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Boosting DR through increased communIty-level consumer engaGement by combining Data-driven and blockcHain technology Tools with social science approaches and multi-value service design

Deliverable
D4.3 Flexible assets DT models – first version

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List of Acronyms and Abbreviations

BRIGHT	Boosting DR through increased communIty-level consumer engaGement by combining Data-driven and blockcHain technology Tools with social science approaches and multi-value service design
CEM	Customer Energy Manager
DR	Demand-Response
EMS	Energy Management System
EV	Electrical Vehicle
HVAC	Heating Ventilation Air Conditioning
PV	Photovoltaics
RC Model	Resistor Capacitor Model

Table 1 List of Acronyms and Abbreviations

Executive Summary

In order to cost effectively unlock energy flexibility from flexible assets a couple of important challenges have to be addressed. One of these challenges is dealing with the enormous variety of assets and the wide range of protocols that are used to remotely control assets. This challenge can be addressed by using a standardized protocol such as S2 (EN50491-12-2) to communicate about energy flexibility.

Using such a protocol, however, is not the whole story. Energy flexibility can be expressed in a uniform way, but for each device one still needs to determine first how much flexibility is actually available. For some assets, such as a heat pump, this can be quite complex. Its flexibility does not only depend on the heat pump itself, but also on the thermal mass of the building it is deployed in.

It is not practically feasible or cost effective to manually create models to determine the amount of flexibility for each unique individual configuration. In order to solve this issue, task 4.3 focuses on creating self learning digital twins that automatically adapt to the unique characteristics of a flexible asset and its environment.

Initial digital twin models for three different flexible assets have been developed: a residential heat pump, a HVAC system for a large apartment building and EV charging stations. Task 4.3 also looked into different training methods that can be used to provide the digital twins with self-learning capabilities.

The digital twins for the residential heatpump and the HVAC system use a grey box approach where a simplified RC model represents the thermal behaviour of the building. In both cases the training method is aimed at finding the correct parameter values of the RC model using sensor measurements as the training set.

For the EV charging a lot of operational data has already been collected both from the car and the charging station side. This data will be used to learn the EV charging behaviour.

In the coming period the digital twin models will be refined further and the training methods will be thoroughly evaluated.

1. Introduction

This D4.3 deliverable describes a first verion of the digital twin models for several flexibile assets.

1.1. Purpose

Energy flexibility from smart devices/assets can play a crucial role in solving the issues that smart grids are facing, such as congestion management or alleviating imbalance. In order to untap the flexibility potential of smart devices, however, there are a couple of challenges that need to be addressed.

To begin with the amount of flexibility per device is relatively small, especially when compared with large industrial assets. Because of this low flexibility margin, the costs required to unlock a device's flexibility have to very low as well. Another challenge is the enormous variety of devices such as heat pumps, PV, EV, batteries, whitegoods that also come from different manufacturers. This often leads to proprietary solutions for individual devices which in turn leads to high costs to unlock their flexibility as each solution is a custom one that can not be reused for other devices.

These challenges can be overcome by creating automated and standardized solutions in order to minimize the costs of interfacing with smart devices. S2 is such a solution; it is a standard protocol that can be used to control energy flexibility of smart devices. This protocol is standardized through CEN-CENELEC as the EN50491-12 standard series.

In order to use the S2 protocol, the native information available on the device has to be mapped to the appropriate S2 parameters. For some devices such as whitegoods this is relatively straightforward, but for other categories of devices such as HVAC and EV charging this can be quite involving as their flexibility is dependent on a lot of different factors. Take a HVAC device for example; its flexibility is not only dependent from the capabilities of the device itself but also from the building characteristics and the behaviour of the users of that building. Manually creating a model for a HVAC device that takes into account the unique building and user behaviour context would take a lot of time. Moreover, this process would have to be repeated for each individual HVAC deployment. This is not a feasible approach as it is too costly and would require too many personhours.

To solve this issue, task 4.3 focuses on developing self learning digital twins for smart devices that are able to automatically adapt to the characteristics of a smart device and the context it operates in. These digital twins should only require a minimum of initial configuration if any. In combination with sensor measurements (e.g. outside and inside temperature, presence sensors, etc.) a digital twin can provide an acurate estimation of the amout of energy flexibility that a device has to offer.

The focus of this deliverable T4.3 is on providing initial designs for digital twins and to explore different training approaches to provide them with self learning capabilities. The smart devices that will be considered in this deliverable are: a residential heatpump, a central heatpump for an apartment building and EV charging stations.

1.2. Relation to Other Activities

Task 4.3 is most closely related to the following WP4 tasks:

- **Task 4.4 - Digital Twins for customers clustering and segmentation.** The electric and thermal load profiles that are the subject of this task are valuable input to the digital twins models for flexible assets.
- **Task 4.5 - Digital Twins for electrical and thermal communities.** The digital twins that are developed in task 4.5 are on the aggregation level of energy communities. It is important that there is a correlation between the community level digital twins and the ones that are developed for the individual device level in task 4.3.

1.3. Structure of the Document

This document is structured as follows:

- Section 2 provides an overview of the S2 standard protocol that is being used to control the energy flexibility of smart assets.
- Section 3 introduces the initial digital twin models for the flexible devices/assets that will be investigated in this task: a residential heat pump, a HVAC system for a large apartment building and EV charging stations.
- Section 4 explains the training and validation approaches of the digital twins for the abovementioned devices/assets. The ability to train the digital twin is very important as this makes it possible for digital twin models to adapt itself to new or changing circumstances.
- Section 5 presents the conclusions of this deliverable and briefly looks ahead at the next steps of task 4.3.

1.4. Intended audience

The target audience of this deliverable are all stakeholders that are involved - or have an interest in unlocking flexibility from smart devices/assets. This may include device manufacturers, aggregators, Energy Management System developers, building owners, etc.

2. S2: Standard Interface for Flexibility

Energy flexibility is an essential part of Demand Response solutions; without flexible assets/devices it would be impossible to perform Demand Response. Despite the fact that energy flexibility is widely recognized as a crucial concept, there are many different interpretations of what energy flexibility actually is. This is also reflected by the many proprietary protocols that are implemented on smart devices to control their flexibility. All these different implementations make it hard to tap into the true flexibility potential of smart assets/devices.

In order to unlock flexibility in an efficient and interoperable manner a uniform standard for expressing and controlling flexibility is needed. Over the past years this standard, which is referred to as S2, has been developed by CEN-CENELEC TC205/WG18. This chapter provides an overview of S2 and explains both the S2 architecture and interface. The S2 architecture (section 2.1) describes the main components involved and their responsibilities and is standardized as EN 50491-12-1. The S2 interface (section 2.2) describes the data models and messages that are exchanged, which are standardized as EN 50491-12-2.

2.1. S2 Architecture (EN 50491-12-1)

The EN 50491-12-1 architecture focuses on the premises side of the smart grid and is mainly concerned with the communication between smart devices and the Customer Energy Manager (CEM). Figure 1 provides a logical view of the components that can be found at the premises side.

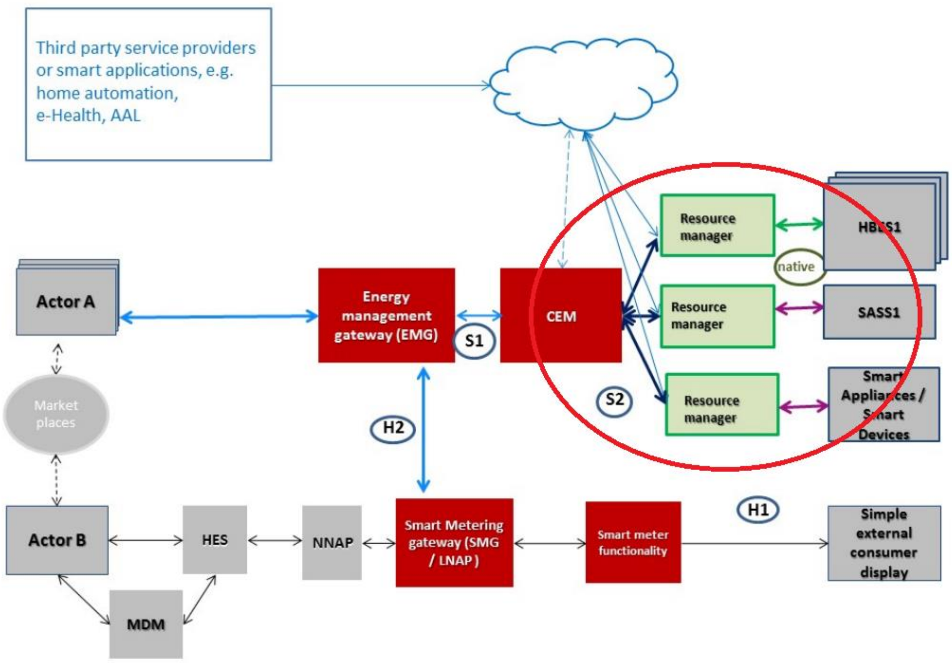


Figure 1: Logical view of a premises smart grid system

The logical view shows all of the relevant smart gird systems on the premises, the red circle outlines the scope of CEN-CENELEC's 50491-12 standard series. Within this standard series the so called S2 interface is being specified.

The S2 interface is used to communicate the energy flexibility of smart devices to the Customer Energy Manager (CEM). The CEM also uses S2 to send instructions to smart devices to exploit their flexibility in a specific way. The components involved in the S2 communication are described below.

- **Smart Devices.** Smart Devices can offer energy flexibility by deviating from their normal consumption/production pattern. These devices can be controlled externally so that they can be integrated into the premises smart grid system. These devices are very diverse and perform a wide range functions within a home or a building, such as whitegoods, PV, HVAC, etc. In Figure 1 this is reflected by the different terminology that is being used. Smart devices/appliances represent devices like whitegoods. The Home and Building Electronic System (HBES) are systems that are used in home or building automation and perform functions such as switching, open and closed loop control. Singe Application Smart System (SASS) are systems that are composed of a group of devices that work together for a single application. Think of a HVAC system that is composed of components such as fans, chillers, radiators etc. Controlling a single component within such a system for flexibility purpose might disrupt the correct functioning of the complete system. Therefore the entire system with all of its components should be treated as a single source of flexibility.

  As is apparent these devices are very diverse in their functionality. This also goes for the protocols that are used to control these devices externally. Examples of such (IoT) protocols are KNX, EEBUS/SPINE, ModBus, Zigbee, Bluetooth, WiFi, Z-Wave, but also proprietary protocols. The same holds for the data models/parameters that are used. It is virtually impossible for a Customer Energy Manager to be aware of and support all possible permutations of functionality, protocols and data models. This is where the Resource Manager and the S2 interface come in.

- **Resource Manager.** The Resource Manager is an intermediary logical component that on one side communicates with the smart devices using its native protocol and data model and understands the functionality that the device performs. On the other side it communicates the flexibility options of the devices to the Customer Energy Manager (CEM). The CEM is only interested in the flexibility that the device has to offer, not in all of the available detailed device parameters and protocols. These would simply overwhelm the CEM and would require adaptations to be made to the CEM every time a new device would be connected.

  The Resource Manager translates the low level device information into more high level information on the energy flexibility that is offered to the CEM via the S2 interface. This is not a straightforward mapping; information that is not relevant for energy flexibility needs to be filtered out while other information needs to be enriched to make it relevant for energy flexibility. Take a thermal buffer for a example; a Resource Manager will have to understand what the capacity of that buffer is and how fast it can be heated. The S2 Control Types sections below describes in more detail which energy flexibility information is conveyed over the S2 interface. The Resource Manager will also receive instructions over S2 from the CEM to use the flexibility in a particular way.

  In providing flexibility to the CEM, the Resource Manager will also take user comfort as well as the operational boundaries/safety margins of the device into account. These aspects will also be checked if the Resource Manager receives an instruction from the CEM. If user comfort or the operational boundaries/safety margins are compromised by executing a CEM instruction it is the responsibility of the Resource Manager to reject that instruction.

- **Customer Energy Manager.** The CEM takes into account the flexibility that is being provided by all Resource Managers on the premises. Based on its optimization objectives and additional external information/incentives, it will decide how to use that flexibility so that its objectives will be met as closely as possible. Examples of CEM objectives could be to optimize on dynamic energy tariffs, promote self-consumption as much as possible or to help the DSO alleviate congestion. After the CEM decided on how to use the flexibility, it will send an instructions to the Resource Managers over S2.

  By using S2 a lot of the implementation details of the devices are hidden for the CEM and it can focus on its core business: managing energy flexibility. This enables the CEM to connect to a wide variety of devices with little effort thus promoting interoperability.

2.2. S2 Interface (EN 59491-12-2)

Resource Managers are all capable (if supported by the underlying smart device) to provide power/energy measurements and forecasts. These are measurements that only comprise individual devices in contrast to the aggregate measurements that the smart meter (gateway) provides via H2/S1. In addition to these basic and generic functions, the S2 interface features five control types that represent different types of energy flexibility. A Resource Manager will map the flexibility of the device it represents onto one of these control types. The CEM will only have to implement these control types to be able to connect to all devices via their respective Resource Managers. The control types are described below:

- **Power Envelope Based Control.** This control type is used for devices that can not be controlled by the CEM to adhere to a specific value for their production or consumption. They can however be asked by the CEM to not exceed certain power limits over time. A typical example of such a device would be a PV panel. The CEM cannot directly control its production as this is dependent from the amount of sunshine, but it can ask the PV panel to not exceed a certain production limit, also known as curtailment. This feature is very useful for congestion management for example. When there is too much production for the local grid to handle, this control type can be used to limit the output of the PV panel to a manageable level.

- **Power Profile Based Control.** The power profile based control type is typical for devices that perform a function with a corresponding power profile that is known or can be predicted beforehand. Their main flexibility comes from the ability to change the start time of that power profile. White goods, such as a washing machine with a delayed start option, are good examples of this category. A consumer fills the washing machine with dirty clothes, selects a program and chooses the final time by which this program should be finished. The CEM can then decide what the best possible start time is, giving its optimization objectives.

  Another type of flexibility is offered by this control type is the ability to choose between multiple alternative power profiles. The heating cycle of the washing machine might have alternative profiles, e.g. one that consumes less power but requires more time to heat the water and one that consumes more power and takes less time to reach the target temperature. The CEM can then choose which one of these alternative to use.

- **Operation Mode Based Control.** Devices that fall within this control type have the possibility to control the amount of power they produce or consume, without significant effects on their future flexibility options. Typical examples for this control type are diesel generators and variable electrical resistors. Such devices are often useful for balancing microgrids. Operation mode devices offer a lot of flexibility; they can assume a range of power levels at almost arbitrary moments in time. When this type of flexibility would be modelled with power profiles, as used for power profile based control, the number of possible permutations would rapidly grow beyond practical limits.

  To avoid such issues, the operation mode control type is modelled as a state machine. A resource manager can declare multiple operation modes for a device. An operation mode is a mode/state that a device can find itself in, that is associated with a specific power value. For example, a diesel generator can have three operation modes: one for being off, one for running at reduced power and one for running at full power. The `off' operation mode has a power value of 0 W associated with it, the `reduced power' operation mode has a power value of -1 800 W (a negative value denotes production), and the `full power' operation mode has a power value of -3 000 W.

  Transitions between operation modes are also explicitly specified. This way, the possible transitions between operation modes may be restricted. Transitions can also be equipped with timing constraints: a device can for example express that it needs to run for a minute in `reduced power', before it can move on to `full power'. This can be achieved by defining a 'minimum on time' timer that blocks the transition when its value is not equal to 0.

  The CEM can send instructions that will tell the Resource Manager which operation mode to go to next. These instructions also contain timestamps to inform the Resource Manager on when the transition to a next operation mode should be made.

- **Fill Rate Based Control.** The fill rate-based control type can be used for devices that have the ability to store or buffer energy. How energy is stored or buffered does not matter, as long as there is a means to measure how full the storage or buffer is.

  There are many examples of devices that can store or buffer energy. Stationary batteries and electric vehicles are examples of devices that store energy in batteries. Heating devices such as CHPs, (hybrid) heat pumps or boilers can buffer energy in a dedicated heat buffer (typically a thermally insulated water tank), but a room with an allowable bandwidth for the temperature can also be used as a buffer.

  Finally, there are also devices that produce cold, like air conditioners, fridges and freezers. Just like heat, cold can be buffered. There are even more ways to buffer or store energy imaginable, such as storing energy in the form of hydrogen, air pressure, water pressure or angular momentum.

  The main component of this control type is the storage itself. A device shall be able to inform the CEM about its fill level, a measure of how full the storage is, and the lower and upper bounds that the fill level should remain within. If applicable it can also inform the CEM about its target fill level and by when that should be reached. This would be useful when charging an EV for instance (in case the EV is able to report on its state of charge). In addition to the storage there are also actuators that can affect the fill level of the storage. E.g. an electrical heating element in a hot water buffer.

The behaviour of the actuators is described with a state machine, just like the operation mode based control type. In this case however the states also specify what their influence on the fill level of the buffer is.

- **Demand Driven Based Control.** Demand Driven Based Control can be used for systems that are flexible in the type of energy carrier they use, but are not capable of buffering or storing energy (in that case Fill Rate Based Control should be used). A typical example is a hybrid heat pump, that generates heat using either electricity (using a heat pump) or natural gas (using a gas boiler), but doesn't have a thermal buffer. The hybrid heat pump must deliver a given amount of heat (hence demand driven), but can still decide whether to generate this heat using electricity or natural gas. Typically, such systems favour the heat pump, but use the gas boiler in case the heat demand cannot be fulfilled by the heat pump alone or when there is a shortage of capacity in the electricity grid.

  Similar to the Fill Rate Based Control, Demand Driven Based Control has the concept of multiple actuators. Again the behaviour of these actuators is described using a state machine. This time the states do not specify their influence of the fill level of the buffer is, but they specify a supply rate that can be matched with the demand. The CEM can select a state for each actuator as long as the demand is being matched by their aggregated supply.

3. Digital Twin Models

This section describes the digital twin models for three flexible assets that will be developed as part of task 4.3. The flexibles assets at hand are: a residential heat pump (TNO), a HVAC System of a Large Building with Diverse Heat Sources (including a large heat pump) and Heat Storage (Comsensus) and EV charging stations (Emotion). The subsections below introduce the digital twin models for each asset in more detail.

3.1 Residential Heat Pump

In order to properly determine the flexibility that a residential heat pump has to offer one also has to take into account the characteristics of the building that the heat pump is installed in. Examples of building characterisics that hugely influence the available flexibility are: the thermal mass of the building, the level of insulation, the surface area of walls, roof and windows, etc. This is why two digital twin models are necessary to determine the flexibility of the whole system: a model to capture the building characteristics and a model of the heat pump itself. In the following sections both these models will be introduced.

3.1.1 Simplified Building Model

The simplified building model is a simple RC model where are building is represented using two thermal masses. The basic idea of the model is that only a relatively small part of the thermal mass of a building is able to exchange heat with the indoor environment effectively.

This part of the thermal mass, called $C_{mass,in}$, consists of the furniture in the house, and the first few cm of the interior walls, roof, floor etc. The rest of the thermal mass, called $C_{mass,out}$, then exchanges heat with $C_{mass,in}$ through a resistance R_{exch}. Furthermore, the loss of heat from the external mass to the ambient or outside temperature T_{amb} is represented by R_{cond}, and loss of heat from the internal mass due to ventilation and infiltration is represented by $R_{vent+infil}$. This model is represented in Figure 2. For more details, please refer to the paper itself [1].

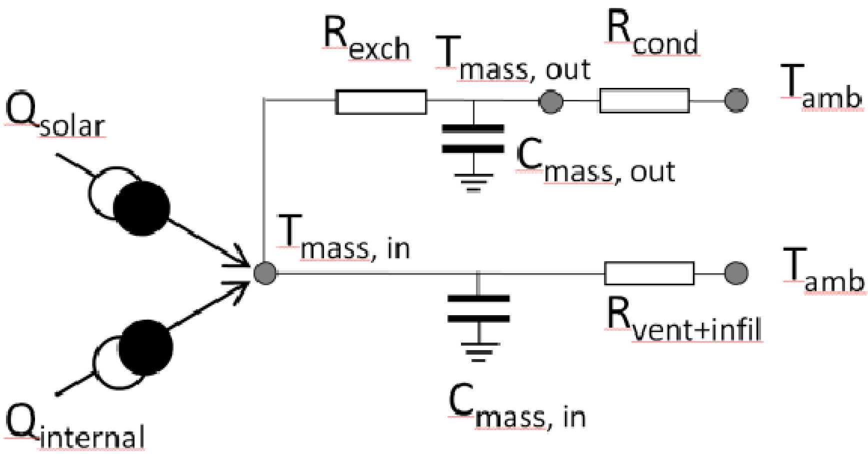


Figure 2 Simplified building model from Koene et al.

3.1.2 Residential Heat Pump

The heating source $Q_{internal}$ of the simplified building model (see Figure 2) can be elaborated to obtain a model which can used to more accurately evaluate scenarions relevant for determining available flexibility.

One of the important characteristics of the residential heat pumps which needs to be modeled is the Coefficient of Performance (COP), which is the ratio of work performed (electrical energy) and heat energy gained. Afjei et al. [2] describes three different methods of modeling the performance characteristics of heat pumps: 1. Calculations methods, which are mostly simple to use calculation methods, used to compare different heat pumps and other heating technologies. These methods mostly use a fixed COP based on the season and building characteristics. 2. Dynamic system simulation, where the COP is based on current conditions such as the ambient temperature. 3. Heat pump design models, where the refrigerant cycle of the heat pump is modeled.

Nyika et al. [3] describe a dynamic model where a performance map of heat pumps is created by fitting measurement data using linear regression. This model allows the COP to be modeled based on conditions such as the outside temperature and the return temperature of the heat pump, without modeling the refrigerant cycle of the heat pump. The parameters of this model can be fitted to work with various types of heat pumps and working conditions, making it a suitable model for the digital twin of the heat pump.

3.2 HVAC System Model of a Large Building with Diverse Heat Sources and Heat Storage

A building used for HVAC modelling in Slovenian pilot is a large retirement home building, where a community of elderly people live together with a nursing staff in a multi-apartment arrangement according to individual care needs and independence level. The building is connected to a district heating service by district heating heat exchanger with capacity of P_h=600 kW. Heat generation for heating of the building can be covered by two heat pumps with individual heating power of P_h=160 kW which gives a P_h=320 kW of heating power in ideal conditions just for heating hot water generation.

The heating power is distributed to radiator heating system with total heating capacity of P_h=340 kW, floor heating system with cumulative power of P_h=40 kW and to hot water air heating system with total heating power of P_h=147 kW.

The building heating system includes a hot water storage tank (heat storage) with capacity of 4000 liters which is mainly used during transitional periods between cold and hot seasons.

Additional to the heating system there is additional sanitary hot water system that is supplied from the district heat exchanger and 3 separate heat pumps with individual heating powers of P_h=27 kW at ambient temperature of T_a=30°C and individually equipped with heat storage vessels with volume of 2500 liters and individual P_h=27 kW electric heaters. The heating system without sanitary hot water generation system is presented in Figure 3.

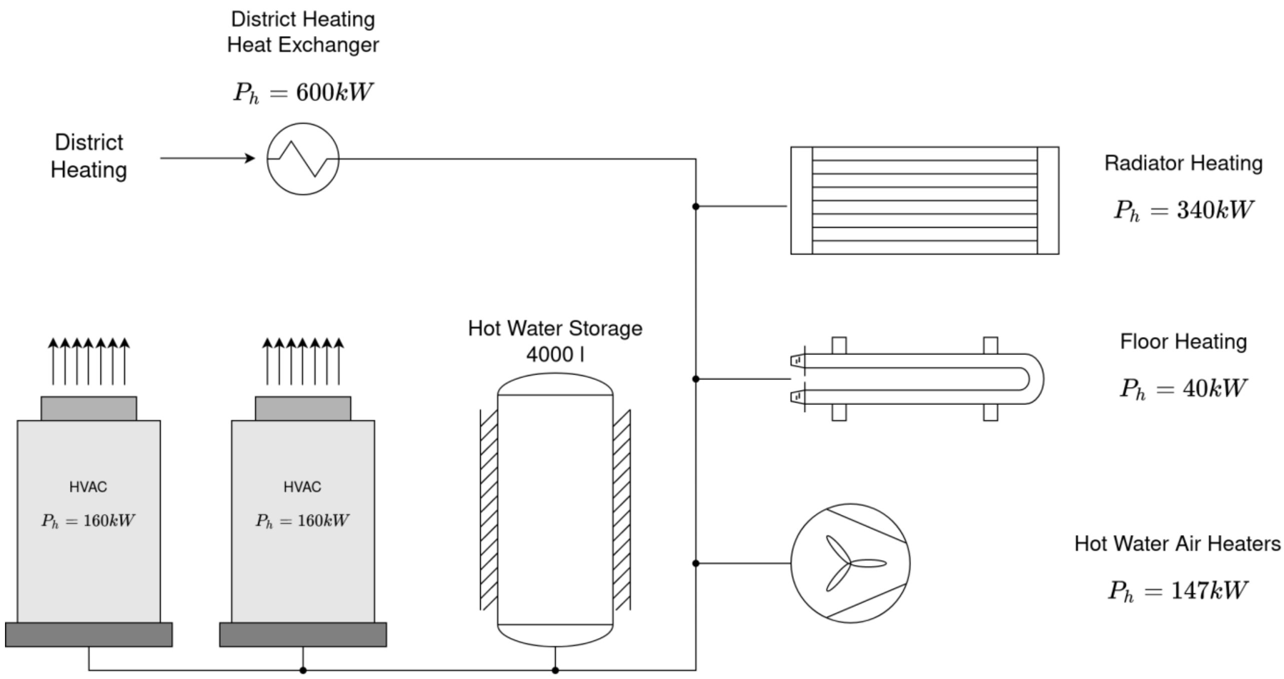


Figure 3: Heating system of a retirement home building in Slovenian pilot.

3.3 EV Charging [Emotion]

EMOT EV charging stations deployed in Terni pilot are characterized by two Type 2 sockets, recharging up to 32 A (22 kW) for each socket. They are equipped with a single-board computer that allows real-time monitoring and remote management of the charging station such as power output, energy price and remote charging session start&stop. SpotLink EVO connectivity is through RJ45 port (LAN) or modem.

Figure 4: Renault ZOE connected to EMOT charging station deployed in Terni pilot site

Regarding EV monitoring, EMOT will use an On Board Device (OBD) device to retrieve data from the EV; OBD is an IoT component that utilize a TCP/IP communication to a TCP/IP server. The network connectivity of the OBD device is via data SIM (UMTS) and the server is a python software, which queries the EV each 5 seconds. The OBD connects to the diagnostic interface from which it is able to extract the information from the electric vehicle control unit using the CAN-bus protocol. The output data format of the OBD is an ASCII string; when the data is sent to the server, it is reorganized into a wrapper, thus obtaining a grouping of the data in JSON format.

Figure 5 describes EMOT network topology estrablished by three main networks: the first, top left, is the network to which the EMOT headquarters and charging stations are connected, the second, bottom left, is the network to which the electric vehicles are connected and the third, bottom right, is the network where the EMOT Virtual Private Server (VPS) is hosted.

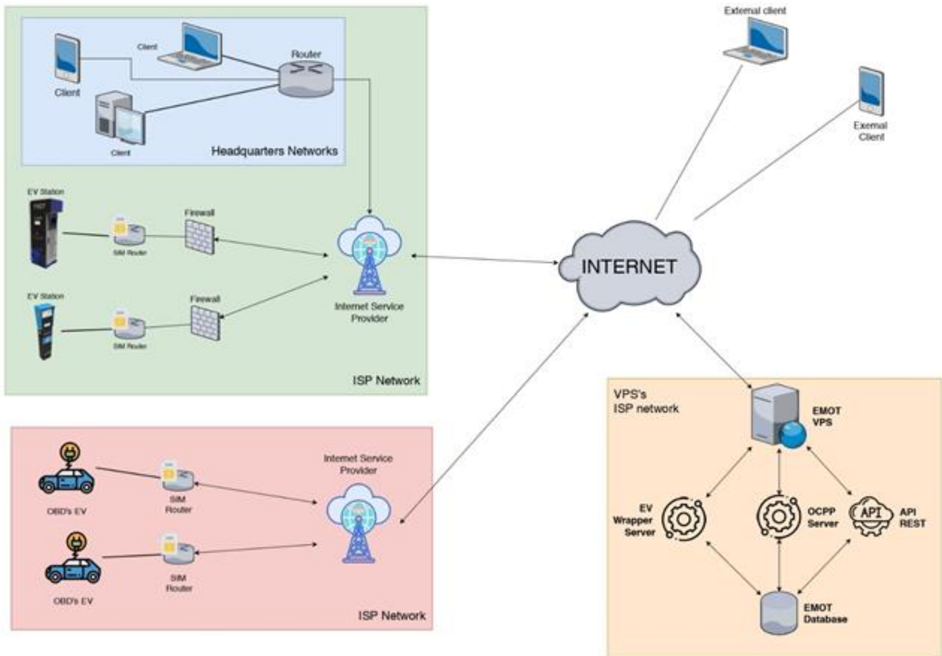


Figure 5: EMOT Network Topology

EMOT charging stations and electric vehicles send data to EMOT VPS whose details are:
• CPU: 2 core 3.1 GHz;
• HDD: 50 GB;
• RAM: 4 GB;
• S.O.: Ubuntu 16.04 LTS.
Into EMOT VPS run the EV Wrapper Server, OCPP server and API REST.

A digital twin machine learning model will be trained for forecasting energy flexibility provision, based on historical and real time data collected from deployed EVs and charging stations in Terni pilot site, detailed in section 4.3.

4. Training and Validation of Digital Twin Models

This chapter presents the training and validation approaches for the digital twin models of the various assets.

4.1 Residential heatpump

Setup

HESI facility

The Hybrid Energy System Integration (HESI) is a facility of TNO where organisations can experiment with the behaviour and robustness of energy-related technologies. The HESI facility accommodates multiple metered electricity and gas connections, a cold and a warm water grid, allowing for various experiments to be performed. The cold and warm water grid supply water of around 15°C and 40°C degrees respectively.

Heat pump setup

The experimental setup consists of a EcoGEO Basic B1 3-12 kW geothermic heat pump which is connected to the HESI grid. Using the cold and warm water grid, and a series of configurable valves, various conditions and environments can be simulated.

The heat pump setup consists a brine circuit and a heating water circuit. In a typical geothermal heat pump setup, the brine circuit is used to extract energy from the ground, while the heating circuit inserts energy into the building. These exchanges of energy can be simulated in the facility using heat exchangers connected to the cold and warm water grid. Three-way valves are used to control the temperature of the water the retour part of both circuits. A series of external sensors and sensors in the heat pump itself can be used to monitor and model the behaviour of the heat pump under the various conditions. Figure 6 shows a diagram of this setup.

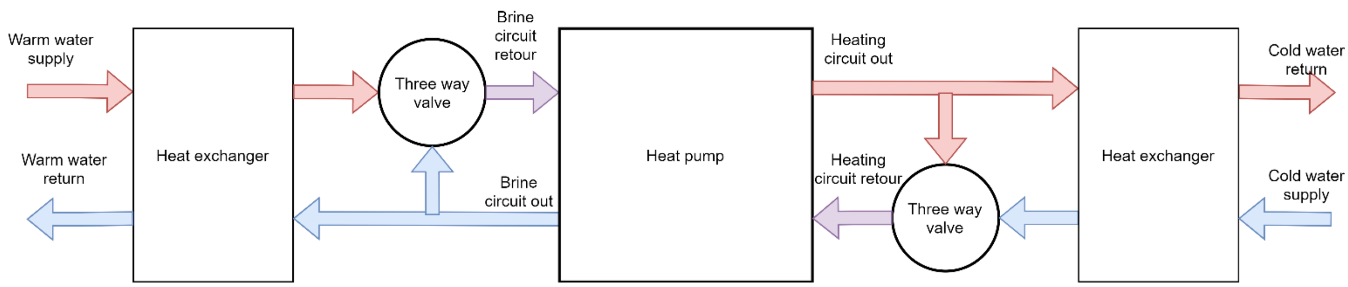


Figure 6: A diagram of the heat pump setup in the HESI facility

Models for digital twin

Heat profile generator

The heat profile generator is a tool which combines various sources of data (see Figure 7) to generate heat demand plots for buildings in the Netherlands. It uses the simplified building model described in section 3.1.1 to model the energy required to keep the average house in a district at certain temperatures.

The tool combines various publicy available sources of data to find the correct parameters for various buildings and districts in the Netherlands. It incorporates average temperature setpoint profiles and weather data to then find the energy demand for a building or a group of building. Figure 7 shows the data pipeline of the heat profile generator. Figure 8 shows what a generated heat profile looks like for a district in the Netherlands

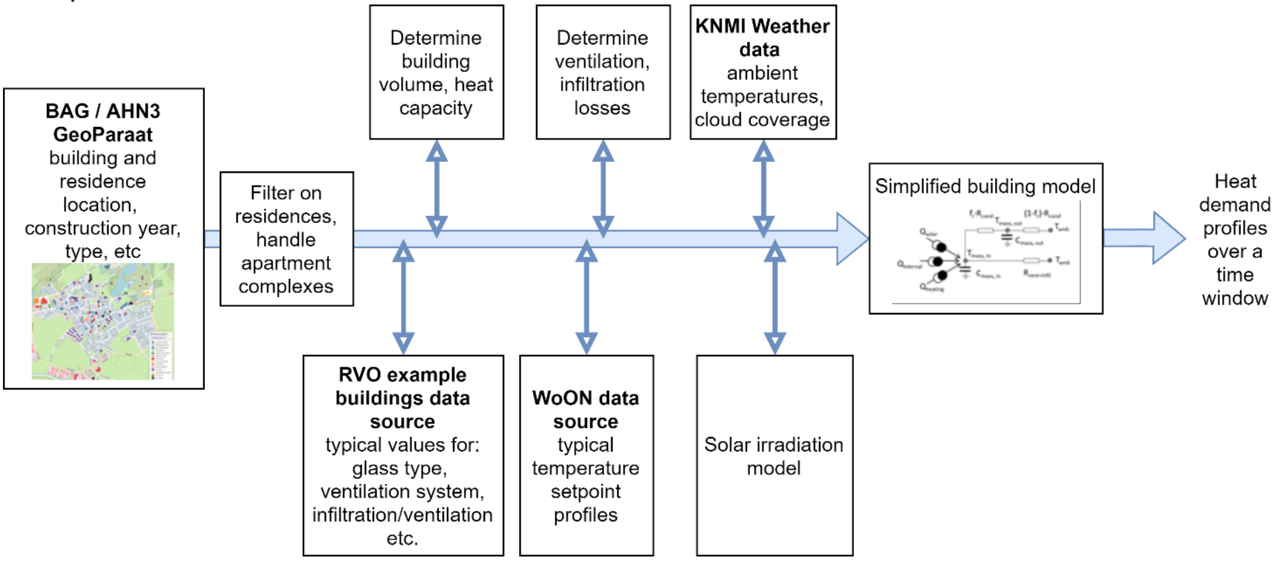


Figure 7: Heat profile generator pipeline

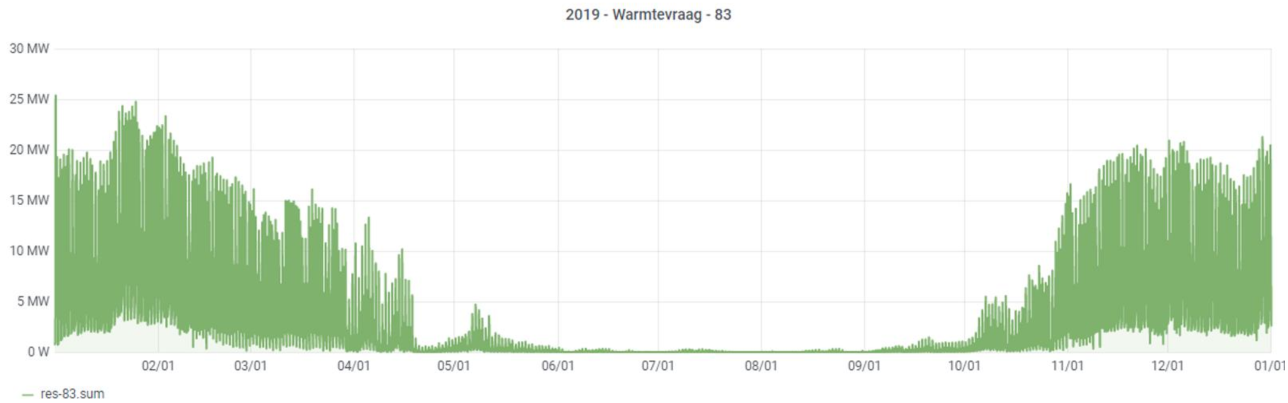


Figure 8: A heat demand profile generated for a district in the Netherlands

Training Digital Twin

The training of the digital twin is currently split up into two phases: initialization and adaptation.

Initialization

In the initialization phase of the digital twin the parameters of models comprising the digital twin are initialized according to a specific strategy. The result of the initialization phase can be regarded as a good initial guess with respect to the values of the parameters of the chosen models. This step can be based around more static variables, e.g. surface area, surface area of windows, orientation of the dwelling, type of heat pump, as opposed to more dynamic variables.

For example, the heat profile generator is chosen to serve as an initialization strategy for the simple building model, taking into account such aforementioned static variables. Afterwards, an initialized simple building model is obtained for a specific dwelling.

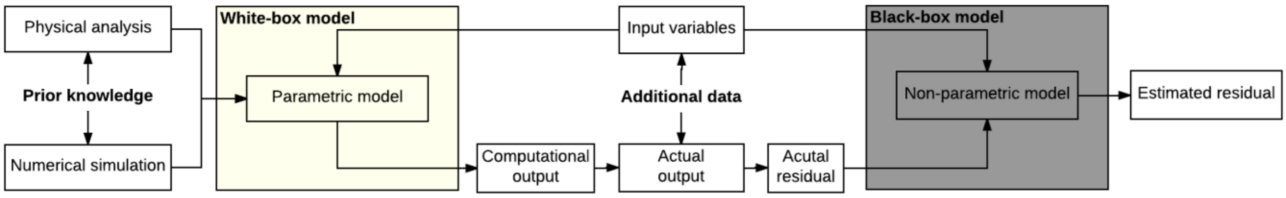
Adaptation

After initialization it is expected for there to still be a difference between the observed behaviour and the predicted behaviour by the chosen model(s) due to a lack of information during the initialization phase of the model. If the difference between observed behaviour and the behaviour predicted by the digital twin is too large, futher adaptation is required. This lack of information is expected to relate to variables which are considered to be dynamic as opposed to the static variables considered during initialization phase. Examples of such variables can be setpoint patterns of users, those derived from meteoreological data, and actual electricity and gas consumption of dwellings.

This approach of initialization and adaptation can be be regarded as a *grey-box modelling* approach. The steps involved in grey-box modelling are as follows (Yang et al., 2017) [4]:

1) construct the foundation for the system with a simplified knowledge model;
2) determine the physical parameters from the description of the system behaviour;
3) identify the values of model parameters from the actual data.

Here steps 1) and 2) overlap with the initialization phase and step 3) with adaptation phase.



For both the simplified building model, as well as the model utilized for the heat pump, the goal is to apply a *grey-box* modelling approach to obtain Digital Twins which are able to accurately model the target entity in its operational environment. For the simple building model the initialization phase is carried out using the heat profile generator. No initialization step has yet been identified for the heat pump.

4.2 HVAC System Model of a Large Building with Diverse Heat Sources and Heat Storage

A building used for HVAC modelling in Slovenian pilot is a large retirement home building, where a community of elderly people live together with a nursing staff in a multi-apartment arrangement according to individual care needs and independence level. Building is equipped with a backup diesel generator, big solar plant, it is connected to district heating service and is equipped with several heat pumps for general heating and separate heat pumps for hot sanitary water generation.

Simplified Heating Model of Building

The most basic approach to create a heat model of the building is to generate a completely analytical physical model of the building based on the exact knowledge of building dimensions and heat propagation and heat exchange parameters. The result of that kind of activity is in most cases very reliable and gives a good building energy model. The approach is suitable for new buildings because the energy models can be created during the design phase of the building creation process. That kind of models are called white box models, because all model parameters are known and can easily be interpreted by humans.

If the existing building is retrofitted with smart energy meters and sensors, the process of creation of white box models (deterministic physical models) is in most cases not economically viable, because all building plans and parameters have to be reproduced in equivalent building constructions and models.

Installed smart meters and various environmental parameter sensors enable various data-driven approaches to create building heat models. In recent years, advances in machine learning and especially deep learning enable creation of various data-driven models of physical systems with one important drawback. No model created by deep learning technology can be meaningfully interpreted by a human being. Those models are called simply black box models.

Another smart data-driven approach is a grey box model approach. Grey box models rely on generalized simplified physical model of modelled system, where model parameters are fitted using similar optimization methods that machine learning community is using. We can understand grey box models as a human interpretable data-driven machine learning models of physical systems.

A physical building heat model can be simplified in many ways. Community of building heating research often use equivalent RC models that come from electronic circuit analysis, where individual heat model components are represented by resistors, capacitors, voltage (temperature) and current (heating power) sources.

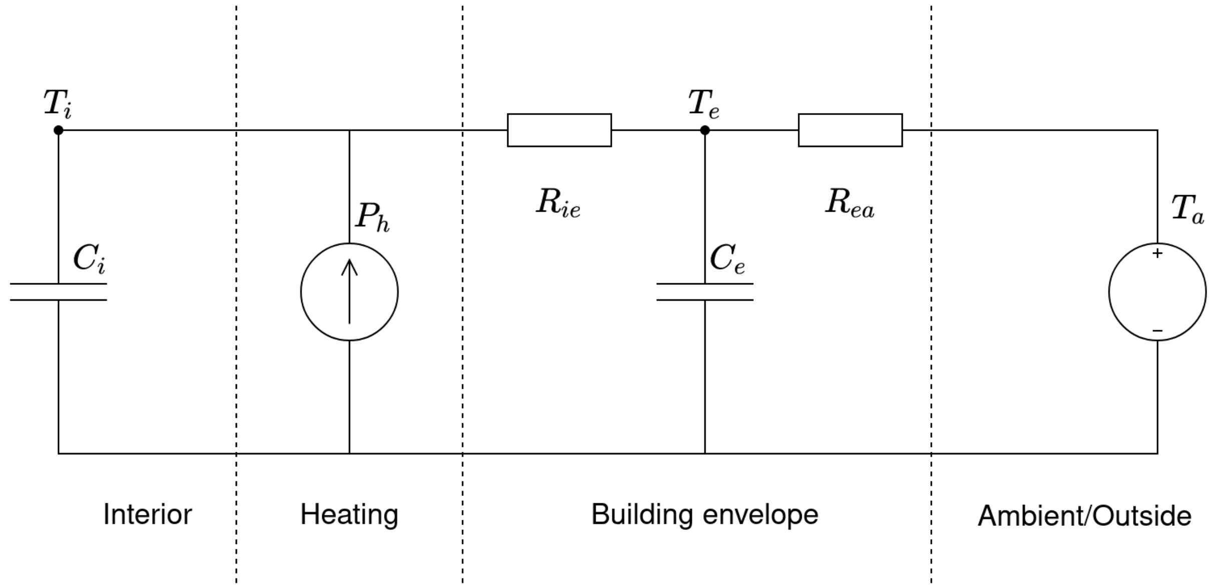


Figure 9: Lumped linear RC model of building heat dynamics.

One of the simplest lumped RC heat models is presented in Figure 9, where TiTe heat model is presented. Outside temperature is presented as a voltage source with ambient temperature designation T_a, building envelope (building construction elements, walls etc.) is represented as RCR circuit composed of R_{ie}, C_e and R_{ea}, where R_{ie} represents a resistance between indoor medium and building envelope, R_{ea} represents heat resistance between building envelope and ambient (outside) temperature, and building envelope heat capacity presented by C_e. Heating energy is introduced to the building by the heating power source P_h and interior temperature by T_i and heat capacity of interior medium C_i.

$$dT_i = \frac{1}{R_{ie}Ci}(T_e - Ti)dt + \frac{1}{C_i}P_h dt$$

$$dT_e = \frac{1}{R_{ie}C_e}(T_i - T_e)dt + \frac{1}{R_{ea}C_e}(T_a - T_e)dt$$

Equation 1: First-order differential equations of TiTe heating model.

Two system parameters as T_i and T_e can be modelled in such system by linear differential equations presented with Equation 1.

Creating Dataset

A complete dataset of the retirement home building includes time series collected from many environmental sensors and smart meters. Very complex and detailed building models can be created from the available data but to support the creation of TiTe heat model only few data sources are needed from the complete dataset.

At this point, we simplify the heat model to the point, that complete heating energy comes from the district heating heat exchanger. The reason for that is, that the building currently uses only district heating heat source for heating during the winter period. Another parameter that has to be sourced from the complete building dataset is internal temperature parameter. Finally, we have to add ambient (outside) temperature that is sourced from the weather station in the vicinity of the building heating heat pumps.

Most of the data sources of the retirement home building have individual sampling intervals, which means that all of data available in selected database have to be resampled to a unified sampling rate to enable data-driven model fitting.

Data from each data source is being downloaded for the selected period and interpolated. Selected interpolation function is cubic splines. The interpolated cubic splines are than sampled with the period of T_s=1h to comply with the selected district heating energy smart meter which has the lowest sampling rate (1h) of all meters involved. 1 hour is therefore the smallest interval for building heating dynamics estimation.

Training of Gray Box Building HVAC Model

The building heating model parameters are fitted using least squares fitting method. Dataset contains 33 days of measurements for the needed parameters P_h, T_i and T_a.

With the increasing size of dataset, the parameter space increases and the possibility of incorrectly set model parameters increase accordingly. The parameter optimization process can reach local minimums that are very far from the optimal heating model parameters. To increase the probability of good model creation we introduce the pre-training step, where several models are trained on smaller chunks of data. We selected the individual models are pre-trained on 24-hour chunks of data.

Resulting pre-trained models are evaluated on test dataset and sorted by the RMSE parameter from the best to worse performant model. The best performing model in population is trained on a complete training data set and probability of convergence is thus greatly increased.

Resulting grey box building heating model parameters are presented in Table 2.

Table 2: Parameters of a trained TiTe model.

C_i	C_e	R_{ie}	R_{ea}
139.6	579.6	0.0137	0.119

Model Evaluation

In a production, the final building heating model will be used to estimate the energy needs for the period of several days in the future. This future-based energy consumption estimation will be based on local weather forecast data that is currently accessible in a hourly fashion for next 48 hours by OpenWeather service and will be extended to 72 hours weather forecast based on 3-hour basis based on a national weather forecast data.

For the evaluation of the proposed TiTe building heating model we can use historical data from the dataset, where we can select a period of past as evaluation data. To estimate the heating energy needed for the selected time period in the future, we can reorganize the dT_e equation in Equation 1. If we set the indoor temperature to a fixed level, the dT_i element does not change because the temperature does not change any more (fixed temperature). Equations for heating power estimation is presented in Equation 2.

$$dT_e = \frac{1}{R_{ie}C_e}(T_i - T_e)dt + \frac{1}{R_{ea}C_e}(T_a - T_e)dt$$

$$P_h = \frac{1}{R_{ie}}(T_e - T_i)$$

Equation 2: Linear equations for heating power estimation for selected indoor temperature.

Resulting HVAC model can be used to estimate the future heating energy needs for the building by setting the desired indoor temperature T_i and using weather forecast data for the selected period to get ambient (outside) temperature T_a. Figure 10 presents a projection of heating energy demands for the next 72 hours based on the OpenWeatherMap temperature forecast and desired indoor temperature reference T[°C]. Initial building temperature is 26°C which brings a discrepancy in the heating energy demand at the lower settings of the indoor temperature due the energy stored in the building walls (envelope). Actual heating energy demand values are presented in the Table 3.

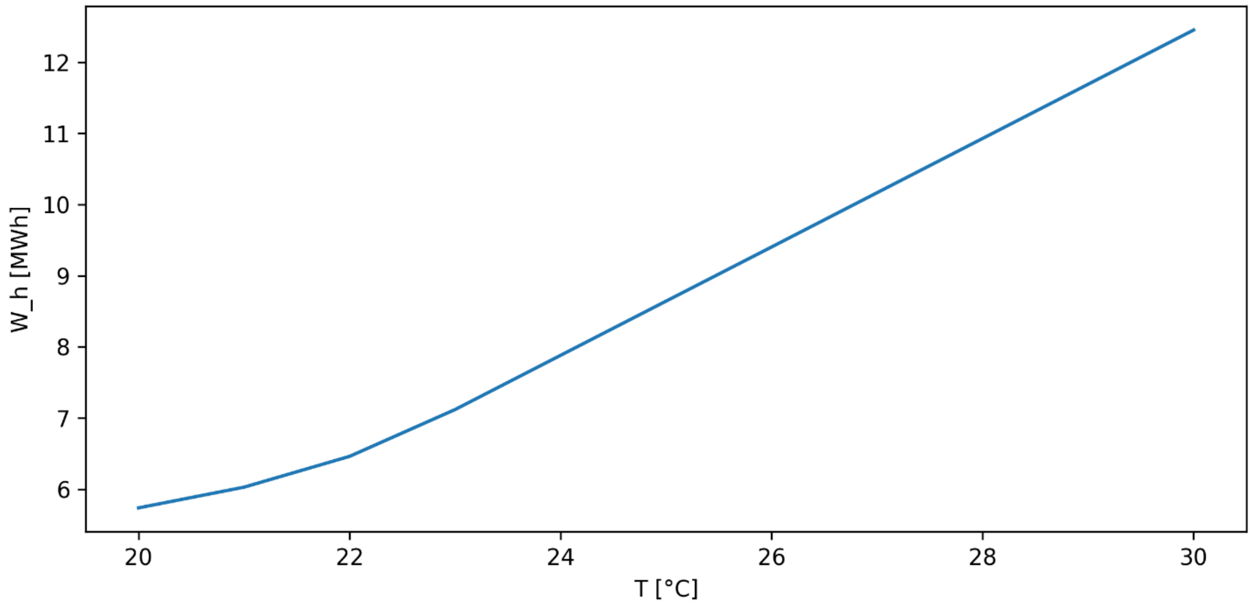


Figure 10: Model-based heating energy demand projection for next 72-hour period for selected indoor temperature reference. Initial temperature is Ti=26°C.

Table 3: Model-based heating energy demand for next 72 hours.

T_{i_set} [°C]	20	21	22	23	24	25	26	27	28	29	30
W_H [MWh]	5.74	6.03	6.46	7.12	7.88	8.64	9.40	10.17	10.93	11.69	12.54

Next Steps

The heating model is very simplistic and neglects many dynamic factors in building heating dynamics. First factor that is neglected is heating energy from district heating source that is used for generation of sanitary hot water and the second parameter is heat energy that comes from the solar radiation through windows and in smaller scale through building envelope (walls).
As a future work the inclusion of solar radiation contribution to building heat dynamics is planned and extension of building heat model with heat storage is planned.
To generalize the building heat model, the model will be extended to also include heat pumps for season transition periods and building cooling for the summer.

4.3 EV Charging

Description of dataset(s)

EV Historical and Real-Time Data

Regarding EV monitoring, EMOT use an on-board diagnostic (OBD) device to retrieve data from the EV; OBD is a IoT component, based on a Raspberry Pi 3 and Carberry; Carberry represents the link between car electronics and Raspberry Pi, which allows the development of end-user applications. OBD utilize a TCP/IP communication to a TCP/IP server. The network connectivity of the OBD device is via data SIM (UMTS), thanks to a Raspberry module that works as a modem, and the server is a python software; OBD protocol is MQTT and the sampling rate is 2 seconds. The OBD connects to the diagnostic interface from which it is able to extract the information from the electric vehicle control unit using the CAN-bus protocol. The output data format of the OBD is an ASCII string; when the data is sent to the server, it is reorganized into a wrapper, thus obtaining a grouping of the data in JSON format.
EV historical data will be provided via CSV file while EV real-time data will be provided via MQTT in JSON format; data are anonymized and classified as described below:

- Measure ID: unique identifier of a specific measurement;
- Vehicle ID: unique identifier of a specific electric vehicle;
- Brand: EV manufacturer name;
- Model: EV model name;
- Battery Power (kW): maximum EV charging power value;
- Battery Capacity (kWh): maximum EV battery energy capacity value;
- Connector Type: EV charging connector type name;
- Autonomy (km): real-time EV kilometers autonomy value;
- Odometer (km): real-time EV odometer value;
- SoC (%): real-time EV State of Charge percentage value;
- Timestamp: record of the time of measurement event.

Charging Station Historical and Real-Time Data

EMOT charging stations exchange data through a Teltonika RUT230 modem connected to a single-board computer, a Raspberry Pi 3; charging station protocols are OCPP (application protocol for communication between charging stations and EMOT central management system) and websocket (computer communications protocol, providing full-duplex communication channels over a single TCP connection). Charging station data format is JSON and the sampling rate is one second.

Charging station historical data will be provided via CSV file; data are anonymized and classified as described below:

- Charging Session ID: unique identifier of a specific charging session;
- dataStart: start time of a specific charging session;
- dataStop: end time of a specific charging session;
- Energy (Wh): amount of energy provided in a specific charging session;
- Socket ID: unique identifier of a specific charging station socket;
- Charging Station ID: unique identifier of a specific charging station.

Charging station real-time data will be provided via MQTT in JSON format; data are anonymized and classified for each charging station socket as described below:

- Power: real-time power value (W).

5. Conclusions

This deliverable introduced the S2 standard protocol that can be used to control the flexibility of smart devices/assets. Although the S2 protocol provides a uniform way to express and control the available flexibility it does rely on an accurate digital twin model of the asset to feed it with the correct parameter values.

Initial digital twin models for three different flexible assets have been developed: a residential heat pump, a HVAC system for a large apartment building and EV charging stations. Task 4.3 also looked into different training methods that can be used to provide the digital twins with self-learning capabilities.

The digital twins for the residential heatpump and the HVAC system use a grey box approach where a simplified RC model represents the thermal behaviour of the building. In both cases the training method is aimed at finding the correct parameter values of the RC model using sensor measurements as the training set.

For the EV charging a lot of operational data has already been collected both from the car and the charging station side. This data will be used to learn the EV charging behaviour.

5.1. Next steps

In the period until the next version of this deliverable which is due in M30 of the project, task 4.3 will focus on the following steps:

- Residential heat pump. The lab setup will become fully operational so that data can be collected in a controlled environment in order to train both the digital twin of the building and the heat pump. Changes in the heat demand profile will be introduced to see how well the digital twins can adapt to a dynamic environment.
- HVAC system in apartment building. The RC model of the building is still relatively simple and will be expanded to a more advanced model that better captures the true characteristics of the building.
- EV charging. A lot of operational EV charging data has already been collected. This data will be used to reliably predict the charging behaviour of EV’s.

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