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A framework for data-driven decision support for operational planning in active distribution networks

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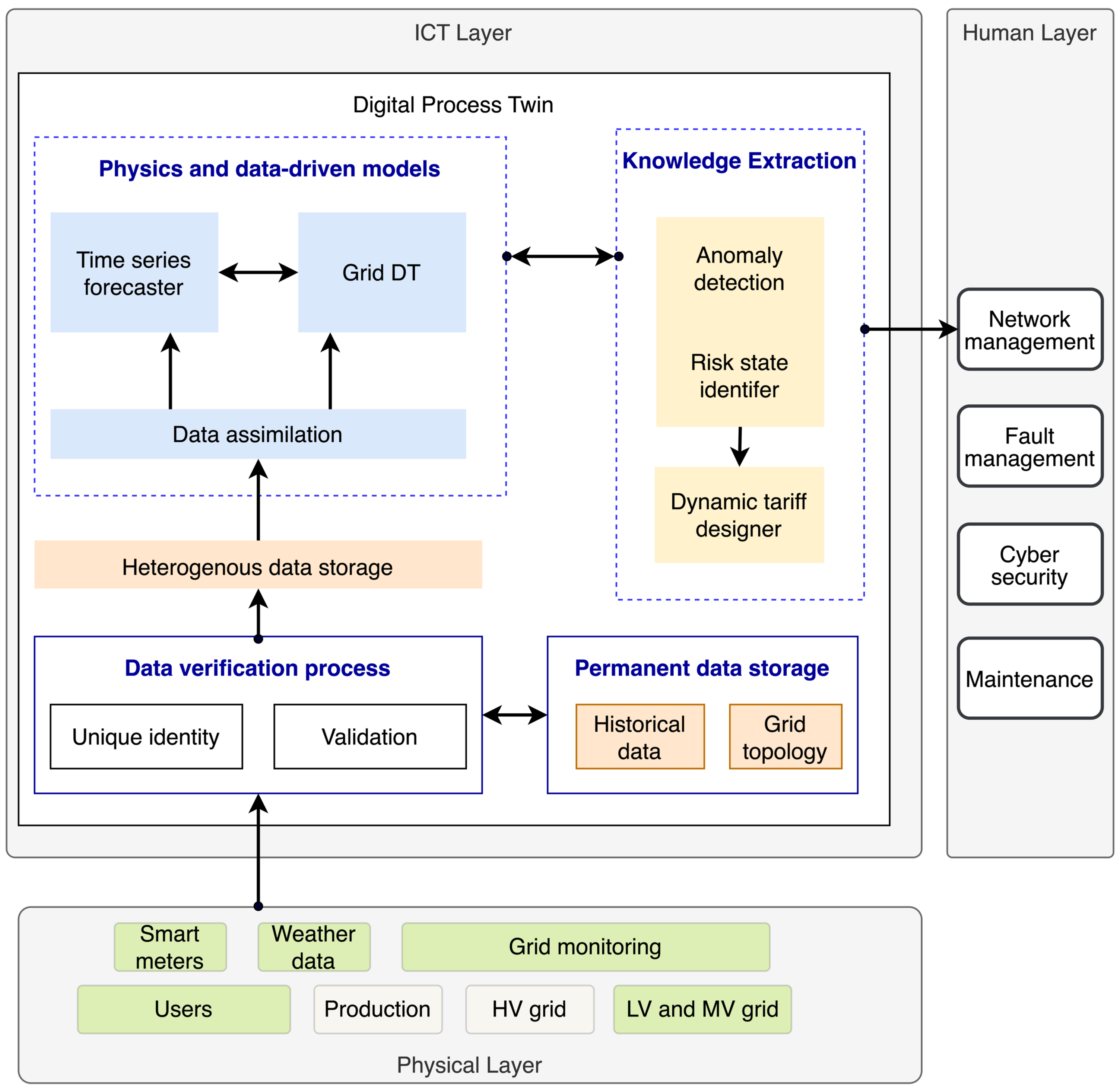
Digital Process Twin



Workflows

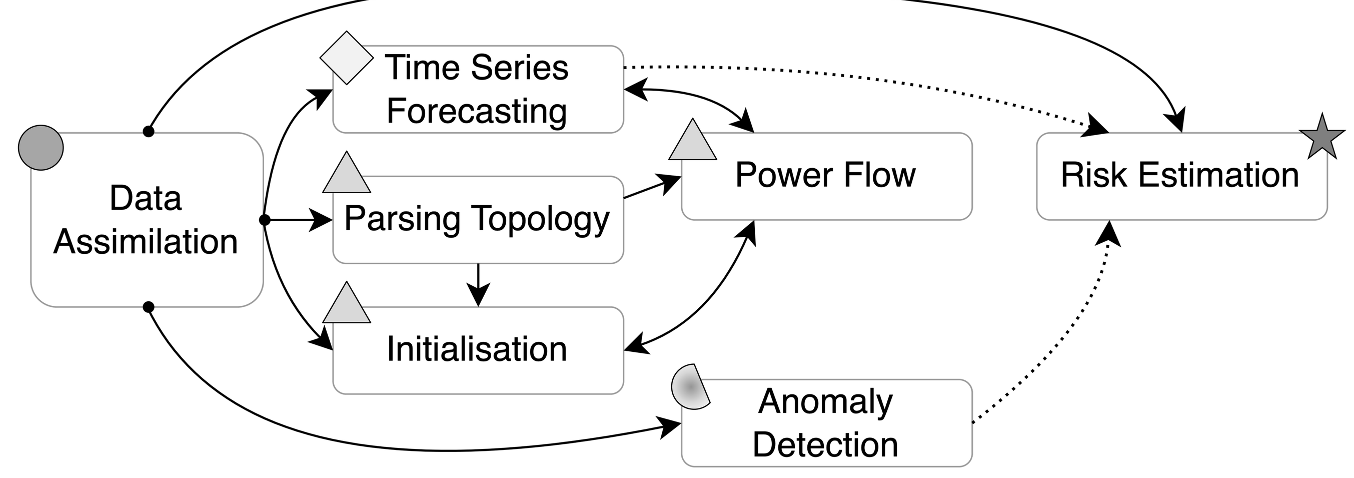
Sequences of processing steps and corresponding software modules that compose the DPT and let us extract information to increase situational awareness and to create dynamic tariffs, ultimately supporting network management decisions.

(a) **Sequential Power Flow Solutions** to characterize the impact of connecting more solar PV, electrical vehicles (EVs), and heat pumps.

(b) **Power Flow Forecasting** to estimate grid conditions in the next day(s).

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

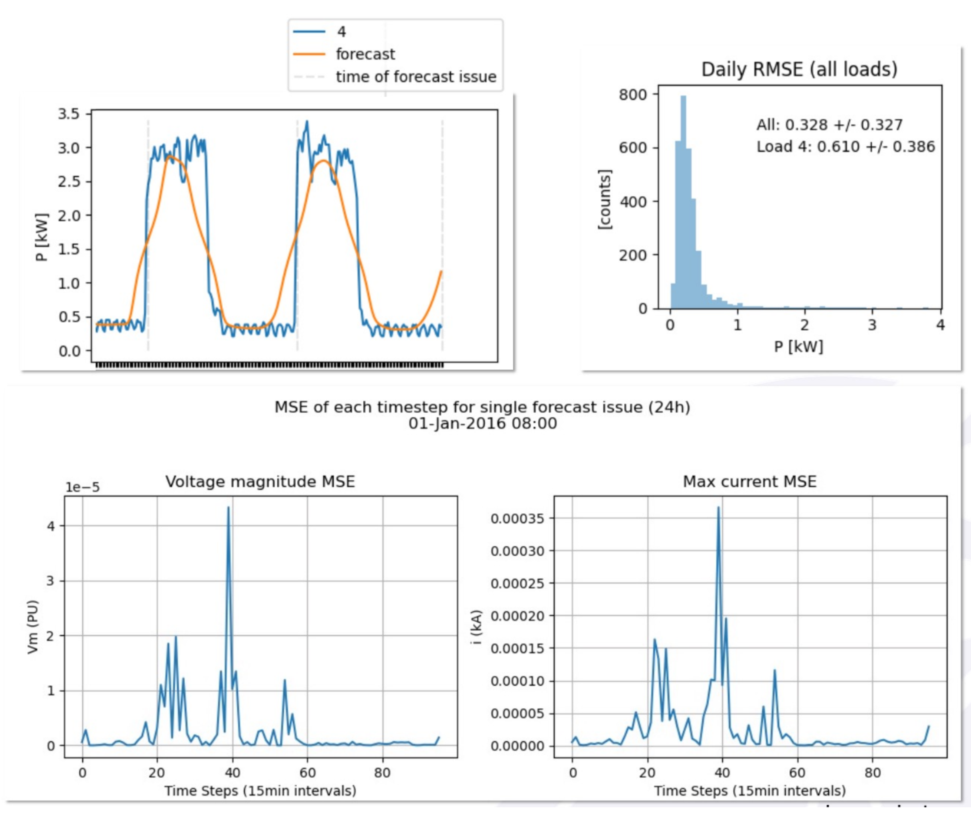
(d) **Risk Assessment** where compliance to EN 50160 is evaluated and risk metrics such as operational Over (or Under) Voltage Risk are calculated.



Forecasting

Preliminary evaluation of **(1)** power flow forecaster on a benchmark LV grid and **(2)** load forecasting with deep learning (DL) zero-shot inference.

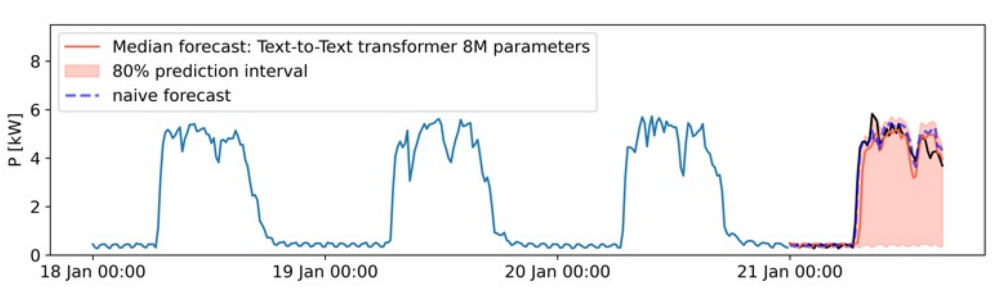
(1) Day-ahead power flow forecasting in terms of error propagation and computation time.
•1-LV-urban6--0-sw Simbench grid: radial network with 1 MV bus with a 20 to 0.4 kV transformer and 58 LV buses with 111 loads (2.0 to 31.0 kW)
•Simbench includes emulated smart meter and generation data by means of generic profiles
•Dummy forecast is created using local linear regressions
•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 via an S3 bucket
•Simbench data corresponding to the generic profiles were mapped and scaled according to the grid topology, resulting in active (P) and reactive power (Q) load profiles
•Power flow is calculated using pandapower tool with Simbench data as input and with forecast data as input to analyse error propagation



Top left plot shows active power from Load 4 and a dummy forecast issued every 24 hours. Histogram shows 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 for All loads, and for Load 4. The bottom plots illustrate the error between the power flow solutions calculated with the Simbench data and those calculated with the forecast.

(2) Load forecasting comparison of dummy, naïve (e.g., average of past data), and DL forecast for P and Q of load 4 over a period of one month. The DL model is a pretrained Text-to-Text transformer, T5 architecture with 8M parameters, used as a zero-shot inference tool, without fine tuning. For both models the input is data of the three previous days. The DL forecast has a mean RMSE lower that the naïve forecast, its standard deviation is significantly larger. Both the naïve and the DL forecast can be easily improved, and more extensive comparisons will be performed.

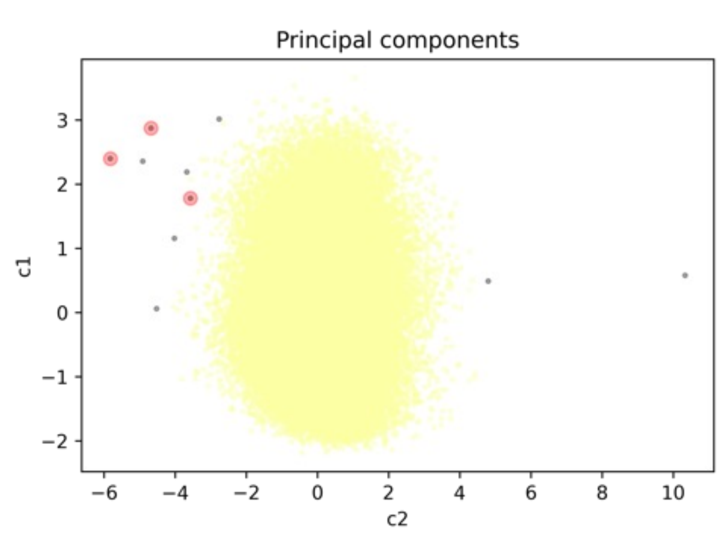
	Dummy	Naïve	T5 zero-shot
P [kW]	0.610 ± 0.386	1.504 ± 0.771	1.281 ± 1.153
Q [kVAr]	0.398 ± 0.323	0.737 ± 0.397	0.692 ± 0.544

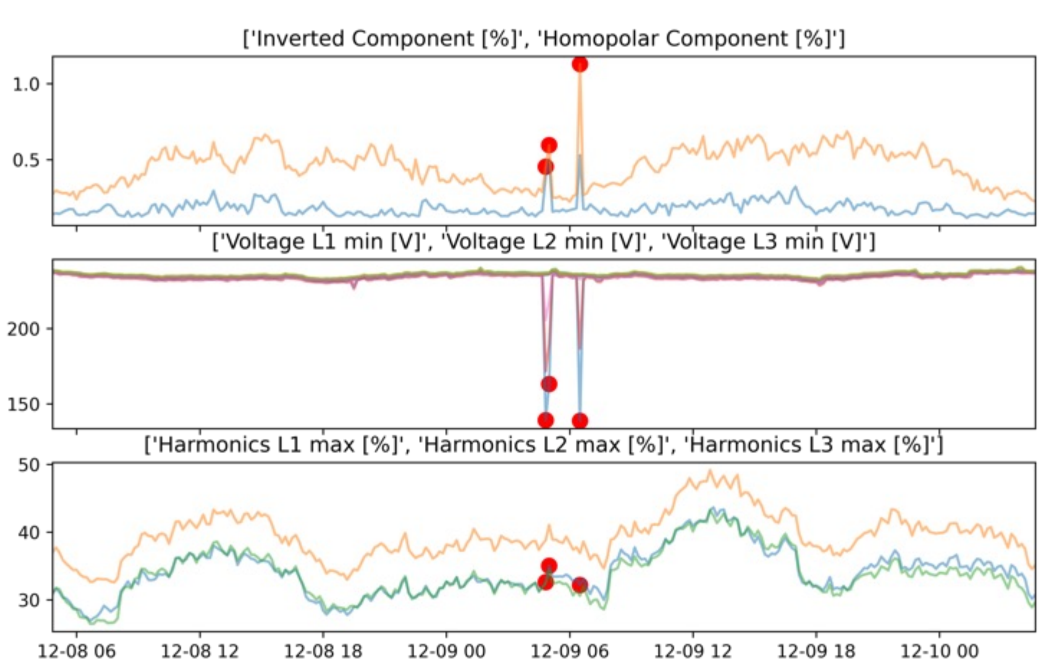


Anomaly Detection

Processing large amounts of grid monitoring data and detecting data different from the bulk is a first step towards identifying potential issues. **Unsupervised learning** can support DSO analysts to filter data and identify periods where disturbances occur. Steps:

1. **Remove mean**, scale to unit variance, remove linear correlations.
2. **Singular value decomposition** to reduce dataset dimensions (15 components explain 95 % of the variance).
3. **Density based clustering** (two hyperparameters: distance to neighbour threshold, and number of samples around a cluster centre).





A data set with 58 quantities that describe voltage, power, current, harmonics, and grid frequency; 10-min values from October 2018 to December 2019 recorded by a grid monitoring device installed at the LV side of a distribution transformer operated. Two clusters of points c1-c2 plane are detected, one corresponds to a normal behaviour, and the other to odd values that might represent an anomaly. Three points are highlighted and mapped to the original time series, where the distortion in the voltage is observed.

Summary and Outlook

- This work gives an overview of the operational planning framework along with examples of data analytics developed in the **AI-assisted decision support for operational planning in distribution systems** (AISOP) project funded by ERA-NET JPP SES program.
- In this framework a Digital Process Twin (DPT) with Single Source of Truth (SSoT) facilitates **data management** from IoT sensors and model outputs; **workflows** define analytics and forecasting tasks to support operator decisions.
- Next steps: apply workflows to data from two sites in Switzerland and integrate risk metrics into the design of dynamic tariffs to facilitate the evaluation of different tariff schemes.