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AISOP

AI-assisted grid situational awareness and operational planning

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The authors bear the entire responsibility for the content of this report and for the conclusions drawn therefrom.

Zusammenfassung

AISOP entwickelt ein **KI-basiertes Entscheidungsunterstützungswerkzeug für Verteilnetzbetreiber (VNB)** welches auf **fortgeschrittener digitaler Technologie** abgestützt ist, um die Dekarbonisierung voranzutreiben. Das Entscheidungsunterstützungswerkzeug akquiriert, verarbeitet, interpretiert und verwertet Daten für die Betriebsplanung von V. In diesem Zusammenhang erweitert AISOP datengesteuerte Methoden für verbesserte Betriebsplanung, Situationserkennung und Marktanreiz in lokalen Verteilnetzen mit hohen Anteilen von dezentralen Energieressourcen durch KI/ML basierte Entscheidungsunterstützung. Im geplanten Projekt werden (i) Datenzugriff und -aufnahme, (ii) Verteilnetz Situationserkennung, (iii) Entscheidungsunterstützung für Verteilnetzbetrieb, (iv) dynamische Tarife, (v) Integration einer digitalen Plattform mit Auswertung via von Test- und Trainingsumgebungen vereint.

Das Projekt begann im Mai 2022, im ersten Berichtszeitraum im November 2022 wurden Arbeiten im Zusammenhang mit dem Arbeitsablauf für die operative Planung, der Identifizierung von Werkzeugen, der anfänglichen Definition von Anwendungsfällen sowie Aufgaben zur Projektinitiierung gemeldet. Die im aktuellen Berichtszeitraum durchgeführten Arbeiten umfassen die Identifizierung von Datenquellen und die Definition des digitalen Prozesszwillings (WP2). Definition der Architektur des Situationsmodells für das Niederspannungsnetz und spezifischer Arbeitsabläufe zur Prognose des Netzzustands und zur Risikobewertung (WP3). Bewertung von Methoden des überwachten Lernens zur Erkennung von Netzanomalien (WP3). Definition von grundlegenden Vorhersage- und Risikoanalysemethoden (WP3). Definition von Inputs und Ansätzen für den Entwurf und die Bewertung von dynamischen Tarifsystemen (WP4).

Insbesondere zeigen die Implementierungen von Arbeitsabläufen für die Vorhersage von Netzzuständen, die in AISOP vorgesehen sind, dass die Berechnungen in den interessierenden Zeitskalen und Netzgrößen handhabbar sind. Grundlegende Risikoberechnungen sind implementiert und dienen der Entwicklung fortgeschrittener Methoden. Es wurde eine grundlegende Schnittstelle zur Verknüpfung von Leistungsflussprognosen und Risikobewertung mit der Gestaltung dynamischer Tarife definiert. Dies trug dazu bei, ein Instrument zur Entscheidungsunterstützung bei der Erstellung dynamischer Tarife zu entwickeln. Darüber hinaus unterstützt die Integration von Endverbrauchermodellen und Leistungsflussprognosen in ReSIM den Fortschritt hin zu einer Prototypversion eines digitalen Prozesszwillings (DPT). Ausgehend von der Analyse der formalen Anforderungen an digitale Zwillinge wurden die Zusammensetzung des DPT von AISOP, seine Ergebnisse und Anwendungen definiert. Ein Schritt in Richtung Living Labs und Integration von AISOPs Werkzeugen in den Geschäftsprozess wurde durch die Befragung von Betriebspersonal gemacht.

Résumé

AISOP vise à créer un système d'aide à la décision alimenté par l'IA pour les opérateurs de réseaux de distribution d'électricité (DSO) afin de favoriser la décarbonisation soutenue par une technologie numérique avancée. Le système d'aide à la décision collecte, traite, interprète et utilise les données de manière sécurisée et privée au profit de la planification opérationnelle des SOPDI. Dans ce contexte, AISOP étend les techniques basées sur les données pour améliorer la planification opérationnelle dans les réseaux de distribution / locaux avec des parts de DER élevées grâce à l'intégration de solutions basées sur l'IA / ML, une meilleure connaissance de la situation et des incitations au marché. Dans le cadre du projet proposé, nous combinons (i) l'accès et l'ingestion des données, (ii) la connaissance de la situation pour le réseau de distribution, (iii) l'aide à la décision pour la gestion du réseau de distribution, (iv) les tarifs dynamiques, (v) l'intégration de plateformes numériques avec utilisation par des environnements de test et de formation.

Le projet a démarré en mai 2022, au cours de la première période de rapport (novembre 2022), les travaux liés au flux de travail pour la planification opérationnelle, l'identification des outils, la définition initiale des cas d'utilisation, ainsi que les tâches d'initiation du projet ont été rapportés. Les travaux réalisés au cours de la période de rapport actuelle comprennent l'identification des sources de données et la définition du jumeau de processus numérique (WP2). La définition de l'architecture du modèle de connaissance de la situation du réseau basse tension et des flux de travail spécifiques pour prévoir l'état du réseau et évaluer les risques (WP3). Évaluation des méthodes d'apprentissage supervisé pour la détection des anomalies du réseau (WP3). Définition des méthodes de prévision de base et d'analyse des risques (WP3). Définition des intrants et des approches pour la conception et l'évaluation des systèmes tarifaires dynamiques (WP4).

Plus précisément, la mise en œuvre des flux de travail pour la prévision de l'état de la grille qui sont envisagés dans l'AISOP montre que les calculs sont gérables dans les échelles de temps et les tailles de grille qui nous intéressent. Des calculs de risque de base sont mis en œuvre et serviront à développer des méthodes plus avancées. Une interface de base a été définie pour relier les prévisions de flux d'énergie et l'évaluation des risques à la conception de tarifs dynamiques. Cela a contribué à l'élaboration globale d'un outil d'aide à la décision qui crée des tarifs dynamiques. En outre, l'intégration de modèles d'utilisateurs finaux et de solveurs de flux d'énergie à ReSIM soutient les progrès vers une version prototype d'un jumeau de processus numérique (DPT). L'analyse des exigences formelles pour les jumeaux numériques a permis de définir la composition du DPT de l'AISOP, ses résultats et ses applications. Une étape vers les laboratoires vivants et l'intégration des outils AISOP dans les processus d'entreprise a été réalisée en interrogeant le personnel opérationnel.

Summary

AISOP aims to create an **AI-assisted decision support system for the electric distribution system operators** (DSOs) to drive decarbonisation that is underpinned by **advanced digital technology**. The decision-support system securely and privately acquires, processes, interprets, and exploits data for the benefit of DSO operational planning. In this context, AISOP expands data-driven techniques for improved operational planning in distribution/local grids with high shares of DERs by integrating AI/ML-based solutions, enhanced situational awareness and market incentives. Within the proposed project we combine *(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 with exploitation through test and training environments.

The project started in May 2022, in the first reporting period November 2022 work related to the workflow for operational planning, identification of tools, initial definition of use cases, as well as project initiation tasks were reported. Work performed during the current reporting period includes identification of data sources and definition of digital process twin (WP2). Definition of architecture of low-voltage grid situational awareness model and specific workflows to forecast grid state and assess risk (WP3). Evaluation of supervised learning methods for detection of grid anomalies (WP3). Definition of baseline forecasting and risk analysis methods (WP3). Definition of inputs and approaches for design and evaluation of dynamic tariff schemes (WP4).

More specifically, implementations of workflows for grid state forecast that are envisioned in AISOP show that calculations are manageable in the time scales and grid sizes of interest. Baseline risk calculations are implemented and will serve to develop more advanced methods. A basic interface to link power flow forecasts and risk assessment to the design of dynamic tariffs was defined. This helped the overall framing of a decision support tool that creates dynamic tariffs. Moreover, the integration of models of end users and power flow solvers to ReSIM supports the progress towards a prototype version of a digital process twin (DPT). From the analysis of formal requirements for digital twins, the AISOP's DPT composition, its outputs, and applications were defined. A step towards living labs and integration of AISOPs tools into business process was done by interviewing operation personnel.

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Abbreviations

AI	Artificial Intelligence
DER	Distributed Energy Resources
DG	Distributed Generation
DSM	Demand Side Management
DSO	Distribution System Operator
DPT	Digital Process Twin
LV	Low Voltage
ML	Machine Learning
MLT	Machine Learning Technique
MV	Medium Voltage
NE	Netzebene (Grid level)
OP	Operational planning
OPF	Optimal Power Flow
PMU	Phasor Measurement Unit
PQ	Power Quality
RE	Romande Energie
RES	Renewable Energy Sources
SCADA	Supervisory Control and Data Acquisition
SFOE	Swiss Federal Office of Energy
SM	Smart Meter
ToU	Time-of-Use
TSO	Transmission System Operator
WWN	Westfalen-Weser Netz

1 Introduction

1.1 Background information and current situation

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 an AI-assisted decision support system for DSOs. The decision-support system securely and privately acquires data using state-of-the-art digital platforms. It then processes and interprets it 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 time scale), the near-term (multiple years), operational planning schemes (intraday to years). 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 that serve to design dynamics tariffs and overall support DSO operation planning decisions. These tools are envisioned to inform on intra-day, day-ahead, and yearly timescales.

In the initial phase of AISOP, concepts of operational planning (OP) for DSOs were linked to a digital process twin (DPT) architecture which fits AISOPs use cases. AISOP's DPT is to be realised on a digital platform that integrates data assimilation, modelling tools, and decision support. The main concepts of OP and DPT were laid out as part of activities in collaboration with our industrial partners. As a by-product of this process, the initial use case development was completed with need owners in Switzerland (i.e., Romande Energie) and Germany (i.e., Westfalen-Weser Netz). Work performed during the current reporting period includes identification of data sources and definition of digital process twin (WP2). Definition of architecture of low-voltage grid situational awareness model (WP3). Evaluation of supervised learning methods for detection of grid anomalies (WP3). Definition of baseline forecasting and risk analysis methods (WP3). Definition of inputs and approaches for design and evaluation of dynamic tariff schemes (WP4).

1.2 Purpose of the project

AISOP explores how data can support decisions that DSOs need to face given new operational requirements that stem from more distributed energy resources and storages. The overarching mission is to prototype a decision support system that creates dynamic tariffs that act as market incentives and result in improved operational planning.

1.3 Objectives

AISOP project objectives are to:

1. Increase grid observability by using data from multiple sources and in different time resolutions,
2. Help DSOs operate the grid using data-driven decision support tools,
3. Improve the efficiency of network operations,
4. Reduce curtailment of renewable energy and distributed energy resources,
5. Improve options for tariffs for DSO's and prosumers.

AISOP's solutions will acquire, process, interpret and exploit data 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.

Table 1 – AISOP project outcomes.

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

In addition to the outcomes described above, AISOP will deliver environmental and socio-economic impacts as described in Figure 1.

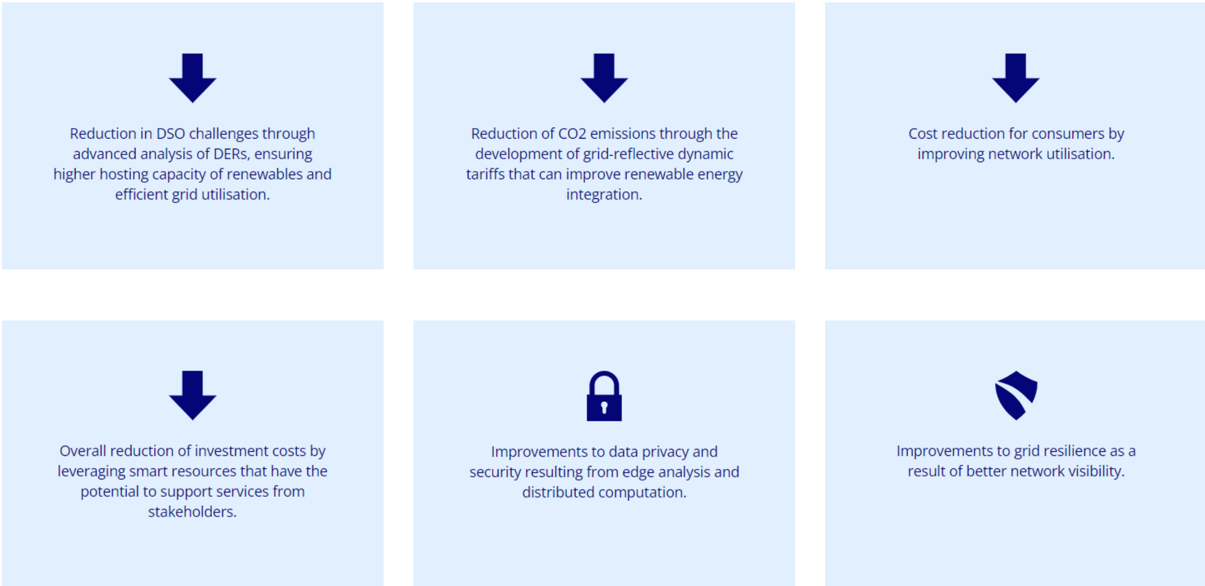

Figure 1 – Environmental and socio-economic objectives in AISOP.

2 Description of facility

AISOP progresses operational planning in the DSO from TRL 2 (formulation of the concept and / or the potential application of the technology) to TRL 6 (verification of an engineering model and prototype in a relevant environment). The project therefore intends to make use of 'virtual test beds' or 'virtual demonstrations', rather than deploy to field trials. In Switzerland, Romande Energie will provide data collected at two locations: Rolle and Chapelle-sur-Moudon.

Activities relating to Rolle will use selected infrastructure from the project P+D REEL Demo – FURIES (SFOE contract SI501523-01). The site at Rolle includes 70 phasor measurement units (PMU's), 100 GridEye units, 750 smart meters, a battery energy storage system, integrated PV, seven remotely controlled stations and a data management system, spread within 36 local LV systems.

The activities within the Chapelle-sur-Moudon test site will also make use of facilities developed in relation to the FURIES contract. These include PV installations with a capacity of more than 300 kVA; two boilers of 800 litres for hot water (7.6kWp each); 1 boiler of 2000 litres (18kWp) for heating; and a heat pump for both space and water heating (27kWp). Also, this district consists of 57 residential blocs and 9 farms, amounting to a total of 88 consumers. 10 Grid Eye units are installed in the site. The soft open point described in the AISOP proposal has been decommissioned due to operational constraints and so will no longer form part of the analysis.

In Germany, DSO Westfalen-Weser Netz will provide static and dynamic data and will support the practical implementation of the digital process twin.

3 Procedures and methodology

3.1 Project Approach

This section gives an overview of the project and describes the main building blocks that compose a workflow to create dynamic tariffs to help congestion management. First, a conceptual architecture for AISOP is provided in Figure 2 where the steps from data assimilation to grid situational awareness, and finally decision support tools are illustrated with blocks indicating data sources, analytics and modelling task that yield information about the grid, leading to decision support tools for operational planning in DSOs. In an earlier stage of the project operational planning was decomposed into data assimilation, anomaly detection, power flow forecasting, risk identification, end user behaviour modelling, and dynamic tariff design. Each of these building blocks were defined in terms of their tasks, inputs, and outputs.

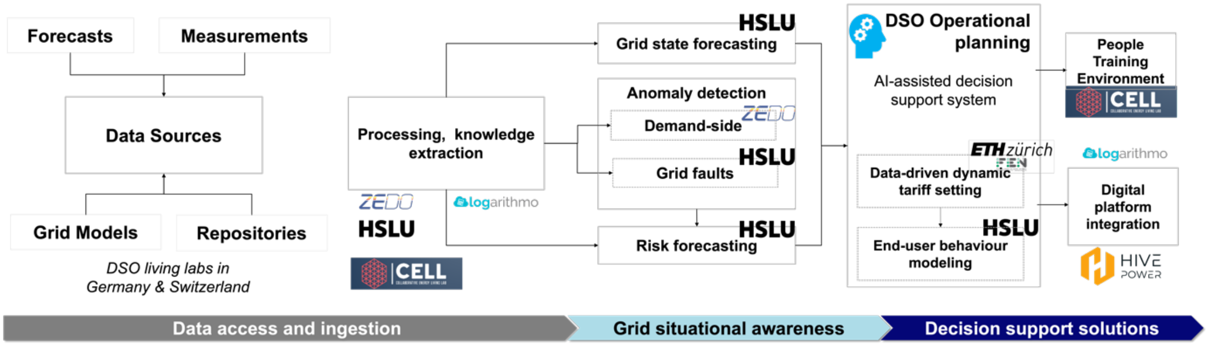

Figure 2 – AISOP conceptual architecture.

A block diagram representing the main AISOP data sources and building blocks is shown Figure 3, the ReSIM simulation framework developed by ETH-FEN serves as unifying framework to combine the inputs and outputs from the different blocks each one developed as standalone packages offering a modular approach. Thus, the implementation of each of the main modules (POWER FLOW FORECASTER, ANOMALY DETECTION, RISK STATE IDENTIFIER, DYNAMIC TARIFF DESIGNER, and END USER BEHAVIOUR MODELLING) is guided by modularity and interoperability. Each module is a stand-alone and data is separated from models to facilitate packaging and execution in different

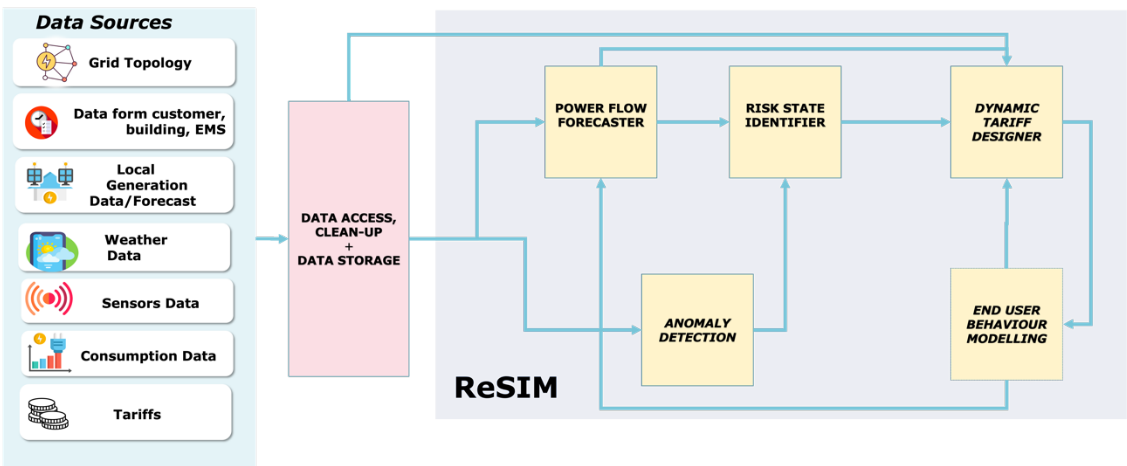

Figure 3 – AISOP data sources, building blocks, and ReSIM simulation framework.

systems. When applicable, mature open-source libraries are used whenever possible, but AISOP keeps its own branches of those libraries that implement core functionalities, such as the power flow solutions. In this way updates can be better controlled, and we can work on our own development versions.

The AISOP models integrated in ReSIM can represent a digital process twin (DPT) for DSOs to improve their operational planning. Namely, it can design dynamic tariffs and evaluate the impact that these incentives, realised through engaged consumers adapting their consumption patterns, have on grid congestion. DPT is a core technology to develop as part of WP2, WP4, and WP5.

Section 3.2 describes our approach for grid situational awareness, which includes power flow forecaster, anomaly detection, and risk state identifier. The following sections 3.3 and 3.4 describe the design of dynamic tariffs and the definition and composition of AISOP DPT. Section 3.4 describes our definition of DPT, its components and applications. Methodologies to identify adequate user interfaces are also described.

3.2 Situational awareness model architecture

The combination of data assimilation, grid state forecasting, anomaly detection, and identification of risks, forms AISOPs grid situational awareness model (WP3). Multiple workflows are possible to extract relevant information that increases the understanding of the situation a grid is operating in. As shown in Figure 4, the main blocks that build our model perform the tasks of data assimilation, time series forecasting, parsing of grid topology, initialization and solution of the power flow equations, anomaly detection, and risk estimation. In this reporting stage we started development of the following workflows:

1. Sequential power flow solutions (Data assimilation, Parsing topology, Initialization, Power flow).
2. Power flow forecasting (Data assimilation, Time series forecasting, Sequential power flow solution).
3. Data-driven risk assessment (Data assimilation, Risk estimation).
4. Supervised anomaly detection (Data Assimilation, Anomaly detection) [7].

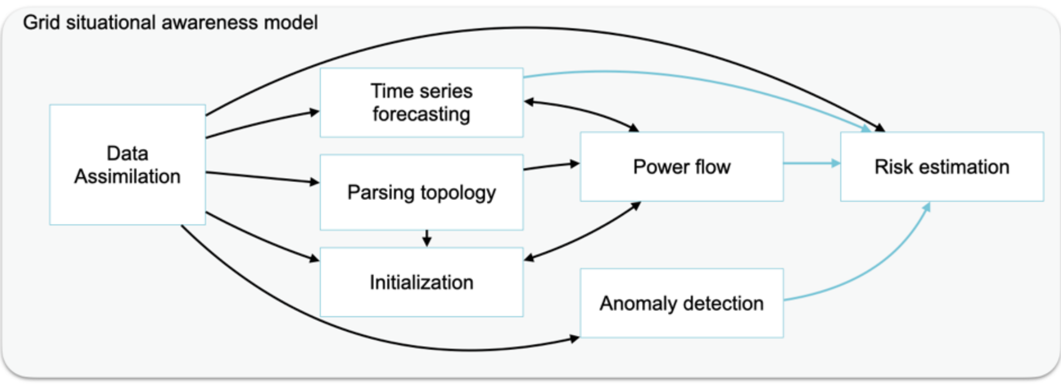

Figure 4 – Block diagram illustrating the main components of the grid situational awareness model (WP3), progress has been done on workflows that are highlighted.

The first workflow consisting of calculating the solution to the power flow equations multiple times with updates to the loads and generation, this is a common approach to use the, otherwise, static power flow solutions that provide specific snapshot in time [8], to estimate a quasi-dynamic simulation that outputs a time series of grid states. Such sequential power flow simulations let us predict the grid state when fed with a forecast of the load and generation [9-12].

The second workflow, power flow forecasting, 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), where load and generation are forecasted and then used as inputs to the sequential power flow solutions. As described in the activities and results section, this is the main approach that we worked on at this stage of the project. Going further, it is also possible to use power flow solutions to fit a model in a supervised learning fashion and perform the power flow forecast without solving the power flow again. Moreover, the power flow or load flow solution itself, can be calculated with iterative methods such as Newton-Raphson which is generally applicable and effective, but it may encounter convergence issues [13,14]. The backward-forward sweep is an approach that is applicable to radial networks, but it might not be scale well compared to novel approaches based on linearized formulations [15].

The steps planned to develop the power flow forecasting workflow are as follows.

i. Create a benchmark of a forecast using local linear regressions. This is useful to estimate a best-case scenario and evaluate error propagation.
ii. Run sequential power flow simulations using data and forecasts. Evaluate the error propagation and computation time.
iii. Create a baseline forecast using naïve seasonal forecasts, and one dimensional convolutional neural networks (1-D CNNs). This provides univariate models that do not have a high computational expense and are relatively easy to retrain.
iv. Create a probabilistic forecast. This lets us represent a non-deterministic grid state to study the incorporation of power flow forecasts into the estimation of risks.
v. Implement and evaluate power flow forecasting workflow on data from Chapelle-sur-Moudon.

Steps (i) and (ii) are approached using a reference grid from Simbench[1] grid representing a LV grid similar to the facilities described in Section 2. A preliminary evaluation is presented in Section 4.1.

The third workflow aims at providing risk assessment using grid monitoring data. For this purpose, a baseline calculation of risk was defined using only 10-min averaged values of the grid monitoring device GridEye.[2] The goal is to identify and quantify risk states that capture the time-varying operating conditions of a given asset in the grid that might give rise to excessive voltages or loadings, thus making assets more prone to failures. Basic reliability calculations based on the exponential distributions and a failure rate or mean time between failures parameters, as well as metrics such as System Average Interruption Duration Index (SAIDI), Expected Energy at Risk (EEAR), such as loss of load expectation (LOLE), expected unserved energy (EUE) are in some cases used to give an impression of how safe or risky is the operation of the grid, though typically in longer time scales and requiring a lot of data to calculate meaningful metrics. Other metrics that refer to less extreme events include lack of ramp probability (LORP), insufficient ramping resource expectation (IRRE), Operational Over (or Under), Voltage Risk indicator (OVR and UVR) [16-20]. The latter two represent the risk when the voltage exceeds upper (lower) thresholds, they can be calculated using an exponential severity function, a binary variable to indicate when an over voltage occurs, and the probability of occurrence of a given state [19]. Line-overload (LOR) and load-loss risk (LLR) indicators are similar to OVR and UVR but using linear severity functions. In some studies, the concepts of reliability and risk are used interchangeable, our focus is on operational risks therefore we stick to the basic definition where risk is the probability of a contingency happening within some time horizon multiplied by a severity factor. Namely, considering

[1] https://simbench.de/de/
[2] Previously developed by Depsys, now part of KrankenFlex, https://www.krakenflex.com/network-intelligence

the compliance to technical standards that specify the required characteristics of voltage (e.g., EN 50160), voltage variations during normal operation should be within +/- 10 % of the nominal voltage during each period of one week 95 %. On this basis OVR and UVR can be calculated given a predefined severity function [19]. On this basis, our baseline calculation of risk is focused on OVR, UVR, and LOR type metrics it is non-parametric since no assumption on the distributions of the data is made. Namely, for the case of over voltage risk, first, the empirical cumulative distribution $F(v)$ is calculated based on recorded voltage data v, and a severity function $\mathrm{Sev}(v, v_{\mathrm{thr}})$ is defined as a function of voltage and a threshold value v_{thr}. The calculation of risk $R = Pr(v > v_i) \cdot \mathrm{Sev}(v_i, v_{\mathrm{thr}})$ is then performed with every updated measurement, proving a time varying risk indicator, which one can also compound over a time window, different sections of the grid, and across different metrics. The extension to multiple variables follows two paths, a common approach is to build an overall risk as is a sum of univariate metrics. Other approaches may consist of calculating a multivariate distribution, reducing the dimension of the data space to components that have the highest influence. The application of such risk estimators in the broader scope of AISOP is twofold, as an input to the design of dynamic tariffs, and as an output of the situational awareness model that can inform DSO operators. In the latter case it is important that the risk indicator(s) are well calibrated to the facilitate their interpretability. Here, the input of users can be very valuable to design the information content and interface to serve the results of the models, as described in Section 3.4.

Finally, the workflow for supervised anomaly detection follows standard practice of multiclass classification and was developed based on numerical simulations in Matlab/Simulink of the IEEE 33 bus test system to create the data and labels, and on open-source implementations of ML algorithms. Details of the methodology can be found in [7].

3.3 Design of dynamic tariffs

Dynamic tariffs are considered for retail prices for demand and for the feed-in prices for the distributed generation. The activities are tackled in two dimensions: **(i)** the manner the tariff is designed and **(ii)** the level of data availability to the utility. In (i), two options are considered: **(i.1)** the tariffs are designed offline for a given time horizon (e.g., seasonal, annual), and **(i.2)** the rule is designed offline, and the tariffs are calculated close to real-time (day-ahead or intra-day). In (i.2) the tariff is a policy dependent where the prices change according to the designed rule. For example, for the next day the feed-in prices decreases if the maximum of excess PV is forecasted to be above a threshold. In (ii), three levels of data availability are considered: (ii.1) is the ideal case where at each node PV generation, conventional demand, EV charging, HP operation are observable (measured), (ii.2) is a realistic future where at each node, net demand is observable (measured), and (ii.3) is today's feasible case where only transformer (NE6) power measurements are available. For each level of data availability, at each time step, for a selected time resolution, statistical correlation analyses are performed to identify daily/weekly/seasonal trends and dynamic retail, and feed-in prices are calculated by considering the annualized cost of grid investment.

To simulate the response of network users to changes in dynamic tariffs, the final step in the operational planning workflow is to model how different predefined users respond to the feed-in prices that change in time and by location. A basic framework for modelling the user response is implemented as mixed-integer linear program, where the constraints are defined for each time step in a given horizon, the objective function is formulated to minimize energy consumption costs, and to maximize consumption of local generation. The solution is implemented using the model predictive control model in gurobi and its default Gurobi Optimizer.[3]

[3] https://www.gurobi.com

3.4 Digital process twin and user interfaces

AISOP's vision on DPT described in Figure 5 gives an overview of the main components of a DPT for grid operations. It is in line with state-of-art conceptions and covers some of the most important characteristics of DPT. As described in [21], at the core of DPT are data models that map valid and linked data, which in turn is feed to algorithms and models. In the context of AISOP [21] specifications of DPT materialise as in

- a virtual representation of an existing of a grid component or the grid itself, and
- a representation of the object or process updated at a relevant time and space resolution.

Ultimately, leading to a decision support system that is closely linked to the grid via information communication technology (up to *real-time* synchronization). As illustrated in Figure 5, the envisioned DPT advocates Single Source of Truth (SSoT) for maintaining the DTs of the grid components as well as the data collected from the field, customers, etc. This is represented in the data verification process block. Models of the grid that can use these data are then applied to generate information about the current and future state of the grid, as well as to design electricity tariffs that act as an incentive for engaged users to change their consumption patterns. The output of AISOP's DPT gives inputs to various departments within a DSP such as the teams for fault management, cyber-security, maintenance, network management, and planning.

In addition to the commercial-scale platforms of Logarithmo and Hive power, ReSIM is used in the AISOP project to demonstrate the "digital process twin" for operational planning envisioned within the scope of the AISOP project. ReSIM is a multi-energy district-level system Simulation Framework developed by ETHZ-FEN within the scope of the ReMaP project[4], funded by SFOE (Project # SI/501810)[5]. ReSIM features a selection of component models, control algorithms and an archive of demand and renewable generation data. The software was written in Python and can interconnect with other software tools if needed. It is highly modular and open for the addition of new models, algorithms, and data. Within the context of AISOP project, ReSIM is used to build a digital twin of a small-scale grid that is used to test the power flow forecaster, risk state identifier, dynamic tariffs and the end-user modeler. The researchers at FEN shared the codebase with the researchers in the HSLU team and guided them towards integrating their modules into ReSIM. In addition, FEN researchers integrate their own developed modules in ReSIM. The resulting "digital process twin", modelled in ReSIM will act as a deliverable of AISOP, while it will be used for testing and improving the developed solutions and applications. A schematic representing the approach is provided in Figure 5 – Digital process twin composition, outputs, and applications.

[4] https://remap.ch
[5] https://www.aramis.admin.ch/Grunddaten/?ProjectID=41788&Sprache=en-US

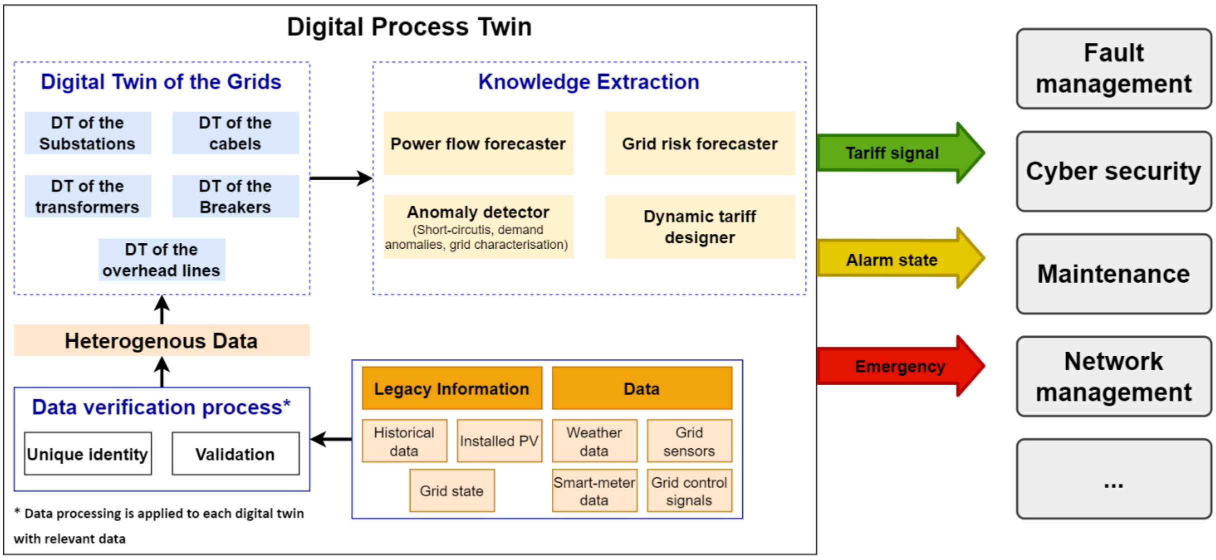

Figure 5 – Digital process twin composition, outputs, and applications.

A key aspect of a decision support tool is how the tool is fitting into stablished workflows. Another one is the preference for interfaces and information as seen by the actual operators or engineers that make use of the tool. Understanding the preferences of users in the different DSO departments is important to design the information content and form of the interfaces to these users, which are illustrated in Figure 2 by the blocks People training environment (CELL living lab) and Digital Platform Integration (Logarithmo, HIVE).

As a first step, we casted the DPT and main building blocks applicable to the grid congestion use case into a block diagram (Figure 6) where the cyber-system layers illustrated. This diagram serves to guide the design of user preference investigations. The focus of such investigations is to identify specific user interfaces that provide the right functionality and then understand if those are compatible with user skills, preferences, and current tools and workflows in place. A first investigation [22] to explore the user current practices, tools, and preferences points out at significant opportunities for innovation and validates the mission of AISOP. It interviewed Swissgrid, CWK and Romande Energie personnel to understand:

1. Current practices in the control room.
2. Tools, data, and workflows.
3. Establish design principles for decision support tools with focus on operational planning.

The results also shed light to the challenges to bring research concepts into prototypes in operational environments, accepted, and integrated into DSOs workflows. Building on [Harris2023], we aim at exploring methods such as the development of user stories, the analysis of operators and their workflows, and look for engaged DSO to join in co-design workshops with the objective to guide the design of content and interfaces.

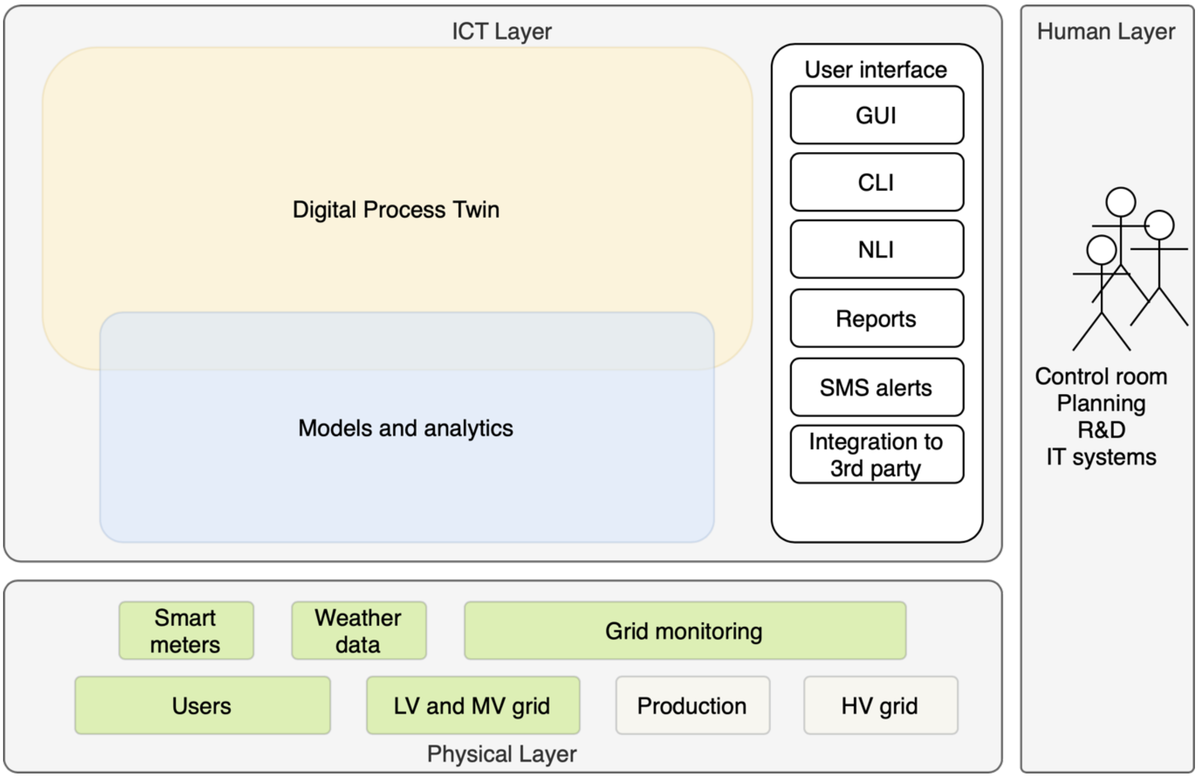

Figure 6 – Decision support tool user interfaces in the context of a cyber-physical system.

4 Activities and results

Research activities on the definition of interfaces, evaluation of methodologies, exploratory analysis of data, definition of benchmark grids, and dissemination have been undertaken. The most important of those research activities during this reporting period are summarized in Table 2. Dissemination activities are described in Section 9.

Table 2 – Research activities during the reporting period from December 2022 to November 2023

Activity	Description
ReSIM integration	Modules such as the end-user model, and power flow forecast need to be tightly integrated to the ReSIM simulation platform to orchestrate the simulation of end user energy consumption and generation as a response to temporally and spatially varying electricity retail and feed-in tariffs. Note that each module is designed as stand-alone. Therefore, first a conceptual interface was designed to determine (i) what inputs each module requires, (ii) what outputs each module produces, and (iii) how these the modules interact with each other: either by means of input and output files using the ReSIM platform, or by calling or implementing each module directly in the ReSIM simulation framework. As the first step, the end-user model codebase **`enduser`** was configured to run from a ReSIM simulation by introducing an interface that allows the **`enduser`** to be called as a component from a ReSIM simulation.

	Second step was to incorporate the power flow solver `pandapower` (an open-source power system analysis tool) in a similar fashion. Current work in progress consists of passing a time varying price signal to `enduser` and solving the power flow with sequential updates of the load as computed by `enduser` during a ReSIM simulation run.
Incipient fault detection	Categories of faults and statistics of their occurrence were reviewed, as well as scenarios for simulations and methods for supervised classification. A study based on numerical simulations was undertaken and published results on detection {0: no fault,1: fault}, and classification of fault type {NF: , LL: , } and branch identification {0: no branch, 1: branch 1, 2: branch 2, }[7]. Current work in progress is the integration of the output of anomaly detection algorithm into the calculation of a risk indicator.
Definition of benchmark grids	Reference grids from IEEE and those defined in Simbench were considered to serve as case studies to develop modules in parallel to acquiring data from DSOs and defining specific case studies linked to real grids. IEEE 33 bus system was selected for incipient fault detection [7]. The power forecaster module and its integration to ReSIM is currently tested on SimBench low voltage grid 1-LV-urban6--0-sw. Grids of the demo sites: Romande Energie exported their network from a power systems commercial software, CYME, in xml format. ETHZ-FEN processed the grid data, which include detailed substation models including sectionalizers, breakers, and fuses. It was then converted to JSON format so that pseudo-anonymization is performed. Once this process is complete, power flow solutions of CYME and FlexDyn [reference], the in-house tool of ETHZ-FEN for dynamic and steady-state power system analysis, were compared and benchmarked successfully. The parts of the pseudo-anonymized RE grid relevant to the AISOP (e.g., Chapelle-sur-Moudon, station Champ Monnet; Rolle, feeder 13) project will be used by the HSLU-DEEP team for testing purposes.
Analysis of data from Rolle site	A preliminary data set obtained from RE consists of data of a feeder in Rolle community, smart meter data, and grid monitoring data at LV of the transformer. This data was analysed for consistency and to set up a first workflow of the power forecaster tool. A good agreement between the smart meter data and the grid monitoring data was observed.
Data modelling	HSLU-DEEP, ETHZ-FEN, and HIVE created a list of data potentially available from measurements, as well as needed as simulation inputs, or obtained from simulations. Current work is to align with German partners to identify common and complementary data with the objective of identifying the scope of research collaboration, respecting the data management plan in line with data confidentiality agreements.
Calculation of risk state	Review of reliability metrics, risk assessment methodologies, and severity functions. Review of relevant standards (e.g., EN 50160). Identification of OVR, UVR, LOR, LLR as risk indicators for voltage and line overload. Evaluation of different risk severity functions. Demonstration of dynamic risk calculation using data from Rolle.
Exploration of benchmark scenarios	Since the power flow forecasting, risk identification and dynamic tariff activities are designed for future scenarios where grid violations and need for flexibility are needed, meaningful proliferations of EVs, electric HPs, and PVs have to be identified, and the selected grids (benchmark grids and demo sites) have to be intelligently populated by the selected scenarios. The team at ETHZ-FEN has

	developed routines in the past projects for bottom-up modelling by estimating the ratings of the HPs, EV charging stations and PVs for selected LV grids per node (e.g., house connection point) and creating time series for each demand and generation type. These routines are employed in the AISOP project.
Dynamic tariff setting	Dynamic tariffs are considered for retail prices for demand and for the feed-in prices for the distributed generation. The activities are tackled in two dimensions: **(i)** the manner the tariff is designed and **(ii)** the level of data availability to the utility. The results of the risk forecaster are planned to be integrated in addition to the results of the power flow forecaster.

4.1 Preliminary evaluation of power flow forecaster performance

The objective is to gain an understanding of the feasibility of the workflows for power flow forecasting. Therefore, we evaluate day-ahead power flow forecasting in terms of error propagation and computation time. This corresponds to the development steps (i) and (ii) described in Section 3.2.

The 1-LV-urban6--0-sw Simbench grid is applied, it is a radial network with 1 MV bus with a 20 to 0.4 kV transformer and 58 LV buses with 111 loads (2.0 to 31.0 kW). Smart meter and generation data is included in Simbench with generic profiles for different scenarios (i.e., today, near future, and future). First a benchmark of a forecast is created using local linear regressions, this allows to create a simple synthetic forecast that can be arbitrarily accurate. The 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 is used at this stage and made available is an S3 bucket. An example is shown in Figure 7 where the Simbench data corresponding to the generic profiles are mapped and scaled to the grid topology, resulting in the active and reactive power load profiles shown in the time series plots (left) of load 4 and its corresponding synthetic forecast issued every 24 hours. The histograms on the right show root-mean square error (RMSE) calculated for every day during a month for each of the 111 loads in this reference grid, mean +/- standard deviation values are shown in each histogram for all the load and for load number 4.

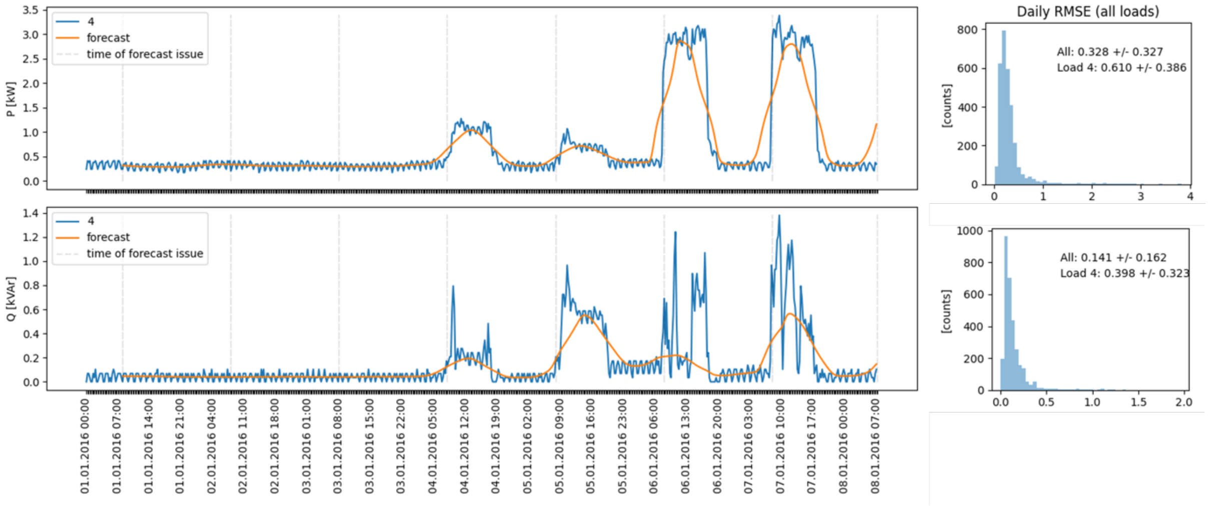

Figure 7 – Example of load scenario and benchmark of load forecast

Sequential power flow solutions are then calculated with the Simbench profiles and with the synthetic forecast. Then errors are obtained from the difference between the solutions obtained from load profiles and forecasted load values, for every time step (15-min intervals) in a 24h forecast period (96 time steps). As illustrated in Figure 8 by the mean square error (MSE) averaged across all nodes of selected outputs, errors are relatively low. A throughout evaluation of the error propagation by analysing the Jacobian of the power flow formulation and using a baseline forecast based on 1-D CNNs are next steps from this preliminary analysis.

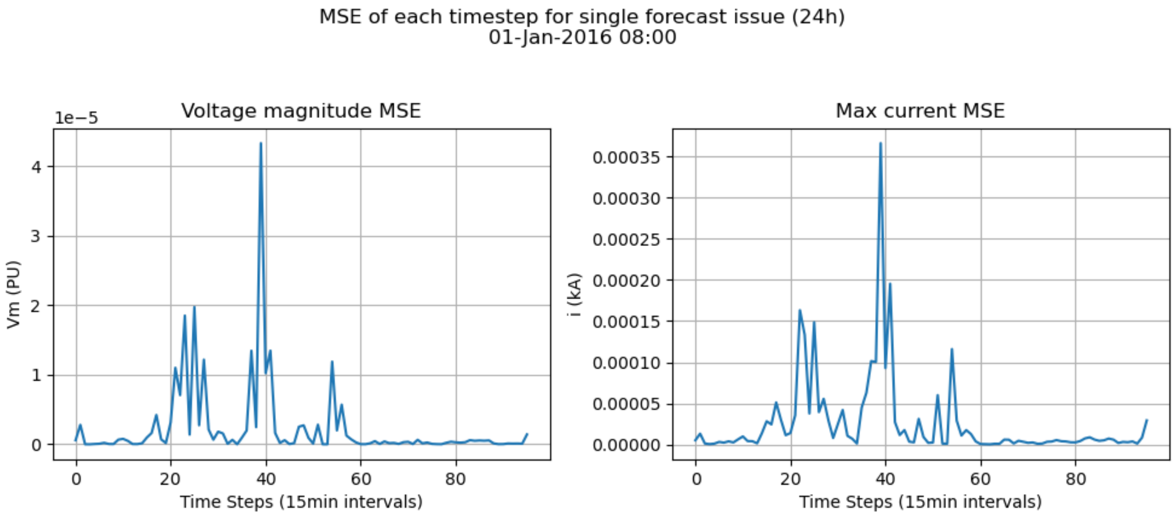

Figure 8 – Errors of power flow when fed with the forecast benchmark.

Estimations of computation time of the power flow showed that it is feasible to calculate a whole year of 15-min well under one minute. As shown in Table 3, where different implementations of sequential power flow solutions within the pandapower tool [23] are evaluated. Namely, **`runpp()`** and **`run_timeseries()`**, the 'No saving overhead' column shows the time it takes to load initial conditions for each time step and solve the power flow, without saving results to a file. The 'Saving overhead' column includes the time it takes to extract and save results in .csv files. The mean and standard deviation values were obtained by running 10 instances of the specified number of iterations *n*.

Table 3 – Evaluation of computation time of Newton-Raphson power flow solver in pandapower.

n	`runpp()`				`run_timeseries()`	
	No saving overhead		**Saving overhead**			
	Mean	**std**	**Mean**	**std**	**Mean**	**std**
10	0.16	0.004	0.21	0.003	0.13	0.005
100	1.6	0.02	2.14	0.03	1.1	0.008
500	8.4	0.08	10.9	0.28	5.8	0.06
1,000	16.5	0.24	21.4	0.14	11.5	0.13
5,000	82.2	0.12	116.5	12.52	57.5	0.99
10,000	165.1	2.1	264.2	1.7	116.4	2.15

4.2 Baseline calculation of risk

Figures 9 and 10 illustrate the calculation of over voltage risk described concerning the data-driven risk assessment workflow in Section 3.2. Data corresponding to the period from October 2018 to December 2019 is available from the grid monitoring device at the transformer of feeder 13 in Rolle site. The left plot in Figure 9 shows the severity functions for calculation of OVR and UVR as reported by [19]. These are to be multiplied by a binary flag {0,1} that yields 1 when the voltage is above a given threshold for OVR (or below a given threshold for UVR); and 0 when the voltage is below a given threshold for OVR (or above a given threshold for UVR). Our implementation, unlike the function described by [19], uses a step function and an exponential bounded to a maximum severity equal to one in order to reflect that the severity factor may be larger when deviations are larger but also bounded to reflect a physical limit. However, when requiring a solid interpretability of the resulting risk a calibration is needed. Proceeding with the risk calculation, the left plot in Figure 9 shows the probability that the voltage exceeds a given value v_i of 10-min average rms values of the voltage in phase each phase L1, L2, L3 recorded by the GridEye monitoring device. Finally, Figure 10 shows the time-varying value of risk of over voltage for phase 1, it shows that for the data recorded with GridEye in the period from October 2018 to December 2019 there was very low risk of over voltage.

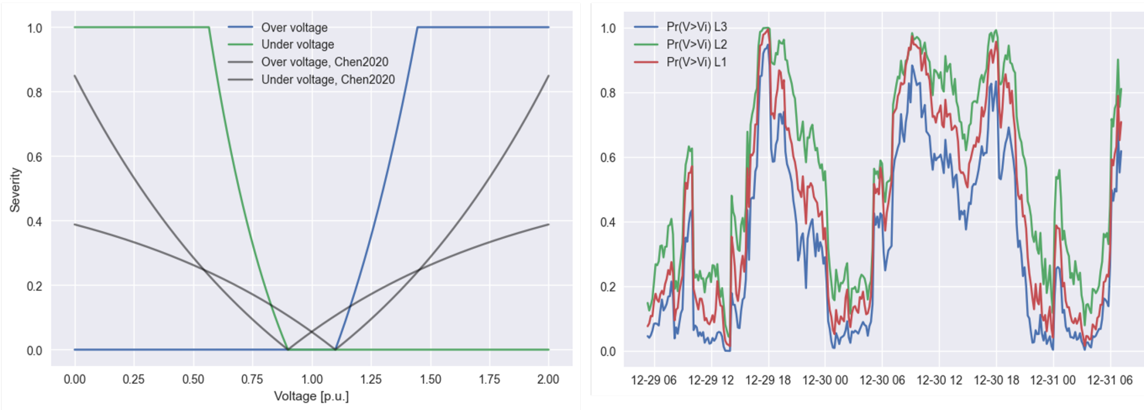

Figure 9 – Severity functions for over- and under voltage as defined by (Chen2020) [19] and as implemented in our risk calculation (left plot); probability of exceeding a voltage value v_i calculated on GridEye measurements in each phase L1, L2, and L3 (right plot).

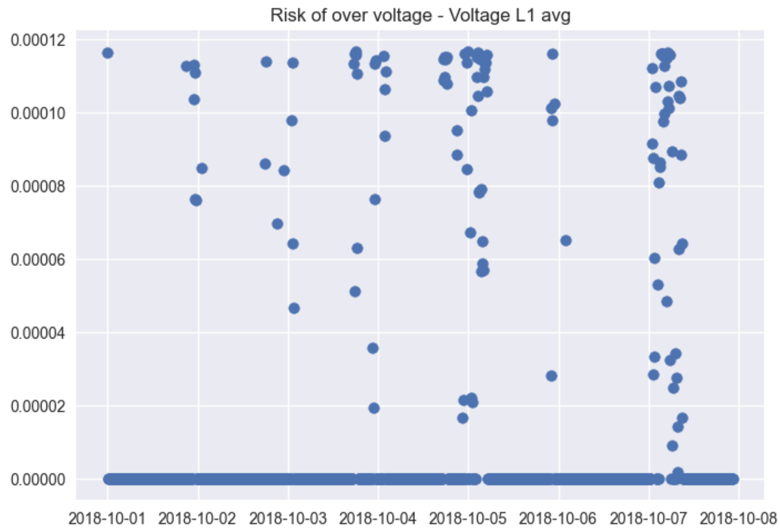

Figure 10 – Time varying risk indicator calculated with 10-min RMS values of voltage.

5 Evaluation of results to date

In this phase of the project, we moved from a procedural description of the steps to perform a power flow forecast, to an actual architecture describing the main components and basic implementations of workflows for situational awareness. The feasibility to calculate power flow forecast was evaluated in terms of computation time and robustness of different solution methods. Although, it is still a preliminary evaluation it shows that the workflows for grid state forecast that we envision within the project are feasible at the relevant time scale and grid sizes. The current risk calculations serve as a baseline to develop more advanced methods. Variables to link power flow forecasts and risk assessment to the design of dynamic tariffs were defined. This helped the overall framing of a decision support tool that creates dynamic tariffs. Moreover, the integration of models of end users and power flow solvers to

ReSIM supports the progress towards a prototype version of the DPT. However, significant effort will be needed on the configuration of end users and other components to simulate the sites of Rolle and Chapelle-sur-Moudon. A step towards living labs and integration of AISOPs tools into business process was done by interviewing operation personnel.

6 Next steps

Based on Table 4 and project plan, the activities that follow are described below, organized in relation to the main modules and linked to WPs (in bold the main WP that each activity refers to).

POWER FLOW FORECASTER. Evaluation of time series forecast and power forecast on Chapelle-sur-Moudon data. (**WP3**, WP2, WP4)

ANOMALY DETECTION. Definition of anomaly metric to inform the risk state identifier. This may consider the output of demand-side (ZEDO), and of grid anomaly detection algorithms. (**WP3**, WP2)

RISK STATE IDENTIFIER. Calibration of baseline calculation. Assimilation of anomalies into risk calculation. Evaluation of advanced risk calculations, using multiple input data and ML. (**WP3**, WP4)

DYNAMIC TARIFF DESIGNER. Simulation of tariff designed offline with end user in the loop and updates to power flow sequential simulations. (**WP4**)

END USER BEHAVIOUR MODELLING. Digestion of dynamic tariff and models of end user archetypes within ReSIM. (**WP4**)

At the level of work packages activities include consolidation of data requirements (WP2), documentation of grid situational awareness model architecture (WP3), documentation of dynamic tariffs approach and scenarios (WP4), definition of specific conditions of virtual testbeds (WP5), participation in Applied Machine Learning Days and Congrès International des Réseaux Electriques de Distribution (CIRED) conferences (WP6).

7 National and international cooperation

Bi-weekly virtual meetings take place among the co-coordinators in HSLU-DEEP and ETHZ-FEN teams. Monthly virtual meetings take place among the Swiss and German coordination teams. Quarterly virtual technical synchronization meetings are held between the Swiss and German researchers. Annual in-person consortium meeting, with the participation of the advisory board members (BKW, Amprion, Elia Grid) was held in May. This structure enables an efficient project execution with maximum cooperation.

8 Communication

Not applicable to our project.

9 Publications

This section list publications, but also participations in events, as well as upcoming activities. The research activities already produced published results on detection of incipient faults with supervised learning [7]. The project participants disseminated results and ongoing work in international events such as the AI4Grids Symposium, the ABB Energy Efficiency Symposium, and at the ETG VDE Workshop. Two deliverables are published: a project handbook, and the definition and requirements for digital process twins, including DPT-based architecture. Details of these activities and upcoming ones are shown in Table 4. Newsletters are prepared and disseminated via social media (i.e., Linkedin) and the project website (www.aisopproject.com), which is updated frequently to disseminate the activities and the project progress. Most of these documents, are accessible in the project website under Resources (www.aisopproject.com/resources/). Moreover, AISOP members participate in ERA-Net Smart Energy Systems working groups on System Architecture and Modelling, and Regional Matters.

Table 4 – Dissemination activities, reporting period December 2022 to November 2023

Activity	Description
Report	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.
Journal paper	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.
Report (deliverable)	AISOP Project handbook (Process). This document describes processes for quality control, risk management, data management and the communications strategy in the AISOP project. Mar. 2023.
Report (deliverable)	Definition and requirements of digital process twin, including DPT-based architecture (Report). This document provides an overview of the digital twin, including its history and definition. In addition, it introduces a new term in digital twin technology, the digital process twin, and explores its application in the power system based on the aims of the AISOP project. Jun. 2023.
Presentation	AISOP presentation to the AI4Grids Symposium on 26. September 2023. Presentation given by Antonios Papaemmanouil to the AI4Grids Symposium – AI in Distribution Networks on 26. September 2023. [Link to slides]
Presentation	Balouchi et al., Datengesteuertes Entscheidungsunterstützungssystem für Verteilernetzbetreiber, ETG CIRED Workshop 2023 (D-A-CH), Nov. 2023.
AMLD	Organization of AI for Utilities track at Applied Machine Learning Days (AMLD), Lausanne, March 2024.
CIRED 2024	Submission of abstracts is planned, upon acceptance participation takes place in Vienna, June 2024.

10 References

[1] P. van den Oosterkamp, P. Koutstaal, A. van der Welle, J. de Joode, J. Lenstra, K. van Hussen and R. Haffner, “The role of DSOs in a Smart Grid environment”, Ecorys, Amsterdam/Rotterdam, 2014.

[2] C. Basu, M. Padmanaban, S. Guillon, L. Cauchon, M. De Montigny and I. Kamwa, "Situational awareness for the electrical power grid," in *IBM Journal of Research and Development*, vol. 60, no. 1, pp. 10:1-10:11, Jan.-Feb. 2016.

[3] “Modern Distribution Grid”, U.S. Department of Energy’s (DOE) Office of Electricity (OE), 2020.

[4] G. de Almeida Terça, A. Delnooz, A. Sanjab, K. Kessels and M.U. Hashmi, “Market Enabling Interface to Unlock Flexibility Solutions for Cost-Effective Management of Smarter Distribution Grids,” EUniversal UMEI, H2020 – LC-ES-1-2019, 2022.

[5] S. Karagiannopoulos, L. Roald, P. Aristidou and G. Hug, "Operational planning of active distribution grids under uncertainty." In *IREP 2017, X Bulk Power Systems Dynamics and Control Symposium*, 2017.

[6] X. He, L. Hancher, I. Azevedo, N. Keyaerts, L. Meeus and J.-M. Glachant, “*Shift, not drift: towards active demand response and beyond*,” THINK, 2013.

[7] 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.

[8] R.J. Broderick, J.E. Quiroz, A. Ellis, M.J. Reno, J. Smith and R. Dugan. “Time series power flow analysis for distribution connected PV generation,” No. SAND2013-0537, Sandia National Lab.(SNL-NM), Albuquerque, NM (United States), 2013.

[9] B. P. Hayes, J. K. Gruber and M. Prodanovic, "A Closed-Loop State Estimation Tool for MV Network Monitoring and Operation," in IEEE Transactions on Smart Grid, vol. 6, no. 4, pp. 2116-2125, July 2015.

[10] I. Herbst, S. Lukovic, A. Gasparin, N. Schulz, J. Witzig and S. Kieber, "LV grid data analysis demonstrated at DSO Arbon Energie," In *25th International Conference on Electricity Distribution*, Madrid, 2019, Paper no. 590.

[11] R. Gonçalves, M. Louro, A. Paulo, P. Ferreira, M. Pinheiro, M. Pedro, L.M. Ferreira and P. Carvalho, "Forecasted chronological Power Flow for enabling timely dynamic tariff activation," In *25th International Conference on Electricity Distribution*, Madrid, 2019, Paper no. 1214.

[12] J. Hermanns et al., “Evaluation of Different Development Possibilities of Distribution Grid State Forecasts,” *Energies*, vol. 13, no. 8, p. 1891, Apr. 2020.

[13] J. Grainger and W. Stevenson Jr, *Power system analysis*, McGraw-Hill, 1994.

[14] P.S. Kundur, *Power System Stability and Control*, MacGraw-Hill, 1994.

[15] J. Chen, W. Wu and L. A. Roald, "Data-Driven Piecewise Linearization for Distribution Three-Phase Stochastic Power Flow," in IEEE Transactions on Smart Grid, vol. 13, no. 2, pp. 1035-1048, March 2022.

[16] C. J. Wallnerstrom, J. Hasselstrom, P. Bengtsson and L. Bertling, "Review of the Risk Management at a Distribution System Operator," *Proceedings of the 10th International Conference on Probabilistic Methods Applied to Power Systems*, Rincon, PR, USA, 2008, pp. 1-8.

[17] M. Marsadek, A. Mohamed and Z.M. Norpiah, "Risk assessment of line overload in a practical power system considering different types of severity functions." In *Proceedings of the 9th WSEAS international conference on Applications of electrical engineering*, pp. 74-79. 2010.

[18] E. Ciapessoni, D. Cirio, S. Massucco, A. Morini, A. Pitto and F. Silvestro, “Risk-Based Dynamic Security Assessment for Power System Operation and Operational Planning,” Energies, vol. 10, no. 4, p. 475, Apr. 2017.

[19] L. Chen, L. Liu, Y. Peng, W. Chen, H. Huang, T. Wu and X. Xu, "Distribution network operational risk assessment and early warning considering multi-risk factors." *IET Generation, Transmission & Distribution*14, no. 16 p. 3139-3149, 2020.

[20] O. Stover, P. Karve and S. Mahadevan, "Reliability and risk metrics to assess operational adequacy and flexibility of power grids." *Reliability Engineering & System Safety,* 231 p. 109018, 2023.

[21] E. Aumann, et al., “Der Digitale Zwilling in der Netz- und Elektrizitätswirtschaft,” VDE Verband der Elektrotechnik Elektronik Informationstechnik e.V., 2023.

[22] J. 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, Lucerne University of Applied Sciences and Arts, 2023.

[23] L. Thurner et al., "Pandapower—An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems," in IEEE Transactions on Power Systems, vol. 33, no. 6, pp. 6510-6521, Nov. 2018.

11 Appendix

No appendices are provided with this report.