Conference Proceedings

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13. Symposium Communications for Energy Systems

„AI-Driven Transformation in Energy Systems: Exploring Advanced Applications and Computational Innovations "

05. – 06. September 2024
Vienna, Austria

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Greetings

Artificial intelligence has been making fast progress since the breakthrough of large language models and the digitalisation of energy systems has not remained unaffected by these advances. Applications of machine learning and artificial intelligence technologies are already known in the energy domain. However, enhanced possibilities and improved computational performance have opened new fields of applications.

The Symposium Communications for Energy Systems (ComForEn) 2024 brings together component and system manufacturers, power grid operators, energy suppliers, and research institutions. The OVE Austrian Electrotechnical Association, supported by AIT Austrian Institute of Technology and TU Wien, have invited experts from academia and industry to discuss new opportunities, insights, and challenges of contemporary artificial intelligence solutions for the energy system.

This year, we co-host the conference altogether with the Open Source Modelling and Simulation of Energy Systems (OSMSES) 2024. Many thanks to our colleague Thomas Strasser, who has put strong efforts in making this unique combination a success.

We wish you a very enjoyable visit at the symposium, many insights, and many inputs for your own work.

Jochen Cremer
TU Delft and AIT Austrian Institute of Technology GmbH

Friederich Kupzog
Mark Stefan
AIT Austrian Institute of Technology GmbH

Stefan Wilker
Technische Universität Wien

We would like to thank the organization team!

Roman Eichinger, Christian Gasser, Natascha Kennedy, Monika Wagner, OVE

Carina Schöfl, TU Wien

Session 1

AI-Driven Control and Decision Support for Modern Power Systems

Session Chair: Jochen Cremer

AI Assistants in Future Control Rooms

Adrian Kelly, EPRI Europe (Electric Power Research Institute), akelly@epri.com

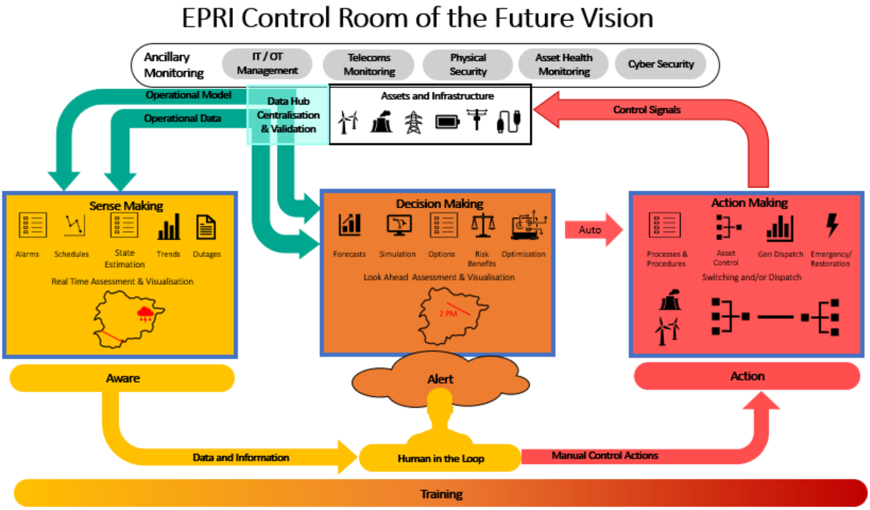
Abstract – Electricity network control rooms (Transmission or Distribution) are high-reliability organisations, operating 24/7/365 to monitor network parameters to keep electricity flowing through networks. The operators that work in control rooms monitor changes to tens of thousands of data points (numerical and binary status), respond in real time, and remotely control assets and generation resources to maintain real time reliability, and to proactively mitigate forecasted changes or contingency events.

Networks are digitizing rapidly – electromechanical generation resources, assets and protection are being replaced by exponentially increasing numbers of inverter interfaced "smart" devices. Market services, cross boundary control and weather-based resources are all adding to control complexity. Digital devices have more controllability and can provide more data which can help and hinder the operators mental model and cognitive workload. New approaches to monitoring, decision making and controllability will be required.

On the surface, network control rooms can be considered good candidates for the adoption of AI. They have massive archives of time-series operational data and generally stable predictable patterns of societal behaviour with reasonably predictable, irregular but recurring failure modes (lightning, equipment failure). In theory, AI should augment operator decision making in the sense making, decision making and action making modes. However, to date, beyond a narrow set of use cases, AI has not been readily adopted in real time electricity control rooms. There are a number of technical and non-technical reasons for this that will be explored in this talk, including:

- Data quality and machine readability.
- Operational technology system integration.
- Network model and simulation efficacy.
- Validation, trust and transparency.
- Compute resources and development resources.

This talk will explore where AI has good potential to provide this decision support capability to operators for a larger set of operational use cases. It will discuss what the barriers are and realistic pathways to breaking the barriers in the near term, through innovation and regulation – calling the entire community to work together to make AI useful in the operational domain.



Author

Adrian Kelly Adrian Kelly is a Principal Project Manager at EPRI Europe working in the Grid Operations & Planning team. He leads research and projects in EPRI in the area of transmission real-time operations situational awareness, in particular developing research for the control center of the future. His research interests and projects include HMI and display design, alarm management, artificial intelligence application in real-time system control, operations security standards and the interface between the real-time system and protection. He also has active interest in operator training, operator decision making, change management and applications to improve operator response to the shifting transmission system. Previously, Adrian worked for 9 years in the Operations and Planning departments of EirGrid, the transmission system operator in Ireland, including working as a real time grid, balancing and market operator.Adrian received a Bachelor of Engineering (Electrical) from University College Dublin in 2007. He is a chartered (professional) engineer with Engineers Ireland and is an active member of CIGRE and IEEE. He lives in Dublin with his wife and son.

Evolving symbolic models to boost trustworthiness

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Francisco S. Fernandes, INESC TEC and Faculty of Engineering of the University of Porto, francisco.s.fernandes@inesctec.pt
João Peças Lopes, INESC TEC and Faculty of Engineering of the University of Porto, jpl@fe.up.pt

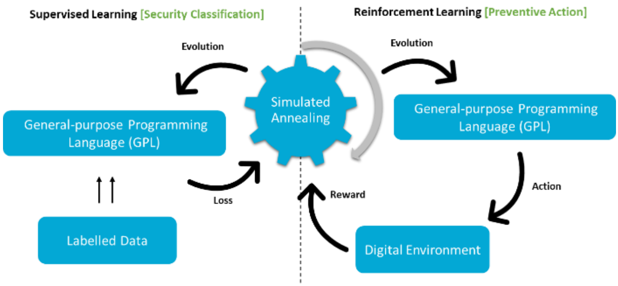

Figure 1- Evolving symbolic models framework

Abstract – The widespread integration of renewable energy sources is leading to operating conditions characterized by low inertia, significant temporal variations in generation, and a growing number of distributed energy resources (DER). This transition will substantially increase human operators' supervisory and control responsibilities in control rooms. Security classification becomes more complex as the system becomes more susceptible to instability and involves more DER components, whose behaviors are influenced by their primary energy sources and control mechanisms. This rising complexity results in large and complicated state models, making applying model-based techniques to online DSA impractical. Data-driven approaches are promising alternatives; however, the benefits of these approaches are often undermined by the "black-box" nature of many artificial intelligence methods. Thus, interpretability is essential for effectively deploying data-driven decision-support systems. This work introduces a new framework, the Evolving Symbolic Model (ESM) – illustrated in Figure 1 – designed to create highly interpretable data-driven models for DSA, namely for system security classification and the real-time definition of preventive measures. The ESM framework uses a meta-heuristic as the core data-driven optimizer of a symbolic template that a human expert defines. The power system of Madeira Island was used as a case study, and the results indicate that ESM achieves classification accuracy by using pruned decision trees while offering greater global interpretability. Additionally, it outperforms an artificial neural network in identifying preventive actions.

Authors

Ricardo J. Bessa earned his Licenciado degree in Electrical and Computer Engineering from the University of Porto (UP) in 2006, followed by an M.Sc. in Data Analysis and Decision Support Systems from UP in 2008. In 2013, he completed his Ph.D. in the Doctoral Program in Sustainable Energy Systems (MIT Portugal) at UP. He is the Coordinator of the Center for Power and Energy Systems at INESC TEC. His research interests include renewable energy forecasting, computational intelligence applied to energy systems, decision-making under risk, and smart grids. He worked on several international projects, such as the European Projects FP6 ANEMOS.plus, FP7 SuSTAINABLE, FP7 evolvDSO, Horizon 2020 UPGRID, Horizon 2020 InteGrid, H2020 Smart4RES and is the Coordinator of the AI4REALNET project. IEEE Senior Member, Associate Editor of the Journal of Modern Power Systems and Clean Energy, received the Energy Systems Integration Group (ESIG) Excellence Award in 2022.

Francisco S. Fernandes received his M.Sc. degree in Electrical and Computer Engineering from the University of Porto (UP) in 2020 and is currently a Ph.D. student in the Doctoral Program in Sustainable Energy Systems at UP and Researcher at INESC TEC in the Center for Power and Energy Systems. His research interests include dynamic power system simulation, integration of distributed energy resources, and artificial intelligence. He is working in European projects, such as ENFIELD and TwinEU.

João Peças Lopes is a Full Professor at the Faculty of Engineering of the University of Porto, Portugal, and a Researcher and Associate Director at the Institute for Systems and Computer Engineering, Technology and Science - INESC TEC, Porto, Portugal. His main domains of work are related to the large-scale integration of renewable power sources in power systems (namely wind and solar PV generation), power system dynamics and stability, grid expansion planning, supply and system resilience security, and the development of dynamic digital twins for stability assessment. Prof. Peças Lopes has over 40 years of experience in the referred topics.

Network Topology Reconfiguration for Reliable Power Systems

Basel Morsy, Austrian Institute of Technology, Basel.Morsy@ait.ac.at

Abstract – Transmission system operators (TSOs) face significant hurdles in integrating variable renewables and facilitating operational flexibility. This has sparked renewed interest in optimizing network capacity utilization. Network Topology Reconfiguration (NTR) is a cost-free way to reroute power flows and hence mitigate congestion. In this work, we investigate the computational complexity associated with NTR. The studies presented are in the context of security-constrained optimal power flow (SCOPF). A decomposition method is utilized along side with a meta-heuristic to address the computational complexity of the resulting NP-hard problem.

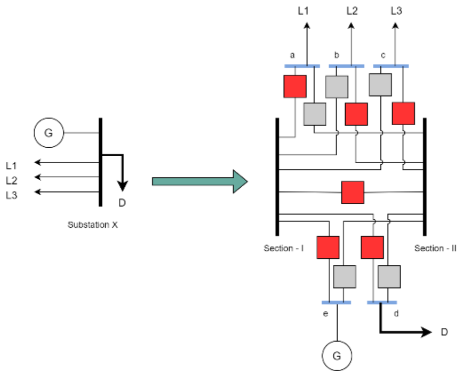

Figure.1: Depiction of substation switching

Author

Basel Morsy holds a MSc degree of energy systems from Skolkovo Institute of Science and Technology, and currently pursues his PhD in Electrical Engineering at TU Delft jointly with AIT. His research interest lies in combinatorial optimization, machine learning, and network science. His PhD thesis is on network topology reconfiguration for congestion management.

Session 2

Advanced Techniques in Fault Detection and Event Analysis for Power Systems

Session Chair: Friederich Kupzog

AI-Driven Anomaly Detection

Stefan Reisenbauer, Reisenbauer Solutions GmbH, stefan@reisenbauer.solutions

Abstract – This presentation introduces the development and implementation of an AI-based system for anomaly detection in energy and charging management. Given the growing importance of real-time data analysis, this solution aims to process large and complex datasets, identifying deviations that could signal potential issues at an early stage. A key aspect is ensuring data quality, as clean and consistent data is crucial for the accuracy of optimization recommendations.

We utilize the Long Short-Term Memory (LSTM) Autoencoder for the AI. In addition to real-time energy data, historical data is also processed. The integration of local weather data to improve analysis accuracy is discussed as well. The presentation also highlights the optimization of the model through continuous training and adaptation to specific requirements, as well as future development towards energy demand forecasting and the local application of AI (Edge AI). This work lays the foundation for future AI-driven applications within our software ecosystem and offers a glimpse into further advancements in this field.

Author

Stefan Reisenbauer is an experienced entrepreneur and technical leader with an impressive career in software development and business management. Since 2020, he has been the co-founder, CEO, and CTO of Reisenbauer Solutions GmbH, where he is responsible for management, product development, marketing, software development, as well as customer support and training. Prior to this, he served as the CEO of Futus Energietechnik GmbH from 2015 to 2020 and as the CEO of Visionlife GmbH from 2008 to 2015, where he held similar responsibilities in both companies.

Stefan began his career as a software developer, working for companies such as Immobilien.Net and UPPER Network, where he contributed to projects for renowned clients like XXXLutz and Red Bull. Additionally, he worked as a freelancer, completing projects for clients like Besser Wohnen and Arbeiter Samariterbund. With his extensive experience in software development and leading technology companies, Stefan has gained comprehensive expertise in developing innovative solutions and managing teams.

Monitoring Application for Devices providing Grid Supporting Functionalities in Power Distribution Systems

David Fellner, Renewable Energy Technologies, University of Applied Sciences FH Technikum Wien, Vienna, Austria, David.Fellner@technikum-wien.at

Abstract – Electric power distribution grids are increasingly integrating distributed renewable generation sources that provide fluctuating power, along with new electrified loads like heating systems and electric vehicles. These additions can lead to issues such as grid overloading or voltage band violations. To address these challenges, these units are typically equipped with grid-supporting control services. However, power system operators and energy utilities often struggle to verify the proper functioning of these services due to limited sensory capabilities in the field. Therefore, additional monitoring capabilities are essential. This work presents an application for detecting misconfigurations in grid assets, particularly inverter-based units, by utilizing operational grid data. This linked monitoring application leverages data from substation transformers and device levels for data mining and misconfiguration detection. The detection methods are integrated with a disaggregation approach to create a comprehensive decision-support tool. The effectiveness of this integrated application is discussed and conclusions drawn about its applicability.

1. Introduction

The transition towards a sustainable energy system poses numerous challenges for electric power grid operators. These challenges encompass environmental concerns, technical issues, and regulatory barriers related to energy storage and transmission. The variability and intermittency of renewable energy sources present a significant challenge for grid operators. The growing trend of households installing their own energy sources also adds to the complexity. For instance, the shift from traditional central power plants to inverter-interfaced PV generators raises concerns about frequency stability, as the inertia provided by the rotational masses of traditional generators needs to be replaced [1]. This can impact the system frequency globally, posing challenges across the grid. Additionally, reliability issues may arise with the integration of volatile renewable energy sources like wind and solar. When renewable energy penetration levels exceed 20-30%, the grid's N-1 reliability criterion may not be guaranteed as it was in previous circumstances [2].

Significant challenges also arise at the distribution level, particularly due to the integration of Distributed Generation (DG) from renewable sources. The operation of distribution grids will also face significant impacts from heating and mobility electrification. The unknown generation and demand profiles resulting from these factors contribute to increased volatility in grid operation and generally higher electricity demand [3].

The distribution of power generation and electrification of loads can lead to local voltage limit violations, overloaded transformers, and congested distribution lines. Electric vehicle (EV) charging, for example, can increase demand or affect bus voltage, potentially causing the voltage to drop below acceptable limits. This may necessitate costly grid reinforcements to address these issues [4]. Additionally, the growing integration of DG can result in local congestions and overvoltages that exceed upper voltage limits [5]. This is exacerbated by the fact that distribution grids are typically not designed to accommodate generation or new loads at decentral locations.

In order to address these challenges without limiting renewable energy generation or requiring expensive grid upgrades, grid-supporting services and innovative devices can be implemented. These solutions may include flexible loads that utilize Demand Side Management (DSM) techniques [6]. Managing the power of Electric Vehicle (EV) charging can also contribute to maintaining grid stability [7]. Additionally, voltage regulation can be achieved through the use of inverter-interfaced units like PV systems or Battery Energy Storage Systems (BESS) [8].

While the active power output of these units can be reduced, adjusting the reactive power injection is commonly employed to regulate local voltage levels [9]. Currently, this reactive power control is primarily carried out at a local level, utilizing local measurements as inputs [10] to adhere to a droop control curve [11].

To further explain the concept of grid-supporting features, Figure 1 displays a local power factor control curve of an inverter-connected generation unit. The top part illustrates the power factor applied based on the active power input, such as from a PV system. At low active power input, the power factor is overexcited, resulting in a capacitive reactive power output as shown in the bottom part of the figure. This elevation in voltage helps to strengthen undervoltage situations. Conversely, an underexcited power factor is utilized at high active power input, causing a decrease in voltage through an inductive reactive power output.

These essential functions are vital for ensuring the grid operates reliably and safely, making it imperative for Distribution System Operators (DSOs) to verify their proper execution. Consequently, DSOs must oversee the controls and configurations of devices. Presently, DSOs face challenges in monitoring these aspects due to the complexity involved. Legal constraints related to data privacy and the absence of sensor equipment in the distribution grid pose significant hurdles [13]. To address these limitations, monitoring is best conducted remotely from a central location, minimizing reliance on Smart Meter (SM) data and avoiding the need for additional sensors. Substation measurement data stands out as the most dependable and accessible data source for DSOs [14]. This data can be utilized for direct identification of misconfigurations and for data mining, extracting valuable insights from specific data to support this task. Moreover, integrating device-level detection with a transformer-level approach can enhance monitoring while considering data availability constraints.

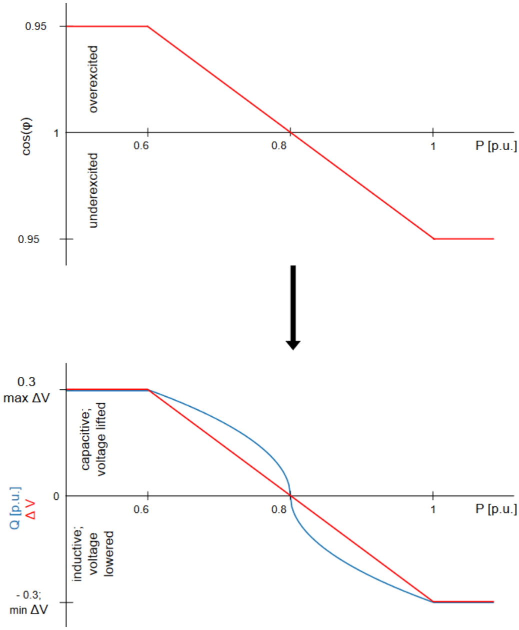

Figure 1. Top: Cosφ(P) power factor control; Bottom: resulting reactive power Q (blue line) as well as voltage lift (red line) [12]

The challenges and requirements outlined earlier have prompted the creation of a data and development framework, along with a monitoring application detailed below. The individual components establish an architecture enabling the monitoring of grid-connected devices and their associated functions using operational grid data. Additionally, an example involving a PV system and its reactive power control is presented. Finally, concluding remarks are provided.

2. Detection Framework

The framework for developing and implementing the monitoring application is available on the corresponding GitHub repository (https://github.com/DavidFellner/Malfunctions-in-LV-grid-dataset). Written in Python, it enables flexible data handling and facilitates the testing of machine learning (ML) methods for data processing, load disaggregation, and identification of misconfigurations in operational grid data. The primary objective of this framework is to serve as a platform for creating and evaluating detection algorithms. As such, it comprises various components for data generation, real measurement data management, load estimation for disaggregation, and algorithm implementation to learn patterns of normal and malfunctioning operations. The chosen implementations of these parts are elaborated upon below, along with detailed descriptions of their functionalities. In general, the framework is capable of managing data gathered using real sensor data and can also process generated data from grid simulations. These simulations replicate scenarios involving misconfigurations in the grid-supporting functions of devices, as well as instances of normal device operation.

2.1 Detection Approach

As mentioned earlier, the application offers multiple opportunities for identifying various malfunctions across a wide range of scenarios by utilizing data from transformers at the medium voltage (MV) level and customers at the low voltage (LV) grid levels, as illustrated in Figure 2. Here the framework used for the application is referred to as the DeMaDs framework. These malfunctions are characterized and simulated as incorrect control curves of devices, which can be identified through operational grid data. The detection process can be evaluated and tested in diverse grid setups, leveraging datasets of different sizes and compositions from various sources. Additionally, there are multiple options available for preprocessing and a variety of data-driven detection methods. Moreover, the application provides a range of metrics and visualization choices for interpreting the results.

In the creation of the device level Deep Learning (DL)-based detection application, producing extensive datasets is pivotal, and this is accomplished through the use of numerous grid models for simulation purposes. DL methods can identify key features from the data, with the goal of detecting malfunctions independently of grid-specific context or knowledge about the data source's location within the grid.

Another means of monitoring involves transformer-level detection, concentrating exclusively on operational data gathered from the substation transformer. This application is grid-specific, since properties differ between the points of application and the amount of data available is therefore too small to pre-train DL models.

In this configuration, load disaggregation is achieved through load estimation to fill data voids that were previously assumed to be accounted for in isolated method testbeds. A neural network (NN) is trained for load estimation, using a training data generation process similar to that used previously for the device-level detection application. By employing this estimation technique for data mining, datasets can be assembled in a way that aligns with the conditions of real-world data collection in the field.

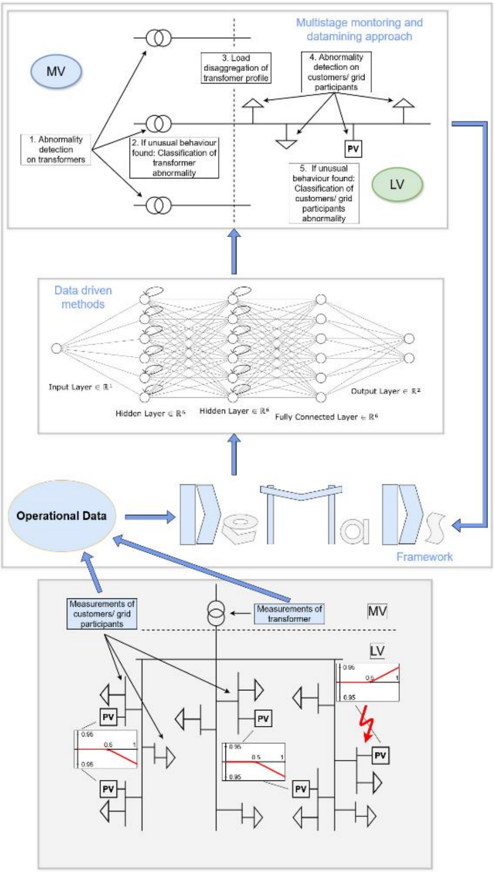

Figure 2. Overview of the framework's functionality with origins of used data for the monitoring application [12]

3. Monitoring Application

This section outlines and provides a detailed description of the specific methods and algorithms employed for device and transformer-level detection, load disaggregation, and finally the overall monitoring solution.

3.1 Device-level Detection

This first application involves detecting and classifying misconfigurations at the low voltage (LV) device level. Collecting data from household connection points, which may have devices providing grid-support functionalities, is challenging due to data privacy regulations and a general scarcity of labeled data necessary for training models. Consequently, models that do not depend on information about their surrounding grid are preferred, as the data gathered, for instance, by SM, can only be processed locally. Therefore, DL methods capable of extracting general features for detection from local operational data that can be pre-trained before deployment are selected for this purpose.

For training these models, data is synthesized through simulations of synthetic grids, such as those available in the SIMBENCH project [15]. Datasets comprising up to 100,000 samples are generated, each sample being a voltage data time series covering either a day or a week at 15-minute intervals. These datasets include labeled instances of regular grid operations as well as cases where, for example, there is a misconfiguration in a PV reactive power control curve.

The evaluation and testing of DL methods, and their comparison with conventional ML techniques for device-level detection, demonstrated that the R Transformer architecture provided the best performance. The R Transformer model [16] (refer to Figure 3) incorporates a recurrent neural network (RNN) [17] to capture time dependencies locally within the time series data. For the entire time series, attention mechanisms are deployed to globally encode dependencies. These attention mechanisms use a concept known as keys to encode the features of specific segments of the time series data. In addition, so-called queries are used, which retain the hidden states linked to the previous output. A scoring function, known as the energy score, evaluates the interactions between the keys and queries to determine the subsequent output. This energy score measures the influence of the queries on the output, thus indicating the significance of the matched inputs encoded in the keys. Therefore, the R Transformer merges the attention features of standard Transformer architectures with the recursive capabilities of RNNs or Long Short-Term Memory (LSTM) models.

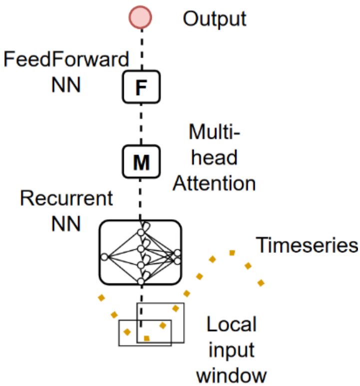

Figure 3. R Transformer architecture [18]

Among all the architectures and methods evaluated, the R Transformer was the only one capable of detecting and categorizing misconfigurations using data from multiple grids, as highlighted in [19]. This demonstrates that the method is effective across various grids, independent of their unique characteristics. In contrast, other traditional machine learning (ML) or deep learning (DL) methods were unable to fulfill this requirement. As a result, the R Transformer architecture proved to be the most appropriate for device-level monitoring due to its capability to handle scenarios that are agnostic to specific grid details. This feature enables the deployment of pre-trained models on edge devices, which process data locally and communicate only the detection flags to the central monitoring system.

3.2 Transformer-level Detection

Due to the higher resolution and the availability of more data channels in this context, traditional machine learning (ML) techniques are employed for detection. This is because meters at substations measure a greater number of variables at a higher frequency compared to SMs in the distribution grid. The Support Vector Machine (SVM) [20] is selected as the most effective method for transformer-level detection, as determined in [21]. In Figure 4, an outline of the method and the operational principle of the SVM classifier are illustrated. The SVM constructs a classifier by identifying a decision boundary that effectively separates the classes while maximizing the margins, which denote the distance to the samples. The figure demonstrates a basic example of binary classification, but it's noteworthy that the SVM is also capable of multi-class detection and classification, enabling the simultaneous identification of multiple misconfiguration.

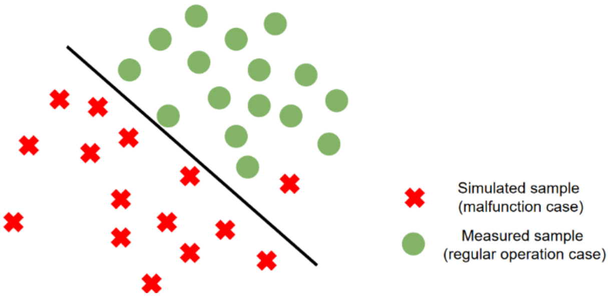

Figure 4. Sketch of the SVM classifier [22]

This classifier is employed to identify instances of operational grid data containing misconfigurations on a daily basis. It is constructed during a calibration phase, supported by load disaggregation and grid simulation, all of which will be elaborated on in the subsequent sections.

3.3 Load Disaggregation

Usually, grid operators record or assume instances of correct operation, unaware of any misconfiguration occurrences. To employ the transformer-level detection classifier mentioned earlier, the monitoring application must understand the characteristics of faulty samples. Thus, it becomes essential to replicate instances of misconfiguration cases through simulation. This necessitates some form of data mining to understand the consumption patterns of loads in the underlying grid from a centralized perspective.

The selected approach implements load estimation to fulfill this objective. To conduct the estimation, it's necessary to grasp the characteristics of the grid where the loads are located. This is accomplished by generating a training dataset of standard load flow outcomes via grid simulations. This entails executing 10,000 load flows, where loads and generation units are allocated profiles with uniformly distributed values. The resultant data is archived as a dataset. The only essential information for this process is the minimum and maximum power values of the loads and generation, which should be accessible to grid operators for billing or device installation purposes. The load flow outcomes encompass power flows and voltage values for each combination of load and generation settings.

The training dataset comprises the same inputs utilized for load estimation, as illustrated in Figure 5. These inputs consist of voltages (V) measured at the substation and critical points in the distribution grid, which can be obtained from measurement units other than SMs, as well as measurements of active (P) and reactive (Q) power at the substation level. Additionally, the production of generation units is presumed to be known through external estimation. For example, estimating the production of PV units is straightforward using radiation models and the installed rated power, leading to accurate estimations. Such estimation is performed retro-spectively, implying that historical radiation data is readily accessible. The outputs in the training dataset, serving as labels, are the estimated active and reactive power consumption of the loads.

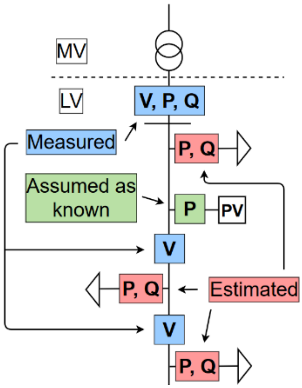

Figure 5. Sketch of the SVM classifier [22]

Having trained a model in this manner and utilizing the aforementioned input data, accurate estimations of the loads can be achieved, enabling the simulation of faulty samples.

3.4 Integrated Monitoring Application

To incorporate the previously described detection methods alongside the disaggregation technique into a monitoring application, they must be integrated. The operational framework of the monitoring application for misconfiguration detection is delineated in Figure 6. In the context of the transformer-level monitoring application, substation data is employed for the detection process, as outlined earlier. To construct a classifier for monitoring purposes, a calibration period is necessary in this setup. During this calibration phase, new, unseen samples of transformer-level data are presumed to have been collected during routine operations without any misconfigurations present, as depicted in part 1 of Figure 5 describing the 'Transformer Level Monitoring'.

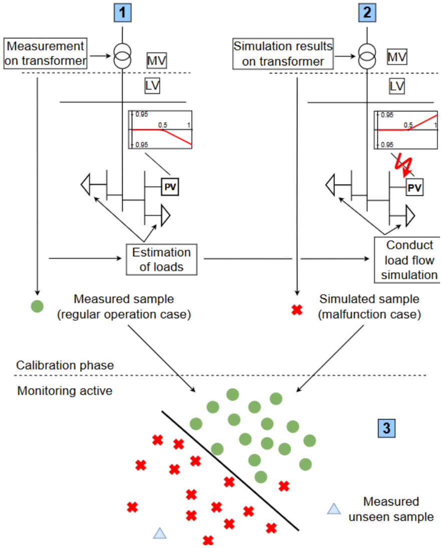

Figure 6. Scheme of the Transformer Level Monitoring [21]

To acquire the corresponding faulty samples, which encompass data gathered under misconfigured conditions, grid simulations are utilized. By joining the measured 'correct' samples with the simulated 'faulty' ones, a comprehensive dataset is created. Generating the 'faulty' samples involves determining the values of individual loads in the underlying grid. This is achieved by employing the disaggregation technique described earlier on the measured transformer power profile. The simulation entails utilizing load and generation profiles (with the latter assumed to be known from external estimations) and adjusting the configuration under investigation to the misconfigured state. The load flow simulation generates the transformer data for each respective misconfiguration, as illustrated in part 2 of the 'Transformer Level Monitoring' in Figure 5. This process can be repeated for multiple misconfigurations without incurring significant computational costs, as the misconfiguration only needs to be modeled once.

Upon completion of the calibration period (which, in the tested scenario, spanned 14 days), the monitoring application becomes operational. New, unseen data is processed following the description of the detection method; a day's worth of data is condensed into one sample. This sample is subsequently categorized as originating from regular operation or not, as illustrated in part 3 of 'Transformer Level Monitoring' in Figure 5. Consequently, the monitoring application offers a daily assessment of the devices' configuration status within a grid segment, which can then be relayed to the grid operators' control room as a flag. The classifier may be updated each day if the collected sample is deemed to represent regular operation. This approach ensures that the application maintains a rolling window of historical data, accommodating potential variations in the grid's operational data resulting from changes in the grid.

For the device-level monitoring application, data gathered at the connection points of households or devices is utilized. As previously discussed, pre-trained models of DL classifiers are trained on simulation data generated from various grids to obtain a grid-agnostic, universally deployable classifier. These models, each tailored for a specific misconfiguration, are subsequently deployed on edge devices, which are integrated with, for instance, SMs, to process data locally. The measurement data is then inputted into these classifiers in the form of a daily time series. The classifier then delivers a determination on whether a misconfiguration case is present at a particular location in the LV grid and submits a corresponding flag containing only the detection outcome. Additionally, this flag is transmitted to the grid operator's control room.

4. Discussion & Conclusions

The outcomes from both transformer and device-level monitoring can be integrated into the comprehensive monitoring application. This integration aids in identifying misconfigurations at specific locations within the grid through device-level detection, while also enhancing detection accuracy with insights from transformer-level detection. This combination seems valuable at this point as the device-level detection currently merely achieves an F-score of 0.6, which is greatly added in confidence by the transformer-level detection's F-score of up to 0.8. both apply to a PV misconfiguration case.

These results can then be fed into a central decision support tool, enhancing the monitoring capabilities of a grid operator's control room. Consequently, the grid operator receives a daily evaluation of the integrity of grid-supporting functionalities. Based on this information, the grid operator can determine where interventions are necessary to rectify misconfigurations, which if left unaddressed, either individually or collectively if multiple misconfigurations persist undetected over time, could jeopardize the safe and reliable operation of a distribution grid.

The approaches described are straightforward to implement and do not demand much expertise for deploying and managing the monitoring solution. This also enhances the commercial viability of the monitoring application. Additionally, integrating local and transformer-level strategies provides clear insights into the type and location of potential misconfigurations, and does so with great accuracy. This precision is crucial to avoid unnecessary maintenance in the event of a false alarm.

Going forward, the framework and the monitoring application implemented by it is planned to enhance its functionality by adding more predefined use cases that identify different types of misconfigurations. Furthermore, the choice and design of predefined machine learning algorithms will be periodically updated to reflect the latest developments in these techniques. Moreover, an approach to the transformer-level monitoring that does not require any calibration phase has been sketched for MV applications and is to be further developed. By using existing HV/MV transformer data as well as generation data to simulate a grid segment in all possible states including operation featuring correct and incorrect configurations and comparing the measured data MV transformer data to the simulated data, a misconfiguration is to be detected.

The mid-term goal for the framework is to conduct thorough field tests to assess and further improve its efficacy as a practical monitoring tool.

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Mr. Fellner's past work treated measures of enhancing voltage stability in weak low-voltage distribution grids, giving him insights into relevant issues of electrical distribution grids. This involved the conception and execution of simulations as well as the evaluation of a real-life demo setup. Furthermore, Mr. Fellner previously supported the AIT with grid modeling and simulations in a project targeting energy self-sufficiency in a rural area of Austria. For these reasons, he has experience with electrical grids and extensive knowledge about protection and automation.

AI and Drones in Energy Grid Management: Catalysts for the EU's Sustainable Transition

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Abstract – This paper examines the strategic use of Artificial Intelligence (AI) and drone technologies at Austrian Power Grid (APG) as key enablers of the European Union's (EU) energy transition. With the EU's focus on sustainability and decarbonization, these technologies are essential for managing the complexities of modern energy systems. AI optimizes grid operations, enhances predictive maintenance, and ensures stability, facilitating the integration of renewable energy sources. Drones, meanwhile, automate infrastructure inspections, improving efficiency and safety, especially in hazardous environments.

The paper highlights the synergy between AI and drones, showing how their combined use enhances energy infrastructure management. It also discusses the impact of the EU's AI Act, stressing the importance of regulatory compliance. Through APG's initiatives, including its AI Center of Excellence, this study underscores the critical role of AI and drones in achieving the EU's sustainability goals, paving the way for a resilient and efficient energy future.

1. Introduction

The European Union (EU) is at the forefront of an unprecedented energy transition aimed at mitigating climate change and achieving sustainability goals. This transition is driven by the integration of renewable energy sources, increased electrification, and enhanced grid resilience. Central to this transformation is the adoption of advanced technologies such as Artificial Intelligence (AI) and drones, which are increasingly recognized as essential tools for managing the complexities of modern energy systems. Austrian Power Grid (APG) exemplifies how these technologies can be leveraged to improve operational efficiency, safety, and sustainability. This paper explores APG's strategic approach to integrating AI and drone technologies, focusing on the role of its AI Center of Excellence, the implications of regulatory frameworks such as the AI Act, and the future potential of these innovations in the energy sector. [1][2]

2. AI in Energy Infrastructure Management

AI has become a cornerstone of APG's strategy for enhancing the stability, efficiency, and sustainability of Austria's energy infrastructure. The establishment of the AI Center of Excellence at APG underscores the company's commitment to systematically evaluating and implementing AI-driven solutions to address the challenges posed by the energy transition *(Figure 1)*.

Figure 1. Dimensions of APG's AI Center of Excellence to ensure the systematic adaptation of new developments to build APG's AI capabilities.

2.1 System Planning and Optimization

AI is crucial in optimizing system planning at APG. By analyzing vast datasets related to electricity demand, supply variability, and grid performance, AI enables predictive planning that ensures the grid infrastructure is equipped to handle the increasing complexity brought on by renewable energy integration. This predictive capability is essential for maintaining grid stability and optimizing resource allocation. [3][4]

2.2 Market Operations Enhancement

AI also enhances market operations within the electricity sector. At APG models have been developed to optimize trading strategies and improve market price forecasts. By analyzing historical and real-time data, AI provides insights that help lower costs for consumers. [5]

3. Deployment of Drone Technology at APG

Drones have become a vital component of APG's strategy for managing its extensive transmission network. By integrating drones with AI, the efficiency and safety of operations, particularly in areas such as substation inspections, power line monitoring, and pylon maintenance can be enhanced.

3.1 Substation Inspections

Drones equipped with infrared and ultraviolet sensors are useful tools for detailed visual and thermal inspections of substations. These drones can be remotely operated or follow pre-programmed flight paths, capturing high-resolution images and thermal data that are crucial for early detection of potential issues such as hotspots. This approach significantly reduces the need for personnel to be physically present in potentially hazardous environments. [6]

3.2 Power Line Inspections

The use of drones for power line inspections, especially in challenging terrains such as mountains or forests, has potential benefits to these critical operations. Drones can be rapidly deployed to assess damage and provide real-time visual data, enabling experts to address issues more efficiently and safely than traditional methods, such as helicopter inspections. [7]

3.3 Pylon Maintenance

For pylon maintenance, drones offer a time-efficient and accurate alternative to manual inspections. Drones are programmed to fly specific routes around pylons, capturing thousands of high-resolution images from multiple angles. These images are then processed using AI to create detailed 3D models that are analyzed for signs of structural defects or corrosion. [8]

3.4 Operational Efficiency and Safety Impact

The integration of drones into APG's operations has significantly improved both operational efficiency and safety. Automated inspections reduce the time and costs associated with maintenance while allowing for more frequent and thorough assessments. Furthermore, drones minimize the need for personnel to work in dangerous environments, enhancing overall safety.

4. Synergy Between AI and Drone Technologies

The combination of AI and drone technologies represents a powerful synergy that enhances the effectiveness of energy infrastructure management. AI can not only improve data processing and analytical capabilities of drones but also provides real-time decision support that optimizes drone operations. During drone inspections, AI algorithms are able to process the vast amounts of data collected to identify patterns and anomalies, such as hotspots in electrical components. This enables transmission system operators such as APG to transition from reactive to predictive maintenance strategies, reducing the risk of unexpected failures.

Machine learning algorithms can enhance drone operations by optimizing flight paths based on past data, ensuring comprehensive coverage while minimizing energy consumption. This not only increases operational efficiency but also extends the lifespan of drone equipment.

5. Regulatory Considerations: The AI Act

The European Union's AI Act is a comprehensive regulatory framework that governs the deployment and use of AI across various sectors, including energy. For APG, compliance with the AI Act is crucial, particularly in ensuring that AI systems used in grid management are safe, transparent, and aligned with European values.

5.1 Compliance and Risk Management

APG must ensure that its AI systems comply with the AI Act's stringent safety and transparency requirements. This involves rigorous risk assessments, particularly for high-risk applications, such as AI-driven drone operations, to prevent malfunctions that could compromise grid stability. [9]

5.2 AI Governance and Quality Management

The AI Act mandates robust governance frameworks for AI deployment. APG has established clear policies for the ethical use of AI, managing data, preventing bias, and ensuring accountability. Continuous monitoring and staff training are essential components of this governance framework.

5.3 Impact on Innovation

While the AI Act imposes strict regulations, it also encourages innovation and adequate – risk-based – quality standards for AI systems. APG's efforts to integrate AI align with the Act's emphasis on promoting safe and effective technologies that enhance grid management and operational efficiency.

6. Future Directions and Innovations

The future of AI and drone technologies in the energy sector holds immense potential. Ongoing research is likely to lead to significant advancements in predictive analytics, autonomous drones, AI-driven energy optimization, and enhanced cybersecurity.

Future AI systems will likely incorporate more sophisticated predictive analytics, enabling APG to foresee grid issues with greater accuracy and implement proactive maintenance strategies. The development of fully autonomous drones capable of conducting inspections and maintenance without human intervention is a promising field of innovation that could further enhance the safety and efficiency of grid management.

7. Conclusion

The paper highlights the strategic importance of integrating Artificial Intelligence and drone technologies in managing the energy grid, particularly within Austrian Power Grid. Key findings include:

1. **Enhanced Grid Stability and Efficiency:** AI plays a critical role in optimizing system planning, real-time operations, predictive maintenance, and many other areas with sufficient data for the application of AI systems. This leads to improved grid stability, reduced operational costs, and extended infrastructure lifespan, all of which are vital for managing the complexities introduced by the increased integration of renewable energy sources.

2. **Operational Efficiency and Safety:** Drones significantly enhance the efficiency and safety of grid inspections and maintenance. By automating and optimizing these processes, drones reduce the need for human intervention in hazardous environments, improve response times, and provide detailed data for more accurate maintenance decisions.

3. **Synergy Between AI and Drones:** The combination of AI and drones creates a powerful synergy that enhances the effectiveness of energy infrastructure management. AI-driven data analysis and real-time decision-making capabilities optimize drone operations, making them more efficient and responsive to dynamic grid conditions.

4. **Regulatory Compliance and Innovation:** The European Union's AI Act plays a crucial role in guiding the safe and ethical deployment of AI technologies. APG's current work to comply in full alignment with these regulations ensures that its innovative use of AI and drones not only meets regulatory standards but also drives operational efficiency and contributes to the broader sustainability goals.

The ongoing development of AI and drone technologies holds immense potential for further advancements in grid management, including more sophisticated predictive analytics and autonomous drone operations. These innovations are expected to play a crucial role in ensuring the resilience and sustainability of the energy grid as the EU continues its transition to a decarbonized energy system.

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Semantics-based explanation of (unusual) events in energy systems

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Abstract – As energy systems increase in complexity during their transition towards smart grids, providing transparency in terms of explanations of anomalies and (unusual) events becomes ever more challenging. Yet, such transparency is important both for end-users and grid-operators to understand the reasons behind unusual system behaviour and, subsequently, implement effective countermeasures, while ensuring understandability and trust even in these increasingly complex systems. In this paper, we provide examples of energy system use cases where explanations are needed and explore in detail the benefits of such explanations for several stakeholders in the energy system domain. We also briefly describe a solution to explainability in smart grids that explores the benefits of Semantic Web technologies.

1. Introduction

Based on European legislation (e.g., Clean Energy Package), the infrastructure of the energy systems within the EU is undergoing a significant modernization process to increase efficiency on both the network and market sides. This modernisation includes: a surge in the use of renewable energy sources (RES), the introduction of electric vehicles (EVs) and the creation of electricity trading markets (e.g., through local energy communities, i.e. LEC) enabled by the increased production of energy on the end-customer side, which are known as prosumers. This change requires that energy systems, traditionally rigid systems with static topologies, evolve into dynamically changing, complex systems where many prosumers can randomly transition between consuming and producing energy. Managing this complexity can best be met through increased digitization thus leading to a transition to smart grids, or cyber-physical energy systems (CPES) [3].

A smart grid ensures stable grid operation by detecting and responding to local changes in energy usage. To that end, it controls physical grid entities using digital communications technologies. During the operation of smart grids, faults, anomalies and other events may occur because of unusual phenomena (e.g., extreme weather) or limited capacities of facilities (e.g., transformer overloads). Yet, the inherent complexity of such grids reduces their transparency: indeed, it is increasingly difficult for interested stakeholders to understand the system behaviour, to identify root causes of anomalies and to act according to the situation at hand. Therefore, the ability to provide explanations for these anomalies – or unusual system states in general– plays a crucial role in understanding, managing, and controlling smart grids.
Against this backdrop, as part of the SENSE project[1], we aim to increase the transparency of smart grids (and cyber-physical systems in general) through the explainability of unusual events that may occur in those systems. In this paper, we discuss key aspects of the project. First, we describe motivating use cases from the energy systems area to exemplify explanations relevant for such use cases (Section 2). Then, as a key contribution of this paper, we focus on key energy system stakeholders and discuss how they could benefit from such explanations (Section 3). Finally, we provide a summary of the proposed SENSE solution and point the interested reader to a detailed technical paper on that topic [4] (Section 4). We conclude with future work insights in Section 5.

2. Examples for Explanations in Energy Systems

Smart Grids enable new scenarios which contribute to increased environmental sustainability, and, at the same time, showcase the need for explanations. In particular, we investigate scenarios related to *electric vehicles* and l*ocal energy communities*. We briefly discuss these as examples of potential explanations in energy systems.
Electric vehicles will lead to sensibly reducing pollution in cities. To meet the EU’s targets on climate neutrality by 2050, 30M E-cars and 80K E-trucks must be on EU roads by 2030 and will require 3M public charging points. There is a need for explanations in the context of the EV infrastructure expansion. For example, the *slow charging at an electric vehicle charging station (EVCS)* is an event that requires an explanation such as:

“overcast weather leads to lower than usual energy production through PVs in the region, this leads to a lack of supply in the grid segment and to a control intervention to reduce charging power by the grid operator”.

Local Energy Communities are local, physically and virtually interconnected communities in which locally generated energy is primarily consumed among their members. For example, a

[1] SENSE project website: https://sense-project.net/

minimal LEC could consist of houses H1-H4 (equipped with PV cells, batteries) connected to a flexibility operator S1 which informs LEC members about best trading actions (selling/buying energy) depending on the energy price on the market M1. The LEC is served by transformer T1, to which other office buildings (B1, B2) and EVCS (C1, C2) are connected. In this setting complex explanations can be derived. For example, the event of *slow charging at C1* (event e8) is caused by an intervention to reduce a transformer overload at T1 (e7). On its term, e7 was further caused by the LEC members (a) consuming a high amount of energy (e4-6) because of a "buy" command of S1 (e3) in line with low energy prices (e1) and low batteries of some houses and (b) producing less energy than usual due to reduced solar radiation (e2). As LECs connect several stakeholders (LEC members, flexibility operators, grid operators), explanations are interesting to all these stakeholders to ensure efficiency and to foster user-friendliness and subsequent community acceptance of LECs [5].

3. Who needs an Explanation?

In this section, we explore possible energy system stakeholders that could benefit from explanations of (unusual) events that occur in the system such as those detailed in Section 2. While in Section 3.1 we report on the result of project internal discussions on this topic, Section 3.2 summarizes the results of a recent survey on the need for energy system explainability performed with energy system customers.

3.1 Stakeholder Analysis

Figure 1 depicts several energy system stakeholders. Central to the figure is the energy system (represented by a grid device and an EVCS) as well as an ExpCPS explainability module that provides explanations of events on this energy system. Furthermore, stakeholders and their interactions with the explainability module are also depicted. The key stakeholders we identified and their benefits from system event explanations are:

- *Customers* benefit from explanations as they can understand (unexpected) system behaviour and increase their trust and acceptance of these systems. Furthermore, they can exercise their right to explainability as mandated by GDPR [2]. A meaningful explanation may increase customer satisfaction, and in the long term, strengthen their loyalty.
- *Customer support representatives* can more efficiently and effectively support end-customers by providing reliable explanations to their queries. An explanation module has the benefit of reducing their workload in finding out why certain events of interest happened.

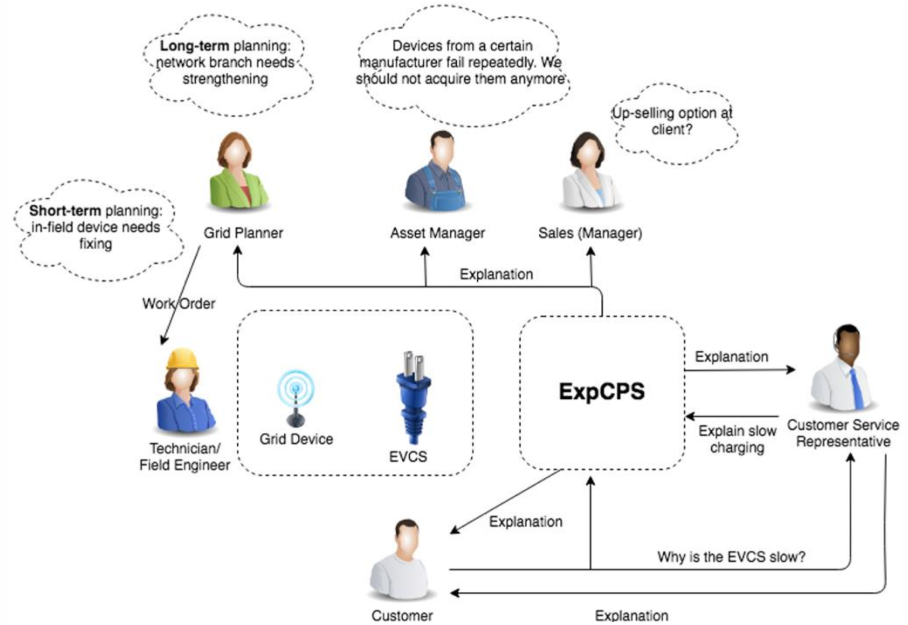

Figure 1. Overview of energy system stakeholders that benefit from explanations of (unusual) events.

- *System technicians/field engineers* can fix root causes of faults occurring in the system quicker when supported by detailed explanation of why a fault occurred in the first place.
- *Grid planners* can obtain an explanation for a fault and act both on short- and long terms. On short-term, they can take appropriate action to resolve faults at once by sending a work order to field engineers. On long-term, they can adjust the grid planning to avoid frequently occurring faults in the future.
- *Sales managers* can propose new business models/engage in upselling based on explanations of undesirable behavior.
- *Asset Managers* can analyze several fault reports and deduce suitable actions related to asset acquisition, for example, replacing those assets that (are likely to) cause the faults.

Beyond the individual stakeholder roles depicted in Figure 1, entire institutions can also benefit from explanations:

- *System operators*, such as distribution system operators (DSO), who can make their systems accepted by end users and increase system transparency and usability. Additionally, they need to comply with legal requirements (GDPR) mandating customers' right to explainability [2]. This legal context makes explainability a mandatory feature for any system, including smart grids.

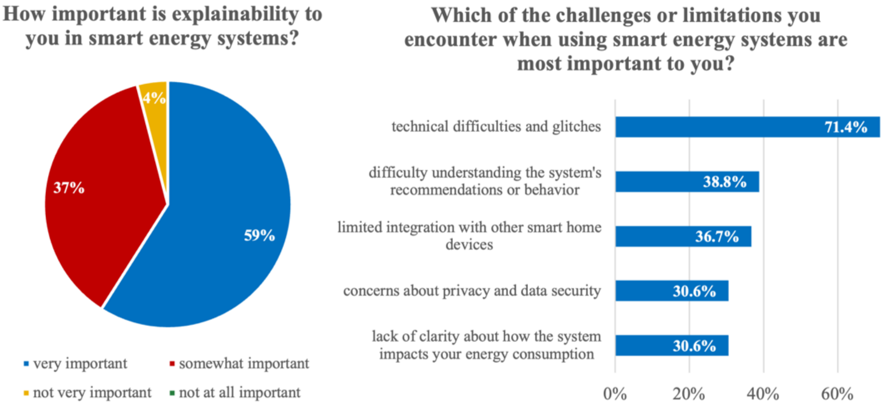

Figure 2. survey results showing responses to two key questions on explainability

- *Cross-system operators* (e.g., operators of Electrical Vehicle Charging Stations) depend on the functioning of several other systems (e.g., if grids are operated by diverse DSOs), and need to understand which of these failed; however, individual DSOs cannot share all details of an explanation. ExpCPS could be a "middleman", revealing only those aspects of the explanation that are not confidential.

3.2 End-user Survey

While the above considerations have been derived in discussions with energy system experts, we also conducted a survey that aims to shed light on the need for explainability of customers in LECs. The survey was conducted as an online survey, directed to LEC members of the 315 Austrian energy communities as they were listed online by the Austrian coordination centre for LECs in January 2024. A call to participation was sent to the respective spokespeople of each energy community, asking them to distribute the survey to their LEC members. With a total of 49 participants, we investigated the main motivations of LEC participants and their pain points in their use of smart energy systems.

In Figure 2, two questions are highlighted, which show an insight into the motivation and needs of LEC participants. In the first question, the general importance of explainability to users is evaluated. A majority of users consider explainability as a "very important" feature of smart energy systems, while a total of 96% of participants find it at least somewhat important. In the second question, a more detailed analysis of the issues encountered is conducted, checking, which challenges are most important to the users. More than 70% of participants defined technical difficulties and glitches as one of their main concerns, and almost 40% mentioning understanding system behaviour as a main concern. Both of these challenges can be addressed by creating an explainable system (ExpCPS), where technical faults as well as system decision can be explained by the system itself. Explaining technical faults can help in several ways: finding solutions to resolve the cause of the problem, finding an alternative temporary solution to bypass the problem until it can be solved, or if the problem cannot be solved, finding more long-term alternatives and raising acceptance in the meantime.

4. Proposed Solution: the ExpCPS Framework and its implementation

As a solution approach for providing explanations in energy systems (and more broadly in cyber-physical systems), the following components have been developed in the SENSE project and reported in detail in [4]:

- The **ExpCPS Framework** is a technology-agnostic explainability framework for developing systems that (1) take as input time series and system data provided by a CPS, (2) process this information and store it in line with a unified structure defined by the integrated data model and (3) derive explanations for system events. The framework identifies all necessary modules to create an explainable CPS in alignment with the interoperability layers defined by the Smart Grid Reference Architecture (SGAM) [1].
- The **SENSE Data Model** is the foundation of an ExpCPS framework that is applicable across various CPS domains and enables the integration of diverse data sources for comprehensive system understanding. We use Semantic Web technologies to exemplify the implementation of the model as the SENSE ontology available at http://w3id.org/explainability/sense#.
- **SENSE technology Stack and Proof of Concepts** materialise the technology agnostic framework and data model by means of Semantic Web technologies. We created both a core technology stack providing implementations of the core functionalities of the framework, and several proof-of-concept prototypes that apply this stack to solve concrete domain problems in the area of energy systems and beyond.

5. Future Work

In ongoing work, we are evaluating the ExpCPS framework and its implementation in the SENSE technology stack for additional use cases in energy systems (e.g., related to energy communities). We offer all the components discussed in Section 4 for reuse to interested third parties.

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Session 3

Unlocking the Potential of Big Data in the Energy Domain

Session Chair: Stefan Wilker

Technology Readiness of GenAI for Energy and ESG Data

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Abstract –The main challenge in building management, especially with ESG (Environmental, Social, and Governance) reporting, is ensuring accurate, consistent, and transparent data collection and reporting across diverse sources. AIVEY, an innovative AI tool powered by Generative AI/LLM, addresses these challenges by automating the integration, analysis, and standardization of data, enabling accurate real-time reporting and decision-making. It seamlessly connects to a company's data ecosystem (e.g., facility data, ESG data, rent roll data, financial data, etc.), handling both structured and unstructured information, and provides descriptive and predictive analyses by combining internal and external data (e.g., weather, holidays, and market trends). Built with strong security and privacy measures, AIVEY is fast, agile, and ideal for scenarios like real-time decision-making during executive meetings.

1. Introduction

The state of data for building management and ESG (Environmental, Social, and Governance) reporting is progressing, presenting both considerable challenges and opportunities. Key issues include the integration and consistency of diverse data sources, such as energy usage and occupancy rates, which are often fragmented and inconsistent. Ensuring data quality and accuracy is critical for credible ESG reporting, as poor data can lead to incorrect assessments of sustainability performance. Real-time data collection, especially for energy and emissions tracking, is technically challenging but essential. As portfolios grow, scalability becomes a concern, requiring systems that can manage increasing data volumes while maintaining performance. In addition, benchmarking and comparability are hindered by the lack of standardized metrics, and interoperability between different systems remains a challenge.
We propose AIVEY, an innovative AI tool powered by Generative AI/LLM, that automates the integration, analysis, and standardization of diverse data sources (e.g., facility data, ESG data, rent roll data, financial data, etc.), enabling accurate, real-time reporting and enhanced decision making to meet regulatory and stakeholder demands for building management and ESG reporting. The end-user of AIVEY can be a property manager, facility manager, asset manager, or even a tenant. The end-user logs into the AIVEY web interface (via desktop or mobile devices) and, after selecting the data source, can execute a report, ask descriptive and predictive questions about the data. The main features of the system can be summarized as follows:

- Leverages both company-structured and unstructured data and external data sources (such as weather data) to conduct comprehensive analyses.
- Automatically maps and integrates data from various sources.
- Autonomously determines the optimal AI agent for each specific task, efficiently extracting pertinent information from extensive datasets.
- Delivers the results in a variety of user-friendly formats, including easily exportable data, visually appealing charts, and detailed textual interpretations. These outputs are designed to support research activities, enhance presentations, and facilitate informed decision-making processes. Furthermore, by analyzing the data, it recommends potential questions of interest or, for regular reporting, it can generate reports from the latest updated data in downloadable format.
- Ensures that the insights generated are readily accessible and can be seamlessly integrated into various business workflows, enhancing overall productivity and strategic planning.

AIVEY is built as a chain of AI agents that utilize various Large Language Models, each handeling specific tasks like database connections, query generation, document comprehension, and result visualization. The system dynamically switches between LLM models based on the task, ensuring transparency by clearly indicating which AI was used, the data sources involved, and the processing steps. Results are presented in an accessible way for both technical and nontechnical users. To enhance accuracy and avoid errors in queries from unstructured documents, a Retrieval-Augmented Generation (RAG) pipeline with a Knowledge Graph is integrated, providing a structured, interconnected data framework that supports accurate, consistent, and comprehensive ESG reporting through contextual data retrieval, validation, and real-time updates.

The proposed system revolutionize the Facility Manager/Real Estate market by significantly enhancing data driven decision-making, operational efficiency, and strategic planning. The innovation lies in the system’s ability to not only perform complex data analyses but also to adapt dynamically to different tasks by selecting the most appropriate AI models. This flexibility ensures high accuracy and relevance in its outputs, reducing the risks of erroneous insights. Additionally, it can autonomously generate actionable recommendations and anticipate market trends, helping stakeholders optimize asset management, sustainability practices, and financial performance.

2. Technology

AIVEY employs sophisticated message processing techniques to interpret user queries. These queries are routed through a series of specialized agents, which interact with powerful language models to generate accurate and insightful responses. The responses are further processed to ensure they are comprehensive and tailored to the user's needs. AIVEY can seamlessly analyze tabular files such as Excel, unstructured documents like Word and PDF, and even databases directly connected to the system.

2.1 Data Integration and Accessibility

AIVEY's versatility is further enhanced by its ability to connect seamlessly to a wide range of data sources, making it an invaluable tool for comprehensive data management. Users can easily upload files directly, or, for more complex and large-scale operations, connect to a database, IoT devices, shared directories such as SharePoint or expansive Data Lakes, such as Azure Data Lakes. This integration facilitates real-time access to vast amounts of information, ensuring that users always have the most current and relevant data at their fingertips. Additionally, AIVEY supports various data formats and sources, enabling it to aggregate and analyze data from disparate systems, which is critical for making informed, data-driven decisions. By centralizing and standardizing data access, AIVEY not only enhances operational efficiency but also improves the accuracy and reliability of insights, making it an essential tool for organizations looking to stay competitive in data-intensive environments. This connectivity also allows for the automation of data workflows, reducing the need for manual data entry and minimizing the risk of errors, thereby streamlining the entire data management process.

2.2 Multi Agents

AIVEY is equipped with a suite of specialized AI agents, each designed to perform specific tasks, ensuring thorough and accurate data analysis. Below a list of most important agents:

- Chart AI: Generates relevant charts based on the data provided.
- DataFrame AI: Specializes in analyzing tabular data within dataframes.
- Column AI: Analyzes individual columns in tabular data or databases.
- Correlation AI: Examines data correlations and provides statistical insights.
- External AI: Integrates external data such as calendar and weather data to enhance the accuracy of analyses.
- Interpreter: Interprets AI-generated interpretations of results and user queries for clarity.
- Suggestion AI: Offers actionable recommendations to enhance organizational efficiency.
- Database AI: Conducts automated analysis of database data and generteing queries for database.
- Document AI: Analyzes unstructured data using advanced RAG Knowldege Graph techniques, and furthumore, leveraging tools like LangChain and LlamaIndex to minimize hallucination and maximize data extraction accuracy.

2.3 Dynamic Model Selection

AIVEY is uniquely capable of switching between different LLMs in real-time through its integration with Portkey[2]. This dynamic selection ensures that the most suitable LLM is used for each specific data type, maximizing the accuracy and relevance of the analysis. Switching between different LLMs enhances ESG reporting accuracy and performance by allowing the system to select the most appropriate model for specific tasks, ensuring optimal results. Different LLMs may excel in various areas, such as natural language understanding, data interpretation, or generating complex narratives. By dynamically choosing the best-suited model for each aspect of the ESG reporting process, the system can more accurately analyze data, generate precise and contextually relevant insights, and adapt to the specific requirements of different reporting standards and regulations. This approach leads to more reliable, comprehensive, and tailored ESG reports.

2.4 Comprehensive Output

AIVEY delivers outputs not just as text, but also in the form of charts and tables (see Figure. 1), complete with necessary calculations, catering to the diverse needs of its users. This multi-format presentation allows users to easily digest and act on the insights provided, whether they prefer a visual summary or a more detailed numerical breakdown. Furthermore, AIVEY enhances the user experience by providing detailed interpretations of the analyzed data, offering context and explanations alongside the visual representations. Figure.2 shows a screenshot of the interpretation of the provided chart, illustrating how AIVEY not only presents data but also guides users through the implications of the findings, turning raw data into actionable intelligence. This comprehensive approach ensures that every piece of data is maximally leveraged, transforming complex datasets into clear, concise, and actionable insights that drive better business outcomes.

In addition to standard charts and tables, AIVEY allows for the customization of outputs to align with specific reporting needs or corporate branding guidelines. Users can tailor the presentation of data to suit their audience, whether it’s for an internal team meeting or an external stakeholder report. The ability to generate exportable formats, such as PDFs or Excel files, further extends AIVEY’s utility, making it easy to share insights across different platforms and with various stakeholders.

2.5 Knowledge Graph RAG Pipeline

To improve the system and avoid hallucinations and low accuracy in queries from unstructured documents, we've integrated a Retrieval-Augmented Generation (RAG) pipeline using a Knowledge Graph. The Knowledge Graph provides a structured, interconnected representation

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[2] https://portkey.ai/

of data, enabling efficient retrieval and ensuring the accuracy, consistency, and comprehensiveness of ESG reporting.

Creating a Knowledge Graph RAG pipeline for ESG reporting involves several key steps. First, data collection and integration are essential, where relevant data from internal databases, external datasets, and unstructured sources are identified, cleaned, and standardized. This integrated data is then used to construct a Knowledge Graph by defining ontologies that establish relationships between various ESG entities, such as carbon emissions and social impact metrics. The Knowledge Graph is populated with data, linking these entities and ensuring continuous updates for accuracy.

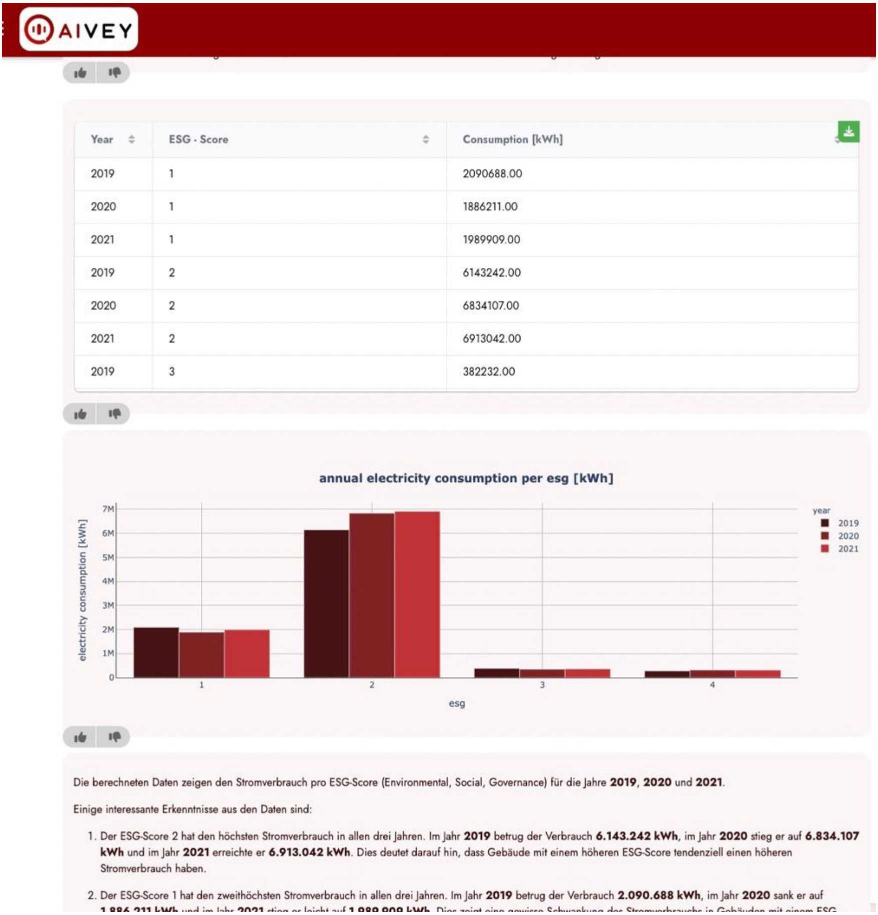

Figure 1. A screenshot of AIVEY, which delivers outputs not just as text, but also in the form of charts and tables

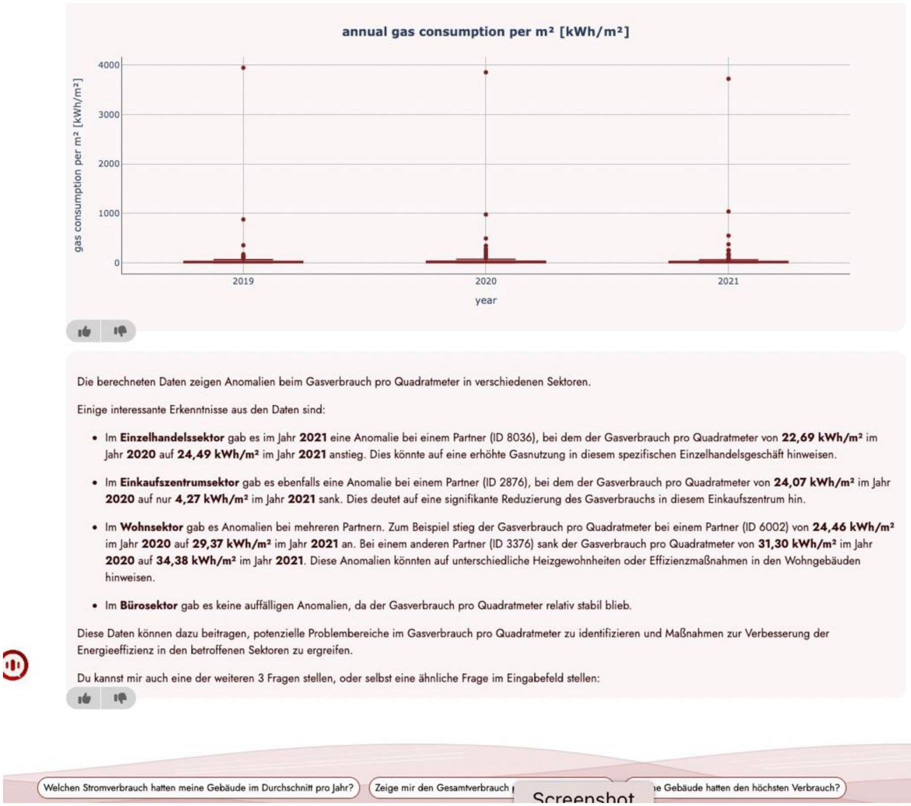

Figure 2. A screenshot of AIVEY, which provides detailed interpretations of the analyzed data.

The RAG pipeline is implemented by selecting appropriate Generative AI models that retrieve contextually relevant data from the Knowledge Graph and generate comprehensive ESG reports. To orchestrate the entire RAG pipeline and ensure that data flows correctly from ingestion through to retrieval and generation, we used Apache Airflow[3]. OpenAI's GPT and models are utilized for the Generative AI part, producing natural language outputs based on the retrieved data, while Hugging Face Transformer (BERT-based) models are employed for more context-aware retrieval tasks and extracting ESG-related entities and relationships.

2.5.1 Data collection for Training

For training a transformer model to extract accurate ESG criteria we continuously collect data from different online sources in English and German [1]. Our crawlers and APIs are working

[3] https://airflow.apache.org/

on a cluster of distributed virtual machines and containers to collect data. They search the news and social media web pages for articles relevant to the given list of companies. As for tweets, the system retrieves related tweets, mentions, and retweets using the Twitter Streaming API. For news articles, news aggregator services developed by Google, MS BING, etc, are utilized to collect online news media articles. To this end, our crawler looks for the given ESG factornear real-time and retrieves the most recently published news links from variouse news web pages. After identifying the links from the news aggregator, the crawler collects articles directly from its news web page. Our crawlers are developed highly efficiently and utilize data storage technologies such as Redis and MongoDB. We use web scraping libraries such as Beautiful Soup and Selenium for our news crawlers and Twitter API to retrieve tweets. We have fed crawlers with the list of target ESG factors, abbreviations, and other potential forms of their names as input. As mentioned earlier, our machines continuously collect data to keep our database up to date. To capture and maintain historical data, we store our data in snapshots of monthly time spans. ESG criteria were initially defined using CFA criteria and categories[4] and then we fine-tuned them using SDG criteria from UN[5].

2.5.2 Knowledge Graph Construction

For extracting relations from unstructured documents we fine-tune REBEL [3], which is an autoregressive model and outputs triplets in the input raw text, using collected data. This model is available on Hugging Face Hub[6]. REBEL frames relation extraction into a seq2seq task and was presented by Cabot and Navigli [3] upon fine-tuning BART-large as the base model. They trained REBEL using a set of Wikipedia abstracts[7] which are page contents before the table of contents. We fine-tuned REBEL to extract relationships related to ESG criteria. The training dataset contains 2000 ESG-related relationships and the model was trained in 6 epochs. On this dataset, the model achieves 74 for micro-F1 and 51 for macro-F1. To structure the resulting triplets, we used the RDF syntax defined by Beckett and McBridge [2].

For the purpose of traceability, each resulting triplet is coupled by another triplet where the predicate is “SourceURI”, and the tail is the URL of the article's source.

Our fine-tuned transformer model extracts relationships related to ESG if a document contains one (or more) ESG keyword(s), this triplet is assigned to the predefined class. For example, if one of the keywords related to air pollution appears in a triplet, it is set to its aspect class “*has_air_pollution*” in addition to its category class, namely “*has_environmental*”.

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[4] https://www.cfainstitute.org/en/research/esg-investing

[5] https://www.un.org/development/desa/disabilities/about-us/sustainable-development-goals-sdgs-and-disability.html

[6] https://huggingface.co/Babelscape/rebel-large

[7] https://dumps. wikimedia.org/enwiki/

Finally, our fine-tuned transformer model is used in our RAG pipeline to extract relationships from relevant documents in response to a user query.

3. Limitations and Future Works

Despite the many advantages of the proposed system, due to the current limitations of technologies, we have listed some constraints below that could be addressed in future work.

- Hallucinations and Errors: Due to incomplete inputs to the LLMs or missing context, erroneous outputs can occur. To address this, we are working on a agent 'Explainer AI,' which displays and interprets the code being executed for the user and further explains how the system arrives at its results.
- Speed: With a large number of tokens, multiple chained AIs, and complex tasks, execution times can become lengthy, which can be detrimental to usability in real-time applications.
- Lack of Long-Term Memory: The model itself has no memory, so it is necessary to identify important parts of the conversation and include them in the pre-prompts. This process can be error-prone/incomplete and may increase the token size.
- Lack of Common Sense: The model trusts the input and does not independently question it when the data is implausible. For example, if the input states that 500k kWh of electricity was consumed in one minute for a single apartment, or that only 2 kWh of electricity was consumed in a year for a busy office building, the AI accepts this and continues to work with it.
- Dependency: Running AI models is cost-efficient only at a large scale. As a result, smaller companies are dependent on large providers, leading to dependencies in terms of costs, consistency of quality, availability, and data protection.

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Concept for an Austrian PV Digital Twin for Now- and Forecasting

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Abstract – The energy and climate policy goals [1] of the Austrian federal government include increasing the annual production of electricity from photovoltaic (PV) power plants to 11 TWh. To achieve this target, an installed capacity of at least 11 GW is required (assuming a generation of 1000 kWh/kWp). Since 2024, PV systems have become the type of power plant with the largest installed nominal capacity [2]. However, this growing number also brings challenges. To ensure the secure integration of these systems into the electricity network and their reliable and stable operation, data from PV systems is becoming increasingly important.
The first challenge is to estimate the installed capacity on national but also regional level as good as possible. The following work is using the Anlagenregister from E-Control [3], which is a non-validated database providing information on nominal power and zip codes for each PV system. But this database also contains incorrect, duplicate, or possibly entries of non-existent plants, as well as potential gaps in their recording. In addition, the status and output of the in-stalled PV capacity change daily due to newly installed plants, as well as performance degradation due to aging, changes in shading of individual plants, and defective or decommissioned plants.

The second challenge is achieving the most accurate possible 'now-casting' of PV plants on both national and regional levels. This work presents a possible method based on data from PVGiS [4], cloud cover data from EUMETSAT satellite data [5], and the aggregated PV generation data from the market transparency database of APG [6].

The third challenge involves intra-day forecasting of PV generation, which is becoming increasingly important as the number of PV installations rises. Since energy generation from PV is subject to significant fluctuations due to cloud movements and other factors, particularly on a regional level but also nationally, accurate forecasts are necessary to ensure secure supply and network operation. This allows for planning and provision of backup capacities for reduced feed-in. This paper proposes an already tested method [7] [8] that uses LSTM to calculate fore-casts based on inverter data distributed over large areas and aggregated by zip code, which are then scaled regionally and nationally according to the now-casting results.

The following Diagram shows the Data and Method Workflow for the different applications of the concept for now and forecasting.

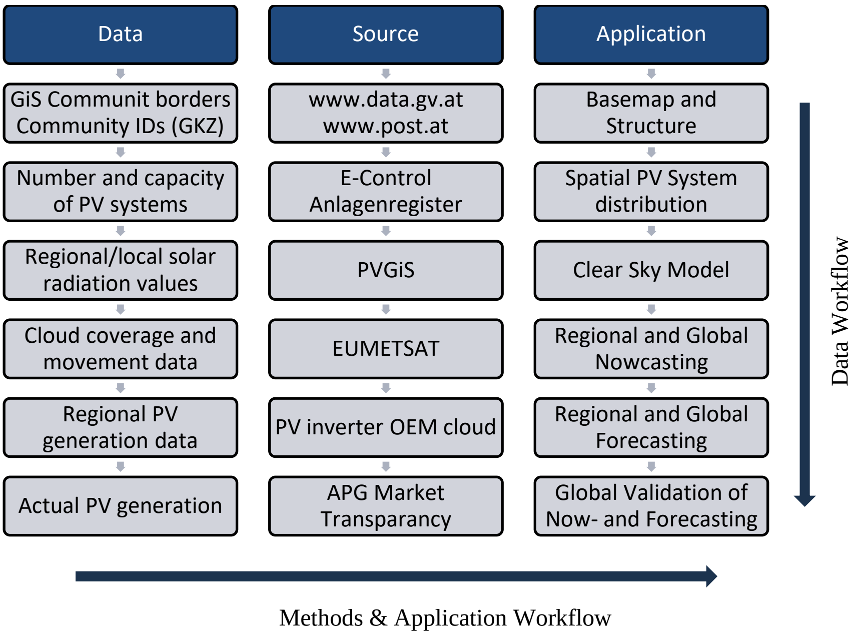

Figure 1: Data and Method Workflow for Now- and Forecasting

The figure shows the accumulated PV power at community districts in Austria, which is used as input data for the PV now- and forecasting methods.

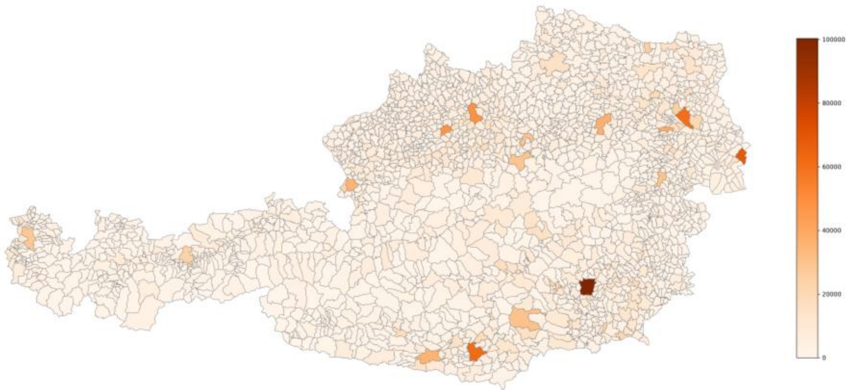

Figure 2: PV power distribution at community level in Austria

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Learning Surrogates of Physical Systems

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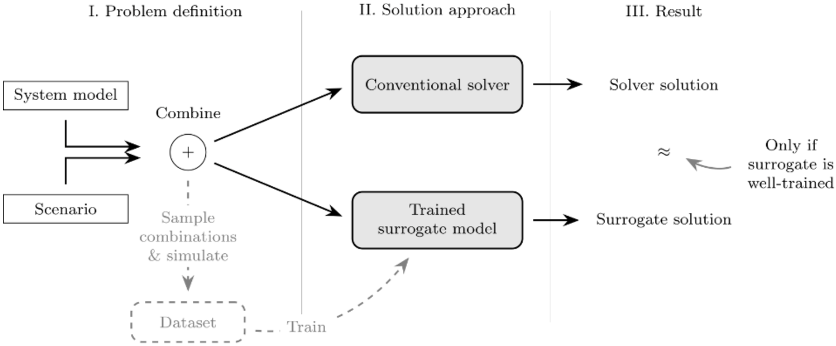
Abstract – Many tasks in the context of energy system analysis, operation, and planning require performing simulations and solving optimisation problems. Such simulations and optimisations often have significant run times and this computational burden increases further due to the growing modelling complexity associated with the energy transition. At the same time, the operation of the future energy system will likely rely even more on simulations and optimisations. To counter these trends, the acceleration of the solution algorithms is of central importance. To achieve such acceleration, we discuss in this talk, how machine learning-based models can serve as surrogate models for the established solution algorithms and where limitations and opportunities of this approach arise.

In this talk, we consider two examples: Time-domain simulations for power system dynamics and optimal power flow problems. They serve as instances of the general process that is shown in the figure below and is structured as follows: The problem is defined based on a system model and a scenario, these then become the input to the solution algorithm (conventional or surrogate), and the solution of these should closely match under the condition that the surrogate was well-trained. As a result, the surrogate could simply replace the conventional solver and, for example, for a standard neural network lead to a great acceleration. However, the condition that the surrogate is "well-trained" needs to be satisfied. This poses a major challenge as the space of all possible variations of the scenarios and system models becomes very high-dimensional. Learning an accurate surrogate will, therefore, require a large dataset, but this dataset needs to be simulated as data collected from the real world are not suitable for this purpose. We argue that this leads to a major limitation for the application of surrogates.

To address this limitation, we present two approaches: First, one can include so-called "inductive biases" in the models to improve their generalisation capacity. Examples of these biases are physics-informed loss terms in the training process and neural network architectures that ensure certain limits and symmetries which we know that they must hold. The second option is to combine learned surrogates with conventional solvers in hybrid schemes. Thereby, we can limit the dimensionality of the surrogate learning problem while benefiting from the flexibility of the conventional solvers.



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Bringing Load Disaggregation to the Consumer: Challenges and Lessons Learned

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Abstract – This paper presents the challenges and insights gained in the development and deployment of a consumer-oriented load disaggregation system, an important component of non-intrusive load monitoring (NILM) and Home Energy Management. Although load disaggregation has demonstrated potential in research contexts, its practical deployment encounters distinctive challenges. The paper draws attention to the discrepancy between the research priorities and consumer needs, underscoring the significance of accuracy and precision over recall in establishing user trust. It addresses the important role of usability, explainability, and efficient real-time analysis for gaining user engagement and system adoption. The paper discusses the technical challenges of implementing a near-real-time analysis system, including data storage and cost considerations. Furthermore, the importance of appropriate communication strategies to demystify the technology for non-technical users is drawn out. The authors introduce the FLEDGED project as initiative to bridge the gap between research and practical application. By sharing these insights, the paper aims to provide guidance for future research and development efforts in aligning load disaggregation technology with consumer expectations and needs.

1. Introduction

Load disaggregation, a fundamental aspect of Non-Intrusive Load Monitoring (NILM), has demonstrated encouraging outcomes in academic trials. Nevertheless, the transition of this technology to the consumer market presents distinctive challenges that extend beyond the capabilities of the underlying algorithms. This paper examines the challenges encountered and insights gained during the development and deployment of a consumer-oriented load disaggregation system.

2. Challenges and Solutions

In the field of energy disaggregation, from our perspective there is frequently a discrepancy between the priorities of academic research and the practical necessities of consumer applications. This section examines the way traditional performance metrics are balanced against user experience, system usability, and implementation challenges when developing real-world energy monitoring solutions. It considers the interplay between accuracy, precision, and recall, as well as the critical factors of usability, efficiency, and cost management that shape the success of consumer-facing disaggregation systems.

2.1 Accuracy, Precision and Recall

In research, the goal for classification tasks is typically of three metrics:

- accuracy
- precision
- recall

There are significantly more metrics, but these are at least considered in most studies. We however could not find studies comparing these metrics in the context of NILM and especially in real world cases. While an empirical study has yet to be conducted, our assessment is based on extensive practical experience. A study in this regard could prove a valuable contribution to the existing research.

Our practical experience shows that accuracy and precision are more important in our consumer application than recall. It has been observed that high recall at the expense of precision can lead to user distrust.

A tipping point in user acceptance was observed, which was primarily influenced by overall accuracy and precision. Once this threshold was reached, other system qualities became more significant, and further improvements in these metrics did not necessarily result in increased customer acceptance.

This phenomenon can be attributed to the divergence in priorities between research and practical application. While research is primarily concerned with enhancing the three metrics and efficiency of algorithms, users are predominantly interested in deriving insights and actionable recommendations from the results.

2.2 Usability and Explainability

Numerous studies have emphasised the need to introduce user-friendly interfaces, regardless of whether they fulfil the task at hand or not. There have been several studies on this, particularly in medicine. Applied to the field of NILM, we can confirm the same.

Most of the research in load disaggregation and NILM is focused on the improvement of algorithms. Nevertheless, the entire workflow, from the initial detection of a new consumer to subsequent training and automated recognition, is of critical importance for the successful adoption of the system by end users. However, this aspect is often overlooked in academic research.

The typical user is not technically proficient and wants to interact with the system via a mobile device. This necessitates an interface that conceals the system's complexity while providing an easily understandable workflow. The two most critical aspects are the user interface itself and the feedback cycle for the training.

To address this challenge, we continuously focus on developing a user-friendly interface that aims to simplify the complex underlying system. This approach improves user engagement and system adoption.

2.3 Efficiency and Live Analysis

Our user journey allows users to start training devices after controller setup with real time data.
This requires a fully automated system capable of near-real-time analysis. This is in contrast to typical research workflows that involve descriptive data analysis, model training, and subsequent data analysis. The data is usually stored on static files. To achieve this, we've adapted research findings for use in a data streaming platform, introducing new challenges in platform engineering and data pipelines.

2.4 Costs

Given that the data is sampled at 4 Hz -- every tuple produces 21 values -- and that over 15 TB have been collected to date, the storage system represents a significant consideration in our system. To meet the near-real-time analysis requirements, it is necessary to utilise fast-access databases for a significant proportion of the dataset, rather than relying on the more cost-effective cold storage options. The dynamic nature of the dataset, which is subject to growth of over 100,000 tuples per second, contributes to the substantial costs associated with data provisioning. To address this, specialised database technologies are being usied with the aim of significantly reducing the data volume by utilizing special codes and the costs associated with it.

3. Current and Future Work: The FLEDGED Project

To address the challenges presented here in a comprehensive way, we are engaged in the FLEDGED project. This initiative enables us to prioritise the enhancement of algorithm recognition while integrating our practical requirements and experiences from the outset. This approach reduces the need for extensive adaptation of research outcomes for practical application, thereby facilitating the transition from research to consumer products. Furthermore, our available data set from practice is highly relevant for science. In this way, both science and we as a company benefit from the project.

4. Conclusion

We presented some practical challenges associated with the implementation of load disaggregation aimed for consumers and tried to yield some crucial insights.
Although this represents only a subset of the broader challenges in the field it is evident that accuracy and precision are of high importance to gain the trust of the user.
Conversely, high recall, which is often emphasised in research, is of lesser significance in real-world applications. For non-technical users it is of the utmost importance that usability and explainability are prioritised. This leads to a focus on intuitive user interfaces and clear communication to foster engagement and system adoption.
The need for real-time analysis has introduced considerable engineering challenges, particularly regarding data streaming and storage. These issues require innovative solutions that can balance cost and performance.

These findings emphasise the need of adapting research outcomes to align with consumer expectations, ensuring that technological innovations are not only effective but also accessible and valuable to end users. However, it is important to acknowledge that these insights address only a portion of the broader challenges in the field of load disaggregation, indicating that further research and development are necessary to fully realise the potential of this technology in consumer applications.

The FLEDGED project represents a forward-thinking project where a part aims to align algorithmic advancements with practical needs from the outset, thus facilitating a more seamless transition from research to usable products. The project aims to apply federated learning techniques to low-voltage (LV) grid applications, addressing challenges such as data privacy, communication bandwidth, and system scalability. The project explores three main use cases. UC1 focuses on PV inverters, aiming to improve performance modeling and forecasting for PV generation without heavy data traffic. UC2 targets heat pumps, developing improved forecasts for domestic hot water and heat demand while enhancing privacy and security. UC3, where most of Watt Analytics contribution will be, concentrates on customer loads. It employs smart meter data for two key applications: 1) improving distribution grid state estimation and load forecasting through a global load forecasting model, and 2) clustering load profiles for user behaviour analysis. UC3 aims to enhance grid observability and stability while maintaining data privacy. It also investigates the potential of federated learning for high-resolution smart meter data analysis, which could provide valuable insights for energy communities and grid operators.

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Session 4

Transforming Energy Systems: Cutting-Edge AI and Data-Driven Solutions

Session Chair: Mark Stefan

HPC-enabled digital twin for modern power networks

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Abstract – This article presents the development of a High-Performance Computing-enabled Digital Twin (HPC-DT) as an innovative solution designed to significantly enhance real-time power system management for grid operators. It begins by providing a comprehensive overview of the HPC-DT architecture, detailing its key components and the technical methodology for integrating the digital twin with actual power systems. Following the architectural discussion, the article introduces a suite of specialized tools, many of which leverage the computational power of HPC systems, to illustrate the practical capabilities of the proposed concept.

1. Introduction

The energy transition towards 100% renewable energy systems necessitates innovative tools to support power system operators in managing networks, particularly in light of the challenges posed by replacing conventional synchronous generation with power electronics (PE)-interfaced renewable energy systems. These PE assets, which are increasingly being integrated into the system, fundamentally differ from conventional synchronous generators: they are programmable, lack mechanical inertia, provide limited short-circuit contribution, and can interact in a wide range of frequencies due to their embedded wideband control structures. Consequently, the power system is shifting from a high-inertia, slow-transient-based system to a highly dynamic and variable one [1]. In this context, operators are seeking innovative tools to maximize their network resilience and real-time performance during the energy transition period, recognizing that certain traditional tools will become progressively less useful or outdated [2]. For example, operators are increasingly shifting power network studies from Phasor-based simulations to Electromagnetic Transient (EMT) simulations, given the latter's capacity to capture with high fidelity the dynamics of modern power systems [3].

In this context, the concept of the Digital Twin (DT) has gained significant attention over the years [4]. While various definitions exist, a common understanding is that a DT involves a bi-directional communication between a physical object and its digital counterpart, enabling full integration and continuous synchronization between the two. This bi-directionality is what uniquely distinguishes DTs. The concept has been widely adopted across industries, with virtually every large-scale manufacturer implementing some form of DT in the past decade. In the power and energy sector, several companies have integrated DTs into their operations [5]. However, most existing DT applications in this sector rely on centralized computation, low-bandwidth communications, and historical data analytics, which are inadequate for capturing the fast dynamics inherent in renewable energy and power electronics-dominated networks, particularly at the device level. That being said, recent advancements in edge computing, high-bandwidth communications, and real-time data-driven analysis capabilities are being integrated into modern DT applications, significantly enhancing their ability to address the challenges posed by modern PE-dominated networks.

This article introduces the concept of a High-Performance Computing-enabled Digital Twin (HPC-DT), specifically designed to enhance the resilience and real-time performance of renewable power systems. The HPC-DT fully leverages the capabilities of High-Performance Computing (HPC) to represent large and complex power networks with the high fidelity required for analyzing and operating power electronics-dominated systems. By integrating vast amounts of data captured from power system measurements, the HPC-DT combines data-driven and physical models to provide an improved real-time assessment of the network's status. A critical aspect of this concept is the integration of HPC systems for coordinated analysis and global decision-making with distributed edge processing, enabling fast, local, and autonomous decisions. These enhanced capabilities pave the way for the development of an innovative suite of tools, further discussed in this article. It is important to note that the tools presented here are proposed to illustrate the potential of the HPC-DT system; they require further refinement, expansion, and validation before being fully deployed in modern power system operation control centers.

The article is structured as follows: Section 2 outlines the architectural framework of the HPC-DT, detailing its key parts and in Section 3 a portfolio of specialized tools to address specific challenges in power system management is presented.

2. HPC-DT architecture

This section introduces the architecture of the HPC-DT. Figure 1 presents a high-level conceptual diagram of the system, which is divided into two main components: the real power system and the Digital Twin. Within the Digital Twin, a suite of tools is available for the operator, supported by a hybrid HPC/Cloud/Edge architecture. These tools can be applied at the Edge, Server, or HPC level depending on their response time scale, input data requirements, and the distributed computing characteristics. Further details on the interactions between these components are provided in the subsequent sections.

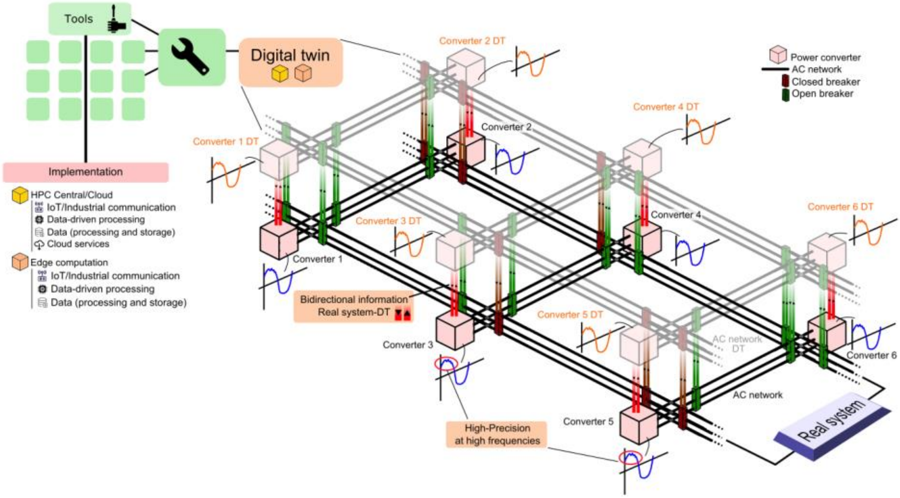

Figure 1. HPC-DT concept definition

The description of the functionality provided by the various components in the architecture is outlined according to the computing capacity of its IT elements, beginning with the resource-constrained components near the physical assets (Edge) and progressing through the Cloud or on-premise Server, where operators can manage their control systems, and ultimately leading to the extensive computing power provided by HPC systems. Three main blocks can be distinguished:

Edge computation: the edge nodes incorporate a software component which has three main purposes: interacting with the network physical elements (e.g., power converters, protections, etc.), send the state of the device to the DT, run a fast, local and autonomous control logic (e.g., AI-inference interaction detection and mitigation algorithm). In terms of implementation, these nodes could be embedded in the control systems of the physical devices.

Server: This asset gathers the information sent by the different edge nodes to present it to the system administrators to allow them to operate the network. This part also incorporates a database to capture historical data from the real network operation, which will be useful for implementing data-driven tools. In addition, the Server also allocates the different DT tools, although certain ones might be distributed across the Edge nodes. As a key particular tool, the Server incorporates the real-time network replica, where different options are considered: (1) Power flow; (2) Phasor; (3) EMT. The Server can be allocated in the Cloud or in a particular machine of the power system operator.

HPC: As a final part, some of the envisaged DT tools require a large computing power capacity that might not be present nor in the edge neither in the Server (depending on the implementation). For instance, training a data-driven model might require processing a large amount of data or the generation of new datasets to generate simple AI models to be deployed in the edge. Therefore, incorporating the access to an HPC system capable of finding the most suitable actions in the shortest time possible is a key feature of the DT. To orchestrate the tasks across the DT architecture levels the COMPS runtime [6] will be considered. COMP Superscalar (COMPSs) is a task-based programming model that allows developing and deploying applications in distributed architectures, abstracting the actual application from the underlying infrastructure. COMPSs can balance and orchestrate the load of tasks among edge nodes, cloud, and HPC, depending on the available resources at the different processing levels.

3. HPC-DT tools

The implementation of the HPC-DT includes different tools developed to maximize networks' resilience and real-time performance to be used by network operators. Each of the mentioned tools can transcend the envisaged HPC-DT application, as they could be individually implemented by network operators, provided that they have the required infrastructure in place. They have been separated in five different groups, to facilitate the description and classification.

T3.1 Online stability and interaction detection tools (Group A)
Tool A.1: Online stability assessment of power networks. This tool aims to provide real-time information on the stability of the system represented by the HPC-DT. A combination of conventional electrical engineering tools (e.g., eigenvalue analysis, participation factors, etc.), together with innovative data-driven methods, are used to provide information on the real-time stability and the margin towards instability of the system.
Tool A.2: Online interaction assessment between power system elements. This tool aims to detect real-time interactions in the system that the DT is representing. Based on the different measurements (edge) and the hybrid cyber-physical models running locally, this tool aims to first detect the interaction between system elements and possibly mitigate it acting locally.

T3.2 Real-time network performance tools (Group B)

Tool B.1: Real-time optimal operation of the network, avoiding system limitations (overload, overvoltage, etc.). This tool will run real-time Optimal Power Flows (OPF) to identify the optimal network operational state. The tool integrates dynamic stability constraints into the OPF formulation by leveraging Group A tools and data-driven techniques. These constraints are expressed as regression functions that map system stability within its operational space. The mapping is derived from offline synthetic dataset generation, after which the regression models are trained and incorporated into the OPF to account for stability limitations in static analysis. To optimize system operation fulfilling stability requirements, the optimization process and stability constraints enable adjustments to the system's operating point and modifications to PE control schemes and modes.

Tool B.2: Real-time network equivalents calculation. Builds online system equivalents at each bus of interest using real-time data such as topology and short-circuit power calculations. Equivalents can be calculated online and at each bus of the system (also with a high presence of power electronics, considering their short-circuit saturable characteristics).

T3.3 Protection with real-time measurements (Group C)

Tool C.1: Adaptive protection based on real-time measurements. Online monitoring of the short-circuit capacity (in power electronics-dominated networks) to assess if protections perform correctly when the short-circuit capacity changes. The tool is able to adapt the protection thresholds and coordination considering the real-time system topology and operative conditions.

T3.4 Probabilistic scenario generation tools (Group D)

Tool D.1: Probabilistic scenario tool. Based on the weather and additionally forecasted variables input, this tool aims to predict the state of the network in multiple time scales (+1min/ +15min / 24h, etc.) for improved decision making. Machine learning techniques are employed to select the most plausible scenarios, to reduce the number of cases to cover (especially when time is limited [1 min, 15 min]). Following this probabilistic scenario analysis, a decision/recommendation optimization-based sub-tool is developed to select the best actions for the sake of improving the network conditions (increase stability, reduce overloads, resilience increase, etc.). This tool can be blended with any of the previous ones, being an ideal complement to expand their scope.

T3.5 Autonomous real-time control tools (Group E)

Tool E.1: Real-time automatic/autonomous operation and control of power systems. This tool makes autonomous decisions acting over the real system, based on available information provided by the previous tools (Groups A-D). It provides recommendations/actions to be executed over the system and coordinates this set of actions, executing them in a secure and reliable manner. This tool is designed to close the loop between the HPC-DT and the real system, covering the different DT layers, including communications, processes, etc., ensuring that the actions can be applied. Its adequate operation relies on the input from other tools.

The presented tools, specifically designed for operators, leverage the key features of the HPC/Edge infrastructure, and while this suite represents a strong foundational proposal, it is inherently expandable and adaptable, allowing for the integration of additional tools.

4. Summary

The HPC-DT concept is an innovative tool designed to support power system operators in managing modern power networks. By integrating HPC, Cloud, and edge processing capabilities, this hybrid approach ensures that the system effectively handles the complex and dynamic nature of today's power grid, providing operators with a new breed of tools to enhance both the resilience and real-time performance of the grid, particularly during the energy transition.

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Development of AI agents for cellular energy systems to increase flexibilities provided by sector coupling and distributed storage

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Abstract – The rise in small-scale power production and high-energy consumers is straining the power grid, especially during peak hours. Addressing this challenge requires both infrastructure upgrades and innovative control strategies. This work introduces a modular architecture for integrating various Power-to-X (P2X) technologies, offering a universal, adaptive control solution. By employing an architecture for integrating several AI agents for optimization problems, we are able to provide different optimization mechanisms with their respective advantages or disadvantages. The proposed system optimizes the available flexibilities through different P2X technologies and aims to enhance the use of renewable energies within the energy cells.

1. Introduction

Due the augmenting surge of private small-scale power production like photovoltaic systems (PV) with energy storage solutions (ESS) and power-intensive consumers, i.e., A/C systems, heat pumps, and electrical Vehicle (EV) the power grid is pushed to its capacity limits especially during peak hours necessitating a number of countermeasures to guarantee uninterrupted power supply to all power network participants. As noted by multiple sources, e.g., see [1-2], high investments are required on all grid layers the prepare the transmission infrastructure for the power demand characteristics of decentralized renewable energy production and electrification of residential A/C systems and individual traffic. Especially the required expansion cost on the low-voltage level is regarded infeasible relative to acceptable cost for customers in the respective service area.

An auxiliary approach to power infrastructure expansion is the control and power limitation of noteworthy devices. With Demand-Response (DR) schemes having proved an effective solution to industrial power consumption, residential consumers, considered too complex in interface and communication, have been widely omitted.
Further developments of DR into the holistic electrical network are cellular energy system [3]. The electrical network is divided into cells of different hierarchical levels. The lowest cell can represent a household and the highest the entire network. The cells are autonomous but hierarchical optimized.

Thanks to recent developments, DR schemes, e.g., Open Automated Demand Response (OpenADR) [4], supports DR signaling down to the energy management system (EMS) of a residential household or the interoperability with the widely established Open Charging Point Protocol (OCPP) [5], a protocol between EV charging points and a dedicated management system.
Despite these advancements and various possibilities in data modeling thanks to the IEC 61850 standard [6] for the active control and interoperability, today’s landscape lags behind in comprehensively adopting to these options. Major reasons for their hesitant utilization are the lack of regulation for private appliances and the design of “energy communities” by the European Union as peer-to-peer networks in lieu of interoperable semi-autonomously controlling low-voltage energy clusters [7]. On this account, manufacturers of power-intensive devices define proprietary interfaces for (limited) interoperability among products of their own product line and the energy saving potential of a full integration of these appliances.
Thus, the continuing electrification of, i.a., the residential and transport sector, and the transition of energy production towards renewable sources cause a divergence and shift of daily power demand and production curves, necessitating new approaches of DR like cellular networks in the low-voltage sector. The current conservative integration of small-scale electronic devices is insufficient for a resilient distribution network and sustainable production system. This work proposes a novel interface between Power-to-X (P2X)-technologies and a controlling entity, that is universal, adaptive and bidirectional. The main contribution of this work is a module-based architecture facilitating seamless integration of various P2X technologies, regardless of the specific device or technology used to enable optimization via AI agents.
The paper is structured as followed. After the comprehensive introduction in Section 1, Section 2 gives brief overview of today’s technical possibilities and approaches in research. In Section 3 the system architecture is described with regard to national regulations, using, categorized flexibilities and including weather forecast to enhance the grid. The outcomes are outlined in Section 4 with a conclusion and an outlook given in Section 5.

2. State-of-the-Art

One of the biggest challenges in smart grids and for the development of the cellular energy system is the lack of an efficient power management system in the low-voltage. The main aspect of this management system is the control of the individual cells, depending, for example, on the local and cell-wide consumption forecasts, using flexible and efficient strategies and the exchange with the higher-level grid levels or neighboring cells [3,8].

In order to shape the demand curve and flatten peaks, the flexibility potential of power-intensive devices is exploited, e.g., EV charging stations are constrained in their maximum power consumption, see, e.g., [9,10]. Takc et al [9] find that EVs in their typical usage patterns hold untapped potential for charging delay or power downregulation. Contrarily, as for residential heating and air conditioning demand, despite being a major share of the overall residential power demand, endeavors predominately comprise the accurate demand prediction in order to adapt the production accordingly, instead of adjusting the ambient temperature, see [11].

The IEC 61850 standard along with its technical report IEC TR 61850-90-8 [12] proposes a practically thorough concept of how information about status and measurements is exchanged between a distribution substation and intelligent electronic devices (IED). Therein, IEDs are regarded as controllable devices that report measurement values to a superior entity. The specification of this standard does not account for the economic feasibility or user comfort of control commands.

3. System Architecture

It is deemed both infeasible and practically impossible that a control entity can effectively process all IEDs' internal states and measurements and be interoperable to all (proprietary) interfaces. The German Energy Industry Act (EnWG), §14a [13,14] foresees to allow grid operators to reduce the supply for certain appliances such as heat-pumps or EV-charging to up to 4.2 kW in case of an actual overload, but regulated to keep a minimum of access to these appliances and allow unrestricted general supply for the regular household electricity. IEDs must report nominal power consumption. They can set individual upper and lower limits for voluntary power adaptation. This flexibility is categorized as:

- *full*: The IED is able to compensate for the granted flexibility at a later point in time. This is however not necessary. This is valid for, e.g., non-volatile ESS.
- *shift*: The IED's flexibility shall be compensated for at a future point in time. An EMS should consider this flexibility for optimizing procedure. This is valid for, e.g., AC systems and heat pumps.
- *loss*: This IED's flexibility may not be available at a later point in time and cannot be compensated for. This is valid for, e.g., PV systems.

EMS systems benefit from indicative nominal values and bounds for optimization. The EMS sets the 'APPLY-FLEX-POWER' flag and forwards power/voltage values to inform embedded processes. IEDs can compensate for phase imbalances based on these values. The data model is shown in Figure 1.
A convenient extension of the proposed interfaces could be the weather forecast. With weather conditions directly influencing heating and A/C demand, the flexibility prediction significantly benefits from related forecast data.

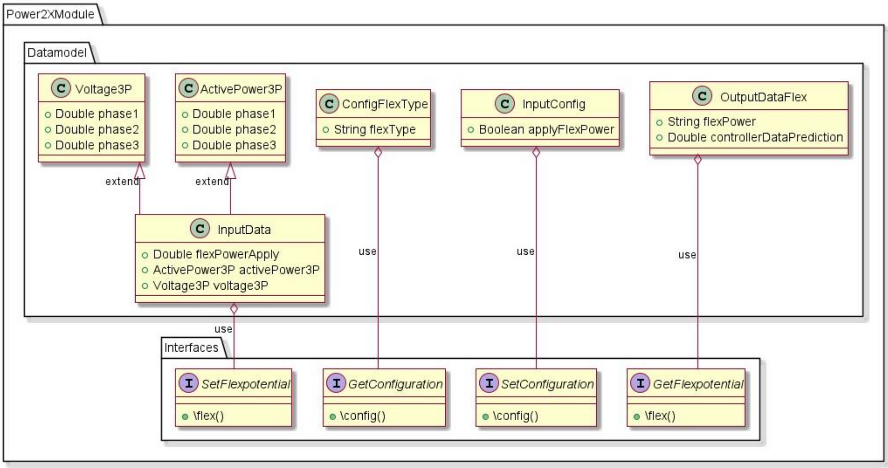

Figure 1. Data model and interface diagram of the general P2X-module

4. On the verge of a universal control solution

The dynamics and variety of smart grid optimization sets various soft and hard constraints to a control entity. Optimization goals, often linear, may only be met if the demand and production prediction can be sufficiently well planned in advance. The classical theory of optimization requires precise models to yield a satisfying solution, as applied as an example by Bauer et. al. in [15]. Reinforcement Learning (RL) presents itself as an alternative approach to this manifold problem, by learning from historical load and production profiles. The key paradigm in RL-supported smart grid control is choosing a sufficiently long training period that contains close to all system states and further states can be approximated, see [10,15]. Application of the Deep Deterministic Policy Gradient (DDPG) algorithm to the research task of IED control and flexibility optimization yielded auspicious results, seen in [15].

Runtime analysis of the DDPG algorithm has shown that non-linear reward functions in RL do not remarkably affect the calculation time in comparison to previous linear programming attempts facilitating more complex optimization targets.

Figure 2 shows a general outline on how the optimization works in the system. The DDPG is implemented and shows improvements against the baseline and optimization via Mixed Integer Linear Programming (MILP) [15]. Other implementations to be tested out will be: Proximal Policy Optimization (PPO), Self Attention, Artificial neural networks (ANN), and Convolutional neural networks (CNN). Rewards in these algorithms are considered with the following: provide and use flexibility, minimize total grid load and smoothing peaks in the grid.

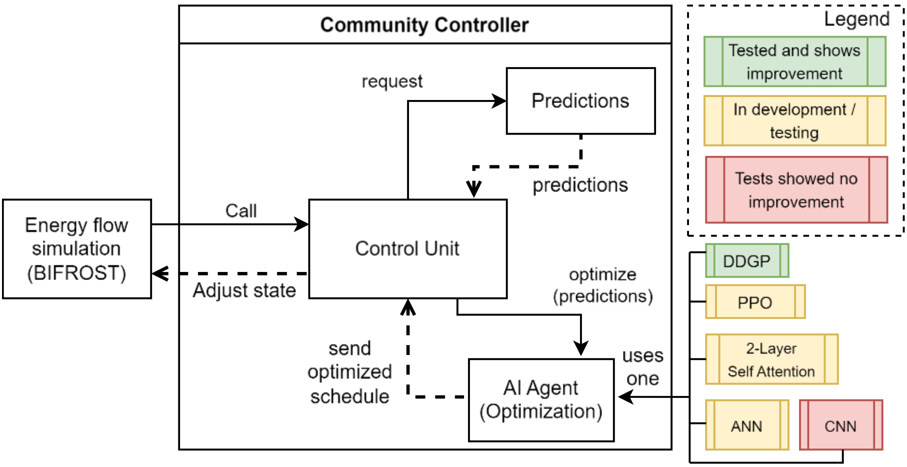

Figure 2. Outline of simulation flow and interaction between control unit and AI agents

5. Conclusion and Outlook

Overall, a modular architecture has been developed and an implemented RL algorithm has proved the capability to solve optimization problems more complex than could be solved with previous mathematical methods. As stated in Chapter 4, more algorithms are in active development and will be published in the final report and following works.

Acknowledgements

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The potential of linked data and semantic technologies in data platforms for urban energy planning

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Abstract – In the Digicities project, we are developing a platform to manage digital representations of real-world assets and energy systems using the best available data. A core aim of the project is to demonstrate the application of novel information technologies in the energy sector. This includes applying linked data and semantic technologies to represent and query interconnected data, using data spaces to ensure secure data exchange between data providers and data consumers, and modular deployment and cataloguing of digital services to enable scalable applications to be implemented across the sector. This contribution presents the potential of each technology for urban energy planning. It concludes with an outlook on how the Digicities platform will integrate these technologies to manage digital replicas to meet the evolving energy demands of modern digital cities. This contribution highlights the potential of linked data and semantic technologies to integrate the functionality of these components as a core feature of the platform. The platform is being piloted in use cases in Switzerland and Austria.

1. Introduction

Energy planning involves strategically assessing, developing, and managing energy resources to meet current and future energy demands while achieving sustainability and environmental targets. Planners often use simulation models to evaluate how the performance of an energy system will react to changing variables and environments. This functionality allows the planner to make assumptions and investigate scenarios into how the system will perform in the future. Knowledge of the most probable future situation is valuable, as it allows planners to optimize their current activities to meet future strategic targets. However, it is already a challenge to determine the current system's performance, particularly at high resolutions, e.g. building scale or behind-the-meter. Digital transformation provides an opportunity to gain a deeper understanding of the energy system's performance; however, robust data practices must be followed to ensure the availability of high-quality, reliable data. Data identification, collection and processing are some of the most time-consuming activities in energy planning. Challenges in data quality, completeness, availability and ownership further complicate this. Digital service providers can find themselves accommodating additional data processing functionalities rather than focusing on their specialist expertise, leading to inefficiencies in the digital value chain. It is more desirable if the system owner already has the best available data to represent their system, which they can then provide to their chosen digital services to gain insight. The Digicities project recognizes the need for a framework to support the creation of such digital replicas of the physical systems.

2. Urban Energy Planning

Municipalities begin transitioning to renewable energy systems "through the formulation of strategies and goals at a local level despite often lacking appropriate tools and resources to conduct the needed complex analyses. Tools for energy system analyses have traditionally been designed either with the scope of national energy systems or detailed project-specific analysis in mind, leaving municipal planners in a state of flux." (Johannsen et al., 2021). There is often inconsistency in harnessing renewable energy potential due to a lack of capacity in local communities (Kleinebrahm et al., 2023); this can also lead to subcontracting of energy planning, leaving municipalities with limited control of the assumptions and outputs of the plan. Other barriers to energy planning include technical challenges and unwillingness or inability to share data. Carrying out energy planning can also be time-consuming and inefficient because each municipality has to create their own methodology and identify and process the required data individually.

The research community have developed several open-source tools to build energy models for strategic decision-making, e.g., Calliope, OSeMOSYS, PyPSA, CEA and TIMES. These slightly vary in their approach to the modelling and simulation of energy systems, but all require a definition of the energy system considered. The scope of energy planning depends on the scale of the evaluated system; for example, national-scale planning has a different focus than municipal-scale planning despite sharing a similar methodology. Regardless of the scale, there are common ways to describe the energy systems of interest. Energy systems are commonly defined by considering the following entities and properties: energy demands, resource potentials, conversion & storage technologies, networks, import & exports, constraints, policy, legislation, infrastructure costs, targets and goals. The data requirements also change throughout the planning process. As the planning process moves from pre-concept to feasibility, the need for detailed, high-quality, and integrated data becomes increasingly critical. Addressing these challenges requires robust data management practices, sophisticated modelling and analysis tools, and close collaboration among stakeholders to ensure that the planning process remains aligned with the overall objectives of the study

3. Information Technologies for Urban Energy Planning

3.1 Semantic and linked data technologies

Semantic web technologies are standards to improve data interoperability, contextual understanding and exchange between knowledge domains. Ontologies are a component of semantic web technologies that describe entities according to a shared and structured framework of concepts and relationships. This allows consistent data interpretation, interoperability, and reasoning across systems and domains. Data linking is also a component of semantic web technologies, allowing for the representation of properties that connect entities found in energy systems and energy networks. The use of a linked graph can capture the complex relationships found in societal, economic, technological, and environmental factors that influence energy systems, and queries can traverse through the complex graph relationships, which can be challenging in relational database systems (Đukić et al., 2024). Semantic technologies also help represent different physical scales and how information should be handled when transforming data across different scales, for example, from individual buildings to districts. While semantics are promising, a review found an abundance of ontologies developed in the energy sector for a specific purpose or project and then abandoned (Tzouvaras et al., 2023). This highlights the need for ontologies to be deployed and documented with a specific implementation to demonstrate the value and relevance to future applications.

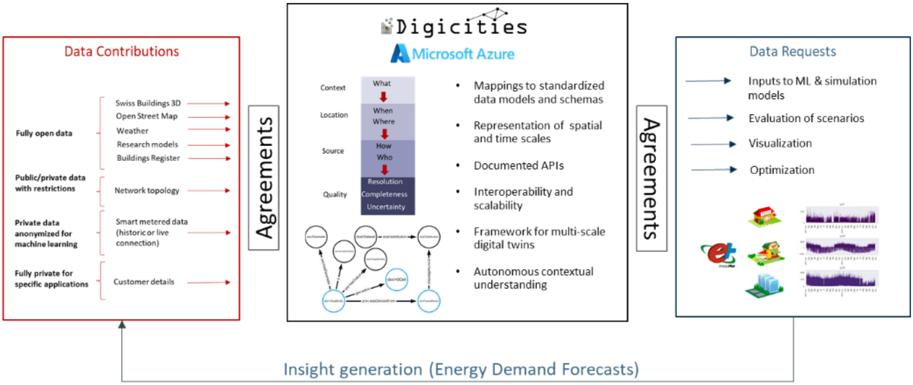

Figure 1. An overview of the data processes handled by the Digicities platform.

Figure 1 provides a conceptual overview of the processes covered in the Digicities project. The Digicities platform is shown in the centre and has a set of semantic requirements that data must adhere to when uploaded to the platform by the data contributors (Allan et al., 2023). These data contributions are categorized according to the conditions of access. Data is requested from the platform to feed machine learning or simulation models. These services generate insight that is fed back as a data contribution. Data usage agreements are implemented between the contributions and the requests, stating the terms of usage and restrictions.

The Digicities platform will handle the semantic representation of the system, including a terminological layer containing the ontologies and a meta-model to handle assumptions, scenarios and provenance and an assertional layer to handle instance data to represent facts about the modelled system. In addition to semantic technologies, traditional databases will be incorporated to handle attribute data. These values will be subject to modification according to assumptions and scenarios.

3.2 Data spaces for urban energy planning

The European Commission defines data spaces as a "secure and privacy-preserving infrastructure to pool, access, share, process and use data"[8]. Data spaces have emerged in the energy sector and offer a promising approach to control data exchange and integration, overcoming fragmented applications and data silos in the energy sector (Janev et al., 2021). The International Data Spaces Association (IDSA) provide standards and rules for exchanging data as part of data space. However, as of August 2024, the protocol detailing rules[9] to facilitate seamless data exchange is in draft status. When exchanging data in a dataspace, it is desirable if the data is ready for analysis without the need for additional processing. Open Data Products (ODPs)

[8] https://joinup.ec.europa.eu/collection/semic-support-centre/data-spaces [Accessed 28/08/24]
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are a potential solution to provide analysis-ready data to the consumer. An ODP can make (geo)data accessible and turn disparate and unstructured data into useful information for a broader audience; however, transparent and trustworthy handling is required (Arribas-Bel et al., 2021). The Open Data Product Specification (ODPS) "is a vendor-neutral, open source, machine-readable data product metadata model"[10] to describe ODPs. An example of ODPS's use is improving internal transparency and reusing valuable data.

3.3 Modular deployment of applications

The Digicities framework is being implemented on a cloud-based platform. Cloud infrastructures allow scalable computing power to handle increasingly complex urban energy challenges. Modular services allow for flexible deployment of applications that can be defined in terms of their specific data requirements. Modularity is designed to support the emergence and integration of new technologies and methodologies as the sector evolves, such as integrating data from smart meters. Modularisation of services in Digicities is achieved by containerizing scripts and implementing an API communication infrastructure between the different services within the platform.

4. Conclusion

Urban energy planning requires information from diverse data sources to evaluate and predict the performance of energy systems. Energy system modelling has increasingly complex data requirements; accommodating these can be challenging for individual applications. Standardization is necessary to improve the efficiency and scalability of energy planning processes reliant on data. In Digicities, a cloud-based platform is being developed to demonstrate how a digital representation of an energy system can be managed and connected to different digital service providers. The core technical features of the framework are summarised below:

Semantic and linked data technologies: Enables complex relations to be stored in a graph that can be queried to provide advanced analytics. This is useful due to the interconnected nature of energy system data.

Data spaces and open data products: Provides a secure environment to exchange data between providers and consumers. Data usage agreements are formalized in the data space, giving data providers confidence that any data usage adheres to the policy. This can help overcome some of the barriers to data exchange within the energy sector. Terms in the ODPS can also be incorporated into the semantic meta-model to facilitate transparency in the data sources used in urban planning studies.

[10] https://opendataproducts.org/

Modular applications: Modularity enables applications to be defined with their data requirements. This aims to provide managers of the digital replica with many options to gain insight into the performance of their system.

Each feature is considered equally important in implementing an effective solution to managing a digital replica in the energy sector. The Digicities platform will be piloted for use cases in Switzerland and Austria.

5. Acknowledgements

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AI-based approaches for automated high-precision energy forecasts

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Abstract - Artificial intelligence (AI) is increasingly recognized as a powerful tool for enhancing the accuracy and efficiency of performance forecasting in renewable energy systems. As the integration of renewable energy sources like solar, wind, and hydropower into the grid continues to grow, accurate forecasting becomes essential for optimizing energy production, balancing supply and demand, and reducing operational costs.

In response to these needs, UBIMET has developed a hybrid forecasting approach that combines machine learning (ML) models with calibrated physical models to predict the performance of wind, solar, and hydro energy systems. This approach leverages neural networks, e.g. multilayer perceptron regression, to effectively correlate historical performance data with numerical weather forecasts. Furthermore, the incorporation of real-time data through a post-processing step significantly enhances prediction accuracy. The resulting forecasts are adaptable across various scales, from transmission grid level to energy portfolios down to individual facilities, and can cover different time horizons, from short-term (15 minutes) to longer-term (10 days) predictions. This hybrid approach offers a robust solution for improving the reliability and efficiency of renewable energy integration into modern power systems.

This presentation will give an overview of UBIMET's high-precision forecasting system for renewable energies, based on AI and weather data. An example will illustrate how UBIMET uses weather data to develop physically motivated features for its hydro energy model.

Authors

David Plavcan, MSc holds a Master's degree in Meteorology, specialized in statistical analysis and forecasting. He has been a Senior Scientist at UBIMET GmbH since 2016 and is a specialist in weather analytics and plays a crucial role in developing advanced statistical and machine learning approaches for forecasting. Among others, he is responsible for AI based weather and energy forecasting and contributes to numerous research projects in this field.

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Supported by the H2020 Programme under Contract No. 870620

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GOALS

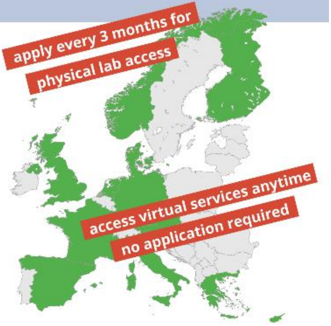
- support the research, technology development, and innovation of smart grid and smart energy systems approaches, concepts, and solutions in Europe taking a holistic and cyber-physical systems-based approach into account
- provide system-level support and education for industrial and academic researchers in power and energy systems research and technology development

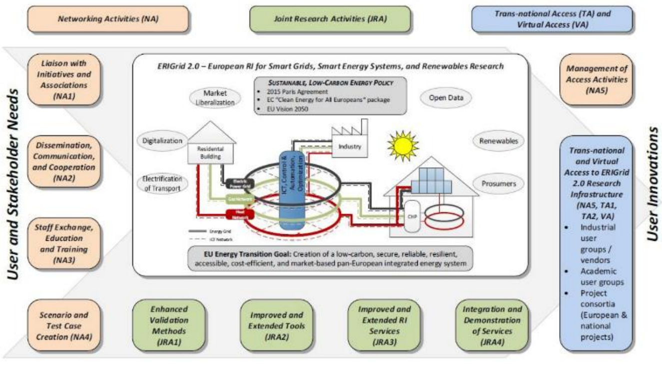
NETWORKING OBJECTIVES

- knowledge-exchange with other European smart grid and smart energy systems RIs
- knowledge transfer between researchers, technicians, and RI managers
- Open Access (OA) provision of achievements and reinforced collaboration with industry and energy utilities
- international collaboration and harmonization

RESEARCH OBJECTIVES

- enhance system-level validation methods
- improve and extend tools to accommodate system-level tests over multiple test infrastructures and domains
- implement and demonstrate the developed concepts, methods, and tools into the research insfrastructures (RI) of the ERIGrid 2.0 partners





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