

A comprehensive table analyzing the existing systems and research gaps from the references for my thesis on "Predictive Modeling of Battery Powered Vehicles (BPVs) Charging Load on the Power Grid: A Machine Learning Approach."

Analysis of Existing Systems and Research Gaps for BPV Charging Load Prediction Research

Table 1: Analysis of Referenced Papers

Ref ere nce	Journal Metrics	Existing Systems/Methods	Research Gaps	Key Contributions
Kla us ma nn et al. (20 23)	Journal: Energies Article: Q1 Impact Factor: 3.252 (2022)	- Adaptive control strategy for stationary battery storage systems - Self-consumption optimization algorithm - Peak load limitation methods	- Limited focus on grid-level impacts of multiple BPV charging - Insufficient integration with renewable energy fluctuations - Lack of machine learning methods for prediction - Not specifically focused on BPV charging loads	- Reliable peak load limitation techniques - Optimization for self-consumption of locally generated energy - Adaptive control strategies for battery systems
Yap rak dal (20 23)	Journal: Energies Article: Q1 Impact Factor: 3.252 (2022)	- Ensemble deep learning for hour-ahead load forecasting - Feature selection approach - Comparative analysis with state-of-the-art methods	- Limited temporal resolution (hour-ahead only) - Lack of spatial distribution consideration in grid impact	- Novel ensemble deep learning architecture - Effective feature selection methodology - Comparative benchmarking of forecasting models

		- Modified First Harmonic Approximation (MFHA)	- Focused on component-level analysis rather than system-level - Limited scalability for grid integration - Insufficient consideration of multiple charging scenarios	- Advanced modeling of power transfer links - Load-independent voltage output techniques - Simulation frameworks for inductive charging
Vulfovic et al. (2021)	Journal: Simulation Modelling Practice and Theory Quartile: Q1 Impact Factor: 4.719 (2022)	modeling - SN-compensated inductive power transfer links - Load-independent-voltage-output frequency systems		
Schreiber & Ulbig (2023)	Journal: Energy and AI Quartile: Q1 Impact Factor: 7.762 (2022)	- Model selection, adaptation, and combination - Transfer learning for renewable forecasts - Wind and PV power prediction	- Focus on generation rather than load prediction - Limited application to BPV charging load profiles - Insufficient integration of charging behavior patterns	- Transfer learning techniques for power systems - Model adaptation methodologies - Renewable energy integration framework
Rath et al. (2024)	Journal: Electric Power Systems Research Quartile: Q1 Impact Factor: 4.630 (2022)	- Reduced complexity model predictive direct power control - Systems for unbalanced grid conditions - Grid stabilization techniques	- Limited focus on demand-side prediction - Insufficient consideration of BPV charging patterns - Lack of machine learning integration for prediction	- Grid stabilization under unbalanced conditions - Reduced complexity control algorithms - Direct power control methodologies
Creispo & Falcao	Journal: Engineering Applications of Artificial Intelligence Quartile:	- Comparative analysis of ML techniques - Short-term grid power forecasting	- Focus on wave energy rather than BPV charging - Limited consideration of charging behavior	- ML comparison framework for power forecasting - Uncertainty quantification

(20 24)	Q1 Impact Factor: 8.036 (2022)	Uncertainty analysis for wave energy converters	variability - Insufficient integration with charging infrastructure	techniques - Short-term grid power prediction methods
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Table 2: Identified Research Gaps

Gap Category	Research Gaps	Potential Research Directions
Prediction Models	<ul style="list-style-type: none"> - Limited application of advanced ML techniques specifically for BPV charging - Insufficient ensemble methods for charging load prediction - Lack of deep learning architectures optimized for charging patterns - Most studies limited to hour-ahead or day-ahead forecasting 	<ul style="list-style-type: none"> - Develop specialized ML models for BPV charging load prediction - Implement ensemble methods combining temporal and spatial features - Design deep learning architectures that capture charging behavior variability - Develop multi-time-horizon prediction frameworks
Temporal Resolution	<ul style="list-style-type: none"> - Insufficient real-time prediction capabilities - Limited consideration of multiple time horizons 	<ul style="list-style-type: none"> - Implement real-time prediction with fast computational methods - Create adaptive temporal resolution based on grid conditions
Integration Aspects	<ul style="list-style-type: none"> - Insufficient consideration of grid constraints - Limited integration with renewable energy generation - Lack of V2G (Vehicle-to-Grid) considerations 	<ul style="list-style-type: none"> - Develop integrated frameworks considering grid limitations - Create models that optimize charging based on renewable availability - Implement V2G-aware prediction models
Charging Behavior	<ul style="list-style-type: none"> - Limited consideration of user behavior variability - Insufficient incorporation of charging patterns - Lack of socio-economic factors in predictions 	<ul style="list-style-type: none"> - Incorporate user behavior modeling in prediction frameworks - Develop clustering methods for charging pattern identification - Integrate socio-economic factors in prediction models
Scalability	<ul style="list-style-type: none"> - Limited focus on large-scale BPV penetration scenarios 	<ul style="list-style-type: none"> - Develop scalable models for high BPV penetration scenarios - Create

	Insufficient methods for handling geographical distribution - Lack of hierarchical prediction frameworks	geographically aware prediction frameworks - Implement hierarchical prediction models for multi-level grid
Uncertainty	- Limited methods for uncertainty evaluation in BPV load	- Develop probabilistic forecasting methods for BPV charging - Implement risk assessment
Quantification	prediction - Insufficient risk assessment frameworks - Lack of probabilistic prediction approaches	frameworks for grid operators - Create uncertainty quantification techniques for charging loads

This analysis reveals several key research opportunities for my thesis on predictive modeling of BPV charging loads using machine learning:

1. There's a clear gap in specialized ML models specifically designed for BPV charging prediction, as most existing research focuses either on general load forecasting or component-level analysis.
2. The integration between BPV charging patterns and grid constraints remains underdeveloped, especially regarding scalability for widespread EV adoption scenarios.
3. Most current research lacks comprehensive consideration of charging behavior variability and user patterns, which are critical for accurate predictions.
4. There's significant potential to develop multi-time-horizon prediction frameworks that can adapt to different grid conditions and charging scenarios.
5. Uncertainty quantification for BPV charging loads is still in early stages, with limited probabilistic approaches that could benefit grid operators.

My thesis has the opportunity to address these gaps by developing specialized machine learning models that integrate charging behavior patterns with grid constraints, potentially incorporating ensemble methods that can handle the temporal and spatial variability of BPV charging loads.

Technology Stack & Tools Used

Category	Tools / Platforms
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Programming Languages / Platforms	- Python : Core programming language for data analysis and modeling - Jupyter Notebook, Google Colab : Development and testing environment
Data Visualization	- Matplotlib, Seaborn : Plotting and analysis of time series and model performance - Streamlit (optional): Interactive dashboard for showcasing forecasts - OpenStreetMap (OSM) : Source for mapping BPV movement from source to destination
Traffic Simulation & Route Modeling	- SUMO (Simulation of Urban MObility) : Used for simulating city-level BPV traffic behavior - TraCI Framework : Python-based API to control SUMO simulations in real-time
Communication Network Simulation	- OMNeT++ : To simulate data communication between BPVs and charging infrastructure (for future smart grid applications)
Sensor & Emission Simulation	- Vehicle Detection Sensors : Virtual sensor data used in SUMO for tracking vehicle count and movement - Emission Generation Modules : For simulating environmental impact alongside power load
Big Data Processing / Workflow Management	- KNIME (optional): For visual workflow creation, preprocessing, and automation in data pipelines

This tech stack not only supports **load forecasting for BPV charging**, but also adds depth by enabling **realistic traffic modeling, emissions impact tracking, and potential communication frameworks**, all relevant to future **smart grid integration**.

✍ Presentation Script for Timeline Slide

🖼 Slide Title: Timeline of the Research Work (12 Months)

What to Say:

"To systematically approach the research, we've structured the entire thesis into **four major phases**, spanning over **12 months**. Each phase is strategically designed to build upon the previous one."

Phase 1: Month 1–3 – Literature Review & Tool Setup

"In the first quarter, the focus is on an extensive literature review to understand current research trends, gaps, and techniques used in predictive modeling of energy consumption and BPV load forecasting.

Alongside, we'll set up the working environment with tools like Python, Jupyter Notebook, and simulation frameworks like SUMO and TraCI."

Phase 2: Month 4–6 – Data Collection & Preprocessing

"Next, we'll begin collecting both real-world and synthetic datasets, including traffic patterns, weather data, and trip data.

This data will be cleaned, labeled, and prepared for model training. Special attention will be paid to aligning spatial and temporal aspects for better accuracy."

Phase 3: Month 7–9 – Model Development & Optimization

"During this phase, we'll develop baseline models such as Linear Regression and Random Forest, followed by advanced models like LSTM and Quantile LSTM.

Each model's performance will be evaluated using metrics like RMSE, MAE, and inference speed. Optimization will be done based on experimental results."

Phase 4: Month 10–12 – Scenario Simulation & Visualization

“In the final phase, we will simulate real-world scenarios like peak-hour charging, weekend usage, and seasonal variations.

We also plan to visualize the predicted load trends using tools like Matplotlib, Seaborn, and optionally Streamlit for an interactive dashboard.

The final report and thesis writing will also be completed during this stage.”

Ending Note:

“This structured timeline not only ensures smooth progress but also aligns each phase with the core objective — to develop a practical, accurate, and data-driven solution for smart power grid management in the age of electric mobility.”