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Progress Report «Project INITIATE»

1 Introduction

This report provides an overview of the progress made in project INITIATE. This project is a research project funded by the funding scheme for railway infrastructure "Bahninfrastrukturfonds" BIF of 2014. In this project, EPFL and SBB work together to improve the detection and prediction of critical conditions in railway power network systems by developing intelligent algorithms for control system data.

The project was initially started at ETH Zurich in 2021 and was transferred to EPFL in March 2022 due to the transfer of the research team from ETHZ to EPFL. In 2024, the project was extended for the duration of 2025.

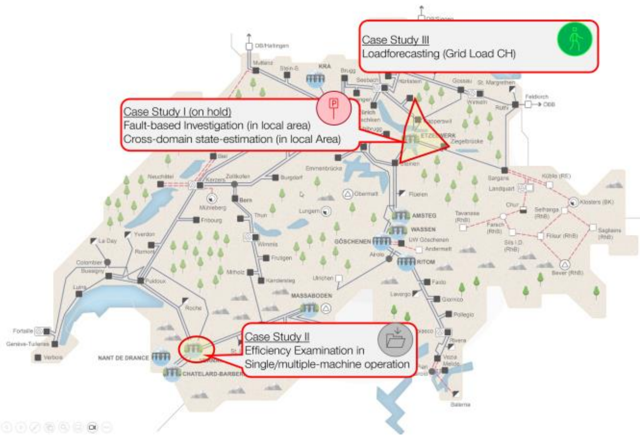

Figure 1: Power grids sites from which the generated data of case study I, II and III originates.

In June 2021, a group of domain experts from different fields collected and rated various case studies as candidates for investigation. The domain experts estimated the highest overall benefits of all case studies as well as immediate benefits if selected as the first case study. Based on these scores, two studies were selected to be the most promising and, thus, were processed first: a case study on state estimation and fault detection from power grid sensors in local areas such as power plants with connected substations (**case 1**) and a case study on hydro-power plant efficiency estimation from hydro and electrical sensors (**case 2**). In 2023, case study 1 was temporarily halted to focus on a new case study, load forecasting in traction power grids (**case 3**) based on findings from case study 1.

During the current reporting period, the focus was on disseminating key findings from Project INITIATE through publications. Up-to-date results on case study 1 had been summarized and published in a conference paper. At the same time, the work on this case study was resumed with an emphasis on real-time state estimation with heterogeneous graph neural networks. Additionally, the results of case study 3 were published, and the project software was handed over to the energy trading department, where its implementation in the production system is currently underway. Two workgroups remain to study the different cases, led by Philipp Wenk from SBB's side and Olga Fink from EPFL's side:

- Project Lead: Philipp Wenk and (SBB) Olga Fink (EPFL)
    - Study case 1: state estimation and fault detection from power grid sensors
        - Robert Strietzel (SBB, Collaboration Lead)
        - Raffael Theiler (EPFL, Research Lead)
        - Robin Carlet (EPFL, Student, Semester Project)
        - Sam Jegou (EPFL, Student, Master Thesis)
    - Study case 2: load forecasting in traction power grids

- Raffael Theiler (EPFL, Research Lead)
- Roland Schäfer (SBB, Collaboration Lead)
- Yvan Tercier (SBB, Passive Participant)
- Aleksander Lelievre (SBB, Passive Participant)
- Emma Lacaille (SBB, Passive Participant)

Public Impact: In 2024, case study 1 and 2 were presented at various conferences and exhibitions:

- Talk at PHME2024, the Prognostics and Health Management Conference in Prague (07/24)
- Talk at PHMUS2024, the Prognostics and Health Management Conference in Nashville, US (11/24)
- A Booth to present "GEMSE4 Smart Grids" at Prototypes for Humanity in Dubai (11/24)
- Talk at Fachtagung Wasserkraft 2024 des Schweizerischen Wasserwirtschaftsverband in Olten (11/24)
- Talk at F&E-Konferenz zu Industrie 4.0 in Zürich (01/24)
- Talk at EA-Fachmeeting DACH-2024 in Graz (01/24)
- Talk at the UIC project consortium meeting "Artificial Intelligence for Predictive Maintenance" (AIPM) in Bern (03/24)
- Poster presentation at IMC2024: the Intelligent Maintenance Conference in Lausanne (09/24)
- Poster presentation at AMLD2024: the Applied Machine Days at EPFL in Lausanne (03/24)

2 State Estimation from Power Grid Sensors (Case 1)

The 2022 INITIATE report highlighted the need for a systematic study on GNNs for sensor data fusion in hydropower plants. In the current reporting period, we have resumed work on this case study (Case 1) and have met this need by publishing our work up to date. This publication on short-term state forecasting for pumped-storage hydropower plants (PSH) was submitted to and presented at the PHME 2024 conference [1]. The published work details our findings on integrating sensor data from the electrical and hydraulic subsystems using spectral-temporal graph neural networks. It summarizes the results of our case study conducted in 2022 on a Swiss pumped-storage hydropower plant, where the integration of electrical and hydraulic data significantly enhanced the short-term state forecasting accuracy. The publication is also a milestone for the follow-up research introduced below.

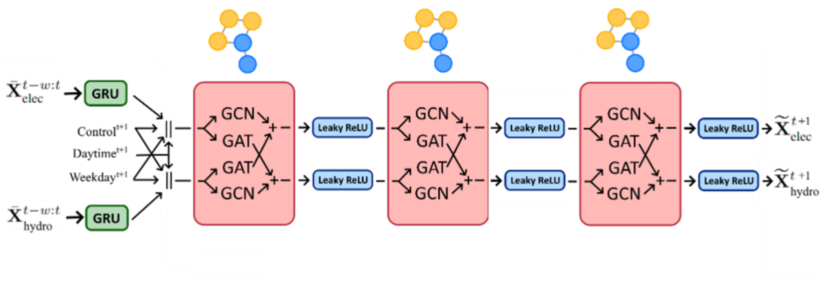

Figure 2: The detailed structure of the proposed HGNN.

Research Objectives: An important aspect of our progress to date is the training of a sensor graph that is learned directly from data. For short-term state forecasting, this method, as detailed in the publication and earlier reports, consistently outperformed conventional homogeneous GNNs applied to graphs derived from electrical schematics. However, a notable trade-off emerges: while learned sensor graphs proved to be highly effective in fusing sensor data across sub-systems, they forgo much of the detailed information on the asset topology available in schematic diagrams, requiring this information to be relearned from data.

Heterogeneous GNN for Hydopwer Plants: To address this limitation, we introduced the application of heterogeneous graph neural networks (HGNNs) to integrate sensor data from the electrical and hydraulic subsytem during this reporting period. HGNN are specialized type of Graph Neural Network (GNN) designed to handle heterogeneous graphs, where the graph's nodes and edges are of different types and have different associated features. HGNN can simultaneously learn homogeneous relationships (within the same subsystem) and heterogeneous relationships (between different subsystems). The proposed HGNN is composed of 2 GRUs for both types of nodes, electrical and hydrological, capturing the time-dependency, each containing a projection layer implemented to 32 dimensions for hydrological nodes and for electrical nodes. To the latter dimensions, additional features are concatenated, such as the control signal, the time of the day, and the day of the week, both sinusoidally embedded. As shown in Figure 2, our model consists of 3 layers of heterogeneous convolutions followed by a leaky-ReLU as an activation function, having been found to provide better results than simple ReLU and sigmoid activations. Homogeneous message passing functions are modeled by standard Graph Convolutional Networks (GCN) layer because it provides efficient and straightforward feature aggregation suited for nodes of the same type. We use Graph Attention Networks (GAT) layer for heterogeneous connections.

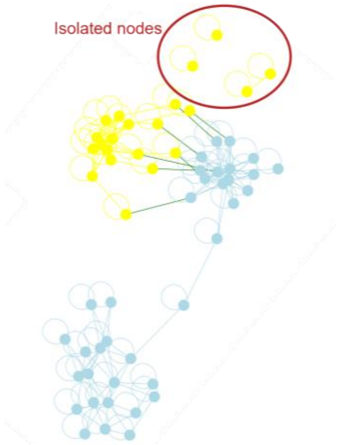

Figure 3: The heterogeneous graph used for message passing derived from schematical drawings of the hydropower plant.

Heterogeneous Graphs Construction: In this work, we follow a rule-based graph construction. We define an edge wherever a direct physical interaction exists between two sensor nodes. Therefore, in the pumped-storage hydropower plant considered in this work, the hydrological network captures interactions such as the basin level of the dam influencing the water flow in the downstream pipe. For the electrical network, we consider the placement of phasor measurement units (PMUs) within the asset's single-line diagram. For heterogeneous connections, we establish connections between sensor nodes located near the generator that electromechanically integrate the two systems. The combined graph as illustrated in Figure 3 therefore serves as the computational graph for the results.

Results and Discussion: We assess the model's forecasting performance in predicting the highly dynamic currents within the electric subsystem, we show the per-node performance in Figure 4. The results in Table 1 highlight that the heterogeneous graph neural network (GNN) approach significantly outperforms the homogeneous approach in terms of short-term state forecasting NMSE. Constructing a heterogeneous graph from data schematics also appears to be effective. However, this approach has revealed certain limitations. First, the graph was constructed based on intuition and is static. Position information on switches and circuit breakers could be used to refine the graph. Achieving an optimal message passing graph may also require additional experimentation with subgraph representations of physical assets and additional expert input. Further hyperparameter tuning in pruning and dropout experiments may also lead to improvements. Dropout appears to stabilize training across different datasets, making it worthwhile to evaluate its effects on model performance across multiple random seeds. To enhance the model's performance further, incorporating additional node types could be beneficial. For instance, weather nodes could provide insights into both hydrological (e.g., rainfall impacting dam levels) and electrical systems (e.g., temperature affecting equipment efficiency). Similarly, railway traffic data, which influences electricity demand could also improve forecasting capabilities. Finally, future work should focus on developing a sensor fault detection model, a priority for SBB. Achieving this would require modifications to the current pipeline and loss function to align with this objective.

Table 1: Normalized mean square error (NMSE) for short-term state forecasting averaged over all electrical current sensor nodes.

Method	El.	Hyd.	Network Diagram	Type	NMSE
Linear	✓	✓		-	1.11e-1
A3-GCN	✓	✓	✓	GCN	8.74e-3
LSTM	✓	✓		RNN	7.51e-3
MLP (3-layer)	✓	✓		FNN	6.84e-3
MLP (4-layer)	✓	✓		FNN	6.21e-3
STF	✓			Transformer	5.84e-3
STF	✓	✓		Transformer	5.83e-3
STGNN	✓			Att. GCN	5.71e-3
STGNN	✓	✓		Att. GCN	5.34e-3
Current Model	✓		✓	GCN/GAT	5.93e-3
Current Model +Pruning	✓	✓	✓	GCN/GAT	5.49e-3
Current Model	✓	✓	✓	GCN/GAT	**3.79e-3**

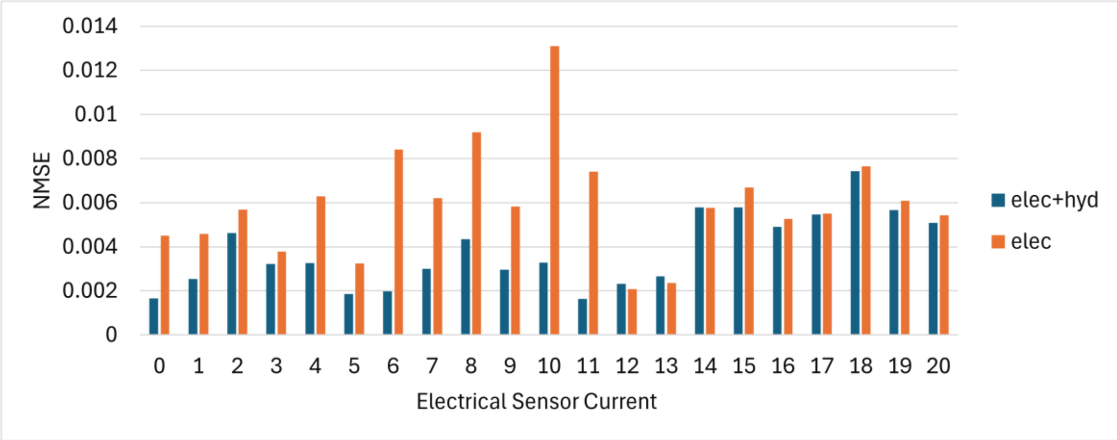

Figure **4**: NMSE comparison of the model forecast with (elec+hyd) and without (elec) information of the hydraulic subsystem by electical current sensor node on the test set.

Temporal Resolution of the Dataset: Building upon the study of HGNNs, we have identified the need to analyze data with higher temporal resolution, specifically at the second resolution, as emphasized in the 2022 report. To facilitate this investigation, an updated dataset was collected, comprising signals analogous to those utilized in our previous publication. This dataset will serve as the foundation for subsequent analyses, aiming to provide deeper insights into the dynamic behavior of PSH systems.

3 Load Forecasting in Traction Power Grids (Case 2)

Timetable-based Energy Forecasting: During the 2022 and 2023 report period, we gathered evidence suggesting that spatial-temporal transformer models – a deep learning architecture that uses attention mechanisms to weigh the importance of different input elements dynamically - are well-suited for forecasting tasks within traction power grid environments. This is due to the flexibility of the spatial-temporal attention, which allows us to effectively incorporate timetable-based information within the model. In railway traction grids, this information is commonly available, as the train scheduling for the next day is usually fixed, and the associated rolling stock weight can be estimated by teams in operation and dispatch. This observation is highly significant for the task of day-ahead forecasting, which is an important source of information for energy trading, grid dispatching and load management applications. In this report period, we finalized the work on the data-driven model that learns to forecast the grid load of the entire traction power grid of SBB from timetable-based information. As indicated in the 2023 report, we used this reporting period to summarize detailed results on the model and evaluation methods in a publication [2]. As of 11/2024, this publication is under review at a major journal publisher.

Experimental Setup and Training Data: The load forecasting datasets for this research were obtained from the SBB traction power grid in collaboration with SBB. The grid load, which is the forecasting target, within these datasets is defined as the boundary integral net input from power plants, neighboring networks and frequency converters. For the publication mentioned above, we compiled the data that was collected in the previous report periods (2022 and 2023) into a comprehensive multi-year dataset that includes measurements of the grid load along with a rich set of covariates from 2020 to 2023. Additionally, during this report period, we collected a novel disaggregated dataset on 4 major regions of Switzerland from 2018 to 2023. This dataset includes 52 covariates of four geographic sectors (west, east, central, south). This regional data includes temperature readings, tonnage, kilometers traveled, gross ton-kilometers, and train counts derived from the timetable for regional, long-distance or intercity, and cargo trains. Results on this dataset are also included in the publication.

Baseline Methods: The objective of this study is to improve the "EUB prognosis", a model maintained by the SBB energy trading department to support traders' decision-making in day-ahead energy bidding. During the previous reporting period, this model served as a baseline for evaluating the performance of our proposed Spacetimeformer (STF) model. For the publication, we analyzed various additional models to demonstrate the competitive performance of our STF model developed in this study case. Specifically, we benchmark our model against the current state-of-the-art in long-range time-series forecasting. Within the transformer-based model family, we incorporate adaptations of Timeseries Transformer (TST) and Crossformer (CF). From recent advancements in multi-step linear models, we include DLinear and TiDE, a dense residual model known for its effectiveness in long-term forecasting as shown in Figure 5. To provide a thorough comparison, we also evaluate the distinctive (inverted) embedding strategies employed by iTransformer traditional time-series forecasting methods, such as bidirectional LSTM, which effectively incorporates future covariates. Furthermore, we extend our analysis to popular gradient boosting frameworks, including CatBoost and XGBoost, recognized for their robustness and efficiency in diverse predictive modeling tasks. These results are summarized in the publication [2]

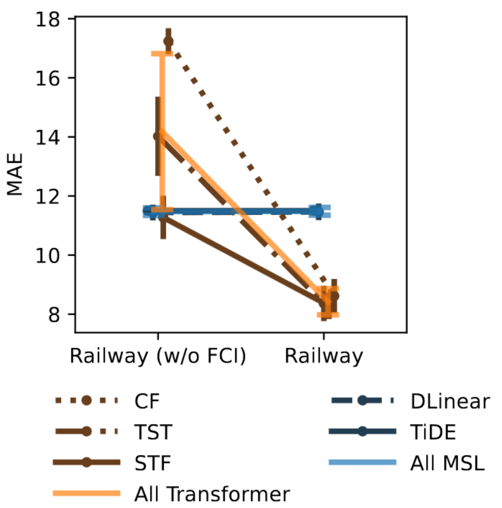

Figure **5**: Normalized MAE in megawatts with and without (w/o) the addition of timetable-based information (FCI). We list all transformer models and multi-step linear models (MSL) included in our evaluations

Analyzing Forecasting Outliers in Energy Production: In energy production, where supply must precisely match demand at every moment, managing large forecasting outliers presents significant challenges for power grid operators. To address this issue, we have conducted a comprehensive evaluation of our proposed contextually enhanced transformer models, focusing particularly on their ability to handle significant outliers that pose a risk to grid stability during operation and are difficult to compensate for. Our analysis reveals that while transformer model generally perform acceptably on average, they tend to produce a higher number of predictions classified as outliers without the integration of timetable-based information. Without timetable-based information, we observe an average of **0.98 %** significant outliers exceeding a **30%** MAPE for the transformer models. This is reduced to **0.07 %** outliers with our proposed STF model.

Additionally, we discovered that upon integrating FCI, all contextually enriched transformer models significantly outperform the linear regression model EUB **(0.37 %)** in managing outliers. This analysis also assists in distinguishing the most robust model among the contextually enhanced transformers, as illustrated in Figure 6. Although the average performances of STF, TST and CF in terms of MAE, MSE, MAPE, and coefficient of determination are similar, STF, when enhanced with timetable-based information, exhibits the lowest count of outliers and the smallest maximum outlier magnitude, establishing it as the most robust model against outliers.

Summary of the Results: Our study underscores the critical importance of integrating timetable-based information to improve the accuracy and robustness of load forecasting models. We observed that while modern linear multi-step models (such as Dlinear or TiDE) perform well on datasets with clear trends and periodicity, they struggle in scenarios requiring timetable-based information. In contrast, our STF model demonstrates superior performance in handling multiple data streams, effectively leveraging timetable-based information. We show that contextually enriched encoder-decoder transformers excel in leveraging timetable-based information, as evidenced by their performance in the novel, complex, multi-year load forecasting case studies introduced in this work. For this case study, the model was delivered to SBB for integration into their production system.

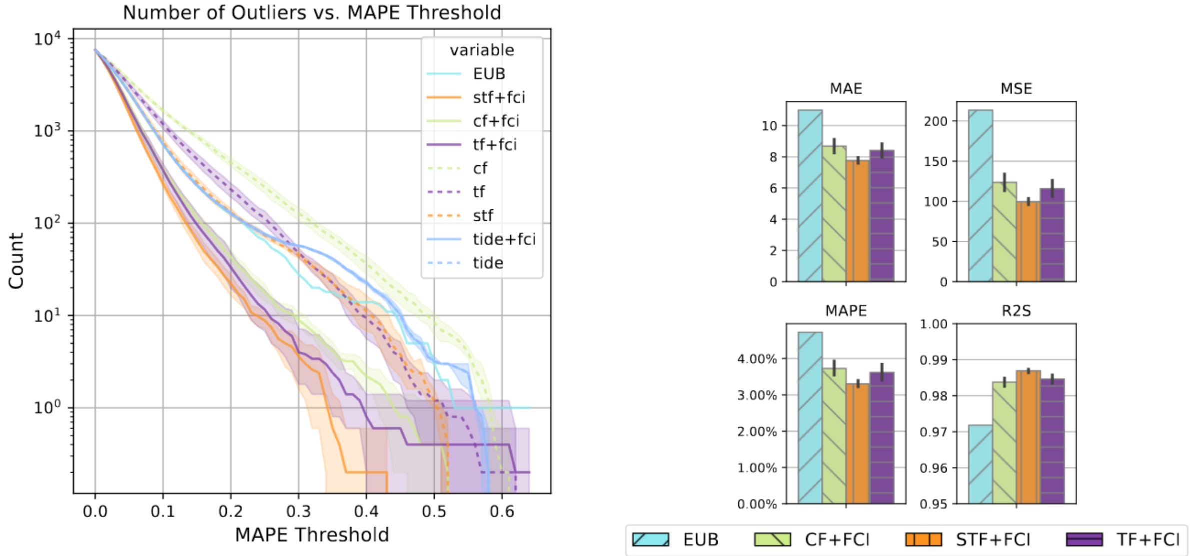

Figure **6**: For the disaggregated dataset: (left) the count of outliers by forecasting model as a function of the MAPE threshold, comparing models with timetable-based information (FCI) and those without; (right) a performance comparison between contextually enhanced transformers and the EUB prognosis.

4. Outlook

The here summarized results and published works achieved under Project INITIATE during this reporting period lay a foundation for future developments in railway power grid energy forecasting and state estimation. As the project progresses to its final phase in 2025, the team will concentrate on further enhancing the model for case study 1. Future work aims at the exploration of higher temporal resolution datasets, particularly at the second level to develop real-time sensor fusion across power plant subsystems for improved state estimation. The newly collected dataset will serve as a resource for these analyses for the remainder of 2024 and for 2025.

The most promising research directions include:

1. The refinement of temporal modeling: leveraging second-level temporal granularity will allow for the development of models capable of capturing rapid transient behaviors of the monitored subsystems and their impact on system operations. The integration of high-resolution datasets requires adapting the HGNN model architecture to manage the increased variability in the data while preserving computational efficiency.
2. Integration of additional (exogeneous) variables: The incorporation of additional node types in such as weather data and consumer information (from railway network) is expected to improve model accuracy. Additionally, expanding the HGNN model to other modalities such as logfiles is promising as this data was collected alongside the new second-resolution dataset.

5. References

[1] : Theiler, Raffael, and Olga Fink. "Graph Neural Networks for Electric and Hydraulic Data Fusion to Enhance Short-term Forecasting of Pumped-storage Hydroelectricity." arXiv preprint arXiv:2404.03368 (2024).

[2] : Theiler, Raffael, and Olga Fink. "Integrating the Expected Future: Schedule Based Energy Forecasting." arXiv preprint arXiv:2409.05884 (2024).