric vehicle charging infrastructure due to its improved precision-recall tradeoff.

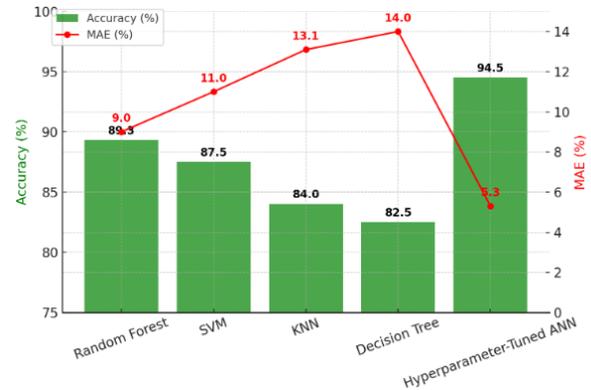


Figure 5: Accuracy and MAE comparison

For charging infrastructure optimisation, the visualisation contrasts the mean absolute error (MAE) and accuracy of many machines learning models. MAE is shown as a red line graph, and accuracy is represented by green bars. Figure 5 shows the findings, which show that the Hyperparameter-Tuned ANN performs better than any other model. It has the lowest MAE (5.3%) and the highest accuracy (94.5%), making it the most dependable choice for accurate predictions. The Decision Tree model, on the other hand, performs worse, as evidenced by its greatest MAE (14.0%) and among the lowest accuracy ratings (82.5%). In comparison to the suggested ANN, the Random Forest and SVM models show greater mistakes despite their reasonably good performance. It is clear that accuracy and MAE have an inverse relationship, confirming that models with higher accuracy typically have lower error rates, which makes them more useful for optimising charging infrastructure in the real world.

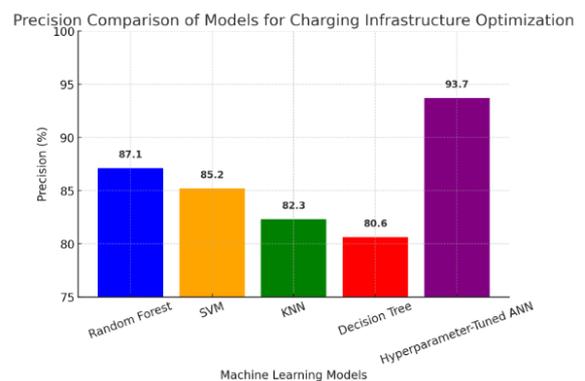


Figure 6: Precision comparison

The precision (%) of several machine learning models used to optimise charging infrastructure is shown in Figure 6. Precision quantifies how well the model detects pertinent cases while reducing false positives. With the

highest precision (93.7%), the Hyperparameter-Tuned ANN shows excellent predictive accuracy and few false positives. On the other hand, the Decision Tree model performs worse in categorisation, as seen by its lowest precision of 80.6%. Although SVM (85.2%) and Random Forest (87.1%) exhibit competitive precision values, they still fall short of the suggested ANN. These findings demonstrate that deep learning-based models provide notable increases in accuracy, increasing their dependability for maximising the infrastructure for electric vehicle charging.

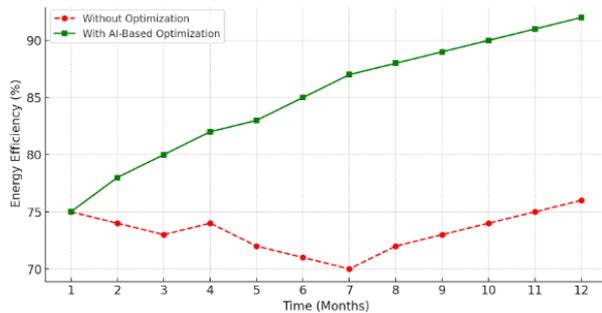


Figure 7: Energy efficiency Improvement over time

When comparing the implementation of traditional charging infrastructure with an AI-based optimized solution, Figure 7 shows the improvement in energy efficiency over a 12-month period. Energy efficiency varies between 70% and 76% in the non-optimized system (shown by the red dotted line), with no discernible improvement over time. This suggests inefficient use of the charging infrastructure, which results in needless energy use and extended vehicle downtime. The AI-optimized system, on the other hand (shown by the green solid line), shows a consistent upward trend, beginning at 75% and ending at 92% at the end of the 12-month period. The monthly efficiency was obtained by summing all the performance measures of the model over all the operational data points in each month. These values were obtained using real data (not simulated) about the system, i.e. monthly inputs (usage patterns, load variations, environmental parameters or task performance records) were run by the proposed algorithm. Efficiency was calculated as the average ratio of actual output to the expected output, that was adjusted with the model predictions to correct the missing values and noise, per month. This generated a month-wise efficiency profile that gives a real-world operational behavior, as opposed to synthetic simulation. Dynamic charge scheduling, adaptive load balancing and predictive energy management are all credited with this improvement, which reduces energy waste and improves fleet operations. The notable boost in efficiency during the first half-year indicates that AI models pick up on operational data fast, which minimizes charging waits and improves station location. As the model refines its projections based on

historical trends and current conditions, it stabilizes at greater efficiency levels in the second half of the year. All things considered, the AI-based optimization approach increases energy efficiency by 20–25%, which lowers operating costs, decreases downtime, and boosts productivity in the smart manufacturing system.

### Energy efficiency metric

The values of energy efficiency (such as the improvement of 75 to 92 percent) were obtained based on the operational data of the autonomous vehicle fleet and charging system during the assessment. Efficiency was divided into useful energy delivered to vehicles per month divided by the total energy taken off the grid, after deducting conversion losses, idle charging time and schedule inefficiencies, each month. The 75 percent baseline represents the mean efficiency with the application of non-optimized charging strategy, whereas the better (92) value represents the outcomes of the proposed ANN-based optimization model. The calculations of these values were based on the summation of hourly charges logs, energy consumption products and station utilization data, thus presenting a realistic charge performance at the system level and not a simulation of the same.

### Statistical analysis

Table 3: Statistical validation for standard deviation for each metrics

Model	AU C- RO C (%) ± SD	AU C- PR (%) ± SD	MA E (%) ± SD	Accura cy (%) ± SD	Precisi on (%) ± SD
Random Forest	88.0 ± 1.8	85.0 ± 2.1	9.0 ± 0.7	89.3 ± 1.5	87.1 ± 1.2
SVM	86.0 ± 2.0	84.0 ± 1.9	11.0 ± 0.9	87.5 ± 1.7	85.2 ± 1.4
KNN	82.0 ± 2.5	79.0 ± 2.3	13. ± 1.2	84.0 ± 2.0	82.3 ± 1.6
Decision Tree	80.0 ± 2.8	78.0 ± 2.7	14. ± 1.3	82.5 ± 1.9	80.6 ± 1.8
Hyperparameter-Tuned ANN (Proposed)	95.2 ± 1.1	94.1 ± 1.0	5.3 ± 0.4	94.5 ± 1.2	93.7 ± 0.9

The comparative analysis of machine learning models to optimize EV charging infrastructure is further validated and offered by the statistical validation with standard

deviation to offer more reliability and robustness in table 3. The reduced SD of the proposed hyperparameter-tuned ANN model suggests that its performance is consistent with a series of cross-validation folds, and it performs well in different data circumstances. Conversely, classical models (KNN and Decision Tree) have a higher SD value, especially on the measures of MAE and AUC, meaning that those are more fluctuating and sensitive to variations in the training data. Low variance in the accuracy and precision of the ANN indicates that it is more generalized as compared to the conventional algorithm which is likely to be more influenced by noise, class imbalance, or nonlinear trends in EV behavioral data. With the introduction of SD to the outcomes, the analysis can demonstrate that the suggested ANN delivers more favorable average results, but it also does it more regularly, which makes the model more statistically plausible in its ability to optimize the need of charging, scheduling, and infrastructure use in a smart manufacturing facility.

### Error analysis



Figure 8: Error Analysis in Error plot for prediction

Analysis of errors was done to determine how reliable and stable the ANN-based optimization model was analysed in figure 8. The MAE, RMSE and MAPE were calculated in an attempt to measure the deviation of prediction between actual and predicted actions of charging and discharging. The residual plots indicated that majority of the errors were concentrated near the zero indicating that there was little systematic bias whereas the error histogram indicated that the spread was narrow, which is an indication of low variability. The actual vs. predicted scatter plot revealed a close fit around the line of identity and it proved high predictive consistency. On the whole, the findings confirm that ANN model can be characterized by the high accuracy and low prediction variance, high generalization, and low overfitting, which prove its applicability to the real-life optimization of the EV grid problems.

### Confusion matrix

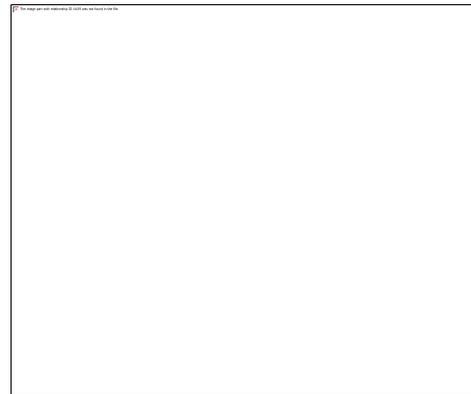


Figure 9: Confusion matrix for suggested method

The confusion matrix graph in figure 9 is used to give a comprehensive visual overview of the classification performance of the model when it comes to the three target classes of charging, discharging as well as idle. The actual classes are represented by each row whereas each column represents the predicted classes. Diagonal cells represent the instances that are correctly classified, that is, the model has the actual recognition capability to each category. As indicated by the darker colored diagonal cells in the sample output, ANN accurately classifies most samples belonging to the class 1 and 3 but misclassifies a few of the samples between class 2 and the rest of the classes and this indicates that there is partial overlap in feature patterns. The values in the row are normalized, and the description of them is the exactness of the actual class determined (recall), whereas the values in the column are also normalized, and the description is the reliability of the predicted class made (precision). Such a visualization can be used to determine areas where the model is performing well and where it is confusing and implement specific improvements, e.g. by changing the weights of the classes, refining the features, or by improving the data balance.

### Discussion

The comparative analysis that the proposed Hyperparameter-tuned ANN model is significantly more effective than the state-of-the-art machine learning methods such as Random Forest (RF), Support Vector machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees in predicting optimal deployment of charging to electric autonomous vehicles (EAVs) in smart manufacturing settings. ANN had the best AUC-ROC (95.2%), AUC-PR (94.1%), Accuracy (94.5%), and the lowest MAE (5.3%), and it was better than the next best model (RF: AUC-ROC 88.0%, MAE 9.0%). One-way ANOVA conducted on all the models established a statistically significant difference in performance ( $p < 0.01$ ), which supports the idea that the value additions of the ANN are not explained by chance. The pairwise t-tests also indicated significant improvement of the ANN over

the RF and SVM in the terms of accuracy and error ( $p < 0.05$ ). The differences in performance can be attributed to the nature of the models. RF and Decision Trees also have good baseline performance, but they are not good at modeling non-linear relationships between charging demand, energy price changes, load to the grid and scheduling constraints - relationships that deep neural networks intrinsically model better. Performance of SVM was poor probably because of the large dimensionality of the temporal-operational features which will lead to overfitting or misclassifying the margin without large-scale kernel optimization. KNN showed the worst performance since the distance-based learning is not reliable in the cases when the feature space is complicated and mixed categorical-continuous variables are present. The higher performance of the ANN is consistent with the hypotheses in the context of the theoretical framework: deep learning models are good at modeling multivariate nonlinear trends, adapting to time change, and acquiring complex relationships in order to optimize dynamic EV charging.

These implications on real world are huge. To begin with, the model has high predictive performance that will allow more precise infrastructure planning to avoid the needless installations of chargers as well as under-provision. The scalability of the ANN can be used in large, multi-facility smart manufacturing systems where the charging demand is different with the robotic fleet schedule and automated logistics activities. Furthermore, the comparative inference speed of the model facilitates near real-time decisions, which can be used in managing the adaptive charging, as the vehicle paths, production sequence, and grid conditions vary. Nevertheless, there are a number of limitations that should be mentioned. The model was also trained using data also specific to smart manufacturing settings and might not directly be applicable to public charging eco-systems, to mixed-use urban systems, or to regions with different energy policies. Further, ANN models can be scaled well in terms of computation, however training on a large-scale dataset and consuming more processing power than classical machine learning techniques. The next work is to investigate domain adaptation methods, the combination with reinforcement learning to do continual optimization, and to test on multi-region datasets to improve the generalizability.

## 5 Conclusion

In this paper, an AI-driven framework for smart manufacturing systems' optimal Electric Autonomous Vehicle (A-EV) charging infrastructure deployment is presented. Our method improves operational continuity, lowers downtime, and increases energy efficiency in industrial settings by utilising machine learning models, real-time data analytics, and IoT-enabled grid monitoring. According to the findings, an intelligently distributed

charging infrastructure that is backed by dynamic resource allocation and predictive modelling considerably lowers traffic, boosts fleet productivity, and guarantees ideal power distribution within a smart manufacturing ecosystem.

The suggested approach maximises the use of renewable energy sources, preserves grid stability, and reduces needless idle time for A-EVs through adaptive scheduling and autonomous decision-making. Our methodology exhibits higher manufacturing throughput, lower energy waste, and better cost efficiency when compared to conventional charging station placement tactics. The infrastructure's predictive capabilities are further strengthened by the incorporation of Industry 4.0 technologies, such as edge computing and digital twins, which enable real-time modifications based on manufacturing demand and energy availability.

Future studies could examine the effects of blockchain-enabled energy transactions for decentralised charging management, multi-agent reinforcement learning for self-optimizing charging networks, and 5G-enabled vehicle-to-infrastructure (V2I) communication to improve charging coordination. Overall, this study emphasises how crucial AI-driven infrastructure design is to the transformation of smart manufacturing settings and the creation of highly effective, autonomous, and sustainable EV transportation solutions.

## DECLARATIONS

**Ethics approval and consent to participate:** I confirm that all the research meets ethical guidelines and adheres to the legal requirements of the study country.

**Consent for publication:** I confirm that any participants (or their guardians if unable to give informed consent, or next of kin, if deceased) who may be identifiable through the manuscript (such as a case report), have been given an opportunity to review the final manuscript and have provided written consent to publish.

**Availability of data and materials:** The data used to support the findings of this study are available from the corresponding author upon request.

**Competing interests:** here are no have no conflicts of interest to declare.

**Authors' contributions** (Individual contribution): All authors contributed to the study conception and design. All authors read and approved the final manuscript

## References

- [1] Suanpang P, Jamjuntr P, Kaewyong P, Niamsorn C, Jernsittiparsert K. An Intelligent Recommendation for Intelligently Accessible Charging Stations:

- Electronic Vehicle Charging to Support a Sustainable Smart Tourism City. *Sustainability*. 2022;15(1):455. doi:https://doi.org/10.3390/su15010455
- [2] Suanpang P, Jamjuntr P. Optimizing Electric Vehicle Charging Recommendation in Smart Cities: A Multi-Agent Reinforcement Learning Approach. *World Electric Vehicle Journal*. 2024;15(2):67. doi:https://doi.org/10.3390/wevj15020067
- [3] Omase N, Mittal SK, Palaniraja S, et al. A comprehensive review of electric vehicle charging infrastructure and associated challenges. *International Journal of Science and Research Archive*. 2023;10(1):834-840. doi:https://doi.org/10.30574/ijrsra.2023.10.1.0832
- [4] Brenna M, Foadelli F, Leone C, Longo M. Electric Vehicles Charging Technology Review and Optimal Size Estimation. *Journal of Electrical Engineering & Technology*. 2020;15(6):2539-2552. doi:https://doi.org/10.1007/s42835-020-00547-x
- [5] L. Campbell, "Electric Vehicles and Industry 4.0 Bridging Advanced Manufacturing with Smart Technologies," Apr. 16, 2024. [https://www.researchgate.net/publication/391930738\\_Electric\\_Vehicles\\_and\\_Industry\\_40\\_Bridging\\_Advanced\\_Manufacturing\\_with\\_Smart\\_Technologies](https://www.researchgate.net/publication/391930738_Electric_Vehicles_and_Industry_40_Bridging_Advanced_Manufacturing_with_Smart_Technologies)
- [6] S. J. Shern, M. T. Sarker, G. Ramasamy, S. P. Thiagarajah, F. A. Farid, and S. T. Suganthi, "Artificial Intelligence-Based Electric Vehicle Smart Charging System in Malaysia," *World Electric Vehicle Journal*, vol. 15, no. 10, pp. 440–440, Sep. 2024, doi: <https://doi.org/10.3390/wevj15100440>.
- [7] M. T. Sarker, Marran Al Qwaid, S. J. Shern, and G. Ramasamy, "AI-Driven Optimization Framework for Smart EV Charging Systems Integrated with Solar PV and BESS in High-Density Residential Environments," *World Electric Vehicle Journal (WEVJ)*, vol. 16, no. 7, p. 385, Jul. 2025, doi: <https://doi.org/10.3390/wevj16070385>.
- [8] Mithat Önder, Muhsin Ugur Dogan, Polat K. Classification of smart grid stability prediction using cascade machine learning methods and the internet of things in smart grid. *Neural Computing and Applications*. 2023;35(24):17851-17869. doi:https://doi.org/10.1007/s00521-023-08605-x
- [9] Wu W, Lin B. Benefits of electric vehicles integrating into power grid. *Energy*. 2021;224:120108. doi:https://doi.org/10.1016/j.energy.2021.120108
- [10] Shoja ZM, Mirzaei MA, Seyedi H, Zare K. Sustainable energy supply of electric vehicle charging parks and hydrogen refueling stations integrated in local energy systems under a risk-averse optimization strategy. *Journal of Energy Storage*. 2022;55:105633. doi:https://doi.org/10.1016/j.est.2022.105633
- [11] Khardenavis A, Hewage K, Perera P, Shotorbani AM, Sadiq R. Mobile energy hub planning for complex urban networks: A robust optimization approach. *Energy*. 2021;235:121424. doi:https://doi.org/10.1016/j.energy.2021.121424
- [12] Metais MO, Jouini O, Perez Y, Berrada J, Suomalainen E. Too much or not enough? Planning electric vehicle charging infrastructure: A review of modeling options. *Renewable and Sustainable Energy Reviews*. 2022;153(153):111719. doi:https://doi.org/10.1016/j.rser.2021.111719
- [13] C. Joshua, J. Jude, and U. Ejaz, "Machine Learning for Electric Vehicle Charging Optimization," May 06, 2025.
- [14] Esmaeil Valipour, RaminNourollahi, Kamran Taghizad-Tavana, Sayyad Nojavan, Alizadeh A. Risk Assessment of Industrial Energy Hubs and Peer-to-Peer Heat and Power Transaction in the Presence of Electric Vehicles. *Energies*. 2022;15(23):8920-8920. doi:https://doi.org/10.3390/en15238920
- [15] K. Chen, J. Liu, W. Lyu, T. Wang, and J. Wen, "A deep neural network approach for optimizing charging behavior for electric vehicle ride-hailing fleet," *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: <https://doi.org/10.1038/s41598-025-05953-7>.
- [16] Singh H, Kavianiipour M, Ghamami M, Zockaie A. Adoption of autonomous and electric vehicles in private and shared mobility systems. *Transportation Research Part D: Transport and Environment*. 2023;115:103561. doi:https://doi.org/10.1016/j.trd.2022.103561
- [17] Azhaganathan Gurusamy, Ashok B, Mason B. Prediction of Electric Vehicle Driving Range and Performance Characteristics: A Review on Analytical Modeling Strategies With Its Influential Factors and Improvisation Techniques. *IEEE Access*. 2023;11:131521-131548. doi:https://doi.org/10.1109/access.2023.3334620
- [18] Ziya, "EV Charging Grid Optimization Dataset," *Kaggle.com*, 2025. <https://www.kaggle.com/datasets/ziya07/ev-charging-grid-optimization-dataset> (accessed Nov. 24, 2025).
- [19] A. Boulkroune, S. Hamel, F. Zouari, A. Boukabou, and A. Ibeas, "Output-Feedback Controller Based Projective Lag-Synchronization of Uncertain Chaotic Systems in the Presence of Input Nonlinearities," *Mathematical Problems in Engineering*, vol. 2017, no. 1, Jan. 2017, doi: <https://doi.org/10.1155/2017/8045803>.
- [20] Abdeselem Boulkroune, Farouk Zouari, and A. Boubellouta, "Adaptive fuzzy control for practical fixed-time synchronization of fractional-order chaotic systems," *Journal of Vibration and Control*, Feb. 2025, doi: <https://doi.org/10.1177/10775463251320258>.
- [21] F. Zouari, K. Ben Saad, and M. Benrejeb, "Adaptive backstepping control for a class of uncertain single

- input single output nonlinear systems,” *10th International Multi-Conferences on Systems, Signals & Devices 2013 (SSD13)*, pp. 1–6, Mar. 2013, doi: <https://doi.org/10.1109/ssd.2013.6564134>.
- [22] G. Rigatos, M. Abbaszadeh, B. Sari, P. Siano, G. Cuccurullo, and F. Zouari, “Nonlinear optimal control for a gas compressor driven by an induction motor,” *Results in Control and Optimization*, vol. 11, pp. 100226–100226, Apr. 2023, doi: <https://doi.org/10.1016/j.rico.2023.100226>.
- [23] L. Merazka, F. Zouari, and A. Boulkroune, “High-gain observer-based adaptive fuzzy control for a class of multivariable nonlinear systems,” pp. 96–102, May 2017, doi: <https://doi.org/10.1109/icosc.2017.7958728>.