Integration of Mainflux platform into a Multi-Agent based HEMS framework

*Aleksandra Kaplar, *Filip Savić, *Aleksandar Kaplar, **Jovana Vidaković, *Jelena Slivka, *Milan Vidaković
* University of Novi Sad. Faculty of Technical Sciences, Novi Sad, Serbia
** Department of Mathematics and Informatics, Faculty of Science, Novi Sad, Serbia
(aleksandra.a, aleksandar.kaplar, slivkaje, minja)@uns.ac.rs
filipsavic1995@yahoo.com, jovana@dmi.uns.ac.rs

Abstract— **Smart homes consist of electronic devices that consume electricity from the electricity grid (EG) or renewable energy sources. The system proposed in this paper aims to lower the cost of consumed energy in smart homes. Cost reduction can be achieved by training a smart HEMS (House Energy Management System) to orchestrate the schedule of loads energy consumption according to the time-varying energy price and the residents' preferences. HEMS can be trained by Reinforcement Learning (RL) if provided a realistic environment. In this paper, we propose a simulated household environment with the help of the Typhoon HIL application. To make our simulated environment realistic, we need realistic measurements of external conditions, such as external temperature and solar irradiation. Thus, we use the Mainflux platform that supplies the simulated environment with real-world data. This paper focuses on integrating the Mainflux IoT platform with Typhoon HIL simulation of smart home devices. In this paper, Mainflux provides two real-world parameters: solar irradiation and outdoor temperature, vital inputs for the realistic simulation of smart home devices such as PV panels and Air Conditioners.**

I. INTRODUCTION

Today's smart homes contain multiple electronic appliances that consume electricity from the electricity grid or renewable energy sources such as solar panels and electric vehicles. In such a compex system, residents rely on HEMS (House Energy Management System) to perform the complex orchestration of various devices. Ideally, HEMS should reduce the electricity cost while satisfying the residents' electricity demands.

HEMS can be trained with Reinforcement Learning (RL) if provided a realistic training environment. While training, RL agent needs to explore various scenarios, some of which might negatively impact the residens' daily life. Thus, we need a realistic simulated environment to train the HEMS. This paper, similar to [4] and [6], proposes a simulated environment for training a RL-based HEMS. To make our simulation realistic, we combine it with real-world data. The Typhoon HIL application [2] enables us to accurately simulate the behavior of smart home devices. However, the simulation of some devices such as a PV panel[1] and Air conditioner, requires information about real-world weather conditions.

The possibility of integrating real-world data in a simulated environment enables a degree of reality while representing a real-world scenario via simulation. Working with "real" data gives us the potential to make accurate predictions for real-world problems. The data used in this paper to supplement Typhoon HIL simulation is solar irradiation and external temperature in the city of Berlin. There is also a level of flexibility in using different types of data from different parts of the world. This data is acquired from Solcast (https://solcast.com/), a global solar forecasting and historical solar irradiance data company [7].

Our Multi-Agent System (MAS) Siebog [1] orchestrates the TyphoonHIL Control Center [2] and the Mainflux platform [3] to provide a realistic household simulation with maximum flexibility and a variety of internal and external factors. Internal factors, i.e., various smart home environments containing different types and numbers of devices, can be simulated with the Typhoon HIL Control Center [2]. The simulated smart home receives external factors, i.e., irradiation and external temperature from the Mainflux platform, and later these parameters affect other components in the simulation (PV panel and AC).

The new real-world input data is evaluated by comparing the average energy produced from real-time irradiation and external temperature data and the computed average energy generated in our HEMS simulation using the Solcast data as input.

The paper is organized as follows. Section 2 gives a brief overview of existing solutions that are multi-agent based architectures for simulating household environments. Section 3 represents a MAS based HEMS framework and we describe the compomenets that preserve this framework. In section 4 we presents the results that we acquired with the integration of the Mainflux platform and section 5 consists of the conclusion of our system and future work.

II. EXISTING SOLUTIONS FOR SIMULATING HOUSEHOLD ENVIRONMENTS BASED ON MULTI-AGENT SYSTEMS

In [4], the authors describe a multi-agent system that loads the outdoor temperature and outdoor illumination as predefined values that are constrained and normalized. These values are later used in an agent that applies fuzzy logic to compute the electric energy consumption for indoor lighting and temperature. The observed temperature and illumaniation values are used during the

[1] PV represents a form of renewable energy resource.

seasons when the AC is required to cool indoor enviroment.The outdoor temperature and illumination values are discretized into three categories: LOW, MEDIUM, and HIGH [4]. This discretization can limit a simulation of an everyday household rendering a less realistic scenario, as more subtle changes in the temperature affect the simulated values for indoor temperature. Moreover, the defined categories can vary between systems depending on the observed interval of the outdoor values. Our solution uses continuous realistic values of outdoor temperature while simulating energy consumption in a household. The values vary depending on the location from where the temperature and solar radiation data are collected. This flexibility enables us to simulate households regardless of their actual location.

Paper [5] represents a system that contains several multi-agent systems that have the goal of energy consumption reduction based on case-based reasoning (CBR) recommender system. Their solution provides a complex system that uses the K-Nearest Neighbor algorithm and Support Vector Machine to optimize energy consumption in a building based on historical data. A multi-agent system proposes a solution for energy consumption reduction. Another MAS system appointed to simulate a building will consider using this solution by applying an auction-based system. The system that simulates an everyday household also manages and controls the devices. Similarly, the system we propose in our paper will regard historical data for decision-making and simulating household appliances. The task of simulating, controlling, and managing devices is decoupled in our solution, which allows for greater simulation flexibility (i.e., simulating various household cases in different climates and with various household devices). While the Typhoon HIL Center simulates a household environment and the appliances, the Multi-agent system Siebog manages and controls these devices. This enables us to obtain scalability in our application with the number of devices that we will add to our future system.

In the solution given in [6], we have another system that describes a set of multi-agent systems that aim to optimize energy consumption in a smart building. They propose a solution where the system evaluates a day ahead strategy. The system predicts and chooses the optimal solution to optimize energy consumption. They also have an additional layer that considers the possibility of uncertainties in their decision-making before the conclusion.

Most of the previous solutions use real-world data in the form of hardware appliances. While this is the most realistic setting, a trained HEMS is limited to a single scenario (i.e., a particular household). On the other hand, simulation offers more flexibility for training different HEMS for different households. In our system, a realistic simulation will be possible with the Mainflux platform's addition that enables us to store or read real-time data from different devices. Currently, we are storing historical illumination and outdoor temperature and using this data in a simulated household environment, and in the future, we can easily modify our system to handle values measured in real-time.

III. METHODOLOGY

Our system (Figure 1) encompasses:

- the MAS that handles the creation of agents and interaction between agents,
- the Typhoon HIL Control Center that simulates household device,
- the Mainflux platform that serves as a middleware – it can collect real-world information from various household sensors and forward it to the MAS.

Mainflux represents a scalable, secure, open-source platform for the Internet of Things (IoT). Through this platform, solar radiance and outdoor temperature are loaded and later used to simulate a household environment in the Typhoon HIL simulator. In our solution, the MainFlux was used as a repository for real-world data. The data is first uploaded into the Mainflux and later from MainFlux distributed to Typhoon HIL simulator. Currently, Mainflux is used as a tool to import historical data. Our future goal is to read real-world data in real-time from physical devices which is the main purpose (function) of Mainflux.

The Typhoon HIL center offers an application for simulating everyday household appliances. In this paper, we have included controllable and uncontrollable devices. Controllable devices are intended to be controlled by

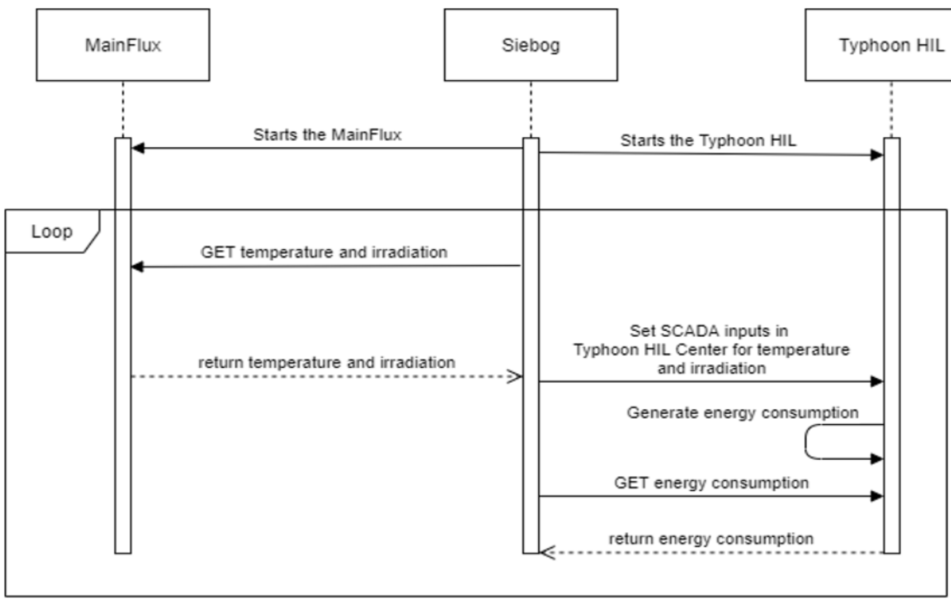

Figure 1 Communication between the Mainflux, Siebog and TyphoonHIL applications

HEMS, while uncontrollable devices are those used on-demand by the residents. Controllable loads include air conditioning, Boiler, Refrigerator, Washing Machine, Dishwasher, PV panel. Uncontrollable loads are loads produced by cooking, lighting, entertainment.

In the Multi-Agent System, all the devices in the smart home simulation are represented with corresponding agents. The PV Panel and the Air Conditioning components of this environment use outdoor temperature and solar irradiation as input values. The data for irradiation and temperature are downloaded from the Solcast [7]. The information can be obtained in different resolutions, ranging from 5, 10, 15, 30, or 60 minutes. With the help of the various irradiation and temperature values worldwide, our system has a better grasp of energy requirements by different households worldwide. The Typhoon HIL simulates energy consumption in a typical household and, after a defined period, waits for the MAS to evaluate a cost function we defined in [8]. This cost function balances the costs of energy used by simulated devices with user comfort.

The entire architectural solution has been presented in [8]. In the following section we will describe a detailed description of the Mainflux middleware which is a novelty to our system.

IV. Mainflux Middleware

Our system incorporates a Middleware, Siebog, used as a mediator between the Typhoon HIL Control Center and the Mainflux platform. The information regarding the solar irradiation and outdoor temperature is represented as rows in a CSV file. As a first step in starting the platform, the system loads the information from the CSV file and into the Mainflux platform with the CSV Reader. During the simulation, the data is sent from the Mainflux every 15 minutes of simulation time to the Siebog. The parameters are forwarded to the Typhoon HIL Control Center and used to evaluate the energy produced in a PV panel and an Air Conditioner unit's temperature. In our model, simulating 1 minute takes 5 microseconds in real-time.

Figure 1. presents a simplified view of the communication between our three systems. The diagram shows that Siebog has the role of a mediator between the Mainflux and Typhoon HIL Center. Siebog obtains temperature and irradiation from Mainflux every 15 min of simulation time and forwards this information to the Typhoon HIL Center. Typhoon HIL simulates household devices using the new input values and calculates the energy consumed for the 15 min of simulation time. Siebog acquires the resulted energy consumption from the Typhoon HIL Center and calculates the cost. In the future, this simulation will be used as an environment for training a reinforcement learning algorithm.

A. *Modeling the HEMS in Typhoon HIL*

The household is modeled in the Typhoon HIL Schematic Editor. The Schematic Editor is a software that is part of the Typhoon HIL Center.

The first model (Figure 2.) represents the irradiation input. We have the signal switch that indicates if our system is using data from the Mainflux or generated data.

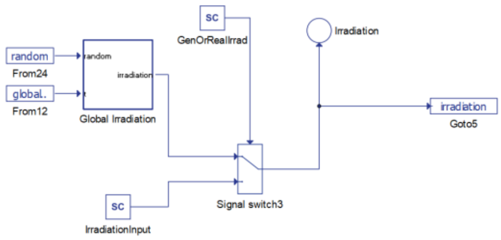

Figure 2 The irradiation component is represented in the Typhoon HIL Schemantic Editor. The value of irradiation output depends if the system is randomly generating irradiation values or real-world values are provided from the Mainflux

The same is presented in Figure 3. where we have the input for temperature.

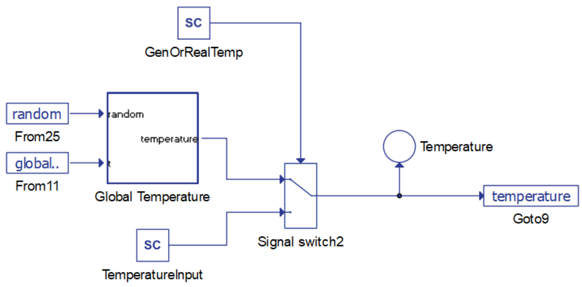

Figure 3 The temperature component that is presented in the Typhoon HIL Schemantic Editor. The value of temperature output depends if the system is randomly generating temperature values or real-world values are provided from the Mainflux

This is later used in household appliances PV and AC Figure 4.

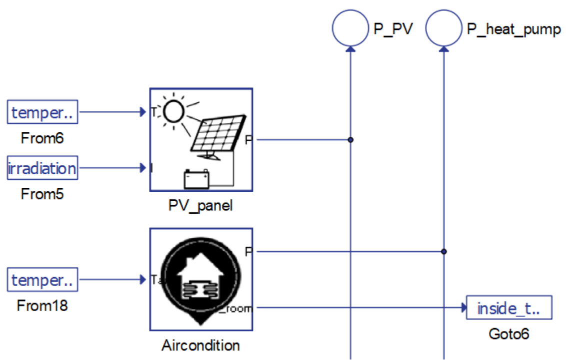

Figure 4 The PV panel and Aircondition components that are presented in the TyphoonHIL Schemantic Editor. The input values are the temperature and irradiation values generated from the previous components. The output values are the produced and consumed electric energy from the PV panel and AC.

The inside temperature will later be used to generate the power usage of the boiler and refrigerator in future household models. For now, we use the consumed power for our cost evaluation function. This function is the cost function described in [1] and in the future, it will represent a reward for an RL model.

V. Results

Figure 5. [10] shows a diagram representing electricity generated in Germany from 08.05.2020. untill 08.05.2021. This electric energy was generated with renewable energy sources (biomass, hydro, solar, and wind). The graph

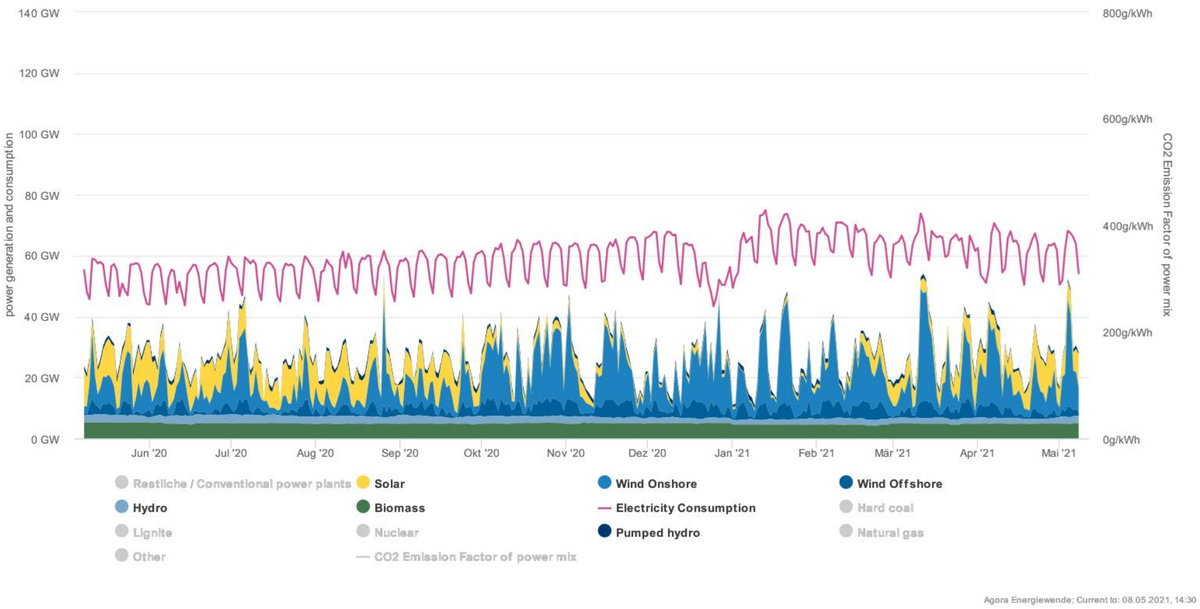

Figure 5 Power Generation and Consumption from May 2020 to May 2021, published by Agora Energiewende [10]

shows the amount of power generated in gigawatts (GW). The electricity generated by wind onshore is dominant during the fall and winter period, and during the spring and summer solar is more frequent. The top squiggly line represents electricity consumption. The average power consumption in Germany per capita, in a household, is 6,771 kWh [10]. Currently, there are not enough renewable energy resources to cover the demand for electricity consumption. Figure 6. [11] presents the change in electricity production. Fossil fuels are having less of an impact on generating power, and the use of renewables is making a trend in Europe [11]. We can see a rising trend in renewable energy resources over the years, and the predictions are that it will keep on growing.

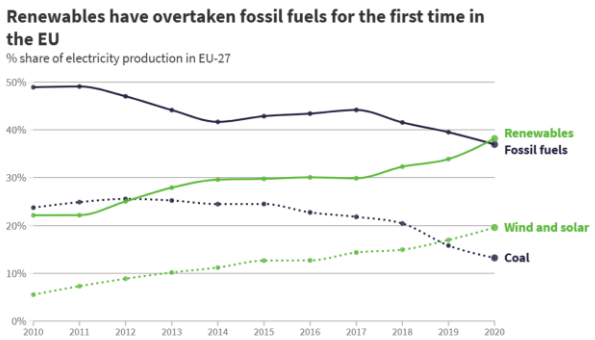

Figure 6 “Europe’s Power Sector in 2020”, published by Ember and Agora Energiewende [11]

External factors such as the weather, outdoor temperature, and solar irradiation are variant and unpredictable. As discussed in [9] it is hard to predict weather conditions and because of this there is a level of uncertainty in regards to the available energy in households that use both energy provided from a PV panel and atmospheric conditions, such as solar irradiation. In [9] one of the more costly household appliances is an AC. The importance of adjusting a system with valid data is major, given the high demand and usability of this device. In our proposed application we use irradiation to represent a working model of an AC.

Figure 7 presents an average per month of generated power from the PV. The PV panel is a component in the simulated environment and it produces electric energy. This energy can directly supply the house loads. In the future, it will also be used to charge the electric storage (eg. house battery) or be sold to the distribution grid. Similar to Figure 1 we can see that in Figure 7 the PV panel on average produces more power during the spring and summer seasons, and less in late fall and early winter. We were able to recreate a realistic PV electric energy production, which we can use in the simulated environment.

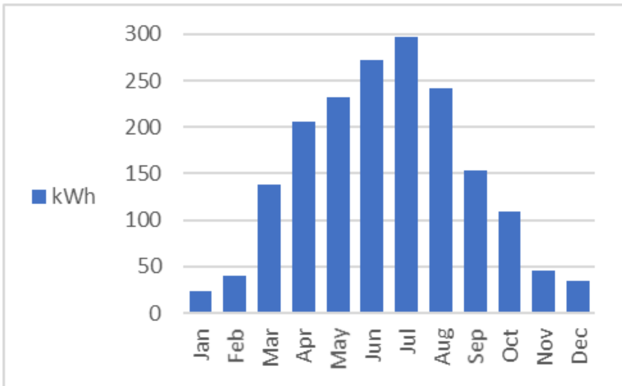

Figure 7 Average monthly electric energy production of a PV panel in kilowatt-hour(kWh)

Observing the average energy generated from renewable enery sources Figure 5 and the average computed energy production in our HEMS Figure 7 we can see that in both cases during the late spring and summer most of the generated energy is provided from irradiation and less during fall and winter.

Figure 8 represents the computed average values of the cost function during the simulation of the HEMS. The simulated devices are the refrigerator, uncontrollable loads and the pv panel. Power usage of the simulated devices hava a negative impact to the cost function, while their benefit has a positive impact. The refrigerator is a high priority device, which means that the benefit of having this device in an activated state is desired by the systems cost function. Uncontrollable loads consist of devices for lighting and entertainment. Their activated state is not beneficial to the system. All of the previous devices consume energy. On the other hand, the pv panel is a device that produces energy and as such it only has a positive effect to the cost function. [8]

Other parameters that are taken into account are user defined priorities of individual controllable devices, and the energy that needs to be bought from the grid. The negative values of the cost function indicate that more energy is being consumed than produced, and positive values denote the opposite, more energy is produced than consumed. Currently, only one device produces energy and the rest consume it. During the spring and summer period when the level of irradiation and temperature is higher, more electric energy is produced. This is also depicted in the evaluation of the cost function in Figure 8.

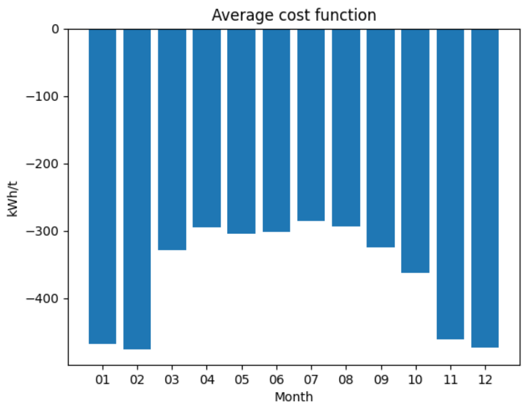

Figure 8 Average monthly cost function evaluation, with uncontrollable loads, refriegerator and pv panel turned on

VI. Conclusion

In this paper, we presented our HEMS solution that manages household appliances to optimize the cost of energy consumption. The system is split into three independent software entities. We expanded our previous application [8] with a third-party software Mainflux, to include data provided from sensors. This data consists of irradiation and outdoor temperature. We presented the trend of renewable energy sources, and how they have a significant impact on energy generation in household environments.

We discussed the importance of a HEMS architecture and how integrating third-party software benefits in simulating an everyday household. There is uncertainty when we observe appliances such as AC and PV. These devices depend on unpredictable factors. The habits of individual households and climate conditions vary. The usage of real-world data in a simulated environment gives us the possibility of simulating profiling in a way we can focus on different family profiles and habits. In our final results we plotted the value of the computed energy production in our system and compared these values with real-time power generation data. These results will later have an impact in training an RL model. The end goal is to achieve a self-learning model that will optimize energy consumption and indulge users' preferences.

Acknowledgment

This work has been partially supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia (project III 44010). This work was also supported by Typhoon HIL, Inc. (www.typhoon-hil.com) by providing the equipment and infrastructure for the project.

References

[1] D. Mitrović, M. Ivanović, M. Vidaković, Z. Budimac, "The Siebog Multiagent Middleware", Knowledge-Based Systems, vol. 103, no. C, pp. 56-59, July 2016.

[2] Typhoon HIL Control Center. Received from https://www.typhoon-hil.com/

[3] Mainflux platform. Received from https://www.mainflux.com/

[4] Soetedjo, A., Nakhoda, Y.I. and Saleh, C., 2019. An Embedded Platform for Testbed Implementation of Multi-Agent System in Building Energy Management System. Energies, 12(19), p.3655.

[5] Pinto, T., Faia, R., Navarro-Caceres, M., Santos, G., Corchado, J. M., & Vale, Z. (2018). Multi-Agent-Based CBR Recommender System for Intelligent Energy Management in Buildings. IEEE Systems Journal, 1–12.

[6] Gazafroudi, A. S., Pinto, T., Prieto-Castrillo, F., Prieto, J., Corchado, J. M., Jozi, A., … Venayagamoorthy, G. K. (2017). Organization-based Multi-Agent structure of the Smart Home Electricity System. 2017 IEEE Congress on Evolutionary Computation (CEC). doi:10.1109/cec.2017.7969458

[7] Bright, J. M. (2019). Solcast: Validation of a satellite-derived solar irradiance dataset. Solar Energy, 189, 435–449. doi:10.1016/j.solener.2019.07.086

[8] Aleksić, A., Vidaković, M., Slivka, J., Milosavljević, B., Kaplar, A. Multi-Agent based HEMS framework. In: Zdravković, M., Konjović, Z., Trajanović, M. (Eds.) ICIST 2020 Proceedings Vol.1, pp.84-88, 2020

[9] Mahapatra, B., & Nayyar, A. (2019). Home energy management system (HEMS): concept, architecture, infrastructure, challenges and energy management schemes. Energy Systems. doi:10.1007/s12667-019-00364-w

[10] Recent Electricity Data 2020, graph presenting Power Generation and Consumption, Agora Energiewende, accessed 8 May 2021, <https://www.agora-energiewende.de/en/service/recent-electricity-data/chart/power_generation/01.05.2020/08.05.2021/>

[11] European Electricity 2021, Graph of Europe's Power Sector in 2020, Ember and Agora Energiewende, accessed 8 May 2021, <https://ember-climate.org/data/european-electricity/>