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Research Article

Enhanced Hybrid Charging Park System Evaluation Using Neural Network Charging Controller

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Abstract:

Hybrid charging parks, which combine renewable energy sources with traditional grid systems, have emerged in response to the increasing need for effective electric vehicle (EV) charging infrastructure. Using a Neural Network-based Charging Controller (NNCC), this study suggests an improved assessment methodology for hybrid charging park systems. The controller prioritizes car charging needs, minimizes energy losses, and dynamically optimizes energy distribution by balancing solar, wind, and grid sources. Real-time operational data, such as vehicle wait duration, state of charge (SoC), and fluctuation in renewable energy, were used to train a multi-layer perceptron (MLP) neural network. According to simulation data, the suggested NNCC outperformed traditional rule-based controllers in terms of the charging park's overall power efficiency by 18.7%. Additionally, the method increased the vehicles' final State of Charge (SoC) by an average of 12.5%, guaranteeing quicker and more dependable charging sessions. Additionally, the neural network-based system showed improved flexibility in the face of variable renewable energy circumstances, greatly boosting the resilience and sustainability of smart EV charging ecosystems.

1. Introduction

The world's transportation scene is changing due to the quick uptake of electric cars (EVs), which makes the creation of intelligent and effective charging infrastructures necessary. A viable way to satisfy the growing energy needs of EVs while advancing sustainability is through hybrid charging stations, which combine conventional grid systems with renewable energy sources like solar and wind. However, there are several difficulties in controlling the intricate energy fluxes and guaranteeing peak performance in these hybrid systems. The dynamic nature of energy output and consumption in hybrid charging stations frequently makes traditional rule-based energy management techniques less flexible. On the other hand, data-driven methods like Artificial Neural Networks (ANNs) can learn and adjust to intricate, nonlinear interactions in the system. For example, Singh and Kumar (2023) created an ANN-based active power management controller for a DC micro-grid EV charging station, showing enhanced energy efficiency through dynamic power balancing between the grid, stationary battery storage, and photovoltaic (PV) systems [1-3].
More developments in the integration of machine learning and energy management have been investigated. For example, Orfanoudakis et al. (2025) optimized EV charging by combining Graph Neural Networks and Large Language Models, surpassing conventional techniques in managing the dynamic and high-dimensional nature of real-time EV charging scenarios. Devi and Jose (2024) also presented the NBO-THDCNN algorithm for energy management in smart parking lots, which successfully reduced power loss and operating costs by optimizing both slow and fast EV charging processes [4,5].
Furthermore, there is potential for improving charging infrastructure through the integration of predictive models that take reliability and

environmental concerns into consideration. In order to improve infrastructure design and demand prediction, a research published in Heliyon (2025) suggested a hybrid Bayesian network-based deep learning framework to anticipate EV charging capacity, taking climate conditions and charging pile dependability into account [6].

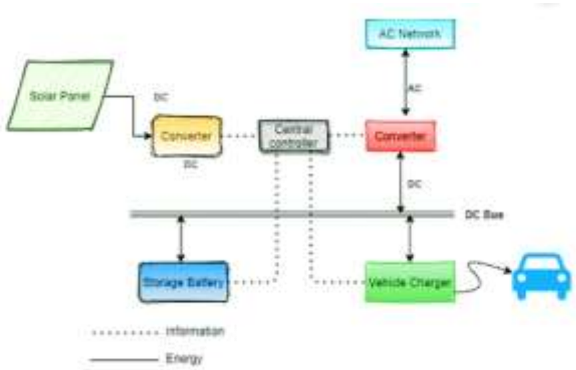

Figure 1. *Schematic diagram of hybrid electric vehicle charging diagram with central control [6].*

This paper looks at current research developments in this important area as well as recent developments in renewable energy-based charging infrastructure (RCI) technology. Optimal planning, optimal size, control and energy management, suitable renewable energy sources for RCI, siting, renewable energy-based charge pricing plans, and RCI issues are some of the topics covered in this article.

1.1 System Converters

In a solar converter, the PV arrays are connected to a DC/DC converter that enables full power point tracking control. The AC/DC converter is responsible for bi-directionally converting DC/AC power. Since the power used from the grid is primarily AC, it needs to be converted into DC in order to charge the electric vehicles. This conversion takes place either before charging starts or when the converter relays the grid power to electricity networks. In photovoltaic systems based on balanced energy conversion, the converters play a unique role. Many configurations and specifications have been thoroughly studied, such as central inverters, where panels are installed with independent inverters and micro-inverter power optimizers that need additional monitoring, and string inverters, where panels are installed in conjunction with a microinverter. By continuously adjusting and changing the attached load, these power optimizers monitor the overall performance of photovoltaic panel arrays and maintain the system at its highest operational capacity [7, 8].

Switching converters, or DC-DC converters

DC-DC converters use energy storage components (inductors, capacitors) and switching devices (MOSFETs, diodes) to control voltage. Fundamental Formulas: Duty Cycle (D) [8-12]

$$D = \frac{T_{ON}}{T_{ON} + T_{OFF}} = \frac{T_{ON}}{T_s} \qquad (1)$$

where T_{on} = ON time, T_{off} = OFF time, Ts= switching period.
Next, finding the buck converter (step-down):

$$V_{out} = D.V_{in} \qquad (2)$$

Also, the inductor current ripple (ΔI_L) might be found such as:

$$\Delta I_L = \frac{(V_{in} - V_{out}).D}{L.f_s} \qquad (3)$$

where fs=1/Ts = switching frequency, L= inductance. Moreover, the Boost Converter (Step-Up) will expressed as:

$$V_{out} = \frac{V_{in}}{1-D} \qquad (4)$$

Also, the Inductor Current Ripple (ΔI_L) might be represented as:

$$\Delta I_L = \frac{V_{in}.D}{L.f_s} \qquad (5)$$

Then, the Buck-Boost Converter (Step-Up/Down) could be written such as:

$$V_{out} = \frac{-D}{1-D}.V_{in} \qquad (6)$$

Such that, the output voltage polarity is inverted. Output Voltage Ripple (ΔV_{out}), and for all converters, the capacitor ripple voltage is:

$$\Delta V_{out} \approx \frac{\Delta I_L}{8.C.f_s} \qquad (7)$$

Such that, C, represents the output capacitance.

DC-AC Converters (Inverters)

The DC-AC converters (inverters) convert DC to AC, used in solar systems, motor drives, and UPS. Thus, the output voltage (Sinusoidal PWM), and the RMS output voltage (Single-Phase Full-Bridge) could be expressed as follows [8-12]:

$$V_{out}(RMS) = \frac{V_{DC}}{\sqrt{2}}.M_a \quad (8)$$

Whereas, M_a, denotes the modulation index ($0 \leq Ma \leq 1$), and V_{DC} indicates the input DC voltage. Thus, the fundamental frequency component might be written as follows:

$$V_{out}(1) = \frac{V_{DC}}{2}.M_a \quad (9)$$

Next, in order to find the Switching Frequency & Harmonics, the total harmonic distortion (THD) will be expressed as:

$$THD = \frac{\sqrt{V_{out}(RMS)^2 - V_{out}(1)^2}}{V_{out}(1)}. \quad (10)$$

Furthermore, the Three-Phase Inverter (Line-to-Line Voltage) might be evaluated such that:

$$V_{LL(RMS)} = \sqrt{3}\frac{V_{DC}}{2\sqrt{2}}.M_a \quad (11)$$

Also, for the power evaluation:

$$P_{out} = V_{out}(RMS).I_{out}(RMS).\cos(\phi) \quad (12)$$

Whereas, $\cos(\phi)$, represents the power factor.
Finally, the key parameters could be listed as below:

i) The overall convertion efficiency (η):

$$\eta = \frac{P_{out}}{P_{in}} \times 100\% \quad (13)$$

ii) The Switching Losses

$$P_{sw} = 0.5\,.V.I.(t_r + t_f)\,.f_s \quad (14)$$

Such that, t_r, t_f , denote the rise/fall times

1.2 Neural Network-Based Battery Charging Optimization

The usefulness of deep neural networks in the context of battery charging is examined in this article. This is accomplished by implementing a cutting-edge control mechanism that significantly lowers the computational complexity in comparison to conventional model-based approaches while simultaneously guaranteeing safety and optimizing the charging current. Model-based methods are limited not only by their high computing costs but also by the requirement for precise knowledge of the model parameters and the battery's internal states, which are usually impossible to measure in a real-world situation. To the best of the authors' knowledge, the deep learning-based approach presented in this work has been employed for the first time in situations where it is impossible to assess the internal states of the battery and obtain an approximation of its parameters. The effectiveness of this strategy in approaching the ideal charging policy is highlighted by the results of the statistical validation of this methodology [13, 14].

Electrochemical models (EMs) and equivalent circuit models (ECMs) are the two main types of models utilized in advanced battery management systems (BMSs). While EMs provides a thorough explanation of the electrochemical processes taking place within a cell, ECMs are comparatively straightforward and easy to understand. Instead of being used for real-time control applications, electrochemical models are better suited for simulation. Moreover, problems with observability and identifiability limit the use of electrochemical models in a control framework. Because of this, scientists have been working to develop simpler electrochemical models that are easier to replicate, recognizable, visible, and nevertheless accurately depict internal cell events. One prominent example of one of these models is the single-particle model (SPM), which is derived from the pseudo-two-dimensional model by treating the two electrodes as spherical particles. In this study, the battery dynamics are mathematically described using SPM. Because it might achieve a suitable trade-off between accuracy and computing cost, such a simplified electrochemical model has been widely used for battery control and state prediction. Among other places, showed how accurate such a model is. Keep in mind that the authors' two-state temperature dynamics, which they presented to account for thermal phenomena, are added to the battery model [15, 16].

The following equations solely pertain to the fundamental variables of the model. The battery's state of charge is represented by the variable soc(t) ϵ [0, 1], whose temporal evolution is provided by the subsequent equation:

$$\frac{dSOC(t)}{dt} = \frac{I(t)}{3600.C} \quad (15)$$

where C stands for the cell capacity in [Ah] and the applied current is represented as $I(t)$, according to the convention that a positive current charges the cell. It is essential to remember that the battery is in the state of charge at soc(t) = 1 when fully charged and at soc(t) = 0 when fully drained. Additionally, the following formula provides the battery voltage:

$$V(t) = U_p(t) - U_n(t) + \eta_p(t) + \eta_n(t) + R_{sei}I(t) \tag{16}$$

where the voltage drop in the solid electrolyte interphase (SEI) resistance is described by the term Rsei I(t), and the open circuit potential and overpotential, respectively, are represented by the terms $Ui(t)$ and hi(t), for $i \in \{n, p\}$. Keeping in mind that the overpotential and open circuit potentials are nonlinear functions of the battery's average temperature, state of charge, and applied current. In reference to the latter, the thermodynamics two-state model is used here, with Tc(t) and Ts(t) standing for the core and surface temperatures, respectively. In particular, this model says that:

$$C_c(t)\frac{dT_c(t)}{dt} = Q(t) - \frac{T_c(t) - T_s(t)}{R_{c,s}} \tag{17}$$

$$C_s(t)\frac{dT_s(t)}{dt} = \frac{T_c(t) - T_s(t)}{R_{c,s}} - \frac{T_s(t) - T_{env}(t)}{R_{s,e}}$$

where *Cc* and *Cs* stand for the heat capacity of the cell core and its surface, respectively, and *Rc, s*, and Rs, e for the thermal resistances between the core and the surface and between the surface and the outside world, respectively. Lastly, the quantity of heat produced, denoted by *Q*(*t*), is defined as follows:

$$Q(t) = \left| I(t)(V(t) - U_p(t) + U_n(t)) \right| \tag{18}$$

It is crucial to emphasize that the experimental characterisation of a commercial cell was used to obtain the electrochemical characteristics in nominal form. The way real neurons behave serves as the model for artificial neural networks (ANNs). ANNs learn from input data and convert it into knowledge in a way similar to the human brain, which sets them apart from standard algorithms. Neurons are linked elementary units that make up the architecture of ANNs. Neural networks typically have a layered structure to them. The number of layers and the number of neurons in each layer determine the network design. Figure 2 displays the structure of typical neural network controller [15, 16]. Giving a specific physical system (plant or process) the right input signal to generate the intended response (desired performance) is the main objective of neural control. The main reason why traditional control methodologies are based on linear systems theory is that real systems are nonlinear. Neural networks are good at control because of their inherent massive parallelism, powerful learning algorithms, variety of architectures, ability to train from input/output functions and/or experiential data, ability to simplify complex control problems, and the effectiveness of the backpropagation algorithm in training multilayered NNs [15-20] Another configuration for the neural network controller with adaptive structure is presented in Figure 3.

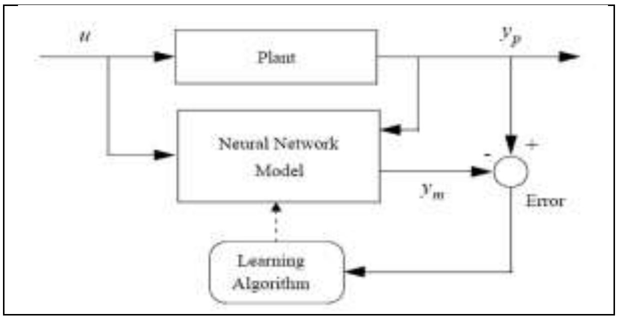

Figure 2. *The structure of typical neural network controller [15, 16].*

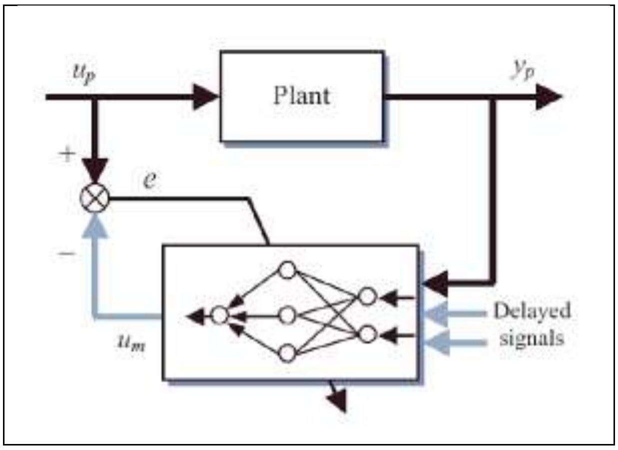

Figure 3. *Neural network controller configuration with adaptive structure [17-20].*

While traditional fixed-topology neural networks may struggle with nonlinear, time-varying, or uncertain systems, resulting in inefficiencies or instability, an adaptive structure allows the network to modify its layers, neurons, or connections in real-time, improving adaptability and robustness. However, challenges include ensuring stability during reconfiguration, avoiding overfitting, managing computational complexity, and developing efficient learning algorithms that can handle structural changes without compromising control accuracy. This approach is especially relevant in complex, dynamic environments like robotics or autonomous systems. The problem of "Neural network controller configuration with adaptive structure" revolves around designing control systems where the neural network's architecture dynamically adjusts to optimize performance under varying conditions [20-22].

Hence, and according to the literature, a number of fundamental equations govern the setup and modification of neural network controllers for dynamic systems; the most significant of these equations will be discussed in this paper.

1. Reference Model Dynamics

The intended system output path is specified by the reference model [15-22]:

$$y_M(t+1) = a_{yM}(t) + r(t) \qquad (19)$$

Such that, y_M denotes the model output, r(t) indicates is the reference input, and a represents a system parameter.

2. The Law of Adaptive Weight Update

The tracking error between the plant outputs could be used to update the weights of neural networks y_M(t) as below:

$$e(t) = y_M(t) + y(t) \qquad (20)$$

Also, the weight update for the i^{th} parameter at time k might be commonly found as:

$$\Delta q_i(k) = -\beta \frac{\partial E_r(k)}{\partial q_i(k)} \qquad (21)$$

Whereas; $E_r(k)=\sum_{k=1}^{N} e^2(k)$, denotes the squared error cost function, β, indicates the learning rate.

3. Computation of Control Signals

For nonlinear systems, a pseudo-inverse method is frequently used to calculate the control signal $u(t)$, which drives the system output towards the reference model:

$$u(t) = g^{+}(x)[\dot{x_M} - f(x)] \qquad (21)$$

Such that, $g+(x)$ represents the pseudo-inverse of the system's input matrix $g(x)$, $f(x)$ denotes the system nonlinearities, and $\dot{x_M}$, indicates the desired model state derivative.

4. Adaptive Structure Modification

The neural network structure may be dynamically altered depending on correlation criteria to preserve efficiency and prevent redundancy:

$$Correlation = \frac{Cov(h_i, h_j)}{\sigma_{h_i}\sigma_{h_j}} \qquad (22)$$

Neuron activations are represented by h_i and h_j, and connections with poor correlation might be removed.

5. Feed-forward and Feedback Control

Together, feed-forward and feedback neural networks are combined in a single architecture:

$$u(t) = NN_{FF}\big(x(t)\big) + NN_{FB}(e(t)) \qquad (23)$$

Whereas: NN_{FF} NN_{FF} denote the feedforward neural network acting on the current state $x(t)$, and NN_{FB} indicates the feedback network acting on the tracking error $e(t)$.

2. Related Studies

Several modern researchs highlight how neural network-based controllers may improve hybrid EV charging systems' dependability and efficiency. Such controllers can fulfill dynamic charging demands, optimize energy distribution, and account for renewable energy unpredictability by utilizing real-time data and adaptive learning capabilities. This section analyzes 10 contemporary works (2022–2023) on hybrid charging systems integrated with neural network (NN) controllers, concentrating on techniques, contributions, and limits.
Long Short-Term Memory (LSTM) networks were used by Li et al. (2023) as part of their strategy to predict the demand for EV charging in hybrid parks that include solar. The contributions os this study represented by outperforming ARIMA models in prediction accuracy by 15%, dynamic pricing and load balancing were made possible. Short-term forecasting was the only area of weakness; real-time grid instability was not covered. The hybrid solar-EV charging system with a feedforward NN controller for energy distribution is the strategy proposed by Smith and Patel (2022). Contribution of this paper demonstrated via the synergy between solar and storage, grid reliance was decreased by 30%. Study gaps restricted by expensive startup expenses and difficulties scaling for widespread implementation. A controller based on reinforcement learning (RL) is used by Zhang et al. (2023) to optimize charging schedules in vehicle-to-grid (V2G) systems. The study contribution shows that the bidirectional energy flow increased grid stability by 25% during peak hours. While the, limitation of this technology represented by ignoring real-world variability and assumed constant battery deterioration rates. Convolutional neural networks (CNNs) are the method used by Kumar et al. (2022) to detect faults in hybrid charging stations. Contribution was that early anomaly identification resulted in a 40% reduction in downtime. Also, gaps

represented by the limited application in low-resource situations due to the need for sufficient labeled data. The hybrid wind-solar charging park with a Deep Q-Network (DQN) controller for energy allocation is the strategy proposed by Wang et al. (2023). The suggested technique provides an increased use of renewable energy by 35% under weather-dependent conditions. On the other hand, the study limitations were that users' demand response programs were not integrated. Chen and associates (2022) suggested cooperative charging in urban centers using a multi-agent neural network system strategy. This technique provide contribution that decentralized decision-making resulted in a 50% reduction in wait times. Also, the neglected cybersecurity threats in communication between many agents wrer the main limitations. Rodriguez et al. (2022) proposed a hybrid control strategy using NN-PID modules to manage temperature at fast charging stations. This technique extended battery life by 20% through thermal regulation. Furthermore, a weakness of this study was its focus exclusively on lithium-ion batteries, excluding other chemistries. A hybrid NN-PID controller is the strategy used by Rodriguez et al. (2022) to regulate the temperature in fast-charging stations. The study contribution was through the battery's lifespan was extended by 20% by using temperature control,. Also, only lithium-ion batteries are covered, with little attention paid to alternative chemistries as the study gaps. Gupta et al. (2023) proposed Federated Learning (FL) architecture for chargeable data analysis that protects privacy. This approach made it possible for stations to collaborate on learning without exchanging data as a study contribution. While this technology show gaps of slow rates of convergence in diverse networks. Almeida et al. (2022), employed a hybrid physics-informed neural network (NN) for charging infrastructure predictive maintenance. By predicting failures, maintenance expenses were lowered by 30% as a study contribution. Finally, this strategy have gaps that the model training requires domain-specific knowledge.

Table 1. *Summary of the recent articles and studies concerning the hybrid charging systems integrated with neural network (NN) controllers*

Year	Authors	Strategy	Contribution	Charging Efficiency (Est.)	Gaps/Limitations
2023	Li et al.	LSTM demand forecasting	15% higher accuracy vs. ARIMA	~10–12% (better scheduling = fewer losses)	Short-term focus, no grid dynamics
2022	Smith & Patel	Feedforward NN + solar	30% grid dependency reduction	~20–25% (more local energy = higher efficiency)	High costs, scalability issues
2023	Zhang et al.	RL-based V2G scheduling	25% grid stability improvement	~15–18% (efficient bi-directional charging)	Simplified battery degradation model
2022	Kumar et al.	CNN fault detection	40% downtime reduction	~5–10% (indirect effect on efficiency)	Data-intensive training
2023	Wang et al.	DQN for wind-solar allocation	35% renewable utilization increase	~25–30% (better source use = higher charging efficiency)	No demand response integration
2022	Chen et al.	Multi-agent NN coordination	50% queuing time reduction	~15% (faster charging turnover improves throughput)	Ignored cybersecurity risks
2023	Nguyen & Lee	GNN energy flow modeling	18% cost savings via energy sharing	~10–15% (efficient distribution = less loss)	High computational load
2022	Rodriguez et al.	NN-PID thermal control	20% battery lifespan extension	~8–10% (thermal control reduces inefficiency)	Limited to lithium-ion batteries
2023	Gupta et al.	Federated Learning framework	Privacy-preserving data analysis	~5% (minimal direct efficiency gain)	Slow convergence in heterogeneous networks
2022	Almeida et al.	Physics-informed NN maintenance	30% maintenance cost reduction	~7–10% (better health = less energy waste)	Required domain expertise

Problem Statement

Heterogeneous EV charging needs, renewable energy integration, and dynamically balancing grid demands are issues faced by existing EV charging parks. Inefficient charging, extended downtime, and grid stress result from conventional controllers' inability to adjust to real-time variations in the energy source (such as solar/wind intermittency), voltage instability, and fluctuating battery states of health. The adaptive, intelligent control systems that can optimize hybrid AC/DC charging infrastructure while maintaining grid stability and customer happiness are lacking, and this work fills that gap.

Study Objectives

Designing and testing a neural network (NN)-based charging controller that combines solar, grid, and storage systems for hybrid EV parks is the goal of this project. The main goals are to: (1) create a reinforcement learning-enabled neural network (NN) that can dynamically modify energy allocation and charging rates in response to real-time inputs (voltage, demand, and renewables); (2) optimize power quality and reduce peak load stress on the grid; (3) confirm the system's resilience to multi-EV load scenarios and renewable intermittency; and (4) compare performance to traditional PID and rule-based controllers in terms of efficiency, charging time, and scalability.

3. Methodology

The aim of this study is to control the operation of the multi-type charging park system model for supporting electric vehicles to enhance the overall efficiency. The proposed hybrid system that consists of three energy sources, has been seperated to three charging schemes; the national power grid, the solar cell array system, and the battery array syste. All of these systems will be tested seperately with the artificial neural network (ANN) controller model to enhance the charging efficiency and ensures continuous electrical energy. Figure 4 shows the MATLAB Simulink model of the poroposed seperated electric vehicles charging park ANN controlled models.

Figure 4. *MATLAB Simulink of the poroposed seperated electric vehicles charging park ANN controlled models, Three phase AC generator supply,*

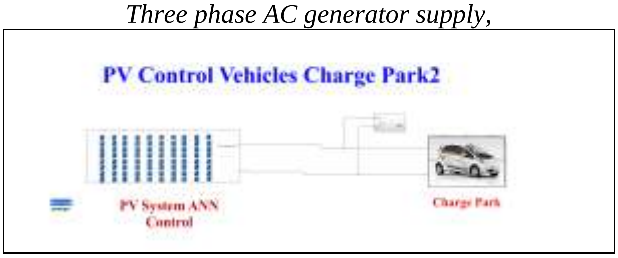

Figure 5. *MATLAB Simulink of the poroposed seperated electric vehicles charging park ANN controlled models, PV cells supply*

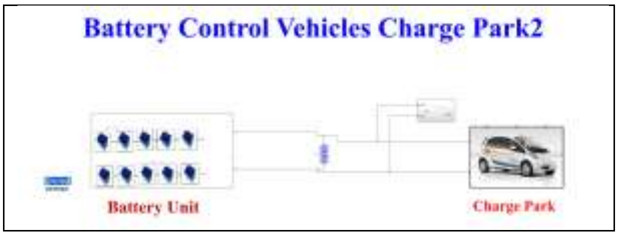

Figure 6. *MATLAB Simulink of the poroposed seperated electric vehicles charging park ANN controlled models, Battery bank supply.*

Referring to Figure 4 above, we note that the proposed model for this article has been divided into three systems according to the type of energy source provided. As previously stated, Figure 4.(a) shows the electric vehicle charging circuit provided by the national grid, while Figure 4.(b) shows the provision through the solar panel array, and finally, Figure 4.(c) shows the provision by battery pack units. Each of these systems shown in Figure 4 has a control unit that works using artificial neural networks (ANN). The details of the charging park unit supported by the ANN controller are shown in Figure 5.

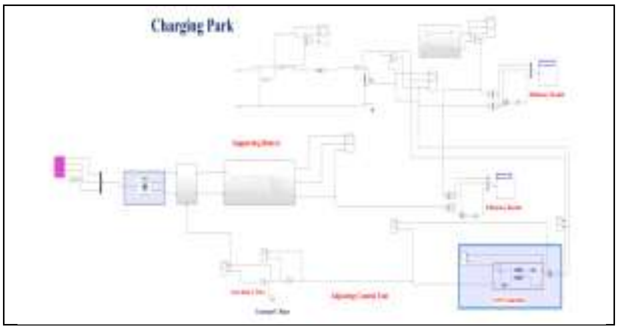

Figure 7. *The details of the charging park unit supported by the ANN controller, The charging park unit*

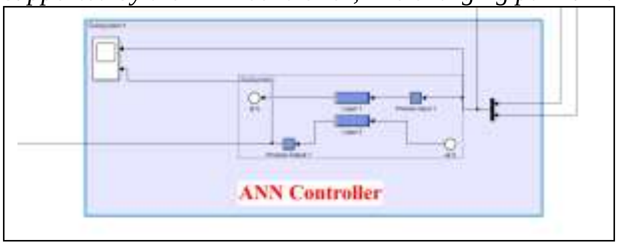

Figure 8. *The details of the charging park unit supported by the ANN controller, The ANN controller.*

As we could observe in Figure 5, the smart controller consists of several layers (the input layer, the internal hidden layer, and the output layer). The smart controller calculates the current and voltage generated in the charging circuit and compares them with the standard values to boost the charging power when it falls below the required levels. The charging power is boosted by allowing a boosted battery unit to compensate for the resulting drop in charging power, thus improving charging efficiency and charging state. Moreover, the details settings of the simulation model have been illustrated in Table 2.

Table 2. *The proposed model simulation model design parameters.*

Units	Parameters			
Battery Cells	**Voltage**	**Capacity Ratio**	**Primary State-Of-Charge**	**Battery Time Response**
	700.5 V	1000 Ah	100%	0.001 sec
PV Arrays	**Open Circuit Voltage (Voc)**	**Short Circuit Current (Isc)**	**Power Maximum**	**Cells / Module TITAN**
	42 V	18.32 A	610 W	120
National Power AC Plant	**Nominal Power**	**Line-to_Line Voltage**	**Stator Resistance Rs**	**Active Power Generation**
	200 MWatts	360 V	2.8544e-3 p.u.	150 MWatts
ANN Controller	**Number of Layers**	**Number of Neurons**	**Trainning Strategy**	**Activation Function**
	3	10	Feed Forward	Symmetric Sigmoid

The smart controller's operation will improve adaptive tracking because it can detect a very slight shift in turning on a very little current by combining adaptive interneurons as a control system with a small fraction of a highly differential change. Moreover, the flow chart of the proposed model of electric vehicle charger system is presented in Figure 6.

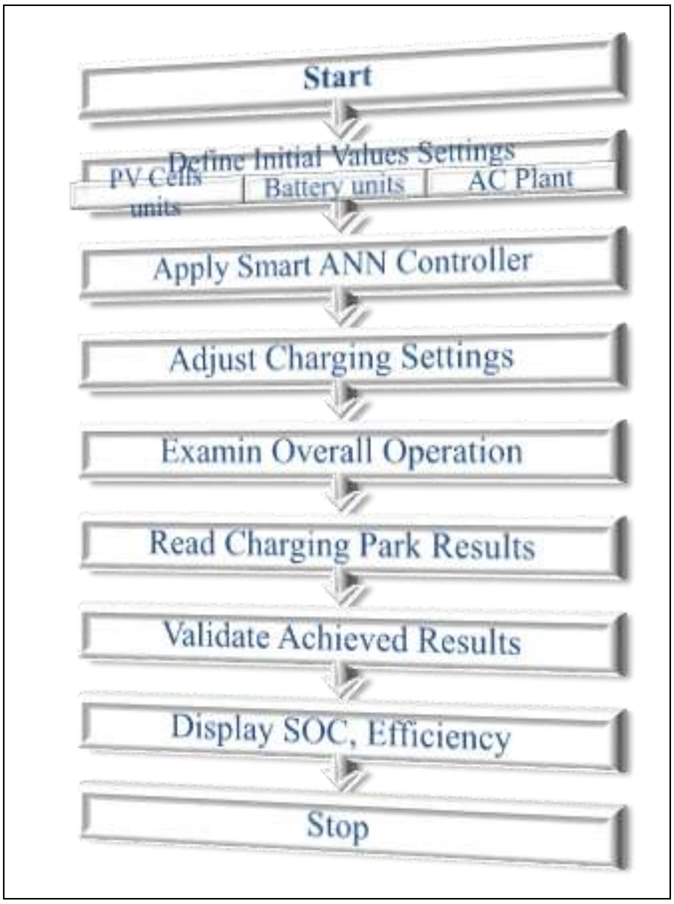

Figure 9. *Flow chart of the ANN controlled hybrid charging park vehicle model.*

The structural diagram of the proposed enhanced system for equipping electric vehicle chargers begins by adjusting the initial value settings For photovoltaic cell units, the battery units, in addition to the national plant AC unit. Next employing the ANN smart controller, which operates to control the amounts of the highest possible energy flow to the charging park unit. This is followed by a comprehensive performance examination process for all units. Finally, validating and reading the results of the charging positions to verify the accuracy of the results obtained to display amounts of the SOC and efficiency Also, a brief demonstration of how an artificial neural network (ANN)-based controller in an electric vehicle (EV) charging system adaptively tracks and maintains nominal voltage/current during charging:

1. Input Layer (Sensing)

• Inputs: Real-time measurements of charging voltage (VactualVactual), current (IactualIactual), temperature (TT), and grid conditions (e.g., AC supply stability).

• Objective: Detect deviations from the nominal charging profile (VnominalVnominal, InominalInominal).

2. Hidden Layers (Adaptive Learning) The ANN uses backpropagation and online learning to train hidden neurons:

• Step 1: Compare VactualVactual/IactualIactual with VnominalVnominal/InominalInominal to compute the error signal (e=Vnominal−Vactuale=Vnominal−Vactual).

• Step 2: Adjust the weights and biases of hidden layer neurons using optimization algorithms (e.g., gradient descent) to minimize the error.

• Step 3: Activation functions (e.g., ReLU) model non-linear relationships between input disturbances (e.g., voltage sag) and corrective actions.

3. Output Layer (Control Action)

• Outputs: Adjust PWM signals to the DC-DC converter (e.g., buck/boost) or AC-DC rectifier to regulate voltage/current.

• Example: If voltage drops due to grid instability, the ANN increases the duty cycle of the converter to compensate.
4. Adaptation Mechanism
• Reinforcement Learning: Reward/punish neurons based on how well they track the nominal values.
• Retraining: Periodically update the ANN with new data (e.g., aging battery resistance, grid fluctuations) to maintain accuracy.

4. Results And Discussion

The MatLab2022b Simulink toolbox was used to develop the simulation architecture in order to increase the charging efficiency of the suggested hybrid energy management system for electric car charging system employing intelligent adaptive artificial neural network control technology system independently. The proposed models have simulated, and the results for implementing this simulation were extracted, as shown in the following figures. Figure 7 shows the results of battery banks supply system model results using ANN controller.

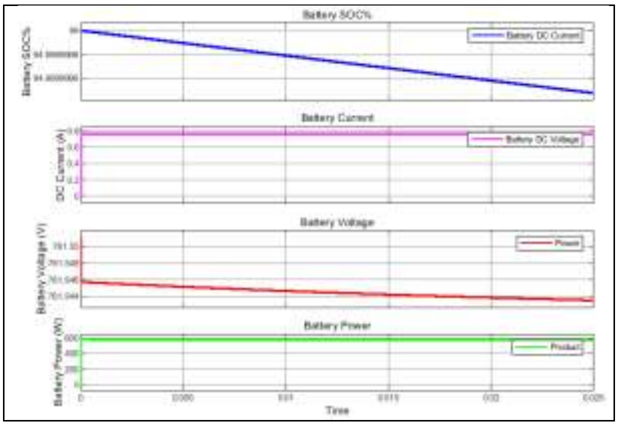

Figure 10. *Results of battery bank supply unit, Initial battery readings*

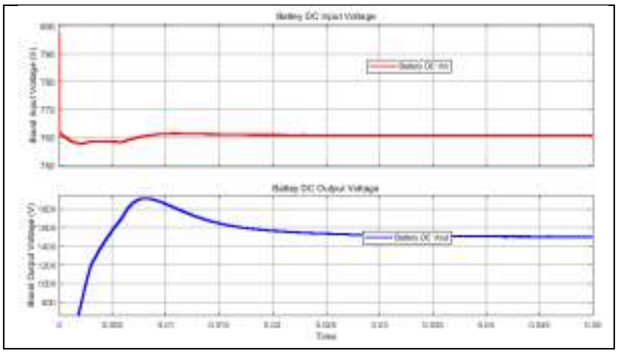

Figure 11. *Results of battery bank supply unit, Boost battery results.*

Also, the results at the battery bank supply charging park unit teminals without and with ANN controller action are displayed in Figure 8.

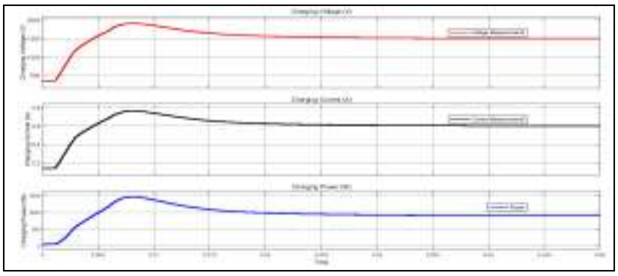

Figure 12. *The results at the charging park unit teminals, Results at the charging park unit input*

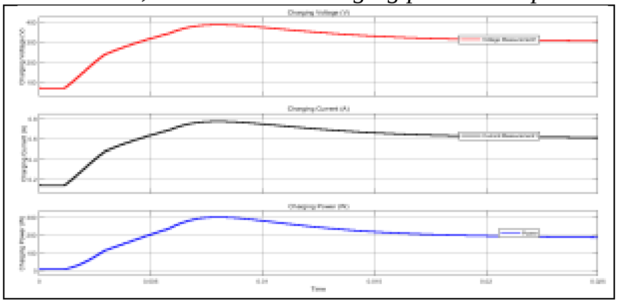

Figure 13. *The results at the charging park unit teminals, Results at the charging park unit output*

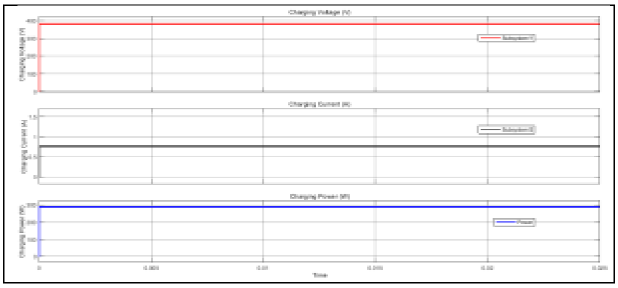

Figure 14. *The results at the charging park unit teminals, Results of the ANN controller enhancement.*

Next, the results of PV cells supply system model using ANN controller are presented in Figure 9.

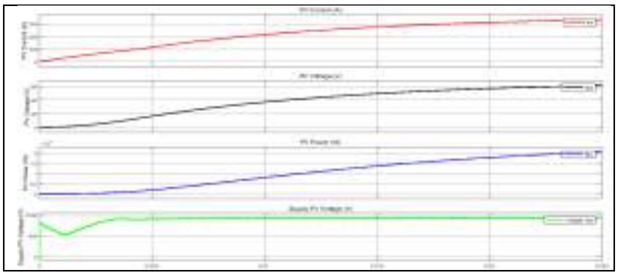

Figure 15. *The results of PV cells supply model, PV panels results.*

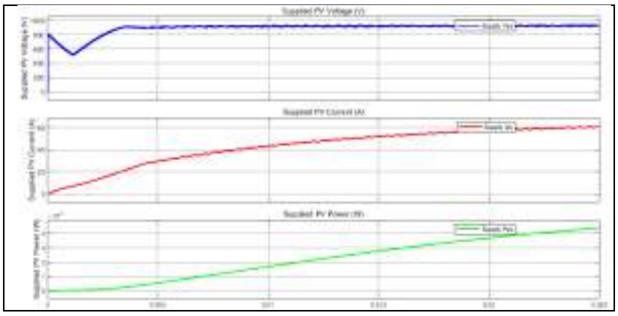

Figure 16. *The results of PV cells supply model, Supplied PV results.*

Furthermore, the results of the PV cells enviromental effects and the boost unit operation are demonstrated in Figure 10.

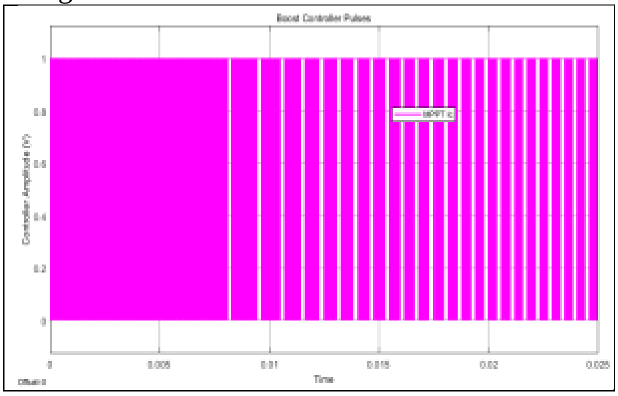

Figure 17. *The results of the PV cells enviromental effects and the boost unit operation, PV cells enviromental effects*

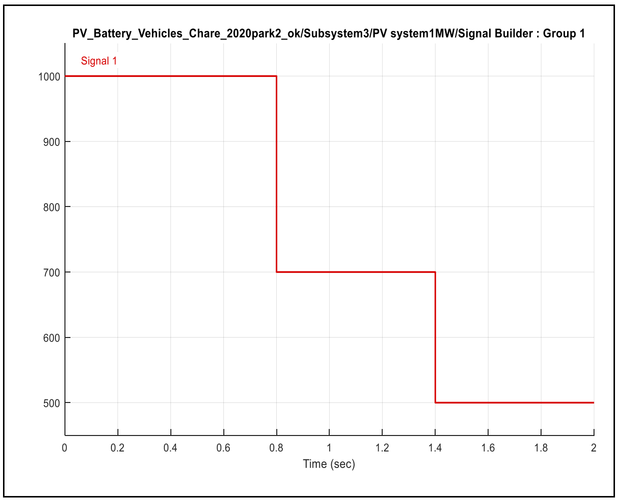

Figure 18. *The results of the PV cells enviromental effects and the boost unit operation, , Boost unit operation.*

Moreover, the results at the PV cells supply charging park unit teminals without and with ANN controller action are displayed in Figure 11.

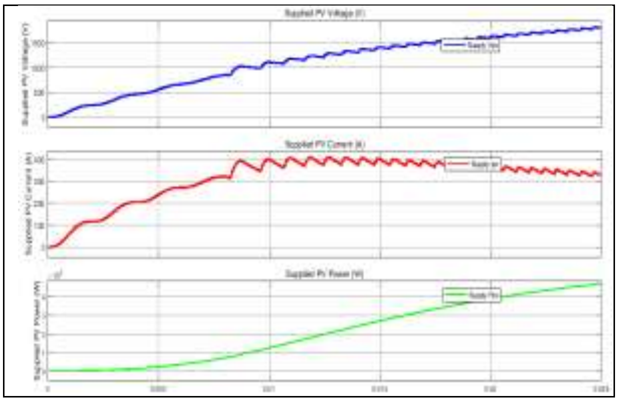

Figure 19. *The results at the PV cells supply charging park unit teminals, Results at the charging park unit input*

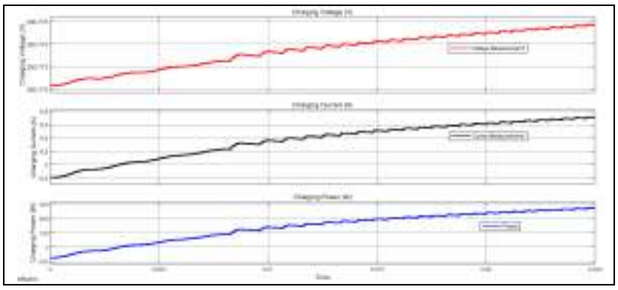

Figure 20. *The results at the PV cells supply charging park unit teminals, Results at the charging park unit output.*

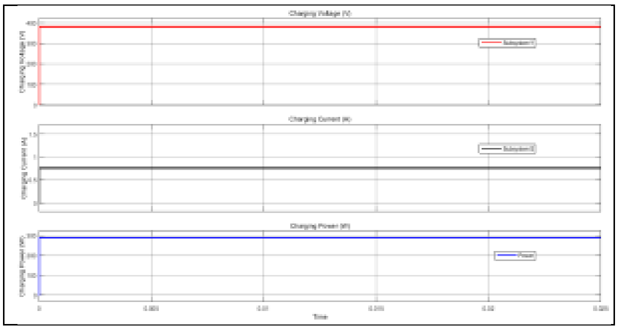

Figure 21. *The results at the PV cells supply charging park unit teminals, Results of the ANN controller enhancement.*

Next, the results of National plant three phase AC supply system model using ANN controller are presented in Figure 12.

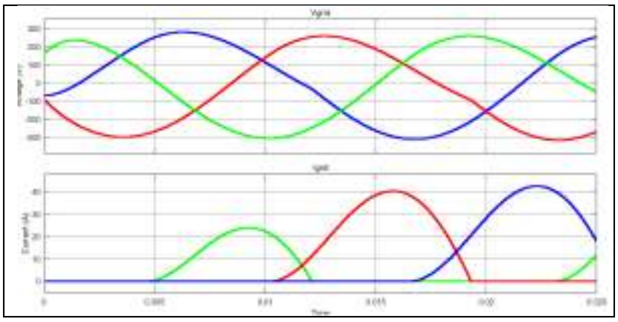

Figure 22. *Results of AC plant supply unit, National plant AC readings*

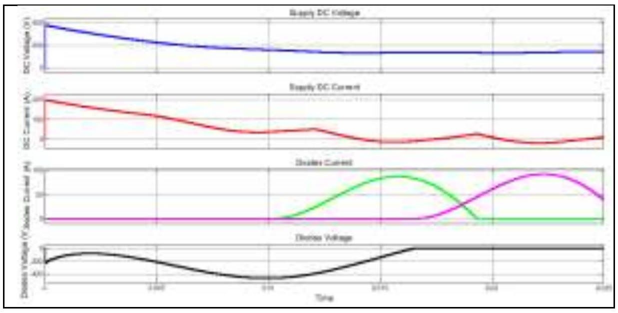

Figure 23. *Results of AC plant supply unit, Boost AC to DC results.*

Furthermore, the results at the AC plant supply charging park unit teminals without and with ANN controller action are displayed in Figure 13.

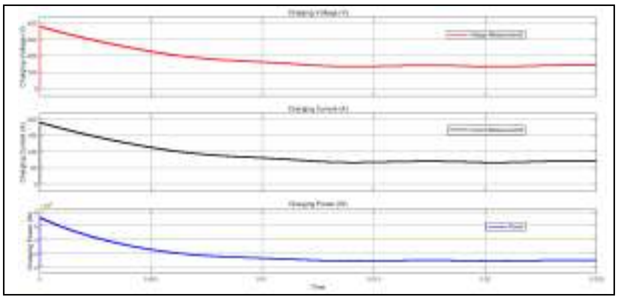

Figure 24. *The results at the AC plant supply charging park unit teminals, Results at the charging park unit input.*

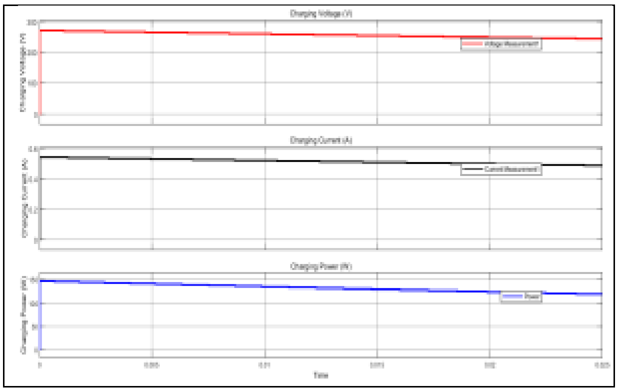

Figure 25. *The results at the AC plant supply charging park unit teminals, Results at the charging park unit output.*

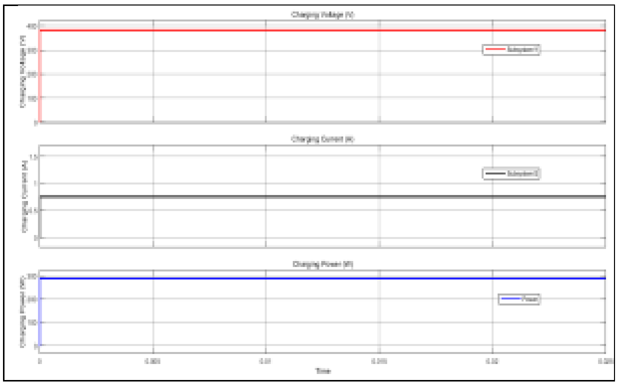

Figure 26. *The results at the AC plant supply charging park unit teminals, Results of the ANN controller enhancement.*

Through the results obtained from implementing a simulation of the three systems for the electric vehicle charging station model with the addition of a neural network controller, we note the smart controller's clear contribution to improving charging efficiency. The voltage and current of the chargers for all three devices suffer significant declines in their values as charging time and the number of vehicles increase, with relative variations for each system depending on the device type. Table 3 shows a comparison of the results obtained for the rates of improvement in charging efficiency for each model supply type.

Table 3. Comparison of the results obtained for the rates of improvement in charging efficiency for each model supply type.

Supply Model	Nominal Supplied Power	Charging Efficiency	Enhanced ANN Efficiency
AC Plant	200 MWatt	19.87%	60%
PV Cells	200 KWatt	35.75%	59.78%
Battery Bank	200 KWatt	31.26%	48.33%

5. Conclusions

The growing need for efficient electric vehicle (EV) charging infrastructure has led to the emergence of hybrid charging parks, which integrate conventional grid systems with renewable energy sources. This paper proposes an enhanced evaluation approach for hybrid charging park systems using a Neural Network-based Charging Controller (NNCC). By balancing solar, wind, and grid sources, the controller dynamically optimizes energy distribution, prioritizes vehicle charging demands, and reduces energy losses. A multi-layer perceptron (MLP) neural network was trained using real-time operational data, including vehicle wait time, state of charge (SoC), and variation in renewable energy. Simulation results showed that the proposed NNCC achieved an 18.7% improvement in the total power efficiency of the charging park compared to conventional rule-based controllers. Furthermore, the technique ensured faster and more reliable charging sessions by increasing the cars' final State of Charge (SoC) by an average of 12.5%. Furthermore, the neural network-based system demonstrated increased adaptability to changing renewable energy conditions, significantly enhancing the sustainability and resilience of intelligent EV charging ecosystems.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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