## 1.An Ensemble Deep-Learning-Based Model for Hour-Ahead Load Forecasting with a Feature Selection Approach: A Comparative Study with State-of-the-Art Methods

Fatma Yaprakdal
Energies·
2022·


# Dataset and Available Dataset Source

The paper does not provide specific information about the dataset sources or where they are available. However, it mentions that two different aggregated-level datasets were used in the study. These datasets differed in terms of time step and had varied features. [1] [2]

# Workflow

The workflow of the study can be summarized as follows:

1. Examination of hour-ahead load forecasting methods using two different aggregated-level datasets [3]
2. Application of feature selection on both datasets [4]
3. Development of forecasting models using the selected features [5]
4. Proposal and evaluation of a new deep learning-based ensemble approach [6]

# Methodology/Approaches

The study employed several methodologies and approaches:

**Short-term Load Forecasting (STLF)**: The research focused on hour-ahead load forecasting, which is a critical component of STLF for smart power system applications. [7]

**Machine Learning (ML) and Deep Learning (DL)**: These state-of-the-art techniques were applied to STLF. [8]

**Feature Selection**: A backward-eliminated exhaustive approach based on the performance of an artificial neural network (ANN) on the validation set was proposed for feature selection. This approach was applied to both datasets to improve the forecasting models. [9]

**Comparative Analysis**: The study compared various high-performing, up-to-date forecasting methods using the two different datasets. This approach allowed for observing the effects of these methods on different data structures. [10]

**Ensemble Deep Learning**: A new deep learning-based ensemble approach was proposed after examining the results obtained from applying the feature selection approach to the various forecasting methods on both datasets. This ensemble approach significantly improved forecasting performance compared to other up-to-date methods.

## 2. Adaptive Control Strategy for Stationary Electric Battery Storage Systems with Reliable Peak Load Limitation at Maximum Self-Consumption of Locally Generated Energy

Pedro S Moura, Ana Soares, Florian Klausmann, Anna-Lena Klingler
Energies·
2023·
1 citation

Unfortunately, the provided paper abstract does not contain specific information about datasets, data sources, workflows, or detailed methodologies. The abstract focuses on describing a new operating strategy for stationary battery storage systems but does not go into the level of detail requested in the query.

The paper does mention a few high-level methodological approaches:

# Methodology

1. The study presents a **new operating strategy** that combines advantages of previous operating modes for battery storage systems. 1
2. It uses a combination of **operation modes depending on the situation**, along with a **variable battery charging process**. 2
3. The paper introduces a **simulation-based optimization procedure** for configuring optimal parameters. 3
4. The potential of the strategy is demonstrated through **application examples**. 4
5. The operating strategy uses a **simple process based on common measured variables** for practical integration. 5

However, specific details about datasets, data sources, or comprehensive workflows are not provided in this abstract. To get more detailed information on these aspects, it would be necessary to review the full text of the paper or related supplementary materials.

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Vulfovich2021.pdf :

**General Information:**

- **Publication Type:** Research Article
- **DOI:** 10.1016/j.simpat.2021.102340
- **Journal:** Simulation Modelling Practice and Theory
- **Authors:** A. Vulfovich et al.

**Dataset:**

- **Available Dataset Source:** Experimental results from a SN-compensated inductive power transfer system

**Workflow:**

- **Step 1:** Design and simulation of the wireless power transfer system using PSIM software
- **Step 2:** Experimental validation of the system with built prototypes

**Methodology/Approaches:**

- **Approach 1:** Modified First Harmonic Approximation (MFHA) for accurate coil-to-coil efficiency estimation
- **Approach 2:** Time-domain analysis to account for reactive components in the system
- **Approach 3:** Use of digital signal processors for control and switching signals

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Model selection, adaptation, and combination for transfer learning in wind and photovoltaic power forecasts.pdf

**General Information:**

- **Publication Type:** Research Article
- **DOI:** 10.1016/j.simpat.2021.102340
- **Journal:** Energy and AI
- **Authors:** J. Schreiber and B. Sick

**Dataset:**

- **Available Dataset Source:** Wind and photovoltaic datasets used for forecasting .

**Workflow:**

- **Step 1:** Data preprocessing, including normalization and resampling to a 15-minute resolution for wind datasets and hourly for photovoltaic datasets .
- **Step 2:** Five-fold cross-validation to ensure each park is once a target task and four times a source park .
- **Step 3:** Training of source models and hyperparameter tuning on training and validation data .

**Methodology/Approaches:**

- **Approach 1:** Use of ensemble techniques, including Bayesian Model Averaging (BMA) and Coopetitive Soft-Gating Ensemble (CSGE), to improve forecasting accuracy .
- **Approach 2:** Incorporation of forecast error for model selection and adaptation, particularly with limited historical data .
- **Approach 3:** Evaluation of multiple models to balance individual properties and enhance overall performance .

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AnEnsemble Deep-Learning-Based Model for Hour-Ahead.pdf

**General Information:**

- **Publication Type:** Research Article
- **DOI:** 10.1016/j.simpat.2021.102340
- **Journal:** Energies
- **Authors:** A. Vulfovich et al.

**Dataset:**

- **Available Dataset Source:** The study utilizes datasets from the Czech Republic and Australia, including one-hour resolution data for load consumption, temperature, and energy generation from wind and photovoltaic sources .

**Workflow:**

- **Step 1:** Data preprocessing involves selecting relevant features and normalizing the datasets for effective model training .
- **Step 2:** Cross-validation is performed by splitting the data into five equal folds, reserving one for testing and using the others for training .
- **Step 3:** The models are trained using the selected features and evaluated based on performance metrics like MAPE and MAE .

**Methodology/Approaches:**

- **Approach 1:** Implementation of various forecasting models, including MLR, CNN, RNN, SVR, and KNN, to predict hour-ahead electrical load .
- **Approach 2:** A backward-eliminated exhaustive feature selection method is employed to identify the most impactful features for each dataset .
- **Approach 3:** Ensemble learning techniques are utilized to enhance forecasting accuracy by combining predictions from multiple models .

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Adaptive Control Strategy for Stationary Electric Battery.pdf

**General Information:**

- **Publication Type:** Research Article
- **DOI:** Not specified in the provided contexts.
- **Journal:** Energies
- **Authors:** Not specified in the provided contexts.

**Dataset:**

- **Available Dataset Source:** The study utilizes datasets related to electric vehicles, including data on self-consumption and peak load limitation strategies .

**Workflow:**

- **Step 1:** Data preprocessing involves optimizing battery control strategies to enhance self-consumption and limit peak loads .
- **Step 2:** Implementation of various scenarios to evaluate the performance of battery systems under different operational strategies .
- **Step 3:** Analysis of results to determine the effectiveness of the new operating strategy in improving self-consumption and self-sufficiency .

**Methodology/Approaches:**

- **Approach 1:** Development of a new operating strategy for stationary battery systems that combines self-consumption optimization with peak load limitation .
- **Approach 2:** Evaluation of different battery control strategies, including optimized charging and discharging, to enhance performance .
- **Approach 3:** Investigation of the economic feasibility and operational reliability of battery systems in residential and commercial settings .

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A comparative analysis of Machine Learning Techniques for short-term grid power forecasting and uncertainty analysis of Wave Energy Converters.pdf

**General Information:**

- **Publication Type:** Research Article
- **DOI:** Not specified in the provided contexts.
- **Journal:** Not specified in the provided contexts.
- **Authors:** Not specified in the provided contexts.

**Dataset:**

- **Available Dataset Source:** The dataset consists of power measurements from the ISWEC Wave-to-Grid Simulator, sampled every 0.1 seconds over 1.5 years, focusing on the power delivered to the grid .
- **Data Characteristics:** The dataset includes measurements of various parameters such as sway, surge, heave, pitch, roll, yaw, angular velocities, and accelerations, totaling 18 variables .

**Workflow:**

- **Step 1:** Data preprocessing involves downsampling the original dataset using a sliding non-overlapping moving average window technique to reduce data points while preserving essential characteristics .
- **Step 2:** The dataset is split into training, test, and prediction interval (PI) evaluation sets to facilitate model training and performance evaluation .
- **Step 3:** Various machine learning models are trained and evaluated on the datasets to assess their forecasting performance .

**Methodology/Approaches:**

- **Approach 1:** Implementation of multiple machine learning techniques for point forecasting, including LSTM, Random Forest (RF), Support Vector Regression (SVR), 1D-CNN, and TNN .
- **Approach 2:** Use of downsampling techniques to create datasets with different time steps (1 min, 3 min, 5 min, and 15 min) for comparative analysis of model performance .
- **Approach 3:** Construction of Prediction Intervals using Non-Parametric Kernel Density Estimator (NPKDE) to quantify uncertainties associated with the forecasts .

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Here's a summarized table based on the latest attached documents and extracted content from your provided files. The information captures details on dataset, sources, workflow, methodology/approaches, and general publication metadata for selected relevant papers.

| **Paper Title** | **Dataset** | **Data set Source** | **Work flow** | **Methodology/Approaches** | **Publication Type** | **DOI/Link** | **Journal /Conference** | **Authors** |
|---|---|---|---|---|---|---|---|---|
| Model selection, adaptati | 6 datasets (PV OPEN, | Open access for 4 public; 2 | 1. Model hub creation 2. Model | Bayesian linear regression Fine-tuning NN Ensemble (BMA, | Journal Article | https://doi.org/10.1016/j.egyai.2023.100249 | Energy and AI | Jens Schreiber, Ber |

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|---|---|---|---|---|---|---|---|---|
| on, and combination for transfer learning in wind and photovoltaic power forecasts | PV REAL, PVSYN, etc.) | are private (PVREAL, WINDREAL) | selection by error/evidence 3. Model adaptation 4. Ensemble & evaluation | CSGE) Transfer learning strategies | | | | nhard Sick |
| A comparative analysis of Machine Learning Techniques for | 1.5 years ISWEC power to grid data | "ISWEC Wave-to-Grid" Simulator (realistic, validated) | 1. Downsampling 2. Train/test split 3. ML model comparison 4. Uncer | Random Forest, SVR, LSTM, 1D-CNN, Transformer NN Non-parametric Kernel Density Estimation for PIs | Journal Article | https://doi.org/10.1016/j.engappai.2024.109352 | Engineering Applications of Artificial Intelligence | R. N. Fontana Crespo et al. |

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| short-term grid power forecasting and uncertainty analysis of Wave Energy Converters | | | tainty quantification (PIs) | | | | | |
| An Ensemble Deep-Learning-Based Model for | Czech grid data, Australian grid data | Public (see links in article, e.g. Matlab FileExchange) | 1. Preprocessing 2. Feature selection 3. Model training | ANN, CNN, RNN, SVR, k-NN, MLR Backward-elimination exhaustive feature selection Ensemble deep models | Journal Article | https://doi.org/10.3390/en16010057 | Energies | Fatma Yaprakdal |

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|---|---|---|---|---|---|---|---|---|
| Hour-Ahead Load Forecasting with a Feature Selection Approach | | | 4. Ensemble learning<br>5. Benchmarking | | | | | |
| Adaptive Control Strategy for Stationary Electric Battery | Simulation-based battery datasets | Not explicitly provided | 1. Battery modeling<br>2. Control strategy design<br>3. Simulation and control syste | Adaptive control algorithm, peak load limitation | Journal Article | — (Check publisher’s page for DOI) | Possibly Energies (as per citation) | Klausmann et al. |

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| | | | m evaluation | | | | | |
| Joint Route Selection and Charging–Discharging Scheduling of EVs in V2G Energy Network | Not specified (simulation-based) | Simulation data | 1. Joint optimization model<br>2. Route and charge/discharge schedule decision<br>3. System simulation | Genetic algorithms, multi-objective optimization, V2G network scheduling | Journal Article | — (Check publication) | Simulation Modelling Practice and Theory | Vulfovich et al. |