

Article

Multi-Objective Hierarchical Optimization Framework for Vehicle-to-Vehicle Trading Integrating Hybrid Deep Learning and Dynamic Greedy Matching

Zhuolin Wu and Bifei Tan *

School of Mechanical and Automation Engineering, Wuyi University, Jiangmen 529020, China;
wuzhuolin58@gmail.com

* Correspondence: j002917@wyu.edu.cn

Abstract

Accelerated electric vehicle (EV) adoption imposes complex requirements on grid integration and energy dispatch. Current Vehicle-to-Vehicle (V2V) trading research frequently utilizes monolithic forecasting architectures that fail to account for the stochastic nature of mobility data. Furthermore, traditional optimization strategies often prioritize financial yields at the expense of user-centric utilities, hindering global system optimality. To resolve these limitations, this paper proposes a hierarchical optimization framework, designed to reconcile the interests of stakeholders. The approach first employs a hybrid deep learning architecture, integrating long short-term memory (LSTM), gated recurrent unit (GRU), and Transformer architectures, dynamically weight predictions and refine available dwell time estimations. Then, a multi-objective optimization model is formulated to identify Pareto-optimal solutions that balance economic efficiency with user convenience. Finally, a dynamic greedy matching algorithm is introduced to facilitate rapid transaction pairing for large-scale, real-time V2V requests under multiple constraints. Simulation results demonstrate that this hierarchical framework improves trading success rates, optimizes resource distribution, and enhances overall user satisfaction.

Keywords: vehicle-to-vehicle (V2V); energy trading; deep learning; matching algorithm

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1. Introduction

The global transition toward electric vehicles (EVs) significantly fosters economic expansion and environmental sustainability [1]; however, their proliferation strains electrical infrastructure and exacerbates user range anxiety. Vehicle-to-Vehicle (V2V) energy exchange technology has emerged as a decentralized solution [2], enabling energy-surplus vehicles to serve as mobile storage units for peer-to-peer sharing. This model alleviates peak grid demand while providing resilient, emergency charging alternatives [3]. Despite its potential, practical V2V implementation remains hindered by inefficient matching protocols and inequitable profit structures [4]. Because current single-objective optimization methods prioritize financial metrics over user utility, there is a critical need for a matching framework that holistically addresses the conflicting interests of various stakeholders.

1.1. Literature Review and Research Gaps

The substantial disparity between rated battery capacity and average daily mileage allows electric vehicles (EVs) to function as both flexible electrical loads and distributed power sources [5]. This dual-attribute paradigm, formalized as Vehicle-to-Grid (V2G) by Kempton and Letendre in 1997, establishes EVs as bidirectional energy storage units rather than as mere power consumers [6]. By leveraging V2G technology, charging infrastructure can be transformed into a dynamic network of energy storage systems, optimizing resource allocation and alleviating stress on distribution feeders. Beyond basic load management, V2G offers a robust framework for integrating surging charging demands with minimal infrastructure expansion while yielding significant environmental and economic dividends [7]. Consequently, the utility of EVs as decentralized storage for ancillary services, including peak shaving, valley filling, frequency regulation, and congestion mitigation, has become a focal point of contemporary grid research [8].

Recent industry assessments highlight that V2G scalability is often constrained by its dependence on extensive physical infrastructure and centralized dispatching protocols [9]. As EV adoption accelerates, the resulting surge in charging demand necessitates a shift toward maximizing the utilization efficiency of existing facilities. To address this, Zhou et al. proposed a scheduling optimization framework intended to minimize user wait times while maximizing charging pile throughput. Their approach utilizes a mixed-integer linear programming (MILP) model to transform complex nonlinear constraints into a solvable linear structure, ensuring operational efficiency [10]. Beyond localized scheduling, research has shifted toward the systemic optimization of charging infrastructure and its impact on the wider urban fabric. Wang et al. addressed the challenge of unmet charging demand by synthesizing k-means clustering with queuing theory to determine optimal station placement and capacity. Their methodology further utilized the mean shift algorithm to identify locations for compensatory charging units, dynamically updating station service regions to align with fluctuating demand [11]. Concurrent research has also integrated the physical limitations of EV hardware into scheduling logic. Khezri et al. developed a MILP-based V2G scheduling framework that accounts for battery degradation, specifically modeling the distinct impacts of calendar aging and cycle aging to ensure that energy trading remains economically viable for the vehicle owner over time [12]. At the macro-scale, the interdependency between transportation and energy sectors has become a primary focus. Li et al. proposed a coordinated MILP framework for the simultaneous planning of coupled power distribution and traffic networks. This model determines the synchronized deployment of new roadways, the strategic placement of charging stations, and the necessary expansion of power distribution networks to sustain increased electrical loads [13]. The emergence of intelligent heuristics and large-scale data analytics has enabled global optimization strategies that utilize iterative particle evolution to ensure algorithmic robustness. Yin et al. [14] proposed a modified particle swarm optimization model designed to minimize both daily grid load variance and consumer-side charging costs. Complementarily, Du et al. employed Monte Carlo simulations to quantify the distribution of uncoordinated charging, subsequently implementing an enhanced PSO algorithm to facilitate structured, orderly charging strategies [15].

As the shared economy and distributed energy paradigms evolve, these efforts are increasingly transitioning toward decentralized vehicle-to-vehicle (V2V) energy exchange [16]. Scholarly focus has increasingly transitioned toward decentralized V2V energy trading models. Unlike the centralized infrastructure inherent to V2G, V2V emphasizes peer-to-peer transactions. This decentralized paradigm effectively mitigates the limitations of insufficient charging infrastructure while simultaneously optimizing energy distribution and bolstering user autonomy. Tao et al. contextualized energy management within the sharing economy, proposing a unified hydrogen–electric framework that facilitates cross-aggregator energy sharing

[17]. Furthermore, optimization and game theoretic methodologies, particularly Stackelberg game architectures involving shared storage and carbon markets, have been employed to incentivize low-carbon generation and facilitate the implementation of V2V applications [18]. Recent advancements in V2V energy trading have shifted toward hybrid frameworks that prioritize both economic sustainability and user equity. Arumugam and Subbaiyan [4] introduced a novel architecture that synthesizes a multi-armed bandit framework with game theory. This hybrid approach utilizes dynamic pricing and commitment-driven penalty mechanisms to safeguard supply-side profitability while ensuring transactional fairness for demand-side participants. From an operational perspective, Somefun and Longe [19] highlighted the practical advantages of integrating V2V protocols within charging station infrastructures. Their research demonstrates that such deployments significantly reduce user latency and enable lucrative arbitrage opportunities, allowing EV owners to capitalize on localized energy market fluctuations. To manage the inherent volatility of distributed energy networks, Wu et al. [20] proposed a framework merging clustering algorithms with reinforcement learning. This configuration facilitates adaptive scheduling in decentralized environments, allowing for rapid convergence to optimal dispatch solutions despite the high stochasticity of EV mobility patterns. Cao et al. [21] focused on the spatial constraints of energy exchange by developing a proximity-based matching algorithm coupled with spatiotemporal coordinated path planning. This methodology enhances overall charging efficiency by minimizing travel-related overhead, ensuring that energy transfer pairs are optimally aligned in both time and space. Luo et al. introduced a Bayesian game-based double auction mechanism complemented by an adaptive price adjustment strategy. To reinforce system integrity, they integrated a blockchain-based decentralized ledger to facilitate immutable auditing of energy transactions while ensuring strong user privacy protection [22]. Complementing this, Shurrab et al. [9] approached the V2V charging problem through multiple-stage decomposition, formulating modular strategies for sequential optimization. Their framework holistically addresses the interdependencies between transaction pricing, individual rationality, and the critical requirements of user security and data confidentiality.

In recent years, advances in deep learning have led to its widespread adoption in EV-related research. Since its emergence in 2006, deep learning has been extensively applied to load forecasting [23,24]. However, the growing participation of EVs introduces substantial uncertainty, posing challenges for conventional forecasting methods. To address this issue, Zafar et al. proposed a hybrid deep learning framework that integrates transfer learning and K-means clustering. The approach first trains a deep learning model on a complete dataset in the source domain and then refines it using clustered user behavior data. For target domains with limited data, transfer learning transfers knowledge from the fine-tuned source model [25]. Bamos et al. [26] emphasized that the rapid growth of EV adoption requires accurate forecasting of EV charging demand, particularly for electricity suppliers and EV aggregators participating in wholesale markets. They developed a scalable hybrid framework combining convolutional neural networks and long short-term memory (LSTM) networks to capture complex spatiotemporal patterns in charging data. Waqa et al. [27] enhanced forecasting performance by integrating domain-specific feature engineering, leveraging lagged and rolling-window statistics, with hyperparameter optimization and a genetic algorithm-based time-step selection method, improving model adaptability across diverse urban environments. Singh et al. [28] introduced a novel attention-augmented LSTM framework in which an attention mechanism prioritizes the most informative time steps, enabling more effective capture of long-term temporal dependencies and improving prediction accuracy. Azab et al. [29] evaluated four short-term load forecasting algorithms, namely RNN, LSTM, GRU, and an adaptive neuro-fuzzy inference system, using a seasonally segmented dataset where temperature served as a seasonal variable, and compared their predictive performance across different

seasons. Cui et al. [30] investigated the spatiotemporal interactions among road networks and developed a traffic-flow prediction model combining LSTM with a graph neural network-fully connected layer architecture. The predicted traffic flows were used to estimate EV charging demand and to formulate a charging demand forecasting approach for future charging stations by translating EV user satisfaction into multidimensional economic costs. Additionally, a dynamic pricing mechanism based on deep deterministic policy gradient learning was introduced. Recent research has also explored fusion prediction architectures in related energy systems. Ma et al. proposed a CNN-LSTM model with a squeeze-and-excitation attention mechanism for performance degradation prediction of proton exchange membrane fuel cells [31]. Their study shows that combining convolutional feature extraction, temporal dependency modeling, and attention-based feature recalibration can improve prediction performance under dynamic operating conditions. This provides useful evidence for the effectiveness of fusion prediction models in energy-related time series forecasting.

Overall, although existing studies have achieved notable progress in the field of V2V energy trading, several limitations and research gaps remain that warrant further exploration. Firstly, with respect to forecasting models, most existing research relies on a single deep learning architecture for load or vehicle state prediction. Although these models perform well in time series analysis, each exhibits intrinsic limitations. Few studies have investigated hybrid frameworks that integrate the complementary strengths of multiple models to build adaptive forecasting architectures capable of responding to dynamic input characteristics. Secondly, regarding optimization objectives, conventional approaches often adopt single-objective formulations, such as cost minimization or profit maximization. Existing models rarely provide a balanced consideration of both service providers' economic benefits and user-side service satisfaction. This imbalance may lead to matching strategies that favor one party, limiting the achievement of system-wide Pareto optimality and potentially reducing user participation. Finally, in terms of practical applicability, although V2V technology is often promoted as a solution to inadequate charging infrastructure, many studies have conducted simulations in urban environments with well-developed charging infrastructure. Consequently, the practical relevance of these findings may be constrained. There remains a lack of systematic research focusing on critical contexts such as rural or underdeveloped regions, where charging infrastructure is sparse, and range anxiety is more pronounced, and where tailored V2V matching and scheduling strategies are particularly necessary.

As further illustrated in Table 1, this study develops a V2V energy trading system designed to improve forecasting accuracy, balance optimization objectives, and enhance scenario-specific applicability, thereby addressing the aforementioned research gaps.

Table 1. Comparison of existing electric vehicle energy trading and multi-dimensional intelligent scheduling approaches. (considered: ✓; not considered: ×).

Ref.	EV Structure	Matching Speed and Valuation	Clustering	Multi-Objective Equilibrium	Underdeveloped Scenario	Optimization Type
[9]	V2V	Moderate	×	×	×	Consider privacy
[10]	V2G	Slow	×	×	×	MILP
[11]	V2G	Moderate	✓	×	×	Heuristic
[12]	V2G	Slow	×	×	×	MILP
[13]	V2G	Moderate	×	×	×	PSO
[14]	V2G	Moderate	×	×	×	PSO
[15]	V2G	Moderate	✓	×	×	PSO
[17]	V2V	-	×	×	×	Not mentioned
[18]	V2V	Slow	×	×	×	Game Theory

[19]	V2V	Slow	×	×	×	Game Theory
[20]	V2V	Slow	✓	×	×	RL
[21]	V2V	Moderate	×	×	×	Heuristic
[22]	V2V	Moderate	×	×	×	Game Theory
This paper	V2V	Fast	✓	✓	✓	Heuristic

1.2. Contributions

A review of existing V2V energy trading approaches indicates that most studies focus on single-objective optimization or rely on static assumptions regarding vehicle availability. Current prediction methods also tend to use a single model or a simple ensemble. The core novelty of this study is not the isolated use of LSTM, GRU, Transformer, or greedy matching. It lies in a prediction-driven hierarchical V2V trading framework for charging-infrastructure-insufficient scenarios. In this framework, charging-session availability and SOC states are first forecast by a dynamically weighted hybrid model. The predicted information is then embedded into a multi-objective matching model that jointly considers provider profit, user satisfaction, time-window feasibility, SOC safety, and one-to-many energy allocation.

(1) To overcome the limitations of existing prediction approaches, which commonly rely on standard architectures or limited fusion models with simple integration strategies, this study proposes a hybrid attention-based ensemble prediction model. The framework integrates LSTM, GRU, and Transformer architectures through an attention-based fusion module that dynamically assigns weights to each sub model according to the data characteristics. By capturing both long-term dependencies and local variations in the data, the proposed approach enhances predictive accuracy and provides a reliable data foundation for the subsequent matching process.

(2) To address the imbalance inherent in single-objective strategies, this study develops a profit satisfaction-oriented multi-objective optimization framework. Unlike conventional models that treat economic returns and service quality separately, the proposed approach quantifies both provider profit and user satisfaction within a normalized comprehensive evaluation metric. This formulation enables a balanced trade-off between service provider revenue and user convenience, thereby promoting global utility maximization while sustaining strong incentives for user participation.

(3) A dynamic greedy matching algorithm with iterative verification is proposed to address the complexity of large-scale, real-time V2V energy trading. During the iterative process, real-time dynamic constraints are incorporated to ensure that each matching decision remains feasible and logically consistent. This mechanism prevents energy over-selling while maintaining high computational efficiency, making the approach suitable for dynamic operational environments.

2. Hybrid Deep Learning Prediction Model

2.1. Model Architecture Overview

In the hierarchical architecture of the V2V energy trading system, the prediction layer serves as the preliminary intelligence that defines the boundary conditions for subsequent matching and allocation processes. In contrast to conventional grid load forecasting, predicting EV behavior in distributed networks presents a multifaceted challenge characterized by three temporal patterns: high frequency stochastic fluctuations, periodic seasonality, and long-term dependencies. Long short-term memory networks are effective at modeling sequential dependencies; however, their performance can degrade when handling very long sequences due to vanishing gradient effects [30]. Gated recurrent units (GRUs), although computationally efficient, may oversimplify complex temporal dynamics because of their reduced gating mechanisms. Transformer architectures, while effective at capturing global

dependencies through self-attention mechanisms, often exhibit weaker performance in representing local temporal patterns and short-term variations.

To address these limitations, this study proposes a hybrid dynamically weighted ensemble framework. Fusion prediction architectures have shown good potential in energy-related time series forecasting. For example, Ma et al. combined CNN, LSTM, and an attention mechanism to improve degradation prediction under dynamic operating conditions [31]. Inspired by this idea, this study develops a hybrid dynamically weighted ensemble framework for EV behavior prediction. Rather than using a simple average, the framework exploits the complementary strengths of LSTM, GRU, and Transformer branches. The fusion module estimates sample-level weights from the three branch outputs. It then combines the outputs and applies a small correction network. This design allows the model to adjust branch contributions. The overall workflow is illustrated in Figure 1.

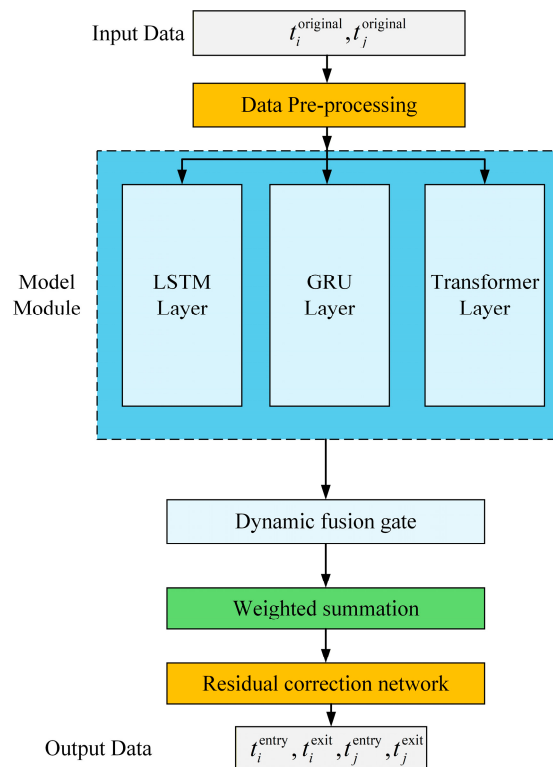


Figure 1. Architecture of the proposed LSTM-GRU-Transformer ensemble prediction model.

2.2. Components of Prediction Model

The LSTM network used in this study is a specialized form of RNN designed to alleviate the vanishing gradient problem and capture long-term dependencies. Its architecture employs gating mechanisms to regulate information flow through a dedicated memory cell. The forget gate determines which portion of the previous cell state is retained or discarded, the input gate determines the extent to which new information is updated in the cell state, and the output gate governs the exposure of the internal cell state to the next hidden state [30]. This cell-based design enables LSTMs to maintain and propagate relevant information over extended temporal sequences, a capability essential for accurately forecasting V2V charging demands. The underlying operations are formally defined as follows:

$$\begin{cases} f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\ C_t = f_t C_{t-1} + i_t \tilde{C}_t \\ O_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\ h_t = O_t \tanh(C_t) \end{cases} \quad (1)$$

As delineated in Equation (1), the forget gate determines the extent to which information from the previous hidden state h_{t-1} and the current input x_t is preserved or discarded, producing an output between 0 and 1 that regulates the prior cell state. The input gate, operating alongside the candidate cell state, controls the incorporation of new information into long-term memory. Through this mechanism, the model extracts salient features from complex market signals and user behaviors. The subsequent cell state update constitutes the core memory operation of the LSTM, enabling a stable yet adaptive memory flow. This structure allows the model to process non-stationary sequences in V2V energy trading, which often exhibit long-term dependencies and abrupt event-driven fluctuations.

Within the GRU architecture, information flow through the memory component is controlled by two primary gating mechanisms. The update gate regulates the degree to which information from previous states is retained and propagated forward, whereas the reset gate determines how much historical information should be discarded. This mechanism enables the model to capture long-range dependencies in sequential data. Compared with long short-term memory units, GRUs employ a simpler structure with fewer gating components, which can facilitate faster training and reduce the risk of overfitting when working with moderately sized datasets. The corresponding operations are formally defined as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (2)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad (3)$$

$$\tilde{h}_t = \tanh(W_h \cdot [r_t h_{t-1}, x_t]) \quad (4)$$

$$h_t = (1 - z_t) h_{t-1} + z_t \tilde{h}_t \quad (5)$$

The update gate regulates the balance between previously stored information and newly generated candidate information. It determines the extent to which the previous hidden state is preserved while controlling the incorporation of new information into the current hidden state. When the value of z_t approaches 1, the model prioritizes newly generated information, enabling rapid adaptation to dynamic signals such as sudden increases in local energy demand within V2V energy trading environments. Conversely, when the value approaches 0, the model retains a greater proportion of historical information, thereby preserving stable patterns such as recurring charging cycles.

Within the Transformer's encoder-decoder framework, the multi-head self-attention mechanism computes pairwise relevance across all elements in the input sequence, irrespective of temporal distance, thereby determining how information is aggregated and weighted. This mechanism enables the model to capture complex global dependencies across the entire sequence in parallel, which is essential for modeling the dynamics of V2V energy trading. In contrast to recurrent structures such as GRUs and LSTM networks, the Transformer architecture removes the requirement for sequential computation, allowing full parallelization during training. This structural advantage improves computational

efficiency for long sequences while facilitating more direct modeling of global interactions. These core processes are defined as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (6)$$

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (7)$$

$$\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \quad (8)$$

The scaled dot-product attention mechanism illustrated in (6) constitutes the core computation of the Transformer architecture. Each element of the resulting weight matrix represents the relevance between two time steps in the sequence, regardless of their temporal distance. The weights are normalized using a softmax function to form a probability distribution, which is applied to compute a weighted sum of the Value matrix. Through this process, the model selectively aggregates information from the most relevant contextual positions, enabling the representation at each time step to incorporate influential past information.

2.3. Heterogeneous Sub-Model Architecture

The proposed framework comprises three parallel branches, each designed to capture distinct characteristics of the data stream. The architecture follows the principle of orthogonal complementarity, employing heterogeneous inductive biases to reduce overlapping error domains. The LSTM network utilizes gating mechanisms to alleviate the vanishing gradient problem and extracts short-term nonlinear variations and immediate temporal trends. The GRU serves as a lightweight alternative with fewer parameters, improving computational efficiency while acting as an ensemble regularizer that enhances robustness against overfitting in simple temporal patterns. The Transformer encoder employs a self-attention mechanism to capture global dependencies. Unlike RNNs, it models relationships between time steps t and $t-k$ regardless of the distance k , enabling effective identification of long-range periodic structures.

The principal innovation of this prediction module is the sample-level dynamic fusion layer. The layer does not use fixed averaging. It learns the relative reliability of LSTM, GRU, and Transformer predictions from their output patterns. This makes the ensemble different from a conventional static ensemble model.

Compared with conventional ensemble learning approaches, the proposed model has three main differences. Firstly, instead of assigning static weights to each branch, the model uses a data-driven fusion gate. This gate takes the concatenated outputs of the LSTM, GRU, and Transformer branches as input and computes sample-specific softmax weights. Therefore, the contribution of each branch can be adjusted according to the current input sequence, rather than being fixed after training. Secondly, the three branches are complementary in temporal feature extraction. The LSTM and GRU branches model sequential dependencies through recurrent hidden states, while the GRU provides a more compact gating structure. The Transformer branch uses self-attention to capture long-range temporal dependencies over the 168 h input window. This combination provides broader temporal representation than a homogeneous ensemble whose base models share similar inductive biases. Thirdly, after weighted fusion, a lightweight residual correction network further refines the fused prediction. During ensemble training, the branch parameters are frozen, while the fusion gate and correction network are updated. This allows the model to reduce residual prediction errors without disturbing the pretrained branch representations. These design choices distinguish the proposed model from standard ensemble strategies such as simple averaging, static weighted averaging, or

conventional stacking, which usually do not include input-conditioned weighting and explicit post-fusion correction.

Let $\mathbf{P}_{LSTM}, \mathbf{P}_{GRU}, \mathbf{P}_{Trans} \in \mathbb{R}^K$ denote the prediction vectors from the three branches.

$$\mathbf{c} = [\mathbf{P}_{LSTM} \parallel \mathbf{P}_{GRU} \parallel \mathbf{P}_{Trans}] \in \mathbb{R}^9 \quad (9)$$

The fusion weights are generated by a trainable softmax gating network. The inputs of this network are the stacked prediction vectors from the three branches.

$$\mathbf{w} = \text{softmax}(\mathbf{W}_2 \cdot \text{ReLU}(\mathbf{W}_1 \mathbf{c} + \mathbf{b}_1) + \mathbf{b}_2) \quad (10)$$

Each fusion weight represents the current contribution of one branch. For stable periodic patterns, the Transformer branch can receive a larger weight. For abrupt local changes, the recurrent branches can contribute more strongly.

The fused representation is obtained by a weighted summation of the three branch outputs.

$$\mathbf{H}_{fused} = \sum_{k \in \{LSTM, GRU, Trans\}} w_k \cdot \mathbf{P}_k \quad (11)$$

The final prediction is obtained after a lightweight correction network is applied to the fused representation.

$$\hat{\mathbf{y}} = \mathbf{H}_{fused} + \lambda \cdot \mathbf{f}_{corr}(\mathbf{H}_{fused}) \quad (12)$$

where $\lambda = 0.1$ is a fixed scaling factor that controls the magnitude of the residual correction, and $\mathbf{f}_{corr}(\cdot)$ denotes a two-layer feedforward network with a ReLU activation.

When one branch is affected by noise or local overfitting, the other branches can compensate through the dynamic fusion layer. This improves robustness without relying on a single temporal model.

The EV behavior parameters used in this study were extracted from ACN-Data reported in Ref. [32]. ACN-Data is a publicly available EV charging dataset collected from two Adaptive Charging Networks located in California, including the Caltech and JPL charging sites. The dataset contains real EV charging session records and provides representative public charging behavior information. Each record provides session level information, including connection time, disconnection time, delivered energy, site ID, station ID, and charging current. Based on these records, EV arrival time, departure time, parking duration, and energy related parameters were obtained. The raw session records were aggregated at a 1 h resolution to match the 24 h scheduling horizon. For time intervals without valid EV observation records, the corresponding average parking duration and average SOC were set to 0, indicating that no available EV sample existed in that time interval.

The implementation details of the prediction model are as follows. The input sequence length is 168 h. Each time step contains some features: normalized vehicle count, normalized average parking duration, normalized average SOC, sine and cosine encoding of hour of day, and sine and cosine encoding of day of week. The prediction targets are the next-step vehicle count, average parking duration, and average SOC. The records are resampled at an hourly resolution. Missing average parking duration values are filled with 0. The three target variables are normalized by min-max scaling.

The first 70% of samples are used for training, the next 15% for validation, and the last 15% for testing. The LSTM and GRU branches each use two recurrent layers, 64 hidden units, and a dropout rate of 0.2. The Transformer branch uses two encoder layers, four attention heads, a hidden dimension of 64, and a dropout rate of 20%. The models are trained with the Adam optimizer and MSE loss. The maximum number of training epochs is 100, the batch size is 64, and early stopping is applied with a patience of 15 epochs. The

learning rate is 0.001 for the individual LSTM, GRU, and Transformer branches, and 0.005 for the weighted fusion layer.

3. Multi-Objective Optimization and Matching Algorithm

3.1. Hierarchical Framework

The system architecture comprises three interconnected layers that collectively enable efficient V2V energy trading. The prediction layer leverages advanced deep learning models to forecast vehicle availability windows and SOC, utilizing historical parking data from rural areas to anticipate when vehicles can participate in V2V transactions. This approach reduces reliance on continuous real-time monitoring and lowers communication overhead. The matching layer performs multi-objective optimization, balancing economic profit and user satisfaction while filtering feasible pairings according to spatiotemporal and energy constraints. The allocation layer implements a dynamic greedy algorithm with constraint verification, allowing supply vehicles to serve multiple demand vehicles while maintaining system-wide feasibility and near-optimal allocation. An illustrative deployment figure of the proposed V2V energy trading system is shown in Figure 2. This figure is designed to explain the interaction among EVs, the transportation network, the distribution network, and the matching and prediction layer.

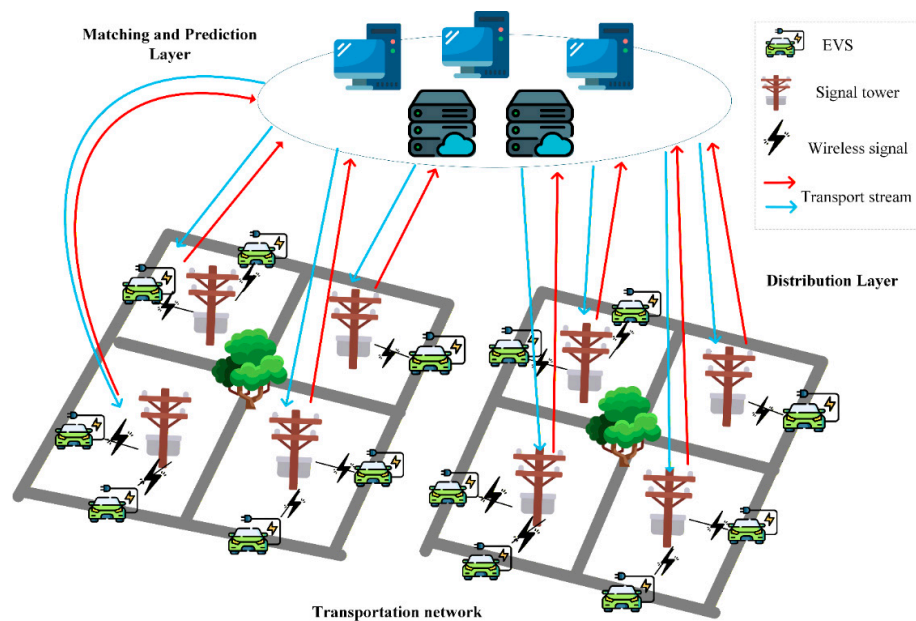


Figure 2. System architecture of the proposed prediction-driven V2V energy trading framework.

3.2. Vehicle Classification and Role Definition

In the proposed V2V system, participating vehicles are dynamically divided into two primary categories according to their real-time state of charge and operational requirements. V_{sv} is a set of EVs that provide charging services. A vehicle is classified as an SEV when its SOC exceeds a predefined threshold S_{min} , which can be formally expressed as follows:

$$V_{sv} = \{i \in V \mid S_i > S_{min}\} \quad (13)$$

For each SEV $i \in V_{sv}$, the system maintains critical attributes including vehicle index, real-time location coordinates $L_i = (x_i, y_i)$, current $SOC_i \in [0, 1]$, and available time window $[t_i^{entry}, t_i^{exit}]$. We calculate their transferable energy as follows:

$$E_i^{\text{avail}} = (S_i - S_{\min}) \times C_{\text{Battery}} \quad (14)$$

where C_{Battery} represents the battery capacity.

V_{DV} is the set of EVs requiring charging service. A vehicle is classified as a DEV when its SOC falls below a target threshold S_T . For each DEV, we calculate the energy required as follows:

$$V_{\text{DV}} = \{j \in V \mid S_j < S_T\} \quad (15)$$

$$E_j^{\text{need}} = (S_T - S_j) \times C_{\text{Battery}} \quad (16)$$

The system adheres to several operational constraints to maintain stability and reliability. SOC boundary constraints ensure that all vehicles operate within safe energy storage limits. Time window constraints require that energy trades be completed within designated periods. Energy conservation ensures that the total energy supplied equals the total energy received. For SEVs, a multi-match constraint limits the cumulative energy delivered, preventing any vehicle from exceeding its capacity when supplying multiple demand vehicles, where $M^{-1}(j)$ denotes the set of SEVs matched to DEV j . Together, these constraints guarantee the physical feasibility, fairness, and stability of V2V energy trading while fostering user trust.

$$0 \leq S_i, S_j \leq 1, \forall i \in V_{\text{SV}}, j \in V_{\text{DV}} \quad (17)$$

$$t_i^{\text{entry}} < t_i^{\text{exit}}, t_j^{\text{entry}} < t_j^{\text{exit}} \quad (18)$$

$$E_{\text{trans}}^{ij} \leq \min(E_i^{\text{avail}}, E_j^{\text{need}}) \quad (19)$$

$$\sum_{j \in M(i)} E_{\text{trans}}^{ij} \leq E_i^{\text{avail}}, \forall i \in V_{\text{SV}} \quad (20)$$

$$|M^{-1}(j)| \leq 1, \forall j \in V_{\text{DV}} \quad (21)$$

3.3. Spatiotemporal Feasibility Filtering

Before optimization, the system identifies all feasible V2V pairings that satisfy fundamental physical and operational constraints. This filtering process reduces the computational search space from $|V_{\text{SV}}| \times |V_{\text{DV}}|$ potential combinations to a manageable set of viable candidates.

For a pairing (i, j) where $i \in V_{\text{SV}}$ and $j \in V_{\text{DV}}$, temporal feasibility requires simultaneous presence for a sufficient duration to complete energy transfer. The overlap calculation and temporal constraint requirements are as follows:

$$\begin{cases} t_{\text{start}}^{ij} = \max(t_i^{\text{entry}}, t_j^{\text{entry}}) \\ t_{\text{end}}^{ij} = \min(t_i^{\text{exit}}, t_j^{\text{exit}}) \\ \Delta T_{ij} = t_{\text{end}}^{ij} - t_{\text{start}}^{ij} \end{cases} \quad (22)$$

$$\Delta T_{ij} \geq T_{\min}^{\text{SV}} \quad (23)$$

If this constraint is violated, such as either $t_{\text{start}}^{ij} \geq t_{\text{end}}^{ij}$ or $\Delta T_{ij} < T_{\min}^{\text{SV}}$, the pairing (i, j) is rejected as temporally infeasible. The computational complexity of this check is $O(1)$ per pairing. Geographic proximity is essential for practical V2V energy transfer, as

excessive travel distance reduces user satisfaction and may negate economic benefits. The Euclidean distance between vehicles i and j is computed as follows:

$$\begin{cases} d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \\ d_{ij} \leq d_{\max} \end{cases} \quad (24)$$

where $d_{\max}$ denotes the maximum acceptable driving distance used in the satisfaction evaluation, which was set according to the existing literature [33].

The pairing must enable the transfer of a sufficient quantity of energy to justify the associated transaction overhead. The corresponding energy transfer calculations are as follows:

$$\begin{cases} E_j^{\text{need}} = (S_T - S_j) \times C_{\text{Battery}} \\ E_i^{\text{avail}} = (S_i - S_{\min}) \times C_{\text{Battery}} \div 0.9 \\ E_{\text{trans}}^{ij} = \min(E_j^{\text{need}}, E_i^{\text{avail}}) \end{cases} \quad (25)$$

$$E_{\text{trans}}^{ij} \geq E_{\min} \quad (26)$$

The minimum energy threshold is established to ensure that each V2V energy transaction is both economically and operationally viable. Trades below this threshold may incur coordination costs, including vehicle scheduling, communication overhead, and physical movement. These costs exceed the value of the energy delivered, rendering the transaction inefficient or even loss-making. Therefore, this threshold essentially acts as a filter, allowing only trades with sufficient energy to justify the associated costs to proceed.

A conversion efficiency factor of 0.9 is applied in the energy transfer calculation to account for inevitable losses during V2V energy transmission, which may result from power conversion, cable resistance, and battery charge–discharge inefficiencies. Incorporating this coefficient allows the system to more accurately estimate the effective energy delivered from the supplier to the demander, preventing overestimation and ensuring the practical feasibility and reliability of scheduling strategies.

3.4. Multi-Objective Optimization Model

The V2V energy trading matching process must reconcile two potentially conflicting objectives: maximizing economic profit for SEVs and ensuring high user satisfaction for DEVs. This multi-objective framework reflects the inherent trade-off between system efficiency and user experience in peer-to-peer vehicular energy exchange. From the supply perspective, profit maximization seeks to optimize energy allocation, increase transaction frequency and volume, and implement incentive-compatible pricing to encourage greater participation, thereby enhancing market liquidity and total system revenue. From the demand perspective, user satisfaction prioritizes responsiveness, charging reliability, cost-effectiveness, and fairness in service access. These objectives can conflict: a purely profit-driven policy may overlook users with urgent energy needs but limited willingness to pay, while overemphasizing immediate demand fulfillment can reduce overall efficiency and discourage supplier participation. Effective matching strategies must therefore dynamically balance these competing priorities to maintain both operational efficiency and ecosystem sustainability.

The profit metric incentivizes SEVs to participate by ensuring fair compensation based on time-of-use pricing, which aligns V2V energy trading with grid load patterns. For a pairing (i, j) with charging start time t_{start}^{ij} , where $h = \text{hour}(t_{\text{start}}^{ij})$ the total profit is as follows, where $p(h)$ is the TOU pricing function.

$$F_{ij} = E_{\text{trans}}^{ij} \times P(h) \quad (27)$$

$$F_{ij}^{\text{norm}} = \frac{F_{ij}}{F_{\text{max}}} \quad (28)$$

Profits are normalized to enable comparison with the dimensionless satisfaction metric. This normalization ensures $F_{ij}^{\text{norm}} \in [0, 1]$. User satisfaction is evaluated based on two key factors: travel distance and waiting time, which represent the primary determinants of user acceptance of V2V services identified in behavioral studies [23]. The distance score is as follows:

$$\text{Score}_{\text{dist}}^{ij} = 1 - \min\left(\frac{d_{ij}}{d_{\text{max}}}, 1\right) \quad (29)$$

This linear decay function assigns a maximum score (1.0) for the same located vehicles and decreases to zero once the distance exceeds the predefined maximum threshold. This linear formulation reflects empirical evidence indicating that perceived inconvenience in rural transportation contexts increases proportionally with distance.

The waiting time score quantifies temporal convenience. $t_{\text{max}}^{\text{wait}}$ represents the maximum tolerable delay used in the waiting-time satisfaction evaluation, which was set according to the existing literature [33]. $\text{Score}_{\text{wait}}^{ij} = 1$ indicates immediate service. $\Delta t_{\text{wait}}^{ij} = 0$ corresponds to a waiting time exceeding 2 h. The composite satisfaction combines both dimensions through weighted averaging. In our model, we set $w_{\text{dist}} = 0.6$ and $w_{\text{wait}} = 0.4$. This ratio design is based on the analysis of existing research [34].

$$\text{Satisfaction}_{ij} = w_{\text{dist}} \cdot \text{Score}_{\text{dist}}^{ij} + w_{\text{wait}} \cdot \text{Score}_{\text{wait}}^{ij} \quad (30)$$

The coefficient settings in the preliminary weighted-score formulation were adopted with reference to the multi-objective EV charging optimization study in [35], which provides a reasonable basis for balancing economic and satisfaction. In this formulation, the profit and satisfaction weights in the satisfaction function are set to 0.7 and 0.3. Distance is assigned a larger weight because spatial proximity affects user acceptance and transaction feasibility in V2V energy trading.

$$\text{Score}_{ij} = \alpha \cdot F_{ij}^{\text{norm}} + \beta \cdot \text{Satisfaction}_{ij} \quad (31)$$

However, the original fixed weighted summation was still simple because it converted the profit-satisfaction trade-off into a single score. To strengthen the analysis, the revised model further formulates the problem as a non-dominated multi-objective optimization task and solves it using NSGA-II. Total provider profit and total user satisfaction are retained as two independent objectives, and the algorithm searches for a Pareto solution set instead of relying on fixed profit and satisfaction weights.

The NSGA-II experiment is implemented in two stages. Firstly, daily Pareto fronts are generated under the dynamic SOC, distance, waiting-time, and energy-transfer constraints. Secondly, the daily candidate solutions are combined at the one-year horizon to obtain a final Pareto front. A compromise solution can then be selected from the Pareto front by its distance to the normalized ideal point. It will be shown in Case 5.

3.5. Greedy Matching Algorithm with Dynamic Constraints

The allocation layer implements an advanced greedy algorithm that iteratively selects high-value pairings while dynamically enforcing operational constraints, achieving

computational efficiency without compromising near-optimal solution quality. The matching algorithm is guided by three core principles. First, all feasible pairings are ranked by their comprehensive score in descending order, prioritizing high-value matches and avoiding suboptimal local decisions. Second, each candidate pairing is subjected to real-time feasibility checks that account for the evolving system state, distinguishing this approach from static allocation schemes that may produce infeasible outcomes. Third, SEVs can sequentially serve multiple DEVs, maximizing resource utilization while adhering to energy and SOC limitations.

For each SEV i , the algorithm maintains a running total of committed energy up to iteration k , where $M_k(i)$ denotes the set of DEVs matched to SEV i up to iteration k . After each matching operation, the effective SOC of the SEV is dynamically updated.

$$E_i^{\text{used}}(k) = \sum_{j \in M_k(i)} E_{\text{trans}}^{ij} \quad (32)$$

$$S_i^{\text{cur}}(k) = S_i^{\text{initial}} - \frac{E_i^{\text{used}}(k)}{C_{\text{Battery}}} \quad (33)$$

$$S_i^{\text{cur}}(k) \geq S_{\min} \quad (34)$$

$$E_{\text{actual}}^{ij} = \min(E_{\text{trans}}^{ij}, (S_i^{\text{cur}}(k) - S_{\min}) \times C_{\text{Battery}}) \quad (35)$$

$$E_{\min} = S_{\min} * C_{\text{Battery}} \quad (36)$$

The formula Equation (34) ensures that SEVs always maintain sufficient charge for their own operational needs. When evaluating pairing (i, j) at iteration k , the actual transferable energy may be constrained by the SEV remaining capacity.

Let N_s and N_d denote the numbers of supply EVs and demand EVs, respectively. The construction of feasible supply–demand candidate pairs has a worst-case time complexity of $O(N_s * N_d)$, because each supply EV may need to be checked against each demand EV under the spatial, temporal, SOC, and energy feasibility constraints. If K feasible pairs are retained after constraint filtering, sorting these candidate pairs according to their matching scores requires $O(K * \log K)$, and the subsequent sequential feasibility verification requires $O(K)$. Therefore, the overall time complexity of the dynamic greedy matching stage is $O(N_s * N_d + K * \log K)$, and the memory requirement is $O(K + N_s + N_d)$. For the NSGA-II-based Pareto analysis, the computational cost further depends on the population size and the number of generations.

Although the dynamic greedy matching algorithm improves computational efficiency, it cannot theoretically guarantee a global optimum. This is because matching decisions are accepted sequentially and are not globally revised after selection. This limitation is acknowledged in this study. The strategy is still reasonable for the V2V energy trading scenario considered here. Vehicle availability windows, SOC states, and residual transferable energy change during the matching process. The algorithm therefore needs to generate feasible decisions quickly. Compared with exhaustive global optimization, the greedy strategy is easier to update under dynamic constraints. Real-time feasibility checks also help maintain SOC safety, energy conservation, and multi-match feasibility. The detailed algorithm flow is shown in Algorithm 1.

Algorithm 1: Matching Algorithm Procedure

Input: P_scored (scored pairings calculated by Equations (27)–(31)), V_{sv} (Equation (13)), V_{dv} (Equation (15)), D_{MD} , U_{SE} , $P(h)$ (time-of-use price in Table 2)

Output: M (match set), U_{SM}

```

1   $P\_sorted \leftarrow \text{Sort } P\_scored \text{ by comprehensive score in descending order;}$ 
2   $M \leftarrow \emptyset$ ;  $D_{MD} \leftarrow \emptyset$ ;  $U_{SE} \leftarrow 0$ ;  $U_{SM} \leftarrow 0$ 
3  for each pairing  $(i, j) \in P\_sorted$  in order do
4      if  $j \in D_{MD}$  then
5          Continue
6      end if
7      Compute  $S_i^{cur}$  using Equation (33);
8      if  $S_i^{cur} < S_{min}$  then
9          Continue
10     end if
11     Compute  $E_{actual}^{ij}$  using Equation (35);
12     if  $E_{actual}^{ij} < E_{min}$  then
13         Continue
14     end if
15     Include vehicle  $j$  in set  $D_{MD}$ ; Include energy  $E_{actual}^{ij}$  in set  $U_{SE}[i]$ ; Add 1
        in set  $U_{SM}[i]$ ;
         $F_{ij} \leftarrow E_{actual}^{ij} \times P(h)$  using Equation (27);
        Record match details: (energy, profit, distance);
16      $M = M \cup \{(i, j)\}$ ;
17 end for
18 return  $M$ ,  $U_{SM}$ .

```

Table 2. Core system parameters.

Symbol	Value	Description
E_{min}	0.1 kWh	Minimum transferable energy
d_{max}	20 km	Maximum acceptable distance
t_{max}^{wait}	120 min	Maximum tolerable waiting time
P_{Peak}	0.9 CNY/kWh	Electricity price during peak hours
P_{Normal}	0.4 CNY/kWh	Electricity price during normal hours
P_{Valley}	0.3 CNY/kWh	Electricity price during valley hours

4. Case Studies*4.1. System Description*

The V2V energy trading simulation framework established in this study leverages real vehicle trajectory data to model interactions between SEVs and DEVs. The system employs a spatiotemporal matching mechanism that pairs EVs according to availability, location, and SOC constraints. All participating vehicles are assumed to have a uniform battery capacity of 40 kWh. To ensure battery health and ensure operational feasibility,

we set 60% for SEVs and 50% for DEVs. Relevant parameters, previously discussed, are presented in Table 2.

Travel time costs and vehicle energy parameters were derived from commercial specifications and previous studies [21–23]. All numerical calculations were conducted in MATLAB R2020b, with optimization tasks executed via the YALMIP R20230622 toolbox on a Windows 11 workstation equipped with a 20-core CPU running at 3.4 GHz and 16 GB of RAM.

4.2. Comparison Framework

The performance of the proposed V2V energy sharing system is assessed using computational results from some distinct test cases.

Case 1. To assess the operational effectiveness and practical feasibility of the proposed V2V trading system, its performance was evaluated in a rural EV charging context. The analysis emphasizes the system's responsiveness to seasonal migration patterns, demonstrating its capacity to act as a flexible infrastructure supplement that mitigates extreme load fluctuations and enhances grid resilience in rural environments.

Case 2. To evaluate the prediction performance of the proposed hybrid ensemble model, this case compares it with individual baseline models and several ablation variants. The individual models include LSTM, GRU, and Transformer. The ablation variants include equal-weight fusion, LSTM-GRU fusion, and Dynamic fusion only. The evaluation focuses on two aspects: prediction accuracy and convergence behavior. Average normalized RMSE is used to compare the final prediction errors, while the MSE loss curves are used to assess the training stability of different models. This case verifies whether the proposed ensemble structure can improve EV availability estimation by adaptively combining different temporal representations.

Case 3. To assess the economic efficiency and resource utilization of the proposed system, we compare trading volumes and economic returns between the centralized framework and a distributed benchmark [33] using real-world vehicle trajectory data. This analysis examines the impact of the matching paradigm, contrasting the proposed one-to-many allocation mechanism with the benchmarks one-to-one constraint. The evaluation emphasizes the system's performance during seasonal peaks and high-demand periods, demonstrating its capacity to enhance overall market efficiency.

Case 4. To evaluate the robustness and scalability of the matching mechanism under variable conditions, we perform sensitivity analyses by adjusting SEV and DEV densities. The algorithm's performance is tested across supply–demand ratios from 20% to 100%, assessing system stability in terms of total matching frequency and aggregated profit relative to the distributed framework [33].

Case 5. This case examines the profit-satisfaction trade-off in the multi-objective optimization framework. The preliminary coefficient settings are supported by [35], but the revised experiment further replaces the simple fixed-weight score with an NSGA-II-based Pareto analysis. Total provider profit and total user satisfaction are optimized as two independent objectives. The Pareto front is used to identify balanced solutions without relying on a single manually selected profit-satisfaction weight.

Case 6. To evaluate the operational boundaries and safety constraints of the V2V energy sharing system, sensitivity analysis is conducted on the SOC constraints. This case investigates the interaction between the minimum supply SOC threshold, ranging from 0.55 to 0.70, and the target demand SOC, ranging from 0.40 to 0.55. Comparative analyses are performed to quantify the relationship between these thresholds, total system profit, and matching quantity. This helps identify an operating configuration that balances economic return, user safety, battery health, and resource availability.

Case 7. To further evaluate the effectiveness and robustness of the proposed V2V matching strategy, comparative experiments are conducted with representative classical optimization and matching methods. In this case, GA, PSO, and an auction-based priority method are selected as baseline algorithms. The comparison focuses on two key objectives, namely total provider profit and total user satisfaction. This case aims to examine whether the proposed NSGA-II-based method can provide a more balanced matching strategy than other classic matching methods.

Case 8. To evaluate the robustness of the proposed V2V matching strategy under user behavioral uncertainty, this case introduces random perturbations to EV entry time, exit time, and SOC. The uncertainty levels are divided into baseline, Low, Medium, and High. The baseline case uses the original input data without perturbation. In the Low, Medium, and High uncertainty cases, the entry and exit times are perturbed within ± 10 min, ± 20 min, and ± 30 min, respectively. The SOC perturbation follows a zero-mean normal distribution, with standard deviations of 0.02, 0.05, and 0.10. After perturbation, SOC values are still limited to the feasible range of $[0, 1]$, and the exit time is checked to ensure that it remains later than the entry time. The EV population size is kept unchanged in this case. The comparison focuses on total profit and total user satisfaction. This case aims to examine whether the proposed NSGA-II-based method can maintain stable matching performance when user behavior deviates from the predicted values.

Case 9. To evaluate the scalability of the proposed V2V matching strategy under enlarged EV populations, this case constructs larger-scale test scenarios based on the original input data. The scale levels are divided into baseline, $2\times$, and $3\times$. The baseline case uses the original supply and demand EV records. The $2\times$ and $3\times$ cases are generated by empirical-distribution-based resampling. To avoid exactly duplicated records, small perturbations are added to the resampled records. The entry and exit times are shifted within ± 5 min, SOC is perturbed by zero-mean noise with a standard deviation of 0.01, and the spatial coordinates are slightly adjusted. These perturbations are only used to differentiate repeated samples in the scalability test. They are not used to model user behavioral uncertainty. Each scale is tested through five independent runs.

Case 10. To evaluate the computational cost of the proposed V2V matching strategy compared with benchmark algorithms, this case conducts a runtime comparison under the same candidate pools and constraints. The compared algorithms include the proposed NSGA-II-based method, GA, and PSO. The same supply and demand EV records, SOC constraints, distance constraints, waiting-time constraints, energy-transfer constraints, and feasible candidate-pair construction procedure are used for all three algorithms. A representative 10-day operating window is selected for this runtime benchmark to provide a controlled comparison with manageable computational cost. In this comparison, NSGA-II optimizes profit and user satisfaction as two independent objectives and generates a Pareto solution set. GA and PSO use the same scalar comparison score and search for a single preferred solution under the same feasible candidate pool.

4.3. Comparisons and Analyses

4.3.1. Case 1

The comprehensive performance of the proposed V2V matching system is illustrated in the generated analytical Figure 3. The analysis focuses on seasonal trends, utilization rates, and economic efficiency.

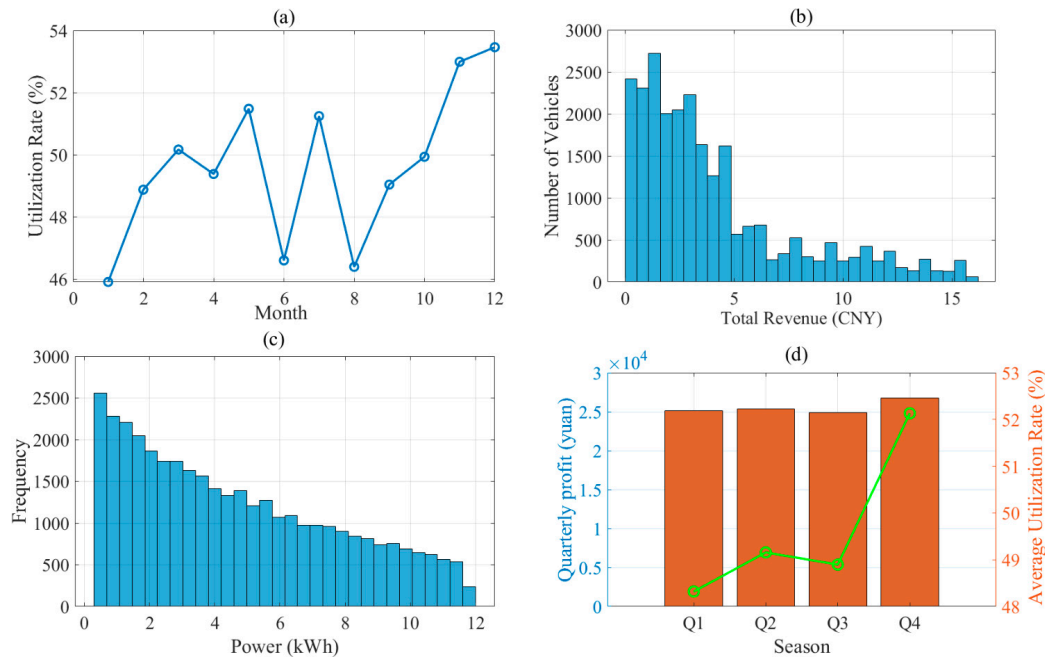


Figure 3. V2V matching analysis diagram: (a) Monthly average utilization rate of SEVs. (b) Distribution of revenue from SEVs. (c) Energy transmission distribution. (d) Comparison of quarterly profits and utilization rates.

Figure 3a illustrates the proportion of available SEVs that successfully complete a match. The results indicate that the algorithm activates a substantial share of SEVs. Notably, the revenue distribution of SEVs exhibits a long-tail pattern, where most vehicles participate in occasional transactions, while those with higher SOC generate greater cumulative revenue. This outcome confirms the effectiveness of the algorithmic design, which permits SEVs with sufficient SOC to perform multiple matches per day, thereby improving overall resource utilization. Unlike urban V2V systems that follow stable daily commuting patterns, rural trading dynamics are closely tied to broader seasonal migration cycles. Notably, the system demonstrates consistently high performance during periods of significant population movement, such as the Summer Vacation (Q3) and the Spring Festival (January). These results demonstrate that V2V trading can function as a flexible infrastructure supplement, effectively mitigating seasonal fluctuations in electrical demand and enhancing grid resilience and stability.

4.3.2. Case 2

In this section, we evaluate the proposed ensemble framework against three baseline models: LSTM, GRU, and Transformer. The evaluation is based on two key metrics: training convergence efficiency and final prediction accuracy.

As shown in Figure 4, the Ensemble model achieves a low average normalized RMSE and performs better than equal-weight fusion and the single-branch LSTM, GRU, and Transformer models. This result indicates that the proposed adaptive ensemble structure can improve prediction accuracy compared with fixed fusion and individual temporal models. Equal-weight fusion uses the same branch models but assigns fixed weights to their outputs. Its higher RMSE shows that fixed averaging cannot fully adapt to the changing temporal characteristics of EV charging behavior. In contrast, the Ensemble model dynamically adjusts the contribution of different branches according to the input sequence, which helps the model better capture different charging patterns.

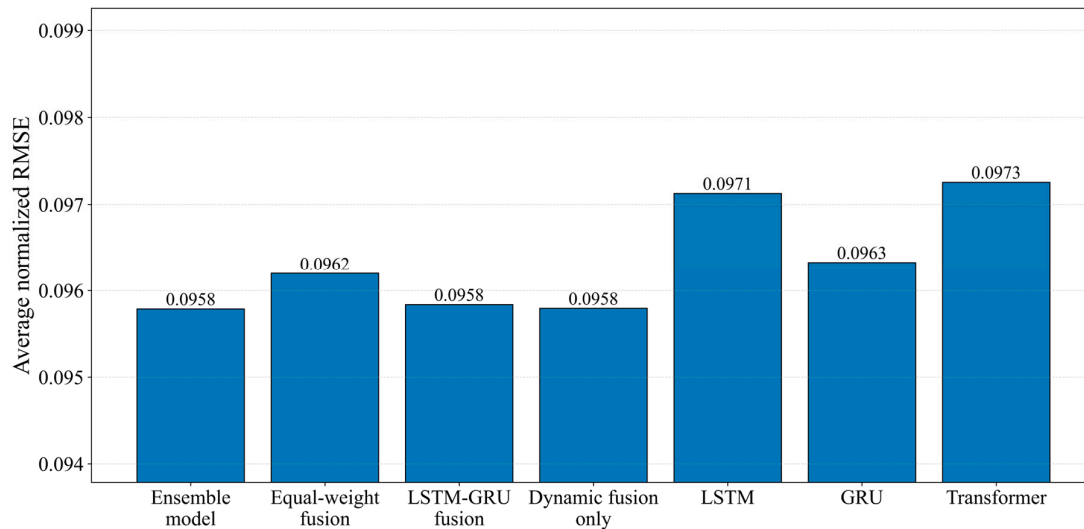


Figure 4. Ablation study of the proposed prediction model.

The single-branch models show higher prediction errors. This suggests that relying on only one model is insufficient for the hourly EV charging dataset. LSTM and GRU are effective in modeling sequential dependencies, while Transformer can capture longer-range temporal correlations. However, each individual model has its own limitation. The results of LSTM-GRU fusion and Dynamic fusion only are close to that of the Ensemble model. This indicates that LSTM/GRU-based temporal modeling and adaptive fusion are important for predicting hourly EV charging behavior.

The improvement brought by the Transformer branch and the residual correction network is moderate. The complete Ensemble model maintains competitive prediction accuracy while preserving a more comprehensive representation. It combines recurrent temporal modeling, global dependency extraction, adaptive branch weighting, and residual correction within one framework. Therefore, the ablation results support the rationality of the proposed hybrid prediction structure and provide a more reliable data basis for the subsequent V2V matching and optimization process.

To examine the sensitivity of prediction performance to random initialization, all prediction models were trained under multiple random seeds. The RMSE values reported in Figure 4 are the average results over repeated runs. The variation among different runs was small, indicating that the prediction results were stable under different initial parameter settings. This also shows that the performance difference between the Ensemble model, fixed fusion, and single-branch models was not caused by one specific random initialization.

As shown in Figure 5, it demonstrates that the proposed model achieves the lowest prediction error, outperforming all individual baseline models. While LSTM may encounter difficulties in capturing long-range dependencies due to gradient attenuation, Transformers can be sensitive to local noise. The proposed framework mitigates these structural limitations through an adaptive integration strategy. The observed performance improvement highlights the effectiveness of the learnable weighting mechanism, which functions as an adaptive selector that dynamically assigns higher importance to the most reliable sub-model under the current input conditions. In this comparison, LSTM and GRU networks are effective in capturing low-frequency periodic patterns, whereas the Transformer is more capable of identifying high-frequency variations. By integrating these heterogeneous features, the proposed framework filters out model-specific biases and improves predictive robustness. This accuracy improvement is crucial for V2V energy

trading, as it reduces uncertainty in energy availability and thereby enables more reliable and economically efficient matching between participating EV users.

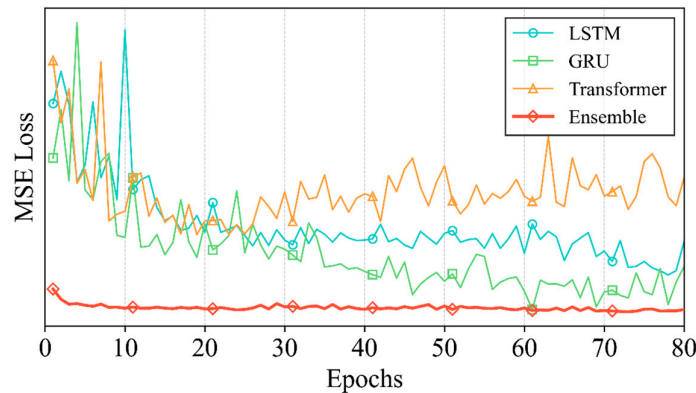


Figure 5. The MSE loss comparison of the proposed ensemble model and baseline models.

To evaluate the sensitivity of the prediction results to random initialization, all prediction models were trained under five random seeds. The same five seeds were used for all models to ensure a paired and reproducible comparison. The average normalized RMSE values shown in Figure 4 represent the mean results over the repeated runs, while Table 3 further reports the standard deviation, 95% confidence interval, and paired statistical test results. A paired t-test was used to evaluate the statistical significance of the performance differences between the proposed ensemble model and each compared model over the five random seeds.

Table 3. Statistical robustness analysis of prediction models under different random seeds.

Model	Runs	Average Normalized RMSE	Standard Deviation	Confidence Interval	<i>p</i> -Value vs. Ensemble
Ensemble model	5	0.095786	0.000405	0.095283–0.096290	-
Equal-Weight fusion	5	0.096200	0.000272	0.095862–0.096538	0.0849
LSTM-GRU fusion	5	0.095836	0.000419	0.095315–0.096356	0.1784
Dynamic fusion	5	0.095793	0.000376	0.095326–0.096259	0.8136
LSTM	5	0.097125	0.000941	0.095957–0.098294	0.0636
GRU	5	0.096330	0.001069	0.095003–0.09765	0.2925
Transformer	5	0.097254	0.000604	0.096505–0.098004	0.0132

As shown in Table 3, the ensemble model achieves the lowest mean average normalized RMSE of 0.095786, with a standard deviation of 0.000405 and a narrow 95% confidence interval. This result indicates that the proposed model provides stable prediction performance under different random initializations. Compared with the single-branch models, the ensemble model obtains lower average errors than LSTM, GRU, and Transformer, suggesting that relying on only one temporal modeling structure is less effective for the hourly EV behavior prediction task. The differences between the ensemble model and the fusion-based variants are small. The close performance of the LSTM-GRU fusion and dynamic-fusion-only variants indicates that the recurrent branches and the adaptive fusion mechanism are the main contributors to the prediction accuracy. Although the additional Transformer branch and residual correction network bring only moderate improvement in terms of mean RMSE, they help form a more complete hybrid structure by combining recurrent temporal modeling, long-range dependency extraction, adaptive

branch weighting, and post-fusion correction. Therefore, the results in Table 3 support the robustness and rationality of the proposed ensemble model.

4.3.3. Case 3

To assess the efficacy of the proposed architecture, we executed comparative simulations utilizing empirical vehicle trajectory datasets. The performance of the proposed model was benchmarked against a distributed framework [33] to quantify improvements in aggregate trading volume and fiscal outcomes. The corresponding experimental results are presented in Figure 6.

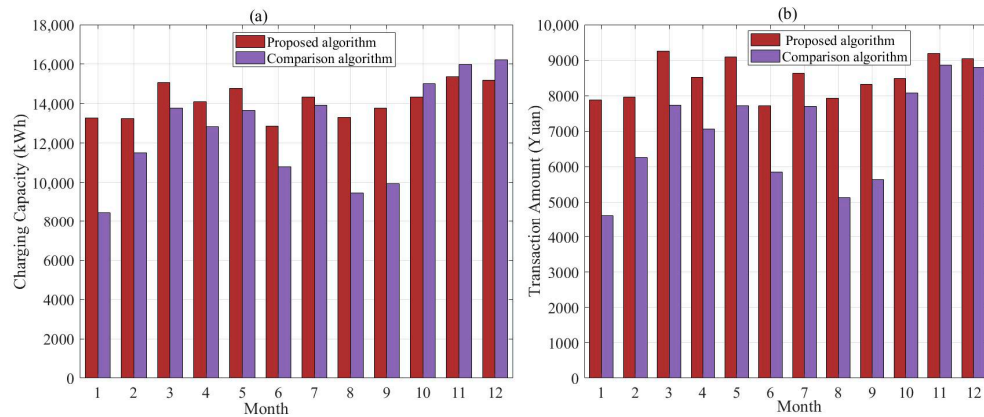


Figure 6. Compared analysis diagram: (a) Charging capacity comparison. (b) Trading amount comparison.

First, from an overall perspective, the proposed algorithm demonstrates a clear economic advantage over traditional distributed benchmarks. While the comparison algorithm prioritizes structural simplicity and trust isolation, it results in severe resource underutilization. For instance, an SEV possessing an 80% surplus may only transfer 5% to a neighboring node; without a robust rescheduling mechanism, the remaining excess capacity is effectively locked out of the market. This structural rigidity becomes a critical bottleneck during high-demand intervals, stifling aggregate trading volumes.

Second, the proposed methodology yields markedly superior economic returns during specific periods, primarily due to its capacity to facilitate multi-stage energy transactions for high-capacity SEVs. This capability provides a strategic advantage during seasonal peaks, such as winter and summer vacation intervals. When seasonal travel triggers significant demand surges, the algorithm enables suppliers with sufficient energy reserves to execute sequential micro-trades across multiple DEVs. As vehicle density increases, the pool of feasible trading permutations expands, allowing for greater market depth. This dynamic and iterative allocation mechanism enhances systemic liquidity and ensures that available energy resources are fully utilized rather than being locked after a single transaction.

4.3.4. Case 4

To evaluate the robustness and scalability of the proposed matching mechanism, we conducted a bivariate sensitivity analysis by modulating the density of SEVs and DEVs. This evaluation measures the system's performance across a spectrum of supply–demand ratios, ranging from 20% to 100%, to benchmark its stability against existing distributed frameworks [33] in terms of aggregate profit and matching frequency. Acknowledging the computational overhead and the temporal periodicity of EV charging behaviors, the simulation environment was grounded in a representative 30-day operational dataset.

This longitudinal scope allows the model to account for multi-cycle demand fluctuations while ensuring the scalability of the hierarchical matching logic.

The corresponding experimental results are presented in Figure 7. As illustrated in the sensitivity analysis results, the proposed algorithm demonstrates a statistically significant performance advantage in both matching volume and economic benefits. This discrepancy is fundamentally rooted in the structural divergence of matching paradigms. The distributed benchmark is constrained by a rigid, one-to-one pairing mechanism. Under this restriction, once a supplier is matched with a single demander, any residual surplus energy becomes effectively “locked,” precluding further transactions even if the supplier retains the capacity to serve additional participants. This results in unavoidable resource underutilization, particularly when a demander’s requirements are substantially lower than a supplier’s total available energy. In contrast, the proposed framework implements a flexible one-to-many matching strategy designed to maximize total energy throughput. By enabling a single high-capacity SEV to serve multiple DEVs sequentially or concurrently, the algorithm ensures that available energy resources are fully exhausted. This mechanism effectively elevates the upper limit of matching volume and aggregate profit, transforming previously idle capacity into active systemic liquidity.

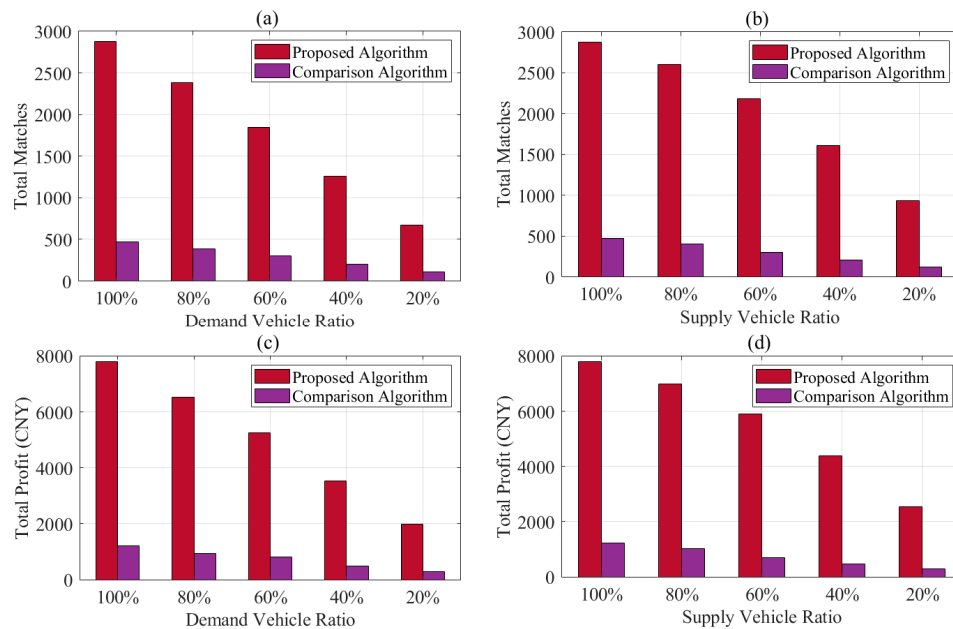


Figure 7. Analysis of the proposed system under varying vehicle densities. (a) Impact of demand variation on matching quantity. (b) Impact of supply variation on matching quantity. (c) Impact of demand variation on economic profit. (d) Impact of supply variation on economic profit.

4.3.5. Case 5

To address the concern regarding objective-weight selection, Case 5 replaces the original simple weighted score with an NSGA-II-based multi-objective optimization procedure. In the revised section, total provider profit and total user satisfaction are treated as two independent objectives. Therefore, the optimization process no longer depends on a fixed profit-satisfaction weighting coefficient. Instead, NSGA-II searches for a set of non-dominated solutions, which provides a basis for analyzing the trade-off between profit and user satisfaction.

As shown in Figure 8, the obtained Pareto front reflects the conflict between profit maximization and satisfaction improvement. Across the 74 non-dominated solutions,

total profit ranges from 49,506.34 CNY to 51,412.91 CNY, while total satisfaction ranges from 27,498.61 to 27,981.89. This result indicates that increasing profit is accompanied by a reduction in satisfaction, and no single solution can maximize both objectives.

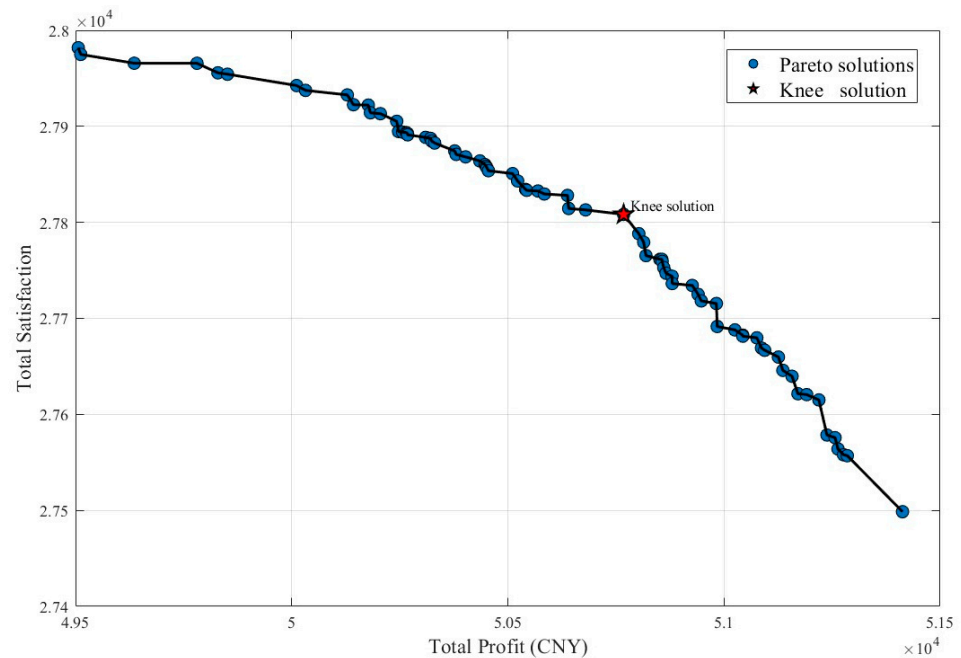


Figure 8. Profit–satisfaction Pareto front obtained using NSGA-II.

To select a balanced operating point, the knee solution is identified according to its distance to the normalized ideal point. This solution achieves a total profit of 50,767.89 CNY and a total satisfaction of 27,808.27. Compared with the maximum-profit solution, it retains about 98.75% of the maximum profit while improving the satisfaction value from 27,498.61 to 27,808.27. Compared with the maximum-satisfaction solution, it retains about 99.38% of the maximum satisfaction while increasing the total profit from 49,506.34 CNY to 50,767.89 CNY. These results show that the selected knee solution provides a reasonable compromise between profit and user satisfaction.

4.3.6. Case 6

This study uses a representative 30-day operational dataset. A bivariate sensitivity analysis of SOC constraints is performed to define the operating range of the system. The tested values are 0.55 to 0.70 for the $S_{\min}$ threshold and 0.40 to 0.55 for the S_T .

The trends in Figure 9a,b are consistent. A higher S_T increases both total profit and the number of matches because each DEV requires more energy to reach the target level. In contrast, a higher $S_{\min}$ reduces both indicators because fewer SEVs can provide surplus energy. For example, when the S_T is 0.55, increasing the $S_{\min}$ from 0.55 to 0.70 reduces total profit from approximately 10,600 CNY to 6800 CNY, and reduces the number of matches from approximately 3350 to 2450.

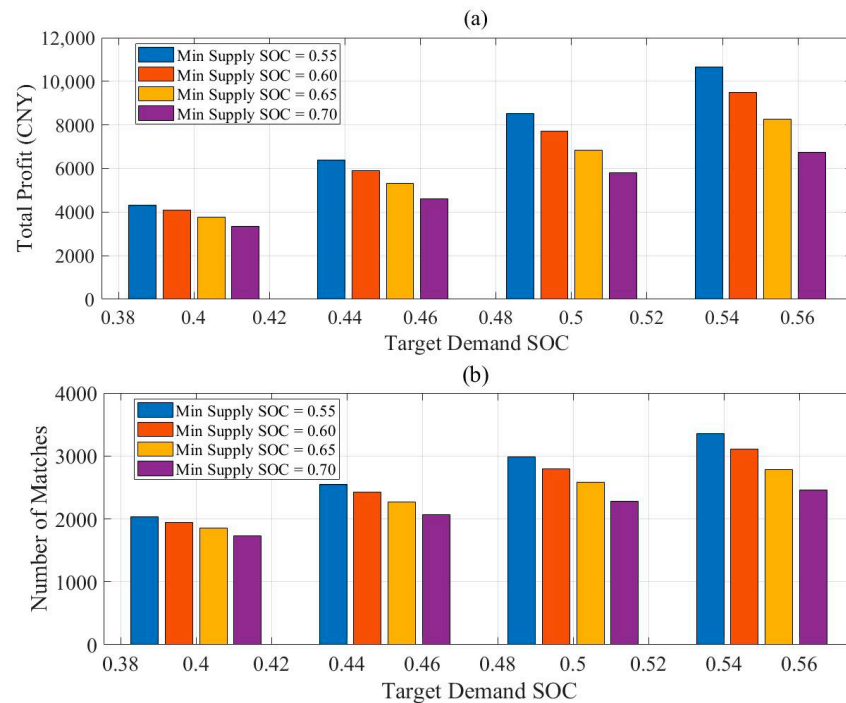


Figure 9. SOC sensitivity test: (a) Impact of SOC thresholds on total profit. (b) Impact of SOC thresholds on match count.

The numerical results in Figure 9a show that the theoretical maximum profit occurs when the minimum supply SOC threshold is 0.55 and the target demand SOC is 0.55. However, this setting leaves less reserve energy for SEVs. The selected baseline setting, $S_{\min} = 0.6$ and $S_T = 0.5$, still provides a profit of about 7800 CNY and about 2800 matches. It therefore offers a more balanced operating point between economic return and SOC safety.

(1) Supply-Side Safety and Battery Health (0.60 vs. 0.55)

Lowering the supply threshold to 0.55 marginally SEVs to 55% exacerbates range anxiety, which may disincentivize long-term participant engagement in real-world deployment. Furthermore, frequent high-depth discharge cycles accelerate battery degradation, compromising the vehicle's residual value. In contrast, the selected 0.60 threshold serves as a vital safety buffer, preserving electrochemical health and ensuring that suppliers retain sufficient energy for unanticipated transit requirements. This conservative limit stabilizes the supply pool and fosters the sustainable growth of the V2V ecosystem.

(2) Demand-Side Efficiency and Service Fairness (0.50 vs. 0.55)

On the demand side, increasing the S_T from 0.40 to 0.55 consistently raises profit and matching quantity. For the $S_{\min}$ of 0.60, the profit increases from approximately 4100 CNY at a S_T of 0.40 to approximately 9500 CNY at 0.55. The number of matches also increases from about 1950 to about 3100. However, a higher S_T also consumes more SEV energy in each transaction. Therefore, the S_T of 0.50 is used as a balanced setting rather than simply choosing the profit-maximizing threshold.

4.3.7. Case 7

To further evaluate the effectiveness of the proposed NSGA-II-based V2V matching strategy, this case compares the proposed method with three representative baseline methods. The proposed method uses NSGA-II to search for non-dominated solutions between total provider profit and total user satisfaction. The final operating solution is selected from the Pareto front according to its distance to the normalized ideal point. The

GA and PSO use the same feasible candidate set and dynamic constraint verification process, but they search the matching sequence through classical evolutionary and swarm intelligence mechanisms. The auction-based priority method ranks feasible transactions according to a bidding priority score related to transaction profit, transferable energy, and user satisfaction. It then accepts feasible matches sequentially according to this priority.

Figure 10 compares the proposed NSGA-II method with GA. As shown in Figure 10a, GA obtains slightly higher profit in several months. However, Figure 10b shows that this profit improvement is achieved at the cost of a clear decrease in total user satisfaction. The proposed NSGA-II method maintains higher satisfaction in all months. This result indicates that GA tends to favor profit-oriented matching decisions and has limited ability to maintain a balanced trade-off between profit and user satisfaction.

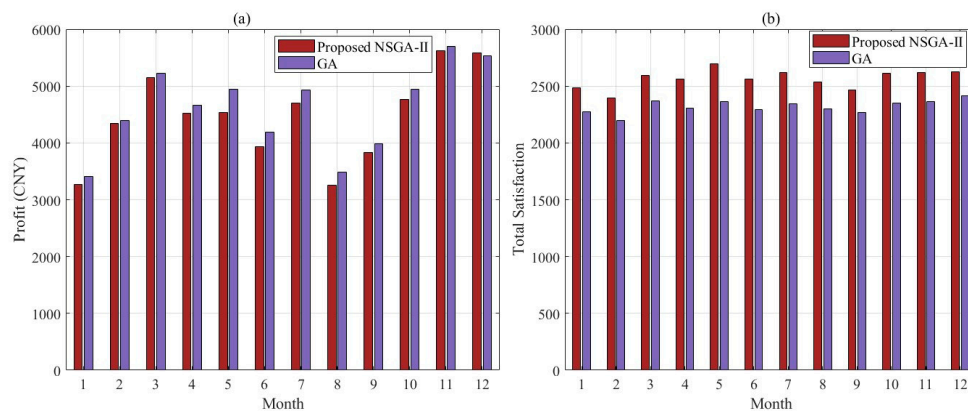


Figure 10. Monthly comparison between the proposed NSGA-II method and GA. (a) Profit comparison. (b) Satisfaction comparison.

Figure 11 compares the proposed NSGA-II method with PSO. The proposed method achieves higher monthly profit in most months, as shown in Figure 11a. More importantly, Figure 11b shows that the proposed method consistently provides higher total satisfaction than PSO. This result suggests that the Pareto-based search mechanism can better preserve user-satisfaction while maintaining profit performance. In contrast, PSO is more sensitive to local search behavior and may converge to solutions with lower satisfaction under dynamic V2V constraints.

Figure 12 compares the proposed NSGA-II method with the auction-based priority method. The auction-based method provides a simple and fast matching rule, and its satisfaction value is close to that of the proposed method in several months. However, as shown in Figure 12a, the proposed NSGA-II method achieves higher monthly profit in most months. This is because the proposed method considers the global profit-satisfaction and dynamically verifies SOC, time-window, distance, and energy constraints during the matching process. The auction-based method depends on local priority ranking. It may accept early transactions that reduce the feasibility of later high value matches.

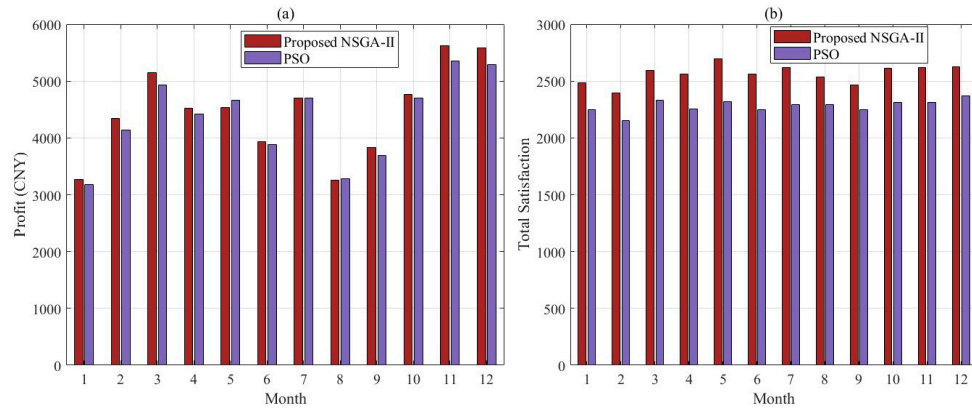


Figure 11. Monthly comparison between the proposed NSGA-II method and PSO. (a) Profit comparison. (b) Satisfaction comparison.

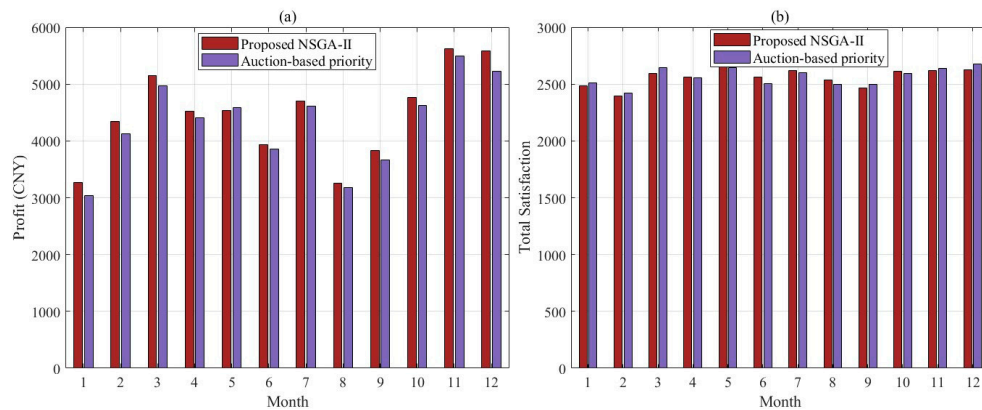


Figure 12. Monthly comparison between the proposed NSGA-II method and the auction-based priority method. (a) Profit comparison. (b) Satisfaction comparison.

Overall, the proposed NSGA-II-based method shows a more balanced performance than GA, PSO, and the auction-based priority method. GA can obtain competitive profit in some months, but it sacrifices user satisfaction. PSO provides feasible results, but its satisfaction performance is lower than that of the proposed method. The auction-based method is simple and practical, but its local priority rule limits its overall profit performance. These results confirm that the proposed method is more suitable for V2V energy trading scenarios where provider profit and user satisfaction must be considered together.

4.3.8. Case 8

In this case, a selected 30-day operating window is used to evaluate the robustness of the proposed matching strategy under user behavioral uncertainty. Compared with a full one-year Monte Carlo test, the 30-day window reduces the computational time required for repeated uncertainty simulations while still containing repeated daily operating cycles and sufficient matching instances. Since the perturbations are applied to entry time, exit time, and SOC using the same uncertainty mechanism, the 30-day test can reflect the main trend of the system response to user behavior deviations. Therefore, the results in Figure 13 should be interpreted as robustness trends under different uncertainty levels.

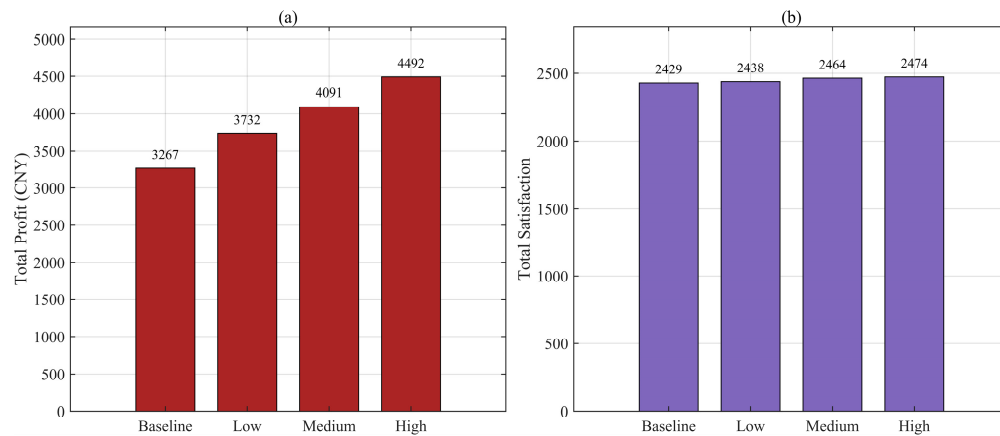


Figure 13. Robustness analysis under user behavior uncertainty. (a) Total profit. (b) Total satisfaction.

Figure 13 shows the performance of the proposed V2V matching strategy under different user behavior uncertainty levels. In this case, uncertainty is introduced by perturbing the EV time window and SOC. The baseline case uses the original input data without perturbation. In the Low, Medium, and High uncertainty cases, the entry time and exit time are randomly shifted within increasing time ranges, and SOC is disturbed by zero-mean normal distribution. After perturbation, SOC values are limited to the feasible range of $[0, 1]$, and the exit time is checked to ensure that it remains later than the entry time.

As shown in Figure 13a, the total profit remains at a feasible level under all uncertainty scenarios. Compared with the baseline case, the total profit increases from 3267 CNY to 3732 CNY, 4091 CNY, and 4492 CNY under Low, Medium, and High uncertainty. This result does not mean that uncertainty is always beneficial. The main reason is that may create more feasible matching opportunities in some cases, thereby increasing the number of effective energy transactions and the profit. Therefore, the profit variation reflects the sensitivity of feasible pair construction to user time-window changes.

Figure 13b shows that total satisfaction remains stable under different uncertainty levels. The satisfaction values increase slightly from 2429 in the baseline case to 2474 in the High uncertainty case. Compared with the change in total profit, the variation in satisfaction is small. This indicates that the proposed matching strategy can maintain stable performance when entry time, exit time, and SOC deviate from the predicted values. Overall, the results show that the proposed NSGA-II-based matching method has acceptable robustness against user behavioral uncertainty. It can still generate feasible V2V matching decisions and maintain stable user satisfaction under uncertain participation conditions.

4.3.9. Case 9

For the scalability analysis, the enlarged EV population scenarios were generated using empirical-distribution-based resampling. In the implementation, the time perturbation was limited to ± 5 min, and the SOC perturbation followed a zero-mean distribution with a standard deviation of 0.01. This setting was used to avoid duplicated records while maintaining the statistical characteristics of the original EV records.

To reduce the influence of random resampling and algorithm initialization, each scale is tested through five independent runs. The displayed runtime is the mean value of these repeated runs for one 30-day scalability test. It should be noted that the reported runtime is the average runtime of one independent 30-day test, rather than the total time of all repeated experiments.

As shown in Figure 14, the average runtime increases from 53.1 s at the Baseline scale to 199.8 s and 350.7 s at the $2\times$ and $3\times$ scales. This trend is expected because larger EV

populations generate more supply–demand candidate pairs. As a result, NSGA-II-based multi-objective search increases with the population scale. These results indicate that the proposed method remains computationally feasible within the tested scale.

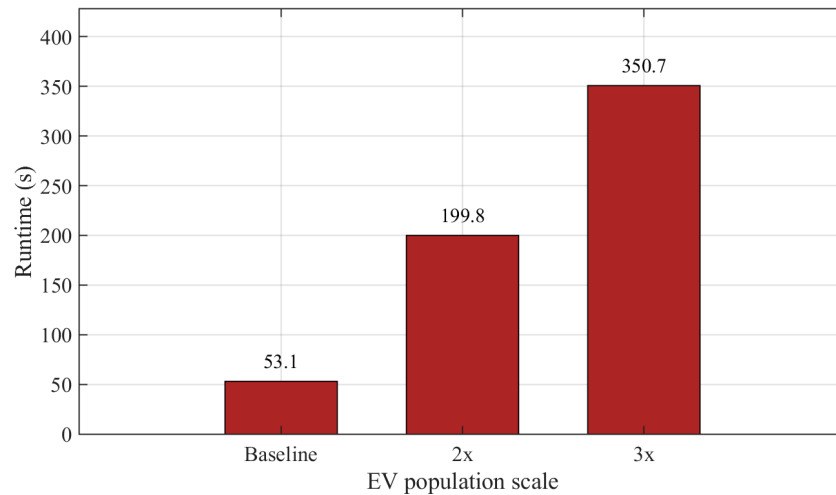


Figure 14. Scalability analysis of runtime under enlarged EV population scenarios.

4.3.10. Case 10

To further evaluate the computational cost of the proposed V2V matching strategy, this case compares the runtime of the proposed NSGA-II-based method with GA and PSO. The comparison is conducted under the same input data, feasible candidate pools, SOC constraints, distance constraints, waiting-time constraints, and energy-transfer constraints. To reduce the computational burden during the revision stage, a representative 10-day operating window is used in this runtime test. The same candidate-pair construction and feasibility verification procedures are used for all three algorithms. In this case, NSGA-II optimizes profit and user satisfaction as two independent objectives and generates a Pareto solution set. GA and PSO use the same scalar comparison score and search for a single preferred solution under the same feasible candidate pool.

As shown in Figure 15, the proposed NSGA-II-based method requires the longest runtime among the three methods. The total runtime of NSGA-II is about 11.6 s, while the runtime values of GA and PSO are about 2.1 s and 1.7 s, respectively. This result is expected because NSGA-II performs non-dominated sorting, crowding-distance calculation, Pareto-front construction, and compromise-solution selection. These procedures increase the computational cost compared with scalarized single-objective GA and PSO. Although NSGA-II has a higher runtime, it provides a Pareto solution set that describes the trade-off between profit and user satisfaction. This enables the platform to select different operating points according to stakeholder preferences. In contrast, GA and PSO have lower runtime in this comparison, but they only provide one scalarized solution under the pre-defined weighted objective. Therefore, the runtime comparison indicates a trade-off between computational efficiency and multi-objective decision capability.

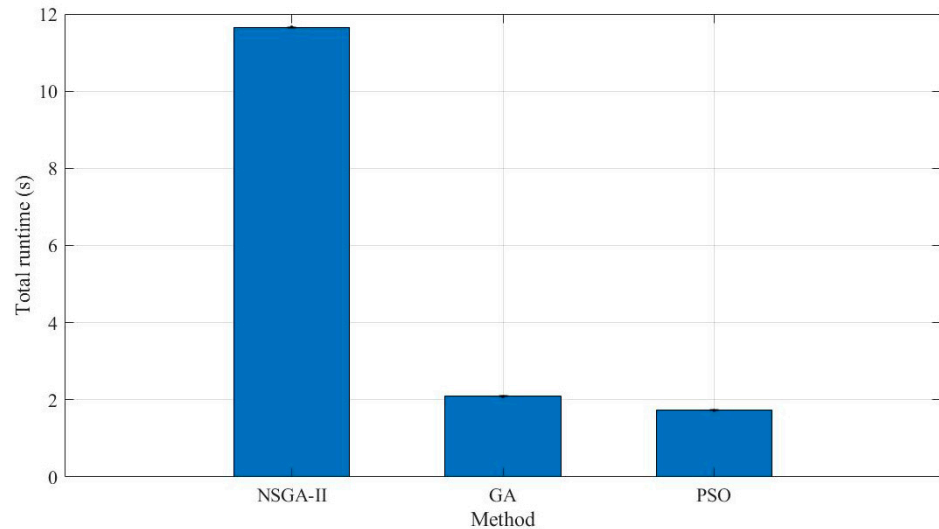


Figure 15. Runtime comparison of NSGA-II, GA, and PSO under the same conditions.

5. Conclusions

This study mitigates two primary limitations in contemporary V2V energy trading architectures: the insufficient predictive precision of monolithic models when processing high-volume vehicular datasets and the inherent imbalance between economic viability and user satisfaction in conventional optimization frameworks. To overcome these challenges, we introduce a hierarchical matching system underpinned by multi-objective optimization. Forecasting accuracy regarding vehicle availability is refined through a hybrid deep learning ensemble that fuses LSTM, GRU, and Transformer architectures. A multi-head attention mechanism is employed to dynamically weight these inputs, capturing complex spatio-temporal uncertainties. The framework utilizes a multi-objective optimization model designed to reconcile the tension between fiscal performance and user convenience. By deriving a Pareto-optimal solution, the system maximizes global utility across the network. We further implement a dynamic greedy matching algorithm which, unlike previous research, permits multiple sequential matches for a single SEV within its residual energy and temporal limits. Empirical simulations demonstrate that this hierarchical structure increases trading success rates and optimizes energy allocation, offering a robust solution for regions with underdeveloped charging infrastructure.

Although the proposed framework improves prediction-driven V2V energy trading, several limitations remain. First, the EV behavior parameters are extracted from historical charging session records. These data can reflect typical charging and parking patterns, but they may not fully capture real-time travel decisions and dynamic user preferences in practical operation. Second, the original records are aggregated at a 1 h resolution to match the 24 h scheduling horizon. This setting improves computational efficiency, but short-term variations within each hour may be ignored. Third, the current framework considers SOC, time-window feasibility, distance, profit, and user satisfaction. In real applications, additional factors such as traffic congestion, user response uncertainty, communication delay, and battery degradation may further affect the matching results. Future work will extend the framework by incorporating more realistic operational constraints, more advanced optimization and matching strategies, and more expressive prediction models such as KAN-based architectures.

We agree that communication latency, cybersecurity and privacy protection, charging hardware compatibility, blockchain verification overhead, memory requirements and regulatory constraints are critical factors for the deployment of V2V energy trading

systems. The proposed study focuses on the energy management layer, including prediction-driven EV behavior estimation, multi-objective optimization, and V2V matching. Therefore, due to the limitations of the current experimental platform, it is still difficult to systematically conduct field-scale experiments or detailed deployment-level modeling of communication protocols, hardware interoperability, cybersecurity mechanisms, and regulatory processes. Nevertheless, these factors may affect the practical performance of the proposed framework. Future work will extend the model by incorporating communication delay, privacy-preserving transaction mechanisms, standardized charging interfaces, blockchain-based verification costs, and regulatory constraints for field deployment.

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Abbreviations

V2V	Vehicle to vehicle
V2G	Vehicle to Grid
EV	Electric vehicles
EVCS	Electric vehicle charging station
EMS	Energy management system
SEV	Supply electric vehicles
DEV	Demand electric vehicles
SOC	State of charge
CNN	Convolutional neural network
RNN	Recurrent neural network
LSTM	Long short-term memory
GRU	Gated recurrent unit
GA	Genetic Algorithm
PSO	Particle Swarm Optimization
Variables	
S_i	The real-time SOC of the supply vehicle i
S_j	The real-time SOC of the demand vehicle j
t_i^{entry}	The time when supply vehicle i enters
t_i^{exit}	The time when supply vehicle i exits
t_j^{entry}	The time when demand vehicle j enters
t_j^{exit}	The time when demand vehicle j exits
E_i^{avail}	The energy that can be transferred by the supply vehicle i
E_j^{need}	The energy required by the demand vehicle j
E_{trans}^{ij}	The energy of this trading between supply vehicle i and demand vehicle j
F_{ij}	The profit of this trading between the supply vehicle i and the demand vehicle j
t_{start}^{ij}	The start time for supply vehicle i and the demand vehicle j about the trading
t_{end}^{ij}	The end time for supply vehicle i and the demand vehicle j about the trading
$T_{\text{min}}^{\text{SV}}$	The minimum time for the supply vehicle i and the demand vehicle j about the trading

d_{ij}	The Euclidean distance between supply vehicle i and the demand vehicle j
U_{SE}	The energy that the supply vehicle i has already consumed
D_{MD}	The demand vehicle that had been matched
U_{SM}	The number of supply vehicles that have been matched
Parameters	
S_{min}	Minimum required SOC for the vehicle
S_T	The SOC that electric vehicles aim to achieve
L_i	Supply vehicles' real-time location coordinates
V_{SV}	The set of supply vehicles
V_{DV}	The set of required vehicles
L_j	Required vehicles' real-time location coordinates
P_{Peak}	Electricity price during peak hours
P_{Normal}	Electricity price during normal hours
P_{Valley}	Electricity price during valley hours

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