A Federated Learning Approach towards Smart Energy Meter Data

Interim Report for Research Project Module 7E02

Supervised by - D.r Shreejith Shanker

Abhishek Dutta Gupta
Trinity College Dublin
aduttagu@tcd.ie

January 2023

This report is submitted in part fulfilment for the assessment required in 7E02 Research Project. I have read and I understand the plagiarism provisions in the General Regulations of the University Calendar for the current year. These are found in Parts II and III at http://www.tcd.ie/calendar.

Introduction

Electricity Demand forecasting [31] is an indispensable function carried out within the energy production industries and boards to bring the supply and demand curve to equilibrium while maintaining a steady load on the energy grid. However, with the inclusion of renewable energy in the grids and the development of the so-called smart grids [11], smart energy meters [2] will manifest a vital component to ease these forecasting tasks.

However, with the usage of these smart energy meters, and machine learning algorithms used for these forecasts becoming data hungrier per training, a huge problem of rises among privacy-conscious consumers that fear a breach of their personal data.

This Interim report of the Master's thesis titled "A Federated Learning Approach towards Smart Energy Meter Data", provides a small demonstration of how privacy breaches of such energy data can be harmful, describing **Federated Learning,** [14] a solution behind this problem, where it has been used in similar fields like this with such application, and abstractly states how this approach and solution differs from other similar approaches where Federated learning has been used for this problem.

Abbreviations

FPGA = Field Programmable Gate Arrays, ML = Machine Learning, DL = Deep Learning, FL = Federated Learning, NN = Neural Networks, SI = Software Implementations, HI = Hardware Implementations, TF = Tensorflow, TFF = Tensorflow Federated, ARIMA = Auto regressive Moving Average, LSTM = Long Short-Term Memory, IoT = Internet of things, HMI = Human Machine Interface, Tx = Task No -, Mx = Milestone No -, ToU = Dynamic Time of Use, StdoU = Standard Time of use.

1 Project Objectives

The principal goals of this project are software implementation of federated learning in a data set obtained from various smart energy meters and then hardware implementation by applying federated learning by collecting data from a set of hybrid FPGA devices [28] or Arduino-based micro-controllers [3] and then confirming the use of federated learning by achieving a comparable accuracy.
Breaking them down into further low-level goals, the following steps are identified.

1. **Software implementation of Federated learning on a smart energy meter data set.**
    - **Understanding of the application of federated learning in similar fields.** This involves going through previous papers published with an application of federated learning in different fields and listing and learning the differences and difficulties faced.
    - **Understanding of the previous ML application on energy data sets.** This involves going through previous papers published where ML algorithms are being used for better prediction of dynamic pricing with data available from smart energy meters.
    - **Selection of energy meter data set where the ML algorithm will be applied as per requirements.** This involves going through various dynamic smart energy meter data set available and selecting the data set suitable for this project.
    - **Preparation and visualization of the selected data set.** This involves building the federated data set(different data sets for multiple clients) from the selected data set, which involves making sure that the federated learning framework does not use the identities of the client. More information is available in the Technical literature section.
    - **Implementation of federated learning using tensor flow federated python library [4].** This involves training the model in federated data.
    - **Debugging, final compilation, and Accuracy confirmation using different performance metrics.**

2. **Hardware implementation of Federated learning on an equivalent smart energy meter data set.**
   - **Confirmation of hardware devices selection (set of Hybrid FPGAs or Arduino's).**
   - **Collection of data and creation of data set from hardware**. This involves storing the data from different hardware devices so that the data can be converted into a federated data set.
   - **Preparation and visualization of the selected data set.** This involves building the federated data set(different data sets for multiple clients) from the selected data set, which involves making sure that the federated learning framework does not use the identities of the client. More information is available in the Technical literature section.
   - **Implementation of federated learning using tensor flow federated python library.** This involves training the model in federated data.
   - **Debugging, final compilation, and Accuracy confirmation using different performance metrics.**
3. **Final Results and conclusion of the project.**
4. **Submission of Dissertation.**

2 Previous Work / Literature Review

2.1 The evolution of the use of Neural Networks for load demand forecasting

With the advent and success of machine learning and the beginning of the use of smart grids, various algorithms have been adapted for load forecasting for dynamic energy pricing, helping consumers to plan their usage and costs accordingly. Moreover, similar algorithms have been tried and tested for other activities like prediction grid maintenance schedules, and customers integrating renewable energy sources to the grid with these dynamic pricing predictions.

While many models have been developed for forecasting peak electric load, there are limited publications for this forecast on the use of the billing period. Guzman Diaz [8] used a model of gradient-boosted regression trees on the Spanish Energy data set for a day-ahead forecast and concluded a very minimum prediction error. This paved the way for advanced algorithms and ML for bringing models with better accuracy.

Adding to the above, Saxena and his colleagues [25] developed a hybrid model, which forecasted whether a day would be a peak load day or not, predicting 70 percent of the actual peak days. The model used comprised ARIMA, logistic regressions, and Neural Networks. Similarly, Andreas Ikonomopoulosa [27] and Sadaei [22] proposed a similar approach but with a different model made of CNNs based on fuzzy time series, achieving superior results than traditionally used state of art models.

Further, a model made from Rolling updates and Bi-LSTMs [30] was proposed and directly tested on Australian Energy Data sets, significantly improving predictions with less computational time.

Moreover, apart from billing forecasts, machine learning, and Neural Networks were also used for fault detection, feeder failures, and predicting maintenance schedules from energy data sets [21].

Further, such information was made useful by the consumers for integrating renewable sources into the grid based on varying grid prices. Manar's [13] model simulation showed that electricity cost was reduced by 48 percent using this approach with increased use of renewable sources.

2.2 The problems ahead using these Machine Learning Models

With the looming of IoT interfaces with smart energy meters, a lot of IoT device developers provide a seamless connection to the meters with monitoring and control options through various HMI interfaces [29]. Despite several network securities and firewalls, country energy boards collecting data from these smart meters for load forecasting paves a way for the problem of sensitive data getting breached [10].
Normal machine learning techniques typically involve training a model on a central server using a data set that is stored on that server, which collects data from these smart energy meters. However, this can have significant privacy implications, as the data is stored and processed in a central location that is potentially vulnerable to unauthorized access or data breaches [26].
One of the main concerns with storing and processing data in a central location is that it can be accessed by parties who are not authorized to see it, leading to the privacy of the individuals whose data is stored on the server being compromised. In addition to these concerns, it could be accessed by unauthorized parties, potentially exposing sensitive personal information. This could have serious consequences for the individuals whose data is affected, as well as for the organization that is responsible for protecting it [17].
A simple whole year of electricity usage data of a single consumer in the wrong hands leaks out pieces of information not only about the identity of the consumer but also patterns of usage, leading to the calculation of what kind of heavy appliances used in that household and prediction of the number of people staying, etc 1. L. AlAbdulkarim's paper [1] on works in energy meters and privacy concerns stated that among the obstacles impeding the energy meter roll-out in the Netherlands are consumers' information security and privacy concerns.
Hence, it becomes an ethical obligation to look after solutions where data privacy and its potential outcomes can be prevented.
Now wait, without adequate data, the machine learning performance is hampered. So if bringing

Figure 1: *This meme from Joy of Tech shows how harmful privacy loss can potentially be, with an example from a different context but with a similar effect.*

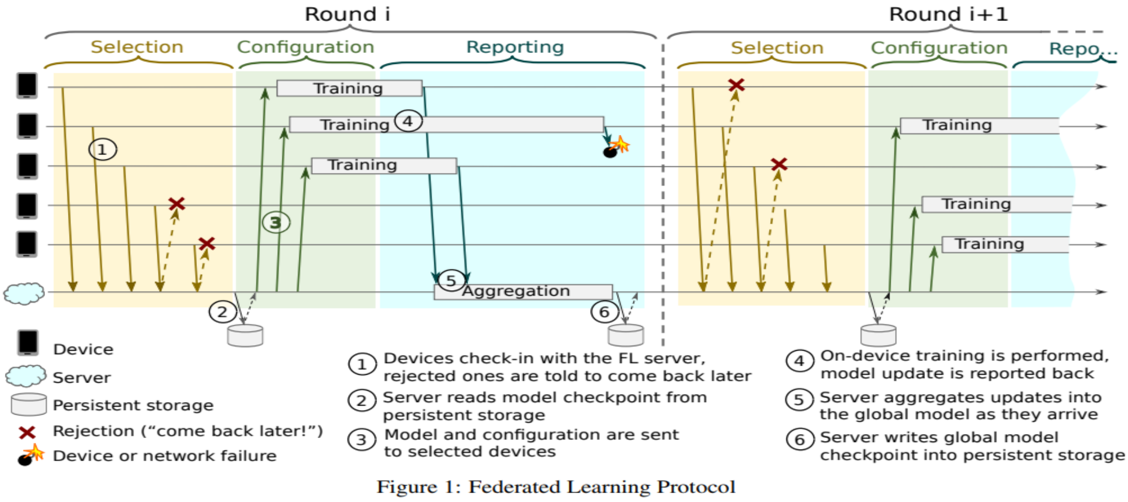

Figure 2: *Federated Learning Protocol as explained in Bonawitz papers.*

data to a central server to create a machine learning model is ethically not possible for the above-described problem, what if we bring the model to the data, such that the data does not have to leave its local domain?
This is where **federated learning** comes in [14].

2.3 Federated Learning

2.3.1 What is Federated Learning

It is a machine learning technique that enables training a model on a data set that is distributed across various devices. This is in contrast to state of art machine learning techniques, which typically involve training a model centrally on a server using the data set that is stored on that server [32].
In federated learning, the devices that hold the data are able to train a model locally, using their own data, and then send the model updates back to the central server. The server then aggregates [5] these updates to produce a global model that is able to make predictions on new data.

The basic explanation of a federated learning model is available in [4], shown in figure 2. Also, Refer to the algorithm followed for a federated training process 1.
Federated learning has several advantages over traditional machine learning methods. For example, it allows for training on large, distributed data sets without the need to accumulate the data on a central server [19, 9]. This can be important in cases where the data is sensitive and cannot be shared, or where it is unrealistic to transfer the data to a central location. Additionally, federated learning can reduce the amount of data that needs to be sent over the network, since only model

updates are sent, rather than the total data set.

Algorithm 1 Federated Learning. K represents the number of clients indexed by 1 to k; B is the local minibatch size; E is the number of local epochs; is the learning rate, w represents the model and P represents the local data. [18]

Step 1 - Device Selection
Server executes:
Initialize w_0
for each round $t = 1, 2, \dots$ **do**
$m \leftarrow \max(C \cdot K, 1)$
$S_t \leftarrow$ (random set of m clients)
Step 2 - Local Device Training
for each client $k \in S_t$ **in parallel do**
$w_{k,t+1} \leftarrow$ **ClientUpdate**(k, w_t)
ClientUpdate(k, w): // Run on client k
$B \leftarrow$ (split P_k into batches of size B)
for each local epoch i from 1 to E **do**
for each batch $b \in B$ **do**
$w \leftarrow w - \eta \nabla l(w; b)$
return w to server
Step 3 - Server Aggregation for Global model Update
$w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{k,t+1}$
Step 4 - Repeat from Step 1

2.3.2 Use of Federated learning on similar areas of applications

While Federated learning has a lot of applications already for mobile devices, recently there has been a rise in publications of papers calling for its use in industrial and medical applications. Below are a few cases that can be studied for a better understanding of federated learning scope in industrial and medical applications.

1. Taking environmental protection as a case point, Hu, Gao, Liu, and Ma (2018) [12] came up with a novel environmental monitoring frame based on federated region learning against the problem of inconvenient interchangeable monitor data. Thus, monitoring data taken from various sensors could be employed and utilized for higher performance of the collaborative model.

2. Upon popularization of EVs, Saputra et al. (2019) [23] sketched a federated energy demand

prediction process for charging stations across to stop energy congestion in the transmission process.

3. Similarly, Electronic health records (EMR) consist of a lot of meaningful clinical data. Pfohl, Dai, and Heller (2019) [20] investigated differentially private learning for EMR in a federated setting. And they further concluded that the performance is comparable with training in a centralized setting.

4. With the utilization of health records, Lee et al. (2018) [15] demonstrated a federated patient hashing framework which detects similar patients located in different hospitals without sharing and disclosing patient-level information, helping doctors to summarize general character and lead them to treat patients with more experience.

For further information on various detailed applications and exploration on the use of FL in different fields refer to. [16]

2.4 Previous Works of Federated learning in energy data sets

While there are hand countable works of federated learning in energy data set. The below two works stand out from the rest.

1. Briggs [7] proposed a federated learning (FL) based approach for training models in a distributed, collaborative manner whilst retaining the privacy of the data. He then compares two approaches: FL, and a clustered variant, FL+HC against a centralized learning approach. He concluded that the model FL+HC can achieve a 5 percent improvement in model performance with a 10x reduction in computation compared to the localized learning models.

2. M Savi's paper proposes [24] a global generalized model which is aggregated from many Long Short-Term Memory (LSTM) models which are locally trained by different users based on their own past energy consumption data. This model is then re-distributed for improved prediction at the edge. Though accuracy and error take up a hit when samples are recorded at an interval of more than one hour, Nevertheless, it keeps sensitive data local and hence guarantees users' privacy.

2.5 Where does my work fit in ?

My Master's thesis titled "A FEDERATED LEARNING APPROACH TOWARDS SMART ENERGY METER DATA", expands on the works done by M Savi [24] by not only exploring federated learning on a software-based energy data set but also confirming the same through a data set made from hardware devices.

Even though enough paper claims equal or poor performance in federated learning due to Non - IID issues, however, Briggs [6] works on improving the federated model performance using Hierarchical clustering could be looked upon, which could turn out to be the solution to the performance issues.

3 Ethical Considerations

Ethical considerations are vital when taking research into consideration as the complete ethical process takes care of whether any human or living subject is harmed in the process, whether the data (personal or not) are stored properly, whether the research abides the GDPR laws, and regulations, which all, in the end, defines the quality of the research. Having said that, it is important to take care of the below ethical concern related to this project.

1. Firstly, the research is designated for federated learning implementation in smart energy meter data. Whilst federated learning has become and will become successful in different application areas (such as image recognition etc, text prediction, etc.), still there are a lot of fields where federated learning frameworks are still being tried and tested. Hence keeping the accuracy of this framework in mind, a similar federated learning framework should be not used for vital medical trials such as something which detects any vital disorders or fatal diseases.

2. The experiment has the potential to harm the households whose smart energy meter data is being used for the research. A breach of half-hourly energy consumption data per household becomes very dangerous if it falls into the wrong hands. Hence, it is impregnable to make sure that client IDs are not used in the federated learning framework and that only the model is shared from clients to the server. Moreover, people of households whose energy meter data is used should be fully informed about the purpose and cause of the study. This ensures that the people know about any risk that may be associated with the research, while also making sure that they are aware of the potential benefits of it.

Therefore, in conclusion, the ethical considerations for a research project should include federated learning being undertaken as it is intended and informed information and consent to the party on whose data machine learning will be performed.

4 Progress to Date

As of date, with reference to the Gantt chart in 5, the completion of four tasks with two milestones has been in progress. The findings of these tasks are detailed below. (Tx and Mx refer to tasks and

LCLid	stdorToU	DateTime	KWH/hh (per half hour)
MAC000363	Std	30:00.0	0.08
MAC000363	Std	00:00.0	0.109
MAC000363	Std	30:00.0	0.113
MAC000372	ToU	00:00.0	0.41
MAC000372	ToU	30:00.0	0.054

Figure 3: *Sample Data set, LCLid refers to household reference, ToU refers to Dynamic time of use, wherein tariff rates (High, normal or low) were issued a day ahead and Std refers to non-time customers with fixed tariffs.*

milestone numbers, like T2 refer to task 2 and M4 refers to milestone 4, all tasks and milestones are detailed in the Project Management section.

- **T1, T2: Understanding of previous ML works in energy data set and previous FL implementations on similar fields.** October was spent understanding the previous works and papers published, where neural networks or other hybrid algorithms were used for load forecasting, and its accuracy. Moreover, a thorough exploration of the various federated learning works which are executed and are ongoing was performed to have a better grip on the subject and note down the problem statement of this thesis.
- **T3-M1: Selection of data set for a software implementation for federated learning** November was spent choosing the data set on which federated learning will be performed. The data set chosen was the smart meter energy consumption data available from UK power networks. The data set consists of energy meter consumption readings from 5,567 London households between November 2011 and February 2014, with readings (KWh) taken at half-hourly intervals. The data set is further divided between the two types of customers, with customers subject to the dynamic type of use and non-time static customers. A sample data set showing different types of information available from the data is shown in figure 3. For more about the data set refer to this link.
- **T4-M2: Conversion of data set to a federated data set** For using and training Federated learning algorithms, it requires a federated data set, i.e., a collection of data from multiple users. Federated data is typically non-i.i.d., which poses a unique set of challenges.

  December was spent trying to figure out how to convert this smart energy London household dataset to a federated data set using tensor flow federated packages. However, due to difficulties faced in installation package imports, it got a bit delayed from the anticipated timeline, for which time is to be made up in the next tasks.

5 Self Assessment

The project has been proceeding exactly according to plan till the completion of Task 3 and Milestone 1. However, it got delayed for task 4, because of the unanticipated installation errors in installing tensor flow federated import packages. This has been encountered due to various versions conflicts of prerequisites import packages for tensor flow federated environment.

However, having solved all the import package errors, the creation of federated data set for software implementation is about to be completed, hence the project will be right back on track, fast-tracking the model training processes.

Even if our final results remain at a low accuracy, we will still be in a position to confirm the usefulness of federated learning and also be in a position to write up our scientific journey so that others will learn from our experiences, given many kinds of research being conducted in making FL optimal. Given the alterations to the project timeline due to the above-missed milestone as discussed, We expect to be able to complete the dissertation on time.

6 Project Management

6.1 Tasks and Milestones

Before the submission of the interim report, considering the time period of the semester I into account, four tasks, and two milestones were set. Work progress achieved in that period is detailed in the **Progress to Date** section of this report. These have been discussed with our supervisor and based on that and the challenges faced, a few alterations had to be made.

Tasks	Milestone	Description	Date
T1	-	Understanding of previous FL applications in various fields	Oct 31,2022
T2	-	Understanding of previous ML applications on energy data sets	Oct 31,2022
T3	M1	Selection of data set for SI of FL	Nov 21, 2022
T4	M2	Conversion of energy data set to an FL data set	Dec 28, 2022

Now, moving on to the next phase of the project, a total of nine tasks and seven milestones are set until the project completion, with detailed descriptions below.

RISK MANAGEMENT					
Risk Title	Description	Likelihood(L) (1-5)	Impact (I) (1-5)	Score (L*I)	Mitigations(s)
Implementation problem (Duration)	Federated Learning algorithm taking longer time for simulation and application.	3	2	6	Specifics of tensor flow packages and data set creation should be through in advance.
Python Package Installation imports problem (Tensor flow federated python package)	TFF installation import packages which might have different versions in different installs.	4	2	8	All python packages as described in the tensor flow federated website and GPU version of tensor flow should be updated as per the requirement before hand.
Hardware Implementation data corruption	Data to be used for training FL algorithm getting corrupted	1	4	4	Version control of the datasets should be maintained with restore policies.
Model Bias (Federated learning problem)	Federated learning relies on aggregating the results from many devices, which can introduce bias into the final model.	2	3	6	It has to be ensured that the data used for training is representative of the overall devices and that any bias in the data is identified and addressed before training.

Figure 4: *Risk Management associated to this project*

Tasks	Milestone	Description	Date
T5	M3	Beginning of training of FL data set for SI	Jan 31,2023
T6	M4	Program Debugging and results Analysis for SI	Feb 21,2023
T7	-	Hardware Implementation device selection	Feb 28, 2023
T8	M5	Creation of data set for HI	Mar 21, 2023
T9	M6	Conversion of data set to an FL data set	Apr 7, 2023
T10	M7	Training of FL data set for HI	April 28, 2023
T11	M8	Final Results analysis	May 30, 2023
T12	-	First draft of dissertation	June 15, 2023
T13	M9	Dissertation submission	July 21, 2023

A Gantt chart showing the complete program with the timeline is in this link. The screenshots of the program are below. 5 The green blocks are for completed tasks, whereas the blue blocks are the pending tasks, and the arrow shows the dependencies between the tasks.

6.2 Risk Management

Whilst, the use of federated learning for this problem induces many benefits, it also introduces new challenges that must be managed to ensure the success and security of the project. Some key

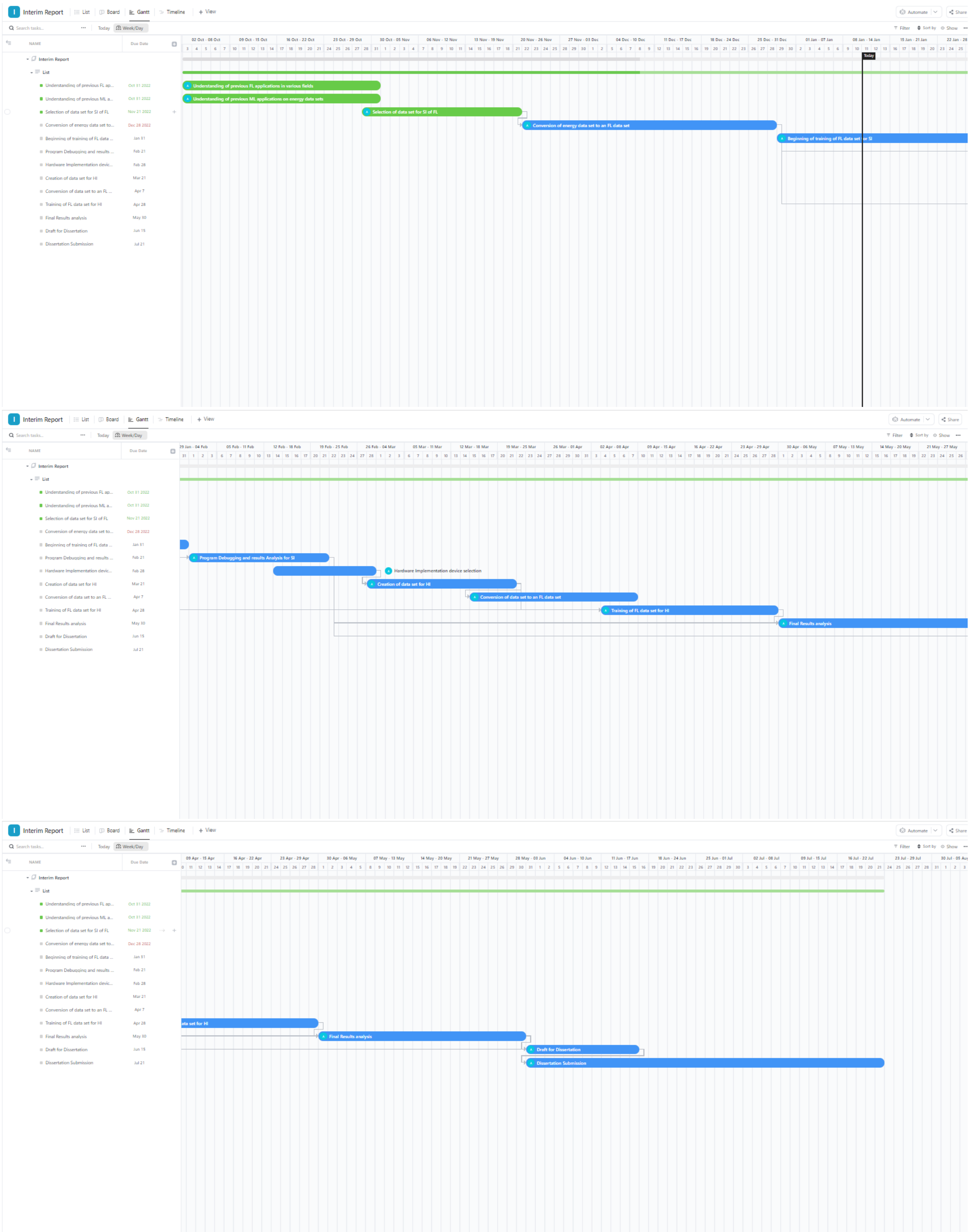

Figure 5: *Complete project program Gantt Chart*

considerations for risk management in this federated learning project are mentioned in figure 4.

Bibliography

[1] ALABDULKARIM, L., AND LUKSZO, Z. Impact of privacy concerns on consumers' acceptance of smart metering in the netherlands. In *2011 International Conference on Networking, Sensing and Control* (2011), pp. 287–292.

[2] ARIF, A., AL-HUSSAIN, M., AL-MUTAIRI, N., AL-AMMAR, E., KHAN, Y., AND MALIK, N. Experimental study and design of smart energy meter for the smart grid. In *2013 International Renewable and Sustainable Energy Conference (IRSEC)* (2013), IEEE, pp. 515–520.

[3] BADAMASI, Y. A. The working principle of an arduino. In *2014 11th international conference on electronics, computer and computation (ICECCO)* (2014), IEEE, pp. 1–4.

[4] BONAWITZ, K., EICHNER, H., GRIESKAMP, W., HUBA, D., INGERMAN, A., IVANOV, V., KIDDON, C., KONEČNÝ, J., MAZZOCCHI, S., MCMAHAN, B., ET AL. Towards federated learning at scale: System design. *Proceedings of Machine Learning and Systems 1* (2019), 374–388.

[5] BONAWITZ, K., IVANOV, V., KREUTER, B., MARCEDONE, A., MCMAHAN, H. B., PATEL, S., RAMAGE, D., SEGAL, A., AND SETH, K. Practical secure aggregation for privacy-preserving machine learning. In *proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security* (2017), pp. 1175–1191.

[6] BRIGGS, C., FAN, Z., AND ANDRAS, P. Federated learning with hierarchical clustering of local updates to improve training on non-iid data. In *2020 International Joint Conference on Neural Networks (IJCNN)* (2020), IEEE, pp. 1–9.

[7] BRIGGS, C., FAN, Z., AND ANDRAS, P. Federated learning for short-term residential load forecasting. *IEEE Open Access Journal of Power and Energy* (2022).

[8] DÍAZ, G., COTO, J., AND GÓMEZ-ALEIXANDRE, J. Prediction and explanation of the formation of the spanish day-ahead electricity price through machine learning regression. *Applied Energy 239* (2019), 610–625.

[9] DRAINAKIS, G., KATSAROS, K. V., PANTAZOPOULOS, P., SOURLAS, V., AND AMDITIS, A. Federated vs. centralized machine learning under privacy-elastic users: A comparative analysis. In *2020 IEEE 19th International Symposium on Network Computing and Applications (NCA)* (2020), pp. 1–8.

[10] EIBL, G., AND ENGEL, D. Influence of data granularity on smart meter privacy. *IEEE Transactions on Smart Grid 6*, 2 (2015), 930–939.

[11] EKANAYAKE, J. B., JENKINS, N., LIYANAGE, K. M., WU, J., AND YOKOYAMA, A. *Smart grid: technology and applications*. John Wiley & Sons, 2012.

[12] HU, B., GAO, Y., LIU, L., AND MA, H. Federated region-learning: An edge computing based framework for urban environment sensing. In *2018 IEEE Global Communications Conference (GLOBECOM)* (2018), IEEE, pp. 1–7.

[13] JARADAT, M., JARRAH, M., JARARWEH, Y., AL-AYYOUB, M., AND BOUSSELHAM, A. Integration of renewable energy in demand-side management for home appliances. In *2014 International Renewable and Sustainable Energy Conference (IRSEC)* (2014), IEEE, pp. 571–576.

[14] KONEČNỲ, J., MCMAHAN, B., AND RAMAGE, D. Federated optimization: Distributed optimization beyond the datacenter. *arXiv preprint arXiv:1511.03575* (2015).

[15] LEE, J., SUN, J., WANG, F., WANG, S., JUN, C.-H., JIANG, X., ET AL. Privacy-preserving patient similarity learning in a federated environment: development and analysis. *JMIR medical informatics 6*, 2 (2018), e7744.

[16] LI, L., FAN, Y., TSE, M., AND LIN, K.-Y. A review of applications in federated learning. *Computers Industrial Engineering 149* (2020), 106854.

[17] LIU, B., DING, M., SHAHAM, S., RAHAYU, W., FAROKHI, F., AND LIN, Z. When machine learning meets privacy: A survey and outlook. *ACM Computing Surveys (CSUR) 54*, 2 (2021), 1–36.

[18] MCMAHAN, B., MOORE, E., RAMAGE, D., HAMPSON, S., AND Y ARCAS, B. A. Communication-efficient learning of deep networks from decentralized data. In *Artificial intelligence and statistics* (2017), PMLR, pp. 1273–1282.

[19] PENG, S., YANG, Y., MAO, M., AND PARK, D.-S. Centralized machine learning versus federated averaging: A comparison using mnist dataset. *KSII Transactions on Internet and Information Systems (TIIS) 16*, 2 (2022), 742–756.

[20] PFOHL, S. R., DAI, A. M., AND HELLER, K. Federated and differentially private learning for electronic health records. *arXiv preprint arXiv:1911.05861* (2019).

[21] RUDIN, C., WALTZ, D., ANDERSON, R. N., BOULANGER, A., SALLEB-AOUISSI, A., CHOW, M., DUTTA, H., GROSS, P. N., HUANG, B., IEROME, S., ET AL. Machine learning for the new york city power grid. *IEEE transactions on pattern analysis and machine intelligence 34*, 2 (2011), 328–345.

[22] SADAEI, H. J., E SILVA, P. C. D. L., GUIMARÃES, F. G., AND LEE, M. H. Short-term load forecasting by using a combined method of convolutional neural networks and fuzzy time series. *Energy 175* (2019), 365–377.

[23] SAPUTRA, Y. M., HOANG, D. T., NGUYEN, D. N., DUTKIEWICZ, E., MUECK, M. D., AND SRIKANTESWARA, S. Energy demand prediction with federated learning for electric vehicle networks. In *2019 IEEE Global Communications Conference (GLOBECOM)* (2019), IEEE, pp. 1–6.

[24] SAVI, M., AND OLIVADESE, F. Short-term energy consumption forecasting at the edge: A federated learning approach. *IEEE Access 9* (2021), 95949–95969.

[25] SAXENA, H., APONTE, O., AND MCCONKY, K. T. A hybrid machine learning model for forecasting a billing period's peak electric load days. *International Journal of Forecasting 35*, 4 (2019), 1288–1303.

[26] SHOKRI, R., STROBEL, M., AND ZICK, Y. Privacy risks of explaining machine learning models.

[27] SIDERATOS, G., IKONOMOPOULOS, A., AND HATZIARGYRIOU, N. D. A novel fuzzy-based ensemble model for load forecasting using hybrid deep neural networks. *Electric Power Systems Research 178* (2020), 106025.

[28] SIMPSON, P. *FPGA design*. Springer, 2010.

[29] SPANÒ, E., NICCOLINI, L., DI PASCOLI, S., AND IANNACCONELUCA, G. Last-meter smart grid embedded in an internet-of-things platform. *IEEE Transactions on smart grid 6*, 1 (2014), 468–476.

[30] WANG, S., WANG, X., WANG, S., AND WANG, D. Bi-directional long short-term memory method based on attention mechanism and rolling update for short-term load forecasting. *International Journal of Electrical Power & Energy Systems 109* (2019), 470–479.

[31] WERON, R. Electricity price forecasting: A review of the state-of-the-art with a look into the future. *International journal of forecasting 30*, 4 (2014), 1030–1081.

[32] YANG, Q., LIU, Y., CHENG, Y., KANG, Y., CHEN, T., AND YU, H. Federated learning. *Synthesis Lectures on Artificial Intelligence and Machine Learning 13*, 3 (2019), 1–207.