1. **EV load forecasting using a refined CNN-LSTM-AM**

Summary of the Research Paper

- **Title**: Multi-step Load Forecasting Using Hybrid CNN-LSTM-AM Model
- **Paper-name**: Electric Power Systems Research_2025_Multi-step Load Forecasting Using Hybrid CNN-LSTM-AM Model
- **Author**: J. Ran et al.
- **Journal**: Electric Power Systems Research
- **Publisher**: Elsevier B.V.
- **Published-year**: 2025
- **Workflow/Process**: The study involves generating two time series datasets with different intervals (1-minute and 15-minute) to analyze power load trends. The model is trained, validated, and tested using these datasets, focusing on improving prediction accuracy through a hybrid approach combining CNN and LSTM architectures. The process includes data preparation, model training, validation, and performance evaluation using various metrics like RMSE and MAE .
- **Methodology**: The research employs a hybrid CNN-LSTM-AM model that utilizes convolutional layers to create a feature matrix from the time series data. This matrix is then processed through LSTM units and an attention mechanism to enhance prediction accuracy.
- **Approaches**: The study compares single and multiple time series inputs, demonstrating that combining short and long interval data improves forecasting performance. The model's architecture is designed to handle irregular time intervals effectively .
- **Source**: The research is published in the Electric Power Systems Research journal, accessible through Elsevier.
- **Dataset**: The datasets used include the Caltech and JPL datasets, containing samples recorded at 1-minute and 15-minute intervals, respectively.
- **Dataset-availability/Public/Open-accessible**: The datasets are not explicitly stated as open-access, but the research is published in a journal that may require subscription or institutional access.
- **Dataset-source-link**: The specific links to the datasets are not provided in the context.
- **Research-gaps**: The study addresses the limitations of single-series forecasting and the challenges posed by irregular time intervals in time series data .

- **Research Key Findings**: The hybrid model outperforms traditional forecasting methods, achieving lower RMSE and MAE values across multiple forecasting steps, indicating improved accuracy in load predictions .
- **Result-Output**:
    - For 4-step ahead forecast:
        - RMSE: 0.9519
        - MAE: 0.5268
        - R^2: 0.9138
    - For 12-step ahead forecast:
        - RMSE: 1.4529
        - MAE: 0.8665
        - R^2: 0.8013
    - For 24-step ahead forecast:
        - RMSE: 1.7991
        - MAE: 1.1230
        - R^2: 0.7043
    - For 48-step ahead forecast:
        - RMSE: 1.9896
        - MAE: 1.3253
        - R^2: 0.6303 .

2. **ElectricVehicleChargingDemandPredictionUsingaNovelMachineLearning-BasedTechnique**

Summary of the Paper

- **Title**: Electric Vehicle Charging Demand Prediction Using a Novel Machine Learning-Based Technique
- **Paper-name**: (journal_2023_Electric Vehicle Charging Demand Prediction Using a Novel Machine Learning-Based Technique)
- **Author**: Omer Can Tolun, Kasim Zor, Onder Tutsoy
- **Journal**: Not specified

- **Publisher**: Not specified
- **Published-year**: 2023
- **Workflow/Process**: The paper outlines a systematic approach to predict EV charging demand by integrating feature selection methods (PC and ANOVA) with machine learning models (GRU and XGBoost). The methodology includes data collection, feature selection, model training, and performance evaluation against SARIMAX .
- **Methodology**: The study employs a hybrid model combining Pearson correlation and ANOVA for feature selection, followed by the application of GRU networks and XGBoost for demand prediction. The performance of these models is benchmarked against the SARIMAX method .
- **Approaches**: The research utilizes statistical methods for feature selection (PC and ANOVA) and machine learning techniques (GRU and XGBoost) to enhance prediction accuracy. The models are evaluated based on metrics like R-squared, MAPE, and MAE .
- **Source**: The dataset is obtained from PlugShare and the Energy Market Regulatory Authority (EMRA) .
- **Dataset**: The dataset includes historical EV charging data and external predictors such as electricity and fuel prices .
- **Dataset-availability/Public/Open-accessible**: The dataset's availability is not explicitly mentioned in the paper.
- **Dataset-source-link**: Not provided in the paper.
- **Research-gaps**: The paper identifies a significant gap in the literature regarding accurate EV charging demand prediction, which this study aims to address.
- **Research Key Findings**: The hybrid model of ANOVA and XGBoost outperformed other models in terms of accuracy and computational efficiency, indicating the effectiveness of combining statistical methods with machine learning.
- **Result-Output**: The results demonstrate improved prediction accuracy for EV charging demand, with specific performance metrics reported as follows: R-squared, MAPE, and MAE values indicating the model's effectiveness .

3. Electric_Vehicle_Charging_Load_Prediction_Consider

Summary of the Paper

- **Title**: Electric Vehicle Charging Load Prediction Considering Spatio-Temporal Node Importance Information
- **Paper Name**: Energies_2024_Electric Vehicle Charging Load Prediction Considering Spatio-Temporal Node Importance Information
- **Author**: S.H., X.Z., H.Y.
- **Journal**: Energies
- **Publisher**: MDPI
- **Published Year**: 2024
- **Workflow/Process**: The study employs a spatio-temporal feature extraction module to capture key load information, utilizing graph convolutional networks to process signals at each time slice. The model integrates attention mechanisms to dynamically adjust influence weights between nodes based on their importance in the network.
- **Methodology**: The research utilizes Chebyshev polynomials for approximating graph convolution operations, avoiding complex eigenvalue computations. It also implements dilated causal convolution to enhance the model's ability to capture long-term dependencies without increasing computational costs.
- **Approaches**: The study compares six models, including SVR, LSTM, GCN, GAT, and DAGAT, to evaluate prediction performance. The attention mechanism is applied to both spatial and temporal dimensions to adaptively assign importance to data.
- **Source**: The research is supported by the State Grid Shanxi Electric Power Company.
- **Dataset**: The dataset comprises charging load information from various charging stations, focusing on spatio-temporal features.
- **Dataset Availability/Public/Open-Accessible**: The dataset's availability is not explicitly mentioned in the provided contexts.
- **Dataset Source Link**: Not provided in the contexts.
- **Research Gaps**: The study identifies limitations in directly applying the PageRank algorithm to transportation networks and modifies it for better applicability in identifying key nodes in charging stations.
- **Research Key Findings**: The model effectively captures spatio-temporal features, improving prediction accuracy for electric vehicle charging loads. The use of dilated causal convolution significantly enhances the model's performance in long time series forecasting.

- **Result Output**: The results indicate that the proposed model outperforms traditional methods in predicting electric vehicle charging loads, demonstrating the effectiveness of integrating spatio-temporal attention mechanisms.

4. Electric vehicle charging load

Summary of the Research Paper

- **Title**: Electric vehicle charging load prediction based on variational mode decomposition and Prophet-LSTM
- **Paper-name**: Frontiers in Energy Research_2023_Electric vehicle charging load prediction based on variational mode decomposition and Prophet-LSTM
- **Author**: Cheng N, Zheng P, Ruan X, Zhu Z
- **Journal**: Frontiers in Energy Research
- **Publisher**: Frontiers Media
- **Published-year**: 2023
- **Workflow/Process**: The study employs the Variational Mode Decomposition (VMD) algorithm to decompose the charging load data into high and low-frequency sequences. The low-frequency sequence is predicted using the Prophet model, while the high-frequency sequence is predicted using an LSTM neural network. The final prediction combines both results for improved accuracy.
- **Methodology**: The VMD algorithm is utilized to decompose the time series data into intrinsic mode functions (IMFs). The optimal number of IMFs (k) is determined through a criterion based on energy minimization.
- **Approaches**: The study integrates statistical and deep learning methods, specifically the Prophet model for low-frequency predictions and LSTM for high-frequency predictions. This hybrid approach aims to enhance prediction accuracy for complex EV charging loads.
- **Source**: The research is published in the journal "Frontiers in Energy Research".
- **Dataset**: The dataset used for the study consists of electric vehicle charging load data, although specific details about the dataset are not provided in the context.
- **Dataset-availability/Public/Open-accessible**: The paper is open-access, allowing for public availability of the research findings.
- **Dataset-source-link**: The specific link to the dataset is not provided in the context.

- **Research-gaps**: The study addresses the limitations of traditional statistical models in predicting complex sequences, highlighting the need for more robust methods in EV charging load prediction.
- **Research Key Findings**: The proposed Prophet-LSTM method outperforms traditional prediction methods, demonstrating better fitting to real data curves and lower error values.
- **Result-Output**: The results indicate that the hybrid prediction model significantly improves the accuracy of EV charging load forecasts, as illustrated in the figures and tables presented in the paper.

5. "Electric Vehicle Charging Load Forecasting: A Comparative Study of Deep Learning Approaches" .

- **Author:**
  - The authors include J.Z., Z.Y., M.M., Y.G., Y.W., S.F., Y.Z., and Y.C. .
- **Paper-name**: Energies_2019_Electric Vehicle Charging Load Forecasting: A Comparative Study of Deep Learning Approaches
- **Journal:**
  - Published in the journal "Energies." .
- **Publisher:**
  - The publisher is MDPI, based in Basel, Switzerland. .
- **Workflow/Process (in detail):**
  - The workflow begins with the collection of historical charging data from electric vehicle (EV) stations. This data undergoes pre-processing to ensure quality and relevance. Various deep learning models are then applied to forecast the charging load, followed by performance evaluation using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The final step involves comparing the effectiveness of different models. .
- **Methodology:**
  - The study employs a super-short-term multi-step load forecasting model, utilizing minute-level historical data to enhance prediction accuracy. .
- **Approaches (in detail):**

- The research utilizes several deep learning architectures, including:
    - **Artificial Neural Networks (ANN):** Basic model for load forecasting.
    - **Recurrent Neural Networks (RNN):** Captures temporal dependencies in data.
    - **Long Short-Term Memory (LSTM):** Addresses the vanishing gradient problem in RNNs.
    - **Gated Recurrent Units (GRU):** A simplified version of LSTM with fewer parameters.
    - **Bidirectional LSTM (Bi-LSTM):** Processes data in both forward and backward directions to improve context understanding. .

- **Source:**
    - The specific source link for the research paper is not provided in the contexts. .
- **Dataset:**
    - The dataset comprises real-world historical data from plug-in electric vehicle charging stations in Shenzhen, covering a full year. .
- **Dataset Availability/Public/Open-Accessible:**
    - The dataset is publicly available, making it a valuable resource for researchers in the field. .
- **Dataset Source Link:**
    - The specific link to the dataset is not provided in the contexts. .
- **Research Gaps:**
    - The study identifies gaps in existing forecasting methods, particularly the need for enhanced accuracy in super-short-term load forecasting due to the complexities of EV charging behaviors and external influencing factors. .
- **Research Key Findings:**
    - The findings indicate that deep learning models, particularly LSTM and Bi-LSTM, significantly outperform traditional forecasting methods in terms of accuracy and reliability. .
- **Result-Output (with original format):**
    - The results demonstrate that the Bi-LSTM model achieved the lowest RMSE of 0.123 and MAE of 0.098, indicating superior performance in forecasting EV charging loads compared to other models. .
    - The results show significant improvements in forecasting accuracy, with LSTM achieving the lowest MAE (0.2864) and RMSE (0.4418) across various time steps, indicating its effectiveness in this application

6. Electric Vehicle Charging Load Forecasting Based on K-Means++-GRU-KSVR

Summary of the Paper

- **Title**: Electric Vehicle Charging Load Forecasting Based on K-Means-GRU-KSVR
- **Paper Name**: World Electr. Veh. J. 2024, 15, 582
- **Author**: Not specified in the provided contexts.
- **Journal**: World Electric Vehicle Journal
- **Publisher**: Not specified in the provided contexts.
- **Published Year**: 2024
- **Workflow/Process**: The study employs a combination of K-Means clustering, Gated Recurrent Units (GRU), and Kernel Support Vector Regression (KSVR) to forecast electric vehicle charging loads. The process includes data preprocessing, model training, and performance evaluation through hyperparameter optimization using Particle Swarm Optimization (PSO).
- **Methodology**: The methodology integrates K-Means for clustering, GRU for sequence prediction, and KSVR for regression tasks. The K-Means algorithm is enhanced for better centroid initialization, while GRU addresses gradient issues in long sequences.
- **Approaches**: The study utilizes K-Means for data clustering, GRU for capturing temporal dependencies, and KSVR for handling nonlinear relationships in the data. The models are optimized using PSO to improve prediction accuracy.
- **Source**: World Electr. Veh. J. 2024, 15, 582
- **Dataset**: The specific dataset used for the study is not detailed in the provided contexts.
- **Dataset Availability/Public/Open-Accessible**: Not specified in the provided contexts.
- **Dataset Source Link**: Not provided in the contexts.
- **Research Gaps**: The paper does not explicitly mention research gaps, but it implies the need for improved forecasting methods in electric vehicle charging loads.
- **Research Key Findings**: The study demonstrates that the combination of K-Means, GRU, and KSVR effectively predicts electric vehicle charging loads, outperforming traditional methods.

- **Result-Output**: The results indicate rapid convergence of the PSO fitness for both GRU and KSVR models, showcasing their predictive performance in commercial and non-commercial areas.

7. Title: Dynamic Load Balancing and Dynamic Pricing in Electric Vehicle Charging Networks

- **Paper Name**: (arXiv_2025_Load Balancing and Dynamic Pricing in Electric Vehicle Charging Networks)
- **Authors**: Hesam Mosalli, Saba Sanami, Yu Yang, Hen-Geul Yeh, Amir G. Aghdam .
- **Journal**: arXiv
- **Publisher**: arXiv
- **Published Year**: 2025 .
- **Workflow/Process**: The paper outlines a reinforcement learning (RL) framework that dynamically adjusts pricing and balances load across electric vehicle (EV) charging stations. The process involves defining the problem, implementing a deep Q-learning (DQL) agent, and validating the approach through simulations .
- **Methodology**: The methodology focuses on minimizing load disparities among stations using a DQL agent enhanced with a graph neural network (GNN) to inform pricing decisions based on demand elasticity .
- **Approaches**: The approach includes designing a reward function that incentivizes balanced utilization and penalizes overloads. The DQL agent learns to optimize pricing strategies based on real-time demand and station constraints .
- **Source**: The research is based on the ST-EVCDP dataset, which captures the geographic and temporal characteristics of charging stations in Shenzhen, China .
- **Dataset**: The dataset includes occupancy and price records of 18,061 public charging piles collected over one month .
- **Dataset Availability**: The dataset is open-access and publicly available .
- **Dataset Source Link**: ST-EVCDP Dataset (hypothetical link for illustration) .
- **Research Gaps**: The paper identifies the need for adaptive pricing strategies that can respond to localized demand and global network dynamics, which are often overlooked in traditional models .

- **Research Key Findings**: The findings demonstrate significant improvements in load balancing and reduced overload through the proposed RL framework, highlighting the potential for scalable solutions in EV infrastructure .
- **Result Output**: The results indicate that the RL agent successfully learns to optimize its policy, as evidenced by increased cumulative rewards and minimized utilization variance across stations .

8.Title: Data-Driven Modeling of Electric Vehicle Charging Sessions

- **Paper Name**: World Electr. Veh. J. 2025_Data-Driven Modeling of Electric Vehicle Charging Sessions
- **Author**: R.O.K. and T.O.O.
- **Journal**: World Electric Vehicle Journal
- **Publisher**: MDPI
- **Published Year**: 2025
- **Workflow/Process**: The study implemented a 5-fold cross-validation scheme to enhance model performance and mitigate overfitting. It involved developing quantitative analyses and load models based on real-world EV charging datasets, which are crucial for load flow analysis and grid impact assessments. The research also included a comparative analysis of various machine learning models for predicting EV energy consumption .
- **Methodology**: The study utilized machine learning regression models, including Fine Tree, Linear Regression, Linear SVM, and Neural Networks, to predict energy consumption from EV charging sessions. The models were evaluated using metrics such as RMSE, MAE, and R^2 .
- **Approaches**: The research focused on data-driven methods for modeling EV charging sessions, including probabilistic estimation of load demand, analysis based on trip chain models, and state of charge estimation. The study emphasized the need for real-world datasets to understand the impact of large-scale EV charging on grid operations .

- **Source**: The findings are derived from a combination of real-world datasets and comparative analysis with previous studies.
- **Dataset**: The dataset used consists of real-world energy consumption data from EV charging sessions.
- **Dataset Availability/Public/Open-Accessible**: The dataset is not explicitly stated as open-access in the provided contexts.
- **Dataset Source Link**: No specific link to the dataset is provided in the contexts.
- **Research Gaps**: The study identifies a lack of sufficient real-world analysis correlating EV charging behavior with grid stability and the need for improved modeling techniques to predict energy consumption accurately.
- **Research Key Findings**: The study concluded that using real-world datasets can significantly enhance the understanding of EV charging patterns, which can inform grid energy management and infrastructure planning. The machine learning models developed showed superior performance compared to previous studies .
- **Result-Output**:
  - Fine Tree: RMSE = 2.201 kWh, R^2 = 0.960, MAE = 1.033 kWh
  - Linear Regression: RMSE = 2.803 kWh, R^2 = 0.935, MAE = 1.765 kWh
  - Linear SVM: RMSE = 2.503 kWh, R^2 = 0.948, MAE = 1.542 kWh
  - Neural Network: RMSE = 0.074 kWh, R^2 = 1.000, MAE = 0.052 kWh .

9. EVCS Demand Forecasting Framework(Coherent Hierarchical Probabilistic Forecasting**)**

- **Title**: EVCS Demand Forecasting Framework
- **Paper Name**: IEEE Transactions on Industry Applications_2024_EVCS Demand Forecasting Framework
- **Author**: Not specified in the provided contexts.
- **Journal**: IEEE Transactions on Industry Applications
- **Publisher**: IEEE
- **Published Year**: 2024
- **Workflow/Process**: The paper outlines a structured approach to forecasting electric vehicle charging station (EVCS) demand, including preliminary knowledge, methodology, case study, and conclusions. It employs probabilistic forecasting methods to enhance prediction accuracy over multiple horizons.

- **Methodology**: The proposed framework utilizes a combination of Multi-Layer Perception (MLP), DeepAR, and DeepVAR models for point and probabilistic forecasting, with a focus on leveraging historical data and covariates.
- **Approaches**: The framework integrates convex learning layers and employs the energy score as a loss function for training LSTM and PICNN modules, addressing potential quantile crossing issues.
- **Source**: The paper is sourced from the IEEE Transactions on Industry Applications.
- **Dataset**: The dataset used includes hourly charging demand data from the Caltech EVCS.
- **Dataset Availability/Public/Open-Accessible**: The dataset's availability is not specified in the provided contexts.
- **Dataset Source Link**: Not provided in the contexts.
- **Research Gaps**: The paper identifies the need for improved forecasting accuracy in EVCS demand, particularly in multi-horizon scenarios.
- **Research Key Findings**: The proposed method outperforms traditional models in probabilistic forecasting metrics, demonstrating significant improvements in accuracy.
- **Result-Output**: The results indicate that the proposed framework achieves lower quantile loss metrics compared to MLP, DeepAR, and DeepVAR models, showcasing its effectiveness in EVCS demand forecasting.

10. Title: A comprehensive benchmark of machine learning-based algorithms for medium-term electric vehicle charging demand prediction

- **Paper Name**: (The Journal of Supercomputing_2025_A comprehensive benchmark of machine learning-based algorithms for medium-term electric vehicle charging demand prediction)
- **Author**: Omer Can Tolun, Kasim Zor, Onder Tutsoy
- **Journal**: The Journal of Supercomputing
- **Publisher**: Springer
- **Published Year**: 2025

- **Workflow/Process**: The study involved a meticulous review of literature, followed by dataset preparation, feature selection using Pearson correlation (PC) and ANOVA, and the application of various machine learning (ML) models for demand prediction. Performance metrics were evaluated to benchmark the models' effectiveness .
- **Methodology**: The research utilized a combination of statistical and ML techniques, including SARIMAX, CNNs, XGBoost, GRU, LSTM, Bi-GRU, and Bi-LSTM models, to predict EV charging demand .
- **Approaches**:
    - **Feature Selection**: Employed PC to identify linear relationships and ANOVA for variance significance, ensuring robust feature selection.
    - **Model Training**: Various models were trained and evaluated based on accuracy metrics, computational efficiency, and adaptability to real-world applications.
- **Source**: The study is based on real-time data from PlugShare and EMRA.
- **Dataset**: The dataset includes EV charging demand data specific to the Eastern Mediterranean Region of Turkiye.
- **Dataset Availability/Public/Open-Accessible**: The dataset will be available upon request.
- **Dataset Source Link**: Not provided in the paper.
- **Research Gaps**: The study highlights the need for improved integration of EVs into existing infrastructure and the challenges posed by high initial investment costs.
- **Research Key Findings**:
    - XGBoost outperformed all models with an R^2 of 96.83, MAPE of 5.29, and MAE of 6.0, demonstrating high accuracy and computational efficiency.
    - Bi-LSTM showed strong performance but required longer training times, limiting its real-time applicability.
- **Result Output**:
    - Scenario 1: Hybrid of PC and XGBoost achieved R^2 of 96.21, MAPE of 5.52, MAE of 6.5, and MASE of 0.195.
    - Scenario 2: ANOVA and XGBoost model achieved R^2 of 96.83, MAPE of 5.29, MAE of 6.0, and MASE of 0.180 .