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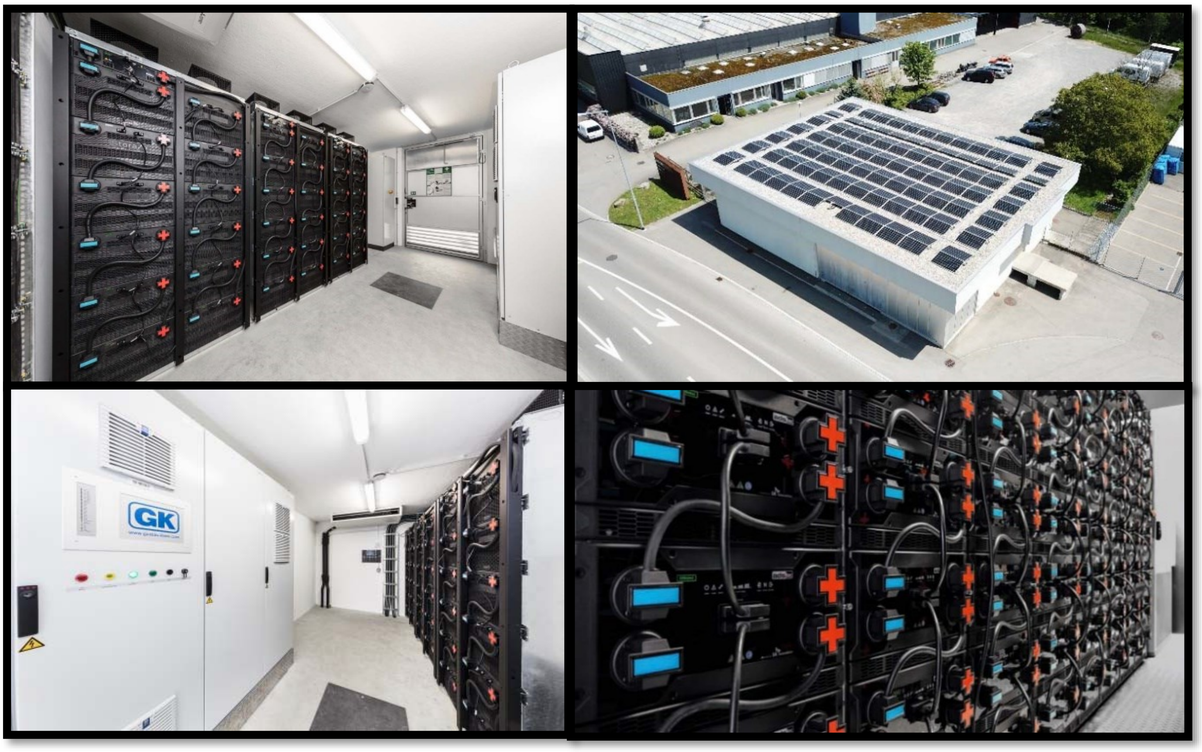
SONDER

Service Optimization of Novel Distributed Energy Regions



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Zusammenfassung

Dieses Dokument enthält die Beschreibung der laufenden Arbeiten und Ergebnisse, die bisher im Rahmen des Forschungsprojekts SONDER „Service Optimization of Novel Distributed Energy Regions“ im Rahmen des ERA-Net RegSys-Programms durchgeführt wurden.

Das Hauptziel dieses Projekts ist die Entwicklung neuartiger Lastvorhersagemethoden auf der Basis „Artificial Intelligence“ (AI), die diese mit fortschrittlichen Steuerungsschemata für den Betrieb eines stationären Batteriespeichersystems (BESS) koppeln, das im Verteilnetz der Stadt Arbon installiert ist. Das vorgeschlagene BESS-Steuerungsschema hängt von der Day-Ahead-Lastvorhersage, der Transformatormessung und der Spitzenleistung der vorherigen Zeitschritte des Monats ab. Im Gegensatz zu bisher publizierten Spitzenkappung-Ansätzen ist das vorgestellte Verfahren robust gegenüber Prognoseabweichungen und belastet den Batteriespeicher weniger als optimierungsbasierte Verfahren. Zudem ist das Verfahren konform mit den regulatorischen Rahmenbedingungen für den Netzbetrieb in der Schweiz und den meisten anderen europäischen Ländern.

Der gut strukturierte Datensatz von Arbon Energie enthält Informationen von mehr als zehntausend intelligenten Zählern, die alle 15 Minuten abgetastet werden, und stellt einen der grössten und wertvollsten Repositorys seiner Art in Europa dar. Dieser Datensatz ist mit Informationen auf MS-Trafoebene angereichert und bietet somit eine sehr gute Testumgebung für das Training mehrerer datengesteuerter Vorhersagemodelle. Unsere Untersuchung hat die Effizienz verschiedener Deep-Learning-Methoden (DL) gezeigt, einschliesslich Graph-basierter Methoden, die ihre Fähigkeit zur Modellierung der nichtlinearen Dynamik der Transformatorlast ausnutzen. Darüber hinaus funktionieren die entwickelten DL-Prädiktoren sehr gut, wenn sie mit einem geeigneten BESS-Steuerungsschema gekoppelt sind, was auch zeigt, wie wichtig es ist, das Modell neu zu trainieren, wenn jedes Jahr neue Daten verfügbar werden. Dies gilt auch für die Online-Anpassung an neu eingehende Daten durch die Feinabstimmung des Modells, während es für Vorhersagen verwendet wird.

Graphbasierte Ansätze wurden für den Arbon-Anwendungsfall übernommen, einschliesslich Clustering von Lastprofilen in mehrere Aggregate und Training von Graph Neural Networks (GNNs). Die Modelle lernten, die Last auf verschiedenen Aggregationsebenen vorherzusagen, mit dem Ziel, die Vorhersagegenauigkeit weiter zu verbessern. Die Experimente bestätigten die Effektivität der graphbasierten Ansätze bei der Aggregation der Smart-Meter-Daten und der Prognose der Nachfrage, obwohl sie eine bemerkenswerte Sensibilität für die Datenqualität gezeigt haben. In verschiedenen Szenarien können GNNs den Fehler im Vergleich zu einfacheren Methoden erheblich verringern. Dennoch erzielen wir im Fall der Arbon MV-Transformatorlast bescheidene Verbesserungen aufgrund der Diskrepanz zwischen den Daten der intelligenten Zähler und der Transformatoren. Daher haben wir uns bei der BESS-Steuerung aufgrund ihrer Einfachheit, ihres schnelleren Trainings und ihrer einfacheren Online-Anpassung an neue Testdaten auf traditionelle Deep-Learning-Modelle verlassen. Dennoch beweist unsere Forschung, dass GNNs vielversprechende Modelle sind, um mehrere Signale von verschiedenen räumlichen Orten vorherzusagen und die Beziehungen zwischen mehreren Zeitreihen zu lernen. Unsere Methoden sind allgemein und könnten auf andere IoT- und Zeitreihen-Vorhersageszenarien angewendet werden, die durch viele verwandte Signale gekennzeichnet sind, die von verschiedenen räumlichen Orten kommen.

In Bezug auf das BESS-Regelungsschema können die relativen Einsparungen durch die Spitzenkappung Jahr für Jahr zunehmen und von 48 % im Jahr 2019 auf 78 % im Jahr 2022 im Vergleich zum theoretischen Optimum bei perfekter Prognose reichen. Darüber hinaus kann das BESS höhere Einsparungen erzielen, wenn es auf der Spitzenlastvorhersage statt auf der Volllastkurvenvorhersage basiert. Der vorgeschlagene Regelalgorithmus hat auch keine negativen Auswirkungen auf die Kosten für Energiebeschaffung und Netznutzung. Darüber

hinaus führt das Kontrollschema zu einer jährlichen Batteriealterungsrate von 2 %, was Raum für eine weitere BESS-Nutzung im Kontext anderer Dienste lässt.

Im Rahmen der für die Verteilnetze von Arbon durchgeführten Sensitivitätsanalyse werden verschiedene Zukunftsszenarien in Bezug auf zunehmende Integrationsgrade von Photovoltaik (PV), EV-Ladeinfrastrukturen (EVSE) und Wärmepumpen (WP) simuliert, mit dem Hauptziel, ihre Auswirkungen auf die Spannungsqualität und die Belastungen der Netzanlagen zu bewerten. Auch die Leistung einer Laststeuerung zum Spitzenkappung auf Basis von Trafomessungen wird untersucht. Auf der einen Seite werden die untersuchten NS-Verteilnetze selbst bei hohen Penetrationsgraden von PV-, EVSE- und WP-Einheiten nicht auf Spannungsqualitätsprobleme stossen. Andererseits werden Überlastungen auf bestimmten Leitungen und auf Trafoebene insbesondere für das TS 1-Netz erwartet, was die Netzverstärkung für die Zukunftsszenarien erheblich macht. Die untersuchte Laststeuerung senkt die Spitzenleistung auf Trafoebene, ohne jedoch die Belastung der Leitungen zu reduzieren. Da die Periode hohen Bedarfs von EV und WP nicht mit der Periode hoher PV-Produktion zusammenfällt, ist es entscheidend, Laststeuerung auf der Grundlage lokaler Smart-Metering-Messungen zu implementieren.

Was mögliche zukünftige Schritte betrifft, so könnte das vorgeschlagene BESS-Kontrollsystem auch für die zweite Hälfte des Jahres 2022 evaluiert werden, da die erste Hälfte sehr vielversprechende Ergebnisse gezeigt hat. Darüber hinaus wäre es sehr nützlich, die evaluierte Methode in einem realen Feld zu testen, da die experimentellen Ergebnisse wichtige Richtlinien in Bezug auf ihre kontinuierliche Anwendung sowie eventuell erforderliche Verbesserungen liefern könnten. In Bezug auf die Sensitivitätsanalyse besteht die Möglichkeit, diese Studie unter Berücksichtigung zusätzlicher Eingaben und anwendbarer DSM-Methoden zu erweitern. Insbesondere dezentrale Verfahren basierend auf lokalen Messungen könnten in einer zukünftigen Arbeit auch getestet werden, da sie zusätzlich Überlastungen der Netzanlagen reduzieren können. Zukünftige Arbeiten zum Energieverbrauch sowie zur Vorhersage erneuerbarer Energien könnten sich auf die Fusion verschiedener Datenquellen in den Vorhersagerahmen konzentrieren. GNN-Modelle können heterogene Datenströme verarbeiten, daher wird es wichtig sein, zuverlässige Wettervorhersagen zu sammeln und diese neben den Netzmessungen zu verwenden. Wir glauben, dass dies der beste Weg ist, um grössere Gewinne bei der Lastprognose mit GNNs zu erzielen, die sogar über die in dieser Arbeit vorgestellte hohe Leistung hinausgehen.

Résumé

Ce document fournit la description du travail en cours et des résultats obtenus jusqu'à présent dans le cadre du projet de recherche SONDER "Service Optimization of Novel Distributed Energy Regions" mené dans le cadre du programme ERA-Net RegSys.

L'objectif principal de ce projet est de développer de nouvelles méthodes de prévision de charge basées sur l'intelligence artificielle (IA), en les couplant à des schémas de contrôle avancés pour le fonctionnement d'un système de stockage d'énergie stationnaire (BESS) installé dans le réseau de distribution de la ville d'Arbon. Le schéma de contrôle BESS proposé dépend de la prévision de charge à J-1, de la mesure de transformateur et de la puissance de crête des intervalles de temps précédents du mois. Contrairement aux approches précédemment publiées, cette méthode est robuste face aux écarts de prévision et utilise le stockage de batterie moins que les méthodes basées sur l'optimisation. De plus, la méthode est conforme au cadre réglementaire pour l'exploitation du réseau en Suisse et dans la plupart des autres pays européens.

Le jeu de données bien structuré d'Arbon Energie contient des informations provenant de plus de dix mille compteurs intelligents échantillonnés toutes les quinze minutes et représente l'un des plus grands et des plus précieux référentiels de ce type en Europe. Ce jeu de données est enrichi

d'informations de niveau de transformateur MV et constitue donc une très bonne plateforme de test pour la formation de multiples modèles de prédiction basés sur les données.

Notre étude a démontré l'efficacité de diverses méthodes de Deep Learning (DL), y compris celles basées sur les graphes, exploitant leur capacité à modéliser la dynamique non linéaire de la charge du transformateur. De plus, les prédicteurs DL développés fonctionnent très bien lorsqu'ils sont couplés à un schéma de contrôle BESS approprié, montrant également l'importance de la réévaluation du modèle à mesure que de nouvelles données deviennent disponibles chaque année. Cela s'applique également à l'adaptation en ligne aux nouvelles données entrantes, en affinant le modèle au fur et à mesure de son utilisation pour les prévisions.

Des approches basées sur les graphes ont été adoptées pour le cas d'utilisation d'Arbon, notamment le regroupement des profils de charge en plusieurs agrégats et la formation de réseaux neuronaux de graphes (GNN). Les modèles ont appris à prévoir la charge à différents niveaux d'agrégation, dans le but d'améliorer encore la précision de la prédiction. Les expériences ont confirmé l'efficacité des approches basées sur les graphes dans l'agrégation des données des compteurs intelligents et la prévision de la demande, bien qu'elles aient montré une sensibilité remarquable à la qualité des données. Dans divers scénarios, les GNN peuvent réduire considérablement l'erreur par rapport aux méthodes plus simples. Cependant, dans le cas de la charge de transformateur MV d'Arbon, nous avons obtenu des améliorations modestes en raison de la discordance entre les données des compteurs intelligents et celles de transformateur.

Par conséquent, nous avons utilisé des modèles traditionnels de DL dans le cas du contrôle BESS, en raison de leur simplicité, de leur formation plus rapide et de leur adaptation en ligne plus facile aux nouvelles données de test.

Néanmoins, notre recherche prouve que les GNN sont des modèles prometteurs pour prédire plusieurs signaux provenant de différentes localisations spatiales et pour apprendre les relations entre plusieurs séries chronologiques. Nos méthodes sont générales et pourraient être appliquées à d'autres scénarios de prévision IoT et de séries chronologiques caractérisés par de nombreux signaux liés provenant de différentes localisations spatiales.

En ce qui concerne le schéma de contrôle BESS, les économies relatives liées à l'écrêtage des pointes peuvent augmenter d'année en année, passant de 48 % en 2019 à 78 % en 2022 par rapport à l'optimum théorique avec une prévision parfaite. De plus, le BESS peut réaliser des économies supérieures lorsqu'il est basé sur la prédiction de la charge de pointe, plutôt que sur la prédiction de la courbe de charge complète. L'algorithme de contrôle proposé ne cause pas non plus d'effets négatifs sur les coûts liés à l'approvisionnement en énergie et aux frais d'utilisation du réseau. De plus, le schéma de contrôle entraîne un taux annuel de vieillissement de la batterie de 2 %, laissant ainsi de la place pour une utilisation ultérieure de la BESS dans le contexte d'autres services.

Dans le cadre de l'analyse de sensibilité effectuée pour les réseaux de distribution d'Arbon, différents scénarios futurs liés à l'intégration croissante de PV, EVSE et HP sont simulés dans le but principal d'évaluer leur impact sur les métriques de qualité de tension et les charges des actifs de réseau. La performance d'une méthode DSM pour peak shaving basée sur les mesures de transformateur est également examinée. D'une part, les réseaux de distribution LV examinés ne rencontreront pas de problèmes de qualité de tension même sous des niveaux de pénétration élevés d'unités PV, EVSE et HP. D'autre part, des surcharges sur des câbles spécifiques et au niveau des transformateurs sont attendues en particulier pour le réseau TS 1, ce qui rend significatif le renforcement du réseau pour les scénarios futurs. La méthode DSM examinée diminue la puissance de crête au niveau du transformateur, cependant, sans réduire les charges des câbles du réseau. Étant donné que la période de forte demande d'EV et de HP ne coïncide pas avec la période de forte production de PV, il est crucial de mettre en œuvre DSM basé sur des mesures de comptage intelligentes locales.

En ce qui concerne les étapes futures possibles, le schéma de commande BESS proposé pourrait également être évalué pour la deuxième moitié de 2022, car la première moitié a montré des résultats très prometteurs. De plus, il serait très utile de tester la méthode évaluée sur le terrain réel, car les résultats expérimentaux pourraient fournir des directives importantes liées à ses applications continues, ainsi qu'à toute amélioration qui pourrait être nécessaire. En termes d'analyse de sensibilité, il y a potentiel pour étendre cette étude en considérant des entrées supplémentaires et des méthodes DSM applicables. En particulier, des schémas décentralisés basés sur des mesures locales pourraient également être testés dans un travail futur, car ils peuvent également réduire la surcharge des actifs du réseau. Les travaux futurs sur la consommation d'énergie ainsi que la prévision de la génération d'énergie renouvelable pourraient se concentrer sur la fusion de diverses sources de données dans le cadre de prédiction. Les modèles GNN sont capables de traiter des flux de données hétérogènes, il sera donc important de collecter des prévisions météorologiques fiables et de les utiliser aux côtés des mesures du réseau. Nous croyons que c'est la meilleure façon d'obtenir des gains plus importants dans la prévision de la charge avec des GNN, qui vont même au-delà des performances élevées présentées dans ce travail.

Summary

This document provides the description of ongoing work and results obtained so far in the scope of the research project SONDER "Service Optimization of Novel Distributed Energy Regions" carried out in the frame of ERA-Net RegSys programme.

The main goal of this project is to develop novel artificial intelligence (AI)-based load forecasting methods coupling them with advanced control schemes for the operation of a stationary battery energy storage system (BESS) installed in the distribution grid of Arbon city. The proposed BESS control scheme depends on the day-ahead load prediction, the transformer measurement, and the peak power of the previous timesteps of the month. In contrast to previously published peak shaving approaches, the presented method is robust against forecast deviations and utilizes the battery storage less than optimization-based methods. Moreover, the method is compliant to the regulatory framework for grid operation in Switzerland and most other European countries.

The well-structured dataset of Arbon Energie contains information from more than ten thousand smart meters sampled every fifteen minutes and represents one of largest and the most valuable repositories of its kind in Europe. This dataset is enriched with MV transformer level information and as such provides a very good testbed for training of multiple data-driven prediction models. Our investigation has demonstrated efficiency of various Deep-Learning (DL) methods including graph-based ones, exploiting their ability to model the non-linear dynamics of the transformer load. Furthermore, the developed DL predictors perform very well when coupled with proper BESS control scheme, showing also the importance of re-training of the model as new data becomes available every year. This also applies to online adaptation on new incoming data, by fine-tuning the model as it is being used for predictions.

Graph-based approaches have been adopted for the Arbon use case, including clustering of load profiles into multiple aggregates and training of Graph Neural Networks (GNNs). The models learned to predict the load at different levels of aggregation, with the goal of further improvement of the prediction accuracy. The experiments confirmed the effectiveness of the graph-based approaches in aggregating the smart meters data and forecasting the demand, although they have shown remarkable sensitivity to data quality. In various scenarios, GNNs can significantly decrease the error compared to simpler methods. Still, in the case of the Arbon MV transformer load, we achieve modest improvements due to mismatch between smart meters' and transformers' data. Therefore, we relied on traditional deep learning models in the case of BESS

control, due to their simplicity, faster training, and easier online adaptation to new test data. Nevertheless, our research proves that GNNs are promising models for predicting multiple signals from different spatial locations and for learning the relationships between multiple time-series. Our methods are general and could be applied to other IoT and time-series forecasting scenarios characterized by many related signals coming from different spatial locations.

Concerning the BESS control scheme, the relative savings from peak shaving can increase year by year ranging from 48% in 2019 to 78% in 2022 compared to the theoretical optimum with perfect forecast. Moreover, the BESS can achieve higher savings when being based on the peak load prediction rather than on full load curve prediction. The proposed control algorithm does not also cause negative effects on the costs related to energy procurement and network usage fees. In addition, the control scheme leads to annual battery ageing rate of 2%, leaving space for further BESS utilization in the context of other services.

In the context of the sensitivity analysis conducted for the distribution networks of Arbon, various future scenarios related to increasing integration levels of PVs, EVSEs and HPs are simulated with the main goal to evaluate their impact on the voltage quality metrics and grid assets' loadings. The performance of a DSM method for peak shaving based on transformer measurements is also examined. On the one hand, the examined LV distribution networks will not encounter voltage quality issues even under high penetration levels of PV, EVSE and HP units. On the other hand, overloadings on specific cables and at transformer level are expected particularly for the TS 1 network, rendering significant the grid reinforcement for the future scenarios. The examined DSM method decreases the peak power at transformer level, however, without reducing the loadings of grid cables. Since the period of high demands of EV and HP do not coincide with the period of high PV production, it is crucial to implement DSM based on local smart metering measurements.

As for possible future steps, the proposed BESS control scheme could also be evaluated for the second half of 2022, since the first half has shown very promising results. Furthermore, it would be very useful to test the evaluated method in a real field, since the experimental results could provide significant guidelines related to its continuous applications, as well as any improvements that may be needed. In terms of the sensitivity analysis, there is potential to extend this study considering additional inputs and applicable DSM methods. Particularly, decentralized schemes based on local measurements could also be tested in a future work, since they can additionally reduce overloading of the grid assets. Future work on energy consumption as well as renewable generation forecasting might focus on fusion of various data sources into the prediction framework. GNN models are able to process heterogeneous streams of data, so it will be important to collect reliable weather forecasts and use them alongside the grid measurements. We believe, this is the best way to achieve bigger gains in load forecasting with GNNs, that go even beyond the high performance presented in this work.

Contents

Abbreviations

AAD	Absolute Average Deviation
BESS	Battery Energy Storage System
DHW	Domestic Hot Water
DL	Deep Learning
DSM	Demand Side Management
DSO	Distribution System Operator
ECO	Energy Community Operator
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
EoL	End-of-Life
EPEX	European Power Exchange
GRU	Gated Recurrent Unit
HP	Heat Pump
KPI	Key Performance Indicator
LV	Low Voltage
MAE	Mean Absolute Error
MILP	Mixed Integer Linear Programming
MIMO	Multiple-Input Multiple-Output
MLP	Multi-Layer Perceptron
MSE	Mean Square Error
MV	Medium Voltage
PDF	Probability Distribution Function
PV	Photovoltaic
PQ	Power Quality
RES	Renewable Energy Source
RMSE	Root Mean Square Error
RNN	Recurrent Neural Networks
SES	Smart Energy System
SGD	Stochastic Gradient Descent
SoC	State of Charge
T&D	Transmission and Distribution
TS	Transformer Station
WP	Working Package

1 Introduction

In the frame of the project “Service Optimization of Novel Distributed Energy Regions” (SONDER), our emphasis has been given to the following aspects:

- Development of a robust control scheme for peak shaving in distribution networks using stationary battery energy storage systems (BESS).
- Deep Learning techniques for peak load forecasting.
- Graph based clustering and GNNs, for load forecasting at different levels of aggregation.
- Tech-economic evaluation of the proposed BESS control scheme for a 3.5-year period using load data of Arbon city.
- Sensitivity analysis of future scenarios related to the growing integration of Photovoltaics (PVs), heat pumps (HPs) and electric vehicles (EVs) in the distribution networks of Arbon city.
- Online adaptation of forecasting models during inference.

One of the main project goals is to develop and assess an innovative control scheme that can be used for peak load shaving in distribution networks. Particularly, in this work, we aim at reducing power peaks at the power distribution network of Arbon city utilizing the stationary BESS that has already been installed and is in operation. The BESS unit has energy capacity of 1.35 MWh and power capacity of 1.25 MW and is connected at the 17-kV distribution level. Due to the volatile load curve of the distribution grid in Arbon, the peak load periods can occur at different times of the day. From the point of the local distribution system operator (DSO), Arbon Energie AG, the peak load periods are very crucial, as the monthly peak power charges comprise the highest part of the total operational costs. In this context, the stationary BESS can used to decrease the power peaks, significantly reducing the respective cost. Albeit the BESS provides primary and secondary frequency response services, there is high interest from the DSO to include a robust method for peak shaving that can significantly reduce the annual operational costs. In the frame of SONDER project, BESS control schemes for peak shaving are assessed with the main goal to conclude on the most optimal to be implemented for Arbon Energie AG. Since the control scheme is expected to be applied in real-time operation, load forecasting tools for the one day-ahead prediction of the peak load in Arbon city are required. Except for the peak load forecast, near real-time transformer measurements are also used to decouple the high dependency from load forecast inaccuracies. Moreover, this study evaluates the impact of BESS operation not only on the reduction of peak power costs, but also on the variation of other cost components, e.g., energy procurement and network usage costs. It is of utmost importance for the energy provider to the peak power costs without increasing the aforementioned energy costs. In the context of grid assets’ management, this study also assesses the reduction in transformer degradation by applying the proposed BESS control scheme.

To successfully respond the project needs, we have developed a number of customized predictors. On top of that, a general framework to learn predictors in large scale sensor networks has been adopted. The single modules of the framework are customized so that they are tailored to a specific problem, in this case load forecasting. The model takes as an input a multivariate time-series coming from different sensors. The input encoder simply conditions each element of the input sequence based on a series of exogenous variables (such as weather data). The sequence is then processed by a series of spatio-temporal processing blocks.

The forecasting problem translates into five different use cases:

- **Use case 1:** standard deep learning predictors (PEAK and MIMO), adopted and applied for the practical use with BESS control algorithm.

- **Use case 2**: graph-based predictor (Graph Neural Networks - GNNs), adding extra information from smart meters, along with total load at MV transformer.
- **Use case 3**: predicting sum of the load of clusters of smart meters using GNN.
- **Use case 4**: predicting directly single smart meters (the ones with high average consumption).
- **Use case 5**: Online adaptation, which gives small boost in performance.

In addition to these activities, the project evaluates the impact of future integration of PVs, HPs and EVs on the distribution networks of Arbon city. Particularly, a sensitivity analysis for different penetration levels of the aforementioned energy assets examining the influence on voltage quality metrics of grid nodes and loadings of grid assets. The assessment aims to define the maximum hosting capacity of energy assets without violating the voltage statutory limits or exceeding the rated loadings of cables and transformers. Moreover, it is examined to which extent the demand side management (DSM) can additionally increase the maximum hosting capacity by shifting the demand of EV and HP at times with high PV production. The results indicate which share of grid assets experience overloadings and voltage violations. Furthermore, the analysis can provide the DSO directional guidelines about the penetration levels of PV, EV, and HP that the networks can safely accommodate, and which parts will be affected first and most severely. With the information at hand, planning can be improved, and long-term plans can be composed to upgrade and extend the current distribution grids. Last but not least, the assessment further helps to understand the need for smart control of EV and HP.

2 Description of facility and data

Concerning the Swiss smart city of Arbon, the main stakeholders involved belong to the following groups: (a) Distribution System Operators (DSOs), and (b) the end-customers that can be either consumers or prosumers depending on the installation of DERs in their properties.

2.1 Distribution System Operator

Regarding the Swiss smart city, Arbon Energie AG plays the role of DSO, and is supplied with electricity by the energy supplier SN Energie, which consists of a consortium with seven different energy suppliers [1].

As for the medium voltage (MV) level of the investigated network, 53 substations of 17 kV were counted with total installed capacity of 118 MVA and the total length of cables is about 42 km. On the other hand, at the low voltage (LV) level, 263 distribution cabins of 0.4 kV exist, and the total length of cables is about 69.1 km. It is also of main significance that the investigated network of Arbon Energie AG consists only of underground cables and no overhead lines at all [1].

According to [1], the energy production from PVs of 2019 showed a drop to about 2600 MWh compared to the period 2017-2018 when it reached almost up to 2900 MWh. In 2020, the energy production from PV displayed considerable rise to about 3300 MWh, while it remains over 3000 MWh in 2021. Moreover, the main composition of electricity purchases by Arbon Energie is made up of nuclear energy (51%). Finally, the energy generated by hydropower plants is the second main source of electricity purchases (42%), while other RES, e.g., PVs include a share of 7%.

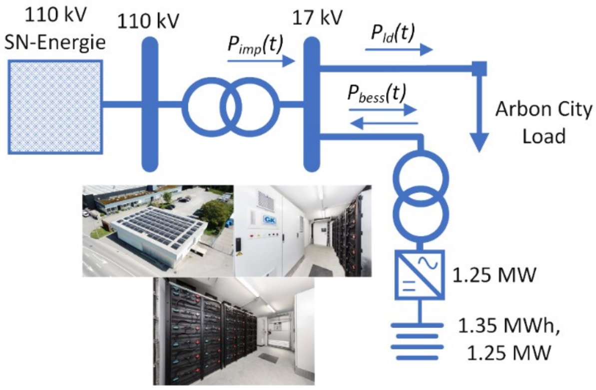

Figure 1: Simplified schematic of the entire system.

As shown in Figure 1, the BESS unit that was installed at the 17-kV distribution level has energy and power capacities of 1.35 MWh and 1.25 MW, respectively and its technology is Lithium Nickel Manganese Cobalt Oxide (LiNiMnCoO2) - NMC. The energy storage system is owned by Arbon Energie AG, however, it is operated by the energy provider, Centralschweizerische Kraftwerke (CKW). The BESS is used for main ancillary services, particularly, primary frequency response and grid voltage support.

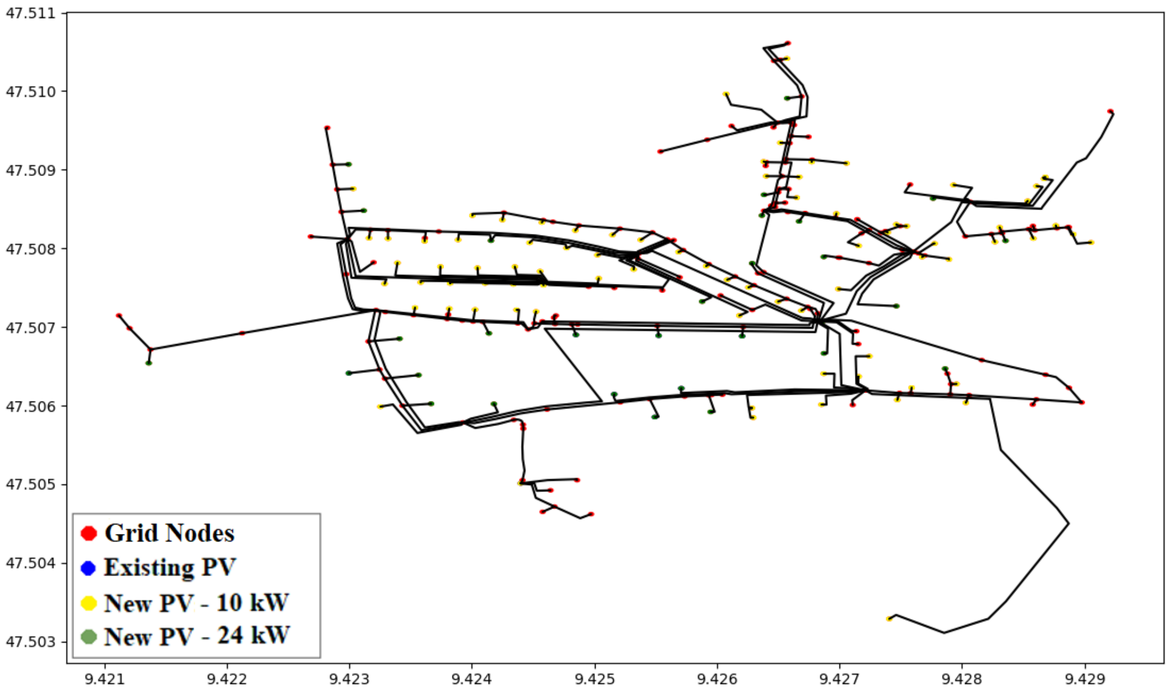

Figure 2: LV distribution network supplied by TS 1 – Scenario with 111 new PV

Figure 3: LV distribution network supplied by TS 15 – Scenario with 27 new PV

The LV distribution networks of two transformer stations (TS) are utilized for the analysis of the scenarios with new installations of PV, EV charging stations, known as electric vehicle supply equipment (EVSE) and HP:

- **TS 1**: the LV distribution grid consists of 119 customers (8 prosumers, 111 consumers), 283 distribution cables and 272 nodes (see Figure 2).
- **TS 15**: the LV distribution grid consists of 28 end-customers (1 prosumer, 27 consumers), 84 distribution cables and 77 nodes (see Figure 3). As for the type of buildings connected to this feeder, their load patterns were analyzed and two of them are non-residential buildings, particularly, workplaces.

The data on consumption and power quality are available from two main sources:

- Smart meter provided measurements that represent load profiles of more than 10'000 end users in 15 minutes time slots from November 2017 till present.
- Power quality (PQ) devices that are getting installed in substations measuring almost 150 different parameters. In the scope of this project, we use several of the most important variables such as voltage, power and current. The measurements are available via installation of specific devices, whose number is in steady increase since January 2019.

2.2 End-Users

The customers of Arbon Energie AG rely on the DSO to provide them with electric energy though they can be either consumers, or prosumers by producing energy through a DER installation in their property. The customers can be sorted as residential, commercial, and industrial, in order to examine the end-users' role in the grid level in more detail:

- **Residential customers** include the highest share of end-users in the distribution network of Arbon Energie AG, and their load profiles can present significantly high variations compared to the other types of end-users.
- **Commercial customers** include facilities, offices, urban lighting, and generally non-residential buildings, municipal or private, with high energy demand, usually in a fixed daily timetable.
- **Industrial customers** are large-scale end-users who are connected to the 17-kV level, so they demand high quality electricity power. Since they can play a vital role in the economy of Arbon Energie AG, they can also put pressure for the provision of low-cost electricity power. On the other hand, they might provide Arbon Energie AG with ancillary services due to their capability to considerably increase or reduce the load.

In 2021, the total sales of Arbon Energie AG to its customers were about 102.4 GWh, a rise of about 2 GWh compared to the previous year [2]. One of the main reasons was the prolonged, cool weather in spring, which led to increased energy sales, particularly among residential end-customers. While at the MV level 12 end-customers were counted in 2021, 9'751 end-users were supplied with electricity according to the data published by Arbon Energie AG.

2.3 Load Forecasting Data

Fully anonymized information from smart meters has been organized and aligned with the transformer load measurements. These datasets were used to train the graph-based load predictors. Data cleansing required to determine the presence of bad data as well as the impact of photovoltaics (connected to the grid in various ways considering point of measurement). For instance, ${P_+}^{(i)}(t)$ represents the average power taken from the grid by smart meter i at time t, while ${P_-}^{(i)}(t)$ represents power given to the grid due to residential PV generation. Considering only ${P_+}^{(i)}(t)$ would lead to an over-estimation of the total load, therefore a corrected model for such a measurement point should be $P^{(i)}(t) = {P_+}^{(i)}(t) - {P_-}^{(i)}(t)$.

Figure 4 shows the effect of inconsistencies in measurements, by plotting the difference between the sum of all smart meters and the total load measured at the MV transformer. Corrections by considering household PV considerably improved alignment, as plotted in orange. The mismatch in the orange signal is almost always negative, as expected mostly due to network losses. But it is not a constant noise and there are also sporadic peaks due to missing values and data collection problems. This mismatch acts as a non-stationary noise component, which complicates the task of predicting the MV transformer load using the smart meters signals.

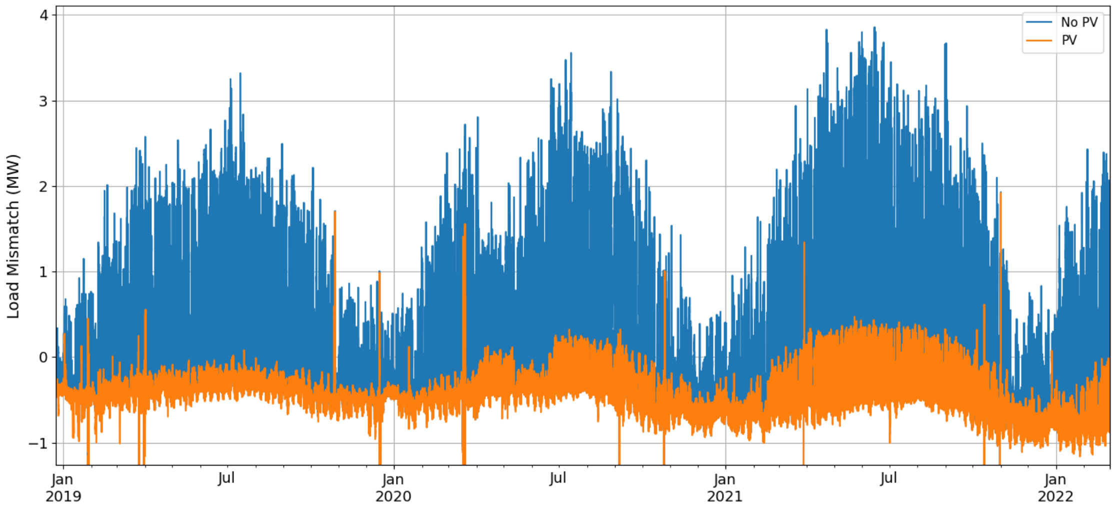

Figure 4 Mismatch between the aggregate load of all smart meters and the load measured at the MV transformer due to inconsistencies in measurements.

Still, to guarantee the best possible level of data quality, we performed input pre-processing. Usable smart meters measurements span more than 4 years, between 28/10/2017 and 01/03/2022. We removed the smart meters with more than 50% invalid values, and also the ones with too little standard deviation or very long periods of zero values. These smart meters were probably correctly measured only for specific time periods and would have made our data inconsistent between the different years. Finally, we considered 9118 valid smart meters that can be used for aggregation and model training, filling their few missing values with seasonal averages.

Clustering is required, to aggregate profiles with similar consumption patterns and get a smaller number of suitable signals. A K-NN (K Nearest Neighbors) graph is defined, with one node per smart meter and the correlation between the weekly statistics of each time series to define the edge weights. The technique of spectral clustering is then applied, dividing the profiles into 50 groups that are aggregated via summation, following the approach presented in [3].

In Figure 5 we show the 10 aggregates with the biggest power, in the period of December 2021. We demonstrate that graph clustering was able to capture very repetitive consumption patterns in the green signal. This cluster has a very predictable nightly consumption, that seems not to change even during the weekend or holidays, and may be due to automated processes. Other signals are more affected by human behavior, showing lower consumption during holidays. To notice is also the aggregates with negative values around noon, which result from the aggregation of households with PV production.

Figure 6 shows a similar analysis for the 3 aggregates with lowest average power. These also show very predictable peaking behavior, with the blue and green aggregates showing a peak every day around 11:30, and the orange one having always big consumption in the late afternoon.

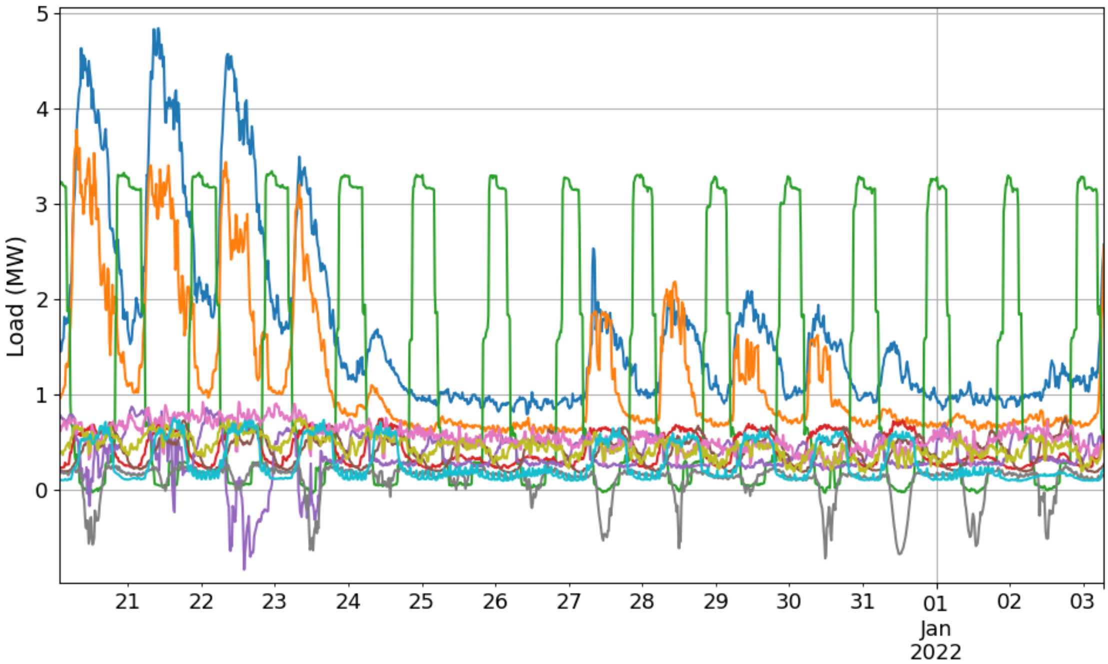

Figure 5: The 10 spectral clustering aggregates with biggest average power.

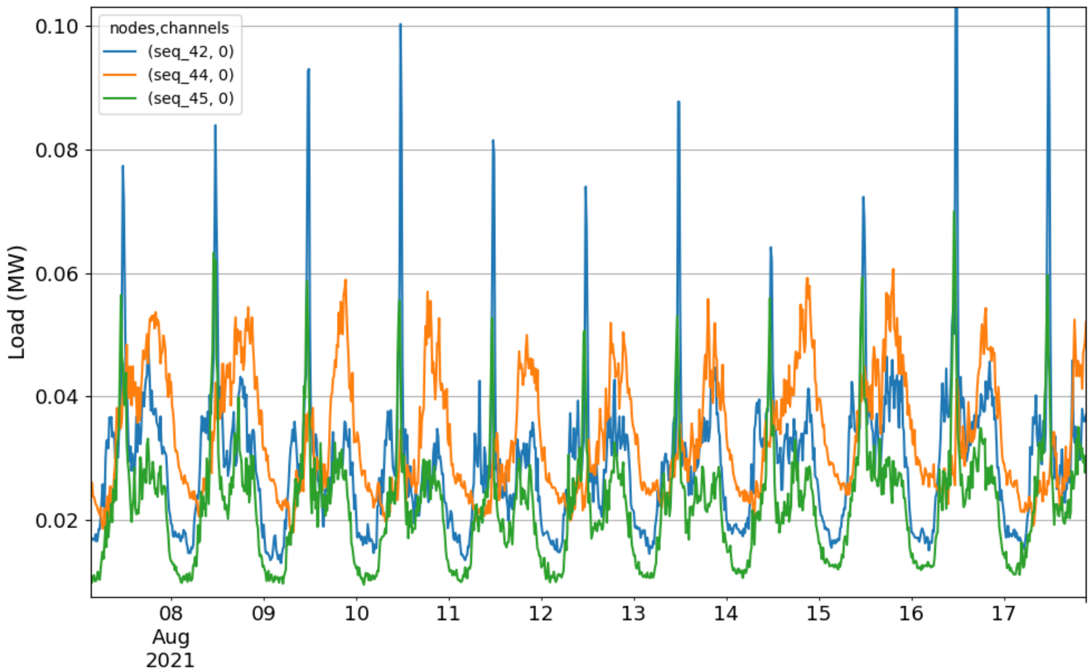

Figure 6: The 3 spectral clustering aggregates with smallest average power

The dataset is then divided in time periods for the training of ML models:

- 73% of data for **model training** (from 2017-10-28 to 2020-12-31)
- 4% of data for **model selection and validation** (from 2021-01-01 to 2021-02-28)
- 23% of data for **test and online adaptation** (from 2021-03-01 to 2022-03-01)

We keep the last full year of data for testing, to avoid bias on specific periods of the year and to have a robust evaluation of the online adaptation strategy.

Figure 7 shows the weekly statistics for the total load on which peak shaving has to be applied. The daily load is characterized by multiple peaks, without a clear pattern to understand if the morning or afternoon peak would be the biggest. The weekend days also have lower average consumption and a different peak distribution.

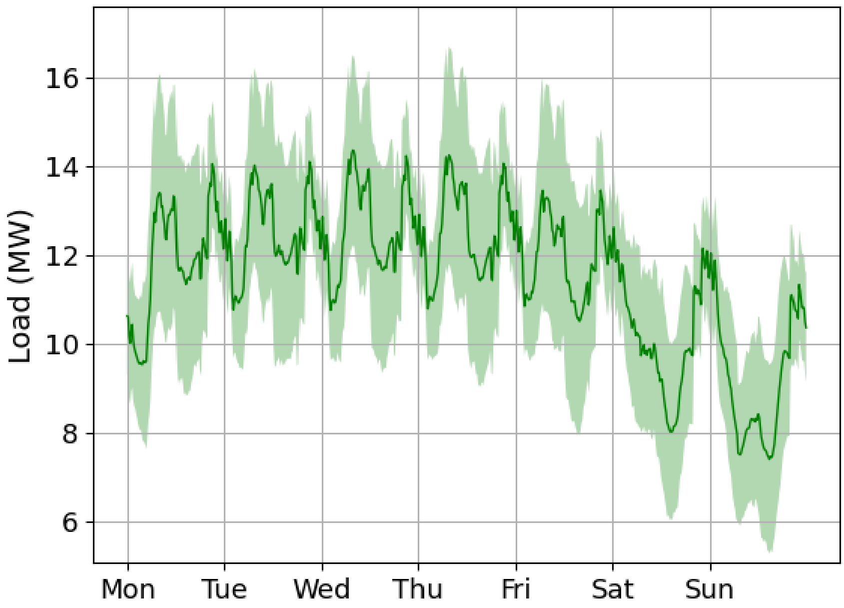

Figure 7: mean and standard deviation for the 2021 weekly load of Arbon

3 Procedures and methodology

In this section, the methodology used for peak load forecasting and the control scheme for peak shaving by utilizing BESS are described. We also describe the graph-based load forecasting models, which consist of spatiotemporal Graph Neural Networks (GNNs) with or without a global attribute. Finally, the methodology used for the sensitivity analysis of future scenarios is presented.

3.1 Peak Load Forecasting

The BESS operation relies on predictions of the peak load in the next 24 hours. Based on a recent review of state-of-the-art deep learning models for electric load forecasting [4], Recurrent Neural Networks (RNNs) with Gated Recurrent Unit (GRU) are selected as the core of our prediction system [7][8]. GRUs are a simple version of gated RNNs, suited for the processing of temporal data. They have already been applied successfully in many load forecasting scenarios [6][9].

Based on [4], we employ the Multiple-Input Multiple-Output (MIMO) strategy and use a window of *w* past observations to directly predict the whole horizon of *h* future values, with a single pass through the model. At each timestep *t* the model receives as input a sequence $\mathrm{P}_{\mathrm{ld}}(t-w+1)$, ..., $\mathrm{P}_{\mathrm{ld}}(t-1)$, $\mathrm{P}_{\mathrm{ld}}(t)$ of *w* past load measurements and a window of corresponding exogenous variables $u(t-w+1)$, ..., $u(t-1)$, $u(t)$. These could be extra data (e.g., weather forecasts). In our case, we define $u(t)$ as a 7-dimensional vector, where the first six variables are sinusoidal encodings of the horizon timestamps. The last variable assumes a value of 0 or 1, indicating if the horizon timestamp to be predicted belongs to a national holiday.

The first trainable operator of our model is a non-linear conditional block [5], which conditions the input $\mathrm{P}_{\mathrm{ld}}(t)$ with the exogenous variables $u(t)$ at each step *t*:

$$\mathrm{g}(t) = \mathrm{ReLU}(\ \mathrm{MLP}_p\big(\mathrm{P}_{\mathrm{ld}}(t)\big) + \mathrm{MLP}_u\big(u(t)\big)\ ) \tag{1}$$

where MLP_p and MLP_u are Multi-Layer Perceptrons (MLPs) with a single hidden layer with ReLU activations and a linear output layer. Both layers have the same size *k*. From the aforementioned block, we obtain a sequence of *w* *k*-dimensional vectors $\mathrm{g}(\mathrm{t}-\mathrm{w}+1)$, ..., $\mathrm{g}(\mathrm{t}-1)$, $\mathrm{g}(\mathrm{t})$ that are directly processed by our temporal encoder composed of 2 stacked recurrent layers with GRU cells. To produce the model output, the last cell state $\mathbf{s} \in \mathbb{R}^k$ is processed by a final MLP_y layer, with *F*-dimensional hidden layer and ReLU activations, which produces the prediction $\hat{\boldsymbol{y}}(t)$ in $\mathbb{R}^h$ for all horizon timesteps.

$$\hat{\boldsymbol{y}}(t) = \ \mathrm{MLP}_y(\mathbf{s}) \tag{2}$$

This describes our standard MIMO model for load forecasting, in which the target to be predicted is the vector $\boldsymbol{y}(t)$ in $\mathbb{R}^h$:

$$\boldsymbol{y}(t) = [\mathrm{P}_{\mathrm{ld}}(t+1), \mathrm{P}_{\mathrm{ld}}(t+2), \ldots, \mathrm{P}_{\mathrm{ld}}(t+h)] \tag{3}$$

For the evaluation of the MIMO predictor, we will use the simple strategy of post-processing its output, by taking max$\{\hat{\boldsymbol{y}}(t)\}$ as input to the BESS control algorithm at each timestep t:

$$\hat{\mathrm{P}}_{\mathrm{pred}}(t) = \max\{\hat{\boldsymbol{y}}(t)\} \tag{4}$$

In line with our application, we also investigate a variant of the model which is optimized to predict directly only the peak load in the future horizon. The true prediction target and the predicted value of this model are simply:

$$y(t) = \max_{k\in\{1,\ldots,h\}} \mathrm{P}_{\mathrm{ld}}(t+k) \tag{5}$$

$$\hat{\mathrm{P}}_{\mathrm{pred}}(t) = \hat{y}(t) \tag{6}$$

We will refer to this model as the PEAK predictor, in contrast with the MIMO predictor described above. Since the future peak is the only forecast needed, the PEAK predictor output can directly be used by the BESS control algorithm.

The described models are trained end-to-end for 150 epochs, using Stochastic Gradient Descent (SGD) with a batch size of 64 training examples [10]. We use the L1-loss with L2-regularization, which tries to keep model parameters small to mitigate overfitting on the training set and Adam optimizer to minimize this prediction loss [11].

3.2 Graph-based forecasting framework

To exploit more fine-grained data from the electric grid, we use spatiotemporal GNNs for forecasting at multiple levels of aggregation. We investigated three different scenarios, with a goal to predict the power load (in MW or kW) 24-hours ahead, with a 15-minutes sampling step:

1) Prediction of single smart meter load profiles. We extracted the 50 smart meters with high average consumption and a very small number of missing values. Here we consider only the positive load ${P_+}^{(i)}(t)$. We will use the **METERS** keyword to distinguish the forecasting models of this use case.
2) Prediction of aggregates of smart meters, obtained via graph-based clustering as described in section 3.2. This represents a level of aggregation which is in the middle between the single household and the MV transformer. Here we also include the photovoltaics, so the nodes' signals can have negative values. We use the keyword **CLUSTERS** to distinguish this use case.
3) Prediction of the total load, along with the aggregates. This scenario uses a GNN with a global attribute to model the total load measured at the MV transformer. We will use the keyword **GLOBAL** for this use case.

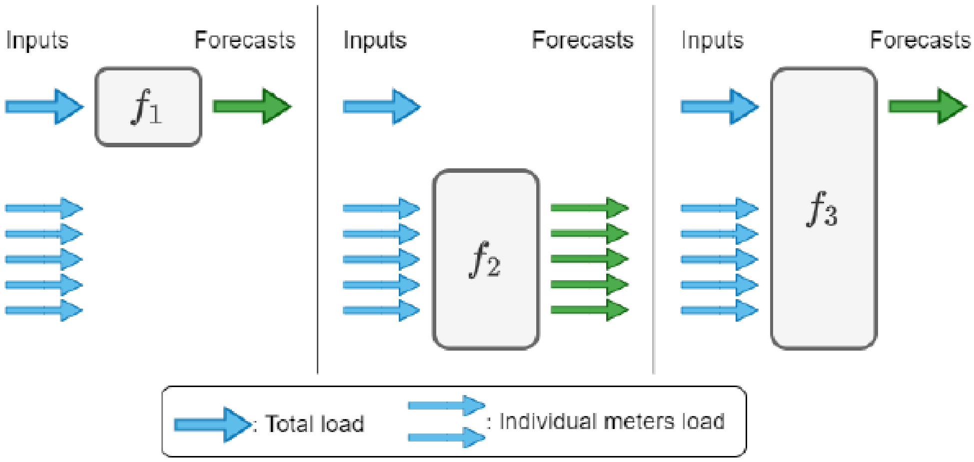

Figure 8: The different load forecasting use cases, from left to right: PEAK/MIMO, METERS/CLUSTERS, GLOBAL [12].

Figure 8 depicts the different forecasting scenarios. PEAK and MIMO predictors correspond to the simple strategy denoted f_1, using only the total MV transformer load as input and prediction variable. Utilization of METERS and CLUSTERS models belong to f_2 strategy, making use only of smaller load signals and predicting them separately. In case of clusters, we also track the prediction performance on the sum of all signals, sign it closely resembles the total MV load. f_3 represents our GLOBAL scenario, in which extra information from nodes signals is used together with the actual total load, measured at the MV transformer.

We build graph-based neural networks based on the message-passing GNN framework. We employ a "time-then-space" approach, in which time information is processed before the exchanging of information via the graph edges. Figure 8 represents this GNN approach schematically. The model uses a trainable encoder block to map the $P^{(\mathrm{i})}(t)$ of each node (combined with global exogenous features from the timestamps) into a fixed size vector representation. A static graph embedding is added, which identifies each node. Then, information is exchanged between all the nodes features z_i via the edges of a learnable graph, to obtain updated node features $\tilde{z}_i$. In our case, we use a fully connected graph for the AGG block (FC-

GNN). This allows learning the connection weights between all pairs of clusters (or smart meters). Finally, a decoder block uses the message passing node features $\tilde{z}_i$ to perform load prediction separately for each node. We refer to [12] for details on the model's theory and motivation[1].

This model can be directly applied for use case f_2, and represents the best performing model for our clusters and meters use case.

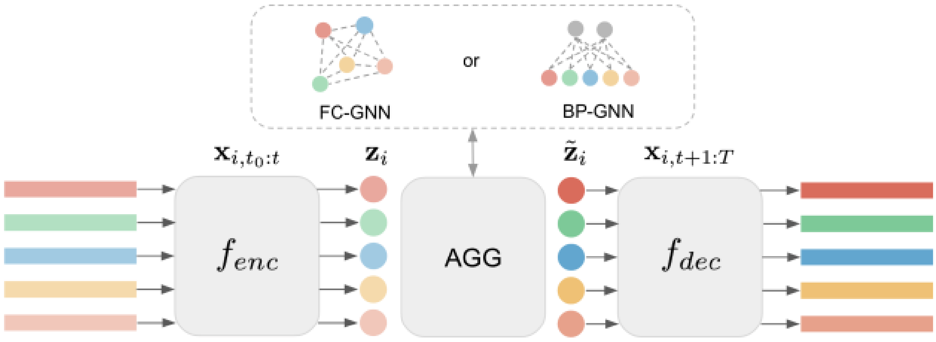

Figure 9: Gated Graph Network Model for time series forecasting [13].

To tackle the f_3 use case, we extend our neural network with a global attribute, which is both an input and a prediction output. This global attribute models the total load measured at the MV transformer, which is slightly different than the sum of all loads from the smart meters. We refer to Section 2.3 for more details on the difference between these two.

Figure 10 shows an example of a GNN with both graph nodes and global attribute. The blue box represents the nodes encoder, while the red one is a separate encoder for the global attribute. Information flows from GNN nodes to global attribute via a trainable pooling layer, represented in purple. Finally, the global and nodes encodings are used to perform prediction via two separate decoder blocks.

We extended the previous "GatedGraphNetworkModel" into the "GlobalGatedGraphNetwork", to obtain a model that predicts simultaneously the total load from the transformer and the smart meter clusters.

[1] Our specific model is implemented in tsl package, as class "GatedGraphNetworkModel" available at https://github.com/TorchSpatiotemporal/tsl/blob/main/tsl/nn/models/stgn/gated_gn_model.py

The global and graph part are optimized jointly, using a weighted sum of 2 loss functions:

$$L(y, \hat{y}, \theta) = w_n \cdot L_n(y_n, \hat{y}_n, \theta) + w_g \cdot L_g(y_g, \hat{y}_g, \theta) \quad (7)$$

In our case, L_n and L_g are L1 loss functions on the nodes and global attribute predictions respectively, while w_n and w_g are weights, properly set to balance the two contributions. Details on the GNN model with global attribute can be found in [12].

GNN models predict the daily load profiles, 24 hours in the future, and are trained end-to-end to minimize the prediction error.

Performance for all models will be reported in Section 4, per each use case. We will compare the GNNs performance with other reference models. These are classic GRU-RNNs, like the MIMO model described in section 3.1.

Nevertheless, GNNs were not applied as a peak load forecasting strategy for BESS control due to practical reason. In fact, collecting of all the smart meters data in near real time is technically impossible in current setup and moreover, processing of such data would be computationally infeasible. So, it is left out of the scope of the BESS control study. Hence, we investigated GNNs given the potential of the pilot, but relied on simpler univariate predictors for the BESS optimization use case.

In order to employ GNN based forecasts for BESS control in the future, a real-time data collection system should be implemented. This would aggregate all smart meter measurements in a local or cloud server to perform inference. The system should have minimal delay, collecting new measurements at least every 15 minutes. Missing data should be absent or imputed, to provide all inputs needed to the GNN model.

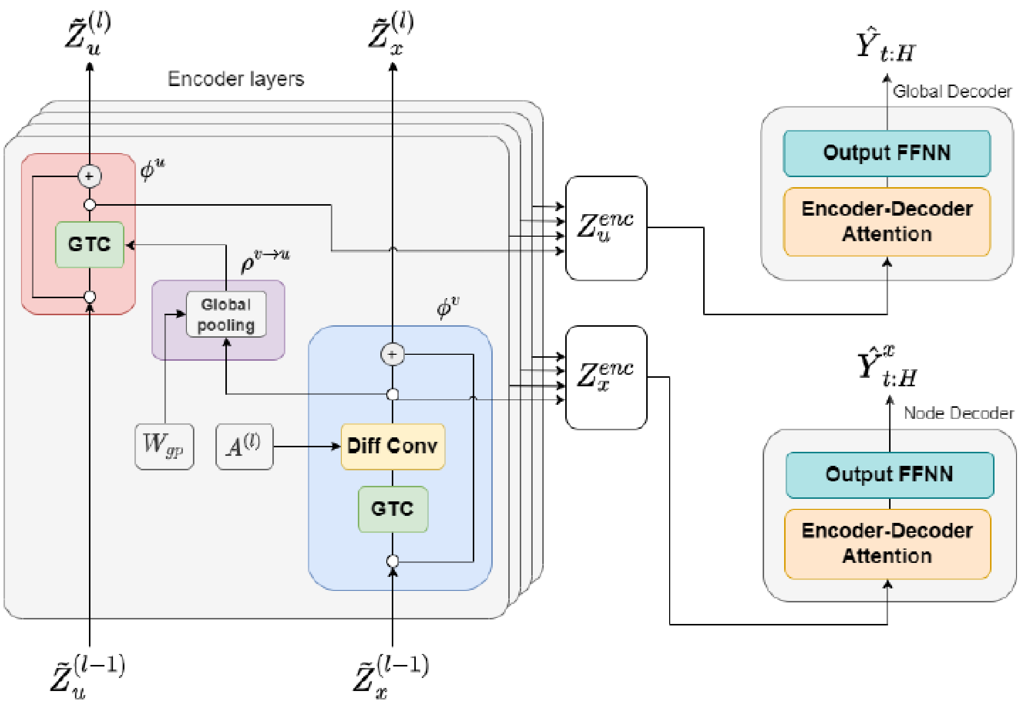

Figure 10: GNN with global attribute and pooling from nodes towards global [12].

3.3 Online model adaptation

Deep learning models require collecting more historical data and re-training them from scratch, to improve performance over time. Full model re-training can yield boosts in performance, but it is a costly procedure that requires work from experts and software engineers. On the other hand, MLOps is emerging as the field of automating and optimizing the costly process of model development, deployment, and improvement. With this approach in mind, we investigated online learning, working towards life-long learning of the forecasting models.

Our approach focuses on optimizing the model on new test data, while the model is deployed and used for forecasting. This process could be automated and lead to continuous adaptation of the model, as it is being used in production.

We accumulate new test data over a period of time and use it as a mini-batch to perform one step of gradient descent on all the models' trainable parameters. This leads to the model being slightly optimized every 24 hours. The gradient descent function is:

$$\theta_{n+1} = \theta_n - \gamma \nabla L(\theta_n) \tag{8}$$

Where θ_n are the model trainable parameters at training step n, $L(\theta_n)$ is the loss function to be minimized and γ is the learning rate, a value that controls the amount of model update at each step.

To avoid excessive gradient values that could overshoot our learning, we performed gradient clipping, putting a limit to the norm of the gradient vector $\nabla L(\theta_n)$. This, combined with a proper choice of the learning rate γ, gives a further improvement in performance when performing inference on streaming test data.

3.4 BESS control scheme based on load forecasting

In the context of *Task 3.3 of Deliverable 3.2 "Advanced battery management system based on novel predictor and regional market situation,"* a rule-based BESS control scheme is developed for real-time peak shaving in the distribution grid of Arbon city. The proposed method is based on day-ahead load prediction and near real-time transformer measurements. In order to evaluate the performance of the proposed control scheme, the results are compared with the theoretical optimum of BESS operation. This task evaluates the impact of BESS operation not only on the reduction of peak power costs, but also on the variations of other cost components (e.g., energy procurement and grid usage costs). The DSO is penalized for the highest monthly 15-min average power exchange with the superior grid level [14]. In order to avoid undesired effects on other cost components, two additional cost factors are considered in the objective function. The total cost Ctot consists of three different components:

$$C_{tot} = C_{epex} + C_{peak} + C_{use} \tag{9}$$

where C_{epex}, C_{peak} and C_{use} represent the total daily cost due to energy purchase, total monthly cost from peak power demand and total daily cost from the usage of transmission and distribution (T&D) networks, respectively. Energy is not purchased by the DSO, and only a small part of the total energy consumption is purchased at the European Power Exchange (EPEX). However, a theoretical total energy cost based on the EPEX prices is included in the objective function, as a worst-case measure for shifts in energy procurement cost due to peak shaving. In this manner, the control schemes are prevented from reducing the peak power cost at the expense of energy procurement and grid usage costs. The individual cost components are:

$$C_{epex} = \sum_{t=1}^{N_s} c_{epex}(t) \cdot E_{imp}(t) \tag{10}$$

$$C_{peak} = c_{peak} \cdot \max\left(P_{imp}(t)\right) \; \forall t \in \{1, 2, \dots, N_s\} \tag{11}$$

$$C_{use} = \sum_{t=1}^{N_s} c_{use} E'_{imp}(t) \tag{12}$$

where:

N_s	Total number of timesteps per day
$E_{imp}(t)$	Total energy consumption at timestep t in MWh
$E'_{imp}(t)$	Energy consumption excluding BESS charging cycles at timestep t in MWh
$P_{imp}(t)$	Power demand of the total load curve at timestep t in kW

As for the definition of the theoretical BESS optimal operation, an optimization-based approach conducts a one day-ahead optimization using an ideal load prediction, and the results are used for the assessment of the rule-based method. It is assumed that the BESS energy content at the first and last timestep of each day are equal to the initial state of charge (SoC). The main reason of this assumption is to guarantee the BESS sustainability for the project lifetime. In case that the energy at the end of the simulation period, N_s is not defined, the BESS can remain at the lowest SoC level, SOC_{min} for a long period, which can have crucial impact on BESS degradation. A representative measure of battery lifetime is the energy throughput that corresponds to the total amount of energy a battery stores during the charging cycles. In this study, the daily energy throughput E_{thr} is of main interest, since the optimization is carried out on daily basis. A constraint for the daily energy throughput is also included so as to limit the BESS degradation throughout the year. The complete optimization problem based on a mixed integer linear programming (MILP) formulation focuses on the minimization of daily C_{tot}.

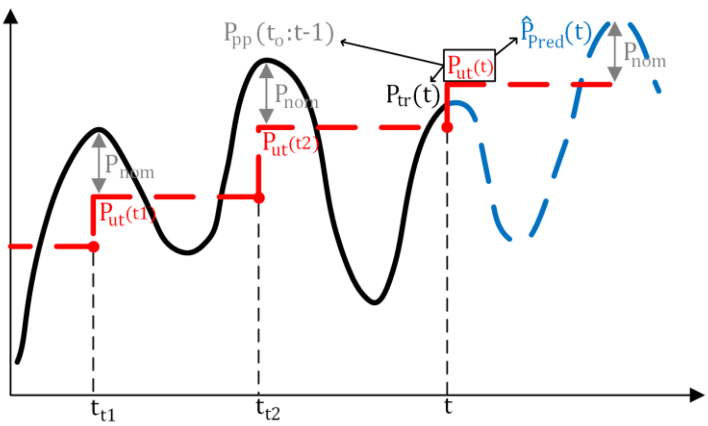

Figure 11: Concept for the update of threshold used for BESS charging and discharging.

The BESS control strategy uses a threshold for both the charging and discharging modes of BESS. As shown in Figure 11, the threshold $\mathrm{P_{ut}}(t)$ at timestep t is updated with respect to the monthly peak power of the previous timesteps $\mathrm{P_{pp}}(t_o\!:t-1)$, near real-time transformer measurement $\mathrm{P_{tr}}(t)$ and the day-ahead predicted peak power $\widehat{\mathrm{P}}_{\mathrm{pred}}(t)$. The threshold $\mathrm{P_{ut}}(t)$ is defined every 15 minutes, as follows:

$$\mathrm{P_{ut}}(t) = \mathrm{Max}\left\{\mathrm{P_{ut}}(t-1), \mathrm{Max}\{\widehat{\mathrm{P}}_{\mathrm{pred}}(t), \mathrm{P_{pp}}(t_o\!:t-1), \mathrm{P_{tr}}(t)\}\right\} - \mathrm{P_{nom}} \quad (13)$$

The threshold $\mathrm{P_{ut}}(t)$ can remain constant or increase at each timestep compared to the previous threshold $\mathrm{P_{ut}}(t-1)$. In particular, the use of both the previous threshold and the monthly peak power of the previous timesteps can prevent fluctuations of the threshold, avoiding any discharging cycles at local peaks. The use of the near real-time transformer measurement can also lead to the continuous update of the threshold. Within the 15-min time interval, the threshold can be updated using the latest load prediction, as a new day-ahead load prediction is provided every 15 minutes. The nominal power $\mathrm{P_{nom}}$ is used in (13) so that the BESS charging power is sufficient to reduce the power peak when using the full power capacity.

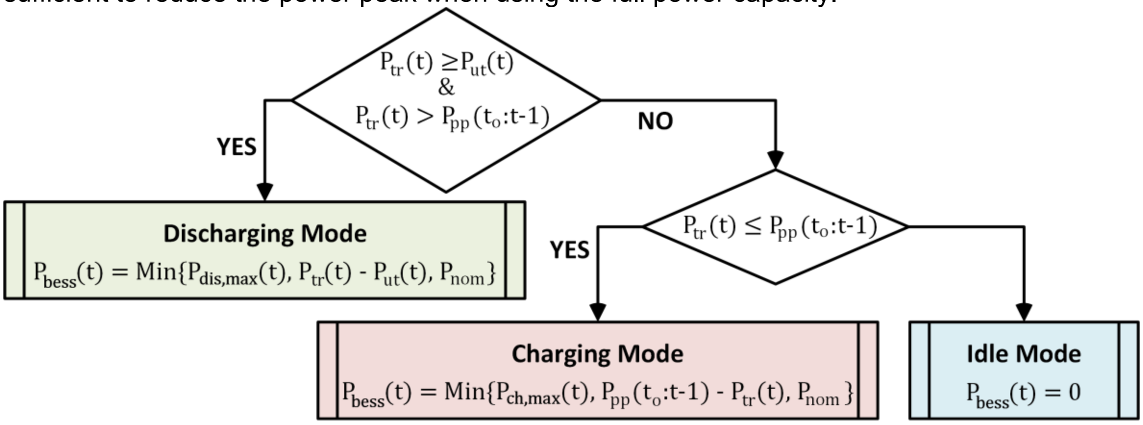

Figure 12: Logic diagram for the determination of each BESS mode.

Figure 12 provides the logic diagram for the determination of each BESS mode. For the discharging mode, two conditions must be met, particularly, the near real-time load measurement $\mathrm{P_{tr}}(t)$ should be equal or higher than the threshold $\mathrm{P_{ut}}(t)$, and higher than the monthly peak power of the previous timesteps $\mathrm{P_{pp}}(t_o\!:t-1)$. In this case, the discharging power is provided by:

$$\mathrm{P_{bess}}(t) = \mathrm{Min}\left\{\mathrm{P_{dis,max}}(t), \mathrm{P_{tr}}(t) - \mathrm{P_{ut}}(t), \mathrm{P_{nom}}\right\} \quad (14)$$

where $\mathrm{P_{dis,max}}(t)$ corresponds to the maximum discharging power at each timestep based on the current $\mathrm{SoC}(t)$:

$$\mathrm{P_{dis}^{max}}(t) = \frac{\mathrm{E_{nom}} \cdot \mathrm{n_{inv}} \cdot \sqrt{\mathrm{n_{rtp}}}}{\mathrm{T_s}}\left(\mathrm{SoC}(t) - \mathrm{SoC_{min}}\right) \quad (15)$$

It is evident that the BESS does not always discharge with the rated power, $\mathrm{P_{nom}}$, as the difference $\mathrm{P_{tr}}(t) - \mathrm{P_{ut}}(t)$ may be lower than $\mathrm{P_{nom}}$, or the BESS remaining capacity limits the discharging power. As for the charging mode, the load measurement $\mathrm{P_{tr}}(t)$ should be equal or lower than the monthly peak power of the previous timesteps $\mathrm{P_{pp}}(t_o\!:t-1)$. The charging power is given by:

$$\mathrm{P_{bess}}(t) = \mathrm{Min}\left\{\mathrm{P_{ch,max}}(t), \mathrm{P_{pp}}(t_o\!:t-1) - \mathrm{P_{tr}}(t), \mathrm{P_{nom}}\right\} \quad (16)$$

where $\mathrm{P_{ch,max}}(t)$ represents the charging power at each timestep based on the current $\mathrm{SoC}(t)$:

$$P_{ch}^{max}(t) = \frac{E_{nom}}{T_s \cdot n_{inv} \cdot \sqrt{n_{rtp}}}(SOC_{max} - SOC(t)) \tag{17}$$

In the same manner to the discharging power, the charging power cannot always be equal to P_{nom}, since the BESS charging mode should not cause higher peaks than the monthly current one $P_{pp}(t_o: t-1)$, or the BESS requires lower power to be charged up to the SOC_{max}. It is evident from the aforesaid concept of charging mode that the BESS can be charged very frequently so that there exists sufficient energy capacity to reduce the power peaks in case of discharging mode. Finally, when neither the charging nor the discharging conditions are fulfilled, the BESS remains in idle mode.

3.5 Sensitivity Analysis – System Modelling and Methodology

The sensitivity analysis is conducted in the context of the national deliverable D4.1 "Sensitivity analysis of prospective flexible loads, generators and future loads," and particularly corresponds to Task 4.1 "*Integration with simulations of future scenarios*," and to Task 4.3 "*Analysis of the future loads effect without any or with demand side management and w.r.t regional energy balance and trade.*" In the study, the models of PV, EV and HP are formulated in order to generate annual power profiles for the PV production, as well as demands of EV and HP. In terms of the DSM, the power measurements at the transformer level are used, and signals for disconnection requests are sent to the end-customers. The end-customers decide if they will disconnect their EV or the HP assuming a uniform probability distribution. The DSM technique focuses on peak shaving at the transformer level without using local power measurements from smart meters.

As for the PV power profiles, the annual profile of solar radiation incident, which is defined by the solar radiation database PV-GIS [15], is used. Based on the BFE statistics [16], we assume that buildings with annual energy consumption lower than 25 MWh are equipped with PV of rated power 10 kWh_{ac}, while PV with rated power of 24 kWh_{ac} are installed in the other buildings.

Regarding the EVSE scenarios, we assume that up to 2/3 of the end-customers can own an EV in each building. The EVs with the top 10 sales in Switzerland are used in this study [17]. The nominal power of the EV chargers in each building is assumed to be equal to the maximum charging power of the cars. Furthermore, only AC charging is conducted, though it is slower than DC charging, as the former one is mostly applied in Switzerland today.

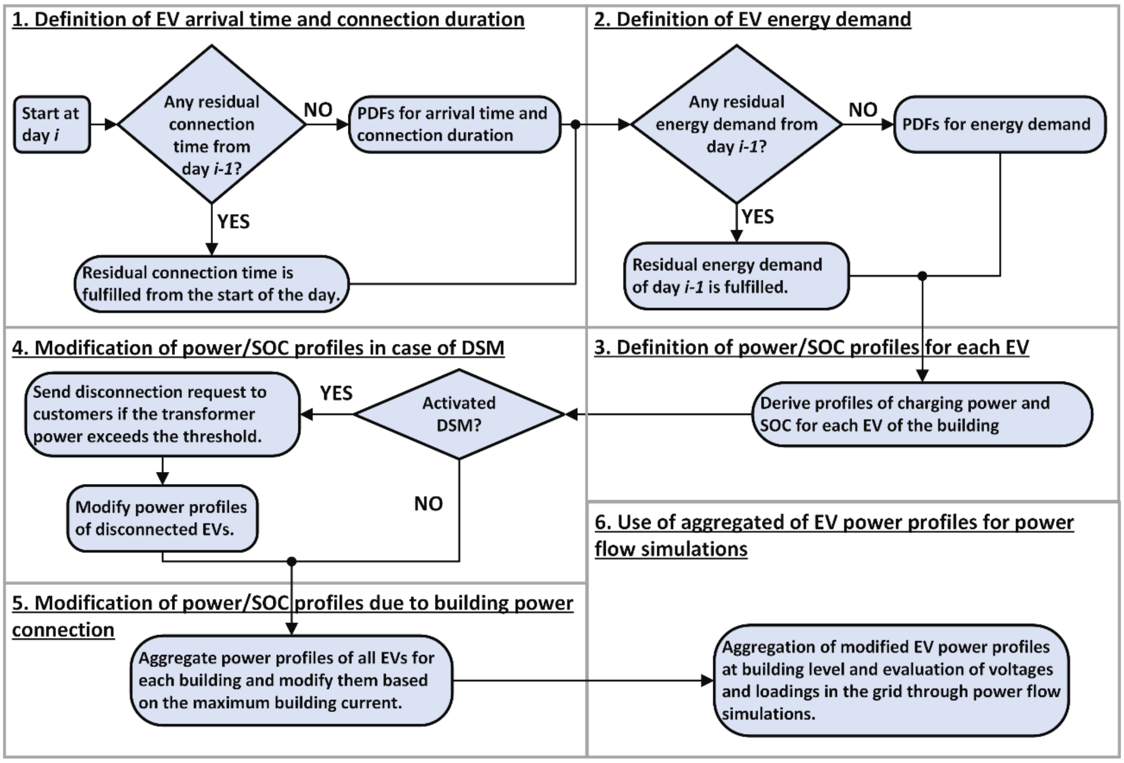

Figure 13: Procedure followed for the generation of total EV power profile in each building.

For the generation of power profiles for the EV charging sessions, the procedure shown in Figure 13 is carried out based on six steps. The arrival time, connection time and energy demand of each EV are defined by respective probability functions (PDFs) with respect to the type of day and the type of building. The PDFs are based on real data of EV charging sessions that are provided by the research centre ElaadNL in the Netherlands [18].

Regarding the HP power demand, it depends on each building and the weather conditions. Due to the lack of data, the thermal model of each building is approximated by a single thermal zone considering a fixed thermal time constant, as approximated by [19]. Temperature drops due to ventilation and infiltration effects, as well as temperature rises due to solar irradiance, occupants and electric devices are not taken into account. In addition, it is assumed that the hydronic system of each building includes underfloor heating arrangement. Concerning the domestic how water (DHW) demand, the respective profiles are defined on a statistical basis by the software DHWcalc Version 2.02b [20]. Air-source HP with non-modulating compressor are assumed for both space heating (SH) and DHW generation. The HP are directly used in SH mode, so no additional thermal energy storage is considered for SH purposes. Considering the underfloor heating arrangement in all buildings, a fixed water temperature of 35°C is assumed in case of SH mode. In case of DHW tank heating, water with fixed temperature of 45°C is supplied by the HP. Regarding the HP modes, first priority is given on the DHW tank generation when the remaining thermal capacity falls under the lowest level. The DHW mode of the HP can be interrupted only if the minimum DHW capacity threshold is not violated, and the room temperature is lower than the minimum setpoint. The temperature setpoint range for SH purposes is set from 21°C to 23°C. In case of room temperatures lower than 21°C, the HP operates until the room temperatures reaches the upper threshold of 23°C. The HP will be activated again, only if the room temperature falls at 21°C. When the room temperature is higher than 23°C, the HP remains in idle mode. As for the DHW tanks, the operational SOC range is considered as [5% 95%].

The distribution network models are generated by importing from the MongoDB server of the DSO Arbon Energie AG the related data for the cables, existing loads, and voltage measurements at transformer level. Next, the software tool pandapower of Python is used to assign each input to the nodes and lines of the network and to run the power flow simulations. For each network, three different scenarios of gradual integration of PV, EVSE and HP are tested considering their combinations, as well as the DSM application. Hence, the following cases are evaluated:

a. **PV**: Integration of PV without considering the other energy assets and DSM.
b. **EV / EV + DSM**: Integration of EV without/with DSM.
c. **EV + PV / EV + PV + DSM**: Integration of both EV and PV without/with DSM.
d. **HP / HP + DSM**: Integration of HP without/with DSM.
e. **HP + PV / HP + PV + DSM**: Integration of both HP and PV without/with DSM.
f. **HP + EV / HP + EV + DSM**: Integration of both HP and EV without/with DSM.
g. **HP + EV + PV / HP + EV + PV + DSM**: Integration of all energy assets without/with DSM.

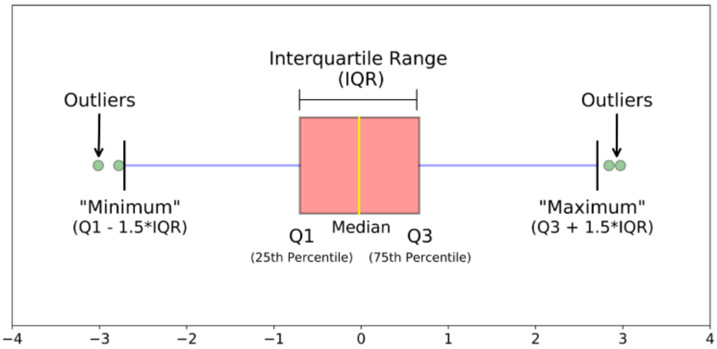

Figure 14: Boxplot used for the distribution of results

In terms of the parameters under evaluation, the fulfillment of voltage quality requirements based on EN 50160 is examined [21]. Furthermore, the maximum line current loadings of the cables and the maximum apparent power loadings of the transformers are compared with their ratings. For each scenario, the distribution of line loadings and voltage magnitudes for the whole year are presented through the box plot shown in Figure 14. In terms of the voltage magnitudes, the value of 230 V is used as base voltage for the conversion to per unit (pu). As for the line loadings, they are calculated in percent by dividing the computed values in Amps with each cable thermal limit.

4 Results and Discussion

We provide detailed report on efficiency of the developed load forecasting models, starting with performance of the PEAK and MIMO models used by the BESS control algorithm. The evaluation of the graph-based predictors follows, along with the results related to adoption of online adaptation strategies.

Following the results relevant for the forecasting, the technical and economic assessment for BESS control and sensitivity analysis are reported.

4.1 Peak load forecasting

Entire assessment process of the developed load forecasting methods is based on utilization of standard metrics, that are defined as:

- Mean Absolute Error (MAE), expressed in MW or kW, depending on the level of load aggregation.
- Mean Absolute Percentage Error (MAPE): expressed as a % relative to the true load values.
- Normalized Root Mean Squared Error (NRMSE): expressed as a % with relative to the true data range (max – min).
- R2: statistical score related to the variance explained by the predictor, with 1.0 being the optimal value and 0.0 indicating bad performance, equivalent to always predicting the global average of the data.

A detailed explanation of the load forecasting metrics can be found in [4].

Given the restrictions in run-time availability of the data (i.e., smart meter information is available at earliest a day after its collection and much later in practice) as well as huge computational requirements considering amounts of collected field data, we focus on the simple prediction strategy f1 as previously defined, as an input for BESS. Table 1 summarizes the performance of peak load forecasting, divided by year and comparing the two models, namely, MIMO and PEAK.

Table 1: Peak load forecasting results, reported as mean and standard deviation over 10 training runs.

Year	Strategy	MAE (MW)	MAPE (%)	NRMSE (%)	R2 (-)
2019	PEAK	0.725 ± 0.014	5.09 ± 0.10	9.91 ± 0.18	0.792 ± 0.007
	MIMO	0.902 ± 0.041	6.01 ± 0.26	12.27 ± 0.49	0.681 ± 0.025
2020	PEAK	0.639 ± 0.027	4.67 ± 0.21	8.12 ± 0.31	0.820 ± 0.014
	MIMO	0.696 ± 0.029	4.78 ± 0.20	8.56 ± 0.34	0.800 ± 0.016
2021	PEAK	0.595 ± 0.011	4.19 ± 0.10	8.16 ± 0.15	0.866 ± 0.005
	MIMO	0.822 ± 0.018	5.51 ± 0.11	11.07 ± 0.22	0.754 ± 0.009
2022	PEAK	0.537 ± 0.020	3.81 ± 0.15	10.43 ± 0.45	0.782 ± 0.019
	MIMO	0.829 ± 0.037	5.73 ± 0.24	15.08 ± 0.57	0.544 ± 0.035

The positive effect of adding more years of training data is evident in both MAE and MAPE, as there is a significant improvement from 2019 to 2022. It is also noticeable that the PEAK model, which focuses only on the prediction of the future peak, performs better than the standard MIMO strategy. This could be expected, as the standard MIMO predictor has to learn how to predict the full curve of future load, at the expense of higher errors at the peak value.

Figure 15 shows the prediction against the true peak value. It is clear the model learned well the seasonality of the peak, with a clear valley during the holiday periods in summer and around Christmas. The error in green is also quite stable, with no big drift, a mean value of 0.048 MW and 0.73 MW standard deviation. On bad predictions, the error could get as big as -3.8 MW.

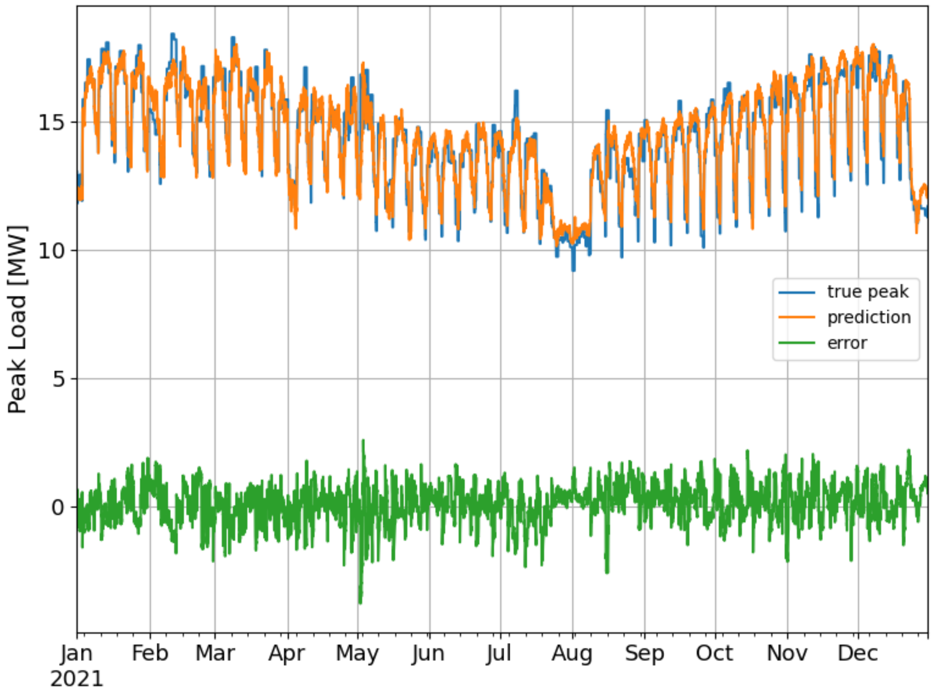

Figure 15: peak load forecasting on the 2021 test year

Table 2: Full load curve forecasting results, reported as mean and standard deviation over 10 training runs.

Year	MAE (MW)	MAPE (%)	NRMSE (%)	R2 (-)
2019	0.769 ± 0.010	6.89 ± 0.09	6.81 ± 0.10	0.359 ± 0.023
2020	0.724 ± 0.008	6.84 ± 0.09	6.02 ± 0.06	0.459 ± 0.015
2021	0.729 ± 0.005	6.88 ± 0.07	6.28 ± 0.04	0.502 ± 0.004
2022	0.788 ± 0.006	7.68 ± 0.07	7.51 ± 0.05	0.505 ± 0.007

To facilitate the comparison with [4] and other works in load forecasting, the performance of the MIMO strategy on the full load curve is also reported in Table 2. In terms of the R^2 metric, the trend of increasing performance with additional training data can also be noticed. Nevertheless, the trend is less obvious than in Table 1, with a big improvement only from 2019 to 2020. On average, the MIMO model has good performance when predicting the future 96 values, but the MAE values of Table 2 are always lower than the ones reported in Table 1 for MIMO, which refer to the day-ahead peak value. This suggests again how the full load curve prediction of MIMO is not suited at predicting the peak with maximum accuracy.

The peak prediction from PEAK model have been used in practice for BESS control and peak shaving, with results presented in Section 4.4.

4.2 Graph-based load prediction results

The developed graph-based forecasting framework has been instantiated and customized for the problem at hand. Model selection was achieved via hyperparameter tuning, by minimizing the error on the validation set (see section 2.3 for details on validation set). The most important hyperparameters to be tuned were the L2 regularization weight, the number of learning units in each layer and the number of layers. for each model family and type. We report the performance of the best model we were able to train based on such model selection. The same amount of effort was spent in optimizing in each model architecture, to guarantee a fair comparison.

Use cases METERS and CLUSTERS (see Table 3 MAE column and Table 4)

We present forecasting accuracy results on the CLUSTERS and METERS use cases, in Table 3 and Table 4 respectively. The results demonstrate the superior performance of the graph-based model in predicting the load at both levels. On the CLUSTERS use case we see a 20% reduction in the MAE of predicting on all 50 clusters of smart meters, compared to FCRNN-Large.

The FCRNN models (Fully Connected RNN), are standard GRU-RNN models, extending the MIMO model idea, and act on features extracted from the 50 load signals using a conditional MLP block [5].

These traditional models make less efficient use of trainable parameters compared to the GNN. The FCRNN-large has ~1.8M parameters, while FCRNN-small has ~378k. The GatedGraphNetwork GNN achieves much better performance than even FCRNN-large, while using less trainable parameters (~350k).

Table 3: results of load forecasting on CLUSTERS, reporting average TEST performance over all clusters and over their SUM aggregation, to compare with univariate predictors of the total load.

Model Name	MAE (MW)	SUM_MAE (MW)	SUM_MAPE (%)
Gated Graph Network	**0.030**	**0.648**	**6.33 %**
FCRNN-large	0.038	0.761	7.40 %
GRU-RNN (univariate)	-	0.678	6.70 %

Table 4: results of forecasting on METERS, reporting average TEST performance over the 50 smart meters with biggest mean consumption.

Model Name	MAE (kW)	NRMSE (%)	R2
Gated Graph Network	**23.572**	**2.50%**	**0.872**
FCRNN-large	29.52	3.02 %	0.813
FCRNN-small	31.568	3.17%	0.794

Use case CLUSTERS, considering the SUM of the outputs (see Table 3)

The performance is better also on the total load from all smart meters, estimated as the sum of all clusters, with performance shown by the SUM_MAE and SUM_MAPE columns in Table 3. The GNN achieves a 4.4% MAE reduction with respect to the best univariate predictor we could train. (GRU-RNN). This highlights the usefulness of multiple load signals and learning complex inter-dependencies among them.

Use case METERS, focus on individual consumers (see Table 5)

To further validate the importance of graph-based learning, we compared the performance of our GNN against univariate predictors, focusing on 3 individual smart meters with high average consumption (supposedly industrial customers). A sample of their weekly load is visible in Figure 16. It can be observed they have very different average consumption, with the orange being the most predictable, the green being mid-way and the blue showing very high frequency components and unpredictable behavior.

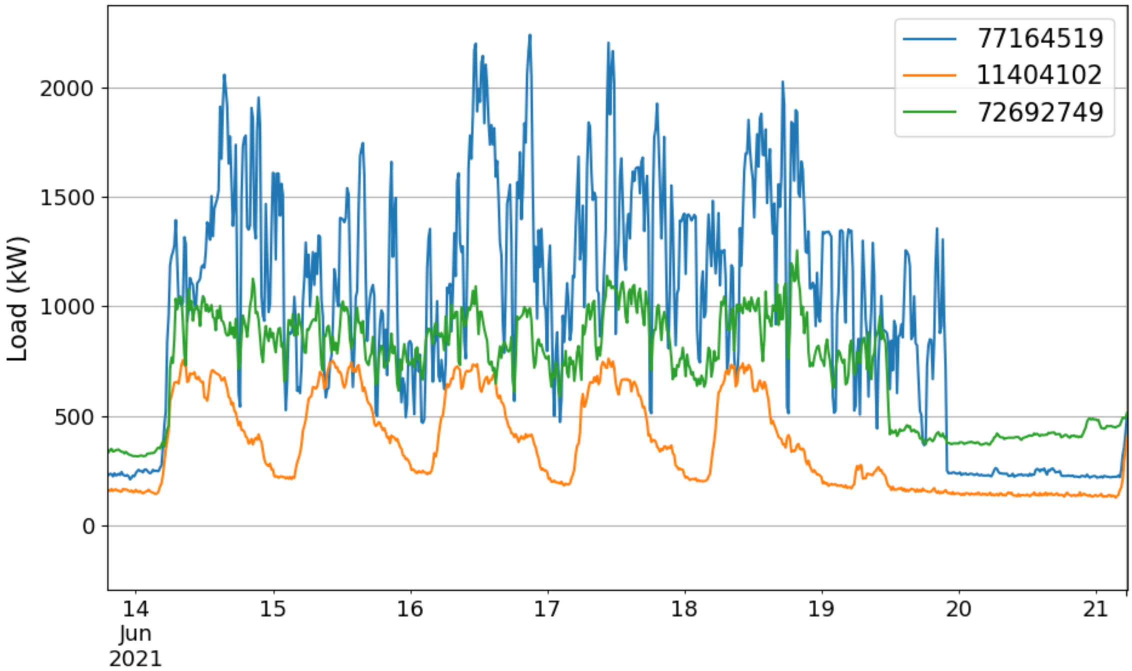

Figure 16: Load in kW for the 3 smart meters investigated. Shown is a sample week in Jun 2021.

Table 5: daily load forecasting results on three sample smart meters. Each column shows MAE and MAPE when predicting on each smart meter (marked by Id)

Model Name	Id 77164519	Id 11404102	Id 72692749
Gated Graph Network	**258.42 kW** **38.75 %**	30.01 kW 9.77 %	**98.47 kW** **17.26 %**
GRU-RNN (univariate)	274.18 kW 42.93 %	**29.07 kW** **9.24 %**	105.40 kW 18.55 %

As it can be noticed from Table 5, the GNN can achieve comparable or superior forecasting performance on the individual smart meters signals. In particular, it achieves better prediction for the two more complex smart meters with less predictable consumption patterns (blue and green signals, Figure 15).

A single GatedGraphNetwork is also a very efficient model in terms of size. It can predict hundreds of smart meters at once, compared to having to train many GRU-RNN models separately for each smart meter, each having more than ~200k trainable parameters.

Use case GLOBAL - total consumption using smart meters and MV transformer (Table 6)

Finally, we report performance for the GLOBAL GNN use case, where we make use of the total load measured at the MV transformer, together with the clusters of smart meters.

Table 6 shows that a specific GNN with global attribute can achieve minor improvement compared to the MIMO GRU-RNN baseline. In other runs, we observed similar performance.

The results, i.e., modest gain despite huge data collection and computation overhead, made us choose the simpler GRU-RNN when it comes to the BESS control application. In other words, for the specific use, the effort of getting much more data from the grid is not motivated, since the prediction of the load at the battery does not improve significatively.

Table 6: results of load forecasting on GLOBAL use case, reporting average TEST performance in predicting the global attribute (Mv transformer load)

Model Name	GLOBAL_MAE (MW)	GLOBAL_MAPE (%)
Global Gated Graph Network	**0.729**	**6.90 %**
GRU-RNN (univariate)	0.736	7.07 %

The poor performance improvement of the GlobalGatedGraphNetwork GNN might be a consequence of significant impact of data quality. In fact, the total sum of smart meters does not follow exactly the load measured at the MV transformer. See Figure 4 in Section 2.3 for a more detailed explanation of this problems. We tried masking the timesteps with big mismatch during training, but this did not result in statistically significant improvements in predicting the total MV load.

We also observed that the information flow from the nodes to the global attribute was not beneficial for the global attribute prediction. In more detail, the training and validation loss on the nodes' prediction was decreasing, but this did not lead to an improvement in predicting the total MV load, which instead went into strong overfitting.

As further evidence, [12] shows how GNNs with global attribute can slightly improve prediction performance of the total load, when no mismatch between the smart meters and total data sources is present.

In general, for all use cases, we observed that GNNs can be regularized much better than traditional deep learning models with multiple load inputs. With GNNs, we could easily find a good L2 regularization weight to avoid excessive overfitting on the training set. The RNN models are instead much more difficult to regularize, and we could not avoid strong overfitting for FCRNN models, even when trying to tune properly the L2 regularization or using Dropout [22]. This is one strength of GNN models, that greatly speeds up the training of good forecasting models for multiple time-series signals.

We believe all presented forecasting results are statistically significant. We performed multiple training runs for each model, to avoid the "lucky guessing" effect for initial model parameters. Evaluation was performed on a whole year of test data (future data unseen by the models).

Using GNNs, we were consistently able to produce better models, with less overfitting on the training set and better predictions on average.

A whole year of test data is a long time. In practice, models would have to be re-trained frequently to follow possible data distribution shifts. We address this problem via online model adaptation in the following sub-chapter.

4.3 Online adaptation results

We developed online adaptation method as defined in Section 3.3. The test setup is fully consistent with previous experiments, it relies on the same data considered in the same period. To facilitate comparison, we consider the period of a full year, from March 2021 to March 2022.

We used the clusters use case to test the adaptation, focusing on the prediction of the sum of total smart meters' load, including the correction of residential PV production.

Table 7 presents the results, where rows contain the performance of standard inference (above) and online adaptation (below). From the table, it can be observed that online adaptation improves the average performance when tested on this full year of data. In particular, with the GNN it achieves an error reduction of 0.0164 MW in MAE, which corresponds to a relative improvement of 2.53%. On the MIMO GRU-RNN, which is the univariate predictor for the sum of all smart meters, it improves MAE by 0.0199 MW, a relative improvement of 2.94%.

The best results were achieved by performing a single step of gradient descent every 24 hours, without L2 regularization and using a learning rate $\gamma = 0.01$.

The gradient is computed on the batch of a full day of predictions, corresponding to 96 input-output sequences (due to the sampling at a rate of 15 minutes). We set a clipping for the gradient norm, using a maximum value of 5.0. This is needed to avoid taking too big optimization steps that might overfit the model on specific test days, or make the model overshoot a minimum and decrease in performance.

Table 7: result of online adaptation on the 2021-22 test set

Test Case	SUM_MAE (MW)	SUM_MAPE (%)	SUM_R2 (-)
Gated Graph Network	0.6485 **0.6321**	6.335% **6.131 %**	0.869 **0.874**
GRU-RNN (univariate)	0.6778 0.6579	6.699 % 6.401 %	0.862 0.868

4.4 BESS Techno-economic analysis

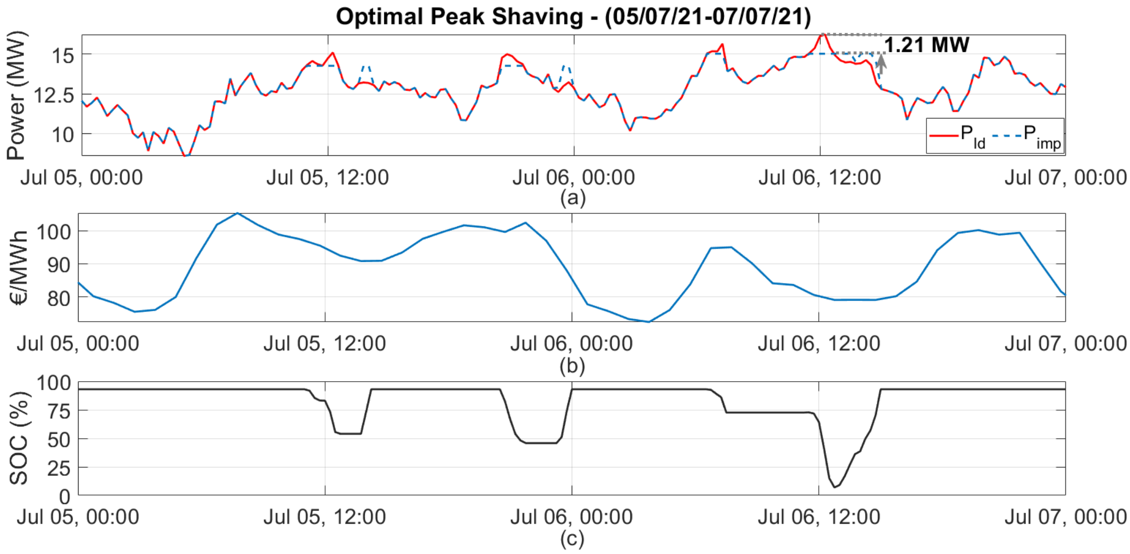

Figure 17: Results applying the optimization-based approach: (a) Measured power load vs. power load with BESS operation, (b) EPEX Spot price, and (c) SoC of BESS.

As illustrated in Figure 17, the optimal case can achieve peak shavings of 1.21 MW on 06th July 2021, since a perfect load prediction is considered. In addition, the BESS maintains the peak power on 06th July 2021 at the level of the previous day. The BESS also follows an energy arbitrage strategy by discharging on high EPEX spot prices and charging on low prices in order to minimize the energy procurement cost in the objective function. It is also evident that the BESS follows a complex SoC pattern due to various charging and discharging modes for the displayed days in July.

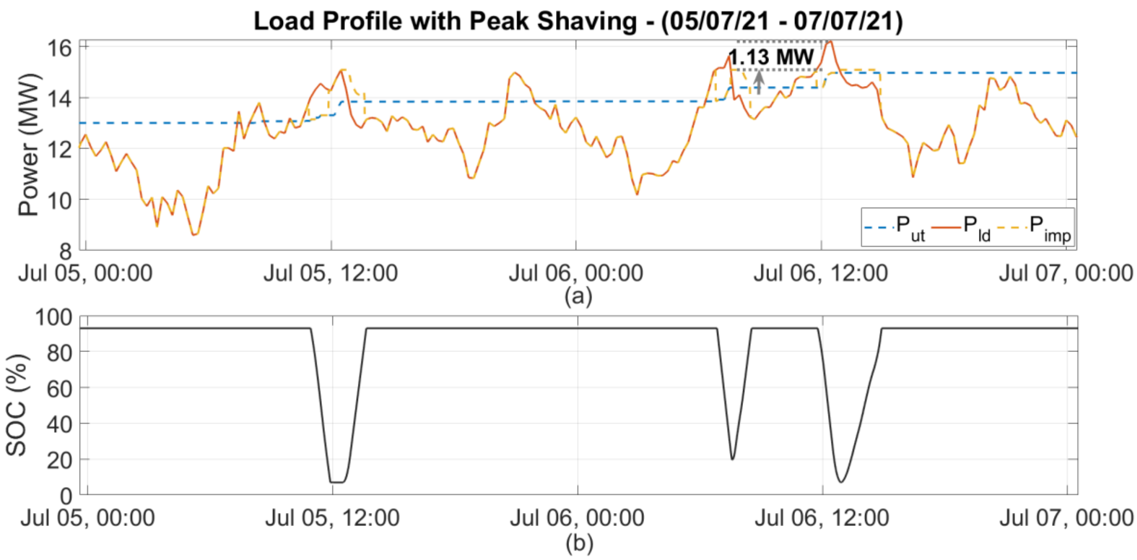

Figure 18: Results applying the proposed control scheme: (a) Total load curve of Arbon city and imported power from the grid, and (b) SoC of BESS.

On the other hand, the proposed technique results in a straightforward SoC pattern as illustrated in Figure 18, since the BESS discharges only when the upper threshold and the previous monthly peak are reached, and charges without deteriorating the previous monthly peak. It is evident that the control scheme cannot always achieve the optimal peak shaving, since the upper threshold depends on the day-ahead load forecast. Charging cycles can also conduct under high load conditions, as the goal is to always keep the BESS at high SoC levels in order to encounter the next power peak. From the economic perspective, the EPEX spot price is not considered for the BESS charging cycles, since a price forecast model was not developed in the context of this study.

Table 8 : Monthly peak shaving in MW for each year under assessment

Use Case	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	AAD
Optimal case	2019	1.25	1.12	1.25	1.08	1.25	1.20	1.24	0.99	1.17	0.86	1.11	1.05	-
	2020	0.88	1.25	0.87	1.23	1.10	1.25	1.09	1.24	0.86	0.95	1.23	0.89	-
	2021	0.91	0.95	1.25	1.25	1.25	0.92	1.21	1.19	0.91	0.86	0.94	0.88	-
	2022	0.81	0.84	1.22	0.95	0.92	1.22	-	-	-	-	-	-	-
Control scheme using MIMO	2019	1.25	1.02	1.25	0.43	0.00	0.54	0.46	0.00	0.00	0.16	0.74	0.20	0.63
	2020	0.00	0.72	0.56	0.48	0.01	0.79	0.67	0.00	0.00	0.31	0.76	0.19	0.69
	2021	0.32	0.00	1.25	1.25	0.18	0.24	1.04	0.79	0.13	0.25	0.05	0.12	0.57
	2022	0.46	0.40	1.01	0.71	0.20	0.88	-	-	-	-	-	-	0.38
Control scheme using PEAK	2019	1.25	0.99	1.25	0.43	0.00	0.55	0.46	0.00	0.00	0.73	0.69	0.19	0.59
	2020	0.00	0.72	0.56	0.48	1.25	0.88	0.44	0.00	0.00	0.31	0.84	0.20	0.62
	2021	0.66	0.37	1.25	1.25	0.18	0.26	1.13	0.79	0.16	0.32	0.05	0.13	0.50
	2022	0.52	0.58	1.12	0.71	0.80	0.88	-	-	-	-	-	-	0.22

In terms of the monthly peak shaving, Table 8 shows the results of each year under assessment in the optimal case, as well as when applying the control scheme with the use of day-ahead load curve forecasts and day-ahead peak load forecasts. In the optimal case, it is evident that maximum peak shaving of 1.25 MW cannot always be achieved, as the optimization aims to minimize the total operation cost including both power and energy cost components. The EPEX spot price variations can be high especially in 2022, hence, peak shaving may lead to lower savings compared to the energy procurement cost reduction. When the control scheme is applied, the peak shavings can have higher fluctuations than the optimal case, ranging from 0 MW to 1.25 MW. For the assessment of the control scheme, the absolute average deviation (AAD) of peak shavings from the optimal ones is calculated in MW for each year. It is evident that when using the day-ahead peak load forecasts smaller deviations can be achieved for the period 2019-2021. On the contrary, the day-ahead load curve forecast can lead to lower AAD from the optimal savings for the 6-month period of 2022. Apart from the year of 2020, where the AAD increase, the AAD decreases over time. This can also be an indication that the use of additional historical data for retraining the load forecasting model can improve the accuracy of monthly peaks, and hence, the performance of the proposed BESS control scheme.

Table 9: Summary of BESS technical results on annual basis.

	Optimal case				Control scheme – MIMO				Control scheme – PEAK			
BESS Characteristic	**2019**	**2020**	**2021**	**2022**	**2019**	**2020**	**2021**	**2022**	**2019**	**2020**	**2021**	**2022**
Number of full cycles	326	328	331	160	77	43	57	33	61	37	53	31
E_{thr} **(MWh)**	1.20	1.17	1.14	1.20	0.29	0.16	0.20	0.25	0.23	0.13	0.19	0.24
$P_{bess}(t)$	[-1.25 1.25]				[-1.25 1.25]				[-1.25 1.25]			
BESS losses (MWh)	56.3	58.2	59.4	27.9	11.9	6.8	9.1	5.1	9.4	5.9	8.5	4.8
$L_{bess}(yr)$ **(%)**	3.23	3.24	3.16	2.02	2.07	2.05	2.05	1.17	2.07	2.05	2.06	1.17

Table 9 summarizes the main technical outcomes from the simulation of each year under assessment. The BESS control scheme based on forecasts of either day-ahead load curve or peak load leads to considerably lower BESS utilization compared to the optimal case. The main reason of this behaviour is that the proposed technique focuses exclusively on the reduction of power peaks and not on the reduction of energy costs. On the other hand, the theoretical optimum is defined considering the EPEX Spot profile, thus, the optimal BESS operation combines both peak shaving and energy arbitrage strategies. The annual equivalent number of cycles when applying the control scheme is less than half of the respective value for the optimal case. Similar conclusions can be drawn with respect to the average daily energy throughput, annual BESS losses, and maximum BESS power. Concerning the annual BESS ageing, it is also evident that the proposed method results in lower battery degradation. Furthermore, an average annual BESS degradation of 2.06% can lead to a capacity depletion of about 20% after almost 11 years of operation. Hence, when an end-of-life (EoL) criterion of 80% is assumed for the remaining battery capacity, the proposed method can be applied for up to 10 years without any BESS upgrades.

Table 10: Annual savings on cost components from BESS operation.

Savings (kCHF)	Optimal case				Control scheme – case A				Control scheme – case B			
	2019	**2020**	**2021**	**2022**	**2019**	**2020**	**2021**	**2022**	**2019**	**2020**	**2021**	**2022**
C_{peak}	122	115	113	54	54	40	51	33	59	51	59	42
C_{epex}	0.2	0.9	0.5	0.1	-0.6	-0.3	-0.7	-0.3	-0.5	-0.2	-0.6	-0.3
C_{use}	3.9	3.8	3.7	1.9	0.9	0.5	0.7	0.4	0.7	0.4	0.6	0.4
C_{tot}	126	120	117	56	55	41	50	33	59	51	59	42

The economic assessment is also conducted for the period 2019-2022 including the first six months of 2022. From our study, it was evident that more than one services need to be provided by the BESS in order to enhance the utilization and depreciate the investment cost. Besides the attractive peak shaving operation, the latest fluctuations of the energy prices have led to additional profitable services, e.g., frequency support. As a result, the study aims not to provide an analytical business model for the whole project horizon of BESS investment, but to define the potential of cost savings with peak shaving in a real use case. As depicted in Table 10, the optimal annual savings range from 126k in 2019 to 117k in 2021, while at the first half of 2022 total savings of 56k could be achieved. It is remarkable that peak shaving can lead to the major part of the annual savings, while the savings on energy costs are negligible. Furthermore, in our study, emphasis is given on peak shaving for improved grid operation, since the use of network assets for decrease in energy purchase costs is not allowed according to the unbundling rules for network operators. Particularly, in Switzerland and also in other countries, a BESS cannot be utilized for energy arbitrage applications by the DSO due to the unbundling requirements enforced by the regulatory framework. Therefore, we aim at decreasing the power peaks, while not deteriorating the energy costs. When applying the control scheme, the relative savings from peak shaving compared to the optimal ones increase year by year apart from the year of 2020. The decline in BESS performance in 2020 is due to the lower accuracy of load forecasts due to changes in load patterns caused possibly by the COVID-19 restrictions. In particular, the relative savings from peak shaving increase from 44% in 2019 to 62% in 2022 when using the day-ahead load curve forecast. Moreover, the respective values with the use of day-ahead peak load forecast range from 48% in 2019 to 78% in 2022. The gradual improvement in annual savings also indicates that the retrained load forecasting models can also have a significant impact on the performance of the proposed BESS control scheme. It is evident that the control scheme shows better performance in combination with the day-ahead peak load forecast. Besides that, the proposed BESS operation does not lead to additional charges due to the energy purchase, though the algorithm does not consider the EPEX Spot price profile. In terms of the network usage costs, it is noticeable that the BESS can also lead to savings, since the charging cycles do not result in additional energy costs for the operator. However, the BESS can achieve low savings due to the low network usage tariff both in the optimal case and when applying the control scheme.

4.5 Sensitivity Analysis - Results

The worst-case scenarios are displayed for each network under examination, however, additional scenarios can be found in the deliverable “Sensitivity analysis of prospective flexible loads, generators and future loads.”

In terms of the TS15 network, 27 new HPs are combined with 27 new PVs and 27 EVSEs.

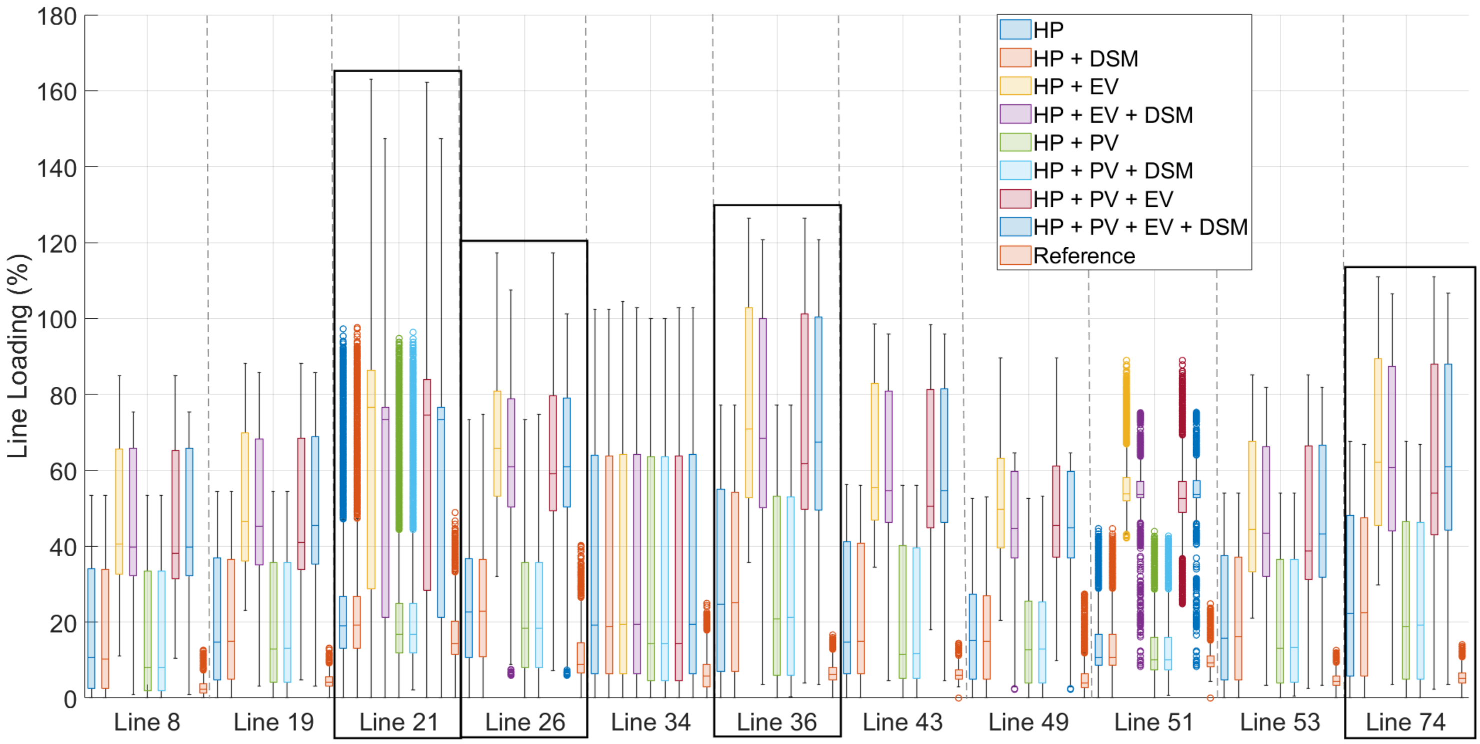

Figure 19: Most loaded lines of TS 15 grid for scenarios with 27 new HP, 27 new EVSE and 27 new PV.

As shown in Figure 19, the lines 21, 26, 36 and 74 need to be replaced, otherwise, the worst-case scenario of TS 15 cannot be deployed. In the HP case, it is noticed that the DSM can decrease the peak loadings of some cables (19, 36, 43, 53 and 74). In the mixed cases of HP + EV and HP + PV + EV, the DSM can also reduce the peak loadings of most cables. The PV integration seems not to affect the peak loadings of most cables, though the boxplots are shifted to lower loadings showing that the peak HP and EV demand take place at times with low or zero solar irradiance yield.

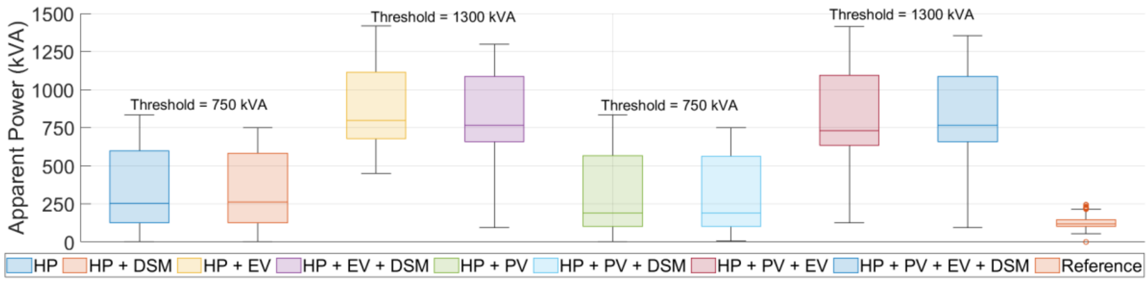

Figure 20: Apparent power of TS 15 grid for the cases of the worst-case scenario.

Next, the apparent power at the transformer level is examined, as shown in Figure 20. It is clear that the realization of HP + EV case requires the replacement of the existing transformers with one that has higher capacity than 1250 kVA. Since peak loadings of more than 1400 kVA can occur, a transformer of 1500 kVA is needed with an additional one of the same capacity for redundancy. As for the DSM method, peak loadings reduce, though they cannot always remain under the DSM thresholds, such as in the HP + PV + EV + DSM case, since the disconnection of EV or HP is decided stochastically by the end-customers.

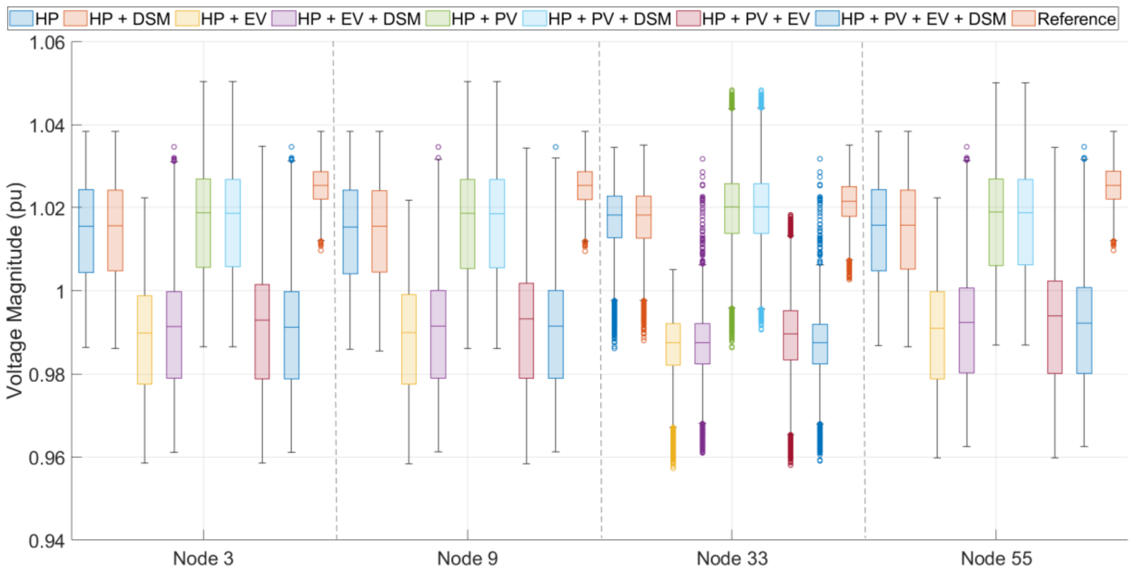

Figure 21: Most loaded nodes of TS15 grid for the cases of the wors-case scenario.

Concerning the voltage magnitudes, no violations of the statutory limits occur in all cases of HP scenario 3, as illustrated in Figure 21. On the one hand, it is noticed that the DSM method has neglective impact on the voltage magnitudes in the HP and HP + PV cases. On the other hand, the DSM can slightly increase the minimum voltages in the mixed cases HP + EV and HP + EV + PV cases due to the shift of EV demand. Though the DSM can also increase the maximum voltages in the HP + EV cases, the peak voltages seem not to be affected by the DSM in the mixed case HP + PV + EV.

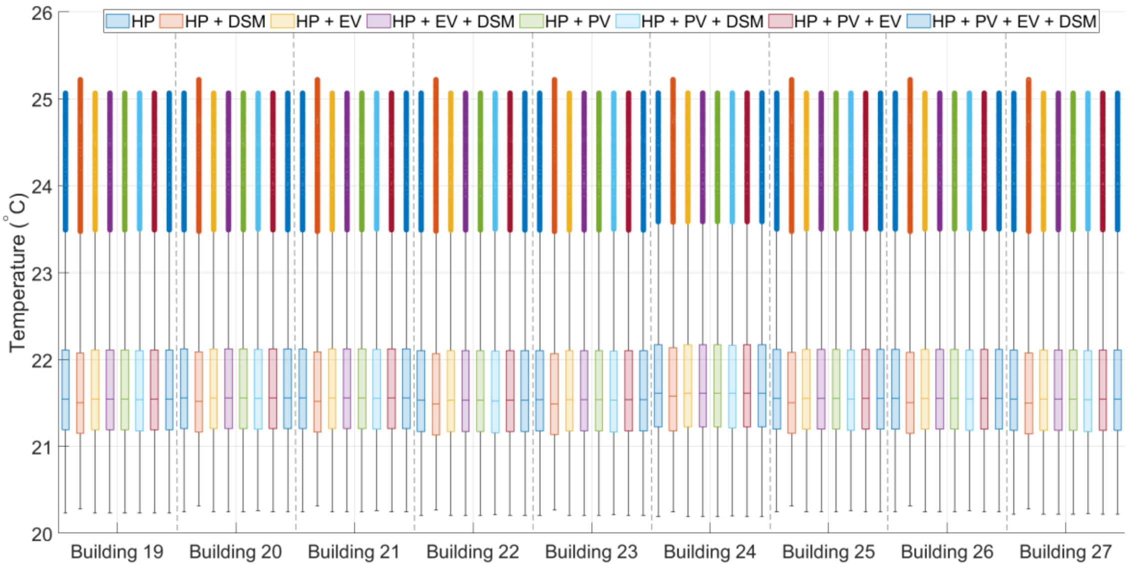

Figure 22: Boxplots of building indoor temperature for the 9 buildings equipped with HP.

As for the indoor temperature of buildings equipped with a HP, it is concluded that it can drop under the temperature setpoint of 21°C for short periods of the year. In Figure 22 we display the indoor temperature of the new 9 buildings equipped with a HP in scenario 3. It should be highlighted that the predefined DSM thresholds can have a high impact on the customers' thermal comfort. It was concluded that lower DSM thresholds can result in lower minimum indoor temperatures deteriorating the customers' thermal comfort. Consequently, the selection of DSM thresholds is a trade-off between the customers' thermal comfort and the network operation.

As for the TS 1 network, 51 PVs, 73 HPs and 99 EVSE are combined for the worst-case scenario.

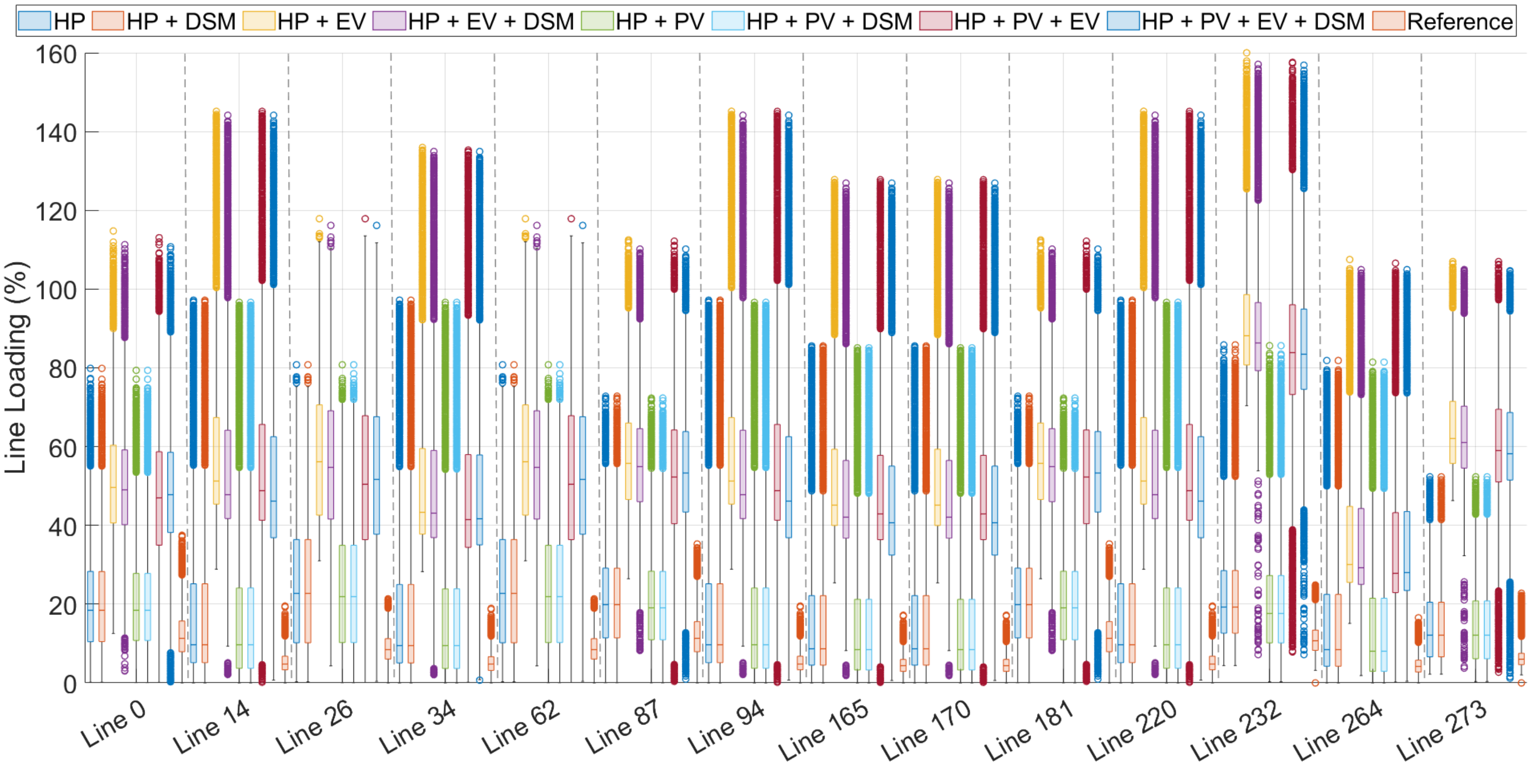

Figure 23: Most loaded lines of TS 1 grid for the scenario with additional 73 HP, 99 EVSE and 51 PV.

It is concluded that the EVSEs can lead to overloadings on 22 cables which need to be replaced in order to realize the worst-case scenario of TS 1. As shown in Figure 23, the HPs and PVs do not cause additional overloadings without the EVSE presence, since the cable loadings do not exceed the cable ratings. When applying the DSM, the peak loadings are not affected in the HP cases, while a slight reduction of peak loadings is noticed in the HP+EV and HP+EV+PV cases.

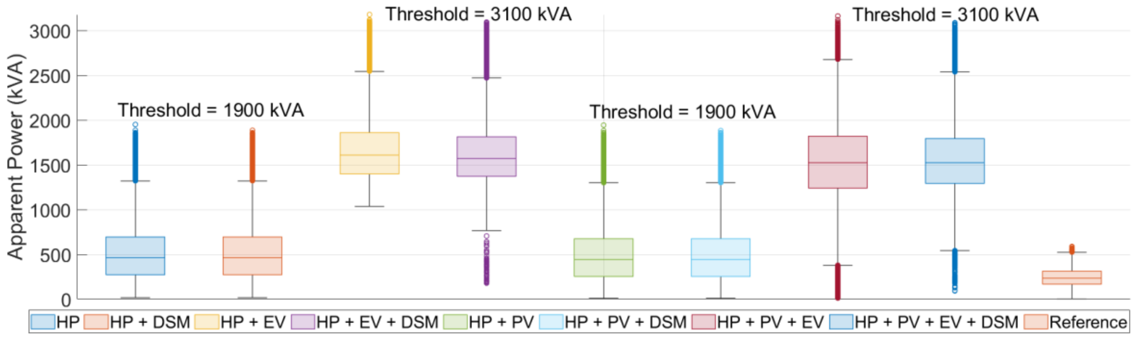

Figure 24: Apparent power of TS 1 transformer for the cases of the worst-case scenario.

Regarding the apparent power of TS 1 transformer for the worst-case scenario, it can be noticed in Figure 24 that the integration of HPs and EVSEs requires the substation reinforcement. In particular, two transformers of 3500 kVA are needed for the realization of HP scenario, as also concluded the EV scenario 3. Hence, the EVSE units determine the suitable capacity of the distribution transformers. Concerning the impact of DSM method on the transformer apparent power, similar conclusions with the previous scenarios are extracted.

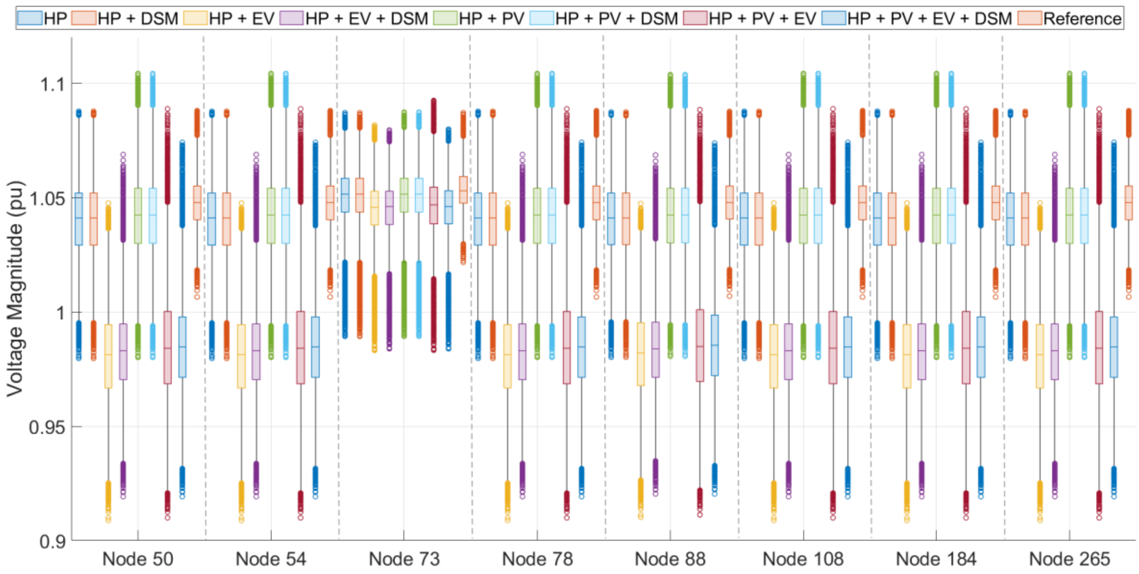

Figure 25: Most loaded nodes of TS1 grid for the worst-case scenario.

In terms of the voltage magnitudes, Figure 25 displays the most loaded nodes of TS1 distribution network for the cases of scenario 3. Though the voltage magnitudes exceed shortly the upper voltage limit of 1.1 pu, they comply with the specific requirement of the EN 50160 to remain inside the range [0.9 pu 1.1 pu] for 95% of the week [21].

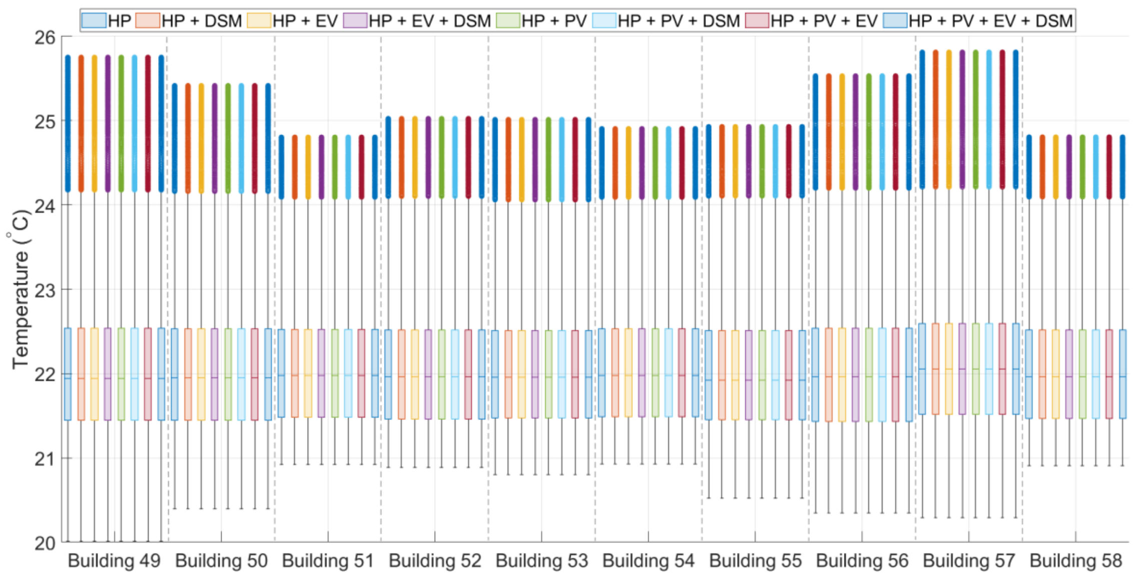

Figure 26: Building indoor temperature for buildings equipped with HP in the worst-case scenario of TS1 grid.

In terms of the building temperatures, Figure 26 displays the boxplots for some of the buildings equipped with a HP in the context of the worst-case scenario for the TS1 grid. It is evident that the minimum and maximum temperatures can vary among the presented buildings. In addition, the DSM seems not have negative impact on the minimum temperatures, which can drop to 20°C.

5 Conclusions

A robust KPI framework was developed for the calculation of the KPIs, not only for the Swiss pilot, but also for other types of smart energy systems (SESs). With the use of the proposed framework, SESs installed in application areas of different scales are evaluated. The KPIs for each case are defined based on the application area, involved stakeholders, SES requirements and stakeholders' objectives. The framework robustness is shown in three different cases based on the international SONDER consortium: (i) BESS control at city level, (ii) control of energy community storage and distributed energy assets at energy community level, and (iii) control of datacenter at building level. Finally, the future scenarios examined in the frame of sensitivity analysis performed for the project, were presented.

The efficiency and effectiveness of all the developed prediction approaches have been assessed on real data from the Arbon pilot and demonstrated in the report. Given the size and quality of the pilot we may say that the provided assessment has solid relevance. In fact, it is demonstrated that standard time-series predictors (like RNNs) are suitable for the task of load forecasting in the scope of BESS control, given the simplicity and ease of training as their core strength. When it comes to peak forecasting, the PEAK approach of optimizing only on the peak future value, and not the full load curve proves as the most suitable method. With this approach, we achieved better than industry standard results in peak shaving and peak forecasting

GNNs demonstrated as superior approach for predicting multiple signals from the grid, both at single meter level and at mid-level of aggregation, where hundreds of meter signals are summed together in clusters. In the context of BESS control, GNNs didn't show practically convenient in predicting the total MV transformer load, since they provide modest improvement compared to the GRU-RNN baseline. This is explained by mismatch between node signals sum and global attribute, due to network losses and data collection problems. In the context of multivariate time series forecasting, GNNs are more efficient in terms of trainable parameters and are easier to regularize compared to RNN with fully connected feature extraction. They can thus be trained without overfitting in an easier manner. GNNs hold the greatest potential for IoT applications with multiple time series signals, and also to incorporate other signals like weather forecasts, that might give greater boosts in performance. Online adaptation shows as a viable alternative, especially when the model has been already trained on multiple years and does not benefit much on full re-training from scratch.

We developed a rule-based control scheme for optimal peak power shavings with the use of BESS. The BESS operation depends on the day-ahead load prediction, the transformer measurement, as well as the peak power of the previous timesteps of the month. Regarding the forecasting model, a non-linear deep learning predictor based on a GRU-RNN shows promising load forecasting performance. In particular, the PEAK predictor achieves forecasts of higher accuracy than recurrent forecasting models that predict the full load curve. Leveraging multiple years of data, the accuracy of forecasts can increase by periodically retraining the model and adapt it to the new test conditions. Concerning the BESS control scheme, the relative savings from peak shaving can increase year by year ranging from 48% in 2019 to 78% in 2022 compared to the theoretical optimum with perfect forecast. Moreover, the BESS can achieve higher savings with the PEAK predictor than the MIMO predictor indicating that peak shaving operation needs to be based on peak load prediction and not on full load curve prediction. The proposed algorithm does not also cause negative effects on the costs related to energy procurement and network usage fees. In addition, the control scheme leads to annual battery ageing rate of 2%, leaving space for further BESS utilization in the context of other services.

A sensitivity analysis for future integration of PVs, EVs and HPs into the distribution networks of Arbon city has been conducted. From the analysis, it is concluded that the TS15 grid can host up to 27 new PVs of 10 kW and 24 kW without causing voltage or thermal issues on network lines and transformers. Moreover, the TS 1 network can host up to 51 new PVs of the aforementioned capacities. In terms of the EV and HP scenarios, it is clear that network reinforcement measures are required. In particular, the TS 15 can accommodate up to 27 new EVSE of 1-13 EV chargers and 27 new HPs provided that four cables are upgraded and both transformers of 630 kVA are replaced with new units of 1500 kVA. In the same manner, the TS 1 network can host up to 99 new EVSE of 1-24 EV chargers and 73 HPs, provided that 26 cables are upgraded and both transformers of 630 kVA are replaced with new ones of 3500 kVA. The examined DSM technique decreases the peak power at transformer level without reducing the loadings of grid cables. Since the period of high demands of EVs and HPs do not coincide with the period of high PV production, it is crucial to implement DSM techniques based on local smart metering measurements. In this manner, the grid upgrade measures could partially be deferred mitigating the expected high loadings due to the high integration EVSE levels.

PQ devices have already been deployed at the distribution networks of Arbon city. Moreover, PQ measurements are collected by the distribution transformers and were used for the evaluation of the BESS controller and the sensitivity analysis. The performance of the proposed BESS control scheme based on the peak load forecasts was evaluated for the period 2019-2022 only in a simulation environment. The assessment of the BESS method in a real-time virtual operation was extensively discussed with the third-party energy service provider, however, it has been postponed due to technical barriers on the deployment stage. The DSO Arbon Energie AG is going to discuss further with the third-party company about the possibility of integrating our approach for peak shaving purposes in the future.

Project activities and achievements have been properly disseminated and technology transfer with industrial partners (in particular Siemens) performed, which guarantees survival of the results beyond the end of the project.

6 Outlook and next steps

The smart city of Arbon has served as a perfect testbed for investigating various load prediction models. Given the results, we do believe that advanced spatio-temporal graph neural networks techniques will be used in future industry applications for short-term (near real-time) load forecasting. The solutions will be scaled to meet forecasting requirements in different IoT scenarios at various level spanning from single signals (i.e., smart meters to regional level) being at the same time able to support online learning and adopt to the changes in the grid.

In the context of the prediction models and related algorithms the proposed BESS control scheme could be assessed for the second half of 2022, since the results of the first half are very promising. To bridge the gap with the optimal forecast use case, collecting and using additional input data might be beneficial. In particular, we expect all forecasting models could benefit from considering weather forecasts as additional exogenous variables (e.g., daily forecasts of temperature, solar irradiance, rain precipitation).

In the context of Sensitivity Analysis, there is potential to extend this study considering additional inputs and applicable DSM methods. It would be useful to examine to which degree the DSM methods can affect the customers' comfort level related to the EV charging load, the indoor building temperature and the DHW temperature. Apart from the proposed DSM technique, which focuses on the reduction of transformer power peaks, decentralized approaches based on local measurements can also be tested in a future work. Finally, the installation of EVSEs and PVs at public network nodes based on future plans provided by the DSO could also be examined in an extension of this study.

In the frame of demonstration setup and solutions assessment, the project envisages the validation of the proposed BESS control scheme in the real field with the main goal to achieve the optimal peak load shaving in the distribution grid of Arbon city. So far, the evaluated method has not been tested in a real field, however, the experimental results could provide crucial guidelines related to its continuous application, as well as any improvements that may be required.

7 National and international cooperation

The collaboration with industrial partners Arbon Energie AG and Siemens Schweiz AG has enabled us to get access to the valuable collection of load and PV data from the city of Arbon, which was of crucial importance for all the research work presented. The practical subject matter knowledge of the companies was of great help in all the phases of the project. On the other hand, we have performed technology transfer to industrial partner (Siemens Schweiz AG) of all the developed load forecasting and graph neural network methods and tools. A significant outcome has been the sharing of our python research library (https://github.com/TorchSpatiotemporal/tsl) completely developed at USI. tsl aims at accelerating research on neural spatiotemporal data processing methods, with a focus on Graph Neural Networks, and has been used for the training and evaluation of all our load forecasting models. We have shared this codebase with Siemens and made ourselves available for tutorials and knowledge transfer.

With respect to scientific-research activities, continuous cooperation is carried out between academic institutions for the sake of development of the foreseen scientific methods and achievement of project goals. In particular, the institute of Electric Power Systems of Fachhochschule Nordwestschweiz (FHNW) has made progress in the development and evaluation of both optimization schemes for BESS while USI advances development and assessment of novel machine learning techniques combined with suitable clustering methods for the accurate prediction of load demand curve. The collaboration between academic partners has resulted in a common publication that has been submitted for peer review at a relevant international conference in 2022.

The international SONDER consortium consists of European partners from Austria, Sweden and Switzerland. While the Swiss test case focuses on the exploitation of the flexibilities provided by the optimal utilization of a central BESS unit at regional level (city of Arbon), the Austrian and the Swedish pilots investigate the integration of innovative models and technologies into local energy communities (Liesing – Austria) and data centers (Luleå – Sweden), respectively.

As for the Austrian partners, the Institute of Computer Technology (ICT), of Technical University (TU) Wien, is the academic institution participating in SONDER. The Technology Platform Smart Grids Austria, which is also involved in SONDER, is an association of relevant stakeholders in the field of electrical power supply and is responsible for the presentation of SONDER results to the Austrian companies. Industrial partners that are going to play consultancy roles in the project are PowerSolution Energieberatung GmbH and Allmobil GmbH.

The MIMO predictor was re-trained and used for the collaboration with Austrian partners, in particular to forecast the energy load of a LV distribution network. These predictions were used to investigate the control of the stationary BESS of an energy community.

It was re-trained and applied also on smart meters data from an energy community in Vienna. The data was confidentially shared by PowerSolution.

Regarding the Swedish partners, the academic institution is the University of Technology in Luleå, while two datacenters, RISE SICS and ACON, will be used as test cases for the application of the proposed methodologies.

Since the test cases have several similarities, the international cooperation as organized by ERA-Net SES Group promotes the knowledge exchange with the main goal to achieve the application of innovative energy management strategies both at local and regional energy systems.

In the context of the international collaboration with the Austrian and Swiss partners, a robust key performance indicator (KPI) framework for smart energy systems (SES) of different scales has also been developed. The KPI framework can be applied to any type of SES regardless of the application area and considers the main SES requirements the involved stakeholders' objectives. Besides that, a benchmark bi-level framework is developed, where the proposed control scheme of stationary energy storage systems for peak shaving is coordinated with the operation of energy community operators (ECO) that focus on optimizing both peak shaving and self-consumption at the EC level. This work is also considered an application of the KPI framework, as various SES, e.g., BESS and decentralized energy assets, are controlled based on the involved stakeholders' goals.

8 Communication

As academic institutions, we are mostly oriented toward presenting our work at scientific conferences. The most important of such events was the International Joint Conference on Neural Networks (IJCNN'20), held in July 2020 in an online form, where we have presented the paper of [3]. The paper [12] has been presented in Padua in July 2022 again at International Joint Conference on Neural Networks (IJCNN'22). Both Swiss academic partners made presentations at JPP ERA-Net SES Conferences in 2021 and 2022.

The annual international project meeting was held in Lugano in April 2022. Regular monthly PCT (Project Core Tram) meetings are organized online. As for Swiss partners, annual project meetings with all the partners i.e., FHNW IEE, USI and Arbon Energie as well as SIEMENS Schweiz AG, have been carried out to review the progress and define future steps. Apart from that, regular online monthly meetings were held, where the detailed actions for the Swiss test case were discussed.

In the context of national collaboration, a study on the proposed BESS control scheme has been published in the peer-reviewed journal "Sustainable Energy Grids and Networks" [23]. Besides that, the work on the sensitivity analysis is also planned to be published in the future. As for the international collaboration, the KPI framework was presented in the 2022 International Symposium on Industrial Electronics (ISIE 2022), in June, in Alaska [24]. Furthermore, an extended version of the KPI framework has also been published in the journal Energies [25]. Within the context of the sensitivity analysis, the FHNW IEE has also submitted a short version of the sensitivity analysis on Bulletin.ch and has been accepted for publication [26]. Finally, a study, which evaluates both rule-based, model predictive control (MPC)-based and hybrid approaches for the control of stationary BESS and distributed energy resources of energy communities, is going to be submitted to a peer-reviewed journal next month.

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