Final report

1. Project details

Project title	Leveraging Smart Meter Data to Optimize Grid Investments
File no.	64022-1049
Name of the funding scheme	EUDP
Project managing company / institution	University of Southern Denmark
CVR number (central business register)	29283958
Project partners	KAMSTRUP A/S, Dinel A/S, Energi Ikast Service A/S
Submission date	29 August 2025

2. Summary

Project summary:

The purpose of the project

In this project, we addressed the challenge of improving maintenance efficiency and investment planning in electricity distribution networks. We developed a software toolset for prescriptive maintenance and predictive asset management, leveraging existing infrastructure data to forecast faults, assess risks, and recommend optimal actions.

Results, conclusions and perspective

The project resulted in the successful development and demonstration of a decision-support toolset for electricity distribution system operators. It combines digital twin models with advanced analytics to predict faults and assess asset risk based on operational, GIS, and environmental data. The tool supports both proactive maintenance actions and long-term asset management planning.

The solution is competitive as it requires no additional hardware investment and integrates directly with existing utility data sources and platforms. It enables earlier interventions, reduces outage risk, and improves the targeting of renovation investments, leading to cost savings and increased grid reliability.

In the future, the toolset will be used to maintain and enhance service quality and cost efficiency in the electricity sector. Its ability to utilize existing infrastructure data ensures it remains a practical and scalable solution for distribution system operators.

Projektresumé:

Formålet med projektet

I dette projekt adresserer vi centrale udfordringer relateret til forbedring af vedligeholdelseseffektivitet og strategisk investeringsplanlægning i eldistributionsnet.Vi har udviklet et softwareværktøj til prescriptive maintenance og predictive asset management, der udnytter eksisterende infrastrukturdatasæt til at forudsige fejl, vurdere risici og anbefale optimale handlinger.

Resultater, konklusioner og perspektiv

Projektet har resulteret i en vellykket udvikling og demonstration af et beslutningsstøtteværktøj til netselskaber. Værktøjet kombinerer digitale tvillinger med avanceret analyse til at forudsige fejl og vurdere asset-risiko baseret på drifts-, GIS- og miljødata. Det understøtter både proaktive vedligeholdelsestiltag og langsigtet asset management-planlægning.

Løsningen er konkurrencedygtig, da den ikke kræver yderligere hardwareinvesteringer og kan integreres direkte med eksisterende datasystemer. Den muliggør tidligere indgriben, reducerer risikoen for afbrydelser og forbedrer målretningen af renoveringsinvesteringer, hvilket giver omkostningsbesparelser og højere driftssikkerhed.

I fremtiden vil værktøjet blive anvendt til at opretholde og forbedre servicekvalitet og omkostningseffektivitet i elsektoren. Dets evne til at udnytte eksisterende infrastrukturdatasæt sikrer, at det forbliver en praktisk og skalerbar løsning for netselskaber

3. Project objectives

The primary objective of this project was to develop an advanced software-based toolset for **Prescriptive Maintenance** and **Predictive Asset Management** in electricity distribution networks.

By creating such a toolset, our aim was to improve maintenance efficiency, reduce outages, and support more accurate, cost-effective investment planning for distribution system operators.

Through the integration of physics-based digital twins, data-driven prediction models, and geospatial risk analysis, the toolset enables the early identification of potential faults, prescribes optimal operational actions, and prioritizes assets for renewal based on risk. This capability allows operators to address issues proactively, minimize downtime, and optimize maintenance resource allocation.

The resulting solution improves upon current state-of-the-art practices, requires no additional hardware investment, and makes full use of existing utility data sources such as GIS, SCADA, and smart meter data. This ensures a practical, scalable, and future-ready platform for data-driven grid operation and asset management.

4. Project implementation

The project was implemented as planned, following the milestones outlined in the project proposal. Development began with requirements analysis and data integration from participating distribution system operators. The prescriptive maintenance and predictive asset management modules were developed in parallel to accelerate progress and ensure that shared components, such as data pipelines and analytics frameworks, could be reused across both tools.

The main risks identified at the start were:

- Limited availability or quality of maintenance records, operational data, GIS data, and environmental data.
- Challenges in integrating heterogeneous datasets from multiple sources.
- Potential delays in validating models on real grid data.

These challenges were mitigated through early engagement with data providers, the implementation of data quality assurance procedures, and the concurrent execution of development and validation activities.

For the prescriptive maintenance tool, some expectations relied on the availability of high-resolution smart meter and operational data. In practice, many DSOs only used a limited subset of smart meter functionalities, often restricted to those required by regulation. Activating additional functionalities requires DSOs to establish clear data models and data management strategies — a process that takes time. As a result, development focused on data already available and of sufficient quality, such as load and consumption measurements at 15-minute intervals (typically collected every few hours). Given the ongoing digitalization of the utility sector, data collection rates, granularity, and completeness are expected to improve, further enhancing the tool's capabilities in the future.

The project progressed according to plan, with only minor timeline adjustments during testing to ensure robust validation. No major unforeseen issues occurred, and all technical objectives were fully achieved within the planned timeframe and budget.

5. Project results

This section outlines the outcomes of the three primary elements of the project, which are *Development, Testing and Validation, and Integration*. The section concludes with a list of publications that have already disseminated the results of the project.

5.1 Development

In this part, the methods and tools that are developed are briefly described. Two toolsets are developed for prescriptive maintenance and predictive asset management consisting of different tools.

5.1.1 Event Forecasting

A critical event forecasting framework for medium- and low-voltage distribution grids is introduced, leveraging smart-meter data to predict faults and provide actionable insights that help grid operators manage systems closer to their operational limits. Designed to handle the complex task of load forecasting for small, low-voltage consumer clusters, the framework incorporates three core modules: A forecasting module using Long Short-Term Memory (LSTM) layers for precise load predictions; a network module that aggregates data from smart meters; and an event-prediction module that identifies potentially fault-prone operations as depicted in Figure 1.

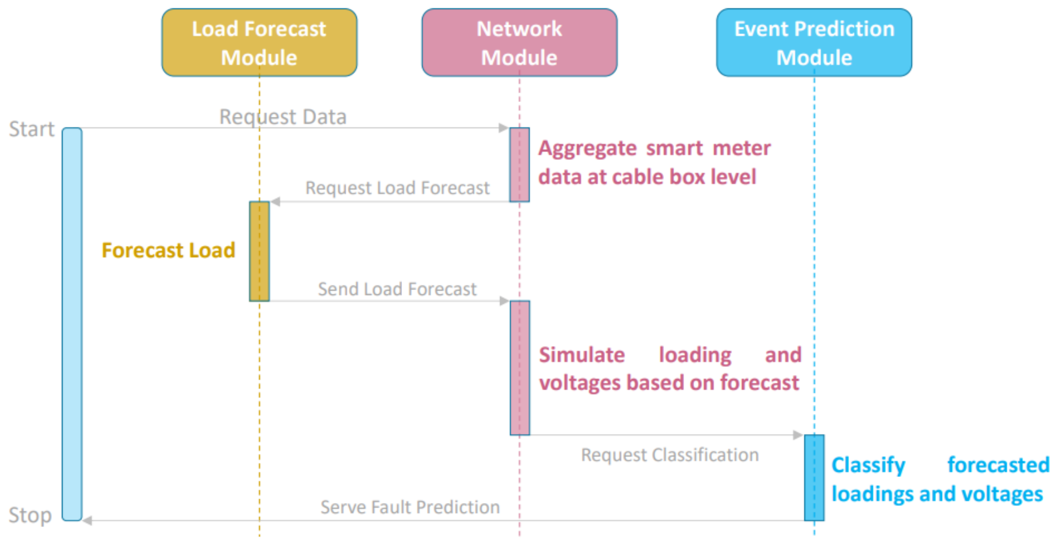


Figure 1: Diagram over the modules of the critical event forecasting model and how they communicate.

In the **forecasting module**, smart-meter data from low-voltage consumers are clustered in a **bus-semi-agnostic** way to reduce computational complexity. Figure 2 shows forecasting module architecture. Each cluster is modelled with a dual-branch LSTM neural network. One branch processes *weekly* patterns by feeding lagged values from the same hour in past weeks; the other branch captures *short-term* dynamics by ingesting the last twelve hours of measurements. Exogenous features—including calendar indicators (hour of day, day of week), weather attributes and solar irradiance—are concatenated with the LSTM outputs before passing through fully connected layers to produce 1-hour-ahead forecasts of active and reactive power. A key innovation is that all nodes within a cluster share the same model, making it scalable to large networks without re-training for each bus.

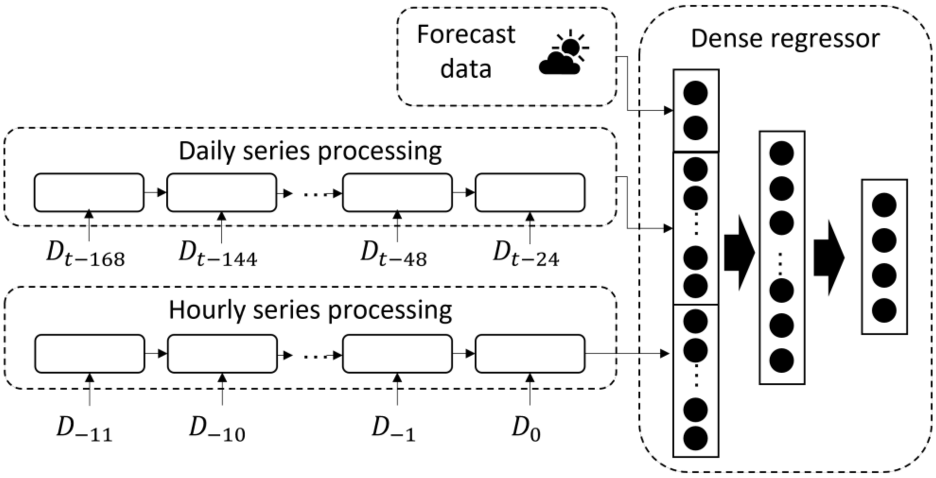


Figure 2: Architecture of power forecasting module.

The **network module** converts these forecasts into voltage and current states by executing a balanced power-flow calculation over the distribution grid. Cable impedances, transformer tap settings and switch positions are taken from the utility's GIS and SCADA databases; the open-source pandapower solver then computes bus voltages and branch currents. Finally, the **event-prediction module** compares the simulated states against operational limits. Any predicted under-voltage, over-voltage or line loading above thermal capacity is flagged as an alarm.

5.1.2 Prescriptive maintenance

This module operationalizes **prediction-to-action** for distribution grids: it forecasts node-level load/production, evaluates the **significance** of impending alarms (including consequences), and **prescribes** fast switching actions that reduce risk—all using existing SCADA/smart-meter–derived inputs and standard power-flow models. The overall process and data dependencies follow the methodology shown in Figure 3.

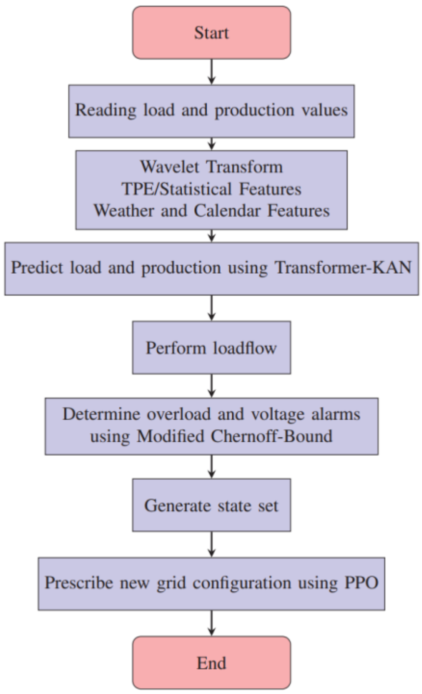


Figure 3: Process flow for prescriptive maintenance framework.

Within the project's Development work, the Prescriptive Maintenance module sits downstream of the data/forecasting components and upstream of the grid-control interface. It consumes 1-hour-ahead forecasts, runs power flow, ranks alarms by **consequence-aware significance**, and selects a **switching configuration** from a curated discrete action set via a trained PPO policy. To ensure scalability across heterogeneous LV/MV feeders without training per-bus models, the module relies on an enriched dataset, needing for a dataset generation block as shown in Figure 4, that augments each 24-step daily window with:

- **Wavelet components** (db21; A3, d3, d2, d1) to capture multi-frequency behavior,
- **Weather & calendar** attributes (lags included), and
- **Statistical descriptors** plus **Tangent Pearson Embedding (TPE)** features that summarize cross-node relations and distinguish consumer/DG types without explicit clustering.

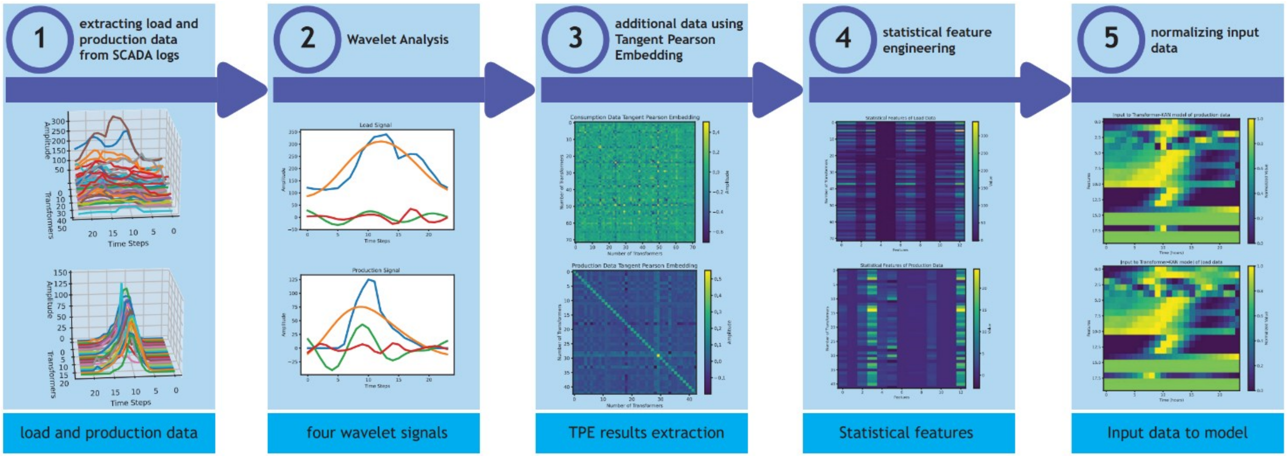


Figure 4: Dataset generation block.

Forecasts are produced by a **hybrid Transformer–KAN** architecture as depicted in Figure 5: a two-encoder/two-decoder Transformer ingests the 2D time–feature grid; auxiliary statistical/TPE features pass through a dense layer and are concatenated before a **KAN layer** that replaces only the final MLP stage to capture higher-order dependencies with limited added complexity. Two identical models are used (one for load, one for DG production). Outputs are 1-hour-ahead forecasts per node.

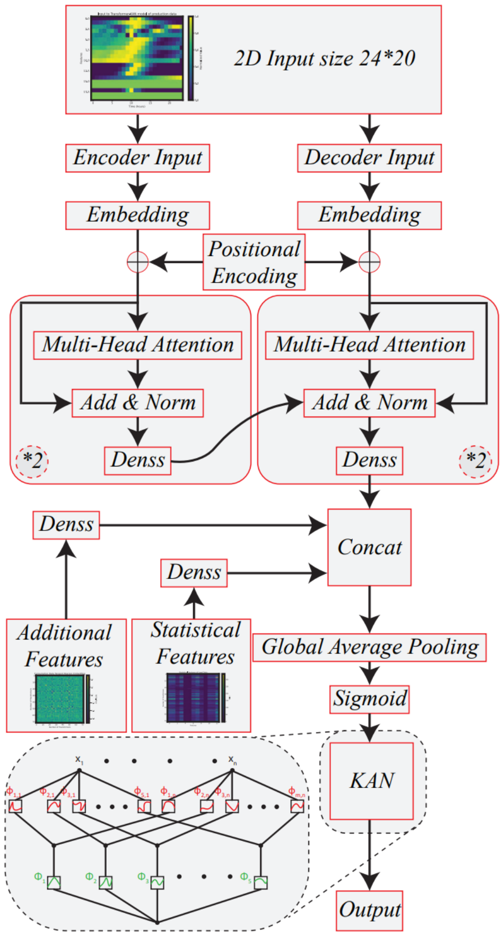


Figure 5: The hybrid Transformer-KAN block diagram.

Using predicted voltages/currents from load flow, alarm **significance** is computed with a modified **Chernoff-Bound** formulation (Figure 6). The baseline deviation-from-threshold probability is **scaled by a normalized count of affected consumers**, yielding a **consequence-aware** score that naturally prioritizes violations that would impact more customers. This produces a consistent ranking across both current (overload) and voltage (over/undervoltage) alarms and serves as the reward signal and state features for the control learner.

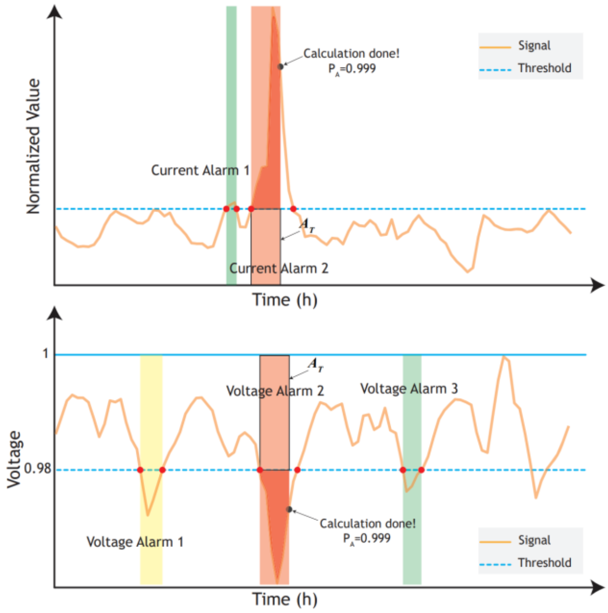


Figure 6: Alarm significance samples for both current and voltage signals. Red, yellow, and green colors show the significance of alarms.

Prescription is framed as a **discrete action selection** problem over a pre-vetted set of **radial switching configurations** (top-20 per time step). The environment is implemented in **pandapower**; states include one-hot time indicators, per-line **current-alarm significance**, per-bus **voltage-alarm significance**, and the previous action; rewards are the **negative sum of alarm significances** at each step. A **Proximal Policy Optimization (PPO)** agent is trained offline and then used online for fast recommendations. The workflow of the prescription stage training and inference is shown in Figure 7. The design was chosen over OPF for speed in large action spaces and robustness to modeling uncertainties while still exploiting deterministic power-flow feedback. For each hour in the historical dataset, all admissible radial topologies are simulated; the 20 configurations with lowest total significance form the **action set** for that hour. This bounds the exploration space, respects operational constraints, and accelerates convergence/stability of PPO compared to value-based baselines in discrete, combinatorial switching tasks.

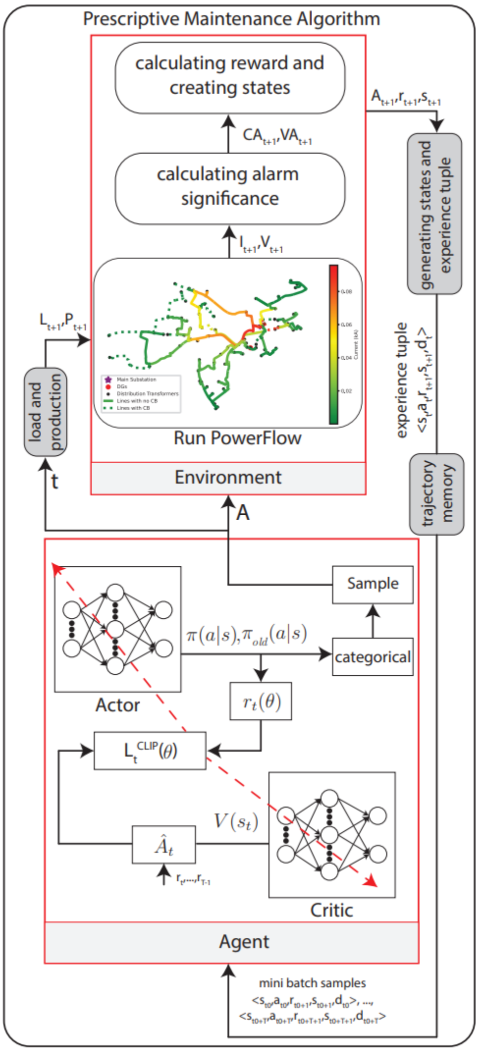


Figure 7: Workflow of the prescription stage training and inference.

5.1.3 Proactive cable replacement planning

This component estimates **cable-level failure risk** using Neural Weibull Proportional Hazard (NWPH) Modeling and delivers per-asset reliability and hazard metrics that downstream modules use for vulnerability ranking and planning. The end-to-end flow—data preparation → model training → inference—follows the methodology shown in Figure 8.

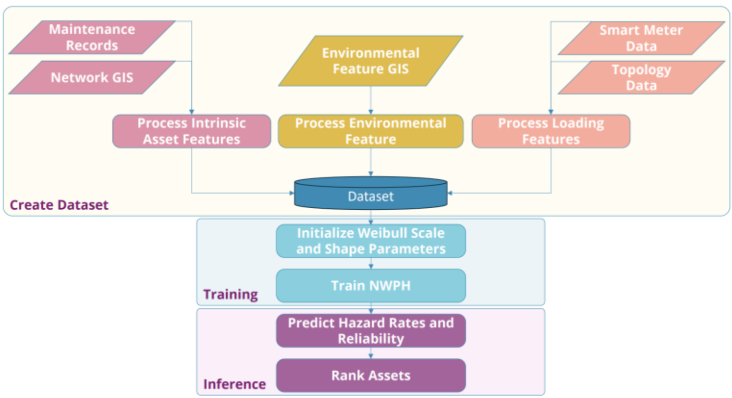


Figure 8: Framework for the application of the NWPH model, consisting of three stages: data preparation, model training, and inference.

A neural network replaces the linear covariate term to capture non-linear effects of environmental, loading, and intrinsic asset features on failure risk; the Weibull baseline governs time dependence. From the trained model we compute the **hazard** and **reliability** per cable and use these for asset ranking. Cause-based features are assembled from GIS and asset systems (soil/roads/excavation context, conductor/insulation/joints, topology), and **pre-failure states are reconstructed** so repairs (e.g., new joints/shortened lengths) are not mislearned as higher risk. The likelihood explicitly accommodates **right- and interval-censoring** and corrects **left-truncation** via inverse-reliability weighting, ensuring early failures and partially observed lifetimes are properly represented. Training maximizes the (scaled) log-likelihood with gradient clipping; and **hazard initialization** is done through grid-search to stabilize convergence.

At run time the model outputs hazard, reliability and a **vulnerability ranking** for all cables. To quantify uncertainty, a **Bayesian nested Monte Carlo** scheme retrains NWPH under Bayesian bootstrap weights (outer loop) and samples failure times for inference (inner loop), as illustrated in Figure 9.

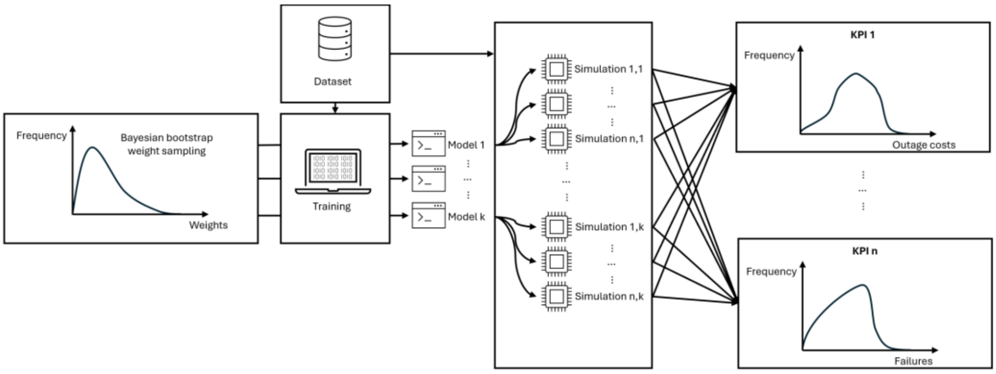


Figure 9: Bayesian nested Monte Carlo scheme for the application of the simulation to consider the dual uncertainties of the NWPH model, i.e., the NWPH model's parameters and the probabilistic nature of the NWPH model.

Outputs include: (i) per-cable reliability/hazard trajectories, (ii) risk-aware rankings, and (iii) uncertainty summaries; these feed the maintenance planner (see Figure 10 for the planner flow and use of ranked assets).

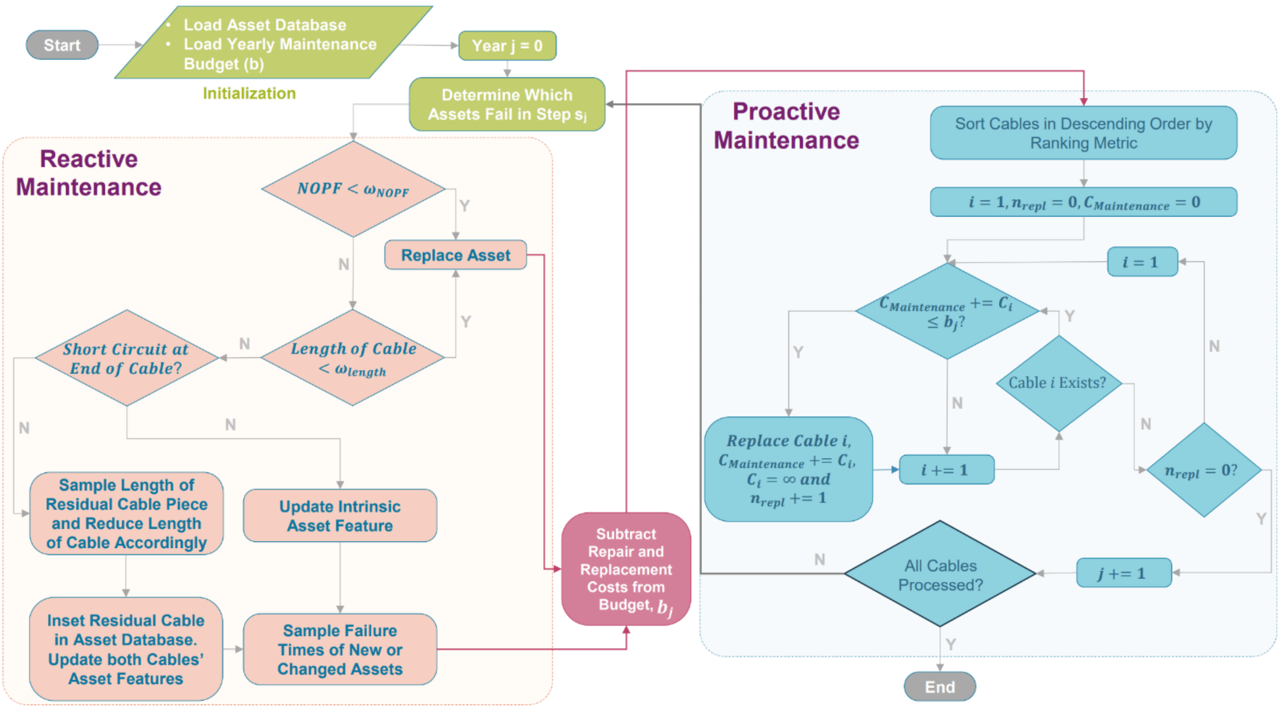


Figure 10: Flowchart of the maintenance simulation. The left side covers reactive interventions (resolving failures), while the right side covers proactive replacements based on planning and ranking.

5.1.4 Reliability-aware asset management

This module translates fault-risk insights into **budget-feasible cable renewal plans** via multi-objective optimization. It ingests geospatial/GIS, operational, and consumer datasets, computes failure and consequence drivers, and selects a replacement set that balances **power-outage cost**, **reliability indices**, and **number of cables**—as shown in Figure 11 of the paper. Required inputs include: cable topology and historical faults, per-cable consumer counts, average power flow, and **population-density classes** used for cost modeling. For missing density labels, a nearest-geometry procedure assigns the category prior to optimization. Relative fault rankings are converted into **absolute fault vulnerability** (faults per length-year) to enable cost/reliability calculations, preserving rank monotonicity across capture intervals depicted in Figure 12. This yields per-cable failure intensity used jointly with consumers and power flow to quantify outage consequences.

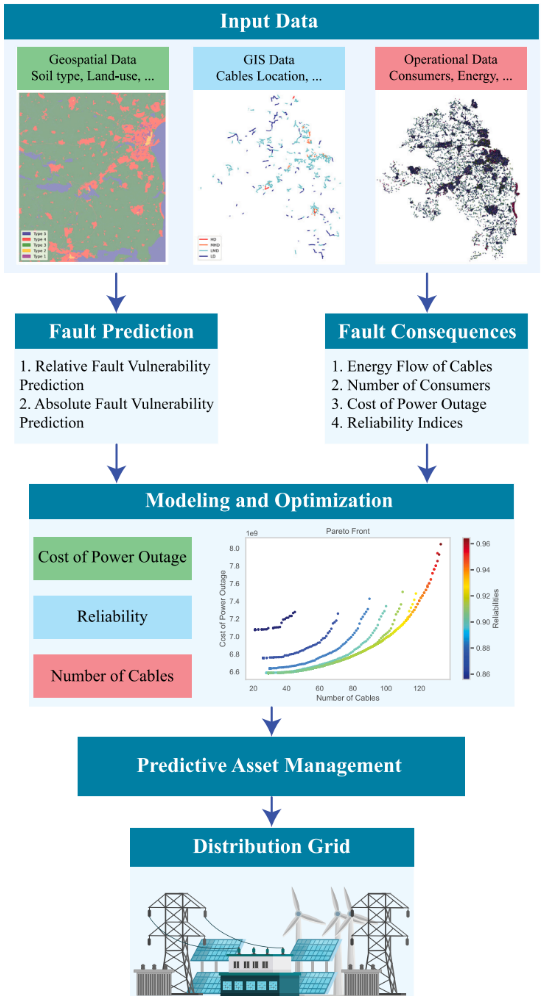


Figure 11: Structure of the proposed underground cable replacement methodology for predictive asset management

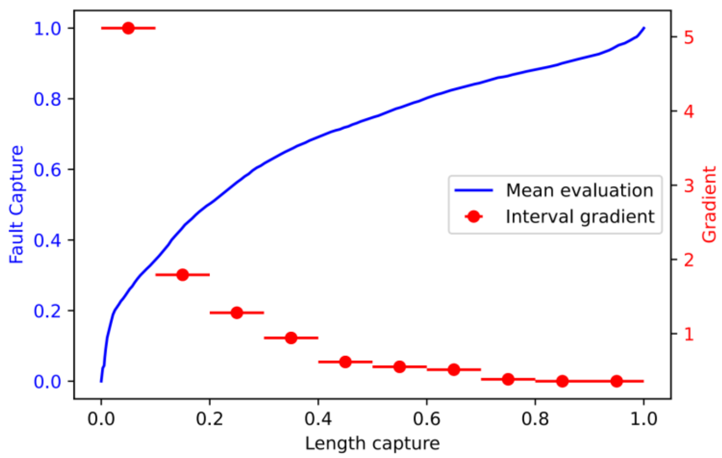


Figure 12: Relative and absolute fault vulnerability.

The module formulates a **mixed-integer, multi-objective problem**: minimize (i) cost of power outage and (ii) a normalized **interruption-related index** (SAIFI, SAIDI, ASIDI), while **maximizing the number of replaced cables**, under an annual budget. The solution is obtained with an **epsilon-constraint** approach that exposes decision trade-offs. For each planning run, the module returns: (1) a **Pareto set** of renewal plans for operator choice, (2) the selected replacement list with expected reliability and cost impacts, and (3) auditable intermediate artifacts (preprocessed inputs and per-cable consequence terms).

5.2 Tests and validation

5.2.1 Event forecasting and prescriptive maintenance

The forecasting framework was validated on a real Danish radial network (10 kV / 0.4 kV) operated by Energi Ikast supplying **822 consumers** with one year of smart-meter data (hourly), complemented by DMI weather and holiday indicators; the pandapower network model underpins power-flow-based target variables. The study area and asset mix are shown in Figure 13; correlation analysis motivating weather/solar features is in Figure 14.

Figure 13: Case study of the Danish grid, showing 10 kV and 0.4 kV cables, along with transformers and the 60/10 kV connection. Red lines represent 10 kV cables, and black lines represent 0.4 kV cables. The grid supplies 822 consumers.

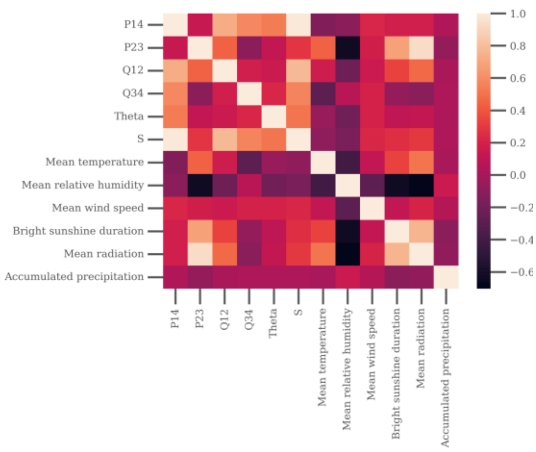


Figure 14: Pearson cross-correlation heat map. Theta and S denote the power factor and the apparent power respectively. This heatmap visually represents the pairwise correlation between features, where darker shades indicate stronger interdependencies.

Across clustering levels, errors drop markedly relative to baselines: Mean-Squared-Error improves from **1.058 (SLP: Standardized Load Profile)** and **0.966 (NARX)** to **0.333** with **12 clusters** (best), with a broad gain across 3–15 clusters. One- to six-hour-ahead **R^2** remains consistently higher than SLP for both currents and voltages (e.g., at 1 h: **0.936** for line loading and **0.927** for bus voltage, vs. **0.849** and **0.822** for SLP). Accuracy degrades only minimally at lower aggregation; for 1–6 h horizons, cable-box-level **R^2** stays close to transformer-level values. In Figure 15, geography-aware MAE maps show industrial zones (stable profiles) yield lower errors; residential areas vary more.

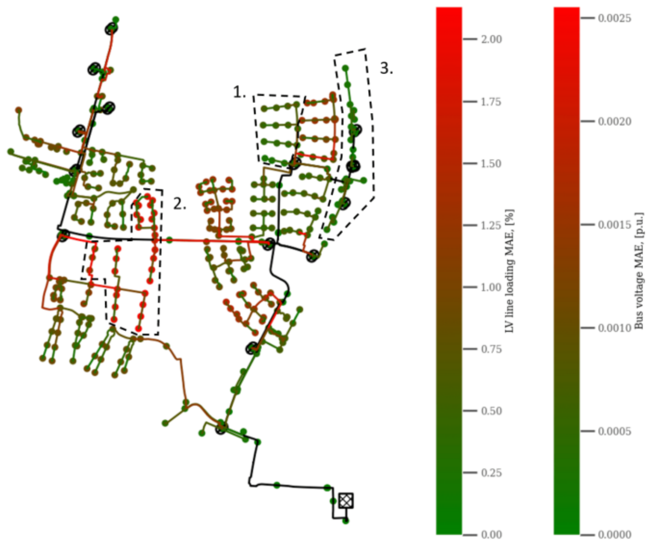


Figure 15: Geographic distribution of mean absolute error in 1-hour ahead forecasts for line loading (low voltage) and bus voltage. Circles represent bus bars, and areas of interest with high/low accuracy are highlighted in dashed lines.

The prescription pipeline was validated on a part of a Danish distribution grid operated by Dinel with **81 buses**, **43 DG units**, and **72 load nodes**, using two years of hourly SCADA-aggregated load/production; top 20 feasible **radial** topologies were considered. The single-line diagram appears in Figure 16.

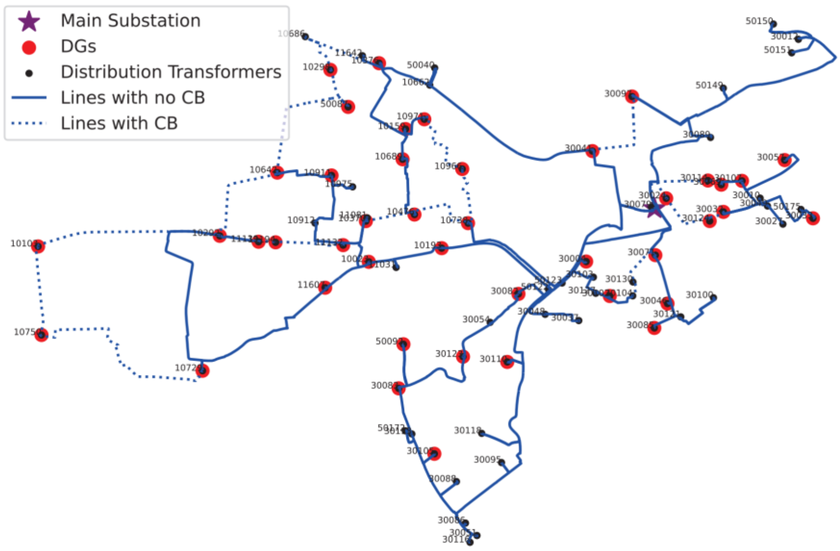


Figure 16: The diagram of studied real danish distribution grid.

The hybrid **Transformer–KAN** forecasters deliver low normalized errors across diverse transformers (industrial/residential). Predicted trends of line currents and bus voltages for some cases is depicted in Figure 17. IIllustratively, line (30104–30102) current prediction achieved **NMAE = 8.8×10^{-3}**, **NMSE = 1.3×10^{-4}**, **MAPE = 1.49%**; bus 30104 voltage prediction achieved **NMAE = 5.6×10^{-3}**, **NMSE = 5.5×10^{-5}**, **MAPE = 0.0136%**. Feature ablations show **KAN-final-layer** converges faster and lower than MLP on validation loss and outperforms an LSTM baseline trained on identical inputs. These accuracies ensure reliable states for alarm ranking and control.

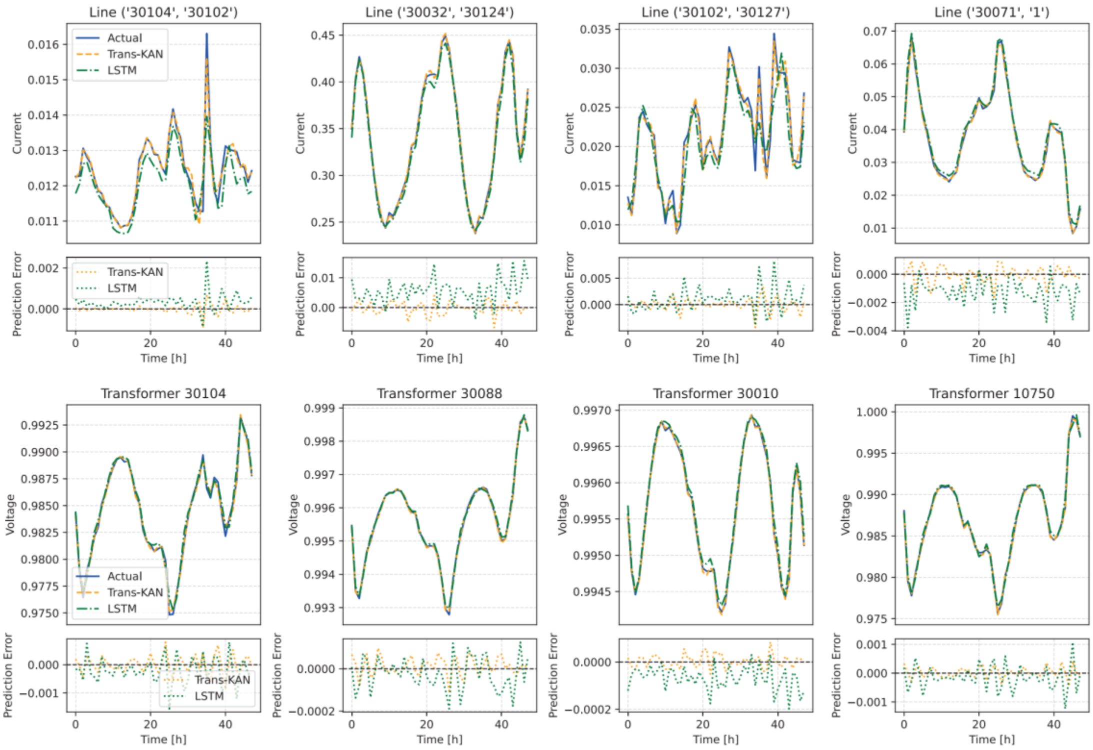


Figure 17: Predicted values of line current and bus voltage trends.

A modified **Chernoff-Bound** quantifies deviation-from-threshold and scales it by the **normalized number of affected consumers**, producing a **consequence-aware significance** that ranks alarms for action. The real and predicted values of line current alarm significance is depicted in Figure 18-19. This shows the good accuracy of the predicted values as the difference of the predicted alarms with the real ones is neglectable resulting in good prescription accuracy.

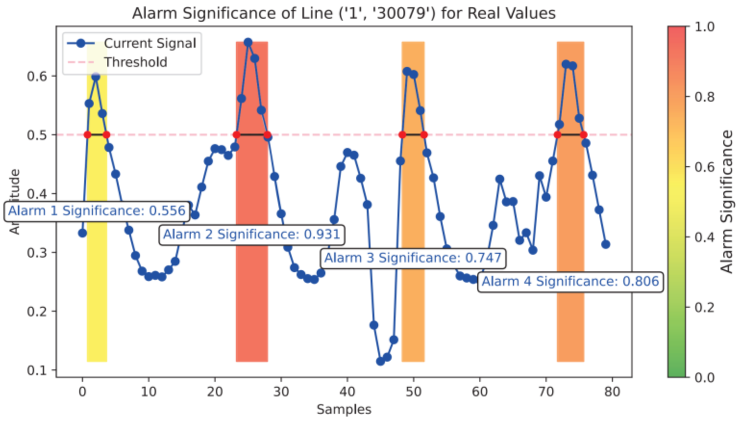


Figure 18: Real current alarm significance.

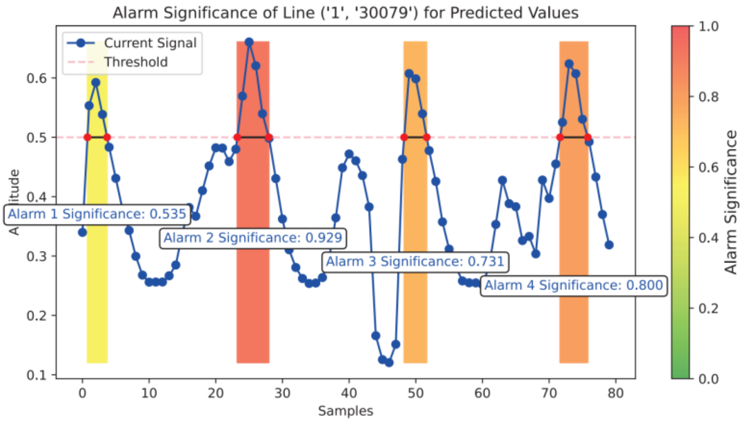


Figure 19: Predicted current alarm significance.

Actions are hour-specific sets of the **top-20 radial switching configurations** (pre-vetted offline for low significance). The **PPO** agent minimizes the cumulative significance across lines and buses (state includes alarm-significance vectors and time one-hots). In comparative experiments, **PPO** achieves **faster convergence** and **lower cumulative alarm significance** than **DDQN**, **SAC**, and **A3C**, reflecting better stability and sample efficiency in this discrete action space. Figure 20 depicted reward trend for these methods over the training dataset.

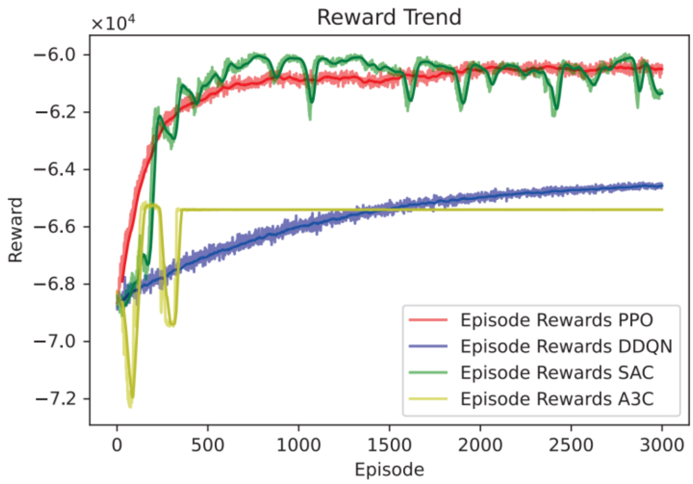


Figure 20: Convergence trend of PPO and DDQN algorithms.

Figure 21 illustrates the cumulative alarm significance over a 38-hour period, showing that adapting the grid configuration using forecasts and PPO-based prescriptive actions reduces alarms relative to a constant configuration. With control limited to existing circuit breakers (i.e., switching among feasible configurations), the PPO policy achieves the lowest total alarm significance (244.86) versus the constant baseline (307.35), corresponding to a 20.3% reduction. Alternative learners perform worse: DDQN 274.01 (−10.8%), SAC 273.33 (−11.1%, but with training instability and larger action fluctuations), and A3C 284.11 (−7.6%). While there are isolated intervals where the constant configuration outperforms due to forecasting/prescription errors, overall results confirm that the proposed prescriptive maintenance approach materially lowers alarm exposure under constrained operational controls.

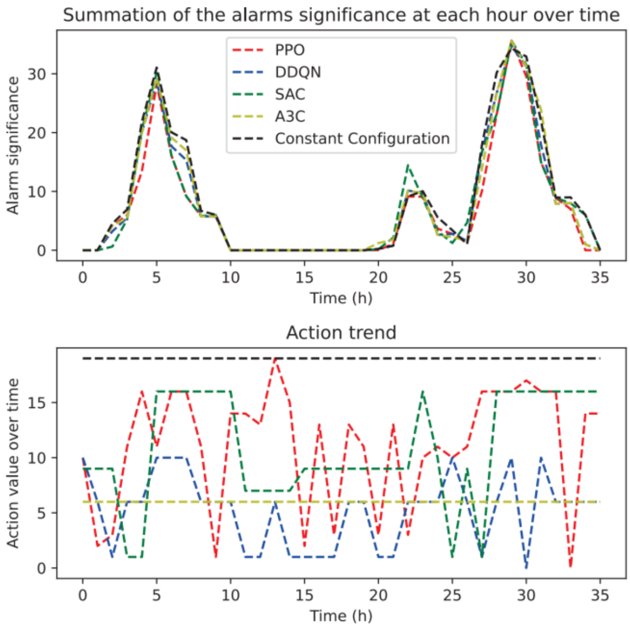


Figure 21: Summation of alarm significance and action trend

5.2.2 Predictive asset management

The NWPH–based planning pipeline was validated on a real 10 kV Danish distribution grid operated by **Dinel** with documented cable interruptions (2016–2022). Only material/aging-related PILC/APB failures were retained. The dataset contains mostly right-censored observations with 56 uncensored and 37 interval-censored cases; installation dates missing for some APB assets were handled via interval censoring and left-truncation corrections (inverse-reliability weighting). The study area and cable inventory are shown in Figure 22.

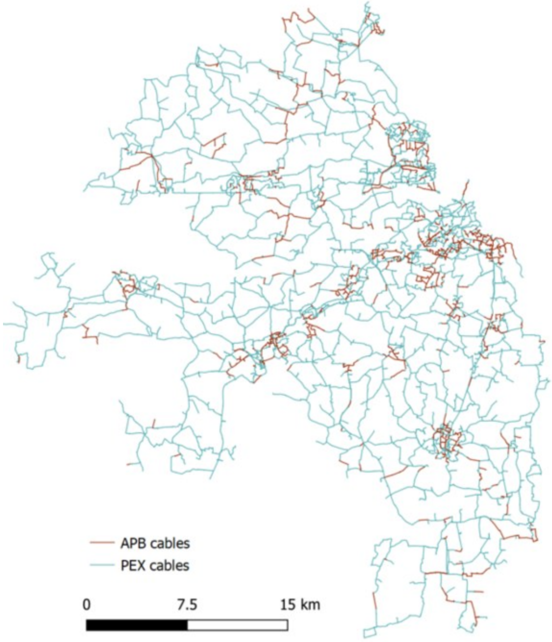


Figure 22: 10 kV cables of Danish power grid operated by Dinel.

The maintenance simulator executes yearly cycles of reactive + proactive actions, while a **Bayesian nested Monte Carlo** scheme captures (outer) parameter and (inner) failure-time uncertainty. Shared parameters include a 45 min average interruption duration, 75 DKK/kWh outage cost, and a 19.85 mDKK annual replacement budget; demand rises linearly to **+219% (2024–2034)** then stays constant. The **NWPH** reliability model outperformed a Weibull-Length proportional baseline and naïve ranking on the Fault-Capture/Length-Capture (FCLC) curve; loading features were dropped as they did not improve capture as depicted in Figure 23. Figure 24 shows that predictive uncertainty remained low over time, with the interquartile range of reliability typically ≤ 0.12.

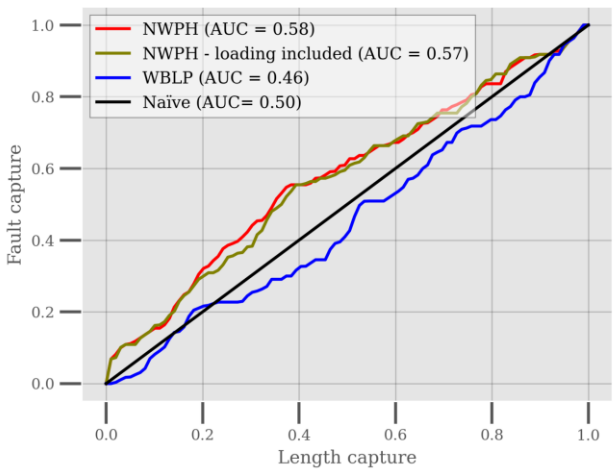


Figure 23: FCLC for the NWPH model, a WBLP model, and a naïve ranking, which represents the average random ranking of the cables.

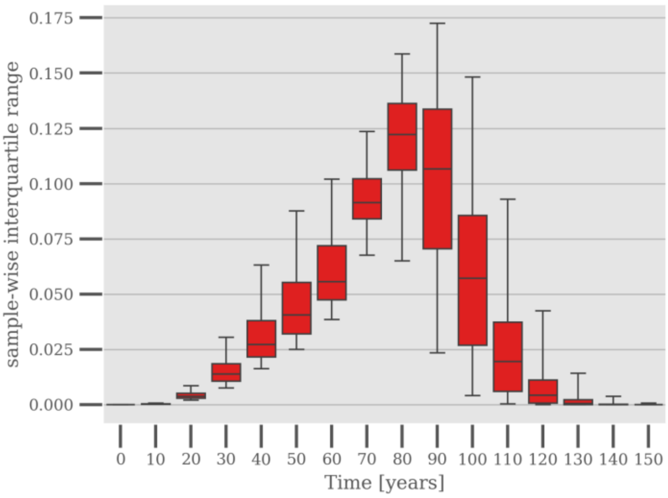


Figure 24: Interquartile range of reliability predictions over time. Higher values indicate greater uncertainty, which contributes to variation in maintenance strategy outcomes. Whiskers show the 5th and 95th percentiles.

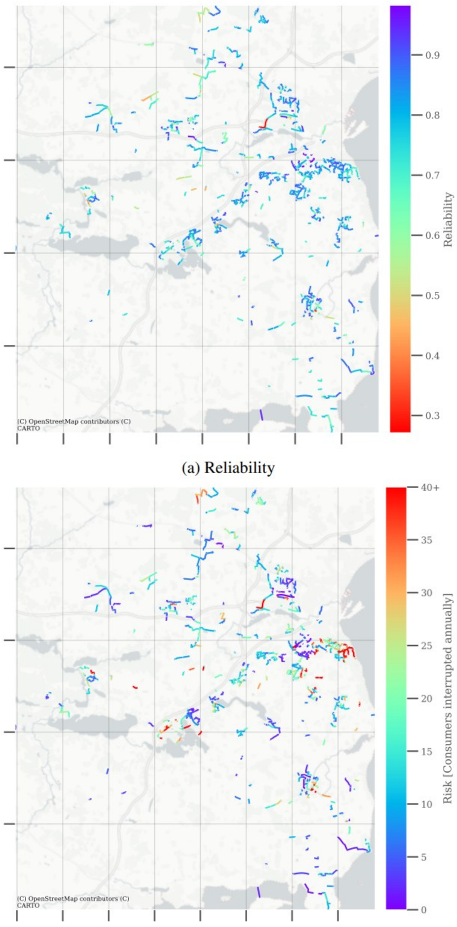
If no replacements are made, total risk from PILC cables grows from **~13,500** to **~24,800** consumers interrupted per year by **2033** (baseline "do nothing" trajectory). Four proactive ranking strategies were tested over **2023–2033**—**Vulnerability** (hazard/length), **Risk** (hazard×consumers per cost), **Consequence** (consumers per cost), and **Naïve**—within the same reactive policy. Figure 25 aggregates total failures, outage costs, and mean SAIFI/SAIDI across 100×100 nested simulations. Headline KPIs:

- **Risk-based** delivers the **lowest outage cost** and **lowest SAIFI/SAIDI**, saving up to **6.16 mDKK** and reducing mean SAIDI by **≈ 4 min** vs alternatives.
- **Vulnerability-based** prevents the **most failures** but is less cost-efficient than **Risk/Consequence**.
- **Naïve** is worst on all indicators.

Statistic	Vulnerability	Naïve	Risk	Consequence
Total Failures				
5^{th} percentile	82	134	102	108
Mean	113	186	138	149
95^{th} percentile	144	243	177	194
Outage Cost [mDKK]				
5^{th} percentile	4.14	7.26	3.03	3.36
Mean	5.88	10.38	4.22	4.74
95^{th} percentile	7.75	13.91	5.51	6.24
Mean SAIFI				
5^{th} percentile	0.04	0.08	0.03	0.03
Mean	0.09	0.15	0.07	0.07
95^{th} percentile	0.16	0.25	0.11	0.12
Mean SAIDI [min]				
5^{th} percentile	1.62	3.40	1.34	1.54
Mean	4.06	6.90	2.98	3.33
95^{th} percentile	7.01	11.03	4.92	5.44

Figure 25: KPIs for maintenance strategies from 2023 to 2033. The KPIs include only material and aging-related failures of APB cables.

Reliability and risk maps (averaged over **100** Bayesian-bootstrap NWPH models) highlight priority replacement corridors—visualized in Figure 26 (red = strong incentive to replace).

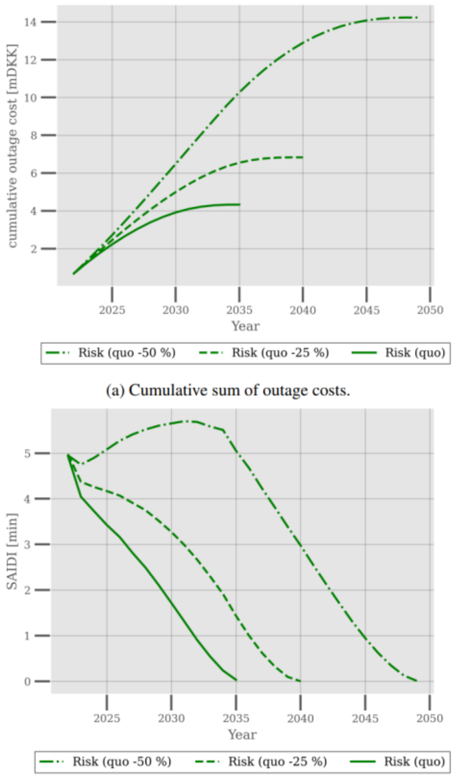


(a) Reliability

(b) Risk

Figure 26: Reliability and risk maps for the PILC cables in 2023 according to the average of the 100 Bayesian bootstrap NWPH models. The color scheme is inverted for the reliability, such that both for metrics red colors are associated with a strong incentive to replace.

Under the **Risk-based** strategy, cutting the annual budget by **25%** and **50%** raises cumulative outage costs from just over **4 mDKK** (status quo) to **~7 mDKK** and **14 mDKK** respectively, while SAIDI remains near **5 min** (status quo, −25%) and peaks at **≈ 5.5 min** with a **50%** cut (Figure 27). Overall, **halving the budget** increases SAIDI by only **~1.5 min** and cumulative costs by **~10 mDKK**, indicating room to reallocate CAPEX toward reinforcements with modest reliability impact. The case study verifies that an NWPH model trained with censoring/truncation awareness, embedded in a nested uncertainty simulator, yields **cost-efficient** renewal plans with quantified risk. It also demonstrates the practicality of **consequence-aware** targeting (consumers affected) for superior SAIFI/SAIDI and cost outcomes, consistent with the Development module's design choices.



(a) Cumulative sum of outage costs.

(b) SAIDI.

Figure 27: Comparison of the risk-based strategy outcomes under different maintenance budgets.

In another work on the same Danish grid case operated by Dinel considers **1,122 APB** cables with heterogeneous load contexts (max avg flow **~1,400 kW**). Replacement cost is **density-dependent**: **650,000 DKK/km** (low density) vs **840,000 DKK/km** (other three classes). Annual planning budget: **1 mDKK**. Histograms of **consumers/cable** and **average power flow** reveal that **~50%** of cables carry < 200 kW, while high-density assets serve disproportionally more consumers; density classes and their consumer/flow distributions are summarized in Figures 28–29.

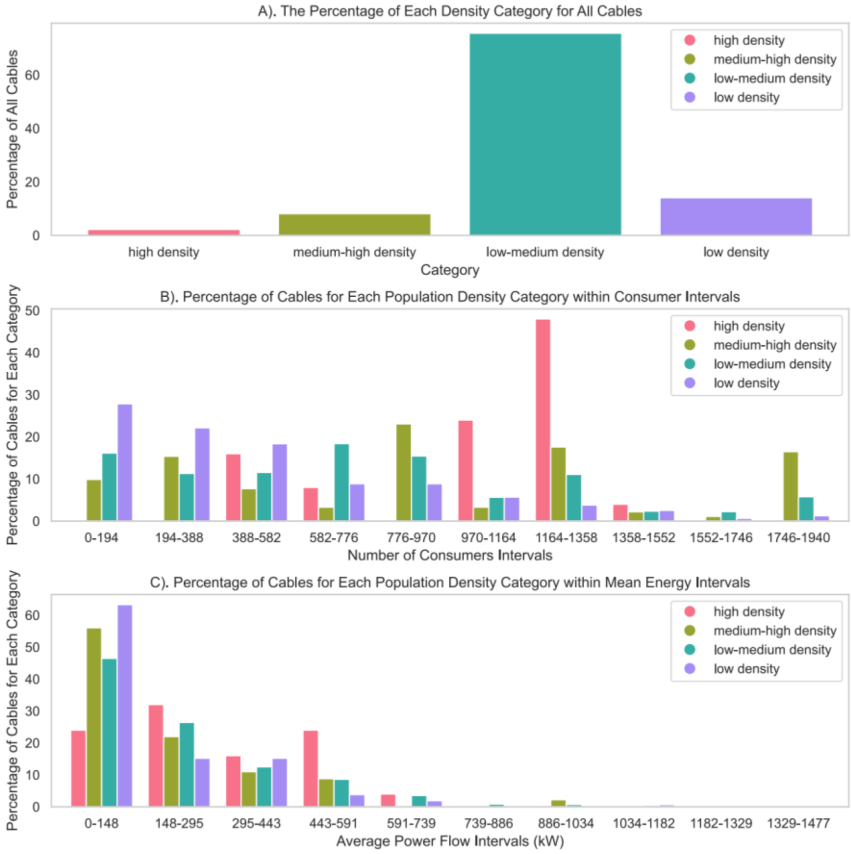


Figure 28: A. Bar plot of different population density categories, and B. Number of consumers intervals, and C. Average power flow intervals for four population density categories.

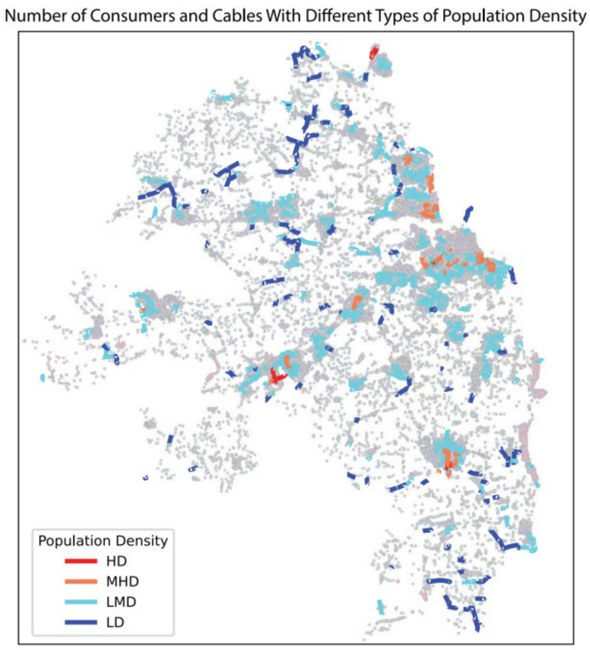


Figure 29: Georeferenced observation of cables with different population density and consumers.

Three objectives—**minimize** (i) cost of power outage and (ii) a normalized **interruption-related index** (**SAIFI, SAIDI, ASIDI**), while **maximize** (iii) number of replaced cables—are posed as a mixed-integer multi-objective problem solved via the **epsilon-constraint** method. Outage-cost normalization uses **7 DKK/kWh** with **25%** of faults > 1 h (factor **7/4** DKK per failure), consistent with Danish benchmarking practice. Missing cable flows are imputed from neighboring geometry (200 m buffer). The **Pareto front** (Figure 30) spans feasible plans from **20** to **133** replaced cables within budget; for a given count, multiple non-dominated plans exist with different trade-offs between outage cost and the interruption-related index. Figure 31 shows a part of the result extracted from Pareto Front. A sample slice shows two distinct **45-cable** solutions with outage costs **696,800** vs **673,694** (units per the paper), illustrating how planners can select a solution based on whether **reliability** or **cost** is prioritized under the same replacement volume. Georeferenced plot of the cable replacement for three optimal scenarios is shown in Figure 32, highlighting the cables needs to be replaced.

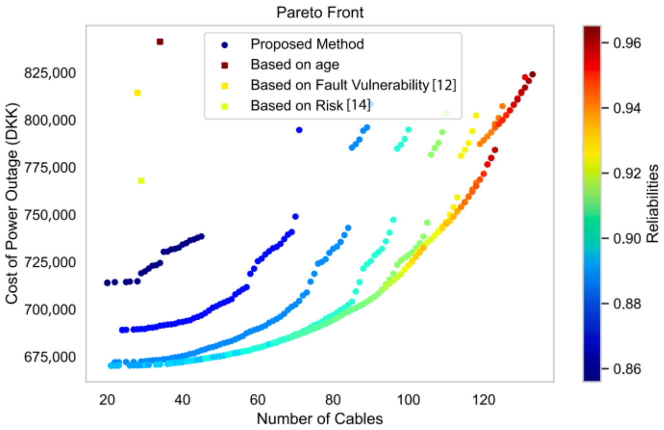


Figure 30: Pareto front using epsilon-constraint multi-objective optimization.

Number of cables	Cost of power outage (DKK)	Interruption-related index	SAIFI	SAIDI (min)	ASIDI (kW)	Length (km)	Budget (MDKK)
20	714,030	0.856	0.121	5.360	1.810	6.129	4.999
21	**670, 278**	0.890	0.132	5.826	**1.695**	5.998	4.999
44	737,839	**0.855**	**0.119**	**5.270**	1.865	**6.188**	4.999
45	696,800	0.870	0.125	5.550	1.76	6.147	4.998
45	673,694	0.891	0.131	5.819	1.703	6.011	4.999
50	702,796	0.870	0.125	5.530	1.777	6.022	4.998
70	749,003	0.870	0.121	5.364	1.894	6.171	4.998
110	746,166	0.927	0.133	5.900	1.887	6.092	4.999
110	745,090	0.933	0.134	5.957	1.884	6.055	4.999
133	824,077	0.965	0.135	5.972	2.084	6.093	4.999

Figure 31: Multi-objective optimization results.

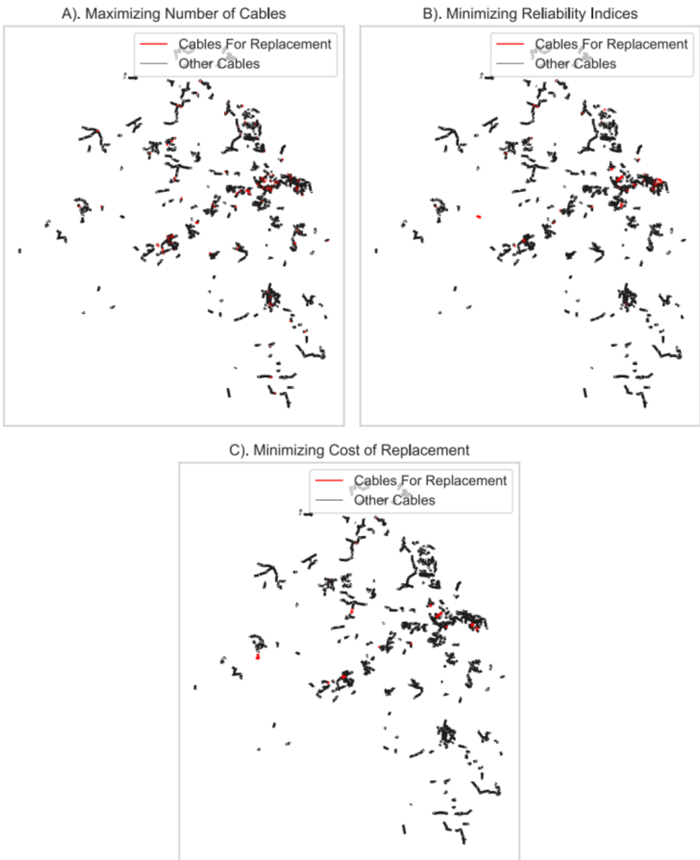


Figure 32: Underground cable renewal under different scenarios.

Across scenarios, the reliability-aware multi-objective approach **dominates age-based**, **vulnerability-only**, and **risk-only** heuristics on both **reliability indices** and **power-outage cost**. This confirms that explicitly co-optimizing **consequences (consumers, ASIDI)** with predictive vulnerability under a **budget constraint** yields superior renewal portfolios. This case demonstrates that, given standard GIS/operational inputs, the epsilon-constraint optimizer provides a **transparent menu of Pareto-optimal plans** (counts, expected cost, and reliability impact), enabling DSOs to select renewal lists aligned with annual budgets and policy targets—consistent with our development module's intended interface and outputs.

5.2.3 Developed toolsets through the project

5.2.3.1 Toolset 1 – Smart Energy Network Operation and Maintenance (SENOM)

SENOM is a demo software package that operationalizes our forecasting and prescription research for distribution grids. It lets operators import grid data, run asset-level load/production forecasts, quantify alarm significance, and visualize/compare switching actions on an interactive map. The app is implemented in Python/Streamlit and has been exercised on Danish MV/LV feeders. SENOM is consisted of the following modules:

- **SENOM Overview:** Explains scope and workflow, links to all modules, and performs a quick file "health check". A screenshot of the page is depicted in Figure 33.

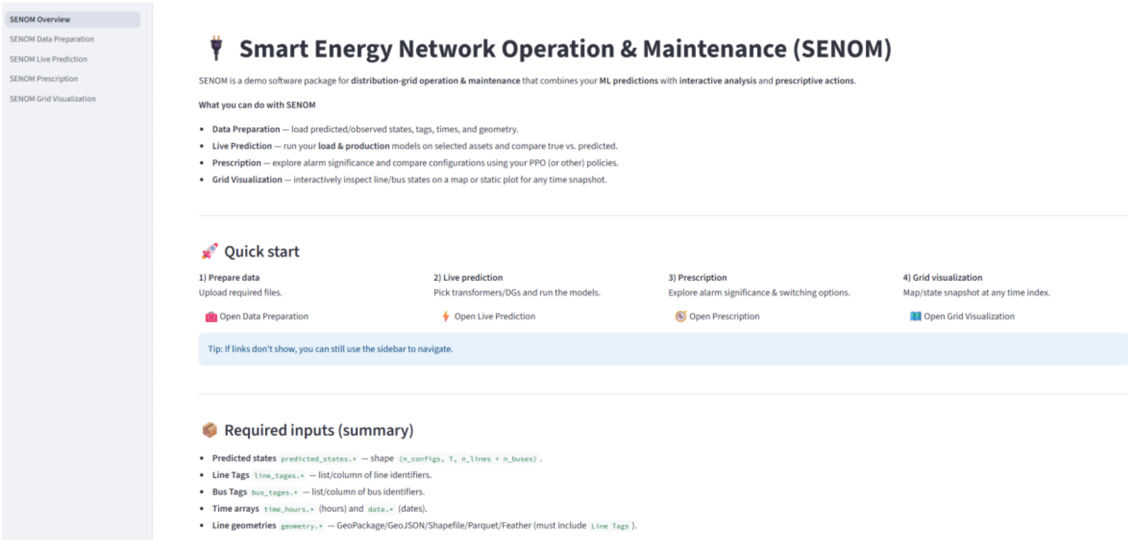


Figure 33: SENOM overview page.

- **Data Preparation:** Guided upload and validation of required inputs and generation of the data for the next steps:
- Predicted/observed states (`.npy/.npz/.csv/.pkl`), line & bus tags, hourly time arrays and dates, and line geometries (GeoPackage/GeoJSON/Shapefile/Parquet/Feather).
- Optional: transformers, main substations, DG list.
- Validation messages and consistent naming are enforced before analysis.
- Generating necessary dataset for next steps. (Figure 34)

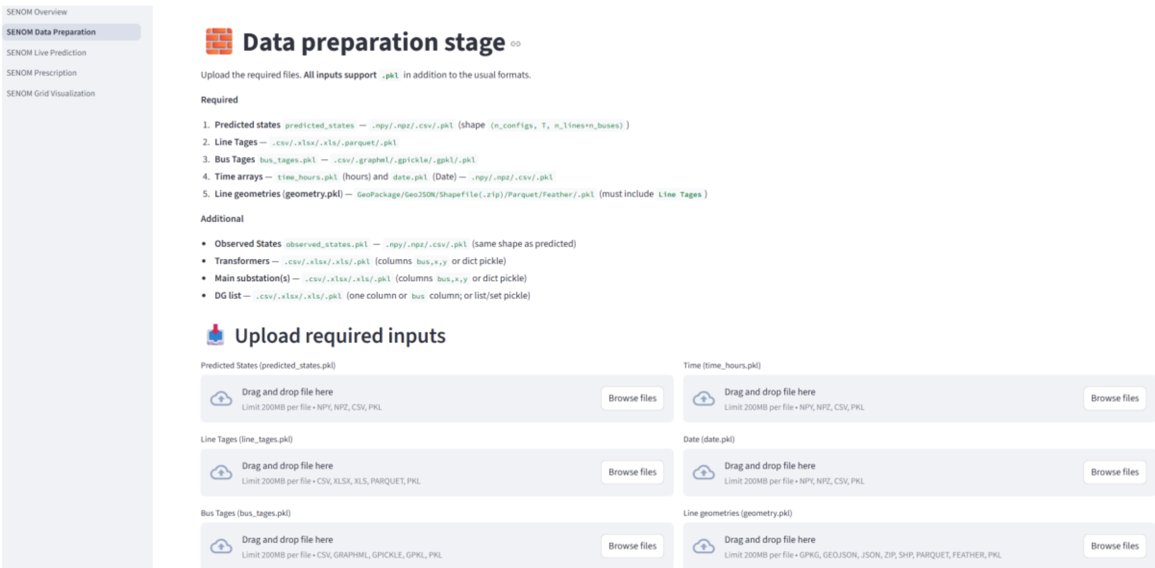


Figure 34: SENOM data preparation module.

- **Live Prediction:** Inference UI for the trained **Transformer–KAN** models (separate heads for loads and DGs):
- Shapes and reshaping handled internally (e.g., `(t,20,24) → (t,24,20)`), with NaN safety.
- Checkpoint tolerant loading (shows missing/ignored keys); supports CPU/GPU.

- Asset selection by **Transformer/DG IDs**, first-72-timestep plotting, and CSV export of true vs. predicted. (Figure 35)

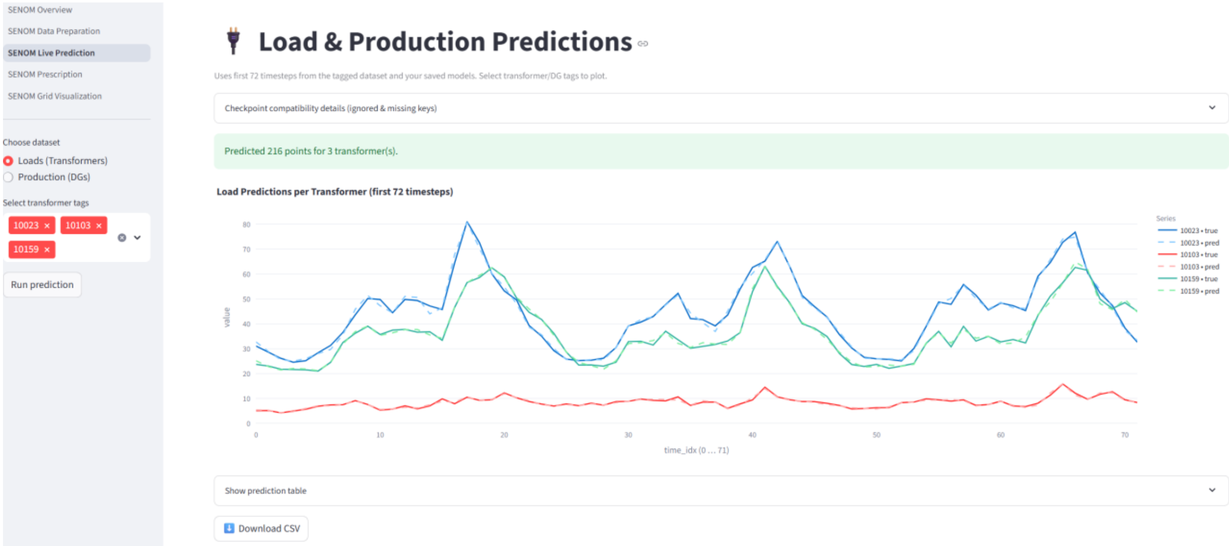


Figure 35: SENOM live predictor module.

- **Prescription:** Time-series explorer for **alarm significance** (current/voltage):
- Plots observed and predicted alarm significance, side-by-side, over user-selected windows.
- Fixed 72-hour evaluation window option to align with training/evaluation protocol.
- Configuration selector for scenario comparison. (Figure 36)

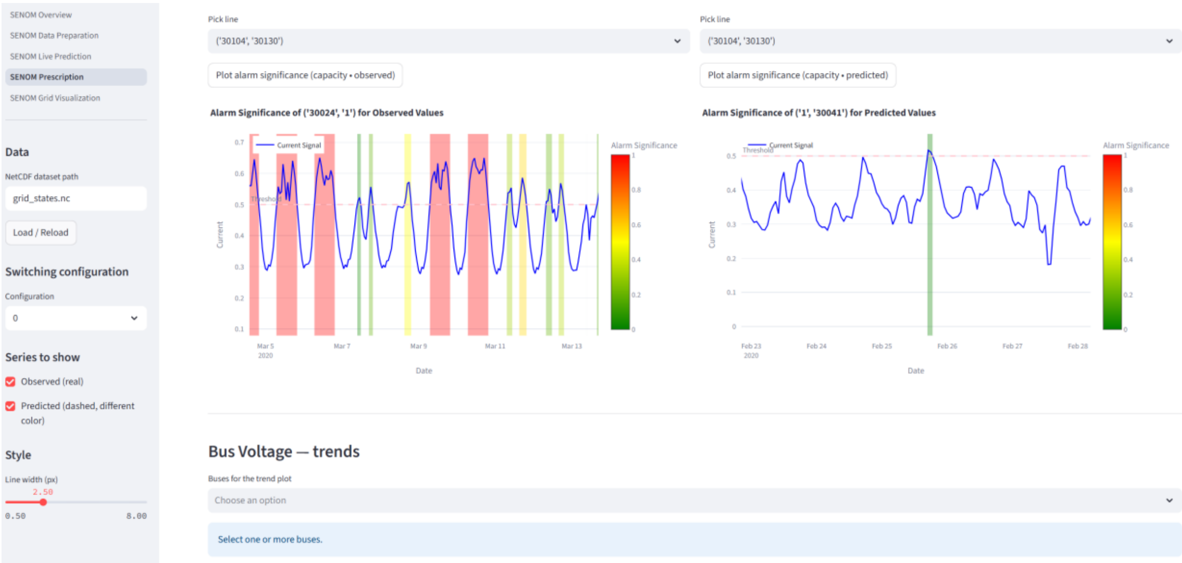


Figure 36: SENOM Prescription module.

- **Grid Visualization:** Interactive and static maps:
- Line color ramps by loading %, bus markers with labels, CB-aware styles (solid vs dashed).
- Date/time controls and basemap styling (opacity, line width). (Figure 37)

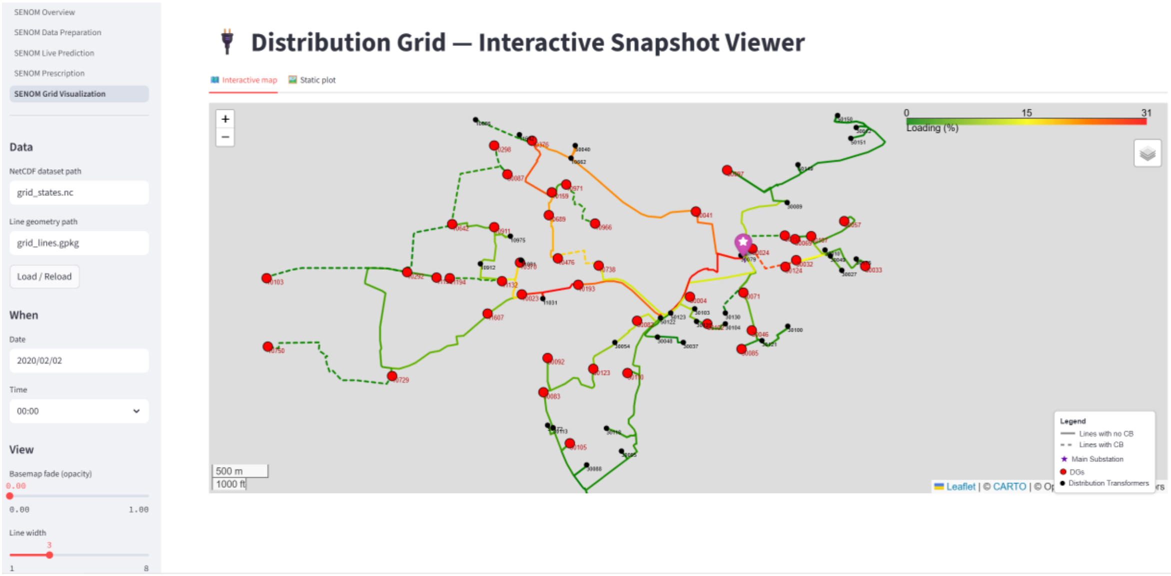


Figure 37: SENOM Grid visualization module.

5.2.3.2 Toolset 2 – Predictive Asset Management Smart Energy Network (PAMSEN)

PAMSEN packages the **predictive asset management** part of the project: it ingests geospatial/asset data and model outputs, runs **multi-year budget-constrained optimization** for cable maintenance (repair vs replace), and exposes **interactive maps** and **result summaries** for planning. PAMSEN is consisted of the following modules:

- PAMSEN Overview: A lightweight start page that states the goal (multi-year maintenance planning under budget constraints), lists the inputs/outputs, and links to each module.
- PAMSEN Data Preparation: Reads and validates the required inputs: (i) the asset table with cable IDs, lengths, costs and customers served; (ii) GeoData (cable geometries); (iii) model artefacts (e.g., failure probabilities / NWPH-derived risk measures). The page standardizes column names, coerces CRS, and stores pickled artefacts for fast reuse.
- PAMSEN Optimization: The planner solves a yearly sequence of actions subject to annual budgets. The UI lets users pick **horizon (years)**, set **budget B_t per year**, and choose a **repair-to-replace cost ratio**. Output is a per-cable action plan (`Replace`, `Repair`, `Do nothing`) per year plus an audit table saved to disk. Figure 38 shows the optimization screen: the top panel is the settings form; the status box confirms the pipeline (“Loading data → Reading models → Preparing fleet & geometry → Solving optimization → Saving outputs”).

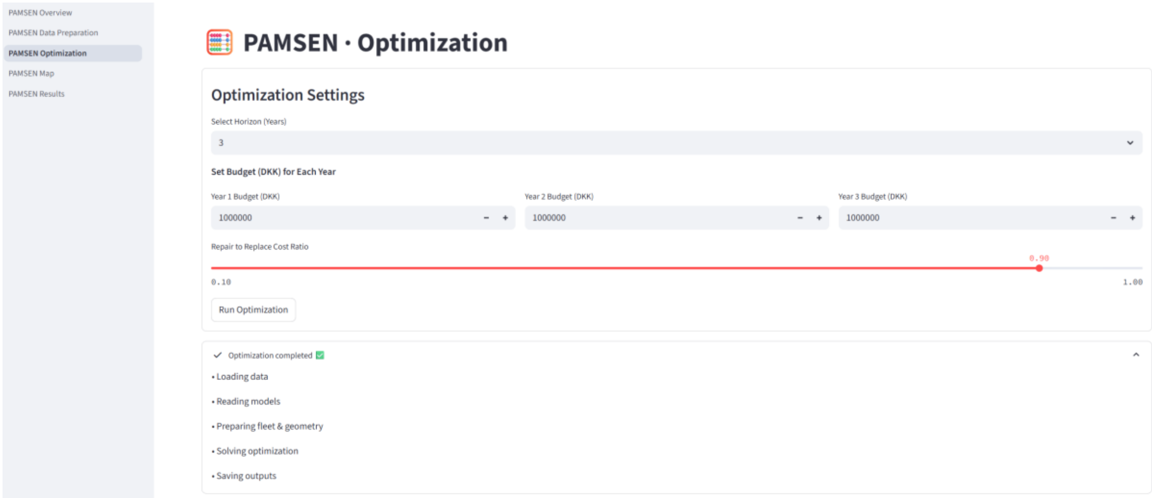


Figure 38: PAMSEN optimization screen and run status.

- PAMSEN Map: An interactive Leaflet map to **explore the plan spatially**. Users choose the year and plot type:
- Action – colors by `Replace` (red), `Repair` (orange), `Replaced` (purple), `Do nothing` (grey).
- Customers – continuous color ramp by the number of connected customers.
- Failure – continuous color ramp by failure probability.

  Style controls include **line width** and **basemap opacity**. The legends are in-map for clarity.
  Figures 39 depict the map in **Action** mode at Year 1 with the legend (left). The opacity slider allows switching between a strong basemap (for context) and a minimal one (to emphasize actions).

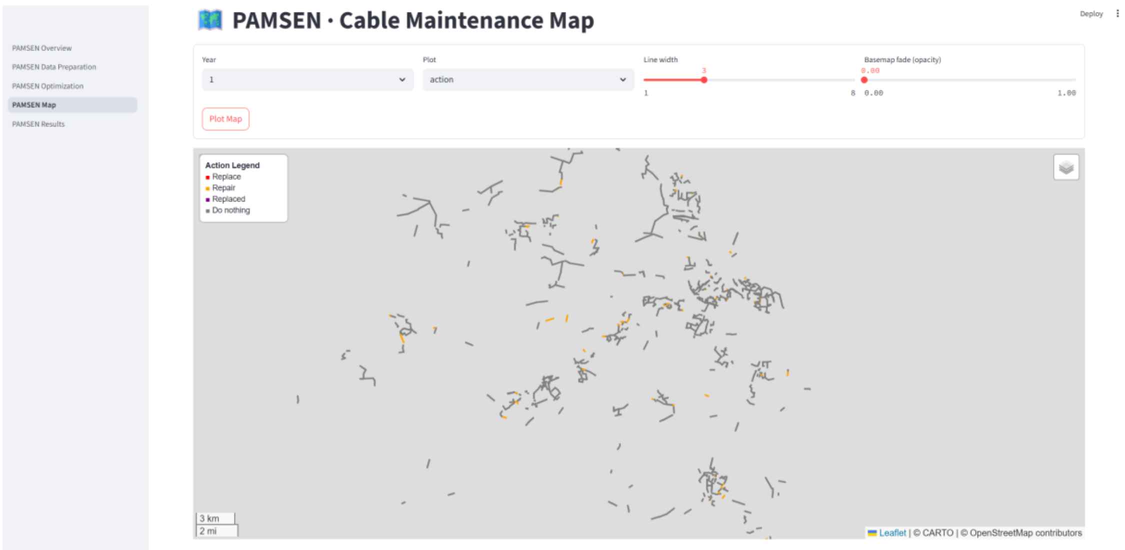


Figure 39: PAMSEN map — Year 1 action plan visualization.

- **PAMSEN Results:** A compact report: yearly counts of replaced/repaired/do-nothing cables, budget utilization, and high-level KPIs (e.g., customers affected avoided, risk reduction). The page includes CSV export for documentation and post-processing.

5.3 Integration

The toolset was designed to be meter-agnostic from the outset. This means that the toolset is developed such that it requires no additional and further integration to specific smart meter brands such as Kamstrup. This reflects the operational reality that Danish DSOs and DSOs in many other countries often operate mixed fleets of smart meters; therefore, the solution must work irrespective of model or vendor and should not require brand-specific features. Kamstrup basic smart meter capabilities, which are common between most available brands have been considered as a baseline requirement for toolset design. The project's solution is software-only, reuses existing infrastructure data, and does not require additional hardware, aligning with the overall EUDP objectives and the report's stated competitiveness criteria.

Integration focuses on data ingestion and exchange, not device coupling. Inputs include AMI/MDMS (hourly load/consumption), SCADA (switch states, transformer taps), and GIS/asset registers (connectivity, cable attributes). These are already present at DSOs and are referenced throughout the report as existing utility data sources to which the toolset connects directly.

The solution can be delivered as on-premises software components that operate within the DSO's data perimeter, exchanging only the minimally required fields with existing systems. This supports the report's commercialization path—no new hardware and direct use of existing platforms—and simplifies IT approval compared to device-level integrations.

5.4 Dissemination

The project results have been disseminated through targeted industry and academic channels to maximize impact and adoption potential. Presentations and workshops were held with participating distribution system operators (DSOs) and other stakeholders in the Danish electricity sector, including contributions to events such as Intelligent Energy (iEnergy) and industry-specific seminars as well as scientific seminars such as the HVL Data Science Webinar Series, Co-hosted by Western Norway University of Applied Sciences and IEEE. These sessions focused on demonstrating the capabilities of the prescriptive maintenance and predictive asset management toolset, sharing implementation experiences, and discussing integration strategies with existing operational platforms.

The results have also been shared through scientific publications, conference presentations, and MSc/PhD projects at the University of Southern Denmark. This has ensured both the integration of findings into graduate-level teaching and the transfer of knowledge to the next generation of engineers and researchers.

Publications and Scientific Output:

- Mirshekali, H., Ghanadi Ladani, F., & Shaker, H. R. (2025). Consequence-Aware Prescriptive Maintenance Framework with Transformer-KAN Forecasting and PPO-Controlled Grid Reconfiguration. *IEEE Transactions on Smart Grid*. Advance online publication. https://doi.org/10.1109/TSG.2025.3579890
- Mortensen, L. K., Renga, D., Santos, A. Q., Meo, M., Shadi, M. R., & Shaker, H. R. (2025). Load Forecasting and Fault Prediction Framework for Distribution Grids: A Bus- and Topology-Agnostic

Solution. In *19th International Conference on Compatibility, Power Electronics, and Power Engineering (CPE-POWERENG 2025)* https://doi.org/10.1109/CPE-POWERENG63314.2025.11027306

- Mirshekali, H., & Shaker, H. R. (2025). Overload Alarm Forecasting in Power Grids Using Q-Learning and Transformer Architectures. In *IEEE 19th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG)* IEEE. https://doi.org/10.1109/CPE-POWERENG63314.2025.11027239
- Gram, I., Mirshekali, H., & Shaker, H. R. (Accepted/In press). Predictive Stress Assessment in Power Distribution Systems using Bi-Mamba+. In *25th International Conference on Environment and Electrical Engineering*
- Madsen, F. W., Bank, T., Mirshekali, H., & Shaker, H. R. (2025). Short-Term Spatial-Temporal Energy Forecasting in a Danish Distribution Grid Using a Hybrid Transformer-Graph Neural Network Model. *Smart Power & Energy Security*. Advance online publication. https://doi.org/10.1016/j.spes.2025.05.002
- Gram, I., Mirshekali, H., & Shaker, H. R. (2025). Strategic DG Placement and Sizing for Alarm Mitigation in Distribution Grids Using Quadratic Programming-Enhanced Particle Swarm Optimization. In *15th IEEE Symposium on Computer Applications & Industrial Electronics* IEEE. https://doi.org/10.1109/ISCAIE64985.2025.11081057
- Shadi, M. R., Mirshekali, H., & Shaker, H. R. (2025). Temporal Fusion Transformer for Alarm Forecasting in a Danish DSO: Embedding Pearson Correlation. In *19th International Conference on Compatibility, Power Electronics, and Power Engineering (CPE-POWERENG 2025) https://doi.org/10.1109/CPE-POWERENG63314.2025.11027287*
- Mortensen, L. K., Sundsgaard, K., Shaker, H. R., Hansen, J. Z., & Yang, G. (2024). Designing Digitally Enabled Proactive Maintenance Systems in Power Distribution Grids: A Scoping Literature Review. *Energy Reports*, *12*. https://doi.org/10.1016/j.egyr.2024.08.044
- Rafati, A., Mirshekali, H., & Shaker, H. R. (2024). Overload Alarm Prediction in Power Distribution Transformers. *Smart Grids and Sustainable Energy*, *9*(2), Article 39. https://doi.org/10.1007/s40866-024-00227-z
- Mirshekali, H., & Shaker, H. R. (2024). Reinforcement Learning-Based Prediction of Alarm Significance in Marginally Operating Electrical Grids. *IEEE Transactions on Industrial Informatics*, *20*(4), 6510-6521. https://doi.org/10.1109/TII.2023.3348819
- Mirshekali, H., Mortensen, L. K., & Shaker, H. R. (2024). Reliability-Aware Multi-Objective Approach for Predictive Asset Management: A Danish Distribution Grid Case Study. *Applied Energy*, *358*, Article 122556. https://doi.org/10.1016/j.apenergy.2023.122556
- Mirshekali, H., Santos, A. Q., & Shaker, H. R. (2023). A Survey of Time Series Prediction for Digitally Enabled Maintenance of Electrical Grids. *Energies*, *16*(17), Article 6332. https://doi.org/10.3390/en16176332
- Mirshekali, H., Shaker, H. R., & Santos, A. Q. (2023). Critical Events Forecasting in Power Grids Operating Close to Margin. In *2023 7th International Conference on System Reliability and Safety (ICSRS)* (pp. 206-212). IEEE. https://doi.org/10.1109/ICSRS59833.2023.10381467

Student Theses and Reports:

- Mortensen, L. K. (2024). *Data-Driven Proactive Maintenance and Asset Management for Energy Distribution Networks* (Ph.D. thesis). University of Southern Denmark.
- Madsen, F. W., & Bank, T. (2025). *Prescriptive Grid Management: Proactive DER Strategies for Grid Asset Protection and Cost-Effective Energy* (MSc thesis, 40 ECTS). University of Southern Denmark.
- Minousis Gram, I. (2025). *Real-Time Control and Predictive Analysis of Distributed Generation Preventing Grid Failures* (MSc thesis, 60 ECTS). University of Southern Denmark.

In addition, knowledge transfer has been achieved through ongoing collaboration with DSOs, enabling direct feedback loops between research outputs and practical operational needs. This has not only improved the robustness of the developed methods but also positioned them for smoother adoption in real-world operational contexts.

6. Utilisation of project results

Technological utilization

The technological results from the project will be used by electricity distribution system operators (DSOs) to improve maintenance planning, reduce outage risks, and optimize investment decisions. The software-based toolset — combining prescriptive maintenance and predictive asset management — has been developed and successfully demonstrated using real DSO data.

Commercialisation pathway

The prescriptive maintenance module has been developed and tested on operational datasets, enabling fault prediction and generation of maintenance recommendations without requiring additional hardware. The predictive asset management module has been demonstrated on operational and environmental datasets, producing risk-based asset rankings for improved investment planning.

While the project expected to utilize a wide range of operational and asset data, we found that many DSOs only actively collect or integrate a subset of available data, often limited to functionalities required by regulation. Activating and standardizing additional datasets requires the definition of clear data models and data management strategies within each utility — a process that takes time.

As a result, the project's developments focused on data that is already accessible and of sufficient quality. Given the ongoing digitalization of the utility sector, data collection rates, granularity, and completeness are expected to improve, removing current limitations and further increasing the toolset's value.

In the short term, the tools can be offered as a consultancy-supported service, providing DSOs with actionable recommendations and asset risk assessments. In the longer term, full commercialization as an integrated, automated software solution will be achieved through:

- Standardizations of data formats across DSOs.
  - Automation of auxiliary data collection (e.g., environmental condition and maintenance record updates).
  - Integration into existing operational platforms (SCADA, GIS, ERP)

Market readiness and competition

The current market is characterized by large international vendors (e.g., Siemens, ABB, GE Grid Solutions) whose solutions often require costly hardware investments or lack integrated prescriptive capabilities. The project's toolset is competitive due to its software-only approach and use of existing infrastructure data. Barriers to adoption include the conservative nature of the utility sector, procurement cycles, and data availability. These will be overcome through demonstration projects, building strong reference cases in Denmark, and aligning with ongoing digitalization initiatives.

Economic impact and policy contribution

The partners expect the solution to create new commercial opportunities, increase turnover, support export potential, and stimulate private investment in scaling and productization. By enabling more efficient, reliable, and data-driven grid operation, the project results directly contribute to Danish and EU energy policy goals, including improving security of supply, supporting renewable energy integration, and extending the lifetime of existing infrastructure to reduce environmental impact.

Integration of Results into Education and Industry Practice

The results from the project have been integrated into academic activities at the University of Southern Denmark, including graduate-level teaching on smart grids, asset management, and data-driven maintenance. They have also been applied in collaboration with industry partners, ensuring that new methods and tools are directly transferred to professional practice.

7. Project conclusion and perspective

Conclusions

The project has successfully developed and demonstrated a software-based toolset that combines prescriptive maintenance and predictive asset management for electricity distribution systems. Both modules were validated using real operational and environmental data from participating DSOs, showing that they can improve maintenance planning, reduce outage risks, and optimize asset investment strategies without requiring additional hardware. The integration of physics-based modelling, data-driven analytics, and existing infrastructure data provides a cost-effective and scalable alternative to current maintenance approaches, which are often reactive or hardware-intensive.

Next steps

The immediate next step is to offer the solution as a consultancy-supported service, allowing DSOs to benefit from the developed analytics while preparing for full integration into their operational environments. Future work will focus on:

- Expanding data integration to include higher-resolution smart meter functionalities and/or additional datasets
- Standardizing data formats across utilities to enable plug-and-play adoption.
- Developing user interfaces and workflow integration with SCADA, GIS, and asset management platforms.
- Conducting larger-scale demonstrations with multiple DSOs to build strong reference cases for market adoption.

Future perspective

As the digitalization of the energy sector accelerates, the availability, resolution, and quality of operational and asset data will continue to improve. This will further enhance the capabilities of the toolset, enabling increasingly accurate and automated maintenance recommendations. Over time, the integration of such tools into utility operations can shift the industry from reactive and preventive maintenance toward a fully predictive and prescriptive maintenance paradigm, reducing operational costs, extending asset lifetimes, and improving reliability.

The project results also align with broader trends in the electricity sector, including the integration of renewable energy sources, the need for higher grid flexibility, and the drive for sustainability. By supporting better-informed, risk-based investment planning, the toolset contributes to more resilient and cost-effective grids, supporting Danish and EU energy policy objectives for secure, affordable, and sustainable energy systems.