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Application Prospects of Time Series Foundation Models in Vehicle-Grid Interaction

Ran Bao,[1,2] Shouquan Tang,[3] Zhengkun Song,[3] Jun Zhong,[3] Jinghua Su,[1,2] and ,[1,2,3] and Junjun Deng[1,2,*]

[1]School of Mechanical Engineering, Beijing Institute of Technology, Beiing 100081, China

[2]National Engineering Research Center for Electric Vehicles, Beijing Institute of Technology, Beijing 100081, China

[3]Shenzhen Power Supply Co., CSG., Shenzhen 518001, China

*Correspondence: Dengjunjun@bit.edu.cn

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The rapid growth of EVs presents both challenges and opportunities for the electric power grid. Frequent and clustered charging events not only trigger peak-load fluctuations but also threaten the grid dispatching and secure operation. Therefore, bidirectional energy coordination between EVs and the grid via Vehicle-to-Grid (V2G)[1] systems are necessary. Effective V2G operation relies on monitoring and forecasting diverse variables—grid loads, EV power flows, and dynamic electric pricing. However, these data exhibit pronounced non-stationarity and multi-scale temporal coupling due to uncertainties arising from weather conditions, user charging behavior, market mechanisms, and grid operating states. Within vehicle–grid interaction systems, temporal variations in power generation, distribution network operating conditions, user charging and discharging behaviors, and energy storage regulation interact across multiple layers, forming a coupled "generation–grid–load–storage" structure. These dynamic processes span multiple temporal scales, thereby imposing stringent requirements on the ability of models to capture multi-scale temporal patterns and achieve cross-layer generalization. However, traditional deep learning approaches (e.g., LSTM, CNN) typically require extensive task-specific tuning and suffer from performance degradation when facing data distribution shifts (e.g., new charging stations with limited historical data).

Recently, Time Series Foundation Models (TSFMs), inspired by Large Language Models (LLMs), have demonstrated remarkable capability in capturing universal temporal representations.[2] By leveraging mechanisms like patching and self-attention, TSFMs enable zero-shot forecasting and cross-domain transfer learning,[3] offering a unified framework to address the complexity of V2G interactions. The next sections review the major time-series tasks and challenges in V2G, introduce the concept of time-series foundation models, and examine their potential advantages in vehicle–grid interaction scenarios.

TIME-SERIES MODELING TASKS AND CHALLENGES IN VEHICLE–GRID INTERACTION

As V2G progresses from small-scale pilot projects to city-level demonstration and commercial deployment, multiple stakeholders participate in several key time-series analysis tasks, primarily including:

① load and power forecasting, to characterize EV charging demand across different spatial levels and temporal horizons for grid operation and planning;[4]

② electricity pricing and ancillary service analysis, to capture price volatility and support demand response and load shifting mechanisms;

③ assessment of energy storage flexibility of EV fleets, to quantify available regulation capacity and dispatchable power over time;

④ safety monitoring and anomaly detection, to identify abnormal operating conditions in distribution networks under high EV penetration.

Beyond these specific tasks, challenges in V2G Time-Series Modeling arise due to the V2G systems involve stakeholders ranging from individual EVs to regional grids, creating unique modeling hurdles:

① Significant Non-stationarity: events such as extreme weather, traffic incidents, or policy shifts can induce abrupt distribution shifts in charging behavior, which makes models trained on historical data less effective.

② Strong Spatial Coupling: Topological correlations and power-flow interactions exist across charging stations, distribution transformers, and regional networks. Concentrated charging can generate spatial spillover effects, rendering localized models fail to capture the global system characteristics.

③ High Uncertainty and Data Heterogeneity: high uncertainty in user behavior (arrival times, charging durations and mobility patterns) and renewable generation leads to significant stochastic variability and distribution shifts in the time-series data. Traditional forecasting methods (from statistical models to single-task deep learning models) must be frequently retrained and tuned for each scenario, and they struggle to generalize across different cities, fleets, or operating conditions.

Therefore, an urgent need arises for more generalizable modeling approaches that can handle non-stationary, multi-variable, and multi-scale data regimes.

EMERGENCE OF TIME SERIES FOUNDATION MODELS

Traditional time-series modeling approaches are typically developed independently for specific tasks, requiring extensive feature engineering and manual model tuning. Different tasks often necessitate distinct model architecture and training workflows. In V2G scenarios with heterogeneous entities, complex multimodal data, and temporal scales ranging from seconds to months, such task-specific methods struggle to share representations and adapt across different regions, seasons, and operating conditions. Their limited generalization capability prevents them from maintaining stable performance under fluctuating demand patterns, changing system states, and external disturbances inherent to V2G systems.

Time Series Foundation Models (TSFMs) have recently emerged as a unifying solution, drawing on the pre-training and representation learning paradigms established in natural language processing.[5] Most TSFMs adopt Transformer-based architectures with self-attention and multi-task learning mechanisms, and encode continuous time series into semantic segments through patching or tokenization rather than treating observations as independent points. This representation enables the attention mechanism to capture local fluctuations, seasonal patterns, cross-variable dependencies, and long-range temporal structures, thereby modeling both high-frequency variations and long-term trends. Leveraging this unified framework, TSFMs

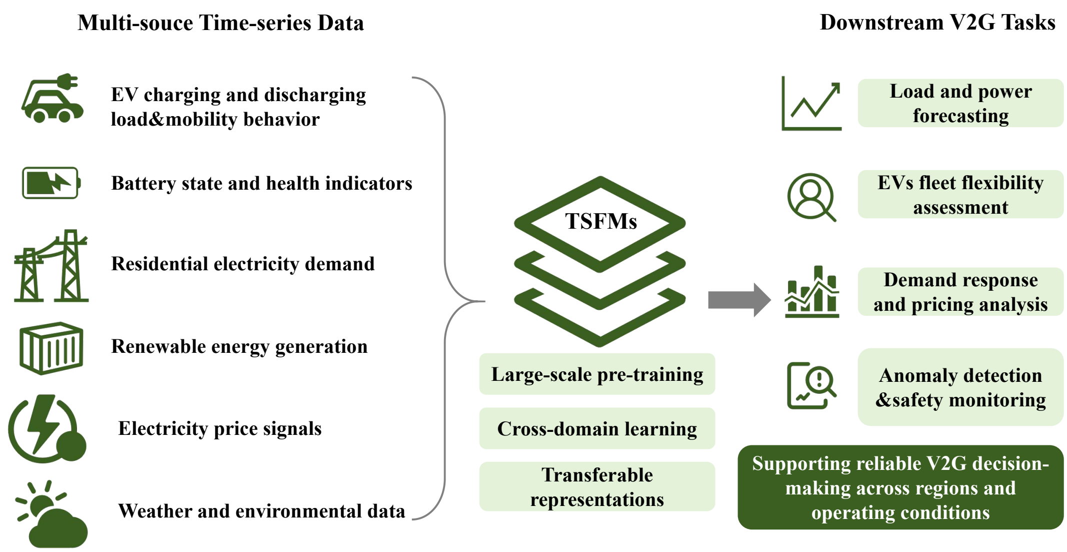

Figure 1. Conceptual framework of TSFMs for V2G interaction.

are pre-trained on large-scale, cross-domain time-series datasets spanning diverse application areas—such as energy systems, power grids, transportation, retail, finance, and meteorology—with temporal resolutions ranging from minutes to months and total scales reaching tens to hundreds of billions of time points. Through joint pre-training across heterogeneous domains, frequencies, and task settings, TSFMs learn universal temporal representations that generalize across scenarios, enabling strong robustness when applied to new regions, variables, or unfamiliar task categories under distribution shifts.

Several large-scale pre-trained time-series foundation models have recently been proposed, highlighting the emergence of a foundation-model paradigm in time-series analysis. Representative examples include Google Research's TimesFM, which demonstrates strong zero-shot and few-shot forecasting performance on multi-frequency data; Salesforce AI Research's Moirai, which supports flexible modeling across heterogeneous frequencies and multivariate inputs; and Amazon AWS AI Labs' Chronos, which adopts a generative tokenization-based approach and achieves strong cross-domain transferability. Collectively, these efforts suggest that time-series analysis is evolving toward a pre-training ecosystem analogous to foundation models in natural language processing, reducing reliance on task-specific models for new V2G scenarios.

Crucially, these foundation models demonstrate the ability to generalize with minimal task-specific data. In practice, fine-tuning a TSFM on a small amount of domain data can yield excellent predictions even with limited new training samples, and the model can even produce useful forecasts for unseen tasks in a zero-shot manner. This suggests that a pre-trained model can be deployed across different cities or EV fleets with only light calibration, instead of training separate models per city. This transferability across cities and fleets is a key advantage in V2G, where operational conditions vary widely. Moreover, foundation models can integrate many exogenous factors (weather, prices, etc.) within one framework, capturing complex cross-factor influences that simpler models might miss.

APPLICATION PROSPECTS IN V2G

The proliferation of intelligent and connected EVs is generating large-scale, high-frequency time-series data during vehicle operation, including battery health indicators, charging session records, mobility patterns, and grid interaction signals. Spanning multiple vehicle models, regions, seasons, and operating conditions, these datasets provide a natural large-scale pre-training corpus for developing TSFMs tailored to vehicle-grid interaction. By pre-training on abundant EV- and grid-related time series, TSFMs can learn intrinsic temporal patterns underlying vehicle behavior, energy flow processes, and battery state evolution, yielding representations with strong generalization capability across regions and tasks.Figure 1 illustrates the overall framework of TSFMs for V2G interaction, from multi-source data pre-training to downstream applications.

Building on these pre-trained representations, TSFMs can support a wide range of downstream V2G applications, such as charging-load forecasting, EV user behavior characterization, grid flexibility assessment, V2G dispatch optimization, and analysis of price-responsive charging demand. Compared with conventional task-specific models, TSFMs offer a unified modeling framework that better captures fleet-level dispatchable power and demand-response potential across heterogeneous operational environments.

Despite these promising prospects, several challenges remain for the practical deployment of TSFMs in V2G systems. These include the high computational cost and inference latency of large models in real-time grid applications, limited interpretability of model outputs for operational decision-making, and the need to incorporate physical constraints, grid topology, and regulatory requirements into data-driven architectures. Future research should therefore focus on developing lightweight and interpretable TSFMs variants, integrating domain knowledge and physical priors, and establishing standardized benchmarks and evaluation protocols for V2G-oriented time-series tasks.

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DECLARATION OF INTERESTS

The authors declare no competing interests.