Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

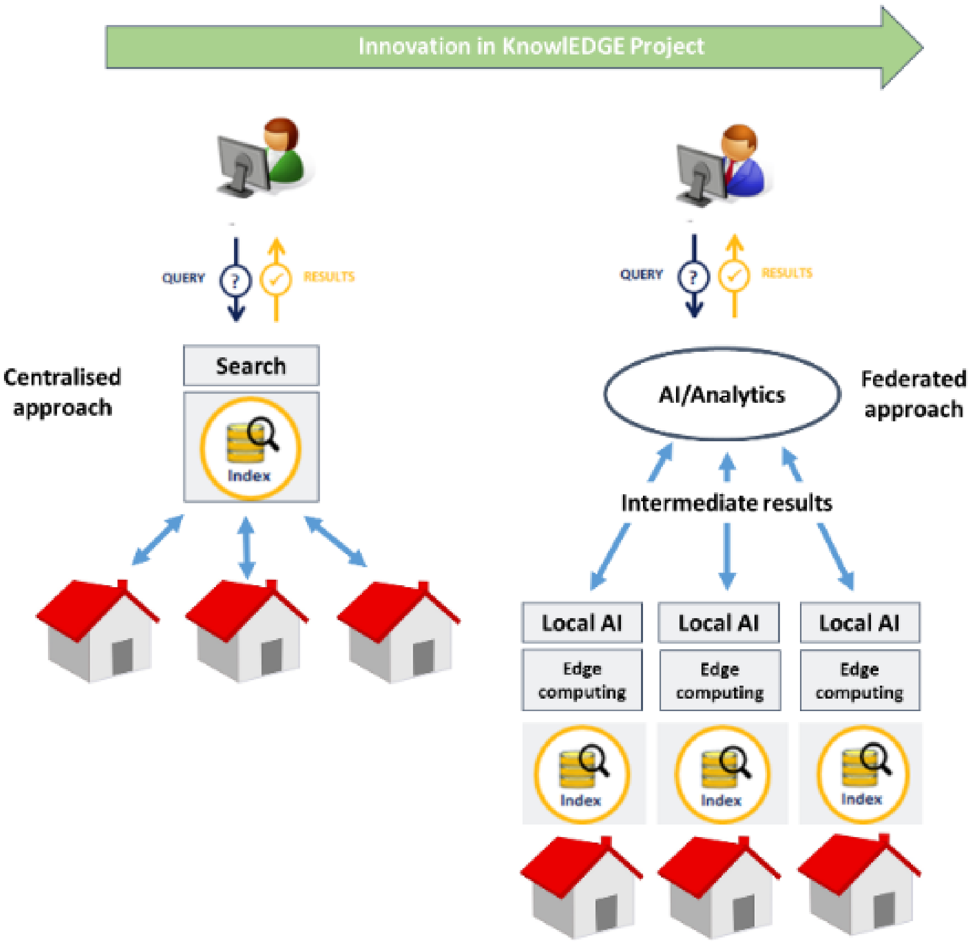
Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

Final report dated 30 March 2024

KnowlEDGE

Decentralised, secure, and privacy-protecting AI to improve grid reliability, resilience, and cost performance for DSOs



Source: HSLU 2021

Date: 30 March 2024

Location: Bern

Publisher:
Swiss Federal Office of Energy SFOE
Energy Research and Cleantech
CH-3003 Bern
www.bfe.admin.ch

Subsidy recipients:
Lucerne University of Applied Sciences and Arts
Technikumstrasse 21, CH-6048 Horw
www.hslu.ch/iet

Landis+Gyr
Theilerstrasse 1, CH-6302 Zug, Switzerland
www.landisgyr.com

VIA Science, Inc.
100 Dover Street, Somerville, MA, 02144, USA
www.solvewithvia.com

Romande Energie SA
Rue de Lausanne 53, 1110 Morges
romande-energie.ch

Authors:
Severin Nowak, Lucerne University of Applied Sciences and Arts, severin.nowak@hslu.ch
Fabian Widmer, Lucerne University of Applied Sciences and Arts, fabian.widmer@hslu.ch
Antonios Papaemmanouil, Lucerne University of Applied Sciences and Arts, antonios.papaemmanouil@hslu.ch

SFOE project coordinators:
Michael Moser, Energieforschung und Cleantech, michael.moser@bfe.admin.ch

SFOE contract number: SI/502076-01

Zusammenfassung

Die Dekarbonisierung der Energieversorgung und die Abkehr von der Kernenergie führen zu erheblichen Veränderungen der grundlegenden Merkmale der Verteilnetze und damit der Verantwortlichkeiten der Verteilnetzbetreiber (VNB). Die Daten von intelligenten Zählern haben das Potenzial, Verteilnetzbetreiber in Zukunft beim Betrieb der Verteilnetze durch daten-basierte Ansätze zu unterstützen. Damit können regulatorische und unternehmerische Ziele für Netzzuverlässigkeit, Resilienz und Kosteneffizienz erreicht werden. In der Regel beruhen solche Data-Science-Techniken auf der Zentralisierung von Daten, führen jedoch zu Verzögerung in der Datenverarbeitung, zu Schwachstellen in Bezug auf Datensicherheit und Datenschutz und schaffen regulatorische Herausforderungen für den VNB oder das Versorgungsunternehmen angesichts der rechtlichen Beschränkungen, die in Bezug auf den Zugriff auf und die Analyse von Verbraucherlastprofilen bestehen.

Das KnowlEDGE-Projekt untersucht daten-basierte Ansätze auf der Grundlage von Smart-Meter-Daten um den Netzbetrieb in Echtzeit zu unterstützen und gleichzeitig Datenschutz- und Sicherheitsbeschränkungen zu berücksichtigen. Das Projekt wendet Algorithmen oder Modelle auf mehrere Datensätze an, ohne sie zu zentralisieren. Dabei werden dieselben Ergebnisse werden durch den dezentralisierten Ansatz erreicht, wie wenn die Daten zentral verarbeitet würden. KnowlEDGE untersucht, wie Algorithmen in Verbindung mit intelligenten Zählern dezentral funktionieren, und berücksichtigt die praktische Integration von KI-Algorithmen und föderierten Analyseansätzen in Wohn-, Industrie- und Gewerbeumgebungen durch Labor- und Feldversuche.

Im Rahmen des KnowlEDGE-Projekts wurde eine dezentrale Lastflussanalyse und Endverbraucher-Lastprognose in einem Feldversuch mit 30 Endkunden in einem Verteilnetz in Rolle VD eingesetzt. Die wichtigsten Beiträge des Ansatzes sind im Folgenden aufgeführt:

1. Ermöglicht Edge-basierte Berechnungen und Vorhersagen von Netzwerkbelastungen in Echtzeit. Im Gegensatz zur bestehenden Smart-Metering-Infrastruktur, die nur alle 24 Stunden 15-Minuten Messdaten überträgt, kann der Netzzustand nahezu in Echtzeit abgerufen werden.
2. Gewährleistet den Datenschutz und vermeidet eine Zentralisierung von Endverbraucherdaten und damit eine effizientere Datenverarbeitung[1].
3. Stellt eine innovative Alternative zum traditionellen Ansatz dar, zusätzliche Messgeräte auf der Trafoebene (Netzebene 6) zu installieren.
4. Stellt eine prototypische Einstellung der Implementierung mithilfe einer IoT-Schnittstelle bereit.

Der vorgeschlagene Ansatz erfordert den Einsatz intelligenter Zähler, die mit erweiterten Rechenkapazitäten ausgestattet sind, um die dezentralen Algorithmen auszuführen. Um Tests an einem realen Verteilungsnetz zu ermöglichen, wurde die Implementierung von Informations- und Kommunikationstechnologie (IKT) auf der Ebene des Verteilnetzbetreibers (DSO) mit einer direkten Internet-of-Things (IoT)-Schnittstelle unter Verwendung des MQTT-Protokolls entwickelt. Der Ansatz eröffnet das Potenzial für eine zukünftige Industrialisierung solcher Lösungen, verspricht eine verbesserte Transparenz der Verteilnetze und letztendlich eine Optimierung des Netzbetriebs.

[1] Das StromVV Art. 8d Abs. 1a & 2a. erlaubt theoretisch die Nutzung von Smart-Meter-Daten der Endverbraucher für den Netzbetrieb, viele Schweizer Verteilnetzbetreiber verfügen aber derzeit nicht über ein System und Prozesse, um diese Daten für den Netzbetrieb sinnvoll zu nutzen.

Résumé

La décarbonation de l'approvisionnement énergétique et la sortie du nucléaire entraînent des changements significatifs dans les caractéristiques des réseaux de distribution et, partant, dans les responsabilités du gestionnaire de réseau de distribution (GRD). Les données des compteurs intelligents ont le potentiel d'aider les GRD à gérer l'évolution du réseau, et ils étudient de plus en plus les techniques avancées de science des données, basées sur les données des compteurs intelligents, pour atteindre les objectifs réglementaires et d'entreprise en matière de fiabilité, de résilience et de rentabilité du réseau. En règle générale, ces techniques de science des données reposent sur la centralisation des données, introduisant des retards dans le traitement des données, des vulnérabilités de sécurité des données et de protection de la vie privée, et créant des défis réglementaires pour le GRD ou le service public, compte tenu des contraintes juridiques qui existent en ce qui concerne l'accès et l'analyse des profils de charge des consommateurs.

Le projet KnowlEDGE étudie des approches basées sur les données des compteurs intelligents qui peuvent améliorer la capacité du GRD à s'adapter à la décarbonisation et à la décentralisation d'une manière qui répond aux contraintes de confidentialité et de sécurité décrites ci-dessus. Le projet applique des algorithmes ou des modèles à plusieurs ensembles de données sans les colocaliser, tout en produisant des résultats équivalents à l'application du même algorithme ou modèle à une base de données centralisée. KnowlEDGE étudie comment les algorithmes fonctionnent en conjonction avec les compteurs intelligents à la périphérie du réseau et envisage l'intégration pratique d'algorithmes d'IA et d'approches d'analyse fédérée dans des environnements résidentiels, industriels et commerciaux par le biais d'essais en laboratoire et sur le terrain.

Dans le cadre du projet KnowlEDGE, une analyse décentralisée des flux de charge et une prévision de la charge des consommateurs finaux ont été déployées dans le cadre d'un essai sur le terrain auprès de 30 clients finaux dans un système de distribution d'échantillons à Rolle VD. Les principaux apports de l'approche proposée sont énumérés ci-dessous :

1. Permet le calcul en temps quasi réel et la prévision de la congestion du réseau en périphérie. Contrairement à l'infrastructure de comptage intelligent existante qui ne transmet que des données avec un intervalle de 15 minutes toutes les 24 heures, les conditions du réseau sont accessibles en temps quasi réel.
2. Assure la protection des données et évite toute centralisation des données des consommateurs, et donc un traitement plus efficace des données[2].
3. Présente une alternative innovante à l'approche traditionnelle consistant à installer des appareils de mesure supplémentaires au niveau du transformateur (niveau de réseau 6).
4. Fournit un paramètre prototype de l'implémentation à l'aide d'une interface IoT.

L'approche proposée nécessite l'utilisation de compteurs intelligents dotés de capacités de calcul améliorées, afin d'exécuter les algorithmes décentralisés avancés. Afin de permettre des tests sur un système de distribution réelle, la mise en œuvre des technologies de l'information et de la communication (TIC) au niveau du gestionnaire de réseau de distribution (GRD) avec une interface directe de l'Internet des objets (IoT) a été développée à l'aide du protocole MQTT. De plus, cette approche ouvre la voie à l'industrialisation future de ces solutions, promettant une meilleure visibilité sur les réseaux de distribution et, à terme, une optimisation de l'exploitation des réseaux.

[2] Alors que l'article 8d al. 1a et 2a du StromVV autorise théoriquement l'utilisation des données des compteurs intelligents de l'utilisateur final à des fins d'exploitation du réseau, de nombreux gestionnaires de réseau de distribution suisses ne disposent pas actuellement d'un système et des processus permettant d'utiliser ces données pour l'exploitation du réseau.

Summary

Decarbonisation of energy supply and a transition away from nuclear energy are driving significant change in the underlying characteristics of distribution networks and hence the responsibilities of the Distribution System Operator (DSO). The data from smart meters has the potential to support DSOs as they manage the changing network, and they are increasingly investigating in advanced data science techniques, based on smart meter data, to achieve regulatory and corporate goals for grid reliability, resilience, and cost performance. Typically, such data science techniques rely on data centralisation, introducing delays in the data processing, data security and privacy protection vulnerabilities, and creating regulatory challenges for the DSO or utility given the legal constraints that exist in relation to accessing and analysing consumer load profiles.

The KnowlEDGE project investigates data-driven approaches based on smart meter data that can improve the DSO's ability to adapt to decarbonisation and decentralisation in a way that addresses the privacy and security constraints described above. The project applies algorithms or models to multiple datasets without co-locating them while yielding results equivalent to applying the same algorithm or model to a centralised database. KnowlEDGE investigates how algorithms work in conjunction with smart meters at the grid edge and considers the practical integration of AI algorithms and federated analytics approaches into residential, industrial, and commercial settings through laboratory and field-based trials.

Within the KnowlEDGE project a decentralized load flow analysis and end-consumer load forecasting has been deployed in a field trial encompassing 30 end-customers in a sample distribution system in Rolle VD. The main contributions of the proposed approach are listed below:

1. Enables edge-based near real-time computation and forecasting of network congestion. In contrast to existing smart metering infrastructure which only transmits 15-minutes measurement data every 24 hours, network conditions can be accessed in near real-time.
2. Ensures data protection and avoids any centralization of end-consumer data, and hence a more efficient data processing[3].
3. Presents an innovative alternative to the traditional approach of installing supplementary measuring devices at the transformer level (grid level 6).
4. Provides a prototype setting of the implementation using an IoT interface.

The proposed approach requires the use of smart meters equipped with enhanced computing capabilities, in order to execute the advanced decentralized algorithms. To allow for testing on a real distribution gird, the implementation of Information and Communication Technology (ICT) at the Distribution System Operator (DSO) level with a direct Internet of Things (IoT) interface was developed using the MQTT protocol. Furthermore, the approach opens the potential for future industrialization of such solutions, promising improved visibility into distribution grids and ultimately optimizing grid operations.

[3] While StromVV Art. 8d para. 1a & 2a. theoretically allows the use of end user smart meter data for grid operation purposes, many Swiss distribution system operators do not currently have a system and processes in place to use these data for grid operation.

Contents

List of Figures

List of Tables

Abbreviations

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
CBA	Cost Benefit Analysis
DC	Data Concentrator
DER	Distributed Energy Resources
DG	Distributed Generation
DSM	Demand Side Management
DSO	Distribution System Operator
DFNN	Dynamic Feedforward Neural Network
ERNN	Equilibrated Recurrent Neural Network
FNN	Feedforward Neural Network
GRU	Gated Recurrent Units
HB-iMS	Handbuch Intelligente Messsysteme (Handbook – Intelligent Energy Systems)
LSTM	Long Short-Term Memory
LV	Low Voltage
MC-CH	Metering Code Switzerland
ML	Machine Learning
MLT	Machine Learning Technique
MV	Medium Voltage
NN	Neural Networks
OPF	Optimal Power Flow
PLC	Power Line Communication
PMU	Phasor Measurement Unit
PQ	Power Quality
PQD	Power Quality Disturbance
QoS	Quality of Supply
RES	Renewable Energy Sources
SCADA	Supervisory Control and Data Acquisition
Seq2Seq	Sequence to Sequence machine learning model
SM	Smart Meter
TCN	Temporal Convolutional Network
THDi	Total Harmonic Distortion (Current)
THDv	Total Harmonic Distortion (Voltage)
ToU	Time-of-Use
TSO	Transmission System Operator

1 Introduction

1.1 Background information and current situation

Decarbonisation of energy supply and a transition away from nuclear energy are driving significant change in the underlying characteristics of distribution networks and hence the responsibilities of the Distribution System Operator (DSO), in particular resulting from the Revised Act on Emission Reductions, the CO2 Ordinance, and the energy strategy for 2050 [1]. DSOs must meet their obligations while accommodating a greater level of distributed generation, electrification of loads such as heating, and an increase in new electrical loads such as electric vehicles.

In addition to legislation relating to a shift in primary energy source, there is an ongoing process of liberalisation in the electricity market, based on the Electricity Supply Act (2008) and the revised Ordinance on Electricity Supply. Under the Supply Act, households and other small-scale power consumers will have the ability to choose their electricity suppliers, and while this aspect of the Act is not yet implemented, utilities and distribution system operators are increasingly preparing for a greater level of liberalisation and consumer choice.

The smart meter roll-out in Switzerland is underway in the context of the energy strategy 2050 as a key part in the digitalization of the power grids: the Electricity Supply Act mandates to have 80% coverage of smart meters by the end of 2027 [2]. The data obtained from smart meters creates a potential opportunity for the DSO to utilise consumption information to support the operation of the distribution network. With the emerging data availability from distribution grids, DSOs are increasingly investigating in machine learning (ML), artificial intelligence (AI) and other advanced data science techniques to achieve regulatory and corporate goals for grid reliability, resilience, and cost performance.

Various research projects are being conducted or have completed in Switzerland that focus on improving the value that can be derived from smart meters, and on applying data analytics to smart meter data. Several projects have investigated ML methods to derive household characteristics from load profiles. These can be used for energy services e.g. [3], [4], promoting energy saving e.g. [4], [5] or providing energy insight to customers and utility companies [6]. There are projects involving artificial intelligence applied to smart meter data, for example the integration of GridSense and smart meter data in [7], looking at the optimisation of real-time energy flows using artificial intelligence.

Typically, data science techniques employed in such projects in power systems rely on data centralisation, introducing data security and privacy protection vulnerabilities, and creating regulatory challenges for the utility given the legal constraints that exist in relation to accessing and analysing consumer load profiles. Although Strom VV Art. 8d technically allows the use of end consumer data to enable efficient grid operation, many DSOs do not have the internal processes in place, to use the data for this purpose. These factors often prevent data utilisation beyond billing purposes, resulting in sub-optimal use of the load profiles. Moreover, smart meter data is typically recorded every 15 minutes, but it is only transmitted to the DSO once every 24 hours. The challenges of accessing, aggregating, and analysing meter data severely limit the rate at which utilities and researchers can adopt and use modern data science techniques (ML or AI). The centralisation process also introduces data security and privacy protection vulnerabilities and creates significant data traffic.

In response, the KnowlEDGE project investigates data-driven approaches that can improve the DSOs ability to adapt to decarbonisation and decentralisation in a way that addresses the data access, privacy and security constraints described above. The project applies algorithms and models to private data without co-locating them while yielding results equivalent to applying the same algorithm or model to a centralised database. KnowlEDGE investigates how algorithms work in conjunction with smart meters at the grid edge and considers the practical integration of AI algorithms and federated analytics approaches into residential, industrial, and commercial settings through laboratory and field-based trials. Finally, it investigates financial, commercial, and operational benefits of deploying edge-based analytics in DSOs, and makes recommendations for regulation, policy, and commercial activities in Switzerland.

1.2 Purpose of the project

The KnowlEDGE project establishes alternative approaches to data aggregation that can significantly reduce the impediments to optimal data utilisation by utilities and develops AI algorithms focused specifically on a set of DSO use cases relating to grid operation activities.

KnowlEDGE develops a federated approach to consumer data analysis that applies an algorithm or model to multiple datasets from different locations without combing them while yielding results equivalent to applying the same algorithm or model to a centralised database.

The DSO use cases under consideration in the project are:

Use case 1: Detecting grid assets' loading for improved visibility of LV network congestion. The project studies how federated analytics can improve the DSO's understanding of low voltage (LV) network congestion and asset loading caused by consumers and distributed renewable energy generation. The approaches developed are intended to improve observability of the LV network (and so by deduction the medium voltage (MV) network), during peak production of decentralised renewable generation.

Use case 2: Predicting future load profiles and load forecasts in the LV and MV network, so helping with grid management, congestion, and curtailment. Currently network forecasting uses a simple extrapolation of future demand based on historical profiles. The project studies how machine learning algorithms and federated analytics can leverage smart meter data to improve the DSO's understanding of future flows in LV / MV networks.

Use case 3: Detecting quality of supply (QoS) issues, network anomalies, Increased RES causes quality of supply issues in the LV network. Current monitoring equipment allows reports to be generated at the substation level, e.g., for EN50160 compliance. However, it is not possible to ensure compliance at the customer location. The project studies how federated analytics can increase the DSO's ability to comply with power quality standards where large, distributed generation is connected.

Use case 4: Predicting network anomalies, quality of supply issues. In a similar way to use case 2, the project investigates how an improved ability to detect network anomalies and quality of supply issues (use case 3) will allow the DSO to predict future issues.

Use case 5: Supporting the implementation of localised tariffs or services. Tariffs are not currently based on specific customer behaviour. There is an opportunity to use federated analytics to improve profiling and build tariffs that motivate consumer behaviour in a grid-friendly manner.

1.3 Objectives

The KnowlEDGE project seeks to prove the value that can be derived by utilities from advanced analytics using federated approaches and investigate their feasibility towards the grid edge. It considers:

(1) How data science algorithms can be designed to reason and learn in a federated manner.

(2) How analytics will be distributed close to where data is collected, studying the role of advanced metering infrastructure.

(3) How the intermediate results will be aggregated together to drive higher-order learning at scale.

(4) The value such higher order learning can provide to the utility, particularly the DSO.

(5) The feasibility of federated analysis approaches to reduce the time, cost and risks to security and privacy relative to centralised analysis approaches.

In the execution of its outcomes, the project:

- validates the use of federated analytics methods for the use cases defined above
- seeks to confirm that the federated approach to analysing advanced metering infrastructure (AMI) data is technically feasible, requires less time and expense, and has fewer data security and privacy protection vulnerabilities than a centralised analysis approach.
- demonstrates that analysis is successful in several configurations, including:
    - in cloud and/or on-premise data repositories owned by a single utility; or
    - in smart industrial, commercial, or residential meters at the “grid’s edge”.
- identifies clear implications for future policy and regulations associated with Swiss energy industry data access and analysis and make appropriate recommendations.

Validation of the KPI’s is achieved through modelling, laboratory tests, and ultimately using field-based trials on smart meters at the grid edge using infrastructures of the project P+D Reel Demo – FURIES (SFOE contract SI/501523-01) in Rolle.

The KnowlEDGE project technical and non-technical objectives are summarised in Table 1.

Table 1 – Project Technical / Non-Technical Objectives and research questions

TO1: Prove the value of applying a federated analytics approach to the use cases identified
Does a federated approach offer a better (more secure, higher resolution) alternative to centralising the data? Can the federated analysis approach reduce or avoid data security and privacy protection vulnerabilities of a centralised approach? What are data access requirements for federated data?
TO2: Prove the value of the AI algorithms in the use cases identified
What is the value of AI algorithms in relation to the use cases identified? Does improved access to data create value for the DSO when combined with PMU measurements? What is the impact on the specification of industrial, commercial, and residential meters? Is additional investment justified?
TO3: Validate, in a laboratory setting and through field tests
Will the decentralised algorithms function? What is the best form of algorithm when considering federation of meter data? Can the decentralised algorithms function in combination with smart meters? How should hardware, location, software be integrated?
NTO1: Document value created for utilities and their customers from the KnowlEDGE project
What are the additional financial costs / benefits from the federated approach? What are the non-financial costs and benefits, such as changes in infrastructure? Is there a gain to be made?
NTO2: Extrapolate lessons from the KnowlEDGE outcomes to inform further development of SFOE’s policy and regulatory framework for data access and sharing within Swiss energy industry.
What intermediate steps are required in existing utility data management protocols?

Uses cases are developed within the project to varying degrees, as shown in Table 2, where grey fields indicate the level of exploitation within the project. The focus for field testing will be use case 1 (Calculating grid assets’ loading using smart meter and PMU data) and use case 3 (detecting network anomalies, quality of supply issues).

Table 2 – Use case development in KnowlEDGE

Project component	Approach for KnowlEDGE				
	Lit. study & SOTA analysis	Develop theoretical basis for implementation	Model-based demonstration	Lab-based demonstration	Field-based demonstration
Federated analytics					
Edge computing approach					
Use case 1 – Detecting loading					
Use case 3 – Detecting QoS issues					
Use case 2 – Predicting loading					
Use case 4 – Predicting QoS issues					
Use case 5 – Localised tariffs					

2 Research approach

Within this section, first an overview of the work packages within the KnowlEDGE project is provided, followed by the uses cases that were developed during the project duration.

2.1 Overview of work packages

The KnowlEDGE project conducted research and validated its effectiveness in a phased series of proofs of concepts, starting first with a literature study where a theoretical base is established. Use cases and solutions were first explored in laboratory simulation in software, then analysis was conducted in laboratory testing on representative hardware and was finally validated in field testing.

KnowlEDGE first investigated the specific use cases within the categories described where data exploration and analysis generate value for consumers and utilities. Use cases relating to network visibility (use case 1 and use case 3) were then progressed to demonstration either in simulation, in the laboratory, or in the field, using a federated approach and incorporating edge processing. The overall approach is summarised in Figure 1.

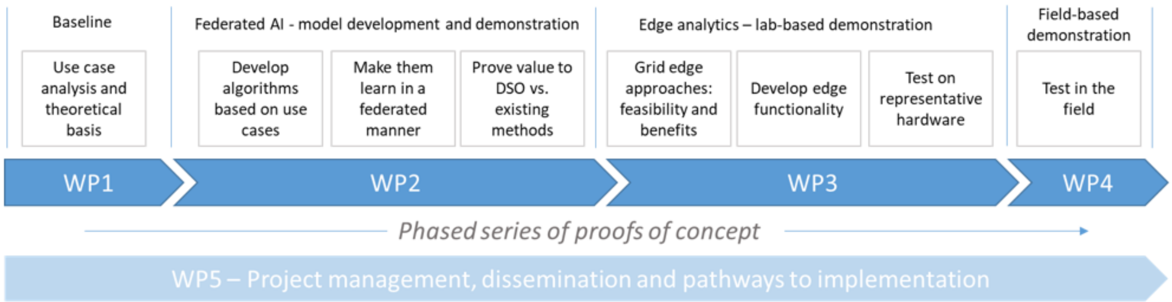


Figure 1 – KnowlEDGE project phasing

2.2 Development of use cases

Specifically, the following concepts have been developed within the KnowlEDGE project to tackle the various use cases:

- **Decentralized congestion calculation to address use case 1:**
  A decentralized load flow algorithm has been developed and implemented based on only meter-to-meter communication between adjacent smart meters. This method facilitates congestion assessment throughout the distribution network without centralizing data, thereby ensuring the aggregation of private data during the process.
  Please refer to Appendix A (Section 7.1) for the developed concept.

- **ML-based load profile forecasting to address use case 3:**
  A machine learning approach has been developed which can be used to forecast end customer loads on smart meter infrastructure. One of the key goals was to enable the personalisation of the ML-model on the specific end consumer. Please refer to Appendix A (Section 7.2) for the developed concept.

- **Detection and Prediction of quality of supply for use cases 2 and 4:**

The latest generation of residential and industrial smart meters provide the full range of power quality metrics as required by EN50160. Therefore, the replication of detecting these quality metrics was not interesting to further pursue. Therefore, we have delved into the estimation of voltage sensitivities at different locations in the distribution grids, however its decentralized implementation is challenging. Please refer to Appendix A (Section 7.3) for the developed concept.

- **Supporting the implementation of localised tariffs or services for use case 5:**
  While this use case was only around state-of-the-art analysis, the implementation of localised tariffs has been researched in a parallel project by the research team and is continued within the AISOP project. Please refer to the publication in [8] for the work on localised tariffs.

3 Field trials and outcomes

This chapter summarizes and discusses project outcomes and presents the field trials. Significant effort has gone into the development of the associated algorithmic frameworks.
Hereafter, the field trial activities and outcomes are presented. This section also represents deliverable 4 of the KnowlEDGE project.

In the field trials, a 6-step-process has been taken in order to come to the final results and analyses. Figure 2 illustrates the 6 steps.

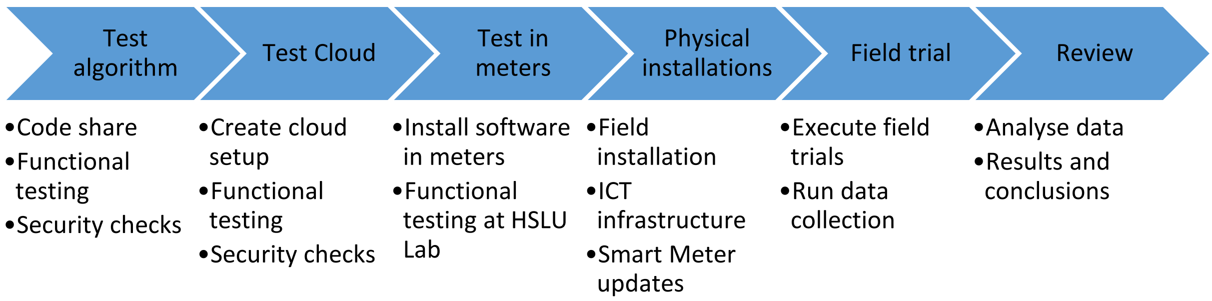


Figure 2 – 6 Steps of process towards field trials in KnowlEDGE

3.1 Description of the test system

Field testing was carried out within the area of Romande Energie in Rolle, using selected infrastructure from the project P+D Reel Demo – FURIES (SFOE contract SI/501523-01). The site at Rolle includes 70 phasor measurement units (PMU's), 100 GridEye units, 750 smart meters, a battery energy storage system, integrated PV, seven remotely controlled stations and a data management system, spread within 36 local LV systems.

A test feeder has been identified within the Rolle area with a mix of multi-family homes, single-family homes, and PV generation units. 30 metering points have been identified within a feeder that was previously equipped with a Depsys GridEye device. The meters in the feeder were replaced with Landis+Gyr S650 industrial smart meters and Landis+Gyr CU-XE remote terminal units (RTU) for the field trials. The RTU is a communication provided by Landis+Gyr which offers a Linux environment to execute dedicated scripts for the field trials. Please refer to Appendix B for specifications of the RTU and the deployment process. This setup allows algorithms to be deployed and operated in customer premises. Customers were approached for an opt-in to use their data for research purposes, even though the data was not directly used or analysed in a raw format, simply for safeguarding purposes.

3.2 ICT Infrastructure

In addition to the deployment of smart meters and RTUs at the customer sites, an IT infrastructure has been established to enable safe and secure meter-to-meter communication.

The field trial setup uses a Romande Energie private metering subnet via GSM modem to enable communication between the RTUs and the virtual machine hosted by Romande Energie on a Kubernetes cluster. A customized MQTT messaging services has been employed to transfer relevant data between the smart meters. All communication links have been secured via TLS encryption (both MQTT and HTTPS). Romande Energie has managed the TLS certificates via their public key infrastructure. From the virtual machine hosted on a Kubernetes cluster, a concentrator as well as a messaging broker were implemented to orchestrate the algorithms. Simulation results were also written to a data base on the virtual machine, which enabled extraction of results from an operator via remote access to the virtual machine.

Finally, the communication has been configured in a way that HTTPS communication allowed remote access to the RTUs webserver and enabling remote firmware updates of the RTUs. Figure 3 illustrates an overview of the IT-infrastructure established for the field trials. Figure 4 illustrates smart meters that have been deployed at a multi-family home with 5 end customers, including the GSM modem and a switch to enable the communication to the virtual machine.

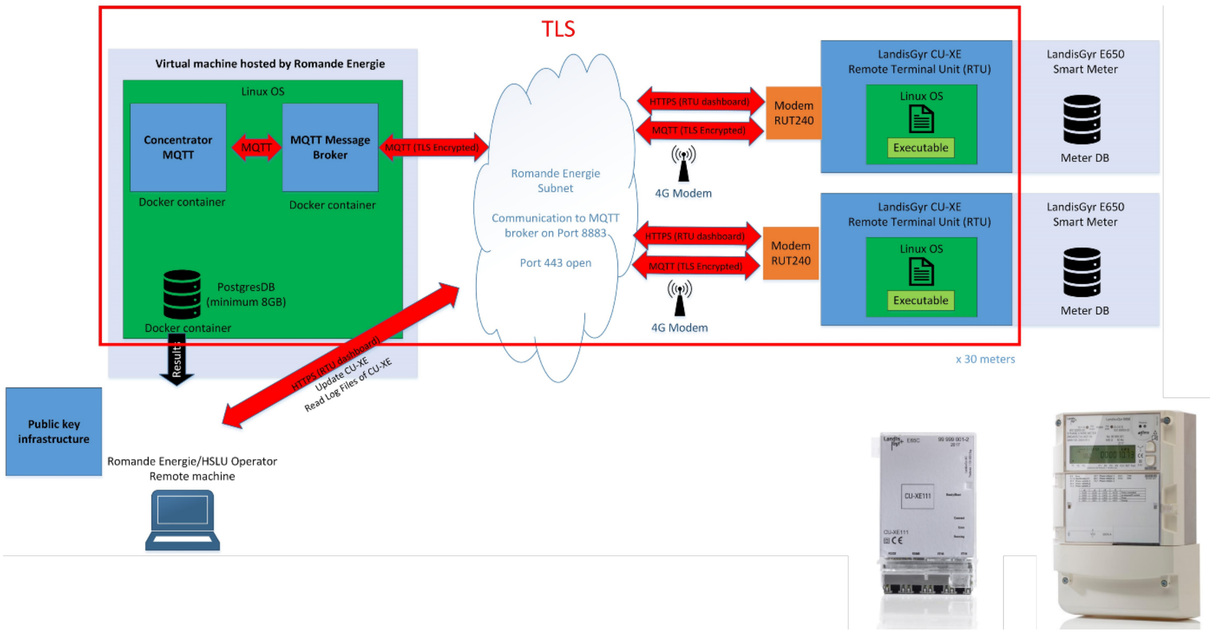


Figure 3 – IT infrastructure set up for field trials

Figure 4 – Installation of smart meter in MFH with 5 end customer and setup with GSM modem and switch

3.3 Outcomes of the field trials

Hereafter, results from the field trials are presented.

Voltage profiles, line/transformer loading profiles and forecasting of transformer loading:
Figure 5 illustrates the field trial results for voltage profiles in all nodes (left) and currents transmission lines/transformers (middle) for an example 15-minute interval. On the (right), the prediction of the transformer load for the next 24 hours is illustrated. The load flow analysis for the past 24 hours using synthetic data aligns with the results obtained from the offline simulations.

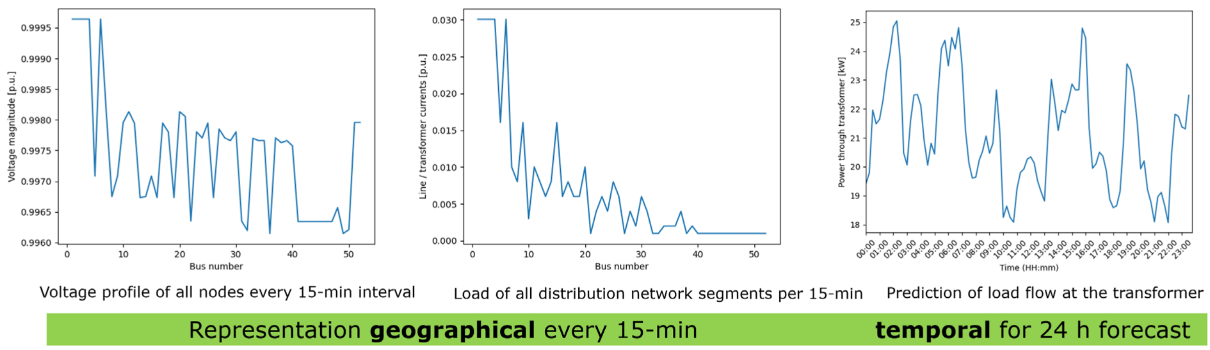


Figure 5 – Summary of load flow and forecasting results

Performance:
The load flow analysis and forecasting are initiated every full hour, analyzing 15-minute values from the past and future 24 hours of load flow across all segments and voltages in each node within the test network. This results in a substantial dataset, comprising approximately 20,000 data points per hour calculated across 192-time intervals, 50 nodes, and 49 edges. In the distribution network of Rolle with

30 end customers, the runtime for both forecasting and load flow analysis is approximately 3.5 minutes. Figure 6 provides a histogram of execution times of the algorithm for two weeks. It is important to note that the runtime is contingent upon the size and topology of the distribution grid due to the sequential nature of the algorithm (refer to Appendix A for a detailed description of the algorithm). For this relatively limited size distribution grid (feeder) it is possible to execute the algorithm in about 3.5 minutes. This is well under 15 minutes, which enables execution in near real-time. The complexity lies in managing the timing and synchronization of various message flows during algorithm execution, presenting a challenge in maintaining efficiency and accuracy in the load flow analysis and forecasting processes. This has been addressed by properly synchronizing the individual edge-devices/smart-meters through the concentrator.

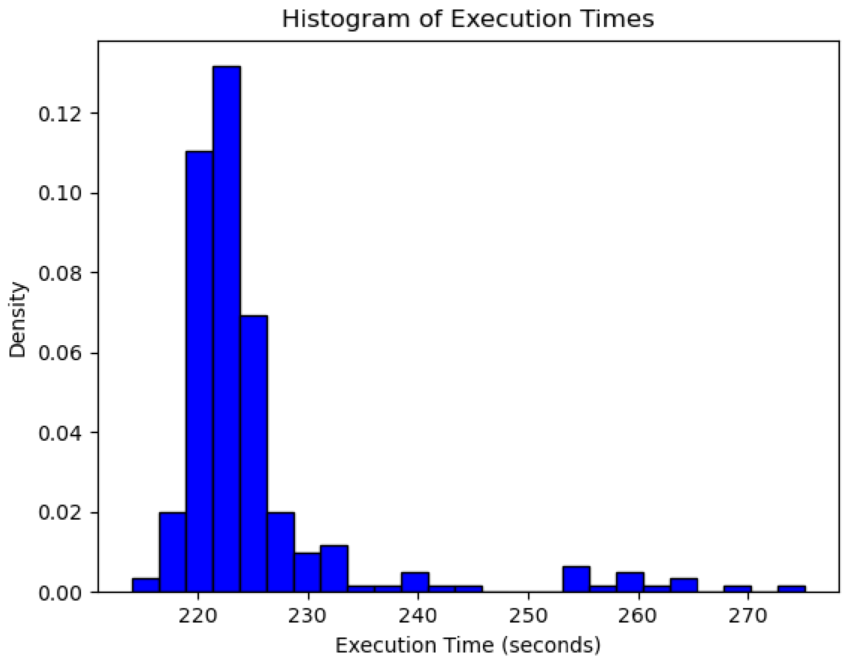


Figure 6 – Histogram of execution times for load flow analysis and forecasting

Deployment of smart meters:

In the initial phase of the field test, the 30 customers in the test system were contacted through opt-in letters, aiming to replace the existing smart meters with new ones hosting the KnowlEDGE software into their homes. Remarkably, 29 of the contacted end customers accepted to participate in the trial agreeing with the replacement of the smart meter. Some technical challenges were encountered during the installation process, as communication could not be established with four smart meters due to issues such as poor reception and incorrect manipulation. Subsequently, during the test phase, communication was unfortunately lost with three additional smart meters. Despite these setbacks, final tests were conducted with 22 real smart meters, providing valuable insights into the performance and reliability of the approach. This comprehensive field test has not only highlighted areas for improvement but also affirmed the functionality of the majority of the deployed smart meters. Figure 7 illustrates the availability of smart meters for the field trials with 22 smart meters remaining for the field trial.

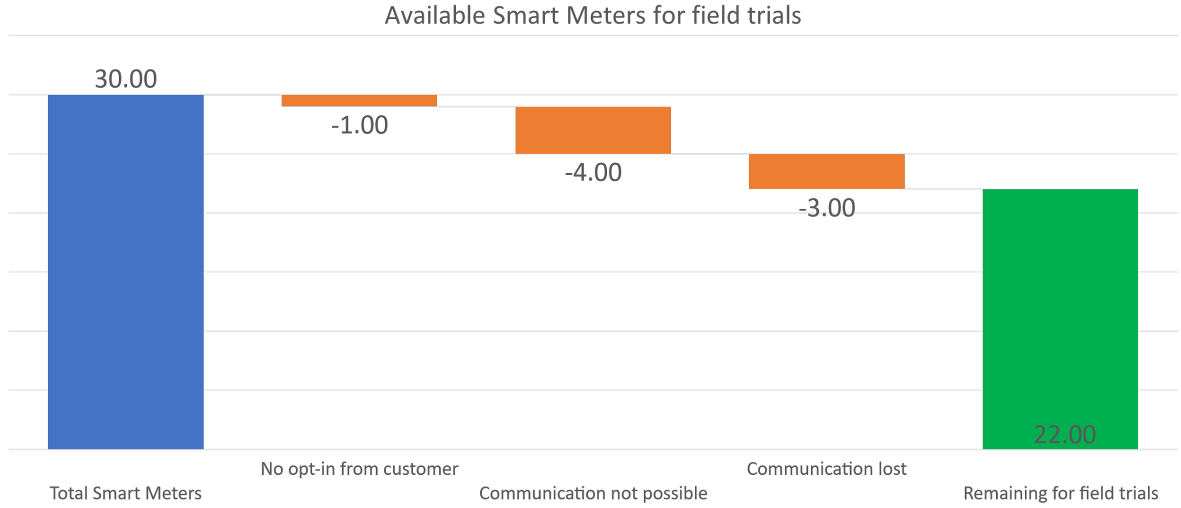


Figure 7 – Available smart meters for field trials

Field test limitations:
Due to the shortcomings as described above, 8 smart meters had to be virtualized, making live data integration impossible for those end customers. While the algorithm is adaptable in the number of end consumers that are included in the calculations, simply dropping 8 smart meters would distort the final congestion results. Consequently, synthetic load profiles were generated to simulate the missing smart meter readings. The live version encountered further challenges as the reading of measured values on smart meters could only be achieved within the controlled environment of the laboratory test setup. Unfortunately, deploying the live version in the actual setup was impeded, requiring an essential software update that could technically be implemented remotely due to the flexibility of the IT infrastructure. Despite these efforts, the field test phase, lasting only one month, imposed limitations on the opportunity for additional iterations of firmware updates. Consequently, the results obtained do not authentically reflect real physical conditions, making direct comparisons with transformer measurements impossible. While troubleshooting of these limitations would be straightforward, the constraints of the field test duration hinder a more comprehensive assessment and refinement of the field trial results via an additional firmware update.

4 Conclusions and main findings

The execution of decentralized load flow / congestion calculation analysis and forecasting marks a significant achievement of the KnowlEDGE project. The proposed method facilitates near real-time computation and forecasting of network congestion at the edge. Unlike existing smart meter systems, which transmit data to grid operators only once every 24 hours, this approach enables near real-time computation of grid congestions and forecasts. Moreover, the system prioritizes data protection and decentralizes end-consumer data, leading to more efficient data processing.

The solution serves as a viable alternative to the installation of supplementary measuring devices at the transformer circuit level, streamlining the integration process without necessitating customer opt-in. This decentralized approach requires smart meters with increased computing capabilities for the additional functionality. The Information and Communication Technology (ICT) implementation at the Distribution System Operator (DSO), featuring a direct Internet of Things (IoT) interface using the MQTT secure protocol, introduces a novel way to interact with field devices for DSOs. Looking forward, the potential for future industrialization of such solutions holds promise for improved visibility into distribution grids, offering a pathway toward optimizing grid operations for increased efficiency and reliability.
The project partners have drawn the following main findings of the project:

- Federated learning can be applied on smart meter data for load prediction.
- The project has demonstrated that **decentralized methods can be applied** supporting the grid operation, which respect data privacy requirements, without ever using personal data, and forgo the centralization of data.
- The approach can offer an **alternative to additional distribution station monitoring** and provide near real-time visibility into the distribution systems.
- In a decentralized approach, **a single device/smart meter/RTU could fail** (even industrial products). It is paramount, that such contingency can be accounted for with a robust, reliable solution. One way to deal with this in the studied approach is the use of synthetic load profiles in the process.
- The **physical implementation of smart meters** with additional resources is relatively straightforward, but the setup and configuration of the IT infrastructure and the cybersecurity considerations are significant challenges involving various stakeholders even internally.
- The project has shown that even **small digitalization projects are challenging** to implement and involve various internal departments and have big complexity in the deployment. The KnowlEDGE project has established a DSO internal process which set a foundation for future projects in the area of digitalization.
- **Potential for future industrialization** on smart meter infrastructure which benefit the grid visibility and operation.

5 Outlook and recommendations

Considering the learnings of the KnowlEDGE project, this section provides an outlook on grid-edge computation and implications for future policy and regulations.

5.1 Outlook on grid-edge computation

The KnowlEDGE project lays a foundation and supports future initiatives that capitalize on grid-edge computation, for example by the utilization of the latest generation of smart meters which enable additional edge-computation capabilities. The paradigm of federated and decentralized data handling has become increasingly important, particularly considering the expanding computational capabilities at the grid edge and ever-increasing amounts of data collected. The KnowlEDGE approach holds promise not only at the lower grid levels but also at higher levels, specifically in the medium voltage (MV) domain where similar algorithms could be applied to calculate congestion levels at transformer stations.

Project partners have engaged in a debriefing on the activities undertaken, exploring future collaborative activities in related domains. It was highlighted, that approaches that leverage the smart meter data will be necessary to implement solutions to harvest end customer flexibility. Furthermore, a new smart meter generation will be rolled out in the horizon of 5 to 10 years, which likely already has additional capabilities. While the additional effort may not look reasonable at the moment to enable edge computation, it is foreseeable that functionalities around edge-based computation and artificial intelligence on smart meters will already be available in the near future by default. One such application could be load forecasting. Based on forecasts of loads, flexible assets could be optimized based on local load and generation forecasts, or tariff signals.

The main project partner (HSLU) is pursuing the conceptual frameworks of grid-edge computation and network calculations and predictions in diverse projects, such as the EraNet funded AISOP project. The AISOP project focuses on operational planning, predicting power flows within the distribution network and formulating dynamic tariffs (use case 5), strategically designed to alleviate congestions in the grid. Romande Energie is also involved as a DSO partner within AISOP.

As such, the KnowlEDGE project has established a foundation on grid-edge processing on smart meters enabling further developments to delve deeper into grid-edge computation, and help advancing the progress of the energy transition.

5.2 Implications for future policy and regulations

Although StromVV Article 8d para. 1a & 2a theoretically permits the utilization of end-user smart meter data for grid operation and planning, many Swiss distribution system operators do not currently have an infrastructure and processes in place to use these data for grid operation. Consequently, internal procedures and tools must be established to harness smart meter data effectively and securely for grid operation and planning purposes. Alternatively, decentralized data processing approaches such as the ones introduced by KnowlEDGE could be leveraged to achieve the same purpose, without centralizing the data.

The significant advantages of incorporating smart meter data into grid operation are evident. Therefore, it is recommended that future regulations consider mandating the use of these data for such purposes. This becomes increasingly important in the future as we transition towards dynamic grid tariffs and procurement of flexibility services to enhance grid operation.

Moreover, leveraging near-real-time data, such as smart meter data at 15-minute intervals, provides significantly more up to date insights into grid operations. Hence, it is advisable to enable access to smart meter data at 15-minute intervals instead of the current 24-hour interval.

6 Dissemination activities

Table 3 and Table 4 indicate the scientific publications and other dissemination activities as well as community engagement during the project duration.

Table 3 - Scientific publications during project duration

Date	Conference/Journal	Title
16/03/2023	Energy and AI Volume 14, October 2023	Data-driven comparison of federated learning and model personalization for electric load forecasting
09/10/2024	13th DACH+ Energy Informatics Conference	Edge-based load forecasting and power flow computation on Smart Meters (in preparation)

Table 4 – Dissemination activities and community engagement during the project

Date	Type	Event / Publication / Journal	Title
26/04/2021	Presentation	AMLD EPFL Conference, Lausanne	Unlocking the future value in private data: opportunities for federated analytics in low voltage electricity networks
02/12/2021	Non-scientific publication	News article, Swissinfo	How could AI help Switzerland shift to renewables?
03/12/2021	Non-scientific publication	Bulletin Article	Mit der Digitalisierung dekarbonisieren
06/07/2022	Conference	LHI Innovationsforum Energie, Poster Session, Zurich	Load curve forecasting
14/07/2022	Presentation	Forum Energie Zürich	Dezentrale künstliche Intelligenz im Stromnetz - Zukunftsmusik?
04/10/2022	Conference	Panel session, AI and Electric Power Summit, Rome	Grand Challenge Session Grid Interactive Smart Communities
15/11/2022	Presentation	Amstein und Walthert, zB 89 EVU der Zukunft	Dezentrale Datenverarbeitung für die Analyse des Netzbetriebs
14/11/2023	Presentation	Landis+Gyr Fachtagung	Dezentrale Datenverarbeitung & Grid Edge
14/02/2024	Non-scientific publication	Bulletin Article	Des algorithmes rendent le réseau transparent

7 Appendix A: Development of algorithmic frameworks

The appendix includes the algorithmic development of the use cases 1, 2 and 3 which forms deliverable 3 of the KnowlEDGE project.

7.1 Algorithmic development: congestion computation (Use case 1)

7.1.1 Overview

Efficient and robust computation of the power flow solution is at the core of many applications in distribution systems, such as the computation of network congestion and voltage levels in distribution networks. Traditional power flow algorithms, such as the Gauss-Seidel or Newton Raphson algorithms require computationally challenging LU decomposition of the Y admittance matrix and inversion of the Jacobian matrix, respectively. To take advantage of the **radial** topological characteristics of distribution systems, [9] has proposed a direct power flow approach, which makes use of oriented bus-branch information. The direct power flow approach, also known as backward-forward sweep algorithm is developed based on the bus-injection to branch-current (BIBC) and the branch-current to bus-voltage (BCBV) matrix and the equivalent current injections from buses of the distribution network.
The algorithm iteratively calculates the voltage magnitudes and angles at each bus in the system until convergence is achieved. The following steps are executed sequentially in order to obtain a power flow solution, containing grid loading (and hence congestion levels) as well as bus voltage information:

1. Initialization: Start by initializing the voltage magnitude and angle at all buses to known values (usually 1.0 per unit for magnitude and 0 degrees for angle).
2. Backward Sweep step: First calculate the current injections based on nodal load and generation values. Starting from the leave nodes, calculate the current in each branch based on the voltage at the current bus and the complex power flowing through the branch upstream towards the head of the radial distribution system (i.e., MV/LV transformer).

3. Forward Sweep step: Once all branch currents have been obtained in the backward sweep step, the voltage drop in each branch can be calculated based on line/transformer impedances in a forward fashion, from the substation/slack bus towards the leave nodes. This yields a new voltage magnitude and phase angle at all buses.

4. Steps 2 and 3 are repeated until the voltage from the most recent and the previous iteration converge to within a specified tolerance.

5. With voltages at all buses, and branch currents in each line segment or transformer defined, a power flow solution has been determined.

In order to accommodate the backward-forward sweep power flow algorithm in a distributed setting, it was decoupled so that the computation can be executed on the edge devices, i.e. on smart meters. The distributed congestion computation will be discussed next.

7.1.2 Distributed congestion computation

This section describes the edge-based power flow computation approach which is at the core of the congestion computation. Within the development of this algorithm the following assumptions made:

- Relevant matrices for the power flow computation are uniquely defined by the equipment installed and its connectivity. The equipment and its connectivity do not change during the simulation or the field trials. Thus, this information is static, known to the DSO and is not considered private.
- The system can be partitioned in arbitrary node divisions. Partitioning can be defined to suit the network topology, i.e., areas will comprise a set of neighbouring nodes.
- Computation is partitioned: The updated elements are uniquely computed by the processor that is responsible for those nodes. No consensus is required.
- Communication between area controllers is a simple broadcast: So long as each processor can hold the whole current/voltage vector in memory, all that is needed is to ensure that all processors receive the entire updated vector.

The distribution network is partitioned into non-overlapping areas collected in the set A. Within area α ∈ A, network buses are collected in the set Eα. For distinct areas α, γ ∈ A, Eα ∩ Eγ = ∅. Denote the upstream bus of area α ∈ A by Bα up and collect the downstream buses of area α ∈ A in Bα down. Additionally, define the area upstream of area α in Aα up and the areas downstream from area α in Aα down.

For all areas α ∈ A, collect the equivalent current injections at buses within the area in vector Iα = [I_i∈Eα]^T, and the branch currents upstream of buses i ∈ Eα in vector Iα Branch = [{$I_{Branch,ij}$ } (i,j)∈B, i∈Eα]^T. The per-area BIBC matrix maps bus current injections to branch currents, such that Iα

$$I^{\alpha}Branch = BIBC^{\alpha}I^{\alpha} \quad (1)$$

In addition, for the bus upstream of area α which connects to the first bus within area α, the current of the first bus in area α (Iα Branch,0) is added to the bus injection so that the load of downstream areas is considered, as expressed in:

$$I_i^{\gamma} = I_i^{\gamma} + I_{\mathrm{Branch},0}^{\alpha} \quad (2)$$

$$\forall\alpha \in A, \gamma \in A_{up}^{\alpha}, i \in B_{down}^{\gamma} \quad (3)$$

Furthermore, the per-area BCBV matrix maps branch currents to bus voltage differences. For the first area connecting to the substation, the voltage drop due to loads is computed as follows:

$$\Delta \mathrm{V}^{\alpha} = \mathrm{BCBV}^{\alpha}\,\mathrm{I}_{\mathrm{Branch}}^{\alpha} \quad (4)$$

where $\Delta V\alpha = [\{V1 - Vi\}, i{\in}E\alpha\,]^{T}$ collects the bus voltage differences at all the buses i ∈ N − from the voltage at the substation V1. To also consider the voltage drop due to upstream loads within area α, for all areas which are not connected to the substation, the voltage drop at the bus of the upstream area connecting area α needs considered:

$$\Delta V^{\alpha} = BCBV^{\alpha}I_{\mathrm{Branch}^{\alpha}} + \Delta V_{i,i\in\mathcal{B}_{\mathrm{u}}^{\alpha}} \quad (5)$$

Finally, convergence needs to be checked for each area according to:

$$\max_{i=\mathcal{E}^{\alpha}}\left|\Delta\,V_i^{\mathrm{l}} - \Delta V_i^{\mathrm{l}-1}\right| < \,\epsilon \quad (6)$$

Once the voltage deviation in each area has converged to some tolerance ε, the algorithm has completed.

From this algorithm line loadings in $I_{\text{Branch}^{\alpha}}$ and voltage levels in ΔV^{α} for all areas can be extracted which provide the key results for the congestion calculation.

7.1.3 Offline simulation of congestion calculation

In the first stage, the distributed power flow algorithm has been tested in an offline simulation, where the congestion calculation was solved by removing all dependencies from an external power flow library such as pandapower. This helps in the development of lightweight software at the later stage when the approach should be deployed to real constrained hardware.

For the evaluation of the congestion calculation algorithm, a reference week of the "Hôpital Feeder 13" distribution network in Rolle within the Romande Energie network has been considered. Smart meter data from 18 locations/30 smart meter endpoints, have been selected.

Figure 8 - Satellite image of test network "Hôpital Feeder 13" (Source: Google Maps)

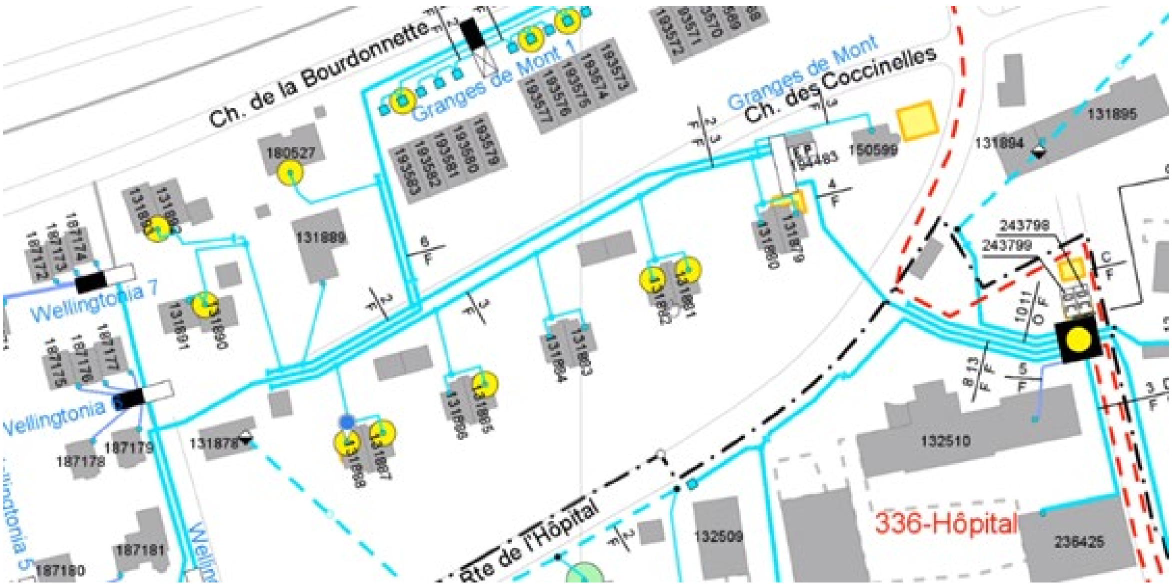


Figure 9 - Extract from Romande Energie GIS showing “Hôpital Feeder 13”

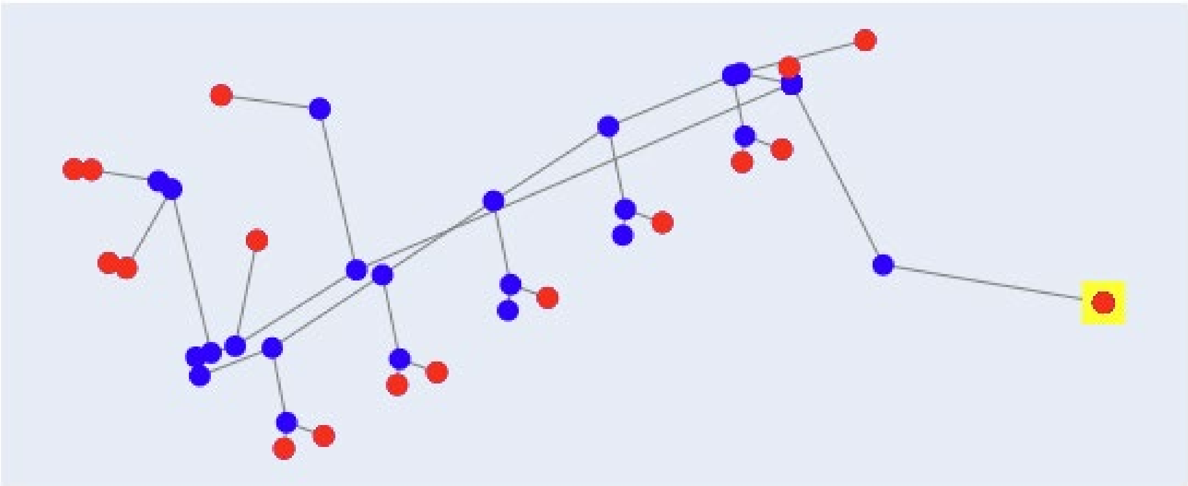


Figure 10 - Test network "Hôpital Feeder 13" abstraction in pandapower

Figure 8, Figure 9 and Figure 10 illustrate the test network “Hôpital Feeder 13” from a satellite image, the Romande Energie GIS System, and the abstraction within pandapower. In Figure 10, smart meter locations are indicated with the red nodes.

For the reference week between March 18, 2019, to March 24, 2019, real time series smart meter data with 1-hour resolution has been considered as illustrated in Figure 11.

Figure 11 - Time series smart meter data for the reference week with 1-hour resolution

Executing the distributed power flow approach with smart meters readings as inputs on the test network allows to calculate all nodal voltage levels and transformer and line loadings in the test network for the reference week as illustrated in Figure 12 and Figure 13.

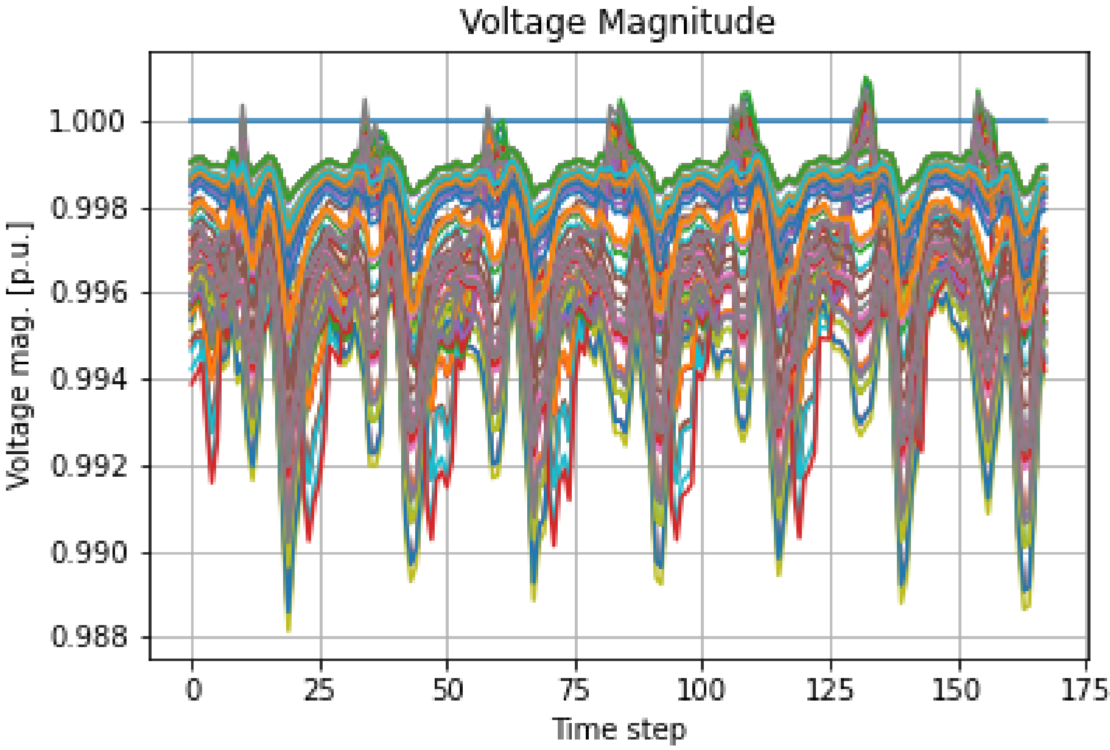


Figure 12 - Nodal voltage levels for the reference week

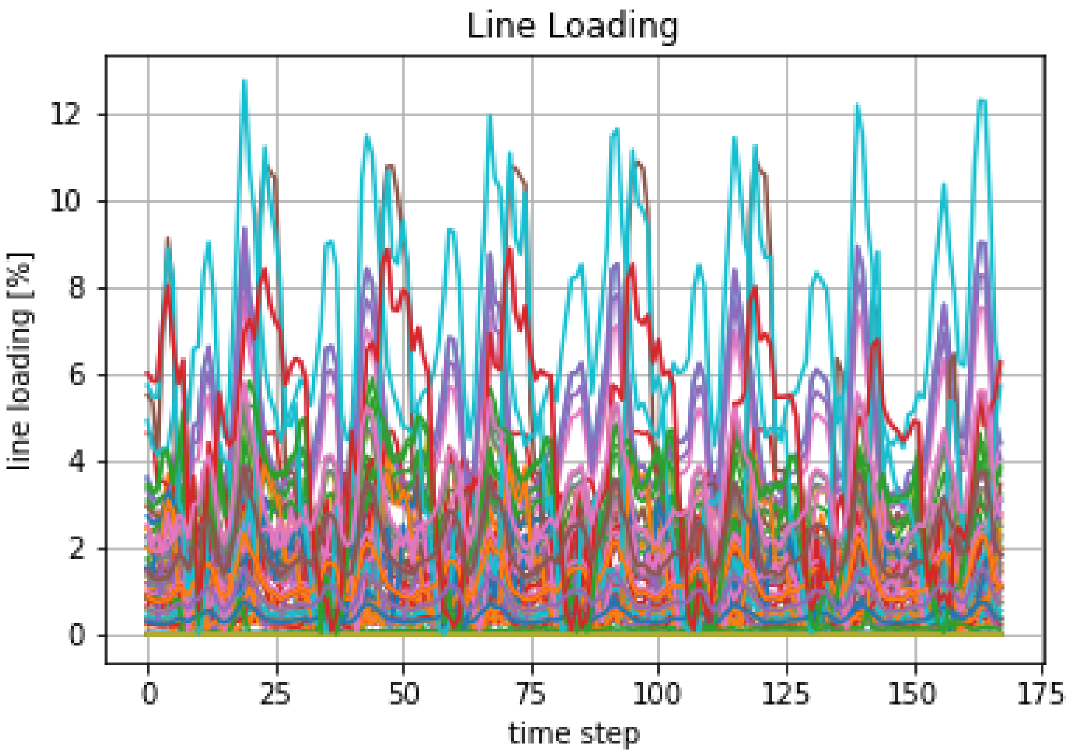


Figure 13 - Line loadings for reference week

In addition, at the substation transformer level of the test network, there is a GridEye sensor which measures active and reactive power flows (and other power quality metrics) and reports at 10-minute intervals. In Figure 14, the substation transformer loading measurement of the GridEye sensor is compared with the calculated loading, which was obtained via the distributed power flow approach. The comparison shows that the smart meter approach provides very similar results as compared to the real measurement, demonstrating the viability and accuracy of the distributed power flow computation via smart meters.

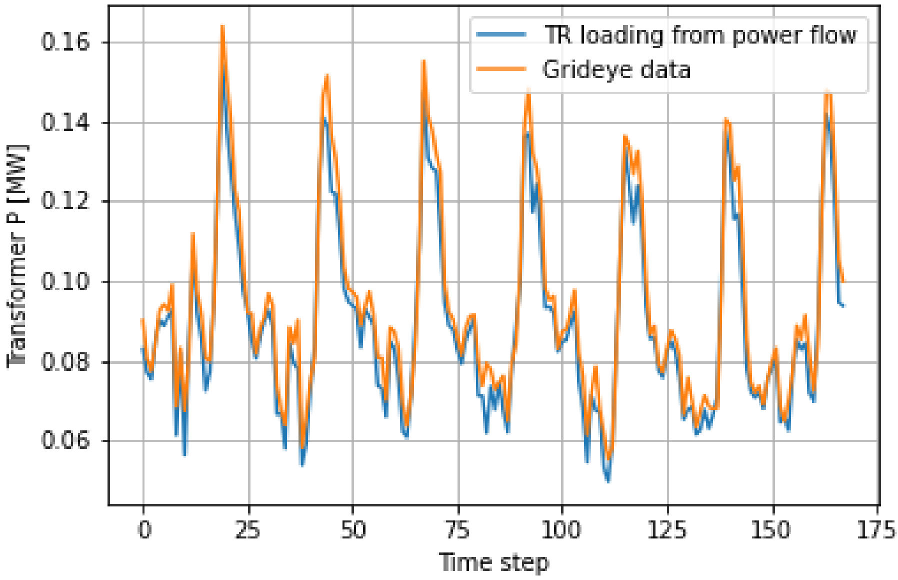


Figure 14 - Comparison at the substation transformer: power flow calculation via Smart Meter vs. GridEye measurement

7.1.4 Hybrid simulation of congestion calculation

Before moving to the real hardware devices, a hybrid scalable simulation environment in a Docker environment was established to prototype and analyse the performance of the distributed power flow approach described in Section 7.1. Messaging services were employed within the environment to coordinate the process, initially with RabbitMQ, and then progressing to MQTT to reduce computational complexity. In the messaging queue the encrypted MQTT protocol has been employed, which achieves secure transmission of data among smart meters with TLS encryption.

Within the environment, each meter is represented by a separate Docker container, with container resources being set to represent the actual computational capability of smart meters. The use of Docker containers in this way allows realistic constraints to be placed on memory and processing power, so improving the representation of 'real world' conditions within the simulation environment. The result is a highly configurable, hardware-agnostic environment that allows to simulate arbitrary networks, combine an arbitrary number of smart meters, and potentially to allow the deployment of identical docker images to actual hardware, where a suitable operating system exists (e.g., smart meters, RTUs, etc.). This, in turn, allows algorithms to be optimised for the target hardware.

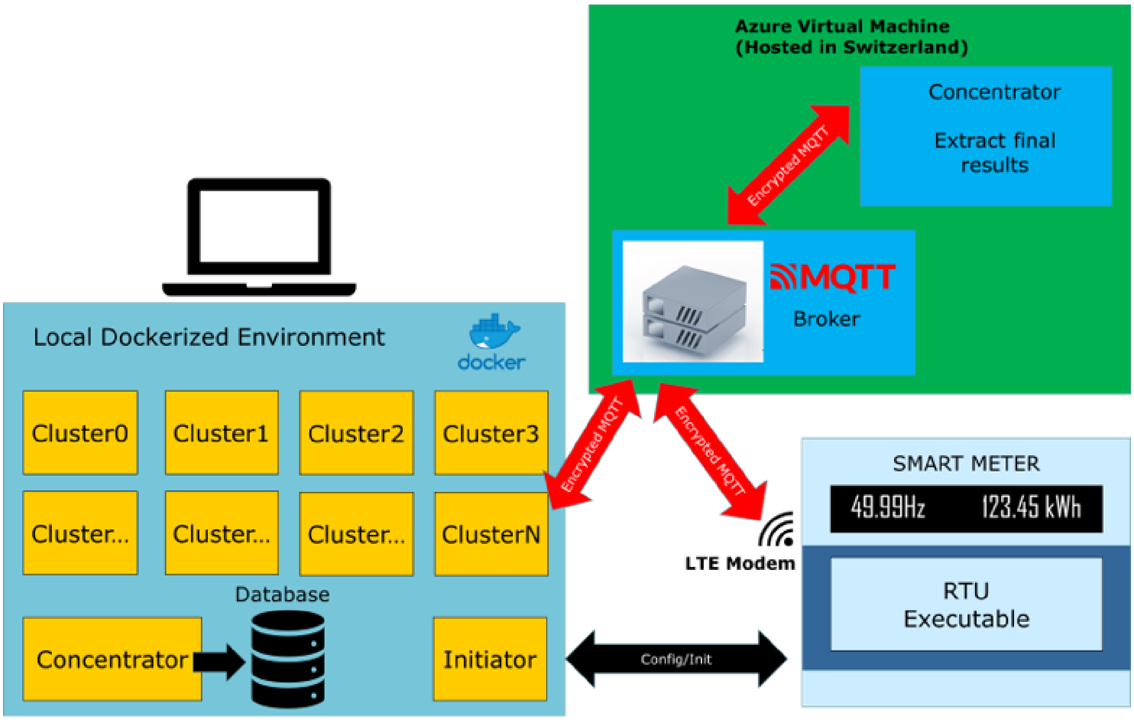


Figure 15 – Hybrid simulation setup

To simulate a swarm of smart meters which are not physically available during the development and testing phase, a hybrid simulation setup was implemented, in which several smart meters which represent clusters of the network are simulated virtually in the docker container environment. In addition, one real smart meter with a communication unit has been used in the distributed approach. Both the “virtual smart meters” in the docker environment as well as the real smart meter/RTU communicate with a message broker over the encrypted MQTT protocol, which is hosted on a virtual machine located in Switzerland. Additionally, a concentrator initialises and orchestrates the hybrid simulation. Figure 15 shows the hybrid simulation setup which was implemented.

This simulation setup allows for simulation of actual protocols, and software packages which will be executed on the real smart meters at a later stage within the field trials.

7.1.5 Results from hybrid simulation

The distributed power flow algorithm has been executed within the hybrid simulation approach. The results of voltage magnitudes at all buses match very closely with the offline simulation, as illustrated in Figure 16, the max. error being < 0.1% with less than 10 iterations of the algorithm. The accuracy is subject to the convergence criteria (tolerance) of the power flow algorithm. Ultimately, it is a trade-off between computational burden and accuracy. These results demonstrate that the dockerised approach using the messaging queue does not introduce a significant error and provides sufficiently accurate results as compared to the offline simulation.

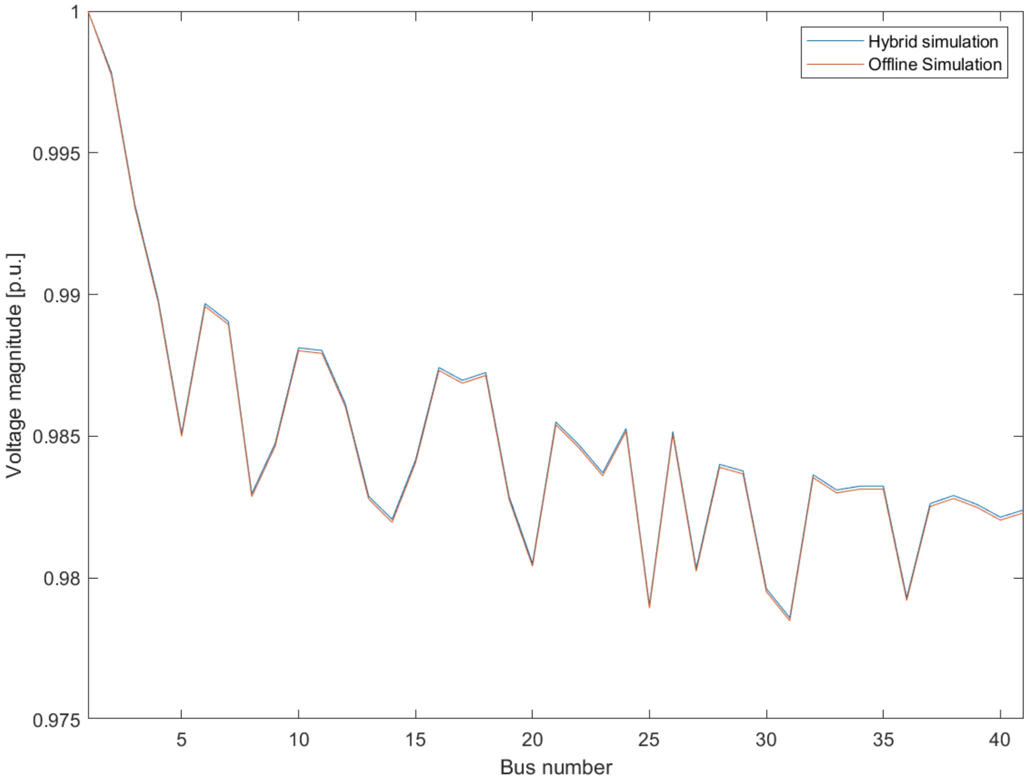


Figure 16 - Comparison of bus voltage magnitudes between the offline and the hybrid simulation

7.2 Algorithmic development: load forecasting (Use case 2)

This section describes the research, development and optimisation used to create a load forecasting algorithm for the KnowLEDGE project. In order to keep the content of this document within an acceptable limit, this section only summarizes the results of this task. More detailed information about the forecasting models, their training methods, optimisation steps, etc. can be found in the Knowledge Deliverable of 2021 and 2022 and the paper [10] published within this project.

Load forecasting describes the process of predicting the future grid load of end users by analysing past data. Figure 17 illustrates a load forecasting example where an algorithm predicts a load profile of the next two days of an end user (green) based on the load profile of the same user of the past five days (blue). The actual load in the next two days (orange) is the target of this prediction, the true consumption profile. The load forecasts have been carried out using only past data profiles and not information on weather condition or temperature forecasts.

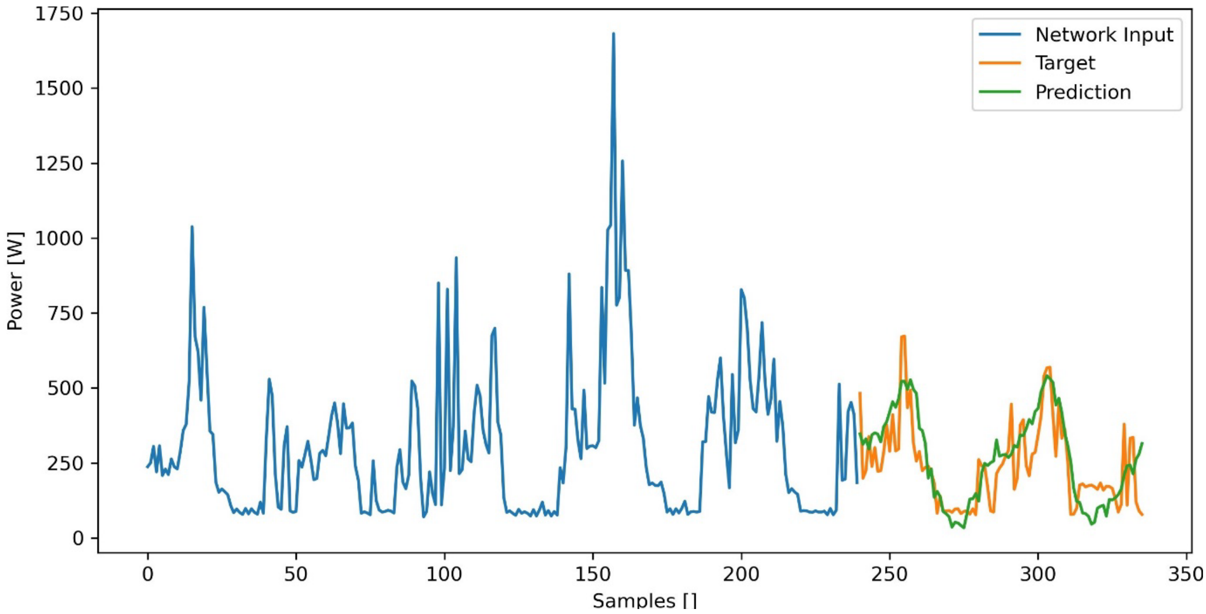


Figure 17 - Load forecasting example

Load forecasting algorithms come in many different variations. The principle behind many of them are machine learning algorithms, or more specifically deep learning models, which learn the structure of the data, by taking parts of the data as inputs, while trying to predict consecutive sequences, which match the target data. The parameters of the models are then adjusted based on the accuracy of their prediction.

7.2.1 Model Selection

As there exist many different neural network architectures which can be used for forecasting and prediction tasks, first the state-of-the-art architectures used for load forecasting were evaluated, and then compared according to their performance on a 5000-household proxy dataset called Low Carbon London (LCL) (1)

According to the analysed references [11], [12], [13] the state-of-the-art architectures are:

- Baseline Predictor (copy of last day)
- Recurrent Neural Networks
    - Long – Short – Term – Memory Models (LSTM)
    - Gated Recursion Units (GRU)
- Dense Network
    - Feed Forward Neural Network (FNN)
    - Deeper Feed Forward Neural Network (DFNN)
- Temporal Convolutional Networks (TCN) (see Figure 19)

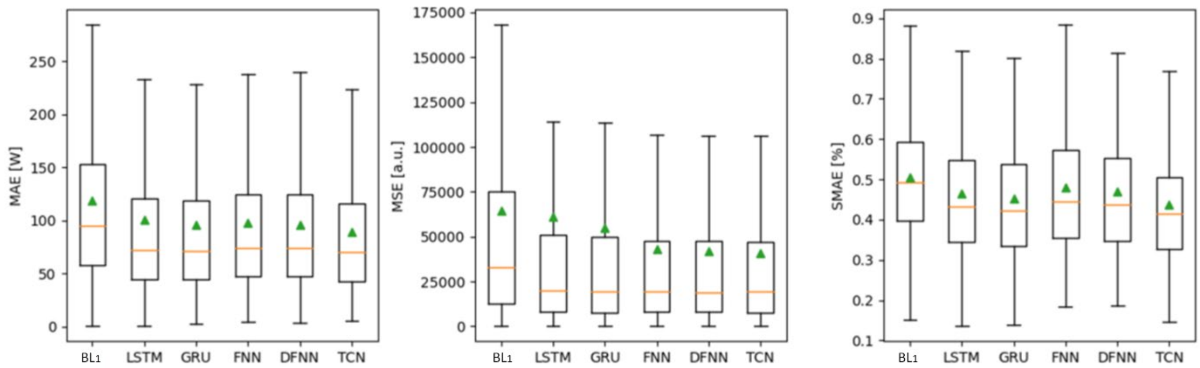


Figure 18 - Results of Model Selection

The research in [11], [12] and [13] identify independently the Temporal Convolutional Network (see Figure 19) to be among the best performing neural network architectures from the analysed models. The independent research of [11], [12] and [13] consisted of the comparison of multiple different neural networks on three different datasets, each consisting of more than 1000 households. Additionally, the fact that TCN networks do not suffer from the vanishing and exploding gradient problems [14], like RNN Models, resulted in its selection as the network architecture of choice for this project.

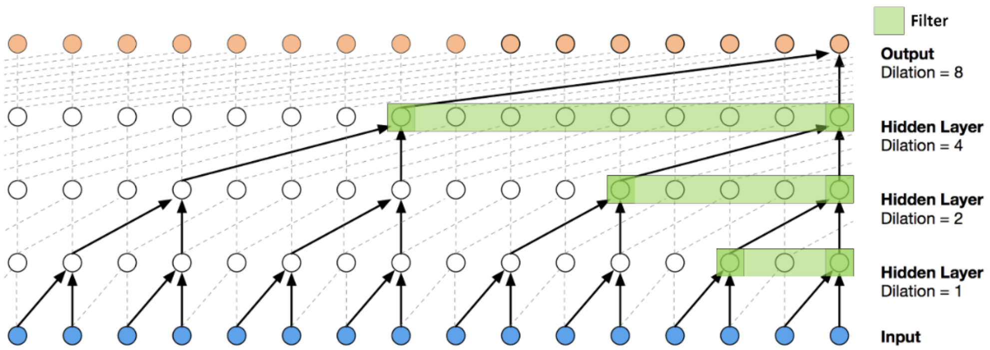


Figure 19 - Temporal Convolutional Network [15]

7.2.2 Hyperparameter Optimisation

The next step in the evaluation process was to optimise the hyperparameters of the selected neural network architecture, as to improve the prediction accuracy of the network. To achieve this, the Bayesian optimisation HyperBand Search [16] in combination with the corresponding scheduler (Hyper-BandFor-BOHB) from the RAY Tune library [17] was employed. This methodology resulted in finding in the optimal values of the evaluated hyperparameters in an efficient manner. The results are summarised in Table 3 - Scientific publications during project duration.

Parameter	Description	Values	Best
Input_length	Size of the historic data provided as input	{48, 2*48, . . . , 7*48}	5*48
Filters	Number of CONV filters in each layer	{8, 16, 32, 64, 128}	64
Batch_size	Size of mini-batches for SGD	{2, 4, 8, 16, . . . , 256}	2
Norm	Type of pre-processing normalization	{standardization, MinMax scaling, per-House-standardization, per-House-MinMax scaling, no scaling }	per-House-standardization
Encode_tod	Boolean parameter For time of day as data input	{True, False}	False
Encode_dow	Boolean parameter for day of week as data input	{True, False}	False

Table 5 - Results of Hyperparameter Optimisation

Interestingly, both the additional features "time of day (tod)" and "day of week (dow)" lead to a decrease in performance of the model, thus the decision was made to omit these two features from the load forecasting algorithm and exclusively focus on the past load data.

7.2.3 Improving the Loss Function

When training a neural network, a loss function is used as a method of evaluating how well a network fits the training data set. The network weights are then adjusted accordingly, as to improve (minimise) this loss value. One problem of conventional loss functions, like the mean square error (MSE), is that they tend to favour the prediction of the average values instead of the prediction of “temporally-offset” peaks. This and the fact that some of these peaks are randomly distributed, actively discourages the network to try to predict peaks. This is an unwanted behaviour, as the peaks are the most important section of the load curve for a DSO.

The authors of [18] present the adjusted error as an alternative metric, which incentivises the prediction of peaks. This is achieved by allowing permutations of the predicted load values in the temporal dimension within ω time steps. Meaning the loss function selects the closest match of the prediction and target time series within a window of size ω (see Figure 20 - Concept Adjusted Error).

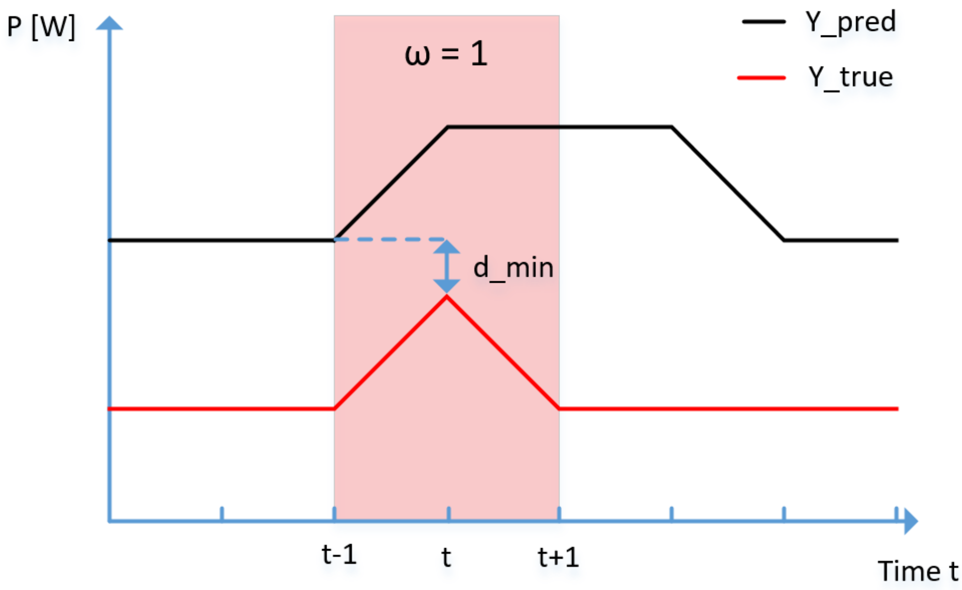


Figure 20 - Concept Adjusted Error

The adjusted error metric, developed by [18], was implemented within the TensorFlow environment as a custom loss function. The developed Tensorflow loss is able to work in tandem with the standard model training functionalities of Tensorflow, as to be able to train the selected TCN network with it.

7.2.4 Evaluating Model Training Methods

Conventional neural network training methods like the baseline (BASE) or centralised (CENT) approach, have the shortcoming of transmitting private and sensitive load data over the internet to a centralised server. This is in direct conflict with the general data protection regulations (GDPR), and only allowed with an end-user opt in. This requirement makes both the BASE and CENT approach not a desirable solution. The KnowlEDGE project thus investigated the training method of federated learning (FL) [19] and model personalisation (PS) [19] as potential alternatives. In comparison to the conventional methods, the alternatives of FL and PS both train a network on the smart meter itself, to avoid any load curve data to a centralised location. In contrast, the FL process transmits the machine learning model weights of all smart meters back to the server to build an averaged server model containing all the respective model updates. As network weights are not considered sensitive data, both methods conform with the GDPR. A more detailed description of all analysed training methods is available in [10].

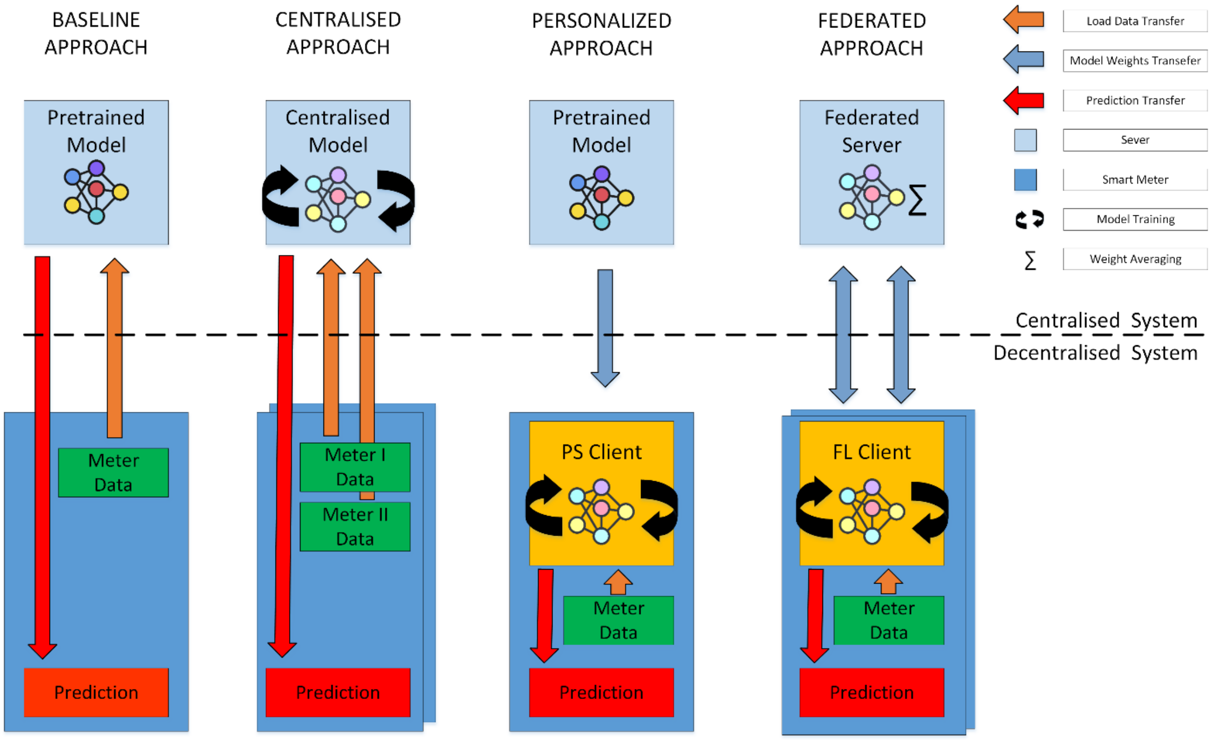


Figure 21 - Training Methods

The four training methods were compared within a simulation approach, to be able to evaluate the best performing method. A simulation approach was chosen, to make statistical relevant statements about the different training methods. Within one simulation run, the different methods would be trained on the same source data, to achieve comparison of their relative performances on the same dataset. This relative comparison was called differential comparison within the developed publication of this project. The differential comparison represents a loss value which is independent from the source data, subtracting the losses of the two compared methods from the same data sample. This is then repeated for all samples in the test set, to create a distribution of differences. Through this approach it was possible to accurately assess and rank the performance of the different training methods (see Table 6).

Table 6 - Results of Differential Comparison the 4 approaches Personalized model (PS), Federated Learning Client model (FL-C), Centralized model (Cent), and Federated Learning Server model (FL-S) compared to the baseline model (Base)

Loss Diff [y - x]	PS	FL-C	Cent	FL-S	Base
PS	0	0.0459	0.0421	0.0459	0.0512
FL-C	-0.0459	0	-0.0038	0.0001	0.0053
Cent	-0.0421	0.0038	0	0.0038	0.0091
FL-S	-0.0459	0.0001	-0.0038	0	0.0053
Base	-0.0512	-0.0053	-0.0091	-0.0053	0
Sum	-0.1850	0.0443	0.0254	0.0444	0.0709
Rank	**1**	**3***	**2**	**3***	**5**

The differential comparison was also used to count the number of times a training method is superior to its comparison, resulting in a superiority rate from one method over a different one (see Table 7).

Table 7 - Results of superiority rate

Sum Cnt [y vs. x]	PS	FL-C	Cent	FL-S	Base
Sum	68440	-21028	16632	-20292	-43752
Superiority Rate	0.591	0.472	0.522	0.473	0.442
Rank	**1**	**3***	**2**	**3***	**4**
Hypothesis	1	3*	2	3*	4

Comparisons: Add $+1$ if method is better, -1 if method is worse
* Difference too similar to be considered different ranks

This comparison revealed that the Personalised (PS) method is the best performing among the analysed training methods, as it is superior to all other methods in approximately 60 % of all cases. We thus propose the personalised training method (PS), as the training method of choice when trying to train a load forecasting algorithm on sensitive user data.

7.3 Algorithmic development: quality of supply analysis (Use case 3)

The latest generation of residential and industrial smart meters provide the full range of power quality metrics as required by EN50160. These metrics are streamed to a cloud, where system operators may obtain visibility of relevant grid metrics. As an additional indication of the current grid state, it would be desirable to have real-time access to a metric which would provide insight into the "weakness" of the grid at a certain connection point or within an area of a network.

A weak network is typically associated with voltage fluctuations which degrade the performance of the connected equipment and potentially cause instability of the internal voltages and currents of electronic equipment. The main causes of voltage fluctuations are pulsed-power output, resistance welders, start-up of drives, arc furnaces, drives with rapidly changing loads, and rolling mill, and high variability of renewable sources [20]. Assessing the network weakness provides an important metric regarding whether additional load or generation can be connected at a certain connection point without deteriorating local power quality constraints such as voltage boundaries. To evaluate the weakness of the grid, information about the voltage dependency on active and reactive power is an important metric. This dependency is quantified using the voltage sensitivity formulation, which indicates how much the grid voltage can be affected if an active or reactive power change occurs. High voltage sensitivities are usually associated with weak points in the grid, as changes in power can lead to significant nodal voltage fluctuations [21].

The network weakness metric (i.e., voltage sensitivities) is most used to allocate distributed energy resources (DER) and energy storage systems in distribution networks and to design DER controllers. Furthermore, controllers based on voltage sensitivity information are effective in increasing photovoltaic (PV) hosting capacity.

Recently, estimating voltage sensitivity using only measurement values and without any network model data has gained attention. In [22], an algorithm based on historical smart meter data is proposed. However, this method requires aggregation of measurements at different locations and historical data and load profiles to train the algorithm. A near real-time approach has been proposed recently [23] to calculate these sensitivities using a generalised least squares method to account for correlated errors. This method relies on real-time monitoring devices such as those provided by Depsys.

It would be very interesting to move the computation of voltage sensitivities onto smart meter infrastructure, since this would maintain data-privacy, leverage more granular data at the grid edge vs. in aggregated form in a concentrator, and finally lead to minimal data transfer to estimate the voltage sensitivities.

7.3.1 Data-driven Voltage Sensitivity Estimation

As an alternative to the network-based approach, a data-driven approach could be implemented, which relies on local smart meter measurements of voltages as well as load active- and reactive-power injections to compute sensitivities of nodal voltages to active and reactive power injections.

Estimating the full voltage sensitivity matrix including all nodes was done in [24], which also contains mutual sensitivities among different buses. This would require the aggregation of the voltage magnitude and active- and reactive-power measurements at centralised location. On the other hand, if only local voltage sensitivities need to be obtained, the estimation could be moved to an edge device, i.e., a smart meter.

Voltage sensitivities could be derived via regression-based methods, linear models would be sufficient to get a good indication. Other linear regression approaches, such as e.g., total least-squares (which would consider measurement errors on both the dependent and the independent variables), partial least-squares (in case of ill-conditioned input data which is a possibility as was observed in [24]), or recursive updates of the sensitivities would be achievable when new measurement samples become available. Furthermore, more sophisticated machine-learning models could be used to evaluate the sensitivities, for example, support vector machines (which would allow to filter outliers) or other Kernel-based Learning Methods [25]. Based on the magnitude of the voltage sensitivities, nodes could then be classified into weak, normal, and strong system nodes.

Within the Knowledge project a suitable simulation platform (i.e. pandapower) to derive an edge-algorithm to compute voltage sensitivities is already in place at HSLU today, where synthetic measurements can be generated. Based on the synthetic measurements, the voltage sensitivities could be derived from measurements using different machine learning algorithms (linear-regression, SVM), and be benchmarked with theoretical ones, obtained via a conventional approach (via the power flow Jacobian matrix).

Furthermore, the simulation studies using the Landis+Gyr smart meter currently available at HSLU would allow to experiment with actual hardware and real smart meter data, and work on a “app” which could directly be executed on the smart meter or its remote terminal unit.

7.3.2 Simulation results

Simulation studies have been conducted in order estimate the voltage sensitivities to active and reactive power injections based on the 33-bus Matpower test network. In two different settings, the bus voltage magnitudes have been plotted, when active and reactive power of loads vary. In the first scenario, only a single load at a time has been subject to variations in the network.

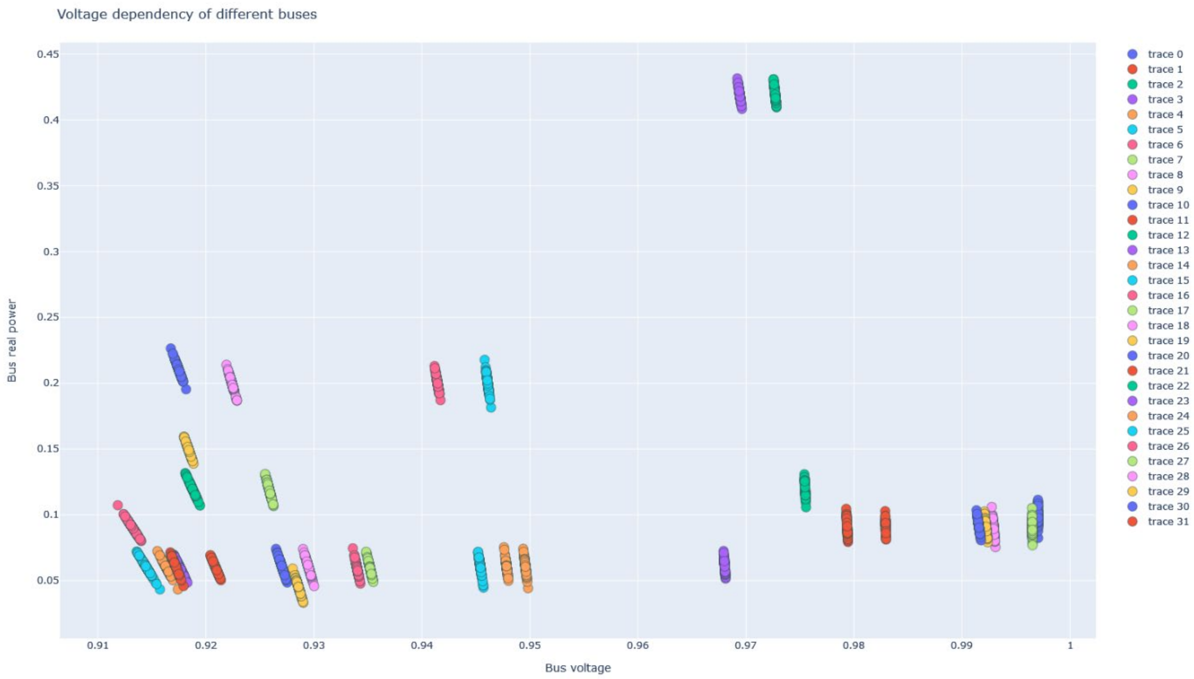


Figure 22 – Voltage variations due to single-load variations at a time

It can be observed in Figure 22 that voltage magnitudes vary nearly linearly with respect to load variations. In this setting, it is foreseeable that voltage sensitivities can be readily estimated using linear regression approaches. This scenario, however, does not seem very practical since loads will vary everywhere within the network simultaneously.

Simultaneous load variations at all locations (buses) have been simulated in the second scenario in Figure 23. In this scenario it is no longer easily possible to link local load variations to local voltage changes due to system-wide effects of load variations on voltages. Hence, local, edge-based detection methods face challenges without system-wide information to estimate voltage sensitivities.

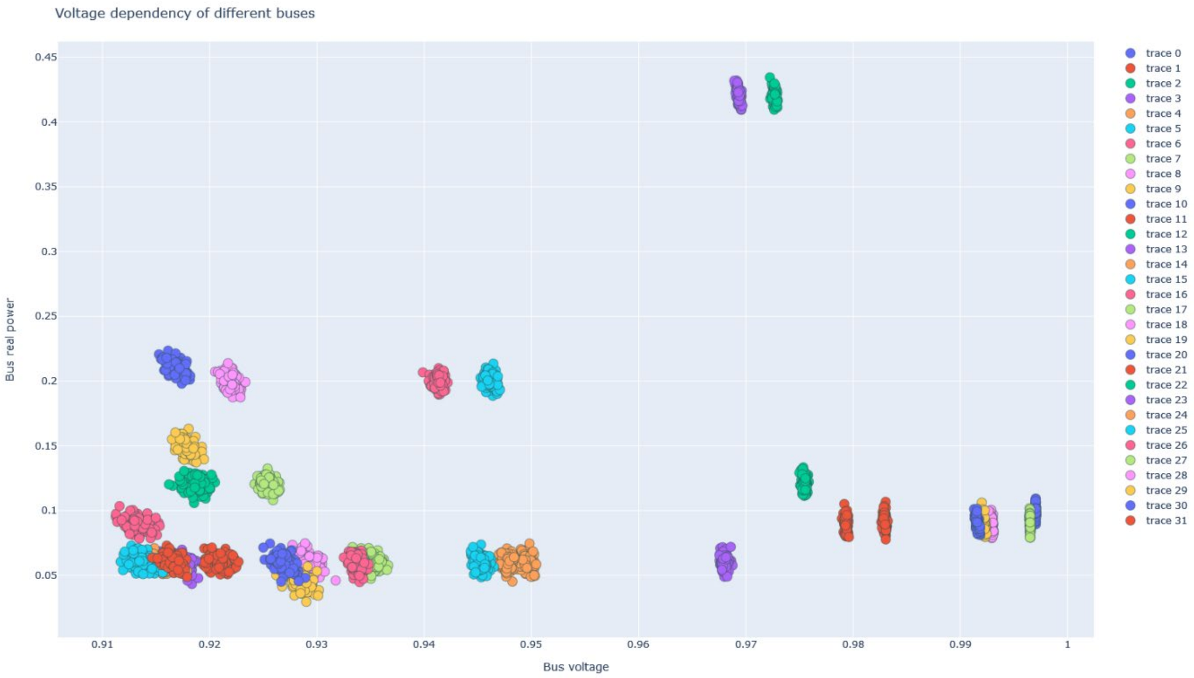


Figure 23 - Voltage variations due to multiple load variations simultaneously

7.3.3 Discussion

The second scenario in Figure 23 illustrates a challenging case for detection of voltage sensitivities at the edge on a single smart meter at a bus in the distribution system. Further work needs to be conducted to determine meaningful voltage sensitivities via edge-based approaches. One such approach would be to either use a centralized approach which collects all voltage and power vectors of the entire network and do the linear regression approach centrally. This was done using partial least squares approach in [26]. Potentially this could also be achieved using a distributed approach based on meter-to-meter communication, however it could not be realized during this project. Future alternatives need to be investigated together with a smart meter manufacturer.

8 Appendix B: Deployment of algorithms

This section illustrates the deployment of algorithms to the smart meter devices.

8.1 Deployment of algorithms to the smart meter device

To prepare the field trial, a load monitoring script, the load forecasting algorithm, and the congestion calculation must be deployed onto the Remote Terminal Unit (RTU) that is connected to the S650 Landis+Gyr smart meter.

The goal is for the load monitoring script to log the current grid load values in a csv file.

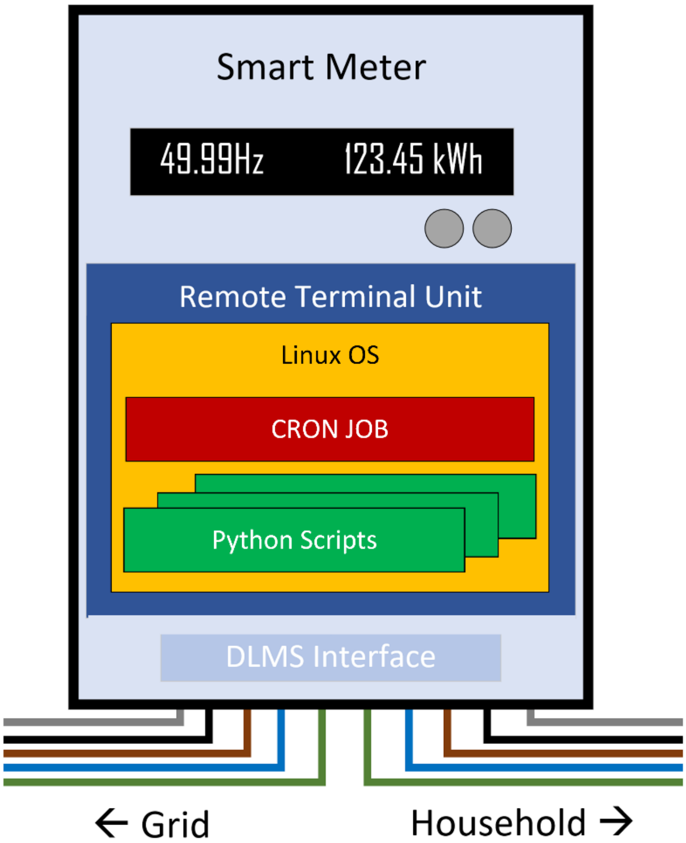


Figure 24 - RTU and Smart Meter Goal

First, the load forecasting script utilizes the last 'n' values of load data to predict the load for the following day. Second, the congestion calculation script will employ these day-ahead predictions to forecast congestion by executing the decentralized power flow. This logging, prediction, and calculation process will be performed periodically, once per day.

The deployment of the previously developed python scripts is not straight. This is because all scripts need to conform with the hardware and software specifications the RTU comes with. The hardware and software specifications are detailed in Table 8 and Table 9.

Hardware Specifications RTU

Table 8 - Hardware Specifications

What	Type	Details
CPU	Core Architecture Frequency	ARM Cortex-A5 Armv7-A 536MHz
Internal RAM	Size	128 kB
External RAM	Size Type Frequency	256MB DDR2 400MHz
Internal Flash	Size	128 kB
External Flash	Size	4 GB

Software Specifications RTU

Table 9 - Software Specifications

What	Type	Details
Operating System	Linux	No pip No apt
Programming Language	Python 3.9	No ONNX No TensorFlow No NumPy No MQTT

8.2 RTU Restrictions and Consequences

The first restriction is the unavailability of required python libraries. This is no problem for the load monitoring script, as it only uses native libraries and thus simply can be deployed as is. However, both the forecasting and the congestion calculation script need specific Python libraries which are not available on the RTU. This would normally not be a problem, as they could simply be installed with pip. However, the lightweight Linux distribution used on the RTU does neither feature the packet installer (pip), nor the means to install it (apt). This has the consequence that an alternative way to either install the libraries or deploy the scripts must be found. Four alternatives were evaluated and rated (See Table 10).

Table 10 - Deployment Alternatives

Approach	Advantages	Disadvantages	Rating
Update Firmware	+Python Modules can be preinstalled +Easiest option	-New Firmware image must be Built by Landis+Gyr	(1)
Manually install Python Modules	+Only one Python Interpreter required	-Meeting dependencies is complicated for big libraries -Deployment to fleet is more complicated -Updating modules can be tedious	3
Bundle with PyInstaller	+No version conflicts on updated Firmware +Easy to deploy +Self-contained Executable Bundle	-Complicated pipeline needs to be setup	2
Convert Model to Micro Python	+Runs on most low power hardware	-Machine Learning Frameworks not easily portable -Limited Python instruction set -Micro Python needs to be installed on RTU	4

The optimal solution would be, to have Landis+Gyr preinstall our required libraries in a custom firmware, so that we could simply deploy the python scripts, as visualised in Table 10. However, the build and testing of a new firmware by Landis+Gyr, is expensive and not at all justified for a field trial of 30 house-holds. The next best alternative is thus to build a bundling – pipeline to be able to bundle all needed dependencies in one executable and deploy the scripts and dependencies as one. Another alternative of manually installing the python modules is not scalable and prone to compatibility errors and lasty using a Micro Python Conversion would only be an option on very low power edge devices.

Thus, the deployment procedure further pursued was the creation of an executable through a PyInstaller bundle.

8.3 Creating a Bundled Executable

One way is to build a BUNDLE of all our scripts and dependencies, with a tool which is called PyInstaller. PyInstaller is an open-source Python project that allows bundling of Python code into an executable so that Python scripts can portably be executed without requiring a pre-installed Python interpreter on the target system. It can bundle most Python modules such as NumPy, matplotlib etc. and is available for Windows, Linux, and Mac.

To achieve this first a bootloader emulating the ARMv7 -a Architecture needed to be built. The Base for this was a the publicly available ARMv7 Docker image. This Docker file was expanded to also include all needed python dependencies.

The PyInstaller was then run within this emulated target platform and converted all Python Scripts with the corresponding dependencies into one compact executable. Both the bootloader generation and the bundling step were automated in a Batch script.

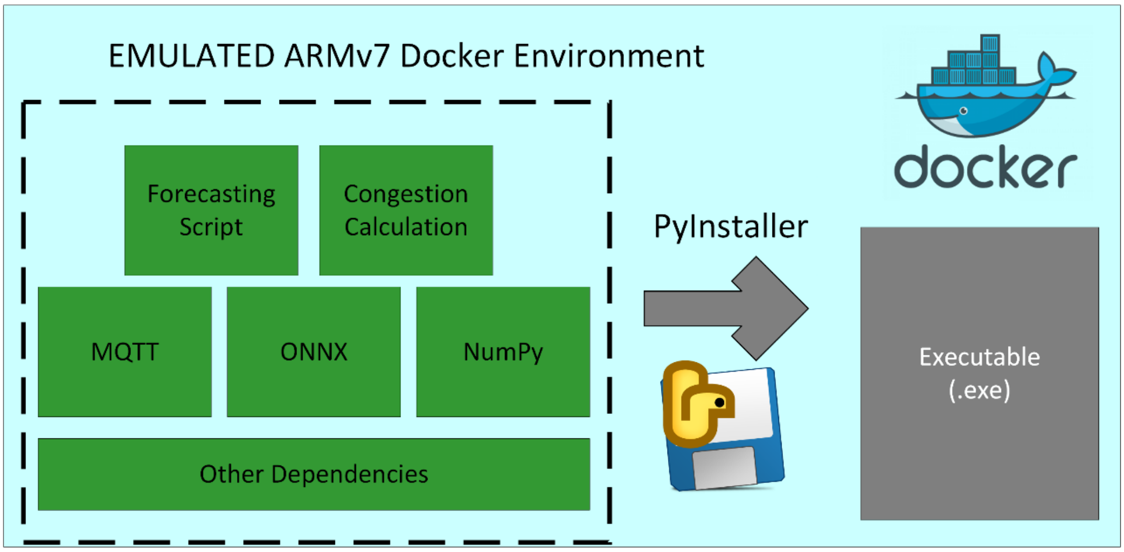


Figure 25 - Simplified Bundling Process

8.4 Difficulties of the Deployment Process

While working on the Deployment process, several difficulties were revealed which had to be solved. Firstly, the PyInstaller software, which is a non-commercial product, features very little documentation especially when it comes to the compatibility issues of the underlying environment and the used Python libraries. Because of this we had to go through a tedious trial and error process to be able to correctly bundle all the scripts. Secondly the Lightweight Linux Distribution on the RTU not only does not feature a package manager like apt or pip, but also does not have a secure handshake functionality like TLS. It was thus needed to include this TLS handshake library in the bundle.

8.5 Summarised Deployment Process

With all compatibility issues worked out, and a finalised bootloader to emulate the target platform it was then possible to bundle python scripts with all the required dependencies and deploy them onto the RTU. Figure 26 summarises this entire process.

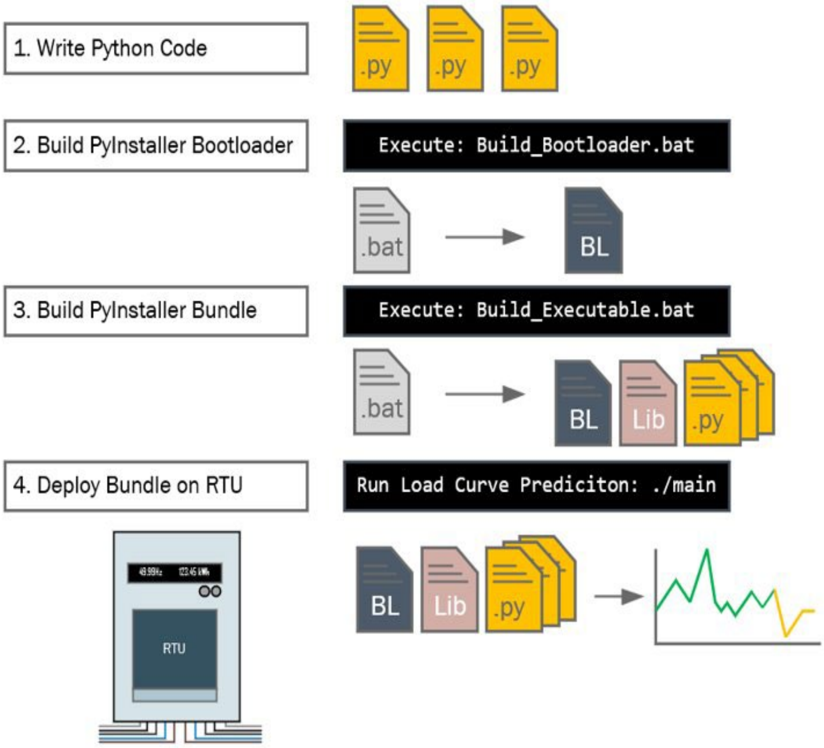


Figure 26 - Simplified Deployment Process

8.6 Load Monitoring Script

In order to facilitate load forecasting and congestion calculation during field trials, Python scripts required bundling into a single executable to handle all dependencies on the RTU. Additionally, accessibility of Smart Meter data to these scripts was crucial. To address this, we developed a load monitoring script that periodically queries data from the smart meter via DLMS requests. A DLMS (Device Language Message Specification) request is a standardized communication protocol used to retrieve data from smart meters and other energy management devices. This script collects essential readings such as current, voltage, and power, which are continuously stored in a .csv file.

Because this load monitoring script only used RTU native python libraries, it could simply be deployed as a python – script, without the need for any bundling. To execute this script periodically a CRON-job was defined which would run the querying and logging process every 15 minutes.

8.7 Storage Space Requirements

With all scripts and dependencies deployed onto the RTU, a storage space requirement estimate could be made. It turned out that all in all, all scripts and dependencies take about 66 MB of storage space. Additionally, there would be a yearly memory “cost” of ca. 21 MB for the logging of all smart meter values and of all prediction, congestion calculation values. However, considering the 4 GB external flash of the RTU, this is a more than acceptable result.

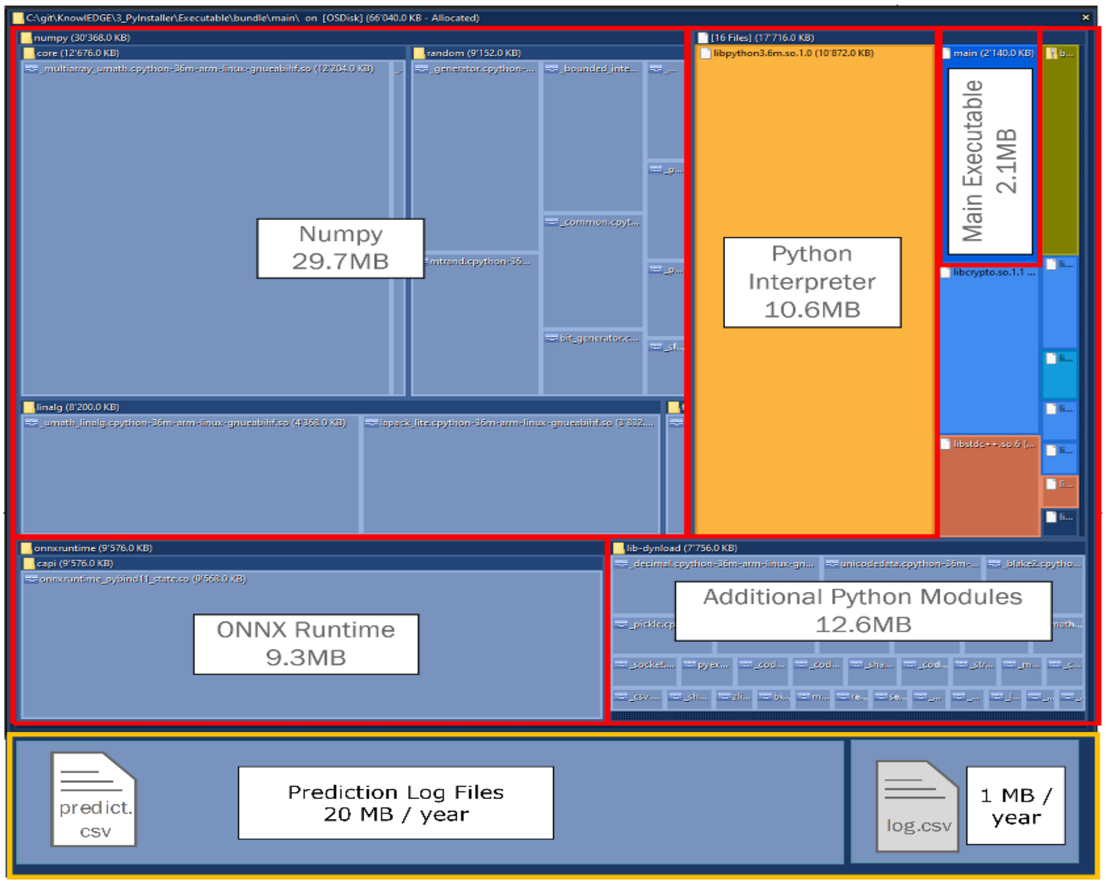


Figure 27 - Memory Usage RTU

8.8 Testing the Deployed Scripts

To test both the deployment process and the developed algorithms themselves, they were executed on the test RTU we received from Landis+Gyr. The load forecasting script behaved as expected and delivered identical results to the previous test version on the PC. Note that in Figure 28, the values of the RTU predictions were multiplied by 1.1, as to have two non-overlapping predictions of the PC and the RTU respectively.

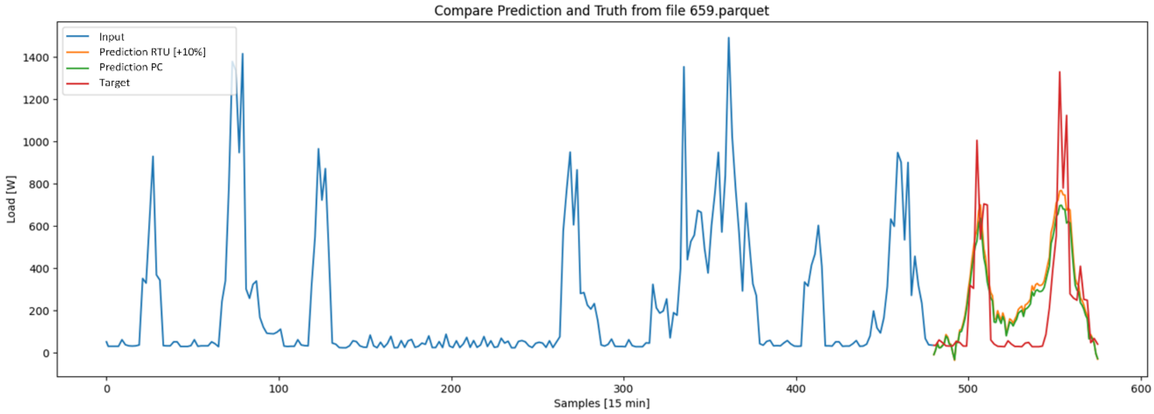


Figure 28 - Comparison of Forecasting on RTU and PC

This lab test was also used to examine the execution time of the forecasting script. One full run of the forecasting script, consisting of the following parts:

- Unbundling (unpacking) deployed executable
- Reading values from the logged .csv file
- Generate prediction with deployed predictor
- Logging Predictions in a .csv file
- Posting results on an MQTT Broker (for the Congestion Calculation Script)

requires a computation time of 6.81 seconds. However, in a commercial product, the unbundling step is not required, as this step becomes obsolete in case of a new firmware which already contains the full set of algorithms. The exact execution times of all mentioned steps are detailed in Figure 29. The simple forecasting step as indicated in the upper part of Figure 29 takes 677.64 ms.

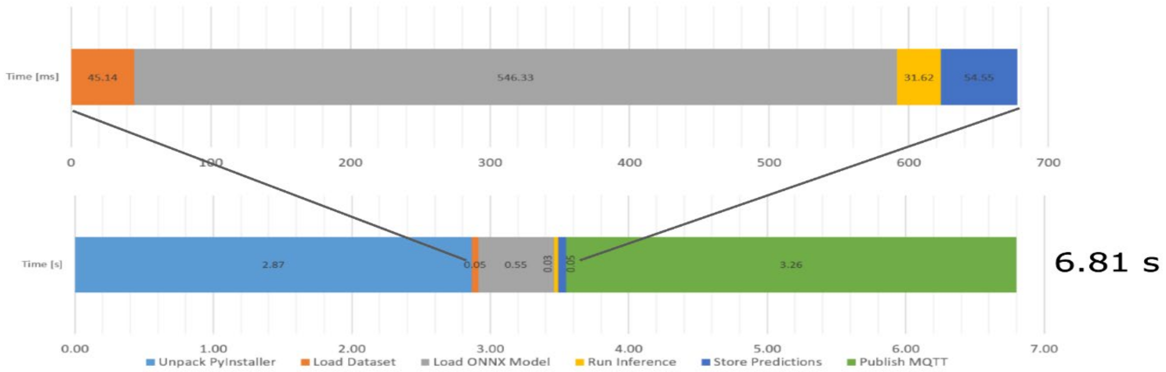


Figure 29 - Timing of Forecasting Script

9 References

[1] "Electricity law and regulation in Switzerland | CMS Expert Guides." Accessed: Jan. 04, 2021. [Online]. Available: https://cms.law/en/int/expert-guides/cms-expert-guide-to-electricity/switzerland

[2] M. D. Galus, "Die Bedeutung digitaler Plattformen für den Informations- und Datenaustausch im Strommarkt 2.0 der Schweiz," in *Realisierung Utility 4.0 Band 1*, Springer Fachmedien Wiesbaden, 2020, pp. 511–528. doi: 10.1007/978-3-658-25332-5_30.

[3] "Smart Meter Data Analytics for the Mass Market Energy Services - Basic data." Accessed: Sep. 03, 2021. [Online]. Available: https://www.aramis.admin.ch/Grunddaten/?ProjectID=35578

[4] "NILM4Bal # Non-Intrusive Load Monitoring for Balancing the Grid - Basic data." Accessed: Sep. 03, 2021. [Online]. Available: https://www.aramis.admin.ch/Grunddaten/?ProjectID=43330

[5] "Smart Metering für die Schweiz - Basic data." Accessed: Sep. 03, 2021. [Online]. Available: https://www.aramis.admin.ch/Grunddaten/?ProjectID=26483

[6] "SmartLoad – Smart Meter Data Analytics for Enhanced Energy Efficiency in the Residential Sector - Basic data." Accessed: Sep. 03, 2021. [Online]. Available: https://www.aramis.admin.ch/Grunddaten/?ProjectID=40143

[7] "Sologrid – Simulation and field test of an intelligent and decentrally managed distribution grid - Basic data." Accessed: Sep. 03, 2021. [Online]. Available: https://www.aramis.admin.ch/Grunddaten/?ProjectID=36952

[8] R. Khatami, S. Nowak, and Y. C. Chen, "Measurement-based Locational Marginal Prices for Real-time Markets in Distribution Systems," *IEEE Transactions on Power Systems*, pp. 1–11, 2024, doi: 10.1109/TPWRS.2024.3369476.

[9] J. T.-I. T. on power delivery and undefined 2003, "A direct approach for distribution system load flow solutions," *ieeexplore.ieee.org*, Accessed: Jan. 14, 2021. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/1208371/

[10] F. Widmer, S. Nowak, B. Bowler, P. Huber, and A. Papaemmanouil, "Data-driven comparison of federated learning and model personalization for electric load forecasting," *Energy and AI*, vol. 14, p. 100253, Oct. 2023, doi: 10.1016/J.EGYAI.2023.100253.

[11] A. Gasparin, S. Lukovic, and C. Alippi, "Deep Learning for Time Series Forecasting: The Electric Load Case." 2019.

[12] D. L. Marino, K. Amarasinghe, and M. Manic, "Building energy load forecasting using Deep Neural Networks," in *IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society*, 2016, pp. 7046–7051. doi: 10.1109/IECON.2016.7793413.

[13] P. H. Kuo and C. J. Huang, "A High Precision Artificial Neural Networks Model for Short-Term Energy Load Forecasting," *Energies 2018, Vol. 11, Page 213*, vol. 11, no. 1, p. 213, Jan. 2018, doi: 10.3390/EN11010213.

[14] O. Barak, "The Exploding and Vanishing Gradients Problem in Time Series," *Towards data Science*, Oct. 2020, [Online]. Available: https://towardsdatascience.com/the-exploding-and-vanishing-gradients-problem-in-time-series-6b87d558d22

[15] S. Bai, J. Z. Kolter, and V. Koltun, "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling," *arXiv preprint arXiv:1803.01271*, 2018.

[16] L. Li, K. Jamieson, G. DeSalvo, A. Rostamizadeh, and A. Talwalkar, "Hyperband: A Novel Bandit-Based Approach to Hyperparameter Optimization," *Journal of Machine Learning Research*, vol. 18, pp. 1–52, 2018, [Online]. Available: http://jmlr.org/papers/v18/16-558.html

[17] R. Liaw, E. Liang, R. Nishihara, P. Moritz, J. E. Gonzalez, and I. Stoica, "Tune: A Research Platform for Distributed Model Selection and Training," *arXiv preprint arXiv:1807.05118*, 2018.

[18] S. Haben, J. Ward, D. V. Greetham, C. Singleton, and P. Grindrod, “A new error measure for forecasts of household-level, high resolution electrical energy consumption,” *Int J Forecast*, vol. 30, pp. 246–256, 2014, doi: https://doi.org/10.1016/j.ijforecast.2013.08.002.

[19] M. N. Fekri, K. Grolinger, and S. Mir, “Distributed load forecasting using smart meter data: Federated learning with Recurrent Neural Networks,” *International Journal of Electrical Power & Energy Systems*, vol. 137, p. 107669, 2022.

[20] M. A. S. Masoum, S. Jamali, and N. Ghaffarzadeh, “Detection and classification of power quality disturbances using discrete wavelet transform and wavelet networks,” *IET Science, Measurement and Technology*, vol. 4, no. 4, pp. 193–205, Jul. 2010, doi: 10.1049/iet-smt.2009.0006.

[21] S. Karrari, M. Vollmer, G. De Carne, M. Noe, K. Böhm, and J. Geisbüsch, “A Data-driven Approach for Estimating Relative Voltage Sensitivity,” in *2020 IEEE Power Energy Society General Meeting (PESGM)*, 2020, pp. 1–5. doi: 10.1109/PESGM41954.2020.9281859.

[22] S. Weckx, R. D’Hulst, and J. Driesen, “Voltage Sensitivity Analysis of a Laboratory Distribution Grid With Incomplete Data,” *IEEE Trans Smart Grid*, vol. 6, no. 3, pp. 1271–1280, May 2015, doi: 10.1109/TSG.2014.2380642.

[23] C. Mugnier, K. Christakou, J. Jaton, M. De Vivo, M. Carpita, and M. Paolone, “Model-less/measurement-based computation of voltage sensitivities in unbalanced electrical distribution networks,” in *Proc. of Power Syst. Comp. Conf.*, Jun. 2016. doi: 10.1109/PSCC.2016.7540852.

[24] S. Nowak, Y. C. Chen, and L. Wang, “Measurement-Based Optimal der Dispatch with a Recursively Estimated Sensitivity Model,” *IEEE Transactions on Power Systems*, vol. 35, no. 6, pp. 4792–4802, Nov. 2020, doi: 10.1109/TPWRS.2020.2998097.

[25] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*. Cambridge University Press, 2000. doi: 10.1017/CBO9780511801389.

[26] S. Nowak, Y. C. Chen, and L. Wang, “Measurement-Based Optimal DER Dispatch With a Recursively Estimated Sensitivity Model,” *IEEE Transactions on Power Systems*, vol. 35, no. 6, pp. 4792–4802, 2020, doi: 10.1109/TPWRS.2020.2998097.