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AISOP

AI-assisted grid situational awareness and operational planning

AISOP

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The author of this report bears the entire responsibility for the content and for the conclusions drawn therefrom.

Summary

Driven by the Energy Strategy 2050 targets, Swiss utilities are investing in advanced planning, control, and flexibility solutions to cost-effectively integrate distributed renewable energies and address the rising electricity demand from the electrification of heating and mobility. Digitalization and intelligence in operational planning play a significant role in guaranteeing the connection of renewable generation and new loads while avoiding excessive grid reinforcements. As the deployment of these technologies accelerates, analysis and planning tools are required to offer new capabilities that go beyond the integration of GIS data.

Within the framework of the AISOP project, a Digital Process Twin (DPT) concept is proposed to support data-driven decision-making for DSOs. The DPT facilitates the integration and systematic management of measurement data and simulation outputs through dedicated workflows intended to help distribution system operators run an operational planning process providing accurate estimations of voltage and load conditions to support active network management strategies.

As part of the operational planning process, non-intrusive flexibility mechanisms such as dynamic electricity tariffs, were combined with a grid awareness risk analysis concept by incorporating measurements and simulation data. The integrated analysis presented a promising alternative to influence end-user behavior. These tariffs can incentivize consumers and prosumers to adapt their consumption or generation profiles in alignment with grid conditions. To this end, a dynamic tariff simulation framework is developed within the scope of AISOP project that builds upon the DPT workflows and incorporates machine learning techniques to update grid usage tariffs for both load and generation in near real time. Such an approach becomes particularly valuable in scenarios where more flexible, adaptive, and user-aware distribution grid management creates value, complementing traditional grid reinforcement measures.

These tools can support the assessment of available grid capacity, detection of risks of overloading critical assets, and ultimately provide direct input to operational scheduling and maintenance strategies, and long-term infrastructure planning that considers future regulatory and digitalisation scenarios. In future implementations, DPT technology has the potential to serve as an initial step toward identifying optimal grid reconfiguration scenarios, enhancing flexibility and resilience in distribution systems.

Zusammenfassung

Getrieben von den Zielen der Energiestrategie 2050 investieren die Schweizer Energieversorger in fortschrittliche Planungs-, Steuerungs- und Flexibilitätslösungen, um dezentrale erneuerbare Energien kosteneffizient zu integrieren und den steigenden Strombedarf durch die Elektrifizierung von Wärmeversorgung und Mobilität zu decken. Digitalisierung und Intelligenz in der Betriebsplanung spielen eine wesentliche Rolle, um den Anschluss erneuerbarer Erzeugung und neuer Verbraucher zu gewährleisten und gleichzeitig übermässige Netzverstärkungen zu vermeiden. Damit sich der Einsatz dieser Technologien beschleunigt, sind Analyse- und Betriebsplanungswerkzeuge erforderlich, die über die GIS-Integration hinausgehen.

Im Rahmen des AISOP-Projekts wird ein Digitaler Prozess Zwilling (DPT) entwickelt, um die datengetriebene Entscheidungsfindung für VNB zu unterstützen. Wie in dieser Arbeit skizziert, wird im Rahmen des AISOP-Projekts ein DPT-Konzept vorgeschlagen, um die datengetriebene Entscheidungsfindung für VNB zu unterstützen. Der DPT erleichtert die Integration und systematische Verwaltung von Messdaten und Simulationsausgaben durch dedizierte Workflows, die Stromnetz-Überwachung, genaue Schätzungen der aktuellen als auch der prognostizierten Spannungs- und Lastbedingungen im Verteilnetz ermöglichen.

Neben aktiven Netzmanagementstrategien stellen nicht-invasive Flexibilitätsmechanismen wie dynamische Stromtarife eine vielversprechende Alternative dar, um das Verhalten der Endnutzer zu beeinflussen. Diese Tarife können Anreize für Verbraucher und Prosumenten schaffen, ihre Verbrauchs- oder Erzeugungsprofile an die Netzbedingungen anzupassen. Zu diesem Zweck wird im Rahmen des AISOP-Projekts ein dynamischer Tarifsimulationsansatz entwickelt, der auf der DPT-Workflows aufbaut und Techniken des maschinellen Lernens einbezieht, um die Netznutzungstarife sowohl für die Last als auch für die Erzeugung nahezu in Echtzeit zu aktualisieren. Ein solcher Ansatz ist besonders wertvoll in Szenarien, in denen ein flexiblerer, adaptiverer und nutzerbewussterer Verteilnetzbetrieb einen Mehrwert schafft und traditionelle Netzverstärkungsmassnahmen ergänzt.

Diese Tools können die Bewertung der verfügbaren Netzkapazität und die Erkennung von Risiken einer Überlastung kritischer Anlagen unterstützen und schlussendlich einen direkten Beitrag zur Betriebsplanung und zu Wartungsstrategien sowie zur langfristigen Infrastrukturplanung leisten, die zukünftige Regulierungs- und Digitalisierungsszenarien berücksichtigt. In zukünftigen Implementierungen hat die DPT-Technologie das Potenzial, als erster Schritt zur Ermittlung optimaler Szenarien für die Netzrekonfiguration zu dienen und so die Flexibilität und Resilienz von Verteilungssystemen zu erhöhen.

Résumé

Motivées par les objectifs de la Stratégie énergétique 2050, les entreprises suisses de services publics investissent dans des solutions avancées de planification, de contrôle et de flexibilité afin d'intégrer de manière rentable les énergies renouvelables distribuées et de répondre à la demande croissante d'électricité liée à l'électrification du chauffage et de la mobilité. La numérisation et l'intelligence dans la planification opérationnelle jouent un rôle important pour garantir le raccordement de la production d'énergie renouvelable et des nouvelles charges, tout en évitant des renforcements excessifs du réseau. À mesure que le déploiement de ces technologies s'accélère, les outils d'analyse et de planification doivent offrir de nouvelles capacités allant au-delà de l'intégration des données SIG.

Dans le cadre du projet AISOP, un concept de jumeau numérique de processus est proposé pour soutenir la prise de décision fondée sur les données pour les gestionnaires de réseaux de distribution. Le jumeau numérique de processus facilite l'intégration et la gestion systématique des données de mesure et des résultats de simulations grâce à des flux de travail dédiés destinés à aider les opérateurs à surveiller leurs actifs et qui fournissent des estimations précises des conditions de tension et de charge afin de soutenir des stratégies de gestion active du réseau.

De plus, des mécanismes de flexibilité non intrusifs tels que les tarifs d'électricité dynamiques constituent une alternative prometteuse pour influencer le comportement des utilisateurs finaux. Ces tarifs peuvent inciter les consommateurs et les prosummateurs à adapter leurs profils de consommation ou de production en fonction des conditions du réseau. À cette fin, une approche de simulation tarifaire dynamique est en cours d'élaboration dans le cadre du projet AISOP. Ce cadre s'appuie sur les DPT workflows et intègre des techniques d'apprentissage automatique pour mettre à jour les tarifs d'utilisation du réseau, tant pour la charge que pour la production, en temps quasi réel. Une telle approche s'avère particulièrement précieuse dans les scénarios où une gestion du réseau de distribution plus flexible, adaptative et axée sur l'utilisateur crée de la valeur, en soutenant les mesures traditionnelles de renforcement du réseau.

Ces outils peuvent faciliter l'évaluation de la capacité disponible du réseau, la détection des risques de surcharge des actifs critiques et fournir des informations directement exploitables pour la planification opérationnelle, les stratégies de maintenance et la planification à long terme des infrastructures, en tenant compte des scénarios réglementaires et de numérisation futurs. Dans les projets futurs, la technologie DPT pourrait permettre d'identifier des scénarios optimaux de reconfiguration du réseau, améliorant ainsi la flexibilité et la résilience des systèmes de distribution.

Main findings («Take-Home Messages»)

→ DSOs need tools and methodologies to leverage smart meter and grid sensor data. This enables better understanding of available capacity for safely integrating new demand and generation, such as EVs, heat pumps and distributed solar PV. Developing these solutions requires coordination across operational technology, IT, software providers, and internal DSO departments.

→ DSOs will benefit from modular digital process twin frameworks that integrate and verify heterogeneous data from physical assets and business processes into a Single Source of Truth (SSoT), automating analytics and supporting operational planning. Data interoperability remains a key challenge, therefore open standards are essential to enable cross-system data flow and prevent vendor lock-in.

→ ML and AI applications for operational planning show strong potential when combined with grid models and data from smart meters and sensors. However, robust performance requires understanding the type and amount of data needed for sufficient knowledge extraction, which is critical for practical feasibility. Using established algorithms ensures robust, explainable systems.

→ Dashboards help utility engineers visualize operational information efficiently, but effectiveness requires easier user interaction and integrated intelligence. While technology for intelligent assistants is evolving rapidly, challenges around dependency on large-scale AI platforms and robustness remain significant.

→ Dynamic grid tariffs for demand and distributed generation can influence end-user behavior without direct control. To avoid rebound effects in high-proliferation scenarios, tariffs must be both temporally and spatially differentiated. Maximum benefits require dynamic feed-in tariffs as well.

→ End-users responding to price signals by shifting demand or deploying storage can optimize their benefits. This grid-friendly flexibility is significant with automation, but requires carefully designed, spatially differentiated tariffs. While this can postpone or reduce grid investments, it cannot eliminate them entirely.

Contents

List of abbreviations

AI	Artificial Intelligence
BESS	Battery energy storage system
DER	Distributed Energy Resources
DG	Distributed Generation
DPT	Digital Process Twin
DSM	Demand Side Management
DSO	Distribution System Operator
DT	Digital Twin
EMT	Electromagnetic Transient
EV	Electric vehicle
GenAI	Generative AI
GKE	Google Kubernetes Engine
HEMS	Home Energy Management System
HP	Heat pumps
LLM	Large Language Model
LV	Low Voltage
ML	Machine Learning
MLT	Machine Learning Technique
MV	Medium Voltage
MVDS	Minimum Viable Data Space
NL	Grid or network level
OP	Operational planning
OPF	Optimal Power Flow
PMU	Phasor Measurement Unit
PQ	Power Quality
PV	Solar photovoltaic
RE	Romande Energie
RES	Renewable Energy Sources
SA	Grid Situational Awareness
SCADA	Supervisory Control and Data Acquisition
SFOE	Swiss Federal Office of Energy
SM	Smart Meter
SSoT	Single Source of Truth
ToU	Time-of-Use
TSO	Transmission System Operator
WWN	Westfalen-Weser Netz

1 Introduction

1.1 Context and motivation

Digitalisation of the electric energy systems creates opportunities to improve grid situational awareness and operational planning. As distribution grids incorporate more renewable energy sources and demand becomes more flexible (i.e., prosumers), more information about the current and future state of the grid becomes vital for operating the grid in a cost-effective way. Digitalization is therefore essential, as it facilitates data acquisition and processing. As distribution system operators (DSOs) explore the use of monitoring solutions, the volume of data and the associated costs increase. Thus, automated processes are required to manage and use energy system data to the advantage of DSOs. However, these processes need to ensure data protection and security and be designed in a way that improves the quality of underlying data sources.

AISOP aims at creating AI-assisted decision support tools for DSOs that securely and privately acquire data using state-of-the-art digital platforms. Such system processes and interprets data to generate knowledge for situational awareness and dynamic tariff setting. Using heterogeneous data, the overall objective is to improve operational planning in active distribution grids by integrating AI- or ML-based solutions, enhanced situational awareness, and market incentives. Thus, it combines (i) data access and ingestion, (ii) distribution grid situational awareness, (iii) decision-support for distribution grid management, (iv) dynamic tariffs, and (v) digital platform integration.

Traditionally, operational planning prepares TSOs for real-time operation such that the probability of experiencing unexpected deviations in the balance of supply and demand is minimized. Such operational planning has not been necessary for distribution systems as the end-customers are only consumers of electricity. However, as the distribution systems are preparing for unprecedented levels of prosumers, DSOs will benefit from planning schemes in the long-term (decades), the near-term (multiple years), operational planning schemes (intraday to weeks/seasons). Such operational planning schemes, need good information of the current and future grid situation [1–4]. Specific applications include better control renewable energies taking into account uncertainty [5], and dynamic pricing of electricity to incentivize flexibility of demand and ameliorate grid congestion issues [4, 6]. The focus of AISOP lies on tools for situational awareness, facilitating information access from smart meter and grid sensors data, to support operators reach a better understanding of how their grids are operating, and to design dynamics tariffs that overall support DSO operational planning decisions. These tools are envisioned to inform on intraday, day-ahead, and yearly timescales.

The AISOP project was funded in the framework of ERA-Net Smart Energy Systems (SES) Joint Call 2020 on Digital Transformation for Green Energy Transition (MICall20), supported by the Swiss Federal Office of Energy and the consortium consists of three (3) research groups, two (2) digital platform providers, and two utilities from Germany (TU Dortmund ZEDO, logarithmo, WW Netz) and Switzerland (HSLU, FEN at ETH Zürich, Hive Power, Romande Energie). The overall AISOP habitat is presented in Figure 1, designed to appropriately address the project objectives.

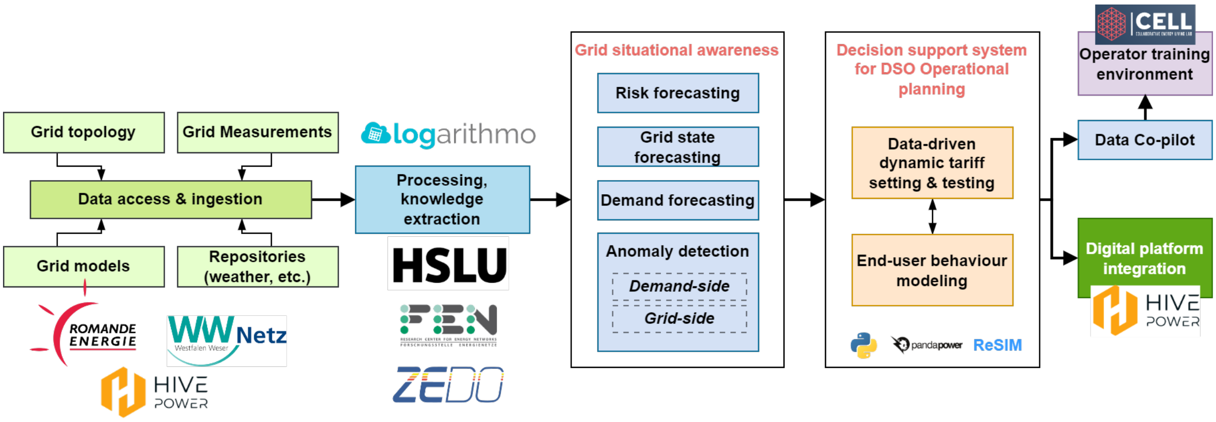


Figure 1: AISOP consortium and the overall habitat.

1.2 Project objectives

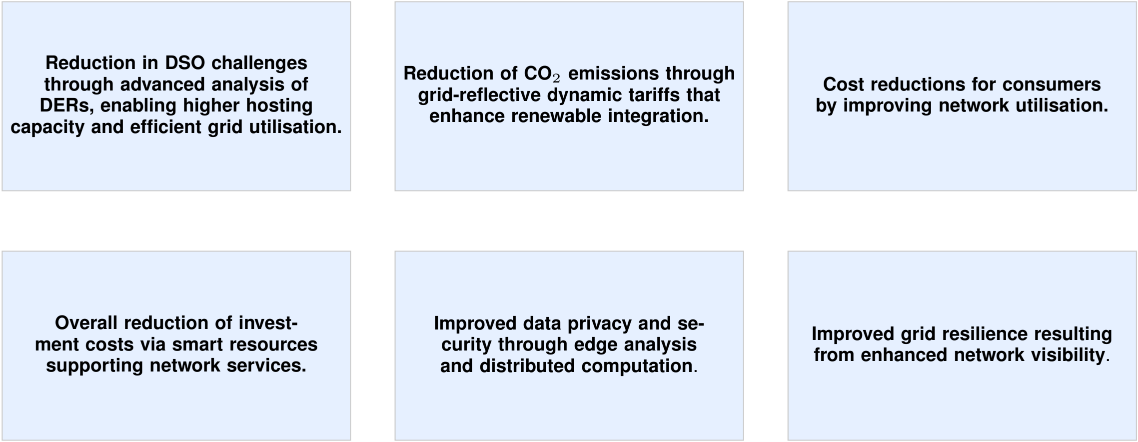
The AISOP project objectives are:

- to facilitate increased grid observability by using data from multiple sources,
- to help DSOs integrate an operational planning approach for proactive grid operations using data-driven decision support tools,
- to improve the efficiency of network operations,
- to reduce curtailment of renewable energy and distributed energy resources, and
- to improve options for tariffs for DSO's and prosumers.

AISOP's solutions will acquire, process, interpret and exploit data at different time resolutions for the benefit of DSO operational planning, integrating AI/ML-based solutions, enhanced situational awareness, and market incentives. The project aims to create actionable, tangible, and applicable outcomes for distribution systems to improve operational planning and support decarbonisation. The outcomes will take the forms outlined in Table 1. In addition to the outcomes, AISOP aims to contribute to environmental and socio-economic goals as described in Figure 2.

Table 1: AISOP project aims.

Methodologies and knowledge	Technologies	Services
Accessing and combining **heterogenous**, dispersed datasets	**Data analytics**, forecasting, end-user optimisation	**Dynamic tariffs**
Developing **grid situational awareness** using edge and embedded network devices	ML-based **anomaly detection**	DSO congestion management
ML-based **risk analysis** and risk quantification	**Digital process twin** for distribution systems	Fault detection
AI/ML-based identification of **dynamic tariffs** for congestion management	Embedded and distributed sensors for LV and MV networks	Operational risk management



Reduction in DSO challenges through advanced analysis of DERs, enabling higher hosting capacity and efficient grid utilisation.

Reduction of CO_2 emissions through grid-reflective dynamic tariffs that enhance renewable integration.

Cost reductions for consumers by improving network utilisation.

Overall reduction of investment costs via smart resources supporting network services.

Improved data privacy and security through edge analysis and distributed computation.

Improved grid resilience resulting from enhanced network visibility.

Figure 2: Environmental and socio-economic objectives in AISOP.

1.3 Research approach

The activities undertaken to progress from a concept of decision support towards a demonstration of non-intrusive control via dynamic tariffs were structured as follows.

- **Decision Support Concept**: Activities related to understanding and identifying DSO needs for decision support systems and barriers to their implementation, including background research on applications of AI for grid situational awareness and for creating dynamic tariffs. Interviews were conducted with personnel working on grid operations and a technical session was organized in a machine learning conference to engage a broader audience resulting in the selection of specific approaches described in Sections 2.1, 3, and 4.
- **Digital Process Twin Context**: Activities concerning digital twin and digital process twin frameworks in collaboration with consortium partners and advisors. State-of-the-art review of digital twin methodologies and implementation paths resulting in the definition of core components, requirements, and scope within our project as described in 2.1 and 2.2.
- **Grid Situational Awareness Model**: Activities defining analytics and simulation processes and tools, including mapping of relevant data and surveying data management approaches leading to workflows for data analysis and power flow simulations described in Sections 2.3 and 3 Moreover, the connection to the design of dynamic tariffs was investigated leading to the implementation of end-user models that respond to price signals and the methodologies for dynamic tariffs as described in Section 4.
- **Virtual Demonstrator**: These activities aimed at prototyping a decision support system that creates/suggests/updates dynamic tariffs and evaluates the impact of the change in end-user behaviour on LV grids based on these dynamic tariffs. Data federation tools and data catalogue schemes were explored, data from pilot sites were used to create scenarios, and the respective end-user, dynamc tariff and grid models were integrated into ReSIM simulation environment as described in Sections 2.2, 4 and 5.

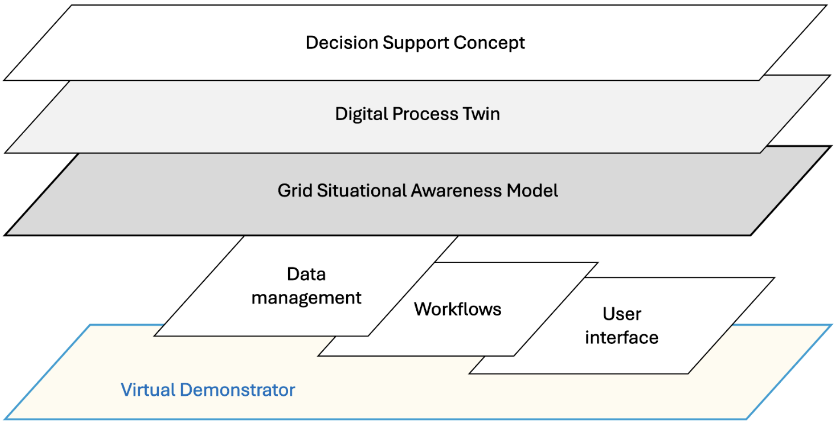


Figure 3: From concept to virtual demonstration of decision support for operational planning.

2 Grid situational awareness to support operational planning

This section describes the grid situational awareness model that is framed in a cyber-physical power system and casted into a digital process twin described in Section 2.1. Functional requirements and workflows are addressed in Sections 2.2 and 2.3.

2.1 Digital process twin framework

Digital Twins and IoT technologies can be leveraged to compose a modular framework that executes specific data analysis and simulation workflows to analyze the impact of future grid and demand conditions on the grid. In this way, creating a digital process that provides knowledge of the grid situation and projections of the next hours or days. Our approach is structured around the layers of a cyber-physical power system.

- **Physical Layer** corresponds to the grid and sensors themselves where data acquisition begins, and automatic control actions or human interventions need to take place.
- **ICT Layer** encompasses the entire software framework with the following core building blocks: data verification process, permanent data storage, physics and data-driven models, and knowledge extraction.
- **Human Layer** represents the grid operator business units and personnel in charge of network or fault management, cyber-security, maintenance activities, or other business applications.

Often, differentiation between DT and DPT is obviated. However, a proper conceptualization brings clarity to the digital strategy of DSOs and the corresponding allocation of effort, prioritization of steps, and selection of commercial or open tools towards the implementation of such technologies. Table 2 offers a basic view on the focus of DTs, which is centered on physical assets, their monitoring, prediction of their lifetime, and optimization of their performance during operation. The focus of DPT, on the other hand, is on process automation. It encapsulates or connects models, or even DTs, to automate workflows that realize operational, planning, or business processes.

Table 2: Characteristics and focus of DT and DPT. Note that in the German-speaking world the term *Digitaler Zwilling der Betriebsmittel* also exists to refer to a DT of machines used to produce goods in a factory, and sometimes this term leans towards a DPT.

	Digital Twin (DT)	Digital Process Twin (DPT)
Scope	A physical asset and its components.	Operational planning, long-term infrastructure planning, or business processes.
Example	A substation DT comprises models of transformer and relay systems, incorporating data from automation and SCADA systems.	An operational planning DPT comprises grid models, tools for creation of load and generation scenarios incorporating data used by DTs, plus technology adoption data and data from advanced metering infrastructure.
Use case	Monitoring of component state and estimation of future component condition to support maintenance scheduling.	Scenario simulations for congestion management, voltage violations, contingency analysis, grid tariffs calculation or cost-benefit analysis of grid reinforcement strategies.

On this basis, we conceptualized a DPT system that lives in the ICT layer, unlike other approaches that combine hardware components, our focus is on augmenting the operator capabilities to take decisions in days to weeks ahead horizons. It accesses data from a variety of sources such as smart meters, meteorological stations, grid monitoring sensors, user data from customer management systems, and grid topology data from grid management systems. The scope in focus is network management, particularly grid congestion use cases addressed by providing data analytics and implicit control schemes as described in Sections 3 and 4. The main four components and their connection to physical and human layers are shown in Figure 4, drawing from software architecture principles [7] , and addressed as follows.

Knowledge Extraction accesses assimilated data and model output data to perform data analytics and design of dynamic tariffs that ultimately provide information for the end user to act on. Methods and results are presented in Sections 3.1, 4, and 5.

Physics and data-driven models consist of data assimilation, time series forecasting, a grid model for power flow and a model of intelligent end users represented in the Grid DT block. Methods and results are presented in Sections 3.2 and 5.

Data verification and **Permanent data storage** establish Single Source of Truth through *(a)* rule-based quality and plausibility checks aiming for consistency and early detection potential issues in the data acquisition pipeline, such as erroneous measurements, communication failures, or sensor malfunctions; and *(b)* historical records of verified data, data retention policies tailored to different data types, with raw measurements, aggregated statistics, model outputs, and metadata stored in structured formats that enable efficient retrieval for model training, validation, and retrospective analysis. This persistent storage also archives grid topology changes and tariff schemes.

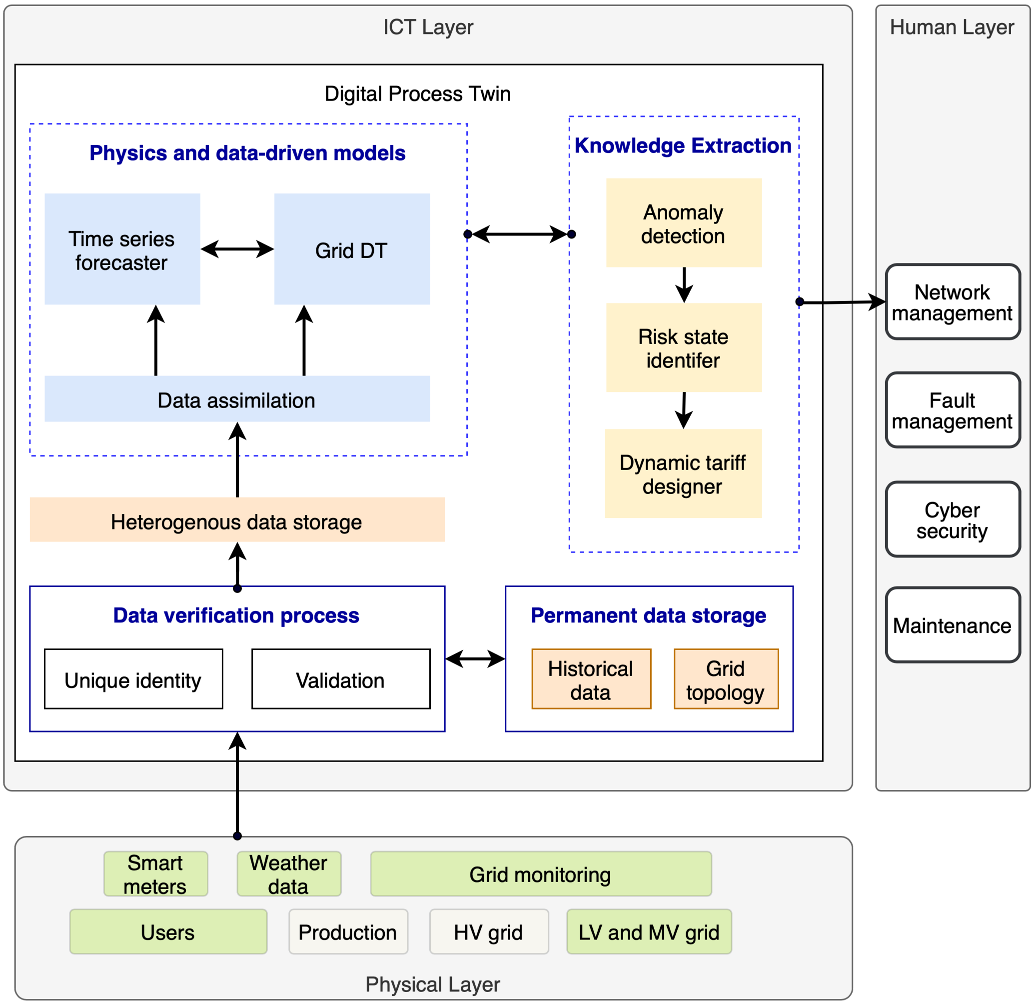


Figure 4: Digital Process Twin system diagram–Process and a physical view of the architecture.

2.2 Functional requirements and data management

Updated data are essential input to DPTs, however, data constantly comming from different systems presents a challenge in the ongoing digitalisation of LV grids [8]. As digitalisation and interoperability progress, DTs can deliver value to DSOs by developing functionalities, such as real-time estimation and forecasting of grid state, into already commercialised SCADA or DMS solutions [9]. Other approaches, such as the one we pursue, are aimed at interfacing with DSO's ICT infrastructure based on standard protocols and using open-source tools, possibly combining multiple stakeholders in the value chain of digital services for grid situational awareness and operational planning.

By defining functional and quality requirements, as well as defining the scope of each software module and the framework, we iterated from the decision support concept, the methodologies for analytics and dynamic tariffs, to specific models using data from the pilot facilities. At this stage, the focus was on functional requirements: *(i)* definition of data requirements by means of creating a data catalogue that lists and describes the available sensor and model data, *(ii)* specification of functional requirements of each software module by defining module interfaces, and *(iii)* investigation of desired features and user interface.

Qualitative research methods were applied to data collected by interviewing personnel from two Swiss DSOs and the Swiss TSO current practices, tools, and end user preferences were studied and multiple potential applications for decision support tools were identified. These point to significant opportunities for digital innovation, validating the vision of the AISOP project and summarized as follows.

1. In real-time operations support tools are needed to suggest grid configurations and operation actions in the case of unplanned outages and emergency situations to facilitate grid restoration to a secured alert or a normal state.
2. In operational planning, support tools to optimise the scheduling of outage requests would make this process faster by combining grid data with operation and maintenance data.

An important finding is that user interface and integration of such tools into current operator workflows requires a co-development process with operators, possibly involving OEMs and third-party software providers.

2.3 Analytics and modelling workflows

Once the architecture of the DPT, basic functional requirements, and modelling scope were established, four workflows that describe sequences of processing steps were defined. The objectives of each one are as follows.

(a) **Anomaly Detection** to detect faults such as short circuits, equipment failures, or incipient faults, and irregularities at the end user side including new consumption patterns indicating new demand and generation from EVs and solar PV.

(b) **Sequential Power Flow Solutions** to characterize the impact of connecting more solar PV, electrical vehicles (EVs), and heat pumps. Involves Data Assimilation, Parsing Topology, Initialization, and Power Flow modules. It is often applied to simulate scenarios and capture the variation of loads and generation with time, thus used to estimate hosting capacities.

(c) **Power Flow Forecasting** to estimate grid conditions in day(s) to week(s) ahead horizons. Involves Data Assimilation and Time Series Forecasting modules combined with the Sequential Power Flow Solutions workflow. Several approaches were considered to forecast load and generation, ranging from classical quantile regression, one-dimensional convolutional neural networks, and novel, powerful deep learning architectures. Several open source power analysis tools were tested with benchmark data and data from the pilot facilities.

(d) **Risk Assessment** to assess the actual and future conditions of the grid by estimating risk metrics that aim to quantify the probability of voltage issues and grid congestion problems, ultimately supporting network management and maintenance decisions.

As shown in Figure 5 all workflows start with accessing data and metadata, then using it to initialize simulations, or to develop forecasting models, or directly to analyze grid conditions.

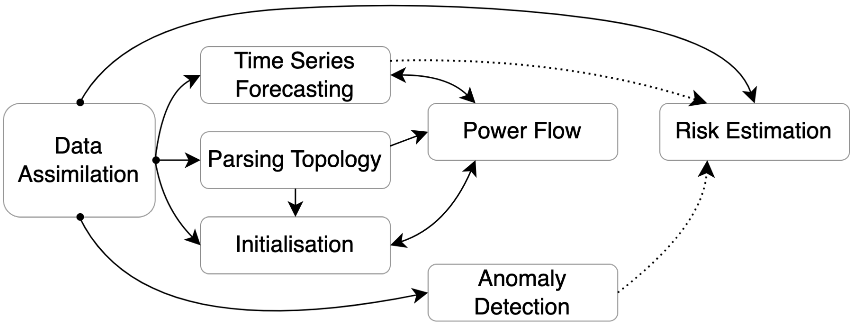


Figure 5: Block diagram illustrating workflows for grid situational awareness.

3 Data analytics and forecasting of grid state

3.1 Anomaly detection

Two types of anomaly detection use cases were studied. *(a)* **Anomalies in the grid**, essentially incipient grid faults, such as short circuits, equipment failure, or incipient faults related to degradation of insulation material or other ageing factors. This was approached by applying grid models and simulating grid faults to train classification algorithms, as well as in a purely data-driven by looking for anomalies observed in monitoring data. *(b)* **Irregularities at the end user side**, which are defined as deviations from expected power quality, usual power consumption, or generation patterns, indicating a new and potentially unregistered loads such as charging of an EV or generation with solar PV. Timely detection of these abnormalities is necessary to ensure efficient energy management, prevent a potential system failure, and optimise resource allocation. Both of these cases can be approached with a myriad of methods ranging from distances measured on probability distributions to thresholds applied to metrics calculated over sliding windows or to the residuals of normal behavior models. In general, the following steps were applied.

1. Definition of use case and mapping of available data. Framing the problem as supervised learning if there are data that has been identified and labeled as anomalies, or as unsupervised learning if there is no clear definition of anomalies nor labeled data.
2. Selection of approach and methods.
    (a) **Supervised learning**: historical data has anomalies that have been identified and labeled, thus these data can be used to train models to classify new data into a single or multiple categories. Other method is to create a normal behaviour model and define anomalies as those that deviate from the expected normal behaviour. In this case, labels of anomalies are used to create a dataset representing only the *normal behaviour* without anomalies, and then train a regression model.
    (b) **Unsupervised learning**: applying cluster analysis and anomaly scoring metrics for cases where the definition of anomalies is vague, or there is no data for training a classification model in a supervised fashion. In this setting, a data set without *anomalies* can be created by applying statistics, empirical methods, or learning the underlying distribution of the data. Once data has been *cleaned* from anomalous values, it can serve to train regression model.
3. Implementation and verification of the chosen approach was tailored for each use case. It typically included the following steps.
    (a) Pre-processing and exploratory analysis of historical measurements from smart meters, or grid sensors at the MV-LV transformers.
    (b) If a supervised approach is applied, select a classification or regression model and proceed with the standard split into test and train to validate it and tune parameters to avoid under and over fitting.
    Otherwise, if an unsupervised approach is followed
        i. define a high-level objective of the analysis, such as *detect multi-variate outliers in power quality data*

ii. set a metric and a threshold, such as z-score to filter about about 1 % of data

iii. apply a few methods and verify results visually

Multiple studies were conducted following the supervised and unsupervised approaches as listed in Section 8 and summarize below in Table 3.

Table 3: Overview of anomaly detection studies in AISOP.

Use case	Data	Approach
Incipient fault detection.	$u(t)$ and $i(t)$ in the IEEE 33 bus system, in normal operation and various fault cases were simulated with EMT simulations in Matlab. Data was then labelled as $l \in \{0, 1\}$ to indicate normal operation and fault cases.	**Binary classification**. Using $u(t)_i$, $i(t)_i$, and l_i algorithms with linear and non-linear decision boundaries were applied to classify each sample i.
Incipient fault type and location identification.	Additionally to $u(t)$ and $i(t)$ described above, fault types $l^{\mathsf{T}} \in \{\mathsf{LG}, \mathsf{LL}, \mathsf{LLG}, \mathsf{LLL}, \mathsf{LLLG}\}$, and fault branch location $l^{\mathsf{L}} \in \{0, 1, 2, 4\}$ labels were created.	**Multi-class classification**. Using $u(t)_i$, $i(t)_i$, and l^{T}, l^{L} algorithms with linear and non-linear decision boundaries were applied to classify each sample i.
End user anomaly detection	Power flow measurements: 15-min resolution data provided by WWNetz, recorded at the secondary side of LV transformers in various points of a grid with high rate of PV generation.	**Normal behaviour model**. Learns normal patterns and flags high reconstruction errors as anomalies.
Monitoring	Grid monitoring measurements: 10-min resolution data provided by RE, recorded at secondary side of LV transformers in various points of Chapelle sur Moudon and Rolle.	**Density based clustering**. Applied on a the principal components of the measurement data: PCA reduces feature space, DBSCAN identifies outliers in low-density regions.

3.2 Power flow simulations and risk estimation

The process of estimating future grid states takes two steps, the first one consists of creating forecasts, the second one consists on calculating the solution to the power flow equations multiple times with updating the input values with load and generation forecasts. This is a common approach to use the otherwise static power flow solutions, that provide specific snapshot in time [10], to perform a quasi-dynamic simulation that outputs a time series of grid states. Such sequential power flow simulations let us predict voltage magnitude and phase in the load nodes, when fed with predictions, or assumed values, of active and reactive power injections in the load and generation nodes [11–14].

Evaluation of power flow forecaster performance. Power flow solutions can be calculated with iterative methods such as Newton-Raphson, which is generally applicable and effective, but it may encounter convergence issues [15, 16]. The backward-forward sweep method is an approach that is applicable to radial networks, but it might not scale well compared to novel approaches based on linearized formulations [17]. Forecasting of power flows can draw from statistical models, including machine learning for time series forecasting, and it can also incorporate physics knowledge or technical constraints. It can be framed as a univariate or a multivariate supervised learning (i.e., regression) problem, where load and generation are forecasted and then used as inputs to the sequential power flow solutions. We implemented it using active and reactive power time series forecasts as a input to a power flow solver. In Section 4, power flow simulations are used as data to train a ML model in a supervised learning fashion to study sensitivities to changes of load patterns triggered by changes to electricity prices.

Aspects that were considered when gauging the performance of power flow forecasts include computational time, forecast accuracy of inputs, initialisation and convergence of power flow solution, error propagation, and forecast accuracy of outputs. The objective was to gain an understanding of the feasibility of running power flow forecasting to support operational decisions. The following steps were taken using a benchmark grid from Simbench [18] and the pandapower grid solver [19].

i. Creation of a benchmark of a forecast using local linear regressions. This was useful to estimate a best-case scenario and evaluate error propagation.

ii. Running sequential power flow simulations using data of benchmark load profiles and forecasts. This was useful to evaluate the error propagation and computation time.

iii. Creation of a baseline forecast using naïve seasonal forecasts, one dimensional convolutional neural networks which do not have a high computational expense and are relatively easy to retrain, and pretrained deep neural networks models.

An evaluation of day-ahead power flow forecasting in terms of error propagation and computation time was conducted on the `1-LV-urban6--0-sw` Simbench grid. This is a radial network with 1 MV bus with a 20 to 0.4 kV transformer and 58 LV buses with 111 loads between 2.0 to 31.0 kW. Simbench also includes emulated smart meter and generation data by means of generic daily profiles for different scenarios. These include *today*, *near future*, and *future* scenarios. First, a benchmark of a forecast (i.e., a dummy forecast) was created using local linear regressions, this allows to create a simple synthetic forecast that can be arbitrarily accurate. The operational planning scenario emulated is that time series forecasts of load are issued every day at 8:00 hrs for a day-ahead. A file-based interface between the time series forecast module and the power flow solver was defined and the files were made available in a Simple Storage (cloud) Service (i.e., S3 bucket). The Simbench data corresponding to the generic profiles were mapped and scaled according to the grid topology, resulting in active (P) and reactive power (Q) load profiles specific to `1-LV-urban6--0-sw` Simbench grid. Figure 6 shows P and Q from Load 4 and the dummy forecast issued every 24 hours, histograms show RMSE calculated for every day during a month for each of the 111 loads, mean-RMSE +/- standard deviation values are shown in each histogram for All loads, and for Load 4.

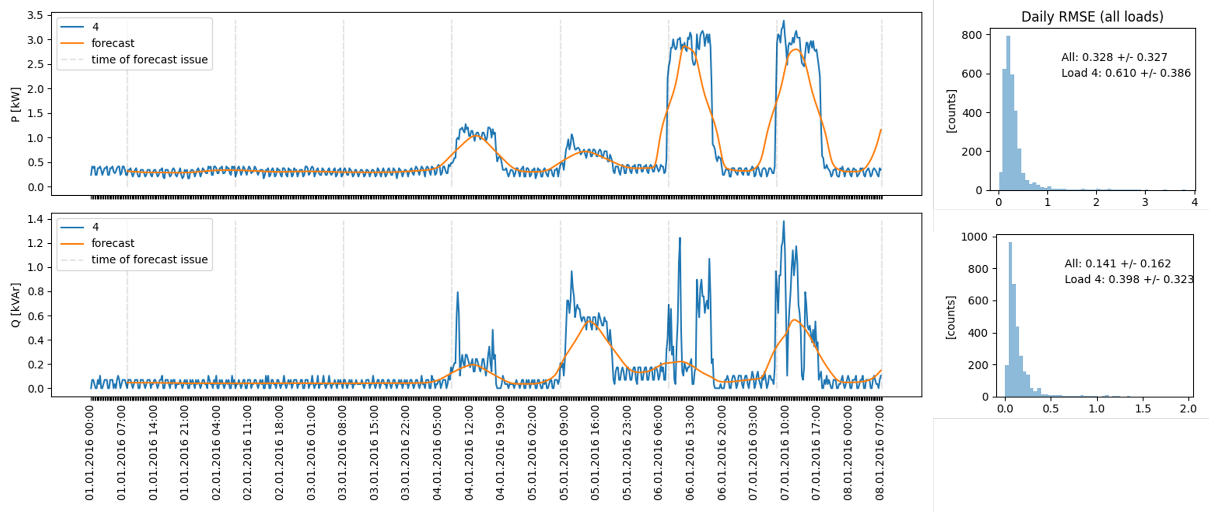


Figure 6: Evaluation of Power Flow Forecasting–Dummy load forecast and Simbench profiles used as input to pandapower.

In order to gauge the propagation of the forecast errors through the power flow solver, power flow solutions using load forecasts as inputs were compared to reference solutions obtained with the corresponding Simbench load profiles as a means to emulate back testing of power flow forecasts with real data. Results showed low errors across all loads as shown in Figure 7.

Comparison results between a naïve forecast and a forecast with a pretrained deep neural network are summarized in Table 4 and and example plot is showed in Figure 8, in this experiments P and Q of load 4 in the `1-LV-urban6--0-sw` Simbench grid are forecasted once a day at 00:00 hrs, over a period of one month. The **Naïve** model is an average of past data, and the **T5 zero-shot** model is a pretrained Text-to-Text transformer base on [20] T5 architecture, and adapted for time series forecasting [21]. The smaller 8M parameters model was used here as a zero-shot inference tool without fine tuning. For both, the naïve and the deep learning model the input was the three previous daily load profiles, as illustrated in Figure 8. Although, as shown in Table 4, the DL forecast yielded a mean RMSE lower than that of the naïve forecast, its standard deviation was significantly larger showing that the forecast quality of this DL model used without fine tuning varies more than that of a naïve forecast. Several possibilities for achieving lower error metrics and increasing their consistency were considered, one of the improvement paths we developed further was the combination of multiple models.

Table 4: Evaluation of Power Flow Forecasting–Comparison of RMSE calculated daily for a month of load data from Simbench.

	Dummy	**Naïve**	**T5 zero-shot**
P [kW]	0.610	1.504	1.281
	± 0.386	± 0.771	± 1.153
Q [kVAr]	0.398	0.737	0.692
	± 0.323	± 0.397	± 0.544

As part of verifying the feasibility of power flow forecast simulations to be updated multiple times a day for operational planning support, estimations of computation time were performed. Showing that it is feasible to calculate power flow forecasts with 15-min time resolution for a whole year, in well under one hour of computation time running them in a standard modern laptops. Focusing, on the implementation aspects, it was observed the built-in function in pandapower `run_timeseries()` to run sequential solutions, is more efficient than that sequential calls to the single step solutions `runpp()` given the over head to load initial conditions for each time step and solve the power flow. Other important factors are the implementation of the data structures, implementation of solver, and the solution algorithm itself, optimized implementations such as LightSim2Grid are easily integrated into pandapower, while other tools such as Power Grid Model offer python wrappers easy to integrate into our workflows.

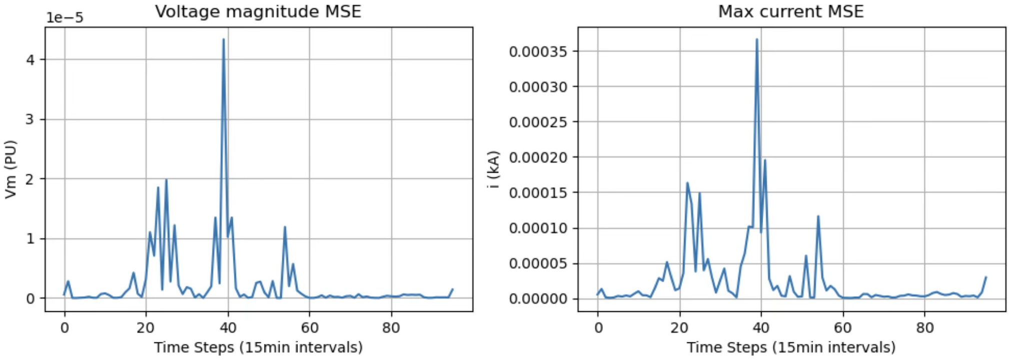


Figure 7: Evaluation of Power Flow Forecasting–Comparison of power flow forecasts to reference solutions in terms of RMSE.

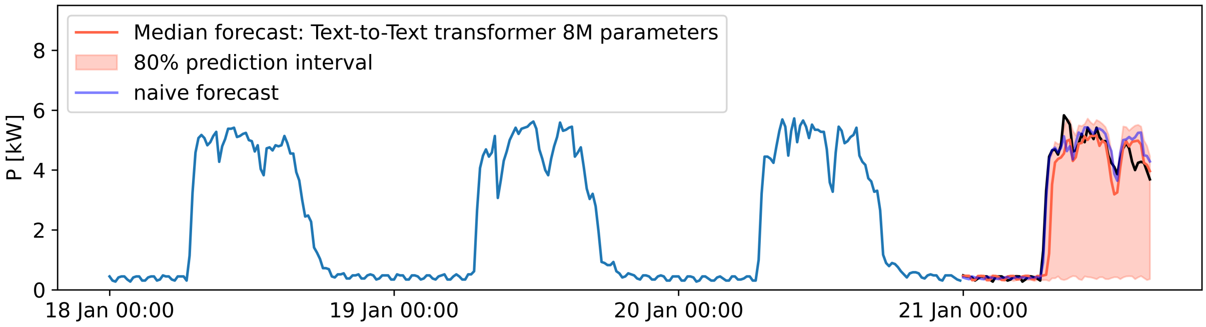


Figure 8: Evaluation of Power Flow Forecasting–Load forecasting with naïve and with pretrained DL model.

Voltage and load risk estimation. DSOs monitor the loading of lines and transformers during operation, in some cases nodal voltage magnitudes and power quality metrics are also monitored in selected nodes. For example in transformers at HV-MV and MV-LV stations, and in some MV branches. Moreover, information about ongoing or planned maintenance activities allows DSOs to maintain a high operational performance of their grids. Updating reliability metrics enables them to gain perspective on the performance over longer periods of time. Recently, hosting capacity and risk metrics are receiving increased attention as valuable to support operational planning decisions, given the increase in stochasticity of load and generation patterns. Table 5 shows a non-exhaustive list of reliability and risk metrics that can support up-to-date informed decisions across multiple time horizons and operational contexts [22–26].

Table 5: Reliability and risk metrics

Metric	**Description**
SAIDI	**S**ystem **A**verage **I**nterruption **D**uration **I**ndex Indicates the average outage duration; requires long-term outage data, used today to approximate the Expected Energy Not Served (EENS).
SAIFI	**S**ystem **A**verage **I**nterruption **F**requency **I**ndex, used today: indicates the average outage frequency, used today to approximate the Expected Energy Not Served (EENS).
EEAR	**E**xpected **E**nergy **at** **R**isk: quantifies the risk of potential energy not served due to system constraints (statistical approach to commonly used EENS).
VaR	**V**alue at **R**isk: indicates expected loss or operational cost in the worst $1-\alpha$ percent of scenarios.
CVaR	**V**alue at **R**isk: indicates the average of losses exceeding VaR.
OVR	**O**ver-**V**oltage **R**isk: indicates the risk of nodal voltages exceeding thresholds; uses an exponential severity function.
UVR	**U**nder-**V**oltage **R**isk: indicates the risk of nodal voltages being below thresholds; uses an exponential severity function.
LOR	**L**ine **O**verload **R**isk: indicates the risk of line overloads; uses linear severity function.
LLR	**L**ine **L**oss **R**isk: indicates the risk of load loss; uses linear severity function.

For strategic planning and investment in the long-term, the combination of reliability metrics (SAIDI, EEAR) with risk metrics (VaR, CVaR, OVR, UVR, LOR) could support prioritization of grid updates. For operational planning, near-real-time or mid-term (e.g., weekly, seasonal) risk metrics may offer early warning signals that are easy to communicate and serve to trigger detailed analyses to understand root-causes and devise remedial actions such as updates in dynamic tariffs. Remedial actions can lead to adjustments of dispatch patterns of distributed energy resources or activation of demand response programs.

VaR and CVaR are statistical metrics that can be empirically estimated from the data without a model, they give and indication of worst case assuming that the risk is defined by the tails of the distribution. CVaR measures the expected deviation in the worst of observations given a confidence level $\alpha = 0.95$, as shown in Figure 9 with voltage data of phase 1, corresponding to the period from October 2018 to December 2019 from a grid monitoring device at the transformer of feeder 13 in Rolle site. It shows that during the period from October 2018 to December 2019 recorded with GridEye in there was very low risk of over voltage, and that the risk is not changing abruptly across different seasons of the year.

Furthermore, metrics such as LLR can contribute to more efficient risk-based maintenance planning when properly updated with recent data representing new load patterns. To monitor and provide situational awareness of voltage issues OVR, UVR, and respectively for load issues LOR can be calculated dynamically every time, or every certain period of time, that new data is available. Standard guidelines for quality of supply also offer indicators to monitor, namely, as specified in EN 50160 supply voltage variations during normal operation should be kept in certain ranges, during each period of one week 95 % of the 10-min mean values shall be within +/- 10 % of the nominal voltage.

The estimation of OVR, UVR, LOR were implemented as follows. First, a distribution function was estimated from historical data, and a severity function defined according to the selected risk metric.

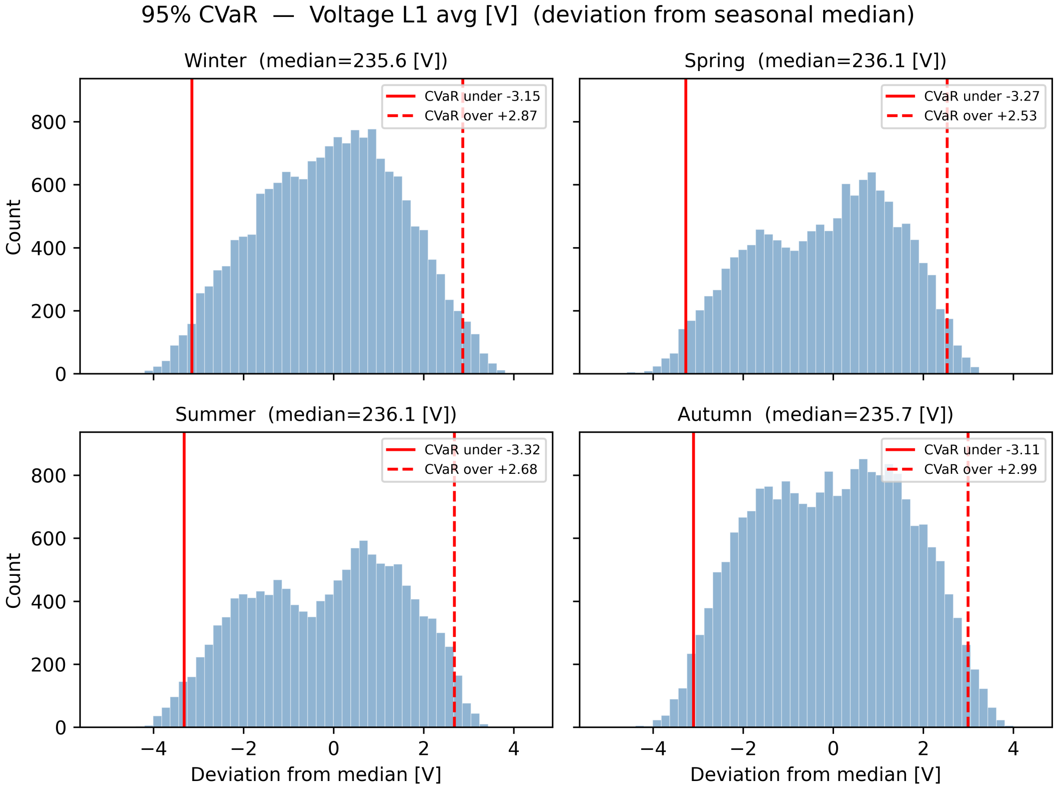


Figure 9: CVaR of 10-min RMS values of voltage, calculated for each season of the year.

The distribution function was estimated with the empirical distribution, by calculating the frequency of occurrence from the data, as illustrated in Figure 9. Alternatively, it can also be created with a parametric approach, fitting a probability distribution function. In a second step, the distribution function is used to calculate a probability of exceedance which is then weighted by the severity function to calculate risk. OVR and UVR where calculated with exponential severity functions as in [25], but using a step function and an exponential bounded to a maximum severity equal to one to reflect that the severity factor may be larger when deviations are larger but also bounded to reflect physical limits. Moreover, the threshold values for the sensitivity functions to activate where calibrated to the under-CVaR and upper-CVaR. Figure 10 shows the resulting time-varying value of risk of over voltage for phase 1. The severity functions are calibrated to activate at values slightly lower than the CVaR estimated for the whole data.

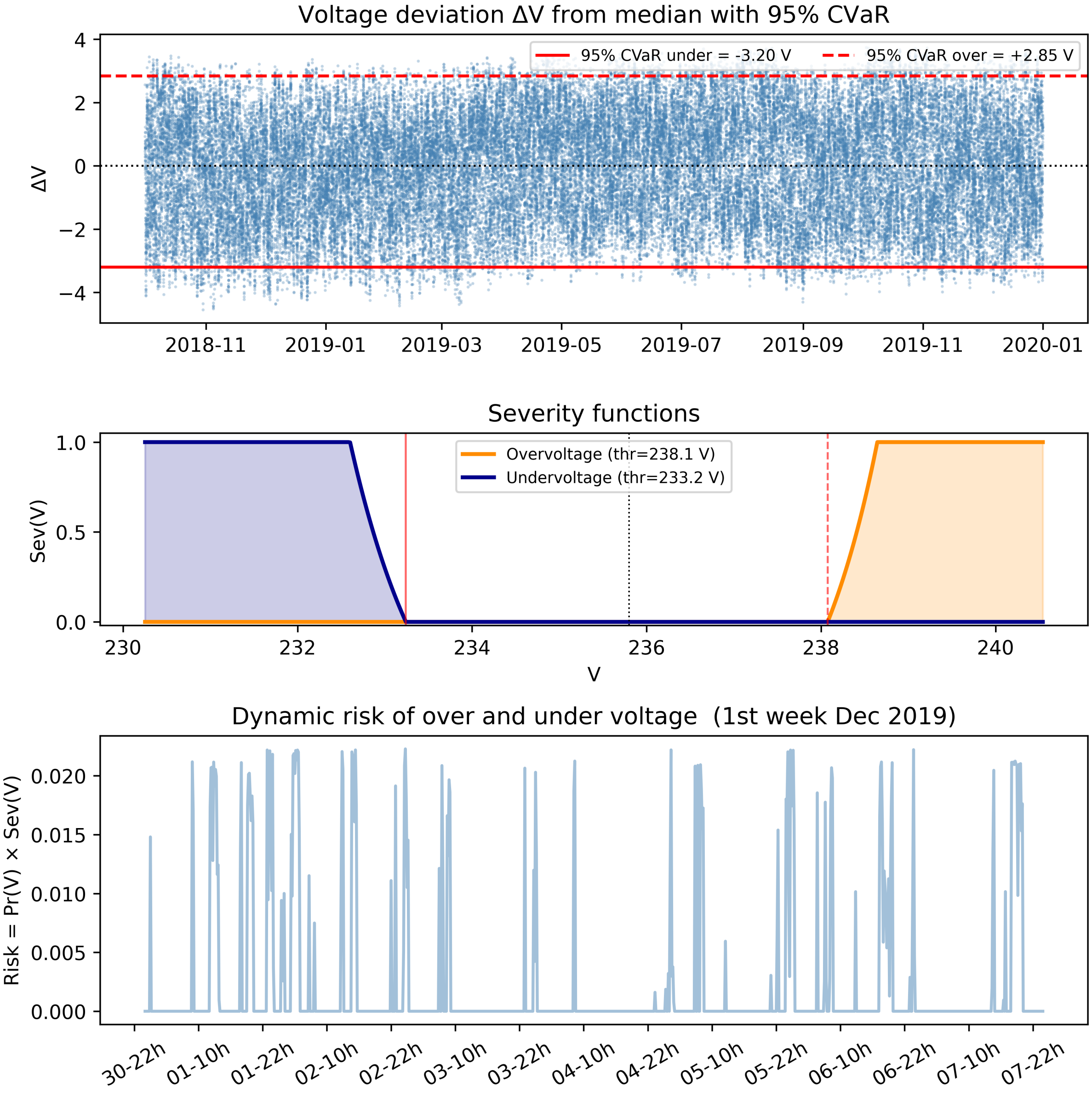


Figure 10: Time varying risk indicator calculated with 10-min RMS values of voltage.

3.3 Modelling end-user behaviour

A key step when linking data analytics and forecasting of grid states is the response of intelligent users to grid management signals. Having the possibility to simulate the response of users that can optimize their consumption or production to respond to curtailment or price signals, opens possibility beyond sequential power flow simulations that rely on load and generation profiles. For example, modelling users that respond to signals in the form of explicit requests to limit their peak solar PV output, or in the form of non-intrusive price signals that EMS use to adapt flexible consumption.

Thus, a model of end users was implemented as an optimization model that maintains energy balance over a 24-hour horizon, keeping grid constraints and energy flexibility constraints, and aiming to minimize the cost of energy. This model is briefly described below, it was used to illustrate the response of future end users that can react to dynamic tariffs as described in Sections 4 and 5 where further details about its configuration are given.

1. **Model inputs**. Price signals that may differ between weekdays and weekends, or that may change dynamically with the time step defined in the optimization routine.
2. **Optimization configuration**. Optimization horizon (T), time step (Δt), selection of optimization framework and settings to cast objective function and constraints into a linear or non-linear problem.
3. **End-user archetype configuration**. Profiles of energy demand, flexibility capacities and grid constraints.
4. **Model output**. Optimized power import and export schedule in a rolling horizon as defined by T and Δt. Thus, the model can be used for generating data to study impacts on the grid, or to perform scenario analyses.

Before going into the detailed creation of scenarios, definition of end user archetypes, and specification of simulation parameters described in Sections 4 and 5, the integration of the end-user behavior optimisation model into the ReSIM code base and virtual demonstration was prototyped and tested for feasibility with generic configurations and benchmark grids. The main steps of the model and the resulting interface are illustrated in Figure 11.

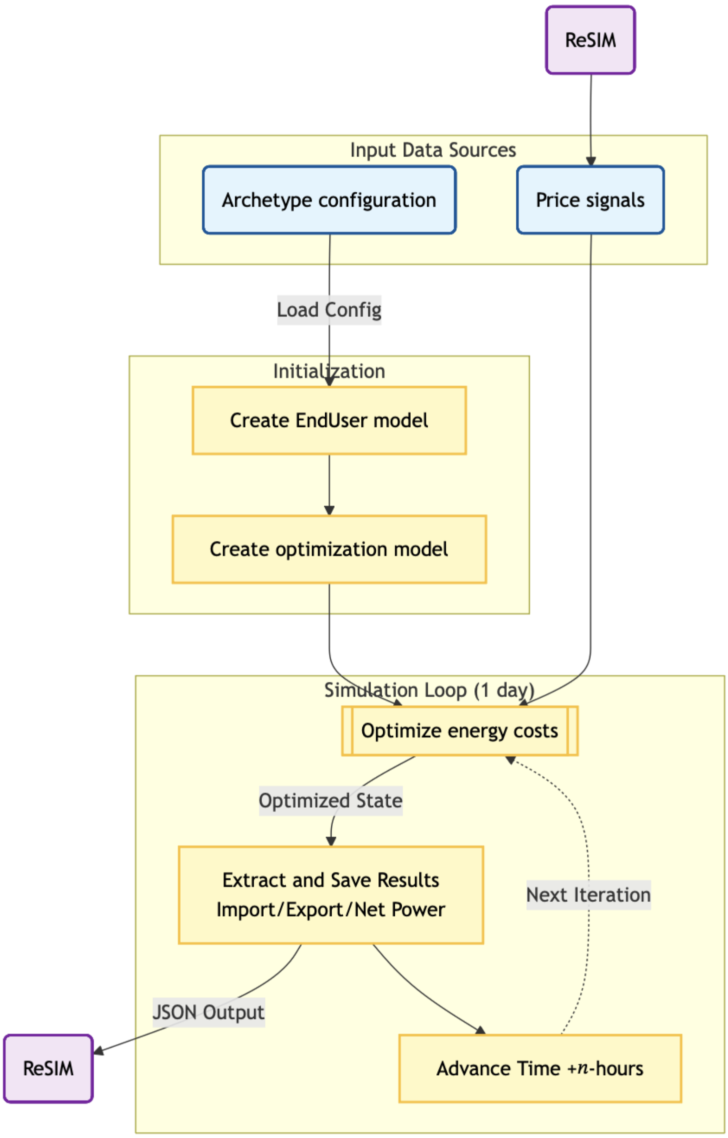


Figure 11: End-user response optimization and its connection to ReSIM.

4 Dynamic Tariffs

4.1 Methodology

Objective: Dynamic tariffs are increasingly seen as a means for a utility to influence the power withdrawal and/or injection patterns of its customers, with objective to eventually reduce the grid loading whenever and wherever this might be desired due to otherwise excessive flows. Designing such a tariff is far from being a trivial task. The utility needs to:

1. **Understand what exactly the tariff should try to influence (the target)**. A utility needs to decide the measure (i.e., KPI) according to which it assesses the success of its tariff scheme. Following is a non-exhaustive list of such KPI candidates:
    - The loading of NL6 transformers
    - The loading of specific cables
    - The average voltage throughout the LV grid (NL7)
    - Nodal voltages at specific buses

    In addition to the above-listed spatial KPIs, temporal aspects can also be evaluated as part of the KPI: focusing only on specific moments in time (e.g., hours of date, months, seasons)
2. **Understand how the target can be influenced**.
    - Targeting the behaviour of specific customers or specific device types (spatial aspect)
    - Targeting the behaviour of customers at certain time intervals (temporal aspect)

Once steps 1 and 2 are completed, a utility can devise a tariff that aims at influencing the behaviour of those customers that we identified as the most relevant in step 2.

Depending on the level of observability of its distribution network, based on substation measurements, grid sensors, smart meters etc., a utility can have access to a heterogeneous set of data that contains potentially useful information. This data can be combined with other sources of information, such as weather measurements (i.e., solar irradiation, temperature). Such data can be collected over lengthy periods of time and grouped into datasets. It is noted that, in addition to (or alternatively to) the measured data, these datasets can also include data created by means of simulation of various scenarios.

The objective of this work has been to develop methods and processes for a utility to **extract knowledge** from such datasets, which can be used to develop appropriate dynamic tariff rules and schemes.

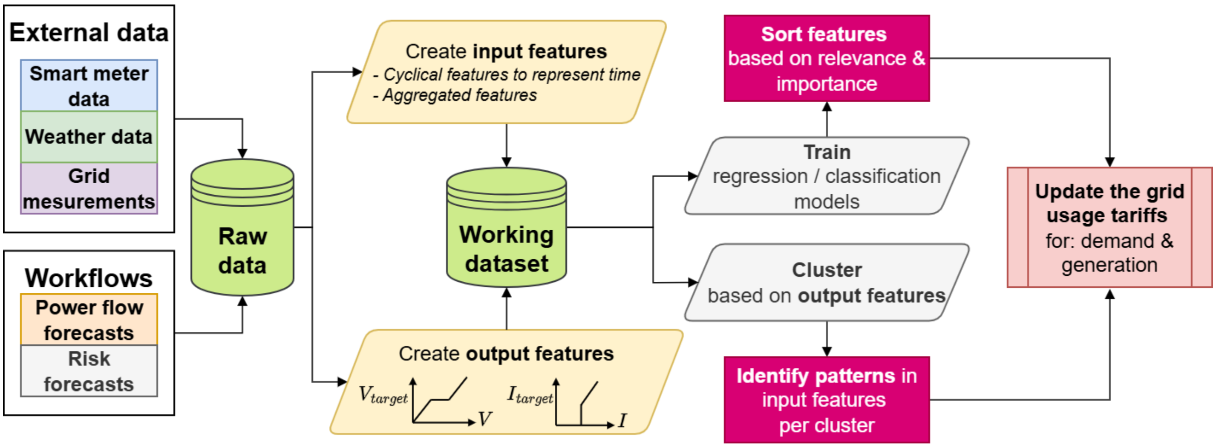


Figure 12: The framework for creating the ML-model to set the dynamic tariffs.

Approach: In its essence, the proposed approach, illustrated in Figure 12, consists of two steps.

- Processing the input data to create appropriate working datasets.

- Extracting valuable knowledge from these datasets, in an automatic manner, by applying appropriate machine learning algorithms.

STEP 1. DATA PROCESSING

Data collection: The required raw input data is collected and/or created by means of simulations. Such data include, but are not limited to, voltage and current measurements at different network nodes and branches, active and reactive power injections and withdrawals at different network connection points, generation, and consumption by various devices (such as PVs, EV chargers, heat pumps), temperature, solar irradiance, and others. They are typically in the form of a time series, at various time resolutions. Other information that can be part of the "raw input data" includes calendar information, such as the hour of the day, the day of the week, month, public holiday information, etc.

The objective is to develop the methodology or a set of methodologies which can be used with various levels and types of data available to the utilities. Therefore, the methodology or the set of methodologies are not dependent on a given set of data.

Input feature creation: At this step, new synthetic input features are created by using the available raw data. The objective is to have features that represent situations not strongly reflected in each variable in the raw data. A representative list of such "data transformations" are the following:

- Creation of cyclical features to represent time
- Aggregate nodal power injections with topological criteria (e.g., along a feeder, downstream from a specific node etc.)
- Aggregate power generation or consumption per type of device

Output feature creation: At this step, different potential "target features" are created. As explained in the previous section, these features shall represent the objective that the utility tries to achieve by applying a dynamic tariff scheme. They will be used by the machine learning algorithms in step 2 (presented in the sequel), to drive the knowledge extraction results. Two examples of such "target features" are:

- Per node, create a new feature for "nodal voltage in violation of the desired limits," which is the nodal voltage magnitude (in p.u.) when the voltage exceeds a selected maximum value (e.g., 1.08 p.u.) or falls below a selected minimum value (e.g., 0.92 p.u.) Otherwise, it is 1 p.u. Such a feature allows the ML-model to distinguish over- or under-voltages while treating values in the acceptable range in the same manner, thus allowing the user to focus on cases when the power injections and withdrawals at electrically nearby nodes have to be influenced so that the voltage falls back into the desired interval.
- Per branch, create a new feature for "branch current in violation of desired thermal limits," which is the branch loading (in %) when the loading is above a selected maximum value (e.g., 80%), and it is 0 otherwise. Such a feature allows the ML-model to distinguish branch currents that approach the limit while treating all the acceptable values in the same manner, thus allowing the ML-model to focus on cases when the power injections and withdrawals at electrically nearby nodes have to be influenced so that the branch current is under the selected limit.

STEP 2. KNOWLEDGE EXTRACTION

Two techniques have been developed to enable automated processing of the data in order to eventually identify the input features that shall be the "targets to influence" by means of a dynamic tariff scheme. In the sequel, we outline what each technique / approach consists of, followed by a description of the way that the two approaches are used, complementing each other, for dynamic tariff design.

Approach I. Identification of the most important input features by means of training of a regression model

General approach: This approach relies on the fact that a side-outcome of the training of certain types of regression models allow the ML-model to identify the candidate input features that turned out to be the most critical for achieving a high-quality model, which is as accurate as possible.

A suitable machine learning model that is selected to identify the most important input features is the "random forest." Random forests are ensemble models. They are created by training many decision trees. The random forest model consists of all the trained decision trees. Its prediction is the average of the individual decision tree predictions. Different decision trees are obtained by repeatedly sampling the training dataset and creating diverse (different from each other) subsets.

During the training of each decision tree, the algorithm uses a metric to identify the feature to use to make the split at each tree node. A metric such as the “Gini importance index” is utilized to select the feature (and the feature value) for which the split at a node maximizes the decrease in impurity (i.e., randomness) of the data in its leaf below that node. Hence, a side-result of the process of training a random forest is that the value of each feature in splitting the data has been estimated many times, as the various trees are being built. Based on these calculations, a by-product of the training process of a random forest is a value per feature indicating its importance in efficiently splitting the data. Typically, this feature’s importance value is in a range from zero to one.

Application: We use this technique to identify the candidate input features, created in step 1, that are the most relevant for each target output feature created in step 1. For example, a random forest is trained as a predictor of the “voltage outside limits” feature (see step 1) for a given node in the network. A by-product of this training is that each candidate input feature (such as those described in step 1) will be assigned a value indicating its relevance. Obviously, the most relevant features are these that the utility shall aim at influencing via a dynamic tariff scheme.

Approach II. Utilization of clustering to identify a range of values of the input features associated with the target output features

Clustering is a powerful unsupervised machine learning technique. It splits a dataset into subsets, such that the data within each subset are “as similar to each other as possible” and “as different from the data in the other subsets as possible.”

Application: First, one or more target output features, among those computed in step 1, are selected. Following, the data are clustered based on the values of these target features. If the number of clusters is selected properly, some clusters will contain the data samples where one or more of the target output features take non-desirable values (e.g., a cluster with nodal over voltages). Finally, the input features of each cluster are analysed, e.g., by performing basic statistical calculations, to identify the desired ranges of the input features, to avoid violations. This information is used to devise appropriate dynamic tariff schemes.

Dynamic tariff design by combining Approaches I and II

Finally, approaches I and II are combined to facilitate an informed selection of dynamic tariffs, based on both spatial and temporal criteria.

Step 1: The clustering technique of approach II is deployed in order to separate the data samples into groups depending on the correction that is required. Typically, one cluster resulting from this step will contain the data samples (i.e. the operating points) when there are no violations (i.e., no branch overloadings or voltage violations) and one or more clusters where the remaining data samples are split, depending on the type and severity of the violation.

Since each data sample is labeled according to various timestamps (such as season, type of day and time of day), this clustering step provides important information on the moments in time when the dynamic tariff scheme shall induce change in the end-user behavior.

In addition, the fact that each cluster contains the data samples where a specific violation has occurred, this provides information on what the dynamic tariff schemes shall intend to influence; i.e. increase/reduce the net power injection or withdrawal.

Typically, a "cluster 1" will contain all the data samples (expected to be the majority) when there is no need for end-user behavior modification.

Step 2: The feature importance identification technique of approach I is deployed in order to identify, per cluster, which end-users have the highest influence on the desired outcome (such as overload alleviation). To achieve this, the techniques of approach I are applied on each of the clusters selected in Step 1, expect "cluster 1" (the cluster when there is no need for end-user behavior modification).

This allows to identify the most influential input features per cluster. For example, these input features could be the net power injections of a subset of grid nodes.

Step 3: Finally, a dynamic tariff scheme is designed that selects the electricity tariffs and the feed-in tariffs such that they have the potential to influence the required users (identified in step 2) during the required moments (identified in step 1) in the appropriate direction of net injection modification (also identified in step 1).

The approach runs iteratively in a simulation environment, where the end-user behavior is modeled by means of an "end-user optimizer". The approach can also be used periodically by the DSO to update the dynamic tariffs after having collected enough new observation data that allow to re-run the analysis and come up with a new dynamic tariff scheme.

4.2 Illustrative results

An LV distribution grid in the region of Champ Monnet within the service territory of Romande Energie with 203 nodes, 202 branches, and 64 end-user connections is used for prototyping, testing, and validating. The distribution grid is provided in CYME format which is processed using the framework illustrated in Figure 13 so that the grid data is anonymized, converted first from CYME format to FlexDYN [27] and then from FlexDYN to pandapower format. Figure 14 illustrates the grid topology.

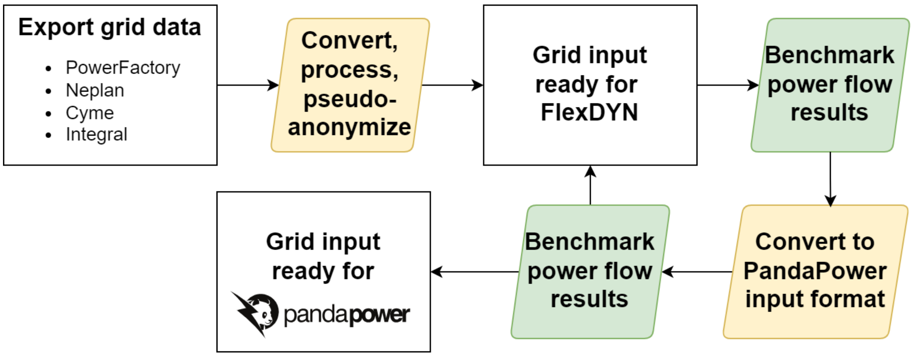


Figure 13: Data ingestion process for the grid topology provided by Romande Energie.

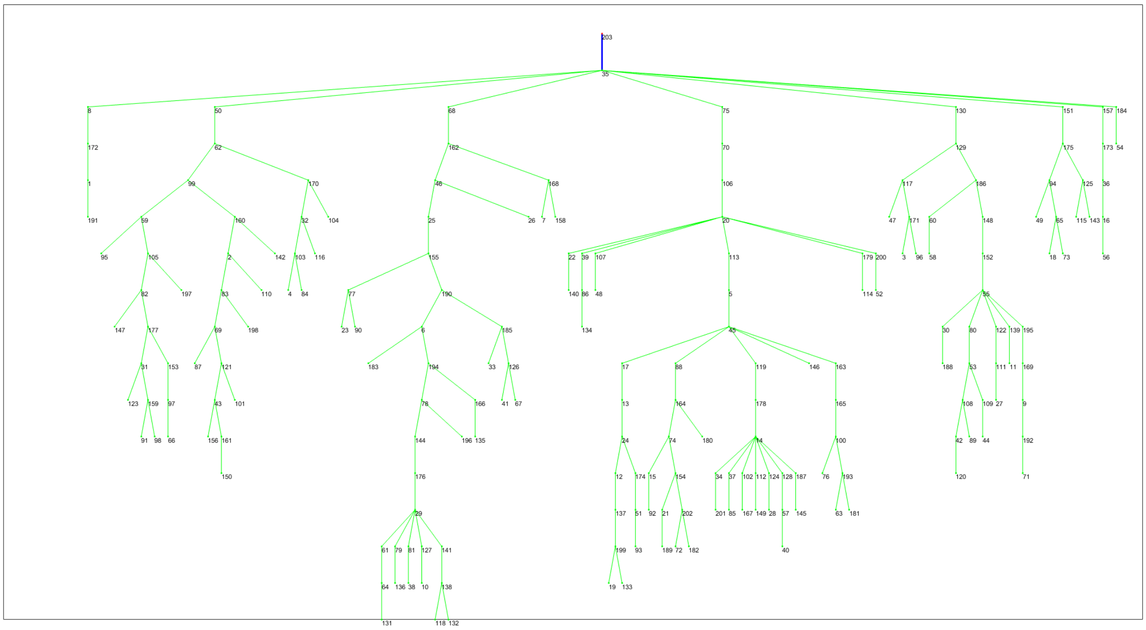


Figure 14: The grid topology of Champ Monnet, provided by Romande Energie, used for analysis and simulations.

For each grid connection point (i.e., Hausanschlusskasten – HAK), synthetic time-series for electric heat pumps, conventional household demand, solar PV generation, EV charging and BESS operation are created for nine (9) representative days (i.e., Workday, Saturday and Sunday in Winter, Summer and Transition seasons) in 15-minute resolution. The HP, EV, and PV proliferation levels correspond to

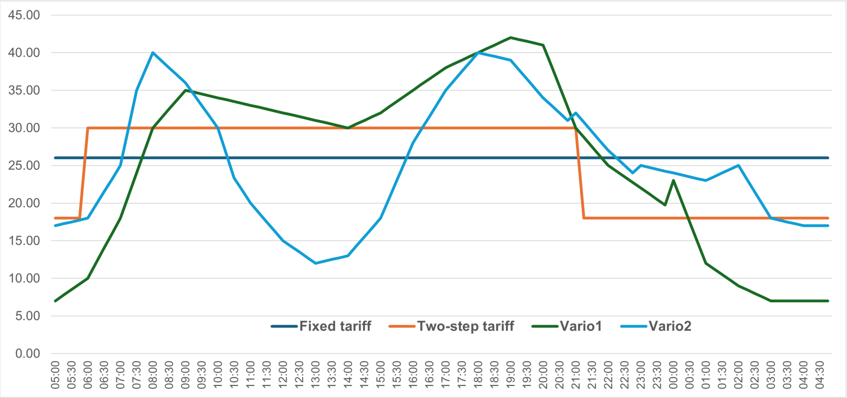


Figure 15: Selected electricity tariffs to generate data for training the ML model for dynamic tariffs.

Energy Perspective scenarios for 2050. It is assumed that each PV is equipped with a residential BESS, representing a high proliferation scenario for BESS. The methodology, referred to as "SyntDERGen" (i.e., synthetic DER generator) hereinafter, used to create the installed capacities and the time-series of household demand, solar PV, BESS operation, HP and EV charging for each grid connection point [28, 29] and used for grid planning exercises with utilities [30]. A total of $1'825$ kWp of solar PV is installed with 773 kW / 1'719 kWh total BESS capacity in the district. The total EV charging capacity is 957 kW and total installed HP electric capacity is 228 kW. A 70% limitation based on the installed kWp of PV is already applied. The grid connection capacities are based on VSE guidelines[1], and the selected levels are: 40 A/28 kVA, 63 A/ 44 kVA, 80 A/ 56 kVA, 100 A/70 kVA, 125 A/ 87 kVA, 160 A/111 kVA. The installed capacities for EV charging infrastructure, solar PV, BESS, HP and thermal storage as well as the time-series are then used in ReSIM (See Section 5.4) in an open-loop manner, assuming that end-users are equipped with an HEMS represented by an "end-user optimizer" (See Section 3.3), responding to tariffs and locally optimizing the energy balance by scheduling the demand, storage and local generation.

First set of results are created to demonstrate the impact of different tariff schemes for three levels of HEMS deployment: (i) none of the end-users has HEMS installed, (ii) 50% of the end-users have HEMS installed, and (iii) all end-users have HEMS installed. Four different tariff schemes (for demand) are used to generate data, with end-user optimizers responding to different tariff schemes (Figure 15): (i) fixed tariff, (ii) step tariff, (iii) two dynamic tariffs inspired by the Vario tariff structure introduced by Groupe E[2], while feed-in tariffs are held constant at 5 rp/kWh. The ReSIM framework is used for each tariff, which are fed to the end-user optimizers (i.e., HEMS) and using the output of each end-user optimizer one time-step at a time, and the grid simulations are performed to record the nodal voltages and branch loadings. It is assumed that the utility either has access to a grid situational awareness system which enables the utility estimate the nodal voltages and branch loadings and/or the utility complements the lack of grid situational awareness by means of power flow simulations using representative end-user profiles or smart-meter data.

Figures 16, 17, 18, 19 illustrate how end-user optimizer reacts to different tariff schemes, fixed, step, vario1, vario2, respectively for one selected node on a winter weekday.

Figures 20 and 21 demonstrate the transformer loadings for a Summer weekday, for a 50% and 100% HEMS (emulated by end-user optimizer) deployments, respectively, and for four tariffs. All branch loadings and nodal voltages as a results of four different tariffs are used for training the ML model to cluster the end-users and identify which end-users affect which nodal voltages and branch loadings, from a purely data perspective.

Data samples were clustered in six clusters, based on the nodal voltages and branch loadings as demonstrated in Figure 22. The limits for nodal voltages are selected to be between 0.94 p.u. and 1.06 p.u. and 80% for the branch loadings. The results illustrate the probability distribution per cluster, expressed in terms of the samples' average nodal voltage (i.e. average over all nodes) and average branch loading (i.e. average over all branches). It is observed that cluster 1 contains the “normal” operating points,

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[1] Branchenempehlung: Werkvorschriften CH, Technische Anschlussbedingungen für den Anschluss von Verbraucher-Energieerzeugungs- und elektrischen Energiespeicheranlagen and das Niederspannungsnetz, VSE, 2021. Download.

[2] Groupe E/Vario.

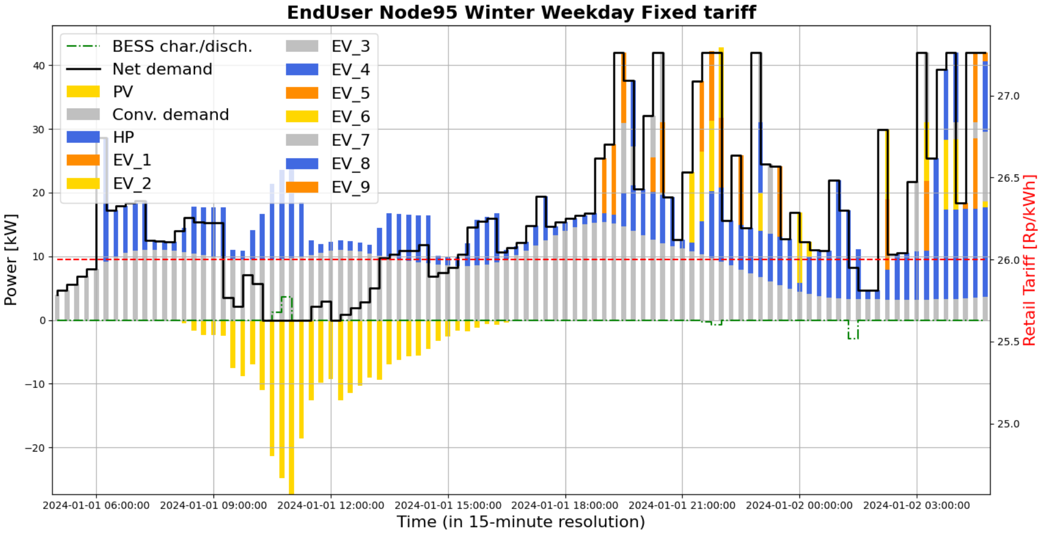

Figure 16: The results of the end-user optimizer for one selected end-user, for a winter weekday, with fixed tariff.

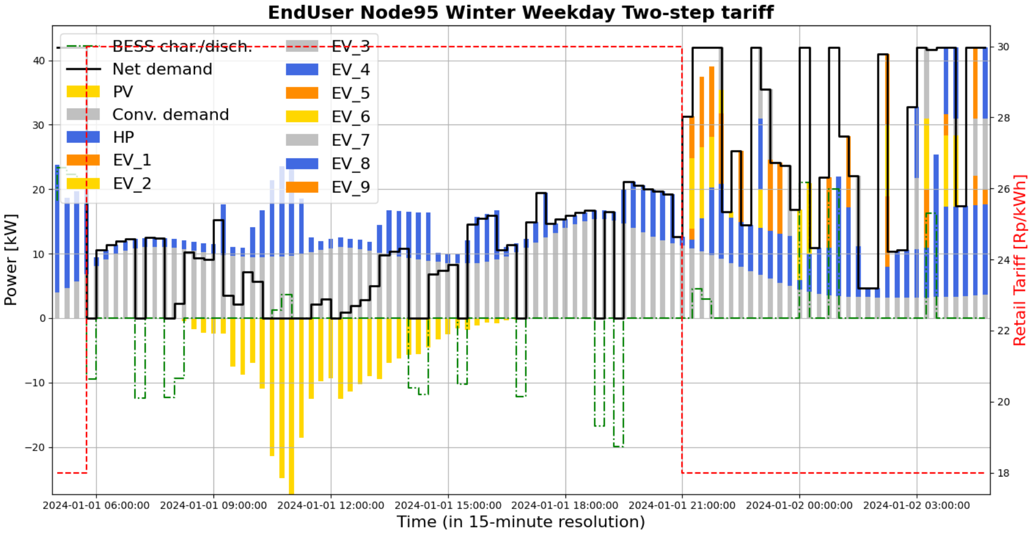

Figure 17: The results of the end-user optimizer for one selected end-user, for a winter weekday, with step tariff.

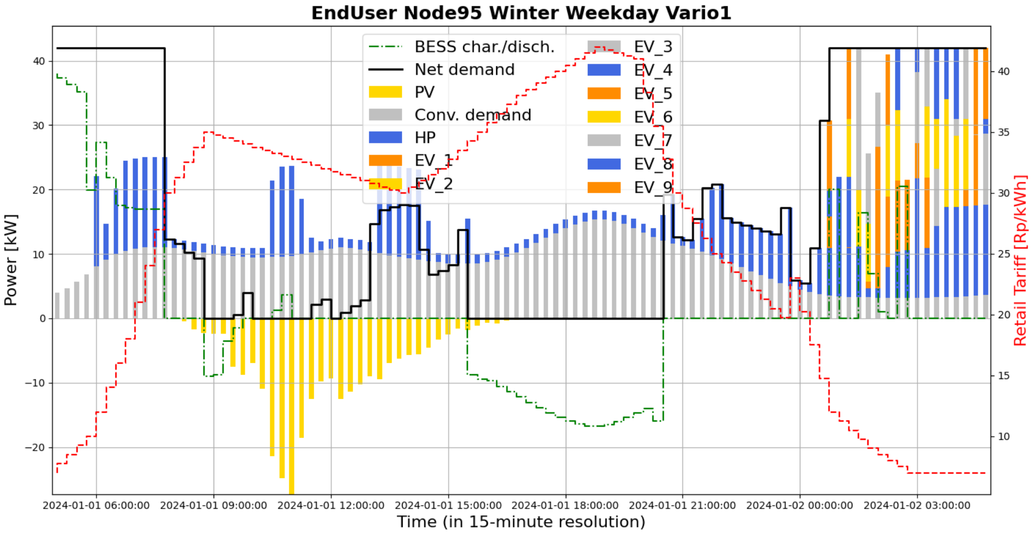

Figure 18: The results of the end-user optimizer for one selected end-user, for a winter weekday, with vario1.

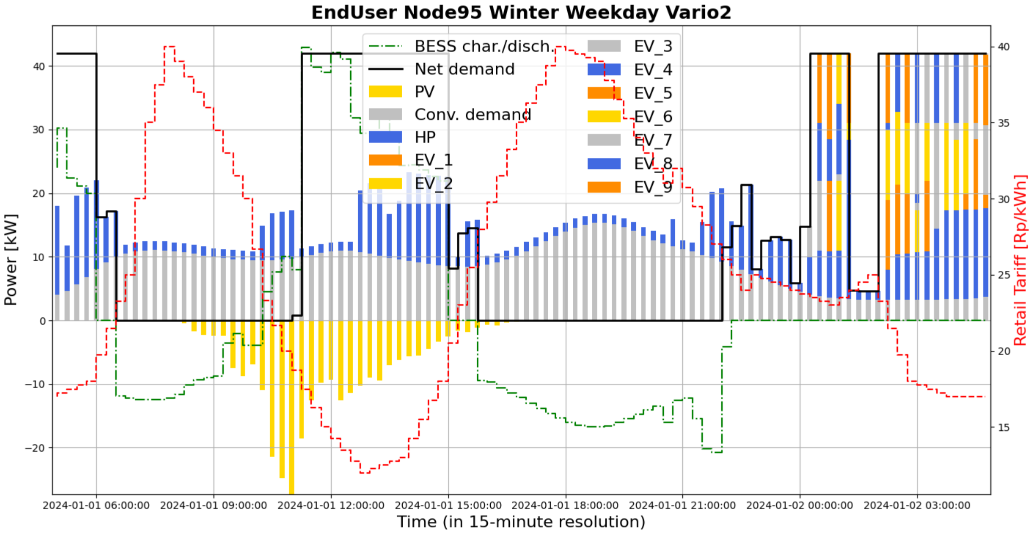

Figure 19: The results of the end-user optimizer for one selected end-user, for a winter weekday, with vario2.

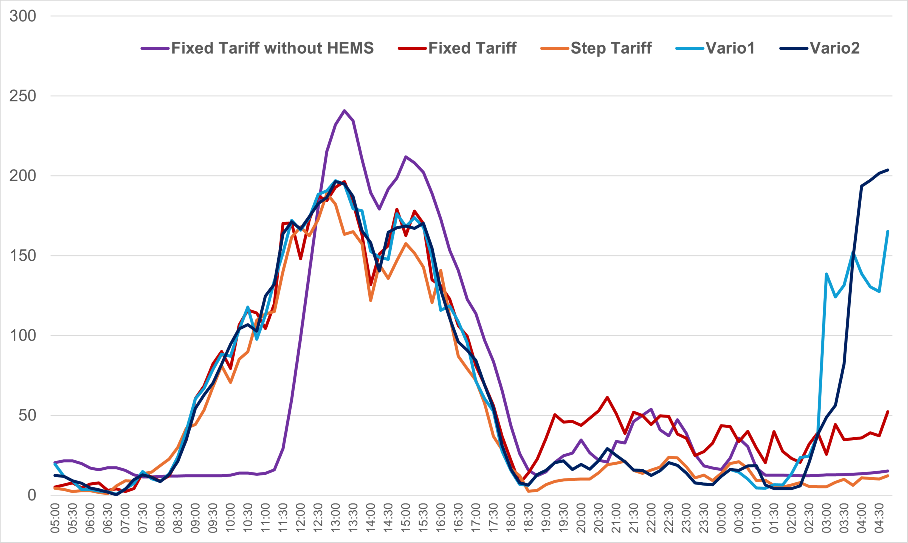

Figure 20: Transformer loadings for different tariffs: fixed tariff without HEMS; fixed, step, vario1 and vario2 tariffs with HEMS. Half of the end-users are equipped with HEMS: **50% HEMS deployment**.

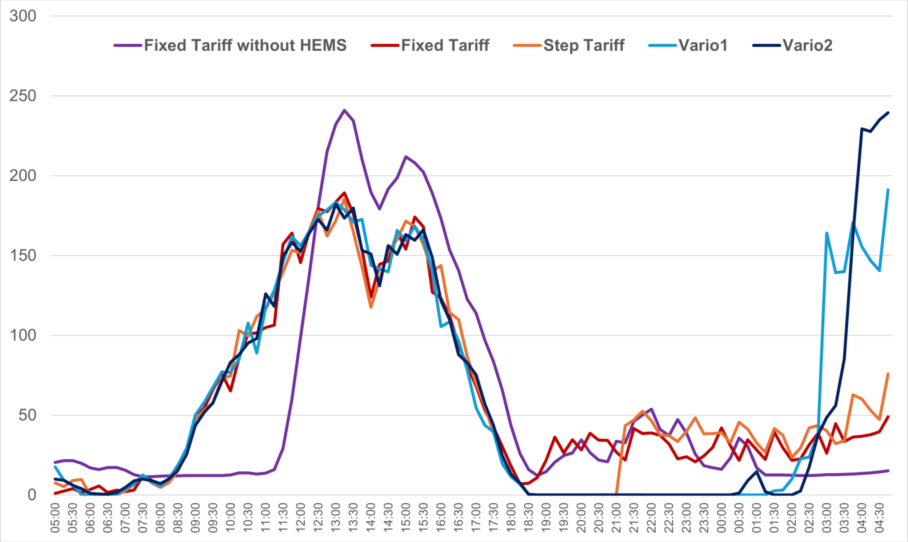

Figure 21: Transformer loadings for different tariffs: fixed tariff without HEMS; fixed, step, vario1 and vario2 tariffs with HEMS. All end-users are equipped with HEMS: **100% HEMS deployment**.

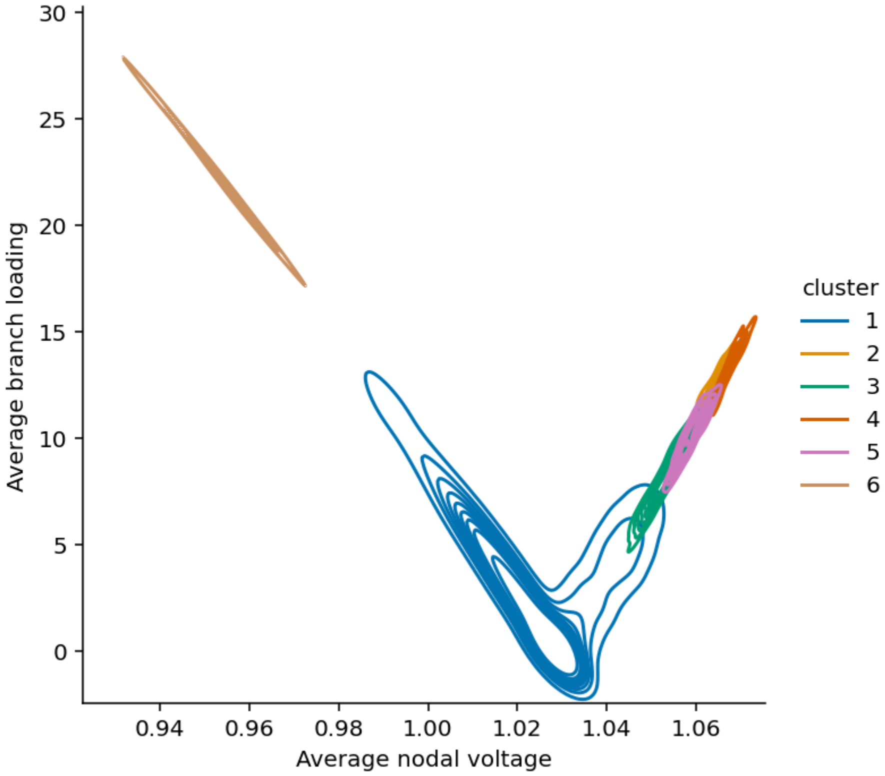

Figure 22: Clustering based on branch loadings and nodal voltages -100% HEMS deployment.

cluster 6 corresponds to operating points where under-voltages are observed, while clusters 2-5 group operating points where over-voltages are observed.

Figure 23 shows the probability distribution for an operating point for a given cluster, plotted against the total net demand (negative values of net demand denote net power injection, due to PV production). One can observe that most samples belong to cluster 1, which typically corresponds to low total net demand (or low net injection) and no branch overloadings or voltage violations. Cluster 6 corresponds to operating points with very high demand (and low, if zero, PV generation), resulting in branch overloads and under-voltages (as shown in Figure 22). Finally, cluster 2-5 contain operating points with different levels of extreme net power injection to the grid.

Figure 24 illustrates the probability distribution for an operating point for a given cluster, plotted against the time of the day (note that because it is a probability distribution, the x-axis also shows values below 0 or above 24, which shall be ignored). It is observed that operating points in clusters 2-5 take place exclusively during the day, with two clusters (2 and 4) being centered around noon and two clusters (3 and 5) containing operating points taking place earlier in the morning or later in the afternoon. Note that in Figure 22 clusters 2 and 4 contain operating points with the more extreme over-voltages and clusters 3 and 5 contain operating points with less severe over-voltages. It is interesting to observe that the operating points of cluster 6 appear most frequently during the late night early morning timeframe. This is heavily related to the Vario1 and Vario2 tariffs used in these examples, which motivate consumers to shift their demand away from the traditional peak demand hours. In our simulations this resulted in demand being shifted to earlier in the morning (or even during the night) as well as noon time. It is worthwhile to note that, in addition to the night – early morning hours, operating points of cluster 6 appear also during hours when one typically expects a higher PV injection. In this case, these cluster 6 points correspond to winter days with less solar PV generation. This indicates the need for a seasonally-adjusted tariff scheme. Figure 25 shows a heatmap, where different explanatory input features (shown in the y axis) are assessed (using the random forest-based approach) according to their explanatory value for each of the considered output features (i.e., each branch loading and nodal voltage, shown in the x axis). The highest the score is, the highest the relevance of the input feature is. For the sake of simplicity, only the 20 input features with the highest average significance score are shown (y axis). It is observed that (i) there are a few nodes (such as nodes 95, 147 and 98) which tend to have the highest overall significance (i.e., their net demand is correlated with voltages in more nodes and loading in more branches), and (ii) the significance is highly location-dependent. The latter indicates that, if regulation

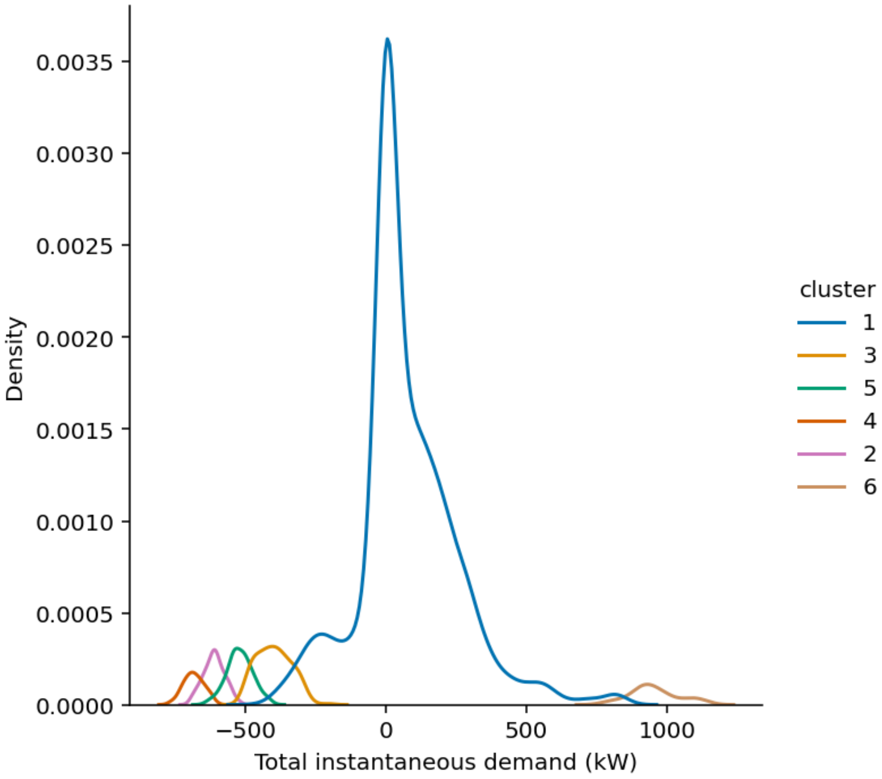

Figure 23: Clustering based on net demand-100% HEMS deployment.

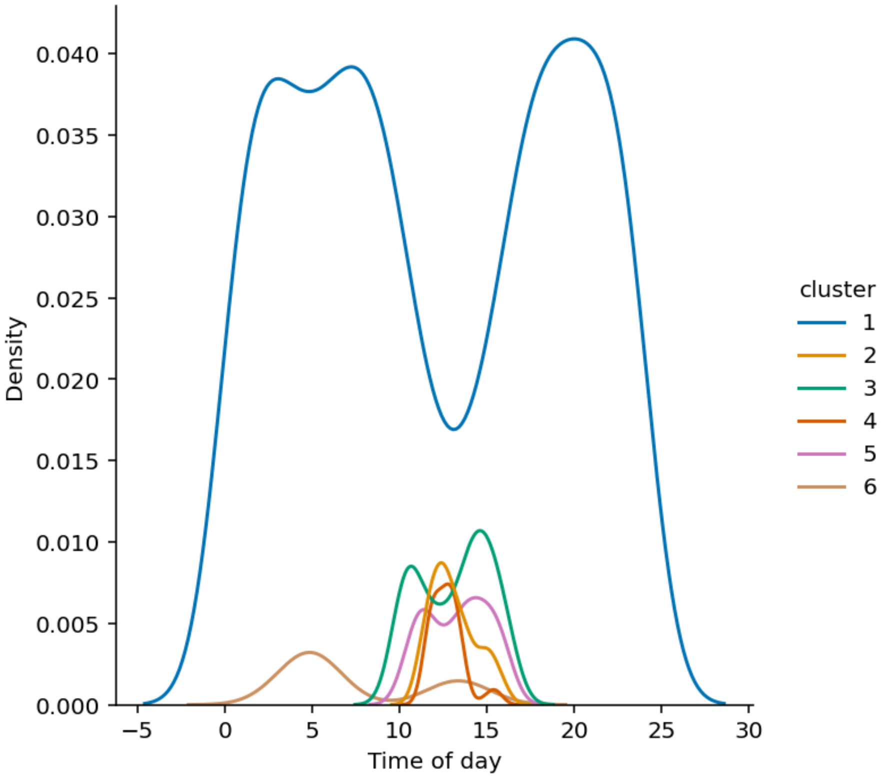

Figure 24: Clustering based on time instances-100% HEMS deployment.

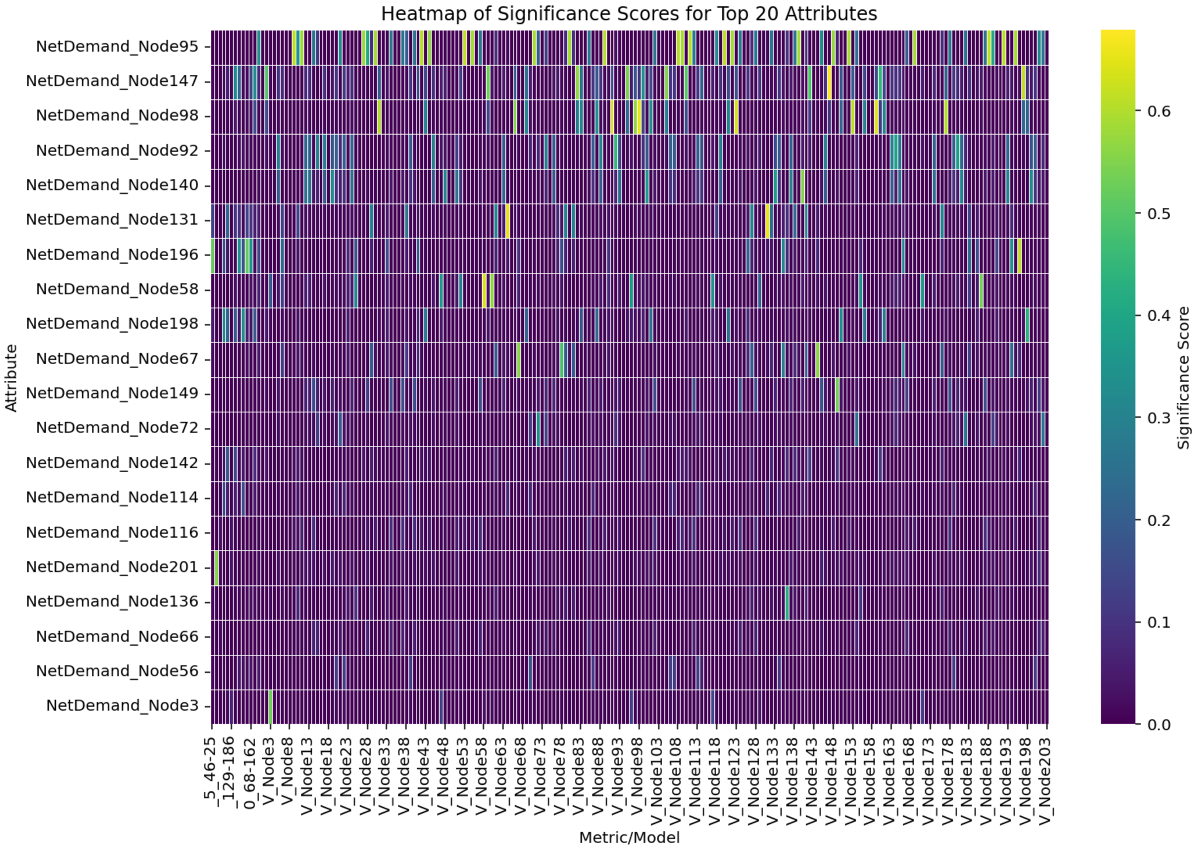

Figure 25: Importance analysis for all outputs: Net demand per node vs. branch loadings and nodal voltages-100% HEMS deployment.

allows, localized (spatially different) tariff schemes will have a more targeted and valuable impact. The tariffs for demand and feed-in are updated based on the results of the importance analysis illustrated by the heatmap.

Figure 26 is a complement to Figure 25, provided for better clarity. In this figure, instead of showing all the output features in axis x, 10 outputs are selected for better visualization.

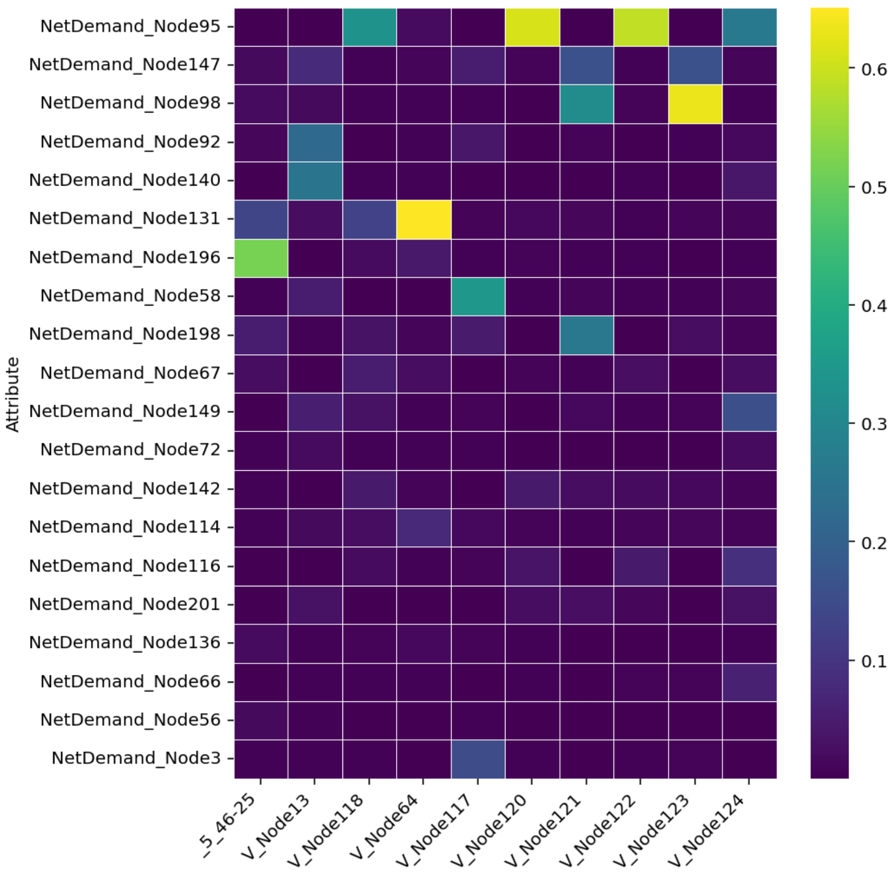

Figure 26: Importance analysis for selected outputs: Net demand per node vs. branch loadings and nodal voltages-100% HEMS deployment.

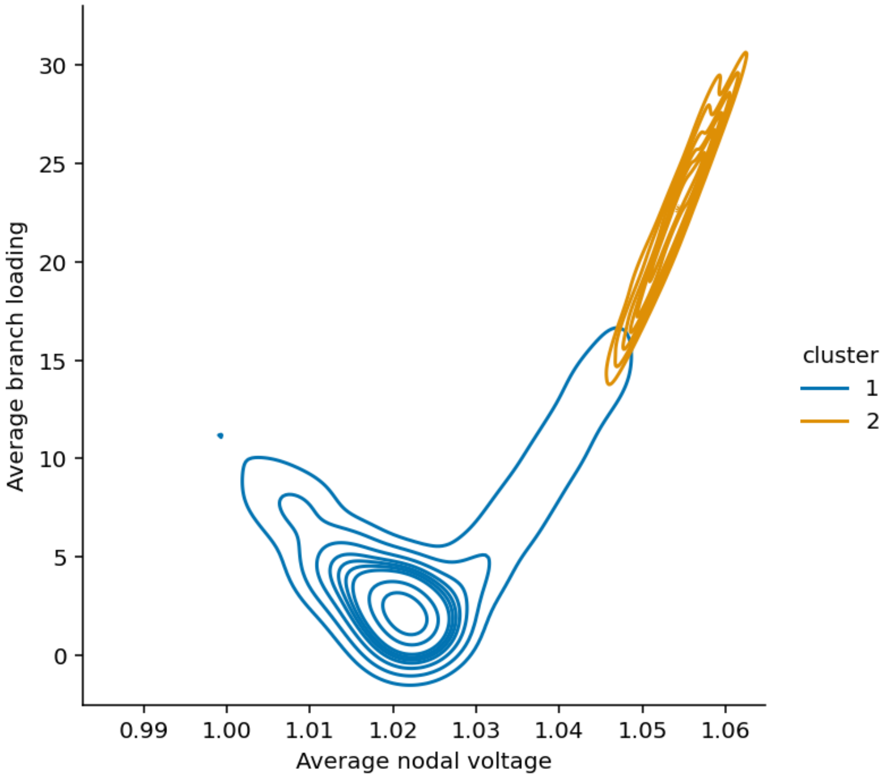

Figure 27: Clustering based on branch loadings and nodal voltages: No HEMS deployment; end-users do not react to tariffs.

Second set of results are created to illustrate how a utility can (i) identify the critical end-users based on a simulation results and available measurements, whose behaviour can result in drastic overloading and voltage violations, (ii) design and test tariffs which can be offered to the identified end-users. The dynamic tariff design by combining Approaches I and II, described in Section 4.1 is used.

The **first step** of the proposed approach consists in clustering the data samples such that specific targets can be identified. Figure 27 illustrates the results of the clustering algorithm. The data samples are grouped in two clusters: one cluster where branch loadings and nodal voltages lie within the acceptable limits and another cluster which groups the data samples with branch overlaodings and nodal overvoltages. In this case, where it is assumed that the end-users have no HEMS, i.e., they are not reacting to tariffs, there are no data samples with undervoltages.

Figure 28 is a histogram showing the number of branch overloadinings observed in each cluster, while 29 is a histogram showing the number of nodal overvoltages. The tariff designer can easily deduce the conclusion that the tariffs need to be applied to the "cluster 2" motivating the end-users to reduce the power they inject to the grid (see Figure 30). One can also observe that most data samples (85% of samples) were grouped in "cluster 1", i.e., the cluster for which there is no need to motivate a change of the end-user behavior.

By observing the clusters, one can see that the tariff shall focus on the Summer and Transition seasons (i.e., not Winter) in the time interval from 10:15 to 16:15 This is illustrated in Figure 31.

The **second step** of the proposed approach consists in identifying which end-users shall be targeted by the dynamic tariff scheme. Following the method described in 4.1, the 20 most influential nodes were identified. With reference to the grid diagram (see Figure 14), the nodes selected by the method are shown in Figure 32.

In the remainder of this section, we will illustrate how progressively enabling HEMS for selected end-users and exposing them to dynamic tariffs helps reducing the overloadings observed in the above-presented reference case (with no HEMS, hence no end-user reaction to tariffs).

Motivating HEMS: As a first step, we assume that the utility motivates the end-users that are located in the 20 nodes that were identified as the most influential to deploy HEMS, allowing them to optimize their consumption and production by reacting to tariffs. At this step, we keep the electricity consumption tariff

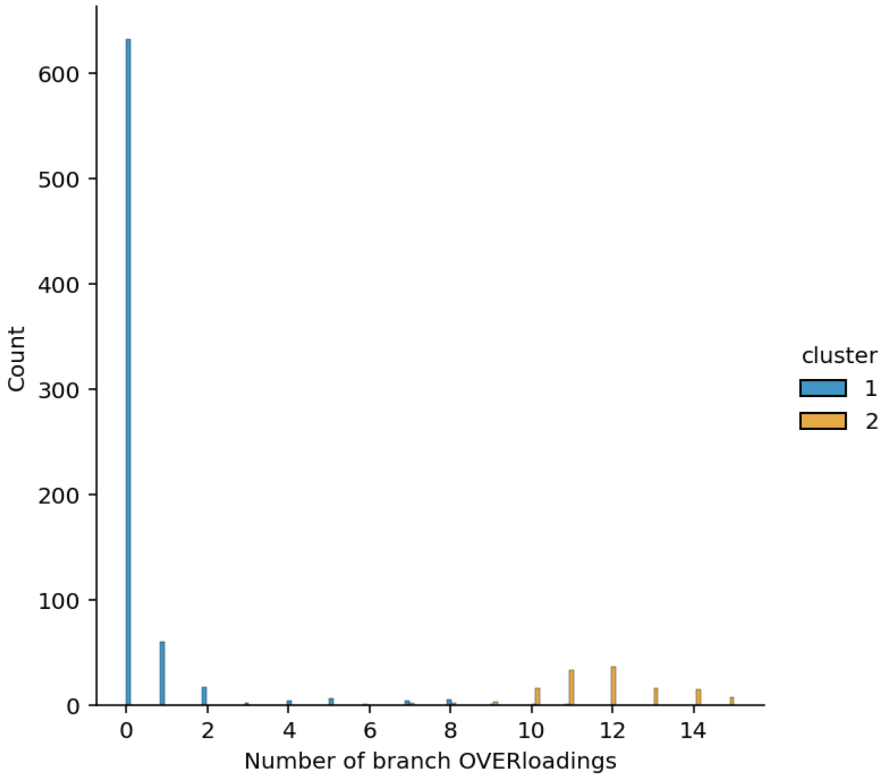

Figure 28: Histogram showing the number of branch overloadings observed in each cluster: No HEMS deployment; end-users do not react to tariffs.

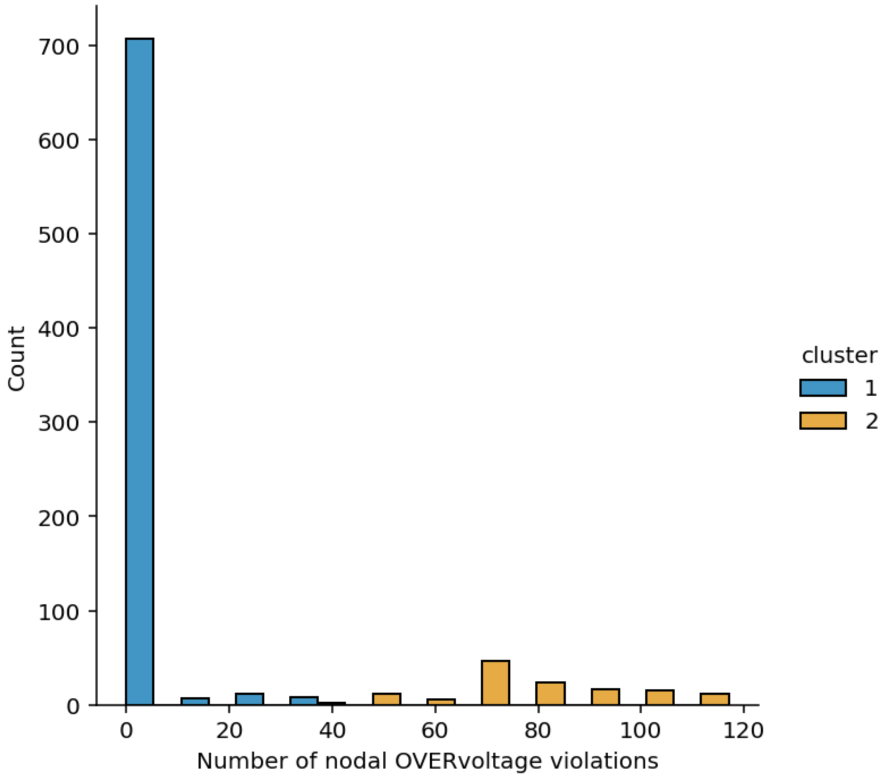

Figure 29: Histogram showing the number of nodal overvoltages observed in each cluster: No HEMS deployment; end-users do not react to tariffs.

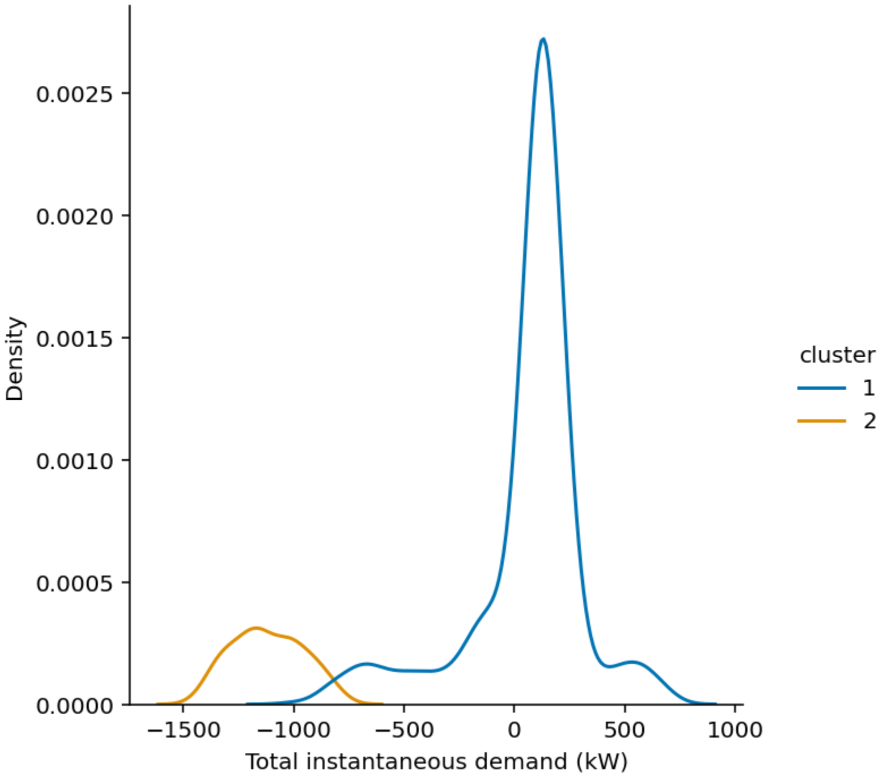

Figure 30: Probability density function showing the likelihood of a data sample to belong to a cluster given the net total power withdrawal of the end-users from the grid (negative value corresponds to a net total power injection): No HEMS deployment; end-users do not react to tariffs.

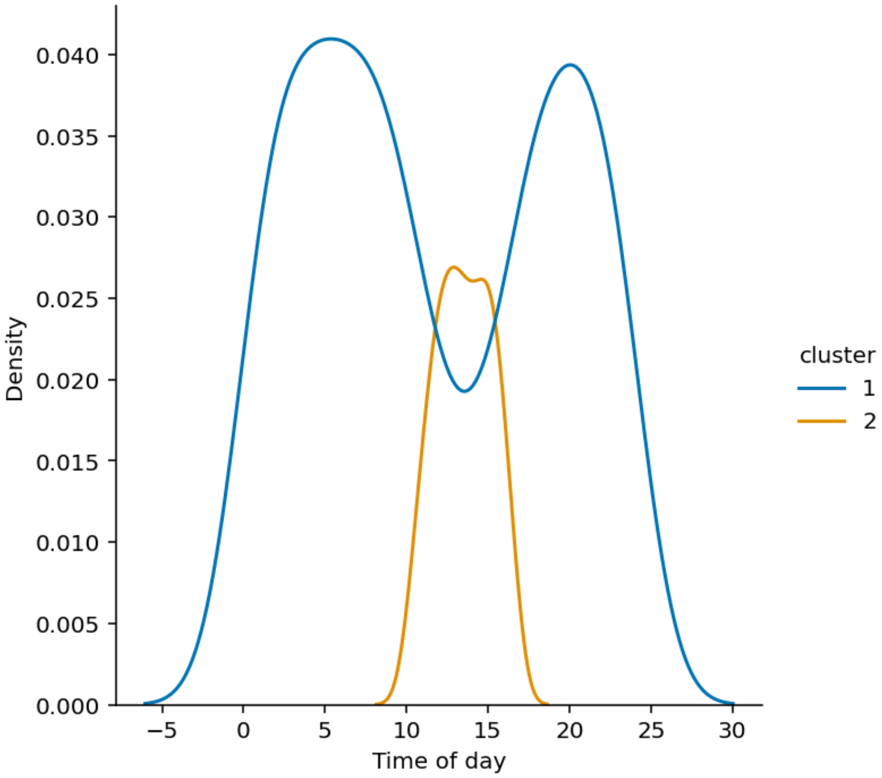

Figure 31: Probability density function showing the likelihood of a data sample to belong to a cluster given the time of day: No HEMS deployment; end-users do not react to tariffs.

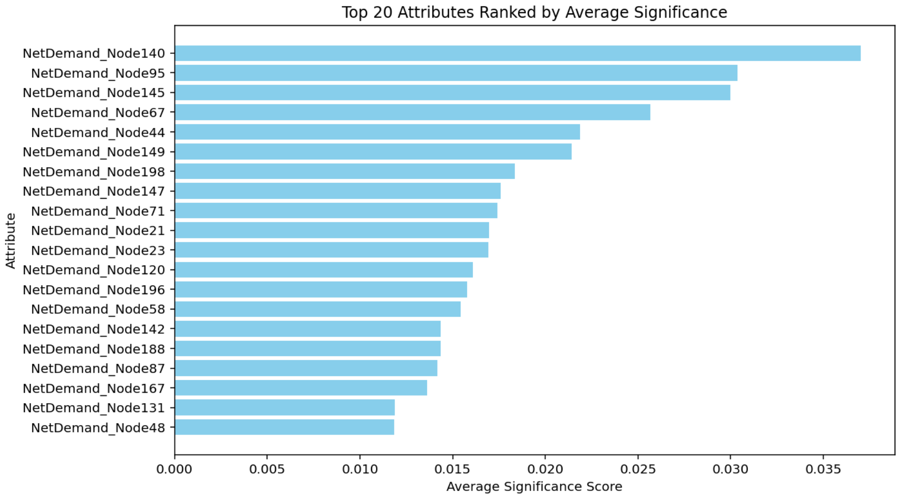

Figure 32: Twenty most influential input features, ranked based on their average significance for being good predictors of nodal overvoltages and branch overloads: No HEMS deployment; end-users do not react to tariffs.

and the electricity injection (feed-in) tariff constant, equal to 26 Rp./kWh and 5 Rp./kWh, respectively. However, even these constant (i.e., not dynamic) tariffs motivate end-users that are equipped with HEMS (i.e., per our assumption, the end-user connected to the 20 nodes identified as the most impactful, shown in Figure 32) to maximize their self-consumption, either by shifting their electricity demand to better align with the high PV production hours or by utilizing their batteries.

Figure 33 shows the histogram of branch overloading in the two clusters. One can clearly observe, by comparing it to Figure 28, that the reaction to the price signals in an automated manner had a significant beneficial impact in alleviating violations in the network.

Next, we implement **a dynamic tariff scheme**, with the objective to further motivate demand shifting to high PV hours. Based on the clustering analysis, we observe that the samples in cluster 2 correspond to operating points that occur in the Transition or Summer seasons, from 10:15 to 16:15. Hence, we devise a dynamic tariff scheme in which, during these hours in the identified 20 nodes, the electricity price is lower during other hours (decreased from 26 Rp./kWh to 20 Rp./kWh) and the feed-in tariff is dropped to zero.

Figure 33 shows the histogram of branch overloading in two clusters for this dynamic tariff scheme. By comparing it to Figure 33 one can observe that the overloadings were slightly decreased.

Table 6 illustrates the impact of motivating the deployment of HEMS and a dynamic tariff scheme on two chosen KPIs: (a) the average net power injection in the data samples of cluster 2, and (b) the average number of branch overloads in the same data samples. One can observe that adding a reaction to price signals (by means of a HEMS-based optimized) can have a very significant impact in network congestion, while further tuning the tariff scheme adds incremental benefits.

Table 6: Summary of results.

With HEMS?	**Tariff scheme**	**Average net injection (kW)**	**Average number of overloadings**
No	Irrelevant	1’118	11.8
Yes (in 20 nodes)	Fixed	626	3.6
Yes (in 20 nodes)	Dynamic (20 nodes)	576	2.5

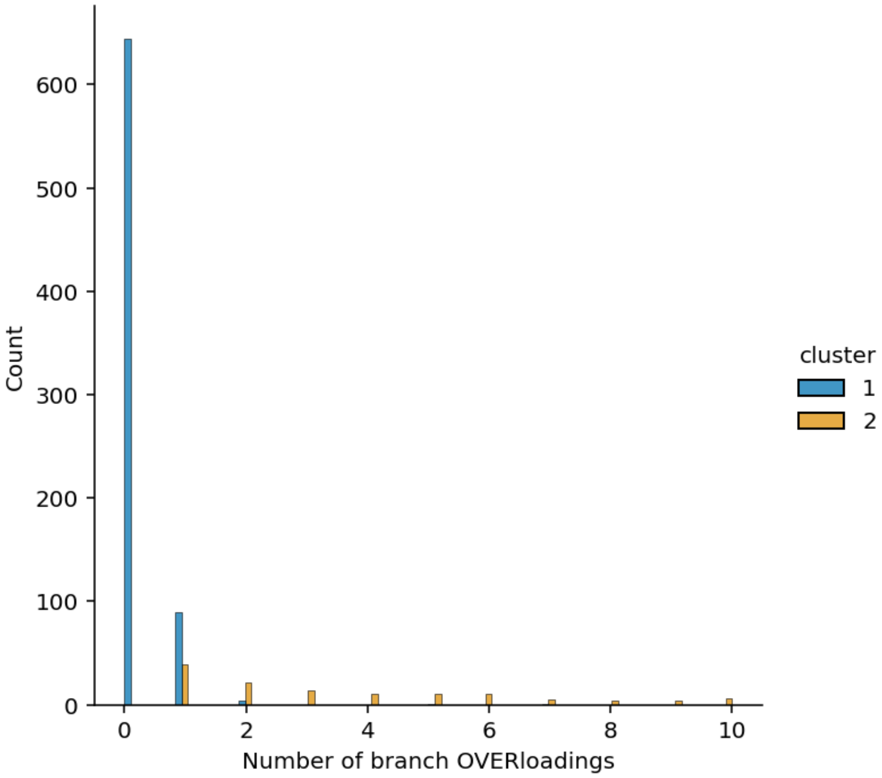

Figure 33: Histogram showing the number of branch overloadings observed in each cluster: HEMS deployed by end-users only in **20** nodes shown in Figure 32; electricity and feed-in tariffs are fixed.

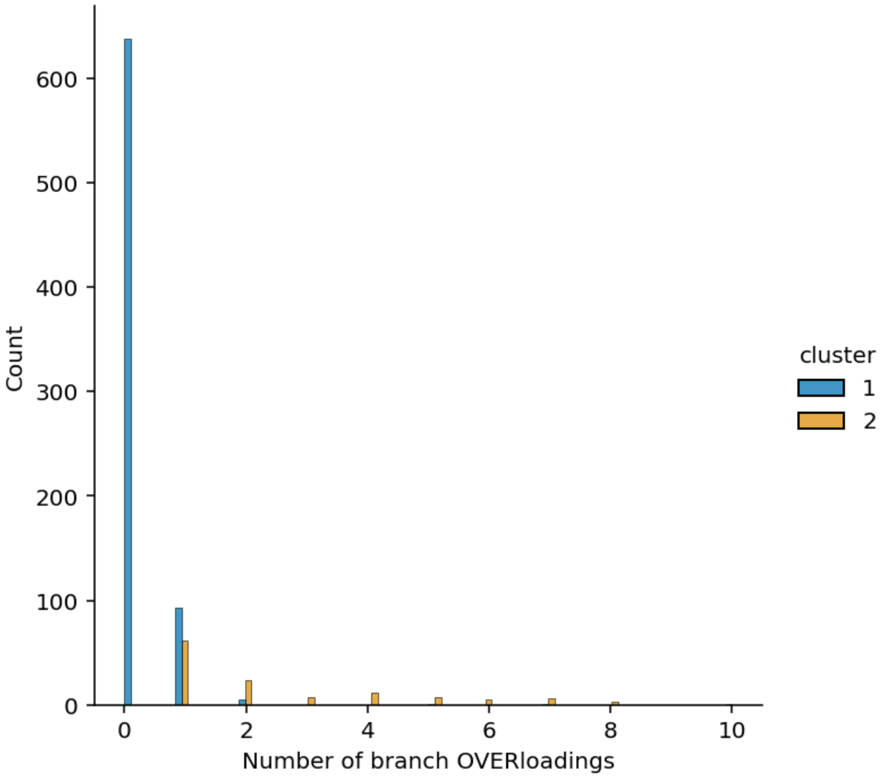

Figure 34: Histogram showing the number of branch overloadings observed in each cluster: HEMS deployed by end-users only in **20** nodes shown in Figure 32; electricity and feed-in tariffs are dynamic (both lower during the PV hours).

5 Virtual Demonstrator

5.1 Copilot user interface

To address questions about the integration of DPT solutions into the daily activities of network management, planning and operations personnel, we looked into various user interface concepts and how they may fit into the already busy array of screens and communication systems[3] available in control rooms. Basic GUIs as dashboards to visualize data, reports summarizing grids conditions, command-line interface for advance users to access low-level functions, and intelligent chatbots to access data via text or voice interfaces were considered. Given the accelerated development and large potential of conversational interfaces based on LLMs, we conceptualized a data co-pilot user interface to interact with the analytics and modelling workflows that are described in Section 2.3. This concept consist of the following components.

1. **Delegator.** Takes the form of a rule-based expert system, with a small knowledge base (i.e., definitions of agents, tasks, and tools) and an inference engine (i.e., set of rules). Its main function is to assign agents and tools to tasks. Its tree structure addresses each case depending on the inputs of the user.
2. **Agents.** Software object with states and memory, and minimal autonomy stemming mainly from rules. It can act and exchange data with other agents, and call tools within its limited scope (e.g., Hewitt's Actor model).
3. **Tools.** Hard coded functionalities that are part of workflows, or functions that wrap models or smaller analytics pipelines that are commonly used to return grid state information to the user.
4. **LLM.** It has the same hierarchy and more autonomy as an agent. Corresponds to agents in Langchain framework and autonomous agents utilizing LLMs in MetaGPT framework. Here, their scope is limited to access tools that provide functions that are not essential for computational workflows.

This concept was taken further in synergy with a research innovation project focused on applications of generative AI to industrial time series data[4] where advanced design patterns and implementation tools for the use foundation models to extract information from time series data were investigated. The focus was on gaining insights from time series data originating from IoT sensors in energy and industrial applications in order to create a time series assistant that makes predictions and identifies and classifies anomalies. A proof-of-concept was built using open-source tools for creating interactive web applications and for integrating LLMs in them. In a further step, a mockup of a UI was implemented as a semi-functional interactive website with a main screen split into 4 panels described as follows. The view displayed by the GUI when selecting power flow forecast workflow is show in Figure 35.

1. Workflow Selection Panel (top-left) with drop-down list of available workflows and a run button.
2. Input Data Panel (top-right) with a data preview table with mocked grid sensor data.
3. Conversational Interface Panel (bottom-left) with a chat message history, input field for user queries, send button, and typing indicator.
4. Workflow Results Panel (bottom-right) a placeholder to visualize output data.

The following qualitative conclusions were reached with these software engineering and UI design experiments.

- Modular DPT software in combination with consolidated, machine readable data are the basis on which to build applications that integrate LLMs and are robust. Frameworks to build these systems facilitate the creation of proof-of-concepts.

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[3] View of control room, Control System and Operational Management, AXPO.

[4] GenAI Time Series Assistant, 129.570 INNO-ICT, INNOSUISSE, https://www.aramis.admin.ch/Texte/?ProjectID=56470.

- The wide range of prices[5] for using LLMs hosted by commercial companies, the cyber-security and data privacy uncertainties, and the availability of open source LLM models make it attractive to develop in-house solutions.
- UI design requires input from technicians and operators involved in operational planning and IT-personnel responsible of OT/IT systems.

It is worth stressing that Generative AI, expressed as LLMs and foundation models, has taken a remarkable position in the development of AI applications, even in technical domains numerous simulation and data analytics commercial offers are developing functionalities based on these technologies to automate tasks and enhance user experience. Recently, a predominant approach to develop these applications resorts to agentic or multi-agent patterns, where LLM agents determine the application control flow. However, relying on LLMs to control task execution does not guarantee high reliability and increases cyber-security risks. Thus, in our concept LLMs had a limited scope of control and were meant to help with retrieving context data and facilitating a conversational interface. Next step is to increase the scope of access that LLM agents have, but keeping the control flow deterministic.

5.2 Flexo platform

FLEXO is a cloud-native distributed energy resource management platform that aggregates and orchestrates virtual power plants and energy communities across Switzerland and Italy, interfacing with TSOs/DSOs and energy markets. It is engineered for scientific pilots with repeatable experiments, end-to-end traceability (raw telemetry -> derived metrics -> control actions -> outcomes), and auditable data products.

It consists of event-driven microservices running on GKE. An overview of the architecture is as follows:

- Ingestion Layer
  35+ specialized ingestors integrate heterogeneous sources (EV charging networks, smart meters, HEMS, PV/BESS/industrial devices) via MQTT, AMQP, REST/webhooks, FTP/SFTP, and Modbus. Ingestion attaches canonical asset identity/metadata and data-quality signals, and distinguishes event-time vs ingest-time.
- Streaming Layer
  Apache Pulsar provides the central event backbone with topic-based routing for telemetry, dispatch commands, and settlement/compliance events. Streams use versioned schemas, replay support, and idempotency to enable reliable processing and reproducibility.
- Processing Layer
  Stateless stream processors harmonize units/keys and aggregate into deterministic 1-minute buckets using watermark-based event-time processing, with defined gap-filling and late-data policies. Aggregates include provenance (inputs + transformation version) for auditability.
- Storage Layer
  PostgreSQL + TimescaleDB store operational and time-series aggregates for control and recent history. BigQuery provides the analytical warehouse for settlement calculations and historical/scientific analysis, with curated “analysis-ready” datasets derived from immutable/raw data.
- Control Layer
  Dispatch APIs and fleet controllers execute optimization setpoints while enforcing safety constraints (min/max power, ramps, SoC, opt-out/fail-safe logic). Closed-loop evaluation links issued commands to device response and delivered service KPIs.

FLEXO Technology Stack is summarized below:

- Backend: Python 3.11+ (FastAPI, SQLAlchemy, Pydantic)
- API Gateway: Go

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[5] Example of model prices reported in early 2024: GPT-4 call costs for input/output per 1M tokens was in the order of 60/120 USD respectively, whereas call costs for a much smaller model, Mistral 7B, were in the order of 0.2/0.2 USD respectively. The release of a plethora of smaller models that deliver very good performance has largely reduced this price difference.

- Frontends: TypeScript/React (Vercel)
- Broker: Apache Pulsar
- Databases: PostgreSQL/TimescaleDB, BigQuery, Redis
- Orchestration: Kubernetes, ArgoCD (GitOps), Argo Workflows
- Cloud: Google Cloud Platform (GKE, Cloud SQL, BigQuery)

5.3 Concepts for data federation

A concept for federating data access based on data spaces was conceptualized and a minimum version of the main components was testing using off-the-shelve open implementations. Such an approach to facilitate access to data in a secured and federated way in a data space, which the International Data Spaces Association (IDS) defines as: " ... a virtual space that provides a standardized framework for data exchange, based on common protocols and formats, as well as secure and trusted data sharing mechanisms. The IDS data space is designed to support data sovereignty, meaning that data owners retain control over their data and can determine who can use it and under what conditions." Moreover, a data space in a given domain, say transport is intended to be compatible with data spaces in other domains. Specific to the energy domain, [31] describes high level goals and use cases such as co-ordination of TSO-DSO for congestion management. Also, uses cases in the interface between local communities and energy utilities, such as grid the facilitation of grid connection processes and maintenance services are mentioned as having potential benefits from accessing heterogeneous data sets within an energy data space. As data spaces aim at being fully interoperable and standardized, along with their definitions reference implementations are provided, for example by IDS, by Eclipse Foundation, and by private companies. To investigate data federation approaches, we tested the deployment of a Minimum Viable Data Space (MVDS) and created a concept to integrated with our digital process twin workflows, as illustrated in Figure 36.

The main learning from deploying the IDS Testbed is the need for more powerful ICT infrastructure than the basic setup that we operated. Namely, we used two virtual machines with 4 and 12 GB of random access memory (RAM) for the implementations file-based implementations that we used to run python scripts representing the different workflows, whereas for testing the basic data space components MVDS we had to upgrade to a separate machine with 18 GB RAM and 500 GB of free disk space. Overall, the MVDS provided a basic understanding of the technologies behind data spaces and generated synergies with research initiatives that are focused on data spaces within the energy domain.

Moreover, although data spaces have recently gained much relevance, their standardization is on-going and there are several challenges when looking into their implementation. Some of them are related to the maturity of the technologies, the learning curve, and costs. Other, are related to the business models and data governance that needs to be in place. Moreover, data spaces as per their definition and standardisation do not consider computation itself. This brings them to some extent in conflict with SSoT, which is a fundamental characteristic of a DT, as the data space federates the access to data. Therefore, implementing SSoT in data spaces is another challenge that does not have standardised practices. Looking further, AI marketplaces where users can access data consolidation workflows, securely share data across stakeholders, and ultimately deploy analytics workflows including state-of-the-art AI models [32] are in active development. Although they are less established than data space, data virtualisation, data as a service (data products), software as a service, or data platform concepts. They focus on the value of data that can be monetized. Thus, AI marketplaces could have benefits over data spaces, as they aim at an ecosystem of digital products and services, where users can trade datasets, provide labelling and curation services, download or run AI models in the cloud.

5.4 Impact of dynamic tariffs

The concept and the interactions among the selected modules in the project are tested and demonstrated using the ReSIM[6] simulation and collaboration environment, which was developed as part of a

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[6] FEN/ReSIM

former project, ReMaP[7], funded by the SFOE.

The goal of the virtual demonstration is to show the benefits of a simulation framework to identify and assess an appropriate dynamic tariff scheme. The simulation framework combines a grid model, data from analytics and grid state forecasting, a dynamic tariff assessor and creator, and end-users represented by "optimizers with perfect foresight" that react to the changing tariffs. Architecture concepts and methodologies to build this virtual demonstration were laid out in Sections 3 and 4. Here, we describe the individual components that are modelled to implement a virtual demonstration using network topology of the Chapelle site, as follows.

- **Grid model**: Champ Monnet grid presented in Section 4.2 is used in pandapower format.
- **End-user optimizer**: The end-user models and the optimizer were integrated into ReSIM via a wrapper class that facilitates the exchange of inputs and outputs as described in Section 3.3. The optimizer is set up to minimize the household's energy cost throughout the day based on the electricity demand and feed-in tariffs. Each end-user (in total 64) is assumed to be equipped with and HEMS represented by an end-user optimizer. The characteristics of the end-users are designed as follows:
  - The grid connection capacity of each end-user is selected based on the industry standards.
  - The base (conventional) electricity demand is based on the time-series generated by SyntDERGen (See Section 4.2.)
  - Solar PV kWp installed capacity and the residential BESS kW/kWh (generated by SyntDERGen). A 20% curtailment based on installed kWp is allowed. This is in addition to the 30% curtailment already applied during time-series generation.
  - The arrival times of EVs as well as their daily energy requirements (generated by SyntDERGen)
  - EV charging infrastructure (i.e., 11 kW)
  - HP installed electric capacity with heat storage tanks (generated by SyntDERGen)
- **Power Flow Solver**: An open-source grid simulation tool, Pandapower [19] is integrated to the ReSIM framework and used for simulations.
- **Data collection**: The power flow results (including transformer and line loadings, nodal voltages, net loads etc.) and the results of the end-user optimizers are collected and stored by ReSIM's internal data management, which makes the data available throughout the simulation and takes care of storing the data at the end.
- **Assessment of tariff impact and network tariff rule**: Key performance indicators (loadings and voltages) are extracted from the power flow results and stored to create a historical trend of grid congestion which serves to both measure tariff impact and guide network tariff rules. Figure 37 illustrates the envisioned layout to test the impacts of different tariffs and various "end-user optimizer" deployments with ReSIM.
- **User interface**: an integration to the visualization dashboard FLEXO, provided by HIVE Power, completes this virtual demonstration with a visual user interface to navigate results of ReSIM simulations. Figures 38, 39 and 40 show selected screenshots of the FLEXO dashboard, which uses the results of the ReSIM simulations runs in the form of .csv files.

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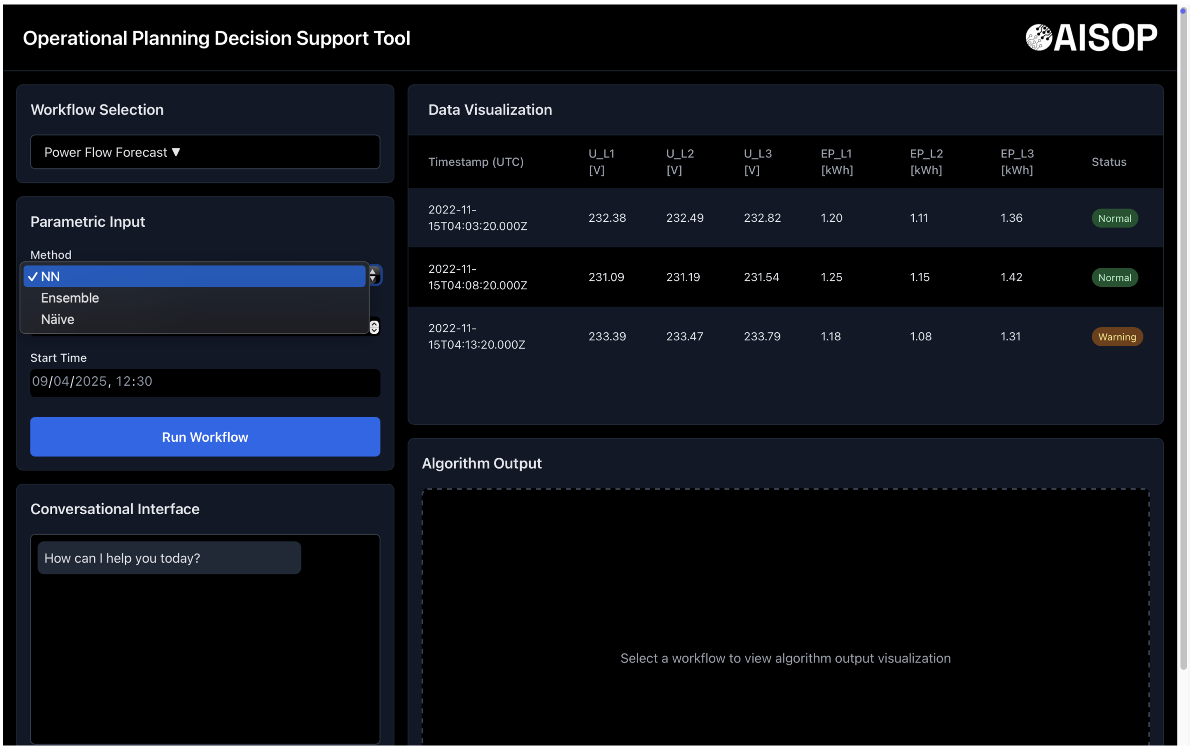
[7] ReMaP – Renewable Management and Real-Time Control Platform, Swiss Federal Office of Energy, Final Report SI 501810-1, 2023. (Chapter 7: ReSIM User guide) SFOE/ReMaP.



Start Time: 09/04/2025, 12:30

How can I help you today?

Timestamp (UTC)	U_L1 [V]	U_L2 [V]	U_L3 [V]	EP_L1 [kWh]	EP_L2 [kWh]	EP_L3 [kWh]	Status
2022-11-15T04:03:20.000Z	232.38	232.49	232.82	1.20	1.11	1.36	Normal
2022-11-15T04:08:20.000Z	231.09	231.19	231.54	1.25	1.15	1.42	Normal
2022-11-15T04:13:20.000Z	233.39	233.47	233.79	1.18	1.08	1.31	Warning

Select a workflow to view algorithm output visualization

Figure 35: View of prototyped mockup of UI.

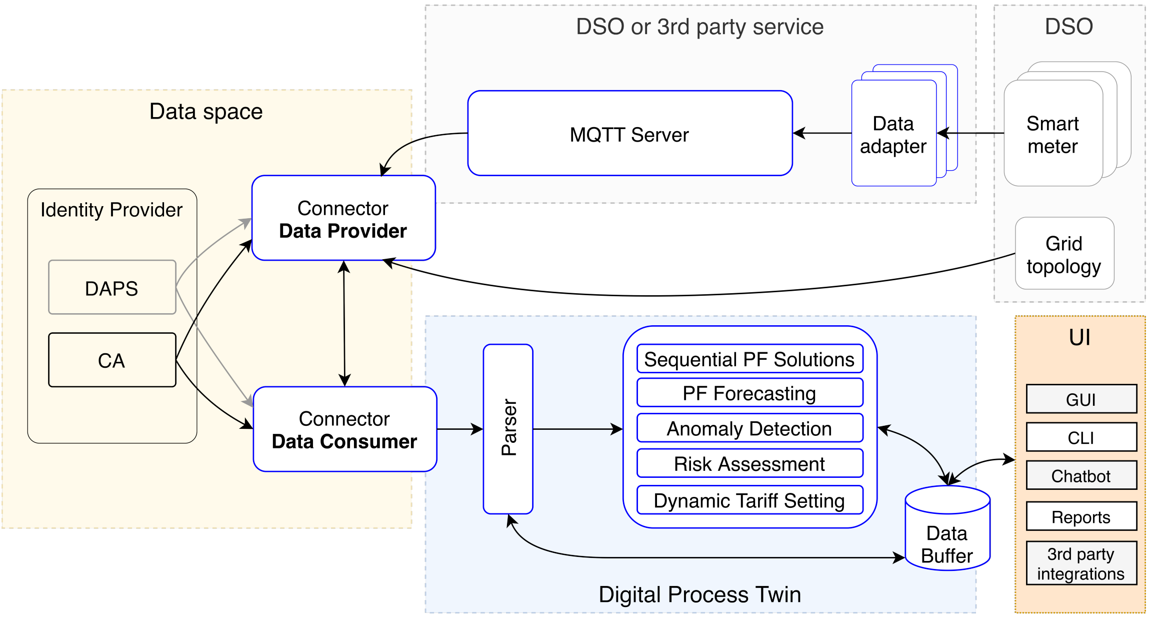


Figure 36: Data space implemented with of the shelve components its connection to DPT and UI.

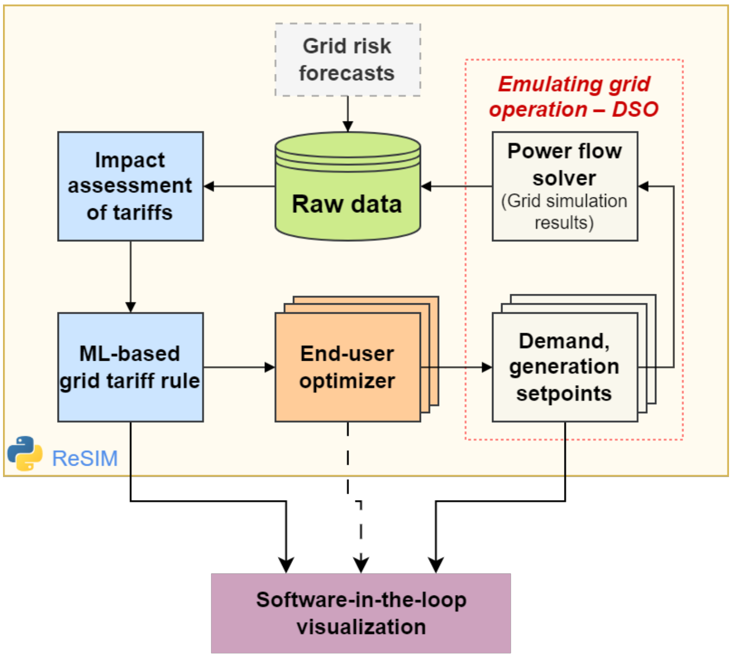
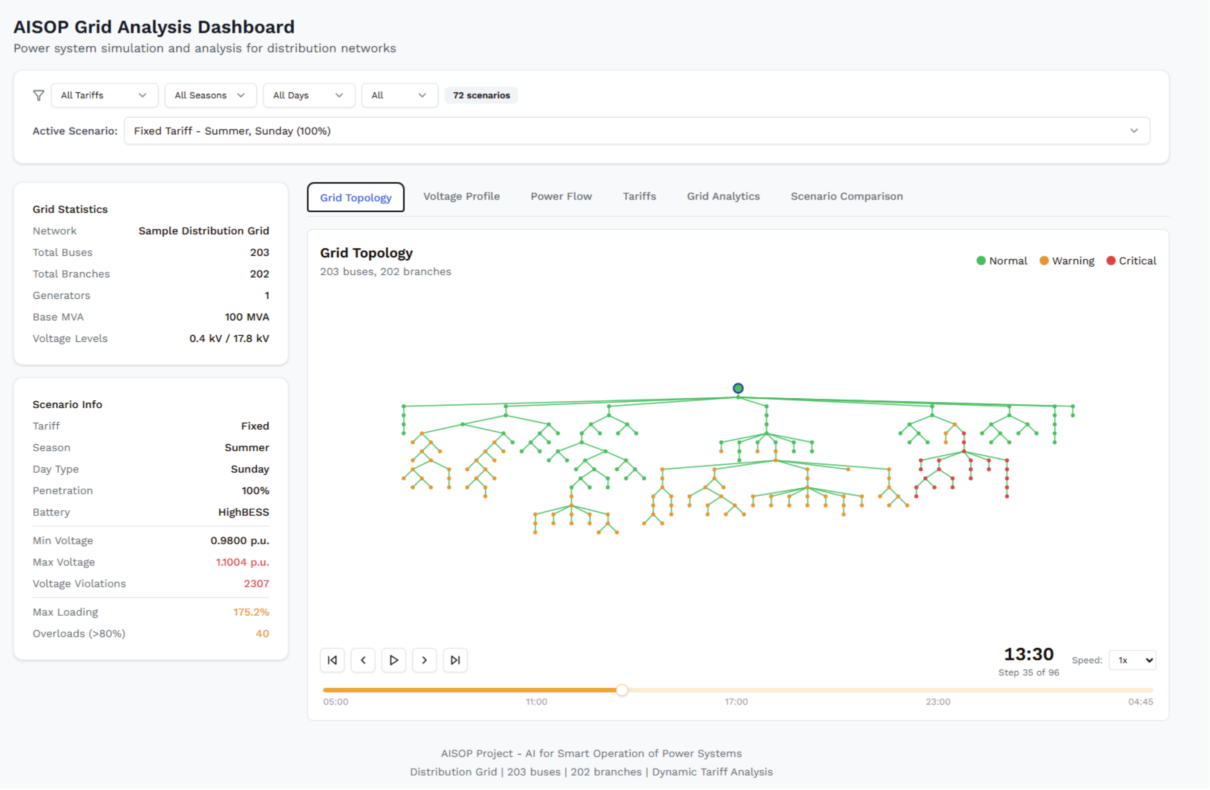


Figure 37: Envisioned layout for testing tariffs with ReSIM.



AISOP Grid Analysis Dashboard

Power system simulation and analysis for distribution networks

Active Scenario: Fixed Tariff - Summer, Sunday (100%)

Grid Statistics

Network	Sample Distribution Grid
Total Buses	203
Total Branches	202
Generators	1
Base MVA	100 MVA
Voltage Levels	0.4 kV / 17.8 kV

Scenario Info

Tariff	Fixed
Season	Summer
Day Type	Sunday
Penetration	100%
Battery	HighBESS
Min Voltage	0.9800 p.u.
Max Voltage	1.1004 p.u.
Voltage Violations	2307
Max Loading	175.2%
Overloads (>80%)	40

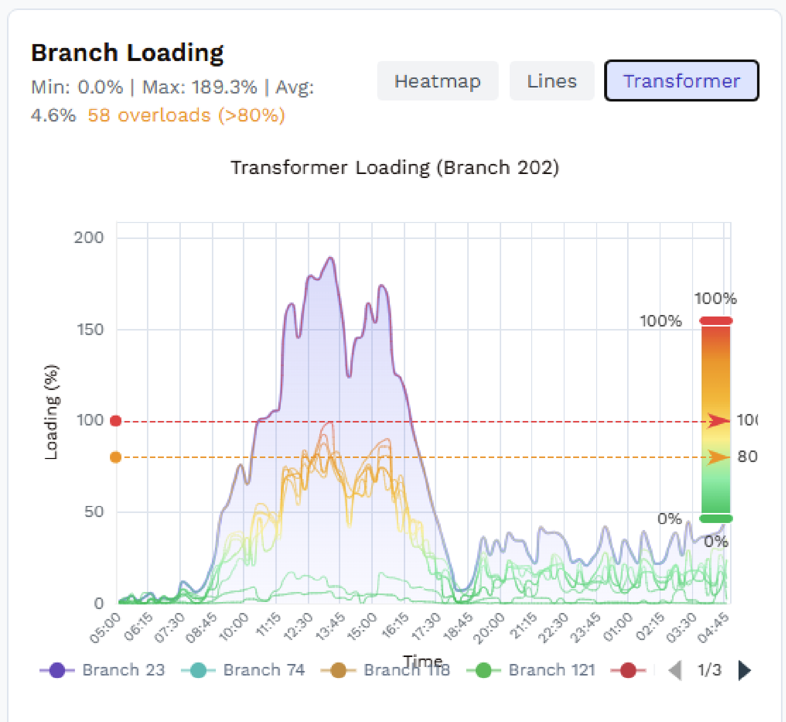
Grid Topology

203 buses, 202 branches

AISOP Project - AI for Smart Operation of Power Systems

Distribution Grid | 203 buses | 202 branches | Dynamic Tariff Analysis

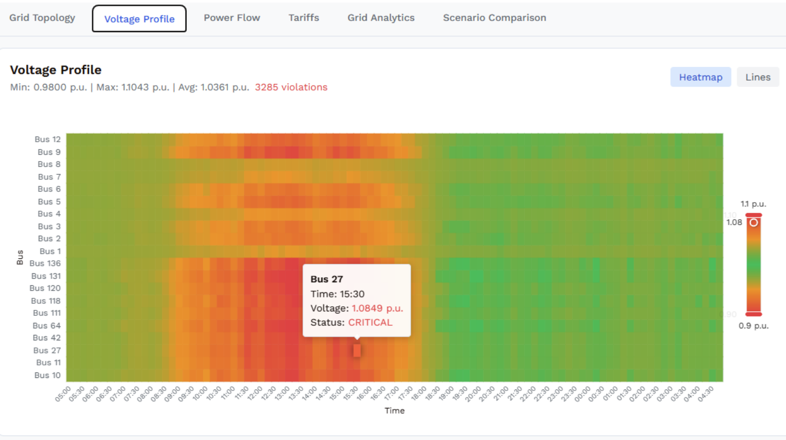
Figure 38: The screenshot of Hive Power dashboard FLEXO: main page



Branch Loading

Min: 0.0% | Max: 189.3% | Avg: 4.6% 58 overloads (>80%)

Figure 39: The screenshot of Hive Power dashboard FLEXO: Grid Analytics - Branch loadings



Voltage Profile

Min: 0.9800 p.u. | Max: 1.1043 p.u. | Avg: 1.0361 p.u. 3285 violations

Bus 27
Time: 15:30
Voltage: 1.0849 p.u.
Status: CRITICAL

Figure 40: The screenshot of Hive Power dashboard FLEXO: Voltage Profile

6 Conclusions and outlook

The work encompassed research on grid monitoring and their application to decision support with data analytics tools and tools for simulation of the impact that dynamic tariffs can have on the grid. Focus was put on bridging the gap between current grid operational practices and the operation in future scenarios where digitalization in low voltage networks is more advanced and instruments for non-intrusive control of active loads are wide spread. Activities included conceptualization of decision support systems, specifically digital process twin and intelligent dashboards technologies. Application of data analytics and ML to detect anomalies and forecast grid operation, as well as their combination with models of the grid and the end user to study the impact of dynamic tariffs. Overall, an integrated grid awareness and risk analysis is essential for the whole operational planning process and the link to tangible actions, such as the assessment and creation of dynamic tariffs. To achieve this, adopting a data management approach with Single Source of Truth (SSoT) is a crucial element to develop robust digital process twins for grid operation, including grid-situational awareness as well as asset management. However, this is often difficult to implement due to legacy systems.

Moreover, an ML-based dynamic tariff assessor can help DSOs to continuously assess whether their tariffs are efficient with changing seasons and changing end-user patterns, with increasing solar PVs and new electricity demand. In the project, the ML-based dynamic tariff assessor was developed by using simulations with synthetically-generated time-series. However, a utility that has access to smart-meter data can combine these data with the data from grid sensors, measuring nodal voltages and branch loadings. In essence, a combination of simulations with the available data can produce more insights and more efficient dynamic tariffs.

Take-home messages

- DSOs need tools and methodologies for accessing and leveraging the information in smart meters and grid sensors data. This will allow them to reach a better understanding of how much margin there is to safely integrate new demand like EVs and heat pumps, as well as to continue integrating solar PV. The development of these tools and methodologies involves many stakeholders in the value chain from operational technology, information technology, software providers and departments within DSOs.
- DSOs will benefit from modular digital process twin frameworks, where heterogeneous data from the physical assets and business processes are integrated and verified resulting in SSoT that facilitates the creation of automated analytics and simulations to support operational planning decisions. An important challenge in the implementation of such frameworks is data interoperability, analogous to hardware interoperability and open standards are key to facilitate data flowing across different systems and to avoid vendor lock-in. Additionally, the use of a SSoT requires a change in mindset, existing workflows and competencies.
- ML and AI applications for operational planning, relying on data from smart meter and grid sensors among other data, show a good potential in combination with grid models. However, for these applications to be successful, their deployment should be feasible, and their performance robust, understandable and transparent. During this project, as we developed concepts for grid situational awareness and design of dynamic tariffs, the identification of the **type** and the **amount** of data required to extract sufficient knowledge showed to be very important to gauge their feasibility in practice. Moreover, granted that sufficient data were available, selecting well-known and established algorithms sets the basis for robust and explainable systems.
- For end-users to be reacting to price signals, it is of paramount importance that they have the automation in place, which would maximize their benefit by shifting their demand and/or deploying storage whenever available. The grid-friendly flexibility potential is significant; however, in order to achieve grid-friendly reactions by the automation systems, the tariffs shall be carefully designed and spatially differentiated.
- Carefully designed user dashboards help the utility engineers to efficiently visualize large amount of data and results, that are insightful for grid operations and for decision making.
- Dynamic tariffs have potential to postpone and/or reduce grid investments, but cannot completely eliminate the need for grid investments.

- Non-intrusive flexibility mechanisms such as the implementation of dynamic grid tariffs for demand and distributed generation present a good potential to help DSOs influence end-user behaviour without direct control mechanisms, however, to avoid "rebound" effects in future high proliferation scenarios, the dynamic grid tariffs shall be carefully designed such that they can be not only temporally but also spatially differentiated. Maximum benefits can be achieved when feed-in tariffs are dynamic as well.

Outlook and future work

- The risk metrics and the weather data could be part of the training dataset of the ML model for the dynamic tariffs.
- It would be insightful if data from different utilities, which offer their customers different tariff schemes, could be used to investigate whether or to what extent ML-based tariff scheme tends to identify similar patterns, hence allowing for general rules and recommendation to be derived.
- Pilot projects in regions with high PV, HP and EV proliferation would provide better insights to design tariff structures that foster grid-friendly responses from end-user automation. This ensures that flexibility doesn't unintentionally create new bottlenecks at different hours. In addition the impacts of the selected dynamic tariff on end-user net-demand profiles would be observable, providing further insights to identify the most efficient tariffs and tariff structure. Such observability would highlight the load shifting achieved by dynamic tariffs.
- In the virtual demo, the steps of dynamic tariff updates, tariff impact assessment and visualization of the results on the FLEXO platform include human in the loop. The advantages and disadvantages of automating the steps including tariff updates and tariff impact assessment shall be investigated as part of future work, ideally as part of a pilot project.
- The integrated framework can be further developed for training activities adjusted for grid operator needs.

7 National and international cooperation

Collaboration in the AISOP consortium was promoted by means of synchronisation meetings scheduled monthly or quarterly with all the members, and advisory board meetings where the activities in both countries were presented to the Advisory Board consisting of representatives from BKW, Amprion, and Elia Grid. Deliverables in the form of conference papers, presentations, and reports were shared and discussed. Feedback obtained contributed to methodologies and focus of development activities towards an application-oriented and user-friendly AISOP decision support tool.

German members of the AISOP project represented by ZEDO e.V. focused on development of digital solutions to support operational decisions and anomaly detection to detect anomalies on the user side. Definition and characterization of DPTs was discussed and agreed in a joint workshop of the German partners. The results were compared with the international partners from Switzerland, leading to a uniform and application-relevant definition of main components and scope. The development of DPT solutions led by logarithmo focused on connecting and making readily accessible data from different silos to various processes within the operations and planning of DSOs. While such approaches to the integration of data applied by logarithmo already exist in other areas, they were transferred and extended to the operational planning of DSOs using modern DPT technologies. In terms of anomaly detection, studies were conducted using power flow measurements taken at WWNetz MV-LV transformers, where unexpected and unregistered PV generation, EV charging, new heat pumps, meter failures, and drastic changes in consumption patterns at the customer end were classified and identified as anomalies, then ML methods were trained and applied to identify such instances. The results were documented in scientific publications and reports to the German funding agency.

Communication channels and synergies were established with groups in other ERA-Net funded projects: Lasagne, OWGRE, and Digicities. Other industry and research organisations active in related topics and have shown interest in the research conducted and synergies were created. Leading to communication activities with companies that contributed to gain perspective on innovative products and the gap between commercial offers and the research work presented here. Particularly, communication activities with the Norwegian project NextGrid led to research synergies and complementary activities were identified for future collaborations.

8 Publications and other communications

Publications consisting on scientific journal and conference papers and posters, data and code repositories; as well as communication activities are listed below. Furthermore, newsletters were prepared and disseminated via social media and the project website[8] which was updated frequently to disseminate the activities and the project progress. Most of these documents, are accessible in the project website under Resources.[9] Moreover, AISOP members participated in the ERA-Net Smart Energy Systems working groups on System Architecture and Modelling, and Regional Matters as well as in CETPartnership TRI5 & JPP ERA-Net SES Knowledge Community Meeting.

Publications

B. Barahona, C. Y. Evrenosoglu, A. Marinakis, P. Buchecker, S. Nowak, U. Häger, A. Papaemmanouil, "Datengetriebene Netzbetriebsplanung: Integrierte Werkzeuge für Netzzustandserkennung und Erstellung dynamischer Tarife [Data-driven grid operational planning: Integrated tools for grid situational awareness and dynamic tariff creation]", Bulletin Electrosuisse, December 2025.

D. Papadopoulos, Analytics and forecasting on grid sensor data, AISOP Project Report, August 2025.

T. Quabeck, Technische Anforderungen, AISOP Project Report, December 2024.

R. Balouchi et al., ML-based demand-side anomaly detection and identification, AISOP Project Report, December 2024

R. Khatami, S. Nowak and Y. C. Chen, "Measurement-Based Locational Marginal Prices for Real-Time Markets in Distribution Systems," in *IEEE Trans. on Pow. Syst.*, vol. 39, no. 6, pp. 6974-6985, Nov. 2024.

R. Balouchi et al., "Data-driven Approaches for Anomaly Detection in Low-Voltage Grid Net Power," 2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE), Dubrovnik, Croatia, 2024.

R. Balouchi et al., "Anomaly Detection in Low-Voltage Grids with LSTM Autoencoders: A Study on Future Scenario Impacts," 2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE), Dubrovnik, Croatia, 2024.

B. Barahona et al., “A framework for data-driven decision support for operational planning in active distribution networks,” in the Proc. of CIRED 2024 Vienna Workshop, June 2024.

B. Barahona et al., “A data co-pilot for electric distribution utilities to support grid situational awareness”, AMLD EPFL 2024, April 2024.

B. Barahona, Mar. 2024, “CKW Smart Meter Data,” Zenodo, doi:10.5281/zenodo.13304499.

D. Papadopoulos, “Low Voltage Load Forecasting Using Ensemble Methods,” M.Sc. thesis, School of Business, HSLU, Lucerne, 2024.

Harris, Human-centric behaviour-based modelling for operational planning in a Distribution System Operator (DSO) as the basis of a decision support tool, Bachelor thesis, Jun. 2023.

M. Hojabri, S. Nowak and A. Papaemmanouil, “ML-Based Intermittent Fault Detection, Classification, and Branch Identification in a Distribution Network,” *Energies*, vol. 16, no. 16, p. 6023, Aug. 2023, doi: 10.3390/en16166023.

R. Balouchi, U. Häger, R. Palaniappan, Definition and requirements of digital process twin, including DPT-based architecture, Report, June 2023.

U. Häger, Der Digitale Zwilling in der Netz- und Elektrizitätswirtschaft, ETG taskforce, May 2023. AISOP Project handbook, AISOP Project Report, March 2023.

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[8] `https://www.aisopproject.com/`

[9] `https://www.aisopproject.com/resources/`

Code repositories and communication activities

Repositories hosting supplementary code with preliminary implementations of some of the work presented include: data parsing scripts, architecture of situational awareness workflows, data space reference implementation, co-pilot user interface. Available: https://github.com/orgs/AISOP-beta/repositories

Newsletter # 3 – Risk metrics to support operational planning, January, 2025.

B. Barahona, et al., AISOP Project in CET Partnership TRI5 & JPP ERA-Net SES Knowledge Community Meeting, November 2024.

R. Balouchi et al., Poster presentation, 2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE),“Anomaly Detection in Low-Voltage Grids with LSTM Autoencoders: A Study on Future Scenario Impacts”, October 2024.

C.Y. Evrenosoglu, AISOP Project in ERA-NET Energy Systems Peer-to-Peer Feedback Sessions 2024, SESSION 2 - AI and ML for Energy Systems, June 2024.

Organization of technical meeting AI for Energy Utilities at the Applied Machine Learning Days (AMLD), EPFL 2024:

- Matthias Bucher, Swissgrid AG. *Where AI could help to keep operating the transmission grid in a safe and efficient way.* (Mar. 26, 2024).
- Stefanos Delikaraoglou, Axpo Group. *AI for energy trading.* (Mar. 26, 2024).
- Arthur Cherubini, Romande Energie. *Data-driven generation of synthetic load curves for grid planning.* (Mar. 26, 2024). Accessed: Nov. 18, 2024. [Online Video]. Available: https://youtu.be/BqYRFtYlwPA?si=wD6Tb41lN4p17CA3
- Max Zurkinden, SwissLLM. *Enhancing LLM performance with Retrieval-Augmented-Generation.* (Mar. 26, 2024). Accessed: Nov. 18, 2024. [Online Video].Available: https://youtu.be/4EnsIOhEKcI?si=W_r1RqUA0e8xI4A7

Newsletter # 2 – Digital twins and operational planning, November 2023.

A. Papaemmanouil et al., AISOP Project AI in Distribution Networks, AI4Grids Symposium, September 2023.

R. Balouchi et al., Datengesteuertes Entscheidungsunterstützungssystem für Verteilernetzbetreiber, ETG CIRED Workshop 2023 (D-A-CH), Nov. 2023.

Newsletter # 1 – Introduction to ASIOP Project, October 2022.

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