AI4GriDs

AI-based methods for optimising the operation and expansion of distribution grids

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Projektbeschreibung

Das Projekt AI4GriDs beschäftigt sich mit den zunehmenden Herausforderungen für Verteilnetzbetreiber (DSOs) durch die steigende Anzahl dezentraler erneuerbarer Energieträger und damit, wie künstliche Intelligenz einen Beitrag zur Lösung dieser Herausforderungen und damit auch zur Steigerung der Effizienz dezentraler erneuerbarer Einspeiser leisten kann.
Die zunehmende Digitalisierung des Energiesystems ist noch nicht bis auf die Verteilernetzebene durchgedrungen. Viele Verteilnetzbetreiber, besonders kleine Netzbetreiber (also nicht Landesnetzbetreiber) haben wenig (digitale) Daten über den Ausbau oder den Betrieb des ihrer Netze. Grenzwerte für den Ausbau und Betrieb Erneuerbare wurden und werden oft anhand von Erfahrungswerten festgelegt.
Anders gestaltet sich die Situation auf der Übertragungsnetzebene, hier sind teilweise bereits umfassende Datenmengen verfügbar, weswegen aktuelle Forschungsinitiativen im Kontext von KI-Methoden sich auch auf diesen Bereich fokussieren. Es gibt aber noch keine Erfahrungen, wie sich diese Methoden auf die Verteilernetzebene übertragen lassen.
Ähnlich verhält es sich mit der Prognose von erneuerbarer Erzeugung (allen voran PV). Aufgrund der Kleinstrukturiertheit von Verteilernetzen müssen diese hier über hohe räumliche Auflösungen verfügen, was eine Herausforderung für die Methoden darstellt.
Im Projekt AI4Grids werden KI-Methoden identifiziert, analysiert und hinsichtlich ihrer Anwendbarkeit für DSOs bewertet. Konkret betrifft das die Prognose der PV-Erzeugung sowie Methode für die Planung und den Betrieb von kleinen Verteilnetzen. Im Laufe des Projektes werden bis zu 6 kleine DSOs in einem partizipativen Prozess eingebunden, um die Rahmenbedingungen und Anforderungen, sowie die verfügbaren Daten zu erheben. Aufbauend auf dieser Erhebung werden KI-Methoden für die PV-Prognose sowie den Betrieb und Ausbau von Verteilernetzen analysiert und hinsichtlich ihrer Umsetzbarkeit bewertet. Die besten Methoden werden anschließend einem experimentellen Proof of Concept unterzogen.
Aufbauend auf diesen Ergebnissen werden neue Forschungsfragen abgeleitet, die dann in weiterer Folge im Rahmen von Forschungsprojekten bearbeitet werden sollen. Ziel ist es in einem Folgeprojekt die identifizierten und validierten Methoden im Rahmen eines Demonstrationsbetriebes umzusetzen.

Abstract

The AI4GriDs project deals with the increasing challenges for distribution system operators (DSOs) due to the growing

number of decentralised renewable energy sources and how artificial intelligence can contribute to solving these challenges and thus also to increasing the efficiency of decentralised renewable feeders.

The increasing digitalisation of the energy system has not yet penetrated to the distribution grid level. Many distribution grid operators, especially small grid operators (i.e. not state grid operators) have little (digital) data on the expansion or operation of their grids. Limit values for the expansion and operation of renewables were and are often set on the basis of empirical values.

The situation is different at the transmission grid level, where comprehensive amounts of data are already available in some cases, which is why current research initiatives in the context of AI methods also focus on this area. However, there is still no experience as to how these methods can be transferred to the distribution grid level.

The situation is similar with the forecasting of renewable generation (especially PV). Due to the small structure of distribution grids, they must have high spatial resolutions, which poses a challenge for the methods.

In the AI4Grids project, AI methods are identified, analysed and evaluated with regard to their applicability for DSOs. Specifically, this concerns the forecasting of PV generation as well as methods for the planning and operation of small distribution grids. In the course of the project, up to 6 small DSOs will be involved in a participatory process to collect the framework conditions and requirements, as well as the available data. Based on this survey, AI methods for PV forecasting and the operation and expansion of distribution grids will be analysed and evaluated in terms of their feasibility. The best methods will then be subjected to an experimental proof of concept.

Based on these results, new research questions will be derived, which will then be addressed in subsequent research projects. The aim is to implement the identified and validated methods in a demonstration operation in a follow-up project.

Endberichtkurzfassung

The AI4Grids project explored advanced AI-driven methods for grid planning, operation, and forecasting of fluctuating renewable energy sources, with a focus on small and medium-scale distribution system operators (DSOs). By engaging DSOs in participatory workshops and interviews, the project assessed current challenges and opportunities in digitalization, data integration, and forecasting accuracy.

Key Insights from DSOs

This section presents findings from interviews and workshops with DSOs, highlighting challenges related to data availability, smart meter rollout, and grid digitalization. The analysis reveals common difficulties across different DSOs, particularly in data integration and real-time monitoring, which impact operational efficiency and forecasting reliability.

Data Availability and Smart Meter Rollout

Smart meter rollout levels varied significantly among DSOs, ranging from 5% (due to system changeover) to 98%.

Despite high rollout levels, data usability remained low as only a small number of users opted for 15-minute data provision.

Standard data provision settings offer daily consumption/infeed values, with annual values for users who opt out.

Additional transformer station measurements are used, though few DSOs integrate these into central systems.

Grid Planning and Digitalization

All DSOs maintain some form of grid plan, from analog documents to GIS-based systems.
A significant gap exists between grid plans and customer databases, with little direct linkage between them.
While referencing via addresses or customer names is possible, data integration remains a challenge.

General Conclusion

The findings indicate that DSOs, despite operating grids of different sizes, face similar hurdles regarding data availability and digitalization. The lack of standardized data integration methods creates inefficiencies in grid management. Addressing these gaps through improved data-sharing frameworks and advanced digital tools will be crucial for enhancing grid operations and integrating AI-based solutions.

Forecasting of PV and Run-of-River Generation

Accurate forecasting of PV and hydropower generation is critical for grid stability. This chapter evaluates different synthetic data providers and explores forecasting methodologies, including spatial, connected, and point forecast models. The study demonstrates the potential of AI-enhanced forecasting techniques in improving renewable energy integration.

Analysis of Synthetic Site Data Providers

A total of six data providers were assessed for synthetic site data generation:

Renewables.Ninja – Uses NASA MERRA-2 and SARAH datasets but has coarse resolution.
SolCast DNV – Combines ERA5, meteorological observations, and satellite data for finer resolution.
Google Sunroof – Currently U.S.-limited, utilizing SARAH 2 or SARAH 3 datasets.
Meteotest
Attite – Free tool using ERA5 data with the Python library pvlib.
Sonnenklar – PV-Austria tool offering data with 100m spatial resolution and 10-minute temporal resolution.

Synthetic site data was further enhanced using stochastic weather generators and neural networks. For hydropower, PyPSA and Attite were used for synthetic time series generation, with eWaterCycle providing a more physics-based model.

Forecasting Approaches for PV-Generation

Three primary forecasting approaches were explored:

Spatial Models – Utilize satellite imagery and numerical weather models (NWP). ConvLSTM models like IrradianceNet and SunCast improve short-term forecasts, while diffusion neural networks aid in cloud cover estimation.
Connected Models – Graph Neural Networks (GNNs) enhance PV forecasting across multiple sites, integrating spatial relationships.
Point Forecast Models – High-resolution, location-specific forecasts using hybrid statistical and machine learning methods,

including LSTMs and transformers.

Key Findings from Forecasting Trials

An analysis of the performance of forecasting models considered within the AI4Grids project was concluded. By comparing forecast outputs with actual measurements, key insights were derived regarding model accuracy, the impact of lead times, and dependencies on satellite data quality. The findings highlight strengths, weaknesses, and areas where improvements are needed to enhance forecasting reliability.

Comparative Forecast Performance:

Forecasts aligned better with Kapfenberg than Mürzzuschlag, with lower extreme errors.
Mürzzuschlag showed higher errors, likely due to grid resolution or station matching issues.

Lead Time Dependency:

Forecast accuracy declined with lead time, with noticeable blurring of localized irradiance changes.

Satellite Data Quality Dependency:

The Meteosat Second Generation (MSG) satellite’s 3 km^2 resolution limited accuracy.
Future improvements with Meteosat Third Generation (MTG) are expected.

Model Performance:

LSTM-based models achieved high accuracy, benefiting from synthetic data generation.
Integration of CAMS and IrradPhyDNet improved granularity.

Hydropower Forecasting

Focusing on three small hydropower plants, this section examines the effectiveness of AI-driven forecasting models in predicting hydropower production. It details key performance metrics, areas for improvement, and the impact of environmental conditions on forecast accuracy, emphasizing the need for refined uncertainty modeling and adaptive forecasting strategies.

Model Validation

Forecast models were tested on three small plants in Upper Styria.
Two plants with continuous run-off data yielded higher accuracy than the third, which relied on interpolated daily averages.

Key Findings:

Mean Absolute Error (MAE): 27.1 MW (18% of mean output), indicating reasonable accuracy.
Root Mean Square Error (RMSE): 43.9 MW (29% of mean output), highlighting occasional large deviations.
Correlation Coefficient: 0.815, suggesting strong forecast alignment with actual output.
Bias: Slight underestimation (-1.74 MW, 1.2% of mean output).

Areas for Improvement:

Enhancing uncertainty modeling (current prediction interval coverage: 33.3% vs. expected 80%).
Reducing outlier impacts and improving variance explanation.
Optimizing short-term forecasts, as MAE doubles after 48 hours.

Conditional Performance & Case Studies:

Errors increased during transitional weather conditions (e.g., temperature fluctuations, precipitation variations).
Best performance observed during stable conditions; worst performance linked to missing input data.
Forecast refinement needed to handle abrupt changes and improve real-time adaptability.

Conclusion
The results show that AI-based hydropower forecasting models provide a strong baseline for prediction but require improvements in uncertainty quantification and adaptation to environmental fluctuations. High-resolution meteorological and hydrological data significantly enhance forecast reliability. Future efforts should target improving model calibration, addressing systematic biases, and developing robust strategies to handle extreme weather conditions.

AI for Grid Planning and Operation

This chapter explores AI applications in grid topology optimization and real-time state estimation. The study evaluates how AI can enhance grid efficiency, improve resilience under high-load conditions, and support real-time decision making by integrating measurement and forecast data. The findings highlight the importance of detailed grid modeling and reliable data sources for effective AI deployment.

Topology Optimization

Objective: Enhance grid efficiency, reliability, and flexibility.
Method: Uses a digital twin for power flow calculations and stress testing under high-load scenarios.
Results:

Kapfenberg: Reduced maximum line utilization from 60.2% to 42.1%, improving resilience.
Mürzzuschlag: Achieved only a 3.9% reduction, indicating an already efficient grid.

Grid State Estimation

Objective: Improve real-time estimation of grid conditions using AI models.
Method: Combines measured data with AI/statistical models to refine estimations.
Findings:

Direct measurements significantly enhance accuracy.
AI-based models fill data gaps, but initial value accuracy is critical.

Conclusion
AI-based methods show promising results in optimizing grid topology and improving real-time grid state estimation. However, the effectiveness of these methods is highly dependent on the availability and accuracy of input data. A well-maintained digital twin of the grid can significantly enhance AI-driven decision making. Moving forward, efforts should focus on refining AI models for grid operation, improving sensor integration, and developing scalable solutions for DSOs of varying sizes.

Conclusion & Future Outlook

The AI4Grids project highlights the transformative potential of AI in grid planning, operation, and forecasting. While AI-driven methods can significantly improve efficiency and reliability, their success depends on overcoming data integration challenges and refining model accuracy. Future work should focus on enhancing data collection frameworks, advancing AI-driven uncertainty modeling, and exploring hybrid approaches that combine AI with traditional grid management practices. The integration of AI into energy systems will require collaborative efforts between researchers, policy makers, and DSOs to develop robust, scalable, and adaptable solutions.

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