5th International
Hybrid Power Systems Workshop

Institut für Prozessdatenverarbeitung und Elektronik

Short-term Industrial Load Forecasting for Battery Energy Storage System Simulation

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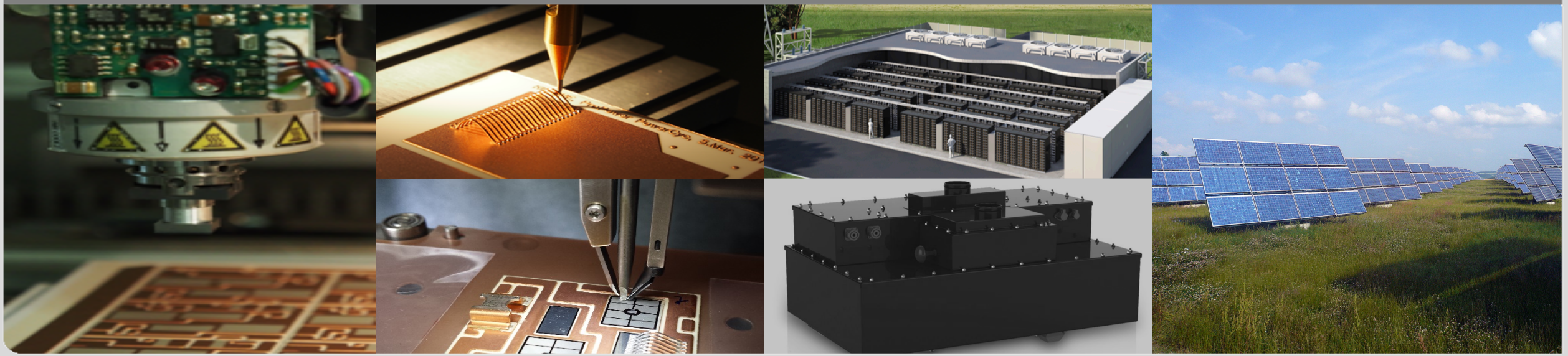
Institut für Prozessdatenverarbeitung und Elektronik (IPE) - Aufbau- und Verbindungstechnik



Outline

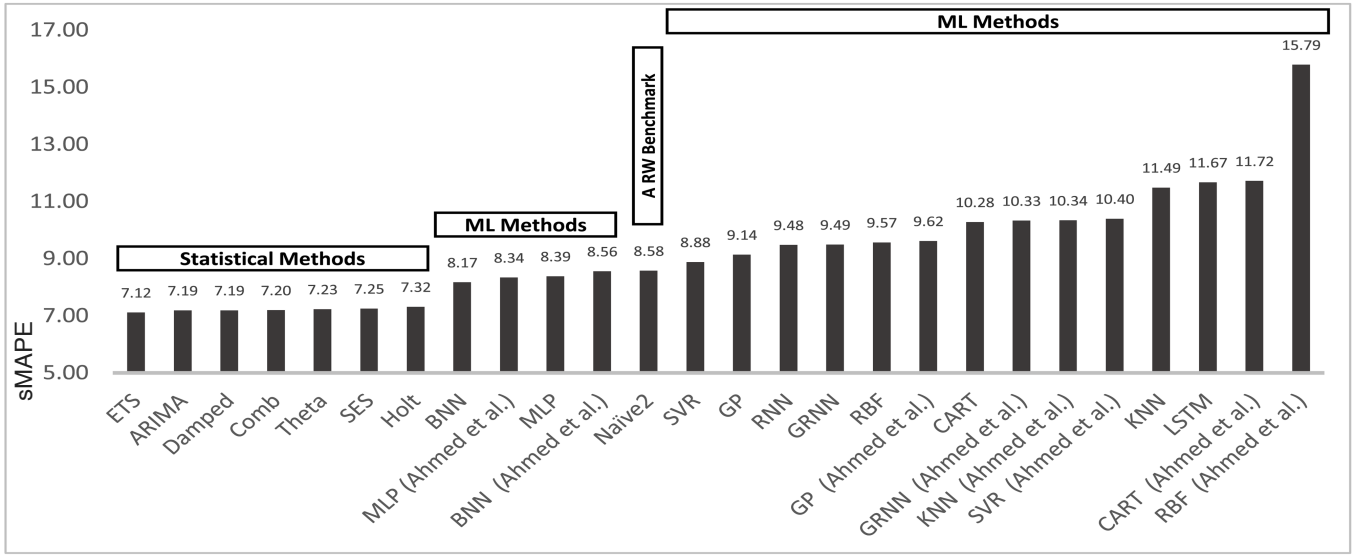
- Introduction
- Objectives
- Data processing
- Load forecasting models
- Experiment system
- Results & Conclusion

Introduction

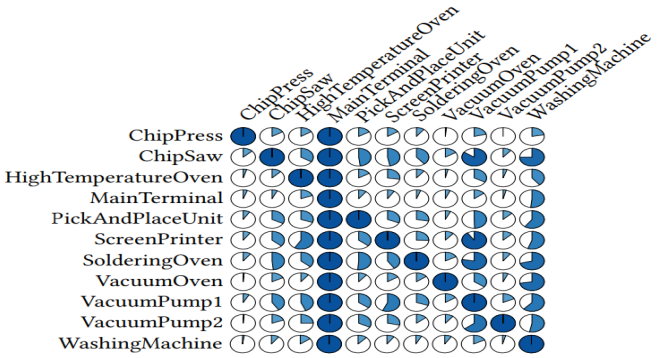
- Background
  - The widely used forecasting method
  - The development of renewable energy generation and energy storage capacity
- Motivation
  - Reduce the peak power to save the network charge based on the annual peak power
  - Improve the utilization of BESS
  - Establish an intelligent energy management system to maximizing renewable share in local energy system

Introduction

- Related work
- Forecasting models
  - Autoregressive integrated moving average (ARIMA)
  - Feedforward neural network
  - Recurrent neural network
- An industrial energy-status-data set



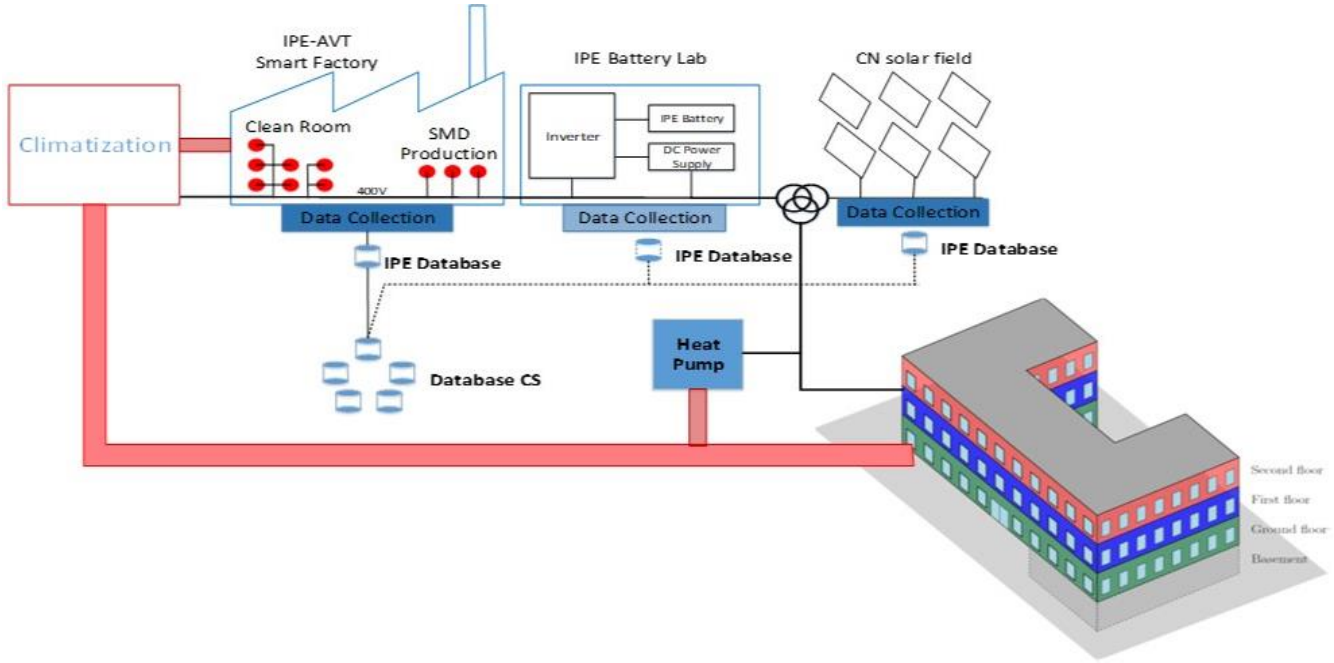
Makridakis S, Spiliotis E, Assimakopoulos V (2018) Statistical and Machine Learning forecasting methods: Concerns and ways forward. PLoS ONE 13(3): e0194889. https://doi.org/10.1371/journal.pone.0194889



Bischof, Simon, et al. "Hipe: An energy-status-data set from industrial production." *Proceedings of the Ninth International Conference on Future Energy Systems*. 2018

Objectives

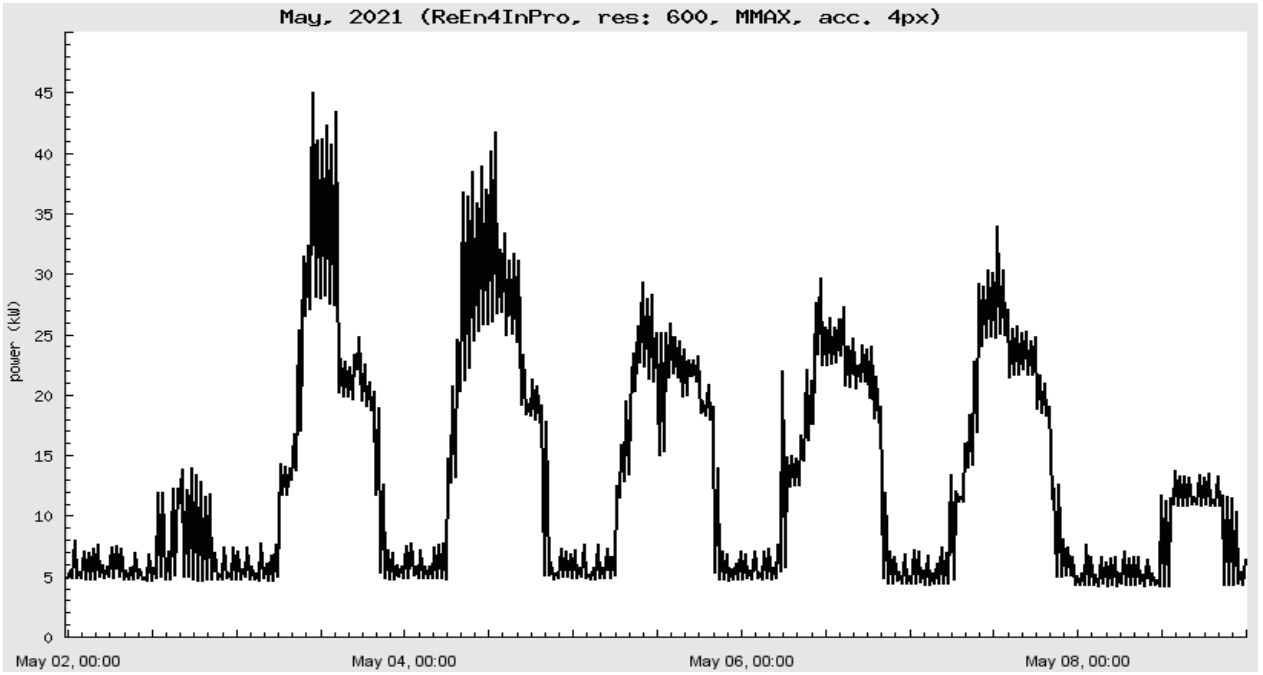
- Modelling of the energy system
  - Battery energy storage system
  - Photovoltaics generation
  - Smart factory
- Load forecasting models
  - Time series analysis
  - Machine learning approach
- Simulation and comparison



Data Processing

- Load Data
  - http://katrin.kit.edu/adei-smartgrid/adei/

- Extraneous Data
  - Weather Data
  - Date
  - Hour
  - Minute
  - Weekday
  - Holiday



DWD Deutscher Wetterdienst
Wetter und Klima aus einer Hand

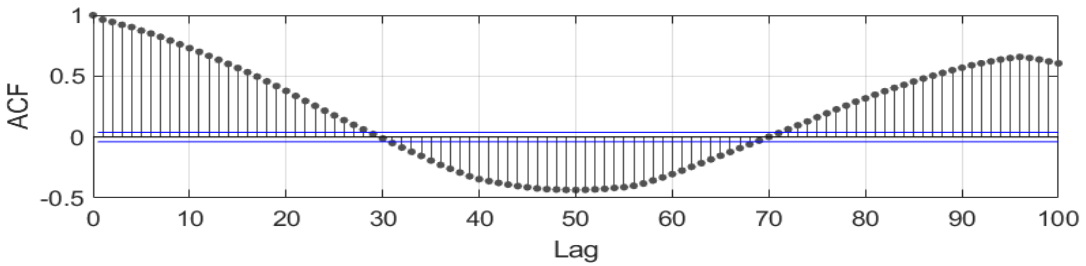
Load forecasting models

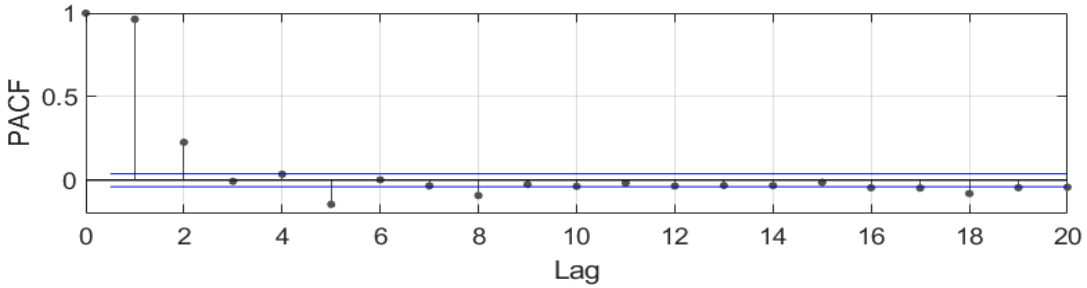
- Time series analysis
- Seasonal ARIMA model

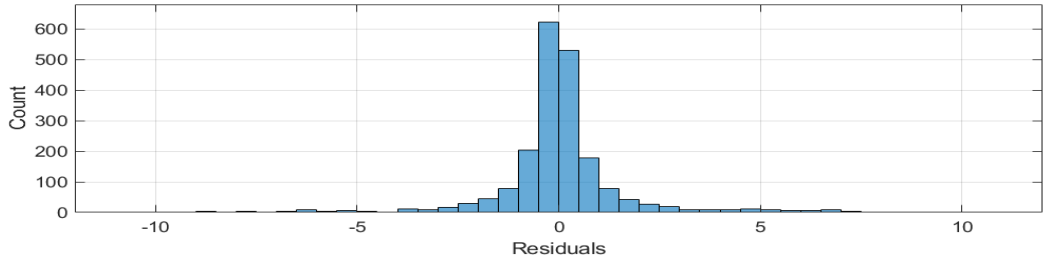
  ARIMA $(p,d,q)\,(P,D,Q)_m$
- Model fitting
  - Augmented Dickey-Fuller (ADF) test
  - Autocorrelation function (ACF)
  - Partial autocorrelation function (PACF)
  - Minimizing Akaike information criteria (AIC)

15-minutes data: ARIMA$(2,0,1)(2,0,1)_{96}$

5-minutes data: ARIMA$(2,0,1)(2,0,1)_{288}$

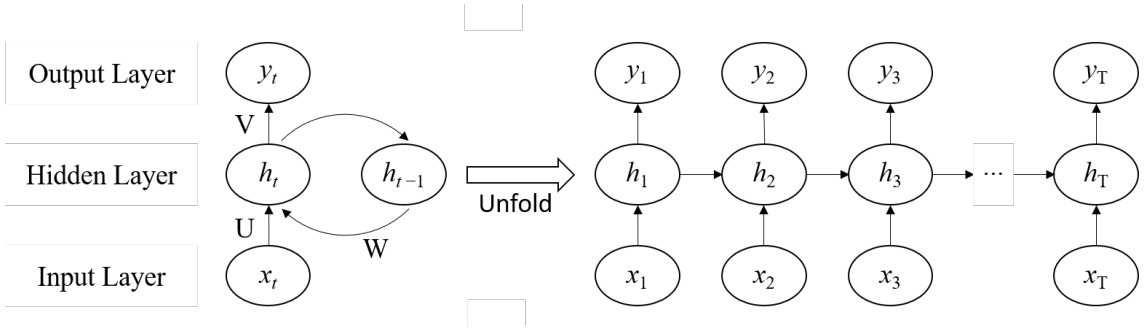


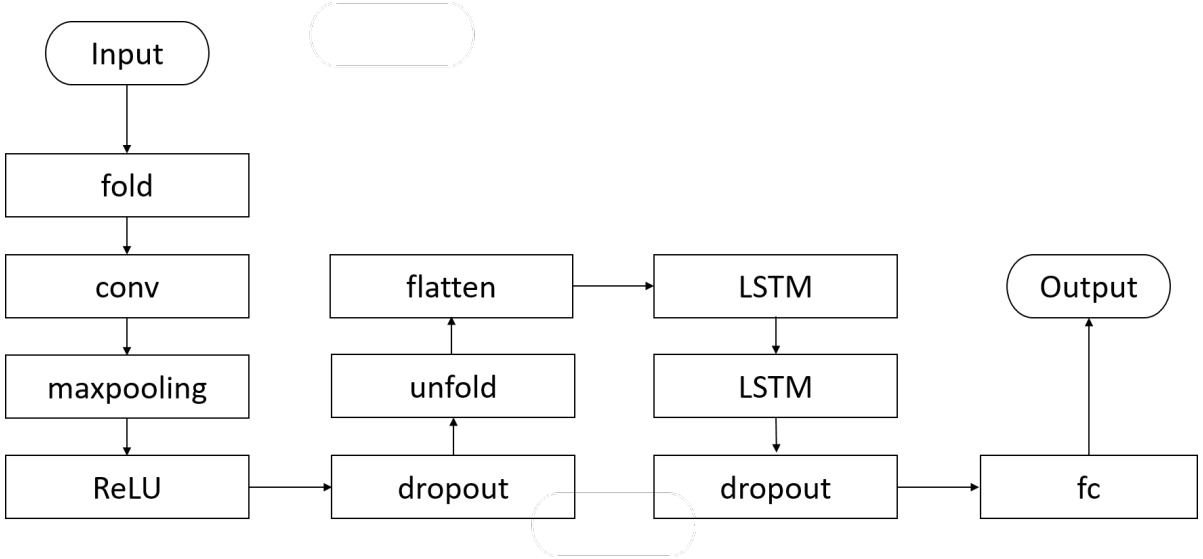




Load forecasting models

- Machine learning method
- Recurrent neural network
  - Long short-term memory
- Convolutional neural network
- Multi-step forecasting
  - Recursive strategy
  - MIMO strategy
- Network input and output

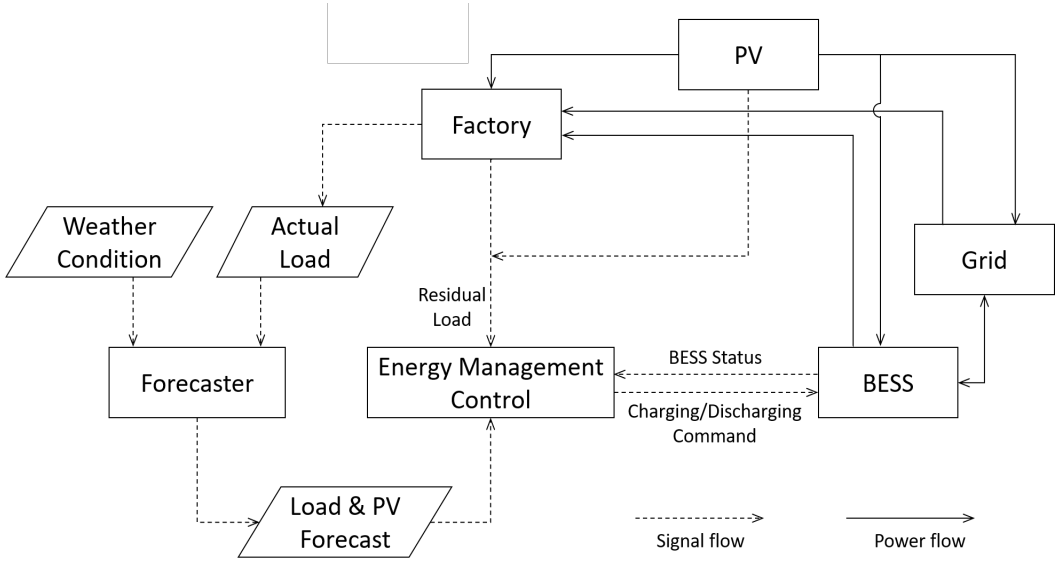


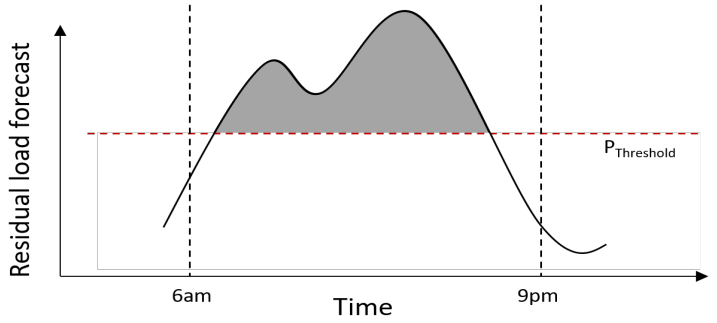


Simulation

- System configuration
  - Peak load (35 – 45kW)
  - Small scale PV production (5kWp)
  - Battery energy storage system (5-200kWh)
- Peak shaving scheme
  - working hour

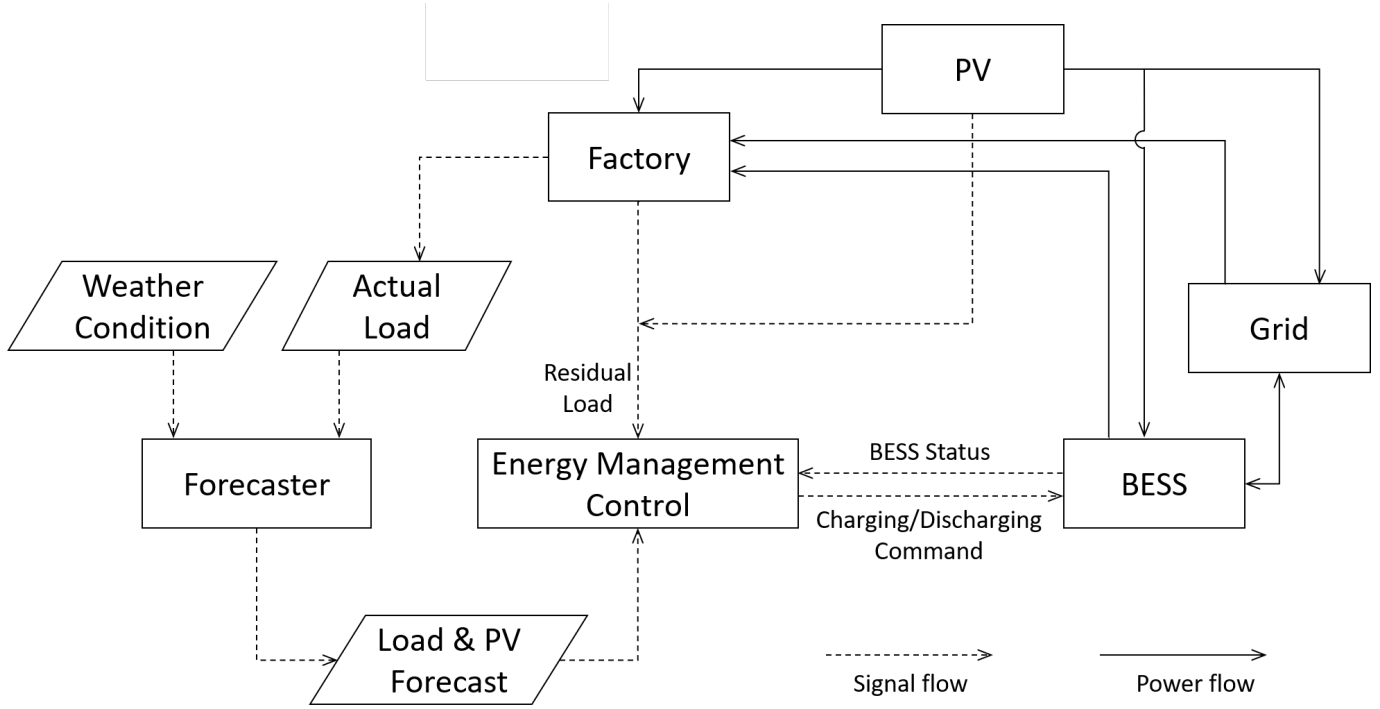
    6:00 to 21:00 Mon-Fri
- Simulation environment
  - Matlab/Simulink
- Output
  - Maximum power
  - Shifted energy





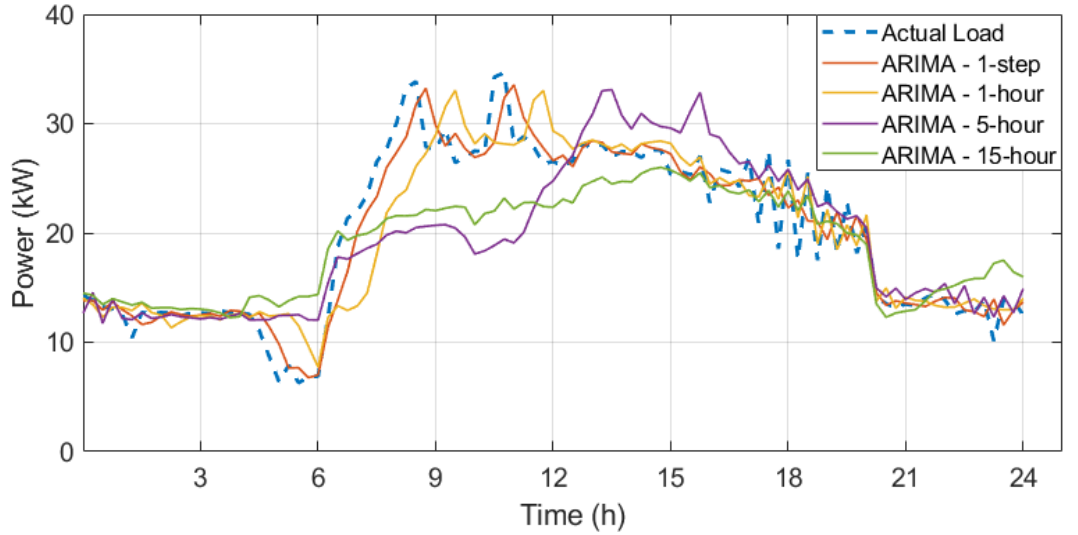
Simulation

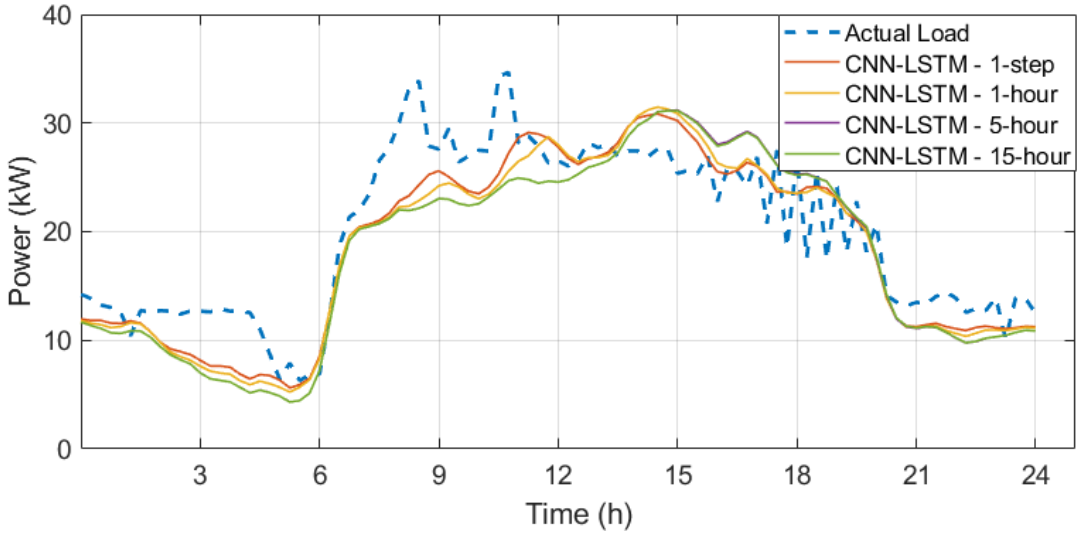
- Energy management
- Residual load forecast
  - Load forecasting
  - PV generation forecasting
- Modify peak shaving threshold
- Battery management
  - Battery status
  - Battery power limit



Result

- Load forecasting performance
- Model comparison
  - ARIMA
  - CNN-LSTM
- Forecast time
  - 1 time step
  - 1 hour ahead
  - 5 hour ahead
  - 15 hour ahead





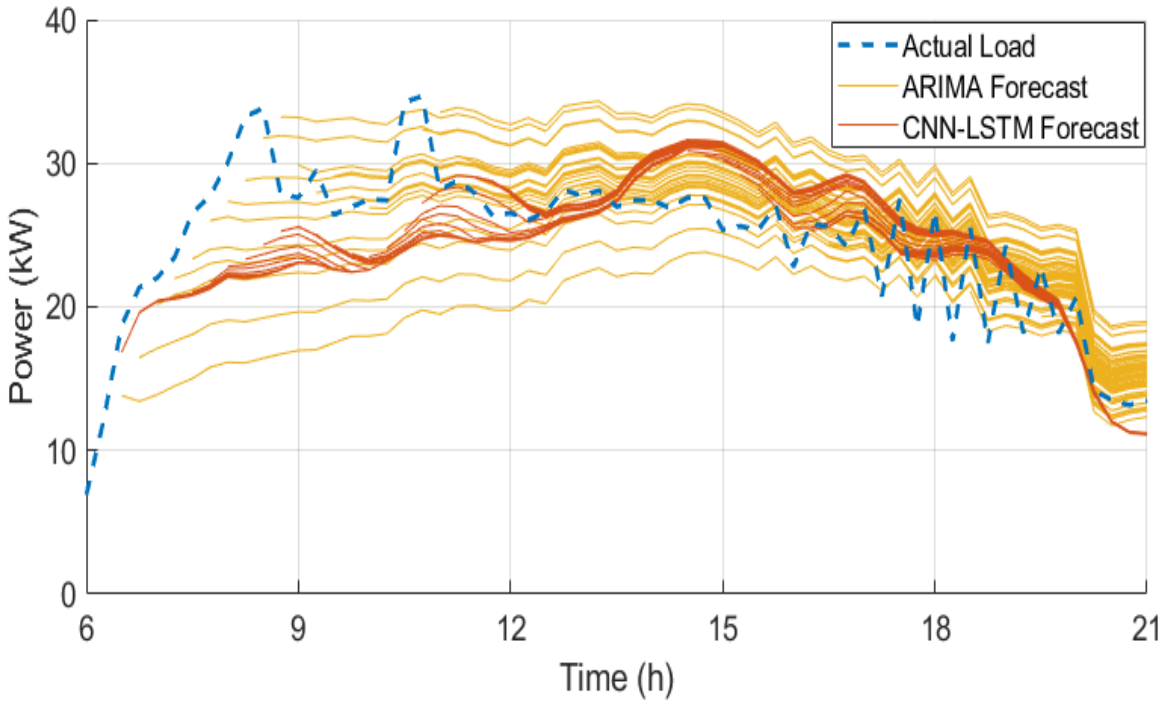
Result

- Load forecasting performance
- Model comparison
  - ARIMA
  - CNN-LSTM

➢ Forecast until end of peak shaving

ARIMA: Rapid response, unstable

CNN-LSTM: Consistent, slow react



Result

- Load forecasting performance
  - Models & Forecasting scenarios

Method	Forecast Scenario	MAE of the Forecast	RMSE of the Forecast
ARIMA	1-Step	1.61	2.30
	1-hour	2.12	3.23
	5-hours	3.49	4.93
	15-hours	3.22	4.28
CNN-LSTM	1-Step	2.80	3.49
	1-hour	3.11	3.85
	5-hours	3.63	4.36
	15-hours	3.61	4.35

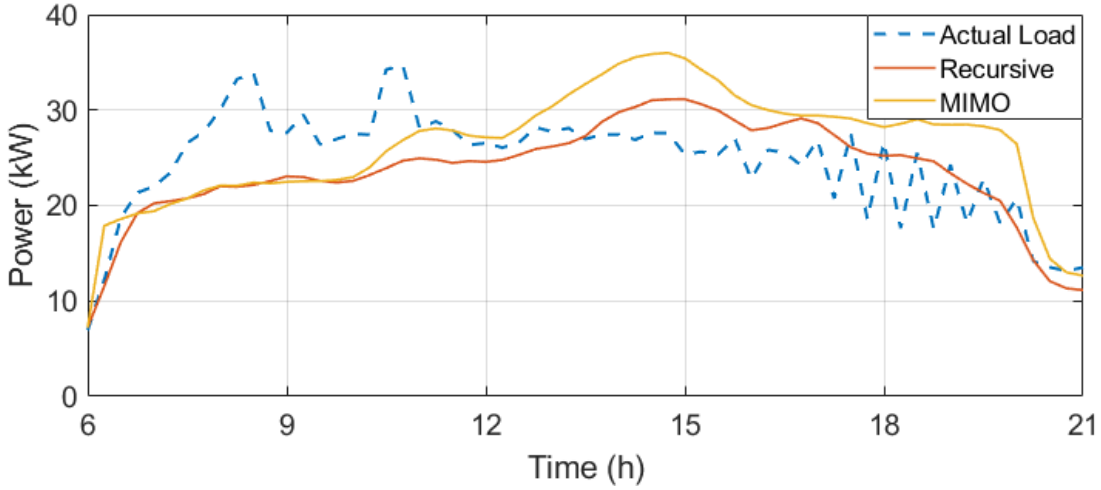
Method	Forecast Scenario	MAE of the Forecast	RMSE of the Forecast
ARIMA	1-Step	**1.83**	**2.05**
	1-hour	2.85	3.99
	5-hours	4.35	5.86
	15-hours	4.33	5.27
CNN-LSTM	1-Step	4.13	5.57
	1-hour	5.25	7.16
	5-hours	5.28	7.17
	15-hours	5.28	7.17

Result

Load forecasting performance

Multi-step strategies

Multi-step Strategies	MAE of the Forecast	RMSE of the Forecast
Recursive	3.74	4.63
MIMO	3.18	6.06



Reference steps

Reference Steps	Forecast Scenario	MAE	RMSE
6 steps	1-step	2.80	3.49
	1-hour	3.11	3.85
	5-hours	3.63	4.36
	15-hours	3.61	4.35

Reference Steps	Forecast Scenario	MAE	RMSE
12 steps	1-step	2.97	3.53
	1-hour	3.29	3.95
	5-hours	3.54	4.44
	15-hours	3.59	4.41

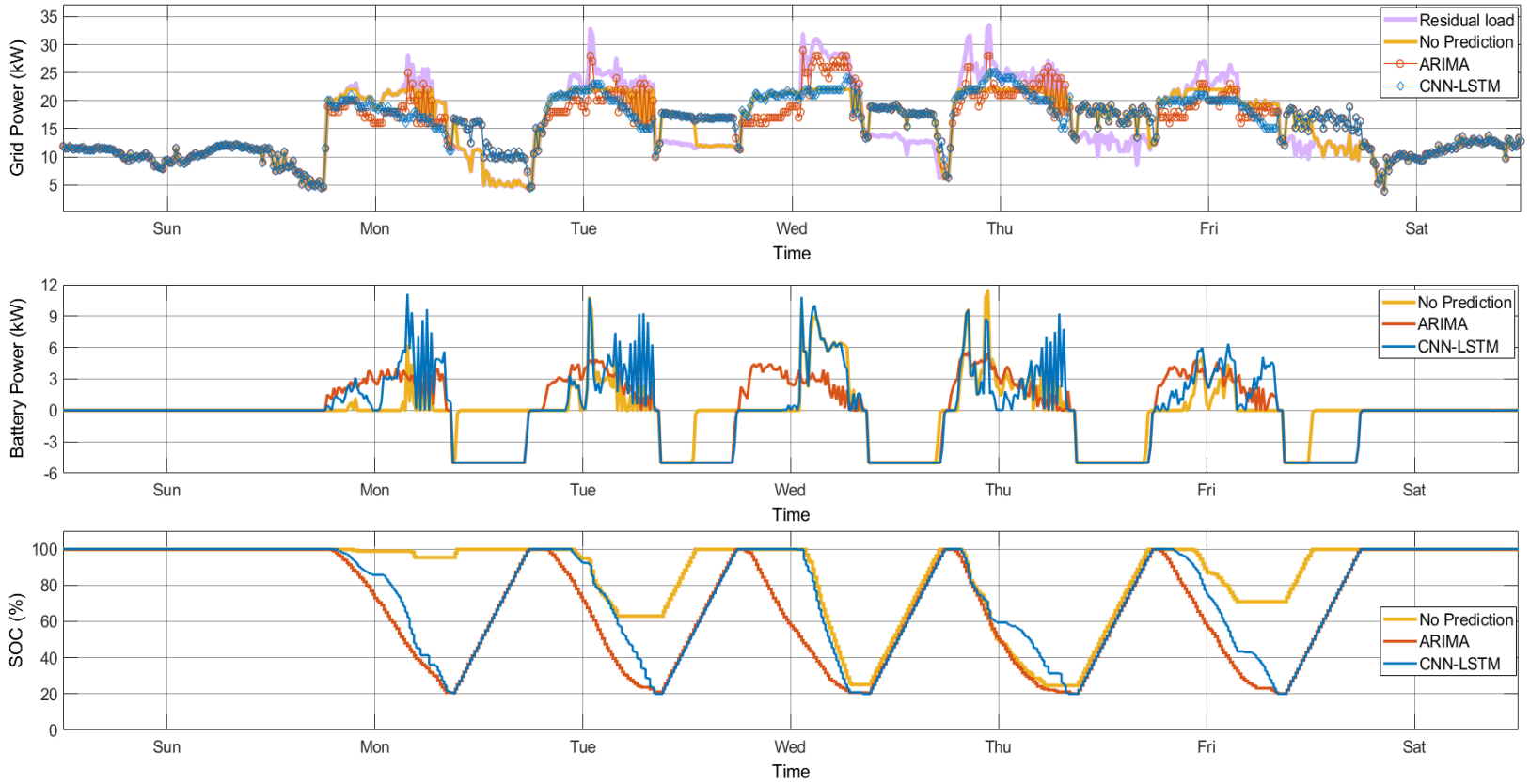
Reference Steps	Forecast Scenario	MAE	RMSE
24 steps	1-step	3.27	4.07
	1-hour	3.48	4.32
	5-hours	3.90	4.87
	15-hours	3.98	4.63

Result

- Peak shaving simulation
  - Without prediction
  - ARIMA
  - CNN-LSTM

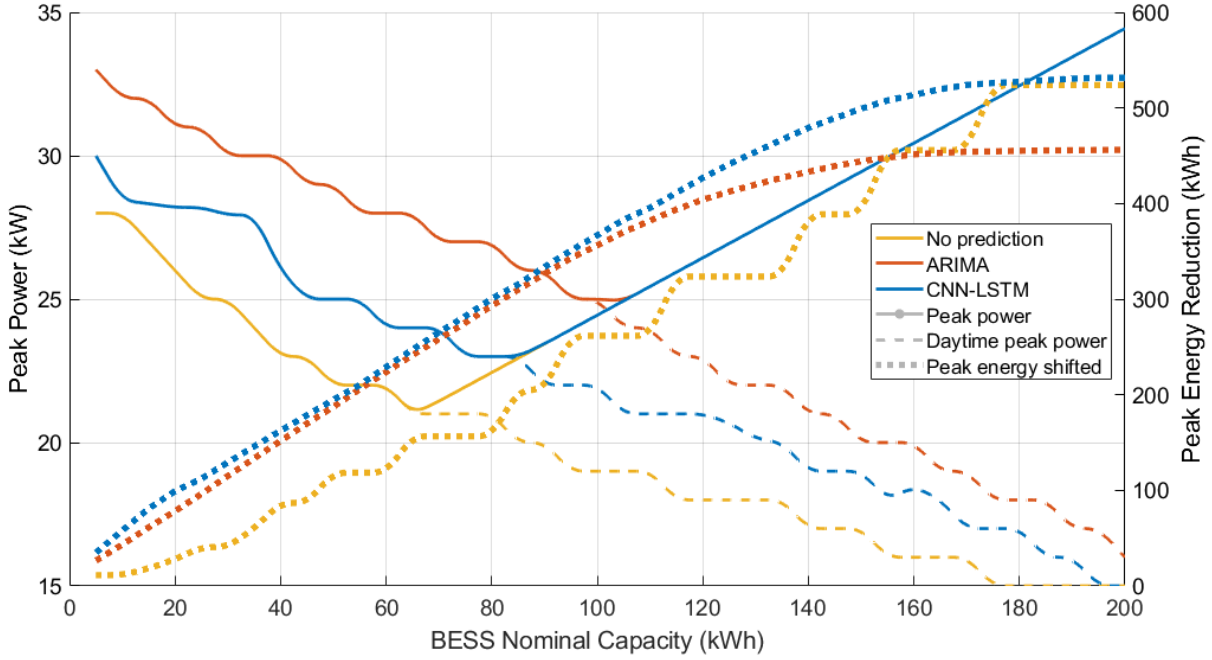
Example：50kWh BESS

Forecast Models	Peak power (kW)	Shifted Energy (kWh)
None	22	118
ARIMA	29	195
CNN-LSTM	25	195



Result

- Peak shaving simulation
  - BESS capacity as variables
  - Daytime peak power keeps decreasing
  - Peak power at night exceeds daytime peak power with large BESS capacity
  - As BESS capacity increase, marginal growth of shifted energy diminishes



Conclusion

- Load forecasting in industrial peak shaving
  - ML-based forecast.
  - 5-minutes resolution data and forecast is unnecessary.
  - Recursive multi-step strategy.
  - Load forecasting helps to improve the utilization of battery capacity in energy shifting.
- Future work
  - Higher VRE contribution
  - Cost optimization


Thanks
Way to a carbon-free future