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RESPOND

DEMAND RESPONSE FOR ALL

Integrated Demand REsponse SOlution Towards Energy POsitive NeighbourhooDs

WP 4 – ICT enabled cooperative Demand Response model

T4.5: DATA ANALYTICS AND OPTIMIZED CONTROL

D4.5 Energy Data Analysis Report and Proactive Energy Use guide

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AUTHOR (S)	Iker Esnaola (TEK) Francisco Javier Diez (TEK) Dea Pujic (IMP) Marko Jelic (IMP) Nikola Tomasevic (IMP) Federico Seri (NUIG) Paulo Lissa (NUIG) Oriol Pla (DEX) Laura Martinez (DEX)
OFFICIAL REVIEWER(S)	Peter Kirketerp (DEV)

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EXECUTIVE SUMMARY

This deliverable presents the work done in task 4.5 "D*ata analytics and optimized control*". The report shows, at the beginning the flow of information from the monitoring of data to the control actions, in order to introduce later the context of each service and module as well as their function in the optimization loop. After this introduction, each of the developed service and module is explained in detail, distinguishing between generic open services and BEMS (DEXCELL) related services.

The order of the related services follows the flow of the information in the analytic services. This is expected to facilitate the comprehension and understanding of their outcomes, and it finishes with the added values provided to the building occupants and facility managers.

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ABBREVIATIONS AND ACRONYMS

AHU	Air Handle Unit
API	Application Programming Interface
App	Smartphone Application
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
DB	Database
CDM	Common Data Model
DHW	Domestic Hot Water
DR	Demand Response
DEV	Develco
DEX	DEXMA
EM	Energy Manager
ENE	Energomonitor
HP	Heat Pump
IMP	Institute Mihaljo Pupin
IPMVP	International Performance and Verification Protocol
IoT	Internet of Things
ISO	International Organization for Standardization
MQTT	MQ Telemetry Transport
OASIS	Organization for the Advancement of Structured Information Standards
PV	PhotoVoltaic

RES	Renewable Energy Source
REST	REpresentational State Transfer
SPARQL	Recursive Protocol and RDF Query Language
STC	Solar Thermal Collector
TEK	Tekniker
TSDB	Time Series Databases

1. INTRODUCTION

1.1 AIMS AND OBJECTIVES

This task deals with the integration of the outcomes of all previous tasks of the work package in order to perform actual control actions and influence the load according to cooperative DR strategy. Therefore, this task will be aimed to translate the results of optimiser into the actual control actions (such as adjusting the indoor set-point temperature). The parameters and values range that meet the user needs are obtained from a comfort analysis and data gathered by mobile app. These control actions will include not only control of home devices, but also management of energy assets related to energy generation and dispatching at both building and district level.

Supporting data analytics (such as building modelling, comfort analysis) will estimate the effect of the control actions to be performed. Additionally, this model will take into account other relevant parameters such as building thermal dynamics, efficiency of energy conversion performed by building systems (such as AHU, boilers, etc.). Predictive maintenance principles like trends detection will be applied to this equipment to ensure their optimal functioning and preventing degradation of their efficiency. In this way, this task will ensure maintenance of the comfort levels and provide relevant information to the household's occupants so they could make decisions and adjust their consumption in a coordinated way.

1.2 RELATION TO OTHER PROJECT ACTIVITIES

With regards to the interaction between Task 4.5 and the rest of RESPOND project activities, the main interactions are listed below:

- This task's services deployed uses de architecture defined in task 2.1
- Deployment of the services according to task 2.5
- Comfort analysis used for optimization has derived from the outcomes of the WP3 tasks
- This task has integrated the optimiser deployed in task 4.2 and 4.3
- Forecasting algorithms developed in task 4.4 has been integrated
- Developments are integrated with the mobile app and dashboard developed in Task 5.4
- It is coordinated with WP5 in order to ensure the integration with building management and home automation systems
- Data generated by the task services are used for validation in WP6

1.3 DELIVERABLE STRUCTURE

The rest of the deliverable is structured as follows. Section 2 briefly introduces the optimization loop explained in more detail in the deliverable 2.5, which is the basis of the orchestration of the services defined in this deliverable. Section 3 describes the set of analytical services developed. Section 4 describes the services developed in the context of the DEXCELL platform. Finally, section 5 exposed the final conclusions.

2. RESPOND Optimization Loop

RESPOND aims to allocate the most suitable demand profiles both at a dwelling and neighbourhood levels as a driver for reducing the load demand in specific time periods. To do so, RESPOND leverages the Optimization loop depicted in Figure 1. This optimization loop (also known as the RESPOND Platform Control Loop in deliverable D2.5 Deployment of RESPOND Cloud-Based Platform) has four main blocks: the measurement, forecasting, optimization and control blocks. Each of these four main blocks is composed of different services, and the adequate interaction between these services ensures the dispatching of optimal DR actions.

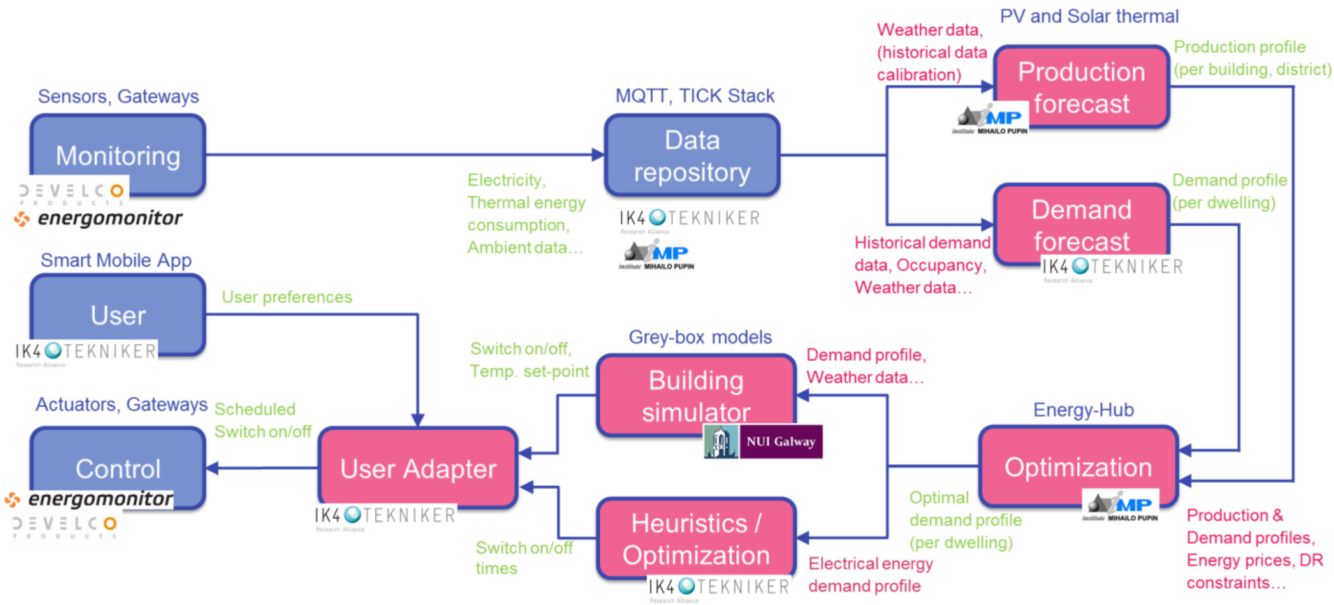

Figure 1: RESPOND Optimization Loop.

3. Core Services

This section describes the core services of the RESPOND Optimization loop.

3.1 Monitoring

The sensor technology, embedded in IoT devices, is continuously becoming cheaper, more advanced, and more widely available. This is one of the reasons why it is estimated that in 2019 the IoT generated more than 500 zettabytes in data [1].

In the context of the RESPOND project, the monitoring of data is performed with different systems and equipment. The two main monitoring equipment providers are project partners ENE and DEV. The former provides a Smart Home Monitoring solution for the acquisition of utility consumption and ambient data, and it is comprised of electricity consumption and production meters (shown in Figure 2), gas consumption, water consumption and thermometers for indoor or outdoor use. As for the latter, it provides its monitoring solution for Smart Energy Management, which encompasses a variety of smart metering equipment for household consumption of electricity, water, heat and gas, as well as motion sensors for occupancy detection, light, humidity or temperature sensors. The Spanish pilot site is equipped with ENE equipment, the Danish pilot site with DEV equipment, and in the Irish pilot, although it was planned to rely on DEV equipment, ENE equipment is installed.

Figure 2: Energomonitor Powersense.

Within the context of the RESPOND project, the monitoring is not limited to physical devices installed within houses. There are other data sources whose monitoring is of interest, including the weather forecast or the electricity price.

However, the monitoring of data without its storage may end up being a little bit limited, as it makes it impossible to apply data exploitation services such as the ones based on machine learning.

3.2 Data Repository

Data repositories enable the storage of the data, and within the RESPOND Optimization Loop, they are complementary to the previous Monitoring service. In this regard, they store the measurements made by the deployed equipment, as well as data registered by third-party services (e.g. weather forecasting services).

MQTT (MQ Telemetry Transport) messaging protocol is used to ensure the adequate storage of data gathered by sensors and external services. MQTT is an open OASIS and ISO standard (ISO/IEC PRF 20922) is publish/subscribe messaging protocol that is widely used in distributed systems where scalability, synchronism and abstraction between devices and server are required. Furthermore, it is the ideal solution for the RESPOND data acquisition due to the low power and memory needed for the implementation of different clients in small devices, and the low bandwidth needed derived from the small overhead and traffic introduced to the network.

IoT data, which is characterized by its abundance, is recommended to be stored in suitable storage systems such as Time Series Databases (TSDB). These repositories are optimized for time series data and designed to handle high write and query loads as well as down-sampling and deletion of old data, thus being able to manage an amount of data while ensuring a high performance. This is why, one of RESPOND's data repositories is InfluxDB, an open source TSDB.

However, InfluxDB is not the only data repository within RESPOND. The integration of static building information and IoT data becomes a prime challenge [2]. Furthermore, it can be stated that more often than not, easy and intuitive ways to rapidly browse, query and use building information combined with IoT data are not available [3]. Semantic Technologies can be leveraged to remedy these issues, as they allow a more dynamic manipulation of the building information in RDF graphs via query and rule languages. Therefore, RESPOND platform leverages a Semantic Repository to store the static building information. Semantic Repositories, also known as RDF Stores or triplestores, are storage systems that are optimized for hosting this type of data and that, usually, support a SPARQL endpoint where data can be queried using SPARQL queries. After making a thorough review of the different repositories available in deliverable D4.1 Semantic Information Model, Openlink Virtuoso was chosen.

3.3 Production Forecast

With years, the energy produced by burning fossil fuels has increased, leading to the concern of increasing amount of greenhouse emission and global warming. Therefore, the share of renewable energy in the energy system was raised in response, contributing to the destabilization of the grid. Namely, due to the stochastic nature of RES production, which is a result of high correlation between the RES production and weather conditions, it was necessary to perform advanced planning and optimization of the production and demand balancing.

Therefore, as a part of Task 4.4, considering three pilot sites with two renewable energy sources (RESs) types present - photovoltaic (PV) panels in Aarhus and Aran Islands and solar thermal collector (STC) in

Madrid, three different day-ahead energy production forecasters with hourly time resolution were developed. Finally, they were exploited as inputs for the optimizer in Tasks 4.2 and 4.3, and, therefore, will be presented as a part of this subsection.

Having in mind that the crucial motivation for developing various models for RES production forecasting corresponds to their stochastic nature, weather forecast parameters were obtained using WeatherBit[1]as inputs, which fulfilled the requirement of providing hourly day-ahead weather forecasts for various factors, with solar irradiance being the most important one. Besides the irradiance, UV, wind direction and speed, outside temperature, cloud coverage and relative humidity were taken as relevant inputs for the renewable production estimator.

Regarding models chosen for estimating renewable production, depending on the availability of the data, various approaches have been chosen – both physical and machine learning (ML) ones. However, apart from the models themselves and required input parameters, for the rest of the system the models appear completely the same. The forecaster service collects all the necessary inputs, such as forecasted weather conditions for 24 hours starting with the given *beginning_timestamp*, and stores the obtained forecasted production in the RESPOND MySQL DB, enabling other parts of the system, such as optimizer, to use these relevant results. Detailed description of these models and their performances are given in D4.4 and examples of day-ahead production forecasts for each pilot sites are given in Figure 3.

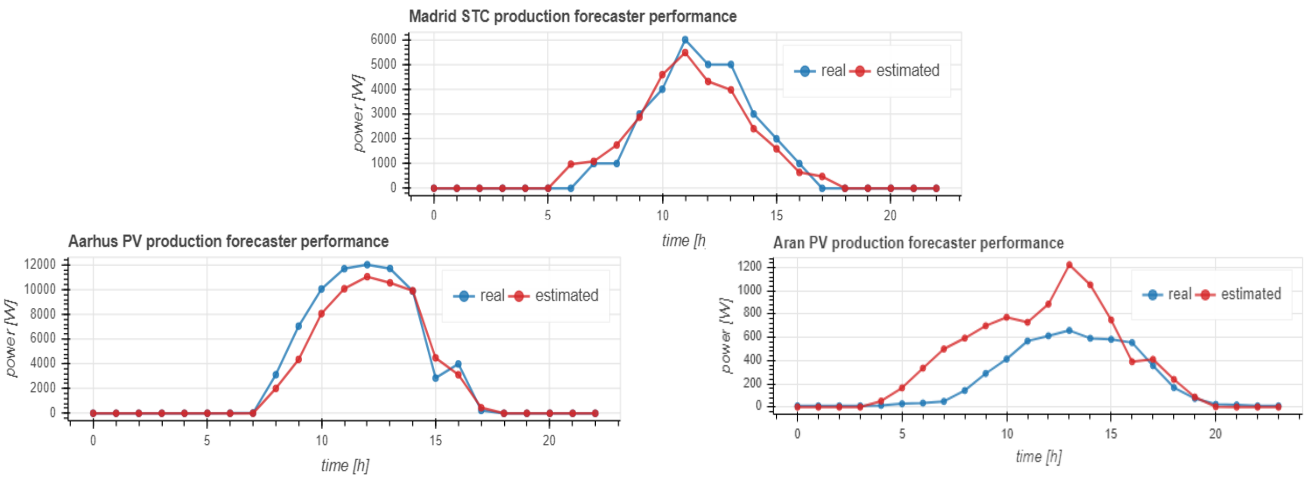

Figure 3:Examples of estimator performances

3.4 Demand Forecast

Alongside with the forecasting of the energy produced from RES, the forecasting of the energy demand is essential in RESPOND to allow the dispatching of optimal DR strategies.

The developed RESPOND Energy Demand Forecasting Service aims at forecasting short-term energy demand both at a dwelling and neighbourhood level. This service is based on data-driven predictive models and leverages the data stored in the corresponding data repositories. In this regard, two main

[1] https://www.weatherbit.io/

energy demand forecasting services can be distinguished: electricity and DHW (Domestic Hot Water) consumption.

Electricity demand forecasting models are developed for each dwelling participating in the RESPOND project, as well as for the Spanish and Danish neighbourhoods (there is no neighbourhood in the Irish pilot site). As for the DHW demand forecasting model, it forecasts the consumption of the Spanish neighbourhood. All the predictive models are based on a k-NN type of algorithm, and they forecast the demand for the upcoming 24 hours with an hourly basis. Figure 4 shows the results of a predictive model developed for forecasting a Spanish dwelling’s electric consumption.

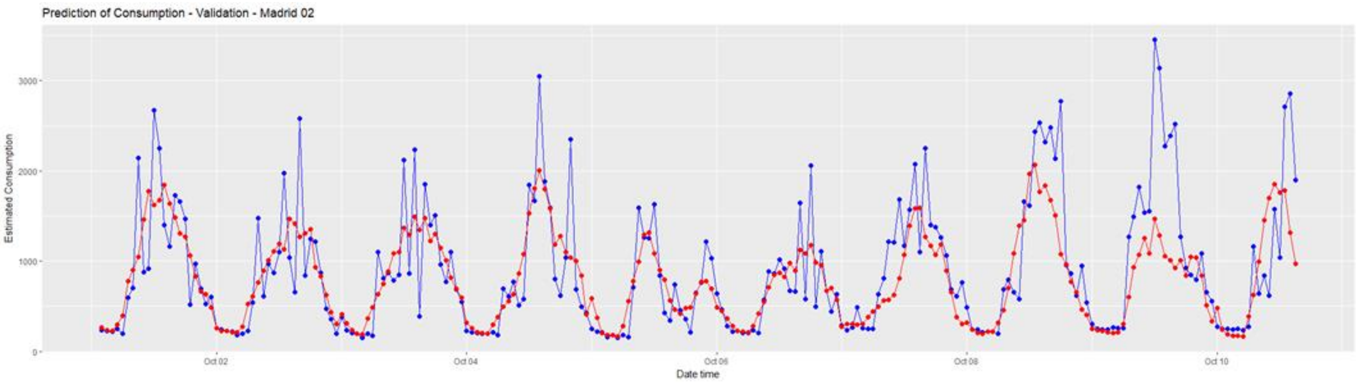

Figure 4: Spanish dwelling's electric consumption prediction vs real consumption.

These predictions are executed on an hourly basis, the execution of the predictive models to perform the upcoming 24 hours’ predictions were automated using periodical tasks. These tasks were developed in Java and deployed within a web service in a Tomcat server. Furthermore, they were scheduled to be executed daily. When executed, these tasks connect the RServe with the models, perform a prediction and retrieve the information to be stored in a MySQL database for later use for visualization by the RESPOND mobile app, as well as any other services that request such data through the REST API

The predicted energy consumption values are then stored in another data repository so that they remain accessible to be consumed by the RESPOND Mobile App (described in deliverable D3.4 Personal Energy Performance Assistant Design and D5.4 Desktop Dashboard and Smart Mobile Client Demonstrator) as well as by the Optimization service, explained in the next subsection.

A more detailed explanation of the Demand Forecast service can be found in the deliverable D4.4: Predictive Energy Production and Demand Algorithms.

3.5 Optimization

The basis for the optimization service that was developed within the RESPOND project relies on the methodology described in Deliverable 4.2 titled Demand response optimisation model and is implemented using aggregate energy management strategies described in Deliverable 4.3 Optimal energy dispatching at neighbourhood level. The optimization service is a key component of the RESPOND platform that takes into account both demand and production forecasts, energy prices and also custom grid-related requests as inputs and produces an adjusted load curve for an entire neighbourhood that can later be used to generate both non-user-specific and user-specific suggestions on ways to modify the load in order to mitigate potential problems with grid stability and respond to requests from a (virtual) DR aggregator, as illustrated in Figure 5.

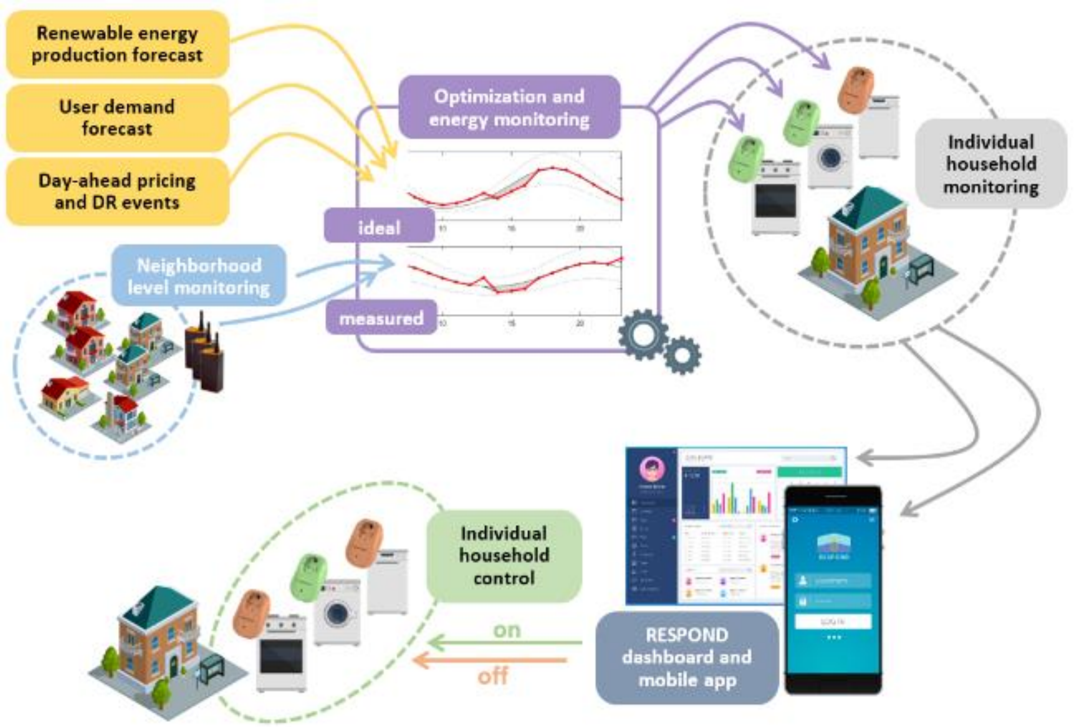

Figure 5: Illustrated RESPOND optimization loop (resources from freepik.com)

The optimiser is implemented as a mixed-integer linear programming (MILP) problem where energy availability from locally available renewable sources is considered to be known beforehand (as given by the production forecaster) and the baseline load is given by the demand forecaster. However, considering appropriate load flexibility margins in the range around the forecasted demand, the optimizer shifts aggregated loads of the entire neighbourhood up or down in accordance with current prices, energy availability and concrete DR requests for load increases or decreases. This is achieved by using a hybrid criterion function that incorporates costs (which by itself would facilitate indirect DR using energy price manipulations as is the case with time-of-use (ToU) tariffs and variable pricing schemas) and optional specific terms that penalize the difference between the output load curve and a predefined required load curve. Such an effect is facilitated by the introduction of a special set of variables in the MILP model that allow for this behaviour.

Given that the optimizer returns an optimal load curve considering the abovementioned criteria, its output can be used in conjunction with the predicted profile and optionally the current on/off statuses of appliances to plan and issue corrective action suggestions to end users. These messages should be conveyed through the RESPOND smartphone app so that users can even perform remote actions to keep the grid stable in response to DR requests for load modifications.

3.6 Building Simulator

3.6.1 Problem identification

A core vision to the future Aran Island smart home revolves around building control technology, due to the residential heating electrification process already in progress. The operation and control of heating systems, renewable systems and appliances would enable buildings to adapt electrical demand and reduce electrical grid instability [4]. The development of control models for dwellings on the Aran Islands would ensure that peak electrical demand is reduced, electricity expenditure is minimised, and thermal comfort is maintained.

However, during the imitation stages of the project, two key barriers were identified which inhibits the advancement and development of such building control models. The two key barriers included:

1. The lack of smart building infrastructure and limited building data availability.
2. The current inefficient operation of building energy systems.

The quality of a control models depends on the quality of the data available [5]. On the Aran Islands, 66% of dwellings are built before the 1980's. This makes it extremely difficult to obtain quality and extensive data for model analysis and development. At the initiation stages of this project, there were no technical drawings, no sensors, no smart meters and no real time data tracking on the dwellings of Inis Mór. In the project initiation, a pilot characterisation of Inis Mór was conducted through various site visits. A detailed analysis of the 11 dwellings was carried out. The dwellings were characterised through site surveys, objective measurements and occupant interviews.

Since 2012, these dwellings have all taken part in the "Better Energy Community (BEC)" schemes provided by the Sustainable Energy Association of Ireland (SEAI). Through this scheme, they have undergone deep-retrofits such as upgrading the building fabric, the implementation of an air source heat pumps, and the installation of photovoltaic (PV) panels and solar thermal systems.

During the pilot characterisation process, it became evident that some installed systems were not being optimised to their potential. The most common problems, leading to occupant dis-satisfaction, were identified as:

- High heat pump electrical demand and electricity expenditure.
- Lack of user knowledge of system operation
- High PV production surplus to the electrical grid.

The Aran dwellings can be categorized within 3 different types, as reported in D4.2; the building simulator is referred to the type 2, in particular to houses equipped with photovoltaic panels and air source heat pumps (house n.2, 3, 4, 5 and 12).

For the development of control models, it is fundamental that the building energy systems are operating efficiently before smart demand strategies are implemented. Prior to any demand response strategy, it is of utmost importance to identify the optimum trade-off between occupant thermal comfort and energy savings [6]. The ideal goal is to identify methods which investigate optimum operation of building energy systems before the deployment of smart strategies [7]. The late deployment of advanced metering network on the Aran dwellings during the project as explained in D2.5, did not help as well to perform a comprehensive analysis.

Building Energy Modelling offers an effective solution to investigate and analyse current dwellings on the Aran Islands prior to smart grid and demand response strategy implementation.

Given the lack of quality building data and uncertainty over system operation, the development of a detailed building energy model acts as a steppingstone to future building control model development. A calibrated building energy model can save time, resources and money, allowing the assessment of the building across a range of weather profiles and time intervals.

The first objective of this study was to develop a detailed calibrated model of a residential dwelling on Inis Mór, which follows a scientific and researched based procedure. The calibrated model will investigate the current building operation and develop operation strategies to optimize building performance under demand response signals. The operation strategies developed aim to maximize the use of PV production (kWh) and maintain occupant thermal comfort (Indoor Temperature °C). The aims and objectives of the work can be summarized as follows:

- Development of a calibrated IES-VE white box model of a residential dwelling on the island of Inis Mór using a systematic procedure.
- Development of a simplified grey-box model using data generated from the previous point.
- Development of optimal building control strategies, which aim to maximize renewable energy use and maintain thermal comfort under demand response testing scenario.

3.6.2 SIMULATION MODEL CALIBRATION

Calibrating building energy models involves configuring model data with reference to actual building data in order to develop an accurate building model. A calibrated model is a highly accurate representation of the actual building. In order to ensure accuracy in the calibration approach, the methodology of this work follows a scientific evidence-based approach as outlined by Raftery [8] and Coakley [9].

The basis of this methodology is to develop a detailed calibrated white box model. Detailed models are law-driven, physics-based models and thus will always maintain a high level of accuracy when calibrated [5]. These models, in turn, can provide understanding and knowledge of system behaviour and aid in developing operation strategies for dwellings on Inis Mór.

One of downfalls of building energy simulation is the discrepancy between simulation results and actual results from real time building data. Many studies highlight the errors of “uncalibrated” models indicating discrepancies between of 30%-50% [10]. Calibration is described by ASHRAE Guideline 14 [11] as the “process of reducing the uncertainty of a model by comparing predicted output of the model under a specific set of conditions to the actual measured data for the same conditions”. As it can be seen, a calibrated model closely represents the real-life operation and is one that, under the same set of conditions can reproduce measured data. Developing calibrated models can reduce uncertainty and discrepancies of building energy models.

The approach taken in this paper is primarily based on a systematic, evidence-based model development as it is suggested as the most appropriate framework for carrying out any building energy performance model [8]. The evidence-based approach prescribes a procedural path to developing the detailed model. The approach has two key features. Firstly, it takes a structured and organised approach to model calibration where each simulation is controlled, monitored and tracked via a version control software. Secondly, the approach ensures that changes to a model are only made with evidence defined by a classification scheme. This ensures that there is a complete history of changes made to the model which promotes the reliability and reproducibility of the calibration process.

The proposed calibration (Figure 6) methodology in this project follows a similar procedure to the systematic evidence-based approach outlined by[8]. The calibration approach was adapted and developed in further in 2014 [9].

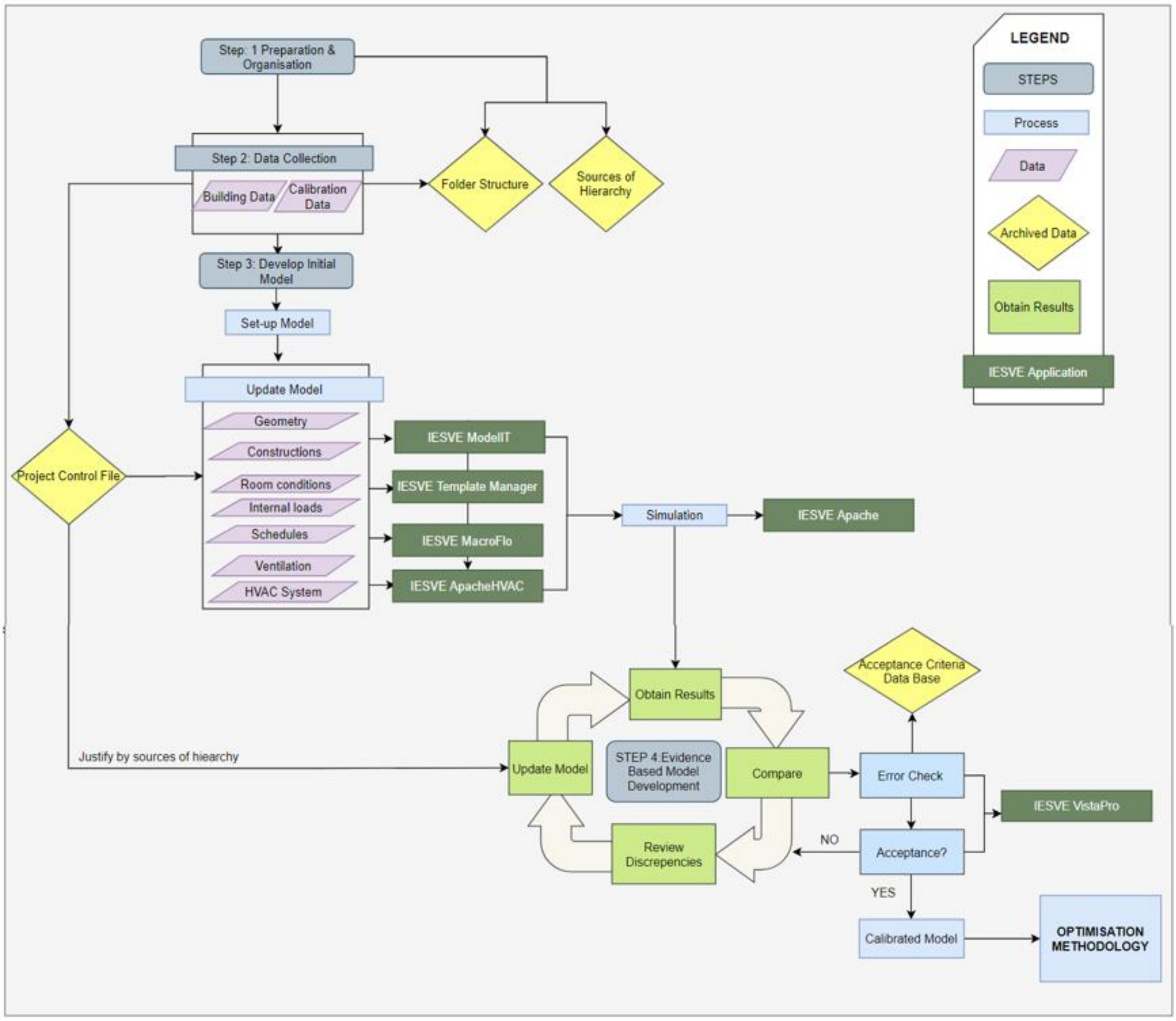

Figure 6: Proposed calibration methodology

The procedure is summarised in four key steps namely, preparation and organisation, data collection, development of the initial model and evidence-based model development.

In the preparation and organisation stages, the foundation of the methodology is set. The first principle of the systematic evidence procedure is that data is sufficiently tracked and stored. Thus, the monitoring and tracking techniques are defined and developed in this step. The second principle of the procedure is that data is based on classified evidence, this is defined through the "hierarchy of sources". The hierarchy ensures that data is classified according to its source and prevents ah-hoc changes to model calibration. Finally, the criteria and guidelines in which the model is deemed calibrated are the defined, these are the Normalised Mean Biased Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error CV(RMSE) with referenced ASHRAE Guideline 14 hourly criteria.

The second step of the systematic procedure describes the way in which data is collected and stored. The data for the project can be classified in two separate categories, model input data and calibration data. Data is obtained from various site visits, homeowner interviews, objective measurements, detailed documents, mechanical and electrical specifications, guidelines and manuals.

The model input data includes weather data, geometry, constructions, internal gains, occupancy, HVAC and comfort criteria. Calibration data includes, varies from utility bills to sub-utility measured data and sensor data. Both the input model data and calibration data are defined by the sources of hierarchy.

The third step describes the initial model development. The data collected and classified in step 1 and 2 is utilised to develop a detailed building energy simulation model. The final step of the calibration process involves the evidence-based model development, error check and acceptance criteria. At the initiation stages of this project, acceptance criteria database is created in Microsoft excel. In this database, the simulated results of the model are compared against the measured values by calculation of the degree of uncertainty. The degree of uncertainty is measured by the previously mentioned statistical indices, Normalised Mean Biased Error (NMBE) and the Coefficient of Variation of the Root Mean Square Error CV(RMSE) with respect to ASHRAE hourly guideline criteria.

Step 4 is an iterative process to determine whether the model is calibrated. To ensure an organised and structured approach, the acceptance criteria database, the project control file and the project folder are updated through each iteration. If the acceptance criteria fall below the required statistical indices guidelines, the user interrogates and analyses the model further. Subsequent, changes through each iteration are only made with reference to the sources of hierarchy. A change is made by the user once data is gathered from a more reliable source on the hierarchy. The process ends once the acceptance criteria are met. In order to maintain a structured and organised approach, three key features are preformed after each simulation, a new naming convention is formulated, the acceptance criteria is calculated and the iteration of the model is stored along with the evidence in which the change is made via the project control file.

DEFINITION OF ACCEPTANCE CRITERIA

The definition of acceptance criteria determines when a model is deemed calibrated. The main uncertainty indices used are the Mean Bias Error (MBE), NMBE (Normalized Mean Bias Error), R2 (coefficient of determination) and CV(RMSE) (Coefficient of Variation of the Root Mean Square Error). The most acknowledged guidelines that have established measures of acceptance for each of these indices are of accuracy of the indices are American Society of Heating Refrigeration and Air-Conditioning Engineers. (ASHRAE) Guideline 14, Federal Energy Management Program (FEMP) and International Performance and Verification Protocol (IPMVP). However, in a recent review of the validation of calibrated energy models[12], highlight the typical mistakes often made when preforming calibration mainly related to incorrect formulas used for MBE and NMBE. To ensure accuracy in the approach, this report follows the correct formulas carefully highlighted by Ruiz & Bandera [12].

Mean Bias Error (MBE) predicts the accuracy of the simulated and measured data. It depicts the mean difference between simulated and measured data points. It dictates bias in model through equating the average errors in a sample space. The MBE formula is outlined as follows:

$$MBE = \frac{\sum_{i=1}^{n}(m_i - s_{i.})}{n}$$

Where m_i is the measured value, $s_{i.}$ is the simulated value, and *n* is the number of measured data points. However, the MBE is subject to cancelation errors in the calculation as positive and negative can often cancel out. Thus, further uncertainty indices are required in the calibration process.

Conversely, the Normalised Mean Biased Error (NMBE) is not subject to cancelation errors. The NMBE divides the MBE by the mean of measured values $\overline{m}$ and outputs the global difference between measured and simulated values. The NMBE formula is outlined as follows:

$$NMBE = \frac{1}{\overline{m}}.\frac{\sum_{i=1}^{n}(m_i - s_{i.})}{n-p}\ x\ 100(\%)$$

Where p holds the value 0 and represents the quantity of adjustable parameters. The Coefficient of Variation of the Root Mean Square Error CV(RMSE) measures variability of data without cancelling positive and negative errors, it predicts the load pattern of the data. The CV(RMSE) formula is outlined as follows:

$$CV(RMSE) = \frac{1}{\mathrm{m}}\sqrt{\frac{\sum_{i=1}^{n}(\mathrm{m}_i - s_i)^2}{n-\mathrm{p}}} * 100(\%)$$

Where p is determined as 1[13] [14]. Finally, to determine the accuracy and distance of the simulated values are to the measured values regression line, the coefficient of determinant (R^2) is calculated via the following formula:

$$R^2 = \left(\frac{n \cdot \sum_{i=1}^{n} m_i \cdot s_i - \sum_{i=1}^{n} m_i \cdot \sum_{i=1}^{n} s_i}{\sqrt{\left(n \cdot \sum_{i=1}^{n} m_i{}^2 - \left(\sum_{i=1}^{n} m_i\right)^2\right)\left(n \cdot \sum_{i=1}^{n} s_i{}^2 - \left(\sum_{i=1}^{n} s_i\right)^2\right)}}\right)^2$$

The three main sources of validating a detailed calibrated model ASHRAE Guideline 14, Federal Energy Management Program (FEMP) and International Performance and Verification Protocol (IPMVP) explained and are assessed by monthly and hourly criteria % as outlined in Table 1.

Table 1: Comparison of main sources of validation criteria.

Data Type	Index	FEMP Criteria	ASHRAE Guideline 14	IPMVP
Monthly Criteria (%)	**NMBE**	± 5	± 5	± 20

	CV(RMSE)	15	15	-
Hourly Criteria (%)	**NMBE**	± 10	± 10	± 5
	CV(RMSE)	30	30	20
	$\boldsymbol{R^2}$	-	>0.75	>0.75

In our methodology, the model was calibrated using the ASHRAE guideline 14. As there is no standard for sub-hourly criteria, the analysis adopted the hourly criteria of $\pm 10\%$ for the NMBE and 30% for CV(RMSE). Both uncertainty indices were formulated in the project control file and assessed at each simulation iteration. If the acceptance criteria are not met, the user analyses the results and interrogates the model further. In order to make subsequent changes, data is reviewed via sources of hierarchy. Based on a classification scheme, parameters are investigated based on their reliability of source. For example, taking the construction of the wall, if the previous simulation has a standard guideline U-Value (W/m2K), the model input can be investigated further to retrieve more accurate information such as a BER report or physical measurements.

The process ends once the acceptance criteria are met. Through each iteration, a new naming convention is formulated, the acceptance criteria calculated via the acceptance criteria database and the iteration of the model is stored along with the evidence in which the change is made via the project control file

Once the simulation model is calibrated, we use it as a test bench to generate high quality data that were missing for late installation of sensors (seasonal characterization of the HP system), not optimal running of the HP due to lack of knowledge of the system, and lacking of heating/cooling system data due to metering constraints (i.e. HP hot water tank temperature), which are analysed in order to generate a simplified grey-box model for each to be implemented for each house in Aran with similar characteristics (envelope, heating/cooling system, PV panels).

3.6.3 Aran Island residential dwellings

This work analyses a one-storey residential dwelling located on the Island of Inis Mór, Co. Galway. The dwelling was constructed in the 1970's, with additional upgrades being made in 2017. The dwelling represents 66% of the building stock on Inis Mór as the most common building category[15]. The building is south facing with a total floor area of $110m^2$. The room types include 3 bedrooms, a kitchen/living space, circulation, a toilet and a living room. The dwelling was renovated through the SEAI Better Energy Community (BEC) scheme in 2017. As part of the retrofit measures, insulation was added to the external wall and roof, an 8.5kW Mitsubishi heat pump was installed along with a photovoltaic panel array consisting with 8 panels with a total nominal power of 2kWp. Building data was collected through physical measurements, an interactive process of interviews and direct communication with the homeowner. At the initiation stages of this project, there were no smart meter infrastructure or metering installed. Thus, sub hourly heat pump electricity consumption and indoor temperature data was obtained through the instalment of sensors.

CONSTRUCTION DATA

Due to the buildings age, the buildings construction data and fabric information were largely undocumented. Through the initial site visits, building construction information was gathered through a series of interviews with the homeowner. This was ranked low on the data classification list due to the uncertainty of the homeowner on various building layers. Through further investigation, stages in a more reliable source of information was identified. As stated in the background of the report, many dwellings on the Aran Islands participated in the national "BEC" program promoted by SEAI. Through this scheme, a contractor would have performed a building energy rating "BER" of each dwelling. A BER is a detailed survey of the building which take various measurements including building fabric, and HVAC. This document provided measured building fabric information. The following Table 2 summarises the U-Values and extracted from the BER certificate. The building fabric information was updated in the model based on the information gathered from the BER.

Table 2: U Values Aran dwellings BEC schema.

Construction	U-Value	Evidence
Wall	0.27 W/m^2	BER
Roof	1.5 W/m^2	BER
Windows	3.0 W/m^2	BER
Ground Floor	0.45 W/m^2	BER
Internal Partition	1.80 W/m^2	BER
Doors	1.35 W/m^2	BER

HVAC DATA

The heating system installed in the dwelling is an 8.5kW Mitsubishi electric Ecodan heat pump system. The heat pump system installed consists of the following parts:

- Ecodan air source heat pump
- Cylinder Unit
- Control Panel
- Radiators

The outdoor unit combines ambient air and electricity to produce heat energy which is used to heat refrigerant to a high temperature. The heat is transferred to water which is used for both central heating and DHW. The heat pumps performance and efficiency characteristics is influenced by the outdoor ambient temperature. The coefficient of performance data of the heat pump was extracted from the manufacturers document.

The DHW tank cylinder is used to store hot water and consists of pumps and safety valves. The cylinder has a capacity of 170 litres with a heat loss rate of 1.63 (kWh/day) as per Figure 7. Heat is emitted to the rooms through hot water radiators located in each room. The temperature is controlled by a panel located in the hallway of the dwelling.

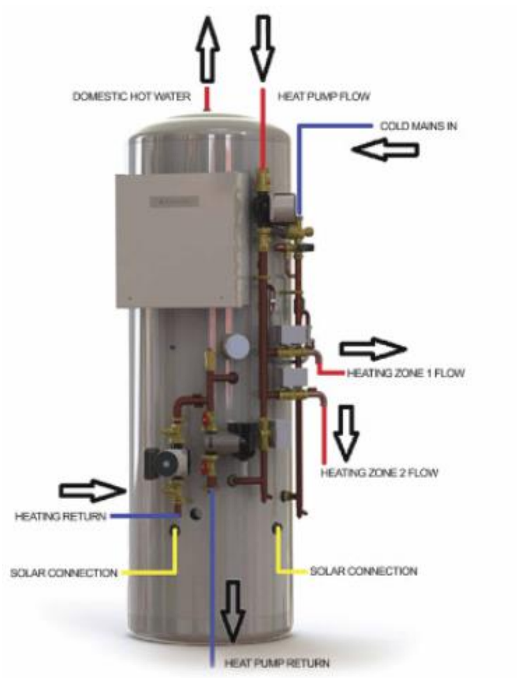

Figure 7: DHW tank cylinder

Figure 8: Heat Pump

HEAT PUMP SYSTEM: HEATING MODE OPERATION

Heat is emitted through radiators in each of the rooms. The heat pump provides lower temperatures for longer periods to achieve efficient operation. The system differs to a conventional heating system as the central heating cannot operate whilst the hot water tank is being heated. During this period, it is expected room temperature may decrease when heating water. The operation of the heat pump can be thus categorised into DHW and space heating.

Heating can be controlled in several ways including a timed mode or constantly on. Heating water temperatures can be controlled by the following measures:

- Weather compensation – the installer pre assigns the flow temperatures at specific outdoor conditions
- Fixed Flow temperature – the flow temperature is maintained throughout operation
- Room compensation – the optimum flow temperature is calculated based on the thermostat indoor temperature

HEAT PUMP SYSTEM: DOMESTIC HOT WATER OPERATION

Domestic Hot Water operates automatically based on the upper and lower limits set by the system installer. This is influenced by the DHW max temperature and the DHW maximum temperature drop as outlined in Table 3. The hot water will automatically be heated once the tank temperature exceeds the DHW max temp drop, as outlined in Figure 9. For example, if the DHW max temperature is set to 50 °C and lower threshold is 40 °C, so a delta temperature of 10 degrees. Hot water mode can also be controlled via a timeclock built in the main control panel. The "forced DHW" function enables the user to instantly charge the hot water tank through the control panel and the tank is heated to the set temperature or for a certain time period (e.g. 30 minutes). General guidelines suggest that if the DHW is predictable and small, a timed control is advisable. Conversely, if the quantity of DHW is large and unpredictable, the re-heat mode is advisable.

Table 3: DHW range and default temperature values.

Parameter	Function	Range [°C]	Default Value [°C]
DHW max temp	Desired temp of stored hot water	40-60	50
DHW max temp drop	Difference in temp between DHW max temp and the temp at which DHW restarts	5-30	10

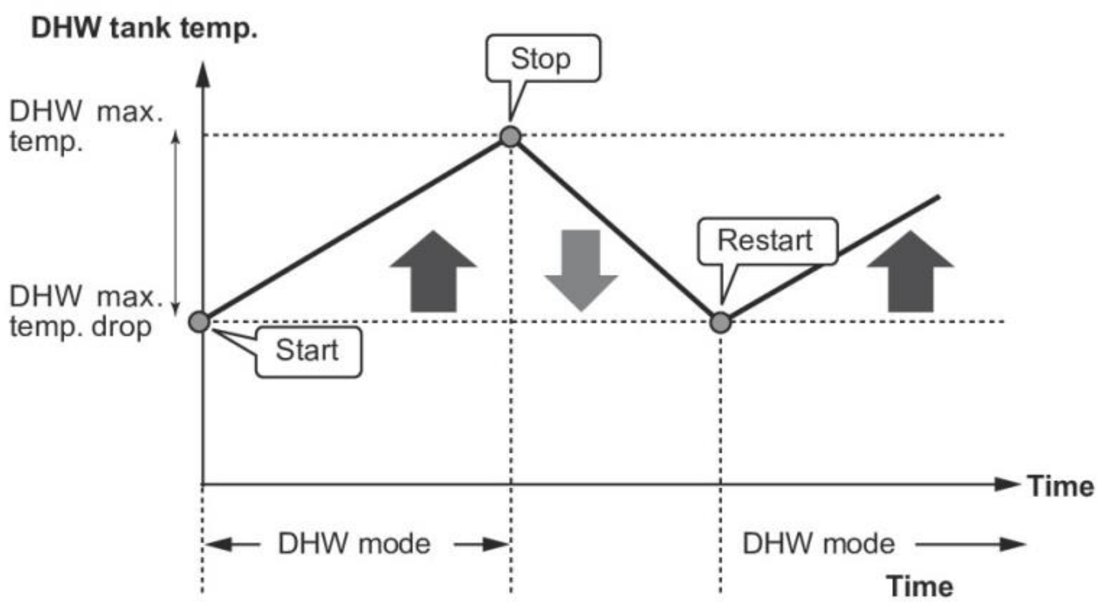

Figure 9: DHW operation

Data for model calibration

At the initiation stages of this work, 2018 year of electricity consumption (kWh) data was obtained from the electricity provider as aggregated values for the periods reported in Table 4.

Table 4: Electricity consumption by period

	2018 Electricity Consumption Analysis	No. of Days	Real
Period 1	12th Jan 2018/12th March 2018	60	2412
Period 2	13th Marc 2018/14th May 2018	63	905
Period 3	15th May 2018/11th July 2018	58	46

Period 4	12th July 2018/10th Sept 2018	61	50
Period 5	11th Sept 2018/8th Nov 2018	59	197
Period 6	9th Nov 2018/ 16th Jan 2019	69	1344

In order to generate a typical profile of energy use for one year, the data was shifted to standard monthly usage as per ASHRAE guideline [16]. The weighted daily average energy use was multiplied by the number of days for the given month. The normalised energy usage for 2018 were calculated.

As there were insufficient real time measurements at the time of the analysis, this data was used in the first calibration of the model. Through this analysis, anomalies were identified and investigated.

It is noted by Raftery [8], that calibrating building energy models with utility bills is insufficient due to the large errors and inconsistencies in both a hourly and daily basis. With this, it is often difficult to determine the exact proportion of end energy usage. For instance, given a monthly total electricity for February, it's hard to define the exact proportion of lighting loads, equipment loads and the HVAC consumption. Any error in the internal loads could easily offset errors in HVAC consumption.

Thus, to improve accuracy in model calibration higher resolution calibration data (daily, hourly or sub-hourly) and acceptance criteria is necessary. During the site characterisation, it was evident that there were no sub-metering or smart infrastructure installed in the building. An installation of sensors measuring Indoor Temperature °C, total electricity consumption (kWh), Total PV production (kWh), heat pump electricity consumption (kWh), allowed to have sub-metering data to perform the analysis.

The Mitsubishi Ecodan heat pump has sub metering and stores data through an SD card. A dedicated site visit was scheduled, and the SD data were collected and analysed.

The SD card extracts various system parameters (Figure 10) such as:

- The Unit mode – whether the heat pump is used for DHW or space heating
- Flow and return temperature (l/s)
- Tank water temperature (°C)
- Outdoor temperature (°C)
- Room temperature (°C)

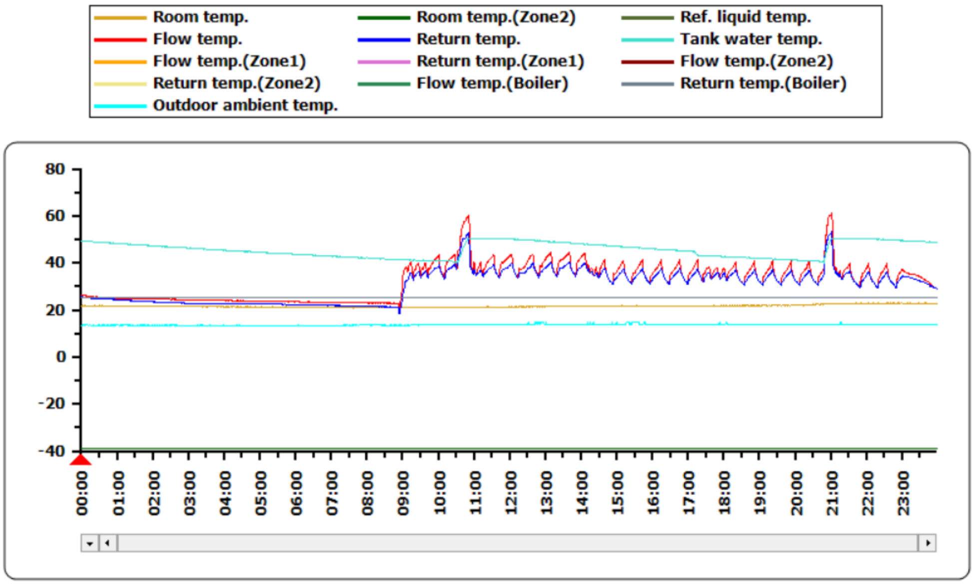

Figure 10: Heat pump system parameters example data

INDOOR THERMAL COMFORT THRESHOLD AND INDOOR AIR TEMPERATURE ANALYSIS

In earlier site visits the homeowner was interviewed on the preferred indoor temperature and occupancy hours homes required temperature setpoints. The home is occupied by an elderly man in his 70's, he has family living nearby and his daughter often visits to helps with meals and washing. The heating is used from (9.00-23.00) with a setpoint ranging from 19°C -20°C. The homeowner had expressed that he has been comfortable since the heat pump instalment and his only concern was the high electricity expenditure. When asked if whether the occupant would be affected by a shift in temperature throughout the day, he expressed that he wouldn't mind unless a drastic change in indoor temperature drop.

The aim of this analysis is to investigate the impact on shifting temperature indoor setpoints with response to a demand response signal. In order to carry out such analysis it is of fundamental to identify temperature thresholds prior to deploying a Demand Response strategy [7].

From the interview with the homeowner we had an idea of the temperature range in which is comfortable (19°C-20°C) , however in order to develop a temperature threshold for the analysis, this work takes an research adopted approach described in Sweetnam [17]. The cited paper carries out a detailed analysis and field study on the effectiveness of heat pump demand shifting using the thermal fabric inertia of a building over the heating season of 2014/2015. For each dwelling in the field study, the mean internal temperature (MIT) and upper and lower thresholds are calculated on 15-minute intervals. Upper and Lower Thresholds are based on calculating the upper and lower deciles of temperature. The outcome of the data analysis is a unified temperature profile.

Assuming the occupant is satisfied over the period of analysis, the same approach has been undertaken to calculate a temperature acceptable bandwidth over the winter months. Data was gathered at 15-minute intervals for each day in October, November and December. In the case of significant outliers or anomalies, data was cleaned by interpolating the temperature based on previous and upoming timeslot.

For each of the winter months, the mean indoor temperature and standard deviation were calculated for each hour of the day (inside the room where the thermostat is placed).

The approach outputted the mean internal temperature for each hour of the selected months and the associated lower and upper threshold limits for analysis.

It is assumed that changes in indoor temperature which are within this temperature bandwidth are acceptable and can be utilised for the demand response strategy. The Winter Mean Internal temperature and associated upper and lower limits are outlined in Figure 11, below.

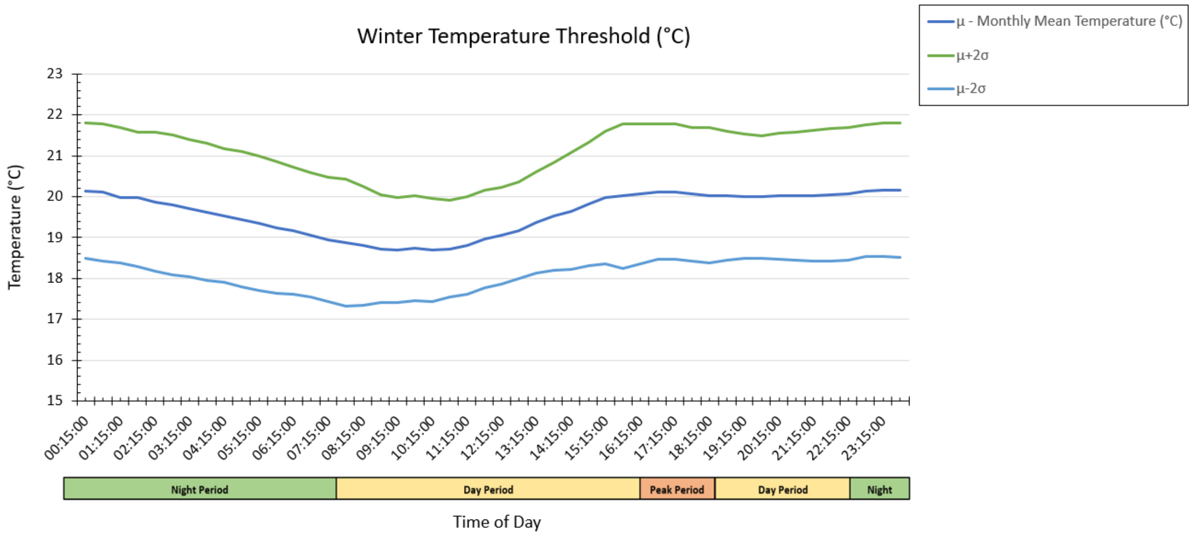

Figure 11: Winter temperature Threshold

3.6.1 Grey-Box Model

The aim of the proposed Building Simulator Grey-box Model is to optimize the use of PV energy production, through a smart control of the domestic hot water (DHW) heat pump and the heating system, while ensuring user's comfort and reducing energy consumption during peak times.

After a detailed and calibrated white-box model created from a house in Aran Islands (as described in the previous sections), simulations had been carried out to identify the main parameters and heating transfer dynamics necessary to build a reduced and more generic model, which can be easily adapted for the other Irish houses in the project. The parameters extracted from the white-box model were indoor air temperature increase and decrease rates for both, DHW and indoor temperatures, considering their behaviour during stationary conditions (system off) or while some action is performed (more information in section 3.6.3). To improve accuracy, different rates have been set for cold and hot days.

The Building simulator grey-box model reads the current environment state every 30 minutes step and estimates the next DWH and indoor temperatures values, calculated from the rates established previously. To reduce development time, these identified parameters will be extracted from RESPOND DB and from SD cards analysis, so it will not be necessary to create a new detailed model for the new houses.

The next step was to create the smart control and the rule-based solution was chosen. The current algorithm version receives a PV production and Temperature prediction of the day ahead and returns as an output a list of actions and setpoints to be performed to achieve an optimal PV self-consumption. The simulated grey-box environment analyses the current states and decide the actions according to the set of rules pre-defined.

3.6.2 List of Inputs

The inputs necessary to initialize the Building Simulator are divided in two main groups, described as follows:

States: this group of features has information about the current environment situation for each timestep, which is used to predict the new action to be taken and also estimating the new timestep state. Each state is composed by:

- Outdoor temperature (°C) (predicted, weather data file).
- Indoor temperature (°C) (from sensor, only for first timestep).
- Tank temperature (°C) (from sensor, only for first timestep).
- PV production (kW) (predicted).

Parameters: This group of features holds information about user's preferences and equipment's capabilities, which are used along with states to define actions. Moreover, parameters play an important role increasing the algorithm flexibility for demand shifting and PV self-consumption optimization.

- Indoor temperature standard setpoints (°C).
- Indoor temperature adapted setpoints (°C).
- Tank temperature standard setpoints (°C).
- Tank temperature adapted setpoints (°C).
- PV thresholds (max and min - kW).
- User's DWH and Heating schedule.

3.6.3 List of Actions (Outputs)

The Building Simulator reads the inputs for each timestep and take actions accordingly. The actions can be direct commands (e.g. DHW On, Heating On or System Off) or change on parameter settings (e.g. to choose DHW and Heating standard or adapted setpoints). Once the simulation reaches the end of the day a list of actions and parameters for the next day is provided for each timestep (Figure 12).

Action	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	1	1	1	1	0	0	0	0
DHW Setpoint	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Heating Setpoint	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Timestep	00:00	00:30	01:00	01:30	02:00	02:30	03:00	03:30	04:00	04:30	05:00	05:30	06:00	06:30	07:00	07:30	08:00	08:30	09:00	09:30	10:00	10:30	11:00	11:30

Action	1	0	0	0	1	1	1	2	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
DHW Setpoint	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
Heating Setpoint	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
Timestep	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	16:30	17:00	17:30	18:00	18:30	19:00	19:30	20:00	20:30	21:00	21:30	22:00	22:30	23:00	23:30

Legend: Action: 1 - Heating ON / 2 - DHW ON / 0 - System OFF
DHW Setpoint and Heating Setpoint: 0 - Standard / 1 - Adapted

Figure 12: Actions and Parameters Output List.

3.6.4 Rules and process Flow

The core of the Building Simulator decision-making algorithm is PV production. For each timestep, the algorithm checks PV production and if its value is higher than max PV threshold, both indoor and tank temperature setpoint parameters are set to “adapted” mode, which are values higher than the standard ones, aiming to create a heat buffer through the use of high PV production periods. For instance, the standard max tank temperature is 50°C and the adapted is 55°C. If PV production is less than PV max threshold and greater than PV min threshold, only indoor temperature setpoint is set to “adapted”, it means that the PV production is not high enough to activate the DHW heat pump, but it is enough for the heating system. Finally, if PV production is lower than PV min threshold, the parameter configurations are set to standard mode. Figure 13 presents a simplified version of the decision-making process.

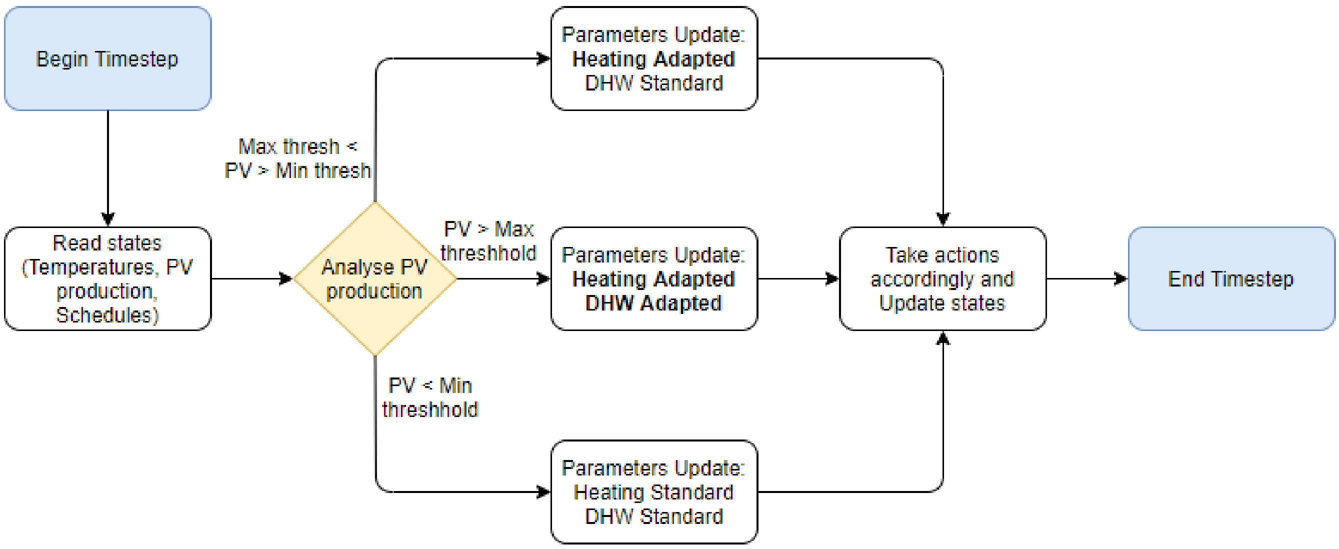

Figure 13: Simplified Process Flow.

After updating parameters, the algorithm checks the current indoor and tank temperature, decides the next action (e.g. Heating On, DHW On and System Off) and updates the next state. Despite decisions being made according to PV production, the user’s comfort is also an important factor, so in case of low production the algorithm looks if there is any schedule with preferences about heating or DHW and will take actions if the temperature is below the min setpoint. It is also possible to set the system to always keep the temperatures in a determinate range over the 24 hours.

As an example, Figure 14 shows the actions taken without the rule-based algorithm. Note that the tank temperature (pink line) drops to below 40°C around 6 pm, when usually there is a high demand peak on the energy system and when PV production is low (green dotted line). The same behaviour happens to indoor temperature, which activates the heating system after 6 pm. The black bars represent the control actions, the biggest is DWH On and the small one is Heating On.

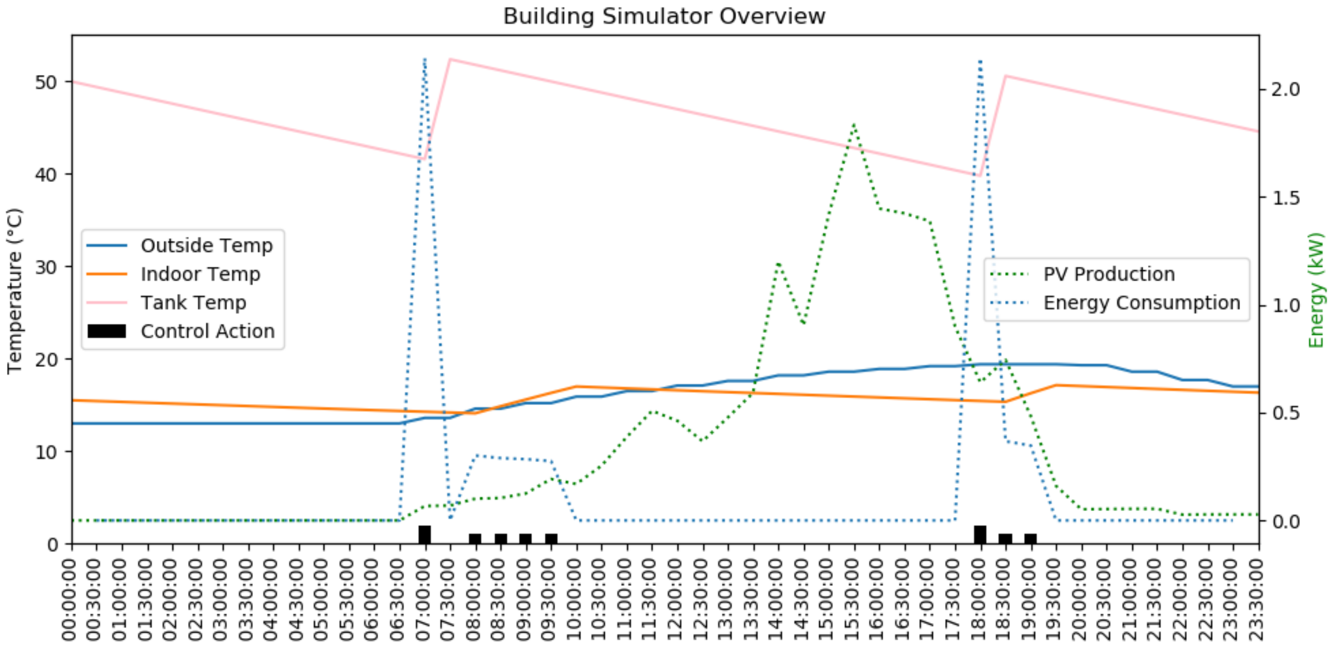

Figure 14: Building Simulator without PV optimization control.

After applying the rule-based control, the actions start to be taken according to PV production. As can be seen in Figure 15, the DHW on action is anticipated to 3 pm where PV production is higher than 1.5 kW. Once the tank reaches the maximum adapted temperature of 55°C (buffer) the heating system is turned on to increase indoor temperature using energy from PV production, until it achieves the maximum indoor temperature adapted. Note that taking actions according to PV production gives flexibility so DHW and heating system can be turned off in the following hours, hence avoiding demand peak times.

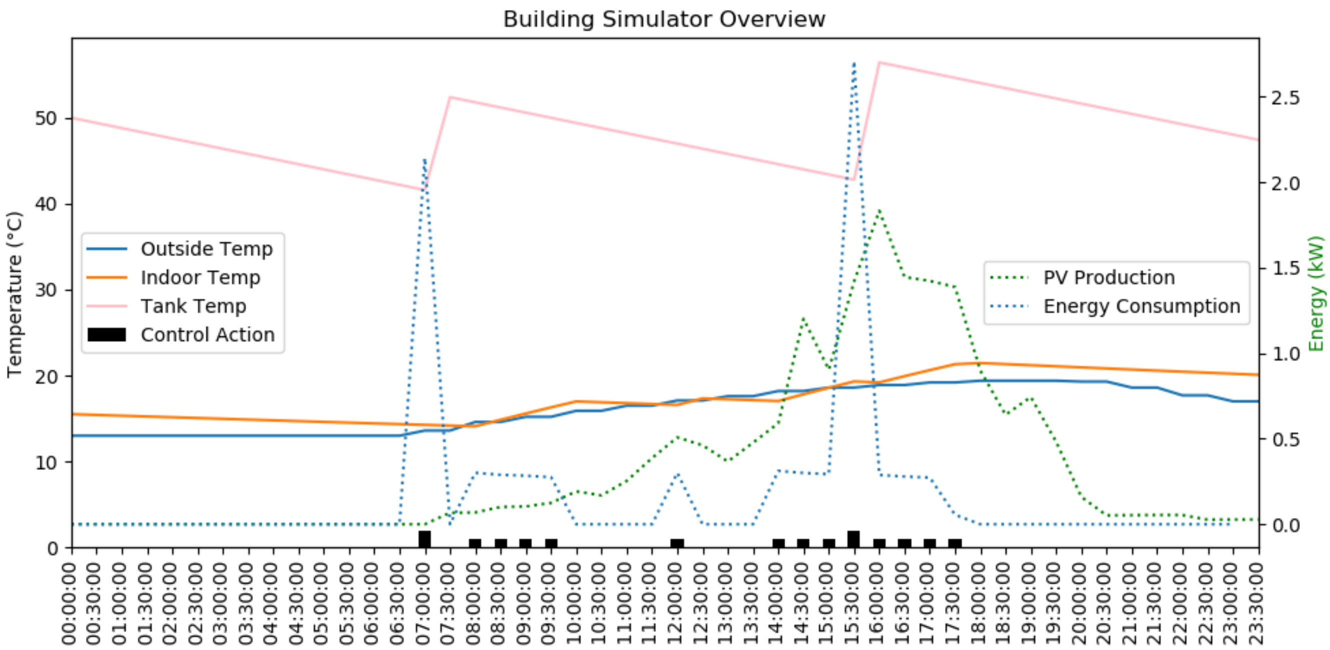

Figure 15: Building Simulator with PV optimization control.

3.7 HEURISTICS OPTIMIZATION

Once the optimal energy profiles are generated for each dwelling and neighbourhood, some specific control actions need to be performed in order to achieve those profiles. The Heuristics Optimization service is aimed at translating the results of the Optimization service into the electricity DR control actions (e.g. turning the dishwasher on). These control actions include not only home devices control, but also the management of energy assets both at a dwelling and district level. The actual actions proposed by the Heuristics Optimization service are guided by the user preferences set in the User Adapter Service explained in the following subsection.

The Heuristics Optimization service is implemented as rule engine system, which is based on both the monitored data and outcomes of the rest of the services towards the generation of the optimal personalized notification or control actions.

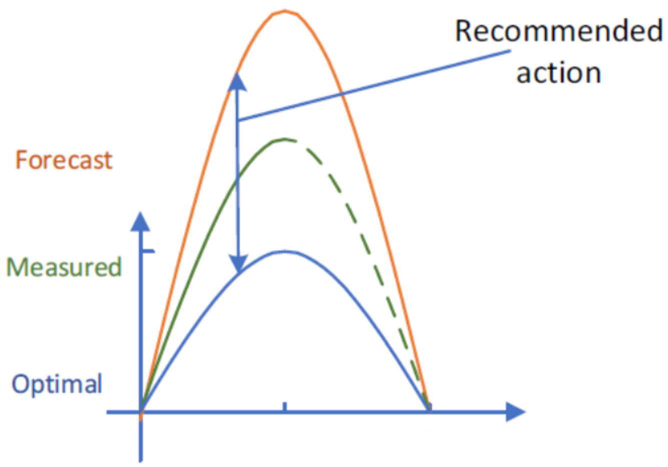

Figure 16: Heuristics Optimization service.

The Heuristic Optimization service as is shown in Figure 16 compares the optimal profile with the forecasted demand. The service has to choose what is the time where the Euclidean distance is higher and send a recommendation or control action for increase or decrease the consumption.

In order to allow the execution of automatic actions, the service must know which are the interruptible appliances and their consumption profile, because it is not possible to start an appliance if it is already started or vice versa. If there is not an optimal profile, the Heuristic Optimization service will use the hourly electricity price list to recommend actions if it is available.

The list of conditions that the Heuristics Optimization service may consider include:

- Optimal energy consumption profile at a neighbourhood level
- Optimal energy consumption profile at a dwelling level
- Energy price

- DR events
- Predicted energy production at a neighbourhood level
- Predicted energy production at a dwelling level
- Predicted energy consumption at a neighbourhood level
- Predicted energy consumption at a dwelling level
- Predicted energy consumption at an appliance level

Furthermore, depending on the type of energy on which to actuate, the list of actions that can be transformed into recommendations or automated control actions differ. On the one hand, for the electric energy, the activation/deactivation of appliances are considered, and on the other, for thermal energy, the setpoint modifications are considered for radiators, air conditioning equipment and heat pumps.

In the upcoming subsection, some use cases that combine both services are described.

3.8 User Adapter

Balancing energy efficiency and user satisfaction is another unresolved DR challenge [18], therefore, the User Adapter Service is of utmost importance towards the success of the RESPOND system. This service aims at collecting the preferences that the users may have with regards to the different events and situations involved in DR events.

Notifications and DR events are sent to the occupants' smartphone using Pop-up notifications as shown in Figure 17. These RESPOND messages are received instantly and the occupant has the option to accept it and view the corresponding information in the App or dismiss it. Depending of the type of message it could include a button to fire an action.

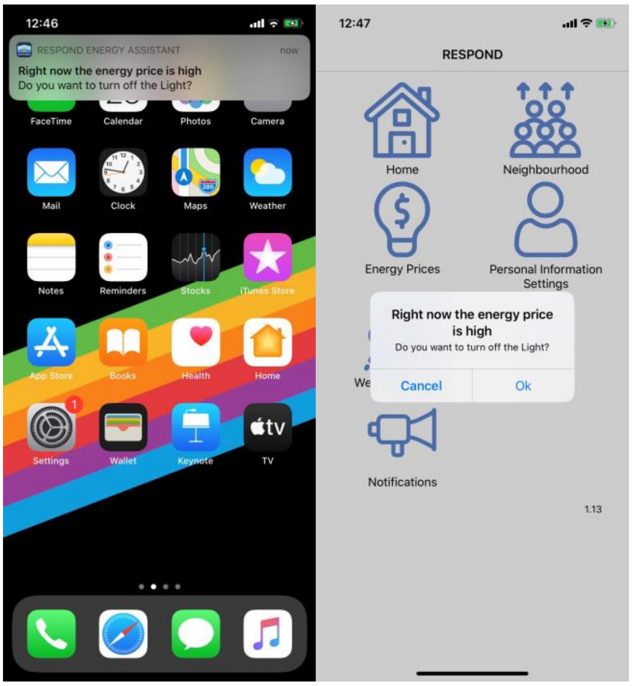

Figure 17: RESPOND Notifications via pop-up messages.

Certainly, the collected preferences include the type of notifications or automation preferred by dwellers. The options are:

- Energy savings tips. Generic messages about ways of saving energy
- Information pills. Short messages highlighting information relevant to save energy
- Changed power prices. Messages informing about important changes in energy prices one day ahead
- Customized recommendations. Recommendations for saving or moving loads based on the energy profile of the user. Optimal profile is used to generate these messages.
- Automation. Automation of switching on-off appliances according to the optimal profile and DR events.

Other preferences that are being considered are:

- The type of actions allowed by each dweller (e.g. switch on or switch off).
- The appliances upon which these actions may be performed (e.g. a dishwasher of a washing machine).
- The periods of time when these actions may be allowed (e.g. from 19:00 onwards).

The set of preferences for each RESPOND user are stored in the RESPOND platform's MySQL database, although the user is not aware of the underlying procedures. As a matter of fact, the user sets his/her preferences in the RESPOND Mobile app, as shown in Figure 18. Within the app's "Personal Information" tab, users may modify these preferences as they wish.

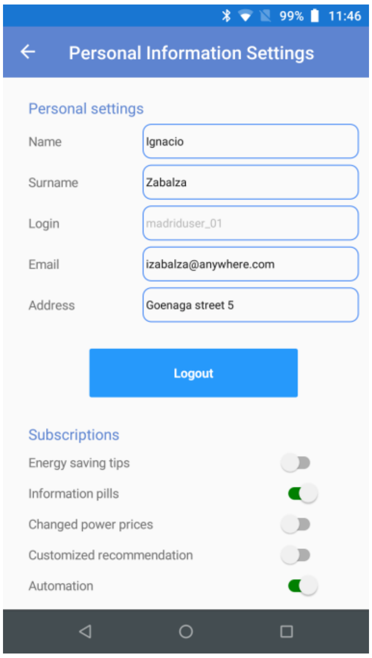

Figure 18: User Preferences within the RESPOND Mobile App.

Some use case examples that combine both the Heuristics Optimization and User Adapter services are described next. It is worth mentioning that notifications will only be sent to those users who satisfy the required conditions:

<u>Use case 1</u>

Leveraging the energy price collected, a periodically executed service obtains the upcoming day's time period in which the energy price is the lowest. This information is then provided to each user by means of an informative notification.

<u>Use case 2</u>

Apart from the information of the use case 1, information about the appliances installed in each house is leveraged. The service identifies the appliance with the highest energy consumption and evaluates if the it is a flexible appliance whose profile could adequate to the specified time period. If that's the case, each user will receive an interactive notification with the option to activate such an appliance.

<u>User case 3</u>

Based on the optimal profile and the predicted energy consumption, the service evaluates which is the moment in which the optimal consumption and the predicted consumption differ most. This information is then communicated to each user by means of an informative notification.

Use case 4

Apart from the information of the use case 3, information related to the appliances and equipment installed in each house are leveraged. The service generates a personalized suggestion regarding when to activate or deactivate appliances towards adapting the real energy consumption with the optimal one. This information is communicated to each user by means of an interactive notification where the user may accept or reject the proposed control action.

Use case 5

Once the predictions of the energy production are generated, the service evaluates which are the periods when biggest production peaks will occur so that it can be communicated to each user by means of a prescriptive notification. Depending on the pilot cases, the information provided may differ:

- In Madrid, a notification regarding DHW of heating consumption
- In Aarhus, a notification regarding the electric consumption at a neighbourhood level
- In the Aran Islands, a notification regarding the electric consumption at a dwelling level

Use case 6

Apart from the information of the use case 5, information related to the appliances and equipment installed in each house are leveraged. The service generates a personalized suggestion regarding when to activate or deactivate appliances towards the maximization of the energy production peaks. This information is communicated to each user by means of an interactive notification where the user may accept or reject the proposed control action.

Use case 7

Based on the optimal profile and the upcoming day’s energy prices, the service evaluates the time periods in which high-consuming appliances activation is the most suitable. This information is communicated to each user by means of an informative notification.

Use case 8

Apart from the information of the use case 8, information related to the appliances and equipment installed in each house are leveraged. The service generates a personalized suggestion on when a user should activate or deactivate installed appliances towards the minimizing operation cost. This information is communicated to each user by means of an interactive notification where the user may accept or reject the proposed control action.

Use case 9

The service receives a DR event in which certain time periods will have certain energy prices. The service generates a recommendation to increase or decrease the energy consumption in certain time periods towards the minimization of each user's operation cost. This information is communicated to each user by means of an informative notification.

Use case 10

Apart from the information of the use case 8, information related to the appliances and equipment installed in each house are leveraged. The service generates a personalized suggestion on when a user should activate or deactivate installed appliances towards the minimizing operation cost. This information is communicated to each user by means of an interactive notification where the user may accept or reject the proposed control action.

Use case 11

Based on the neighbourhood thermal demand peak, heating setpoint is increased at an instant t_0 prior the peak. In an instant t_1 after the peak, the heater is deactivated until an instant t_2. The room or building's thermal inertia is expected to ensure that temperature will not surpass the lower range of thermal comfort criterion set by the user. Likewise, this use case can be applied in an analogous way for the refrigeration of spaces by means of air conditioning equipment.

3.9 Predictive Maintenance

Appliances, equipment and other devices deployed within the RESPOND pilot sites may suffer from performance worsening caused by their deterioration due to the passing of time, as well as damages and break downs. In order to alleviate and minimize these underperformances or even downtime periods, RESPOND sets the Predictive Maintenance Service.

Predictive maintenance is a technique that uses condition-monitoring tools and techniques to track the performance of equipment during normal operation to detect possible defects and fix them before they result in failure. When predictive maintenance is working effectively as a maintenance strategy, maintenance is only performed on machines when it is required. That is, just before failure is likely to occur. This brings several cost savings:

- Minimizing the periods of time the equipment is being maintained
- Minimizing the production hours lost to maintenance
- Minimizing the cost of spare parts and supplies

Driven by the performance prediction of different component and assets, early anomalous performances are expected to be identified, in order to suggest the corresponding maintenance tasks. Figure 19 shows the different scenarios identified in predictive maintenance tasks regarding performance of different components and systems.

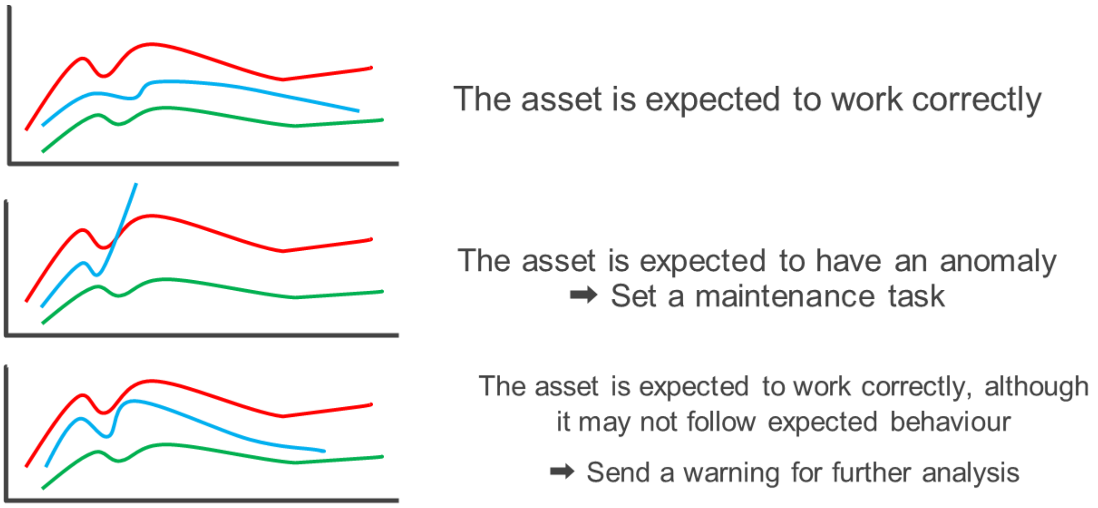

Figure 19: Potential performance of different systems and components.

In order to perform the data analysis for predictive maintenance purposes and create a baseline curve for equipment's performance, having a complete data set of energy performance during a long time is essential. Due to the problems in the setup of the monitoring devices and troubles in communications at month 30, currently there is not enough data for developing this service. This analysis will be performed again on month 33 and results will be included in deliverable D6.2 "Validation analysis of operational scenarios".

4. DEXMA Related Services

4.1 DEXMA's integration into RESPOND platform

DEXMA's platform role in the RESPOND platform is to provide a desktop platform that displays information sent from:

- Gateways located in the pilot buildings. This includes mainly temperature, electrical consumption and electrical production readings, which are displayed graphically in DEXMA Analyse, formerly known as DEXCell EM.
- Demand Respond events generated by the project's Analytic Services.

Both readings and DR events are sent to DEXMA Analyse from a MQTT [19] broker. An integration bridge has been developed in order to store the readings in DEXMA Analyse's DB. The MQTT broker acts as a central node: 1) it receives inputs from pilot gateways and the Analytic Services' modules, and 2) it resends this information to DEXMA Analyse and RESPOND's mobile app.

In order to gather DR events created and sent from Pupin's Analytic Services, an endpoint was created in DEXMA's API v3 [20] in order to gather the event timestamp and Demand Response instruction and publish it on DEXMA Analyse's Consumption page.

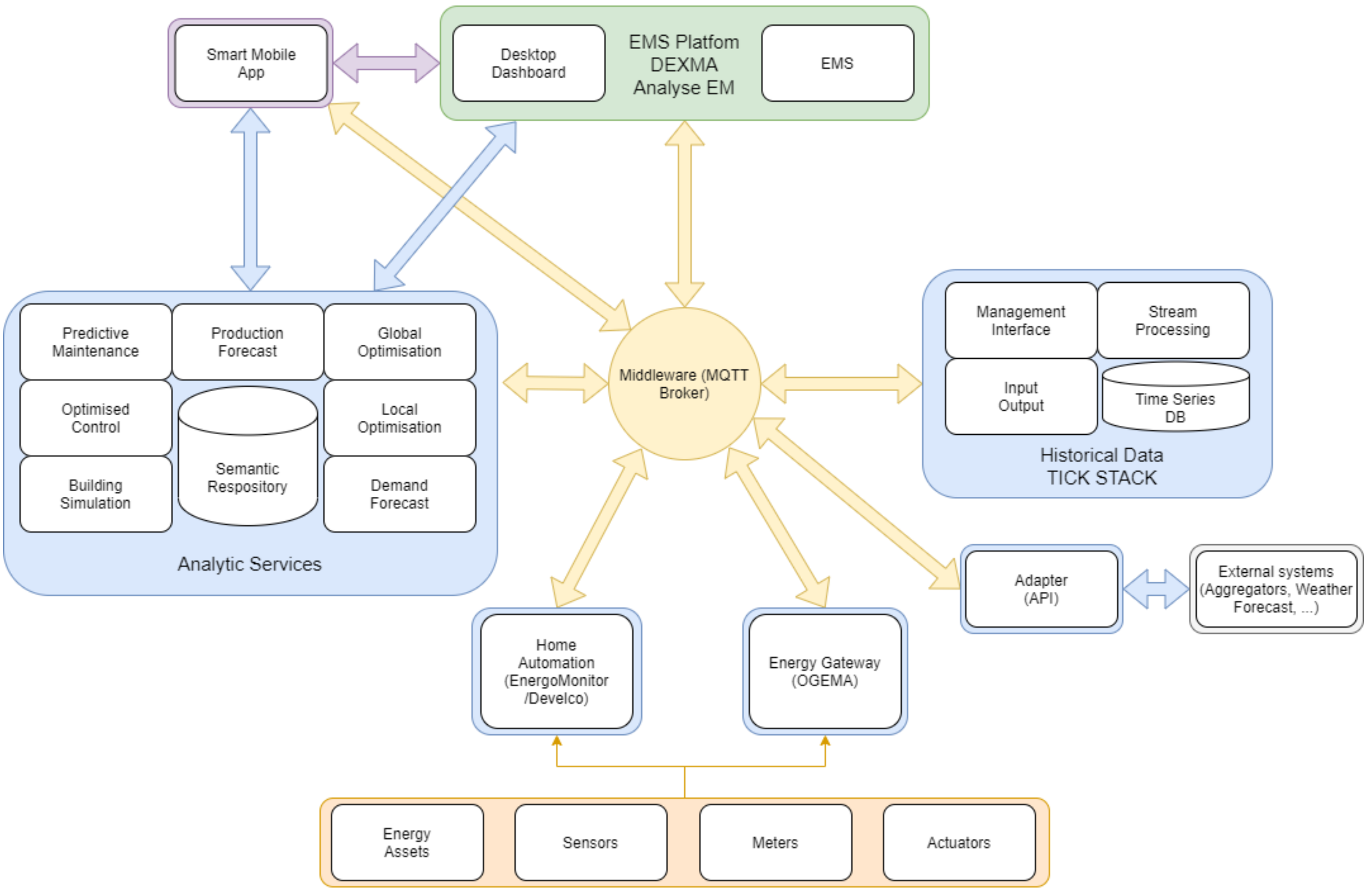

Figure 20:RESPOND's project general architecture

4.1.1 Backend development

This section describes the backend development carried out in order to retrieve the readings from the meters and sensors installed in the pilot buildings.

First, the field mappings between the CDM [21] and DEXMA Analyse DB were established. Then, a bridge between the MQTT server and DEXMA Analyse DB was developed so that meter and sensor readings could be sent to the latter. Furthermore, the bridge listens to the DR events generated in Pupin's Analytical Services and inserts them in DEXMA Analyse DB so that they can be displayed in DEXMA Analyse.

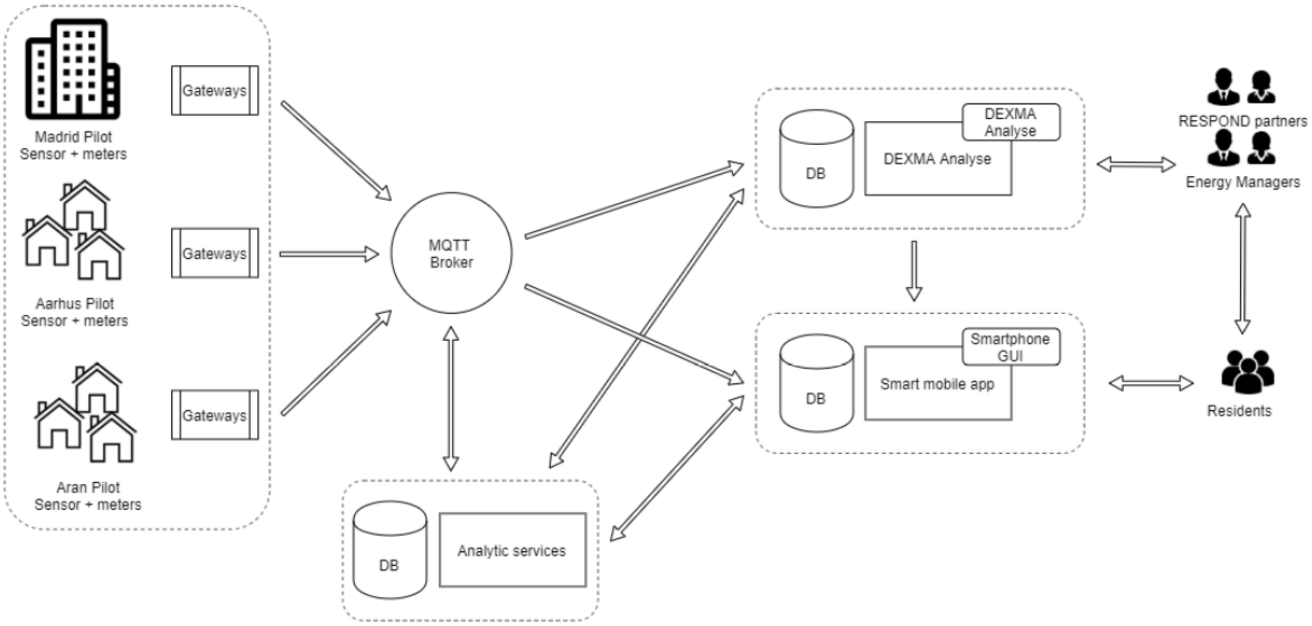

Figure 21: RESPOND's project backend architecture

4.1.2 Reading mappings

Prior to the development of the bridge between the MQTT server and DEXMA Analyse, it was decided the information from the readings in the pilots to be stored in DEXMA Analyse DB. The mappings between the fields is displayed on the following table:

Table 5: Field mapping between MQTT broker and DEXMA Analyse

Field name in RESPOND cloud according to CDM	**Description**	**Units**	**Parameter in DEXMA Analyse**	**Units mapping**	**Subdevices**
demand	Power consumption	W	401a/401b/401c	Direct	Used to represent phases

energy	Accumulated energy consumption	Wh	402	x/1000	-
acfrequency	AC Frequency	Hz	414a/414b/414c	Direct	Used to represent phases
voltage	AC Voltage	V	405	Direct	-
current	AC Current	A	406	Direct	-
onoff	Smart plug on/off status (on = true, off=false)	Boolean	501	Direct	Subdevices used for other Booleans: occupancy, alarm
occupancy	Presence = true, no presence = false	Boolean	501	Direct	-
alarm	Door/window open/presence = true, else = false	Boolean	501	Direct	-
illuminance	Light illuminance	Lux	303	Direct	-
temperature	Air temperature	ºC	301	Direct	-
humidity	Relative humidity	%	302	Direct	-
battery	Sensor battery voltage	V	610	Direct	-
networklinkstrength	Network link strength applicable to Develco devices	0-100 scale	503	Direct	-
rssi	RSSI (signal strength) in dB applicable to EnergoMonitor devices	dB	603	Direct	-
co2	Data sent by CO_2 sensor	ppm	307	Direct	-
voc	Data sent by VOC sensor	ppb	342	Direct	-
dhwc	Domestic hot water cumulative consumption	m^3	803	Direct	-
temperature_setpoint	Thermostat setpoint	ºC	805	Direct	-
heat_energy	Heat energy	Wh	802	x/1000	-
Inlet_flow_temperature	Measure inlet temperature	ºC	805	Direct	-

Measured return temperature	Measured return temperature	ºC	806	Direct	-

As it can be observed on the table, all mappings are direct mappings except for those in Wh, which must be converted to kWh, as it is the energy unit used in DEXMA Analyse. It must also be noted that subdevices are needed for variables like power or current (to represent the different phases in AC) and boolean (to represent different variables using the same parameter to store it in DEXMA Analyse).

4.1.3 BRIDGE DEVELOPMENT

In DEXMA's backend, a bridge was developed with the aim to receive the readings from the devices installed in the pilot buildings. A new type of virtual gateway was developed in DEXMA's backend specifically for this development. The bridge uses the gateway's serial number to subscribe to the MQTT channel of the Energomonitor or Develco gateway in the pilot building. Serial numbers for these gateways follow the following rule:

- "ENE"- followed by 16 hexadecimal characters for Energomonitor gateways
- "DEV"- followed by 16 hexadecimal characters for Develco gateways

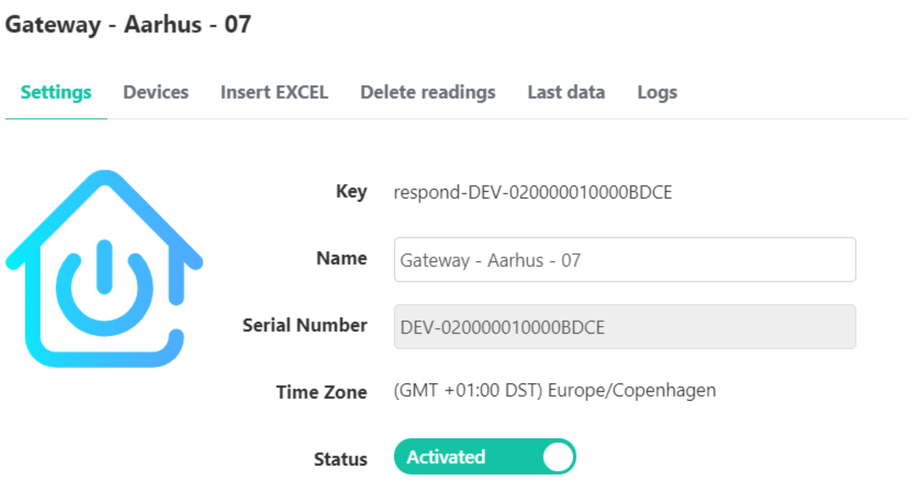

Figure 22: RESPOND virtual gateway creation in DEXMA Analyse

The bridge retrieves the serial number from the virtual gateway in DEXMA Analyse and subscribes to the MQTT channel for the gateway with the same serial number or GATEWAY_ID in the CDM. The topic used in the MQTT channel to publish the readings from meters and sensors is GATEWAY_ID/data.

Once it is subscribed to the MQTT channel, it starts sending device readings every 5 to 10 minutes to the virtual gateway. For each type of measure or parameter sent by the pilot gateway, a datapoint is created in the virtual gateway. The user then must accept the datapoints and assign them to the correct location in DEXMA Analyse. Once this is completed, the user can graphically view the readings in several sections in DEXMA Analyse:

- Consumption: for electrical and thermal energy consumption and electrical production readings.

- Comfort: for temperature and humidity readings.
- Advanced Analytics and by device sections: rest of readings.

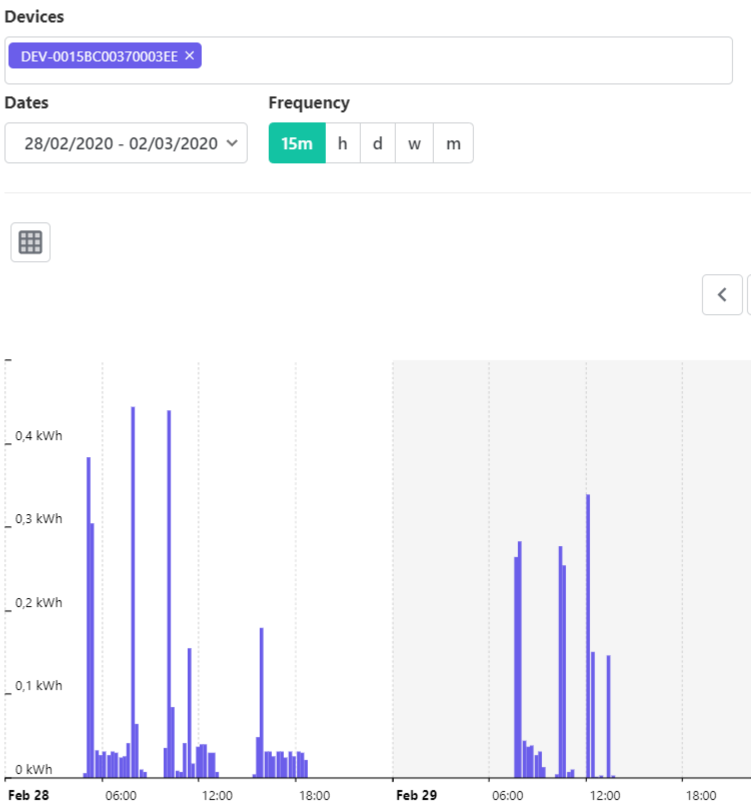

Figure 23: Energy consumption in a pilot building at Consumption section in DEXMA Analyse

4.1.4 Insertion of readings in DEXMA Analyse DB

DEXMA's insertion API has an endpoint which is used for the insertion of readings from external gateways or other types of insertion (e.g. FTP server, CSV file, etc). The URL for this endpoint is the following:

- http://api.dexcell.com/v3/readings

A JSON example for the POST message to this endpoint:

```
[
  {
    "did": "3a",
    "sqn": 1,
    "ts": "2014-10-02T10:30:00+02:00",
    "values": [
      {
        "p": 401,
        "v": 3505
      },
      {
        "p": 402,
        "v": 5600012
      },
      {
        "p": 404,
        "v": 123504
      }
    ]
  }
]
```


Figure 24: Example of JSON POST message body to readings endpoint

Where *did* is the device name in DEXMA Analyse, *ts* is the timestamp, *p* is the parameter in DEXMA Analyse and *v* is the meter or sensor reading. The bridge developed by DEXMA obtains the readings available in the MQTT channel and inserts the readings in a JSON message with the structure in Figure 24.

4.1.5 Integration of Analytic Services results in DEXMA Analyse

An iframe has been created in DEXMA Analyse in order to visualize results from Pupin's Analytic Services. Production, demand and optimal consumption results from Pupin's Forecasting and Optimization modules are displayed in the 'Production, demand and optimal consumption' section in the Analytic Services iframe in the Analysis section in DEXMA Analyse. Furthermore, generated DR events are displayed in the section 'Demand (DR) events', which is displayed just below the 'Production, demand and optimal consumption' section.

These results are available for 3 types of loads: electrical, thermal and domestic hot water system. Furthermore, the location for which the results are displayed can be selected in a picklist.

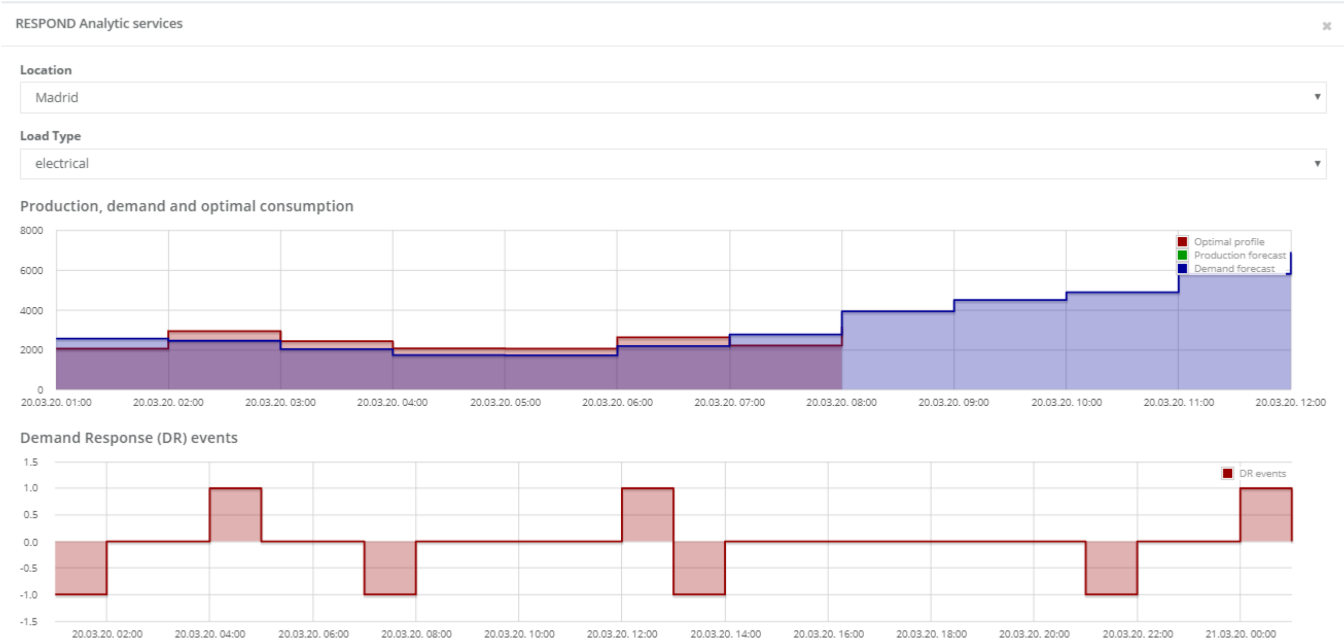

Figure 25: Example of visualization of Analytic Services results in DEXMA Analyse

4.2 DR EVENTS TRACKING

As mentioned in section 4.1, Pupin's Analytic Services create and send Demand Response events to RESPOND's desktop EMS (DEXMA Analyse) and mobile app through the MQTT broker. The DR events are generated in Pupin's Analytic Services by combining information from the smart meters and sensors in the pilot buildings (energy consumption, generation, outdoor & indoor temperature…) together with information from the energy market and the grid.

DR actions are also generated by Analytic Services and involve more concrete messages (turn on/off equipment, for instance). DR actions are not meant to be displayed in DEXMA Analyse as they are specific to each end user, who can see them in their smartphone.

4.2.1 MESSAGES

DR events are generated for each pilot site, that is, DR events affect all the buildings in one pilot at once. They only contain 2 instructions: reduce or increase the consumption. For Madrid pilot, the input used by the Event generator module is the energy pricing while on the other two pilots the PV production is the main factor that drives DR events. The DR events are published in these MQTT topics:

- dr_events/PILOT_ID

Where PILOT_ID can have the following values:

- 1 for Aran Islands pilot
- 2 for Aarhus pilot

- 3 for Madrid pilot

The message contains information about start and end of the DR event and a value which can be 1 (increase consumption) or -1 (reduce consumption). These messages are listened by the bridge, which inserts the in DEXMA Analyse through DEXMA's API v3.

DR event messages inserted in DEXMA Analyse contain information regarding:

- Start and end of the DR event (datetime)
- Duration of the DR event in minutes
- Instruction to the user: reduce/increase consumption
- Zone of the DR event: One of the 3 pilot zones (Madrid, Aarhus or Aran). DR events do not affect a specific location but a pilot zone.
- User who posts the DR event.

DR event messages are displayed in the Consumption section under the Analysis section in DEXMA Analyse. The DR events appear as comments under the Consumption graph. This can be observed in the image below.

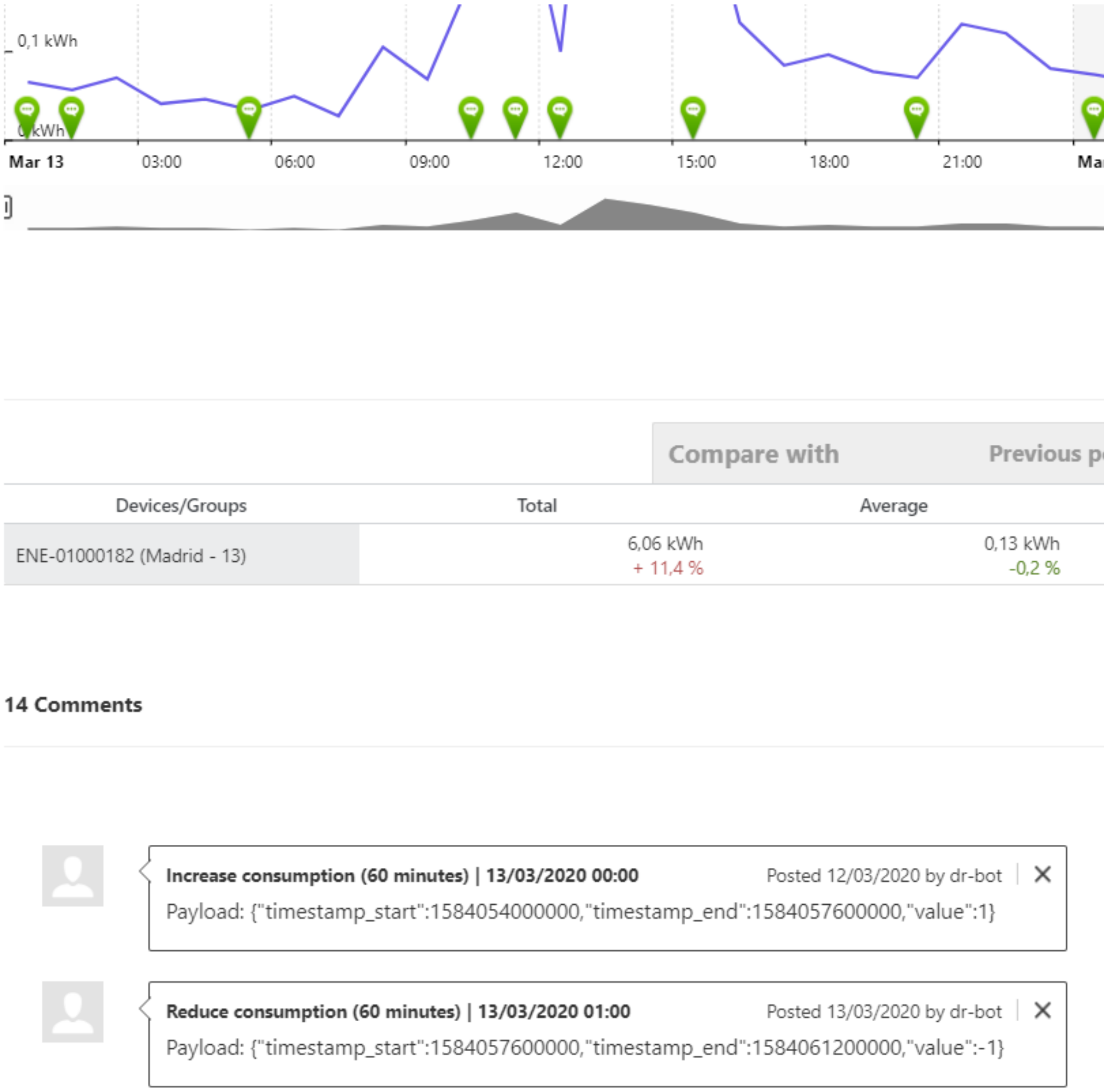

Figure 26: DR events as comments under consumption graph in DEXMA Analyse

It can also be observed that each DR event is also indicated in the consumption graph using a small green symbol. It is a way for the user to quickly see the DR events for every day.

4.2.2 DR events and actions Flow

The DR Events & Actions follow a flow from the input of external information to Pupin's Analytic Services (through the MQTT broker) to the display of a DR Event in DEXMA Analyse and the sending of a DR Action to the end user through the mobile app. The diagram below describes in detail the flow of the DR Events and Actions through the different modules.

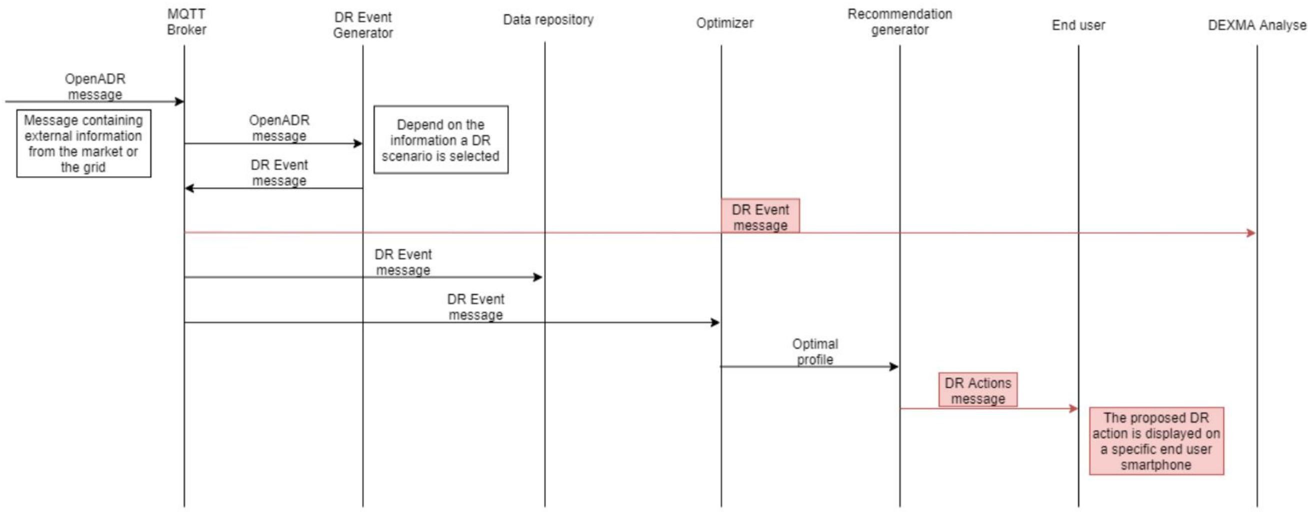

Figure 27: DR Events and Actions flow diagram

Once the DR Event is sent and displayed in DEXMA Analyse, it is sent to the Optimizer module in Pupin’s Analytic Services. This module takes DR Events as an input which uses to create DR Actions to be sent to RESPOND’s mobile app.

4.2.3 API ENDPOINTS

In order to insert DR Events in DEXMA Analyse’s DB an endpoint was created in DEXMA’s API v3 and another one was created to query the existing DR Events in DEXMA Analyse DB. An example of the structure of the JSON message to send a DR Event using DEXMA’s API:

```
curl --location --request POST 'https://api.pre.dexcell.com/v3/comments' \
--header 'Content-Type: application/json' \
--data-raw '{
    "subject": "Increase consumption (60 minutes)",
    "comment": "Payload: {\n\"timestamp_start\":1577858400000,\"timestamp_end\":1577862000000,\"value\":1\n}",
    "type": "EVENT",
    "visibility": "PUBLIC",
    "reference_date": "2020-01-01T06:00:00Z",
    "post_date": "2020-03-05T14:30:04.641Z",
    "user_id": 22625,
    "location_id": 178135
}'
```

As it can be seen, the endpoint is http://api.dexcell.com/v3/comments. Regarding the JSON variables, “subject” is the text in bold and “comment” is the text below. DR Events have “type” set to “EVENT” and “visibility” to “PUBLIC” so that all users with access to the specific pilot zone can see DR Events. Date fields reflect the event start and the event posting date (“reference_date” and “post_date”, respectively). “user_id” refers to ID in DEXMA Analyse of the user who posts the DR event, while “location_id” refers to the pilot zone where the DR Event is published. These details can be checked in Figure 26.

To retrieve the DR Events already in DEXMA Analyse, the same endpoint can be queried. An example of GET request is provided below:

```
curl --location --request GET 'https://api.pre.dexcell.com/v3/comments?from=2019-12-07T00:00:00&to=2019-12-09T00:00:00&visibility=PUBLIC' \
--header 'Content-Type: application/json'
```

The main parameters refer to the date the DR Event starts and its visibility.

4.3 KPI INPUTS IN DEXMA ANALYSE

Several RESPOND project KPIs defined in Deliverable D6.1 have inputs which can be obtained directly from DEXMA Analyse. This section describes the obtention of these inputs in DEXMA Analyse.

4.3.1 ENERGY KPIs

RENEWABLE TOTAL ENERGY CONSUMPTION

According to its definition in Deliverable D6.1, this KPI reflects the amount of renewable energy being consumed in a building for a certain time period. Hence, the amount of energy produced locally, and the total energy consumed must be obtained. These amounts can be visualized in the Consumption section in DEXMA Analyse. By selecting the Electricity button, the electrical consumption is displayed:

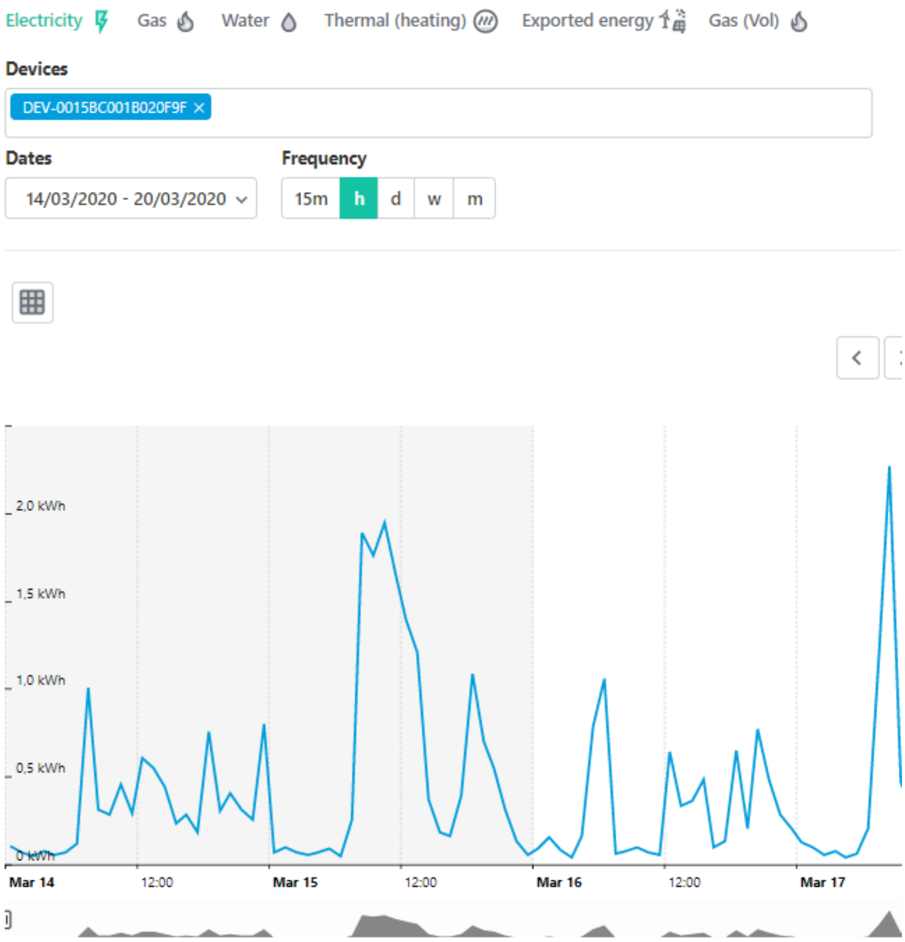

Figure 28: Electrical consumption in kWh in DEXMA Analyse

Below this line chart, which can also be a bar chart, there is a summary table with the total amounts:

Table 6: Summary table in Consumption section

	Compare with	Previous period (07/03/2020 - 13/03/2020)	
Devices/Groups	Total	Average	Median
DEV-0015BC001B020F9F (Aarhus - 08)	65,46 kWh + 15,1 %	0,41 kWh + 18,7 %	0,28 kWh + 128,8 %

Produced energy can also be obtained in the same section by clicking on the Exported energy button:

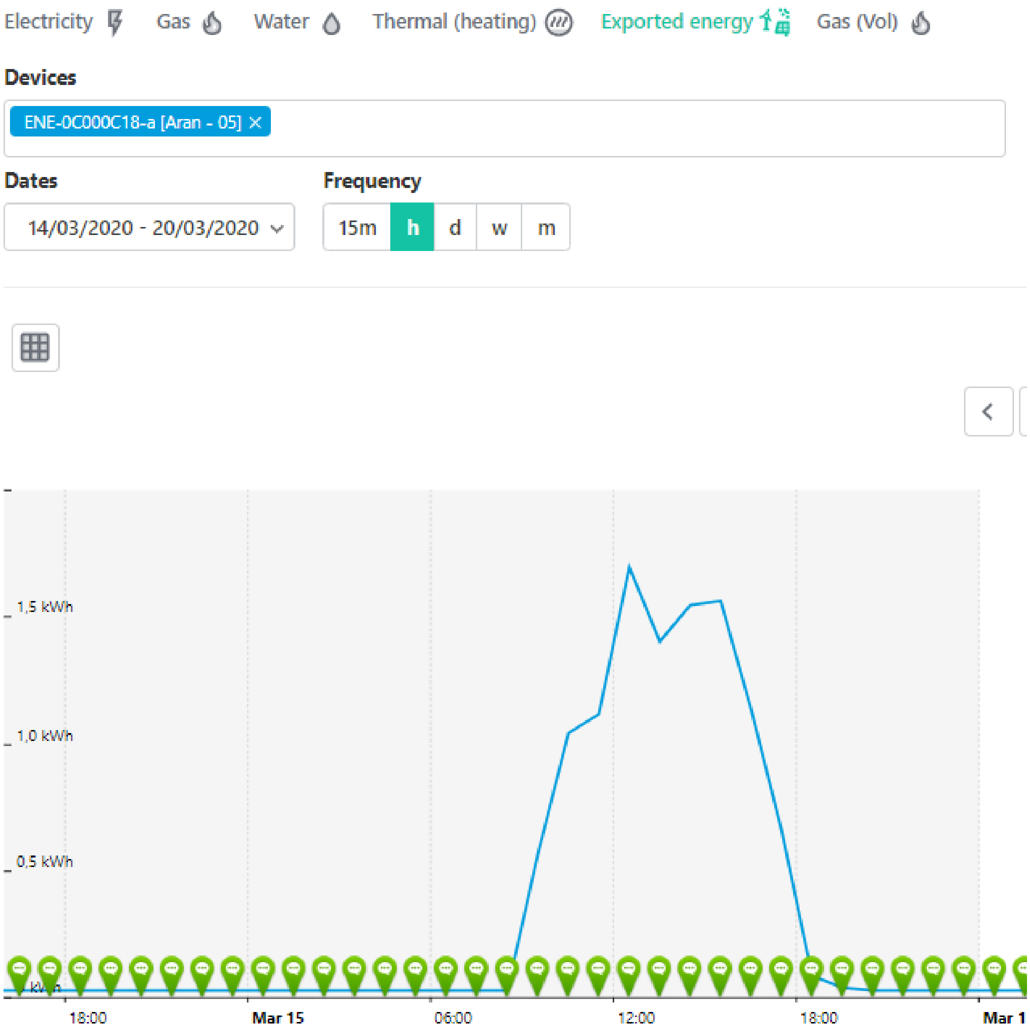

Figure 29: Produced energy in kWh in Consumption section

The same table as in Table 6 can be found below the chart.

Energy savings

The energy savings generated can be obtained by comparing the energy consumption in a certain period with the consumption baseline. In this case, this can be easily done using the Comparison tool in the Analysis section in DEXMA Analyse. In Comparison, up to 4 periods for the same device can be compared at the same time for a limited number of windows (1/2/5/7/28 days, 1/3/6 months or 1 year).

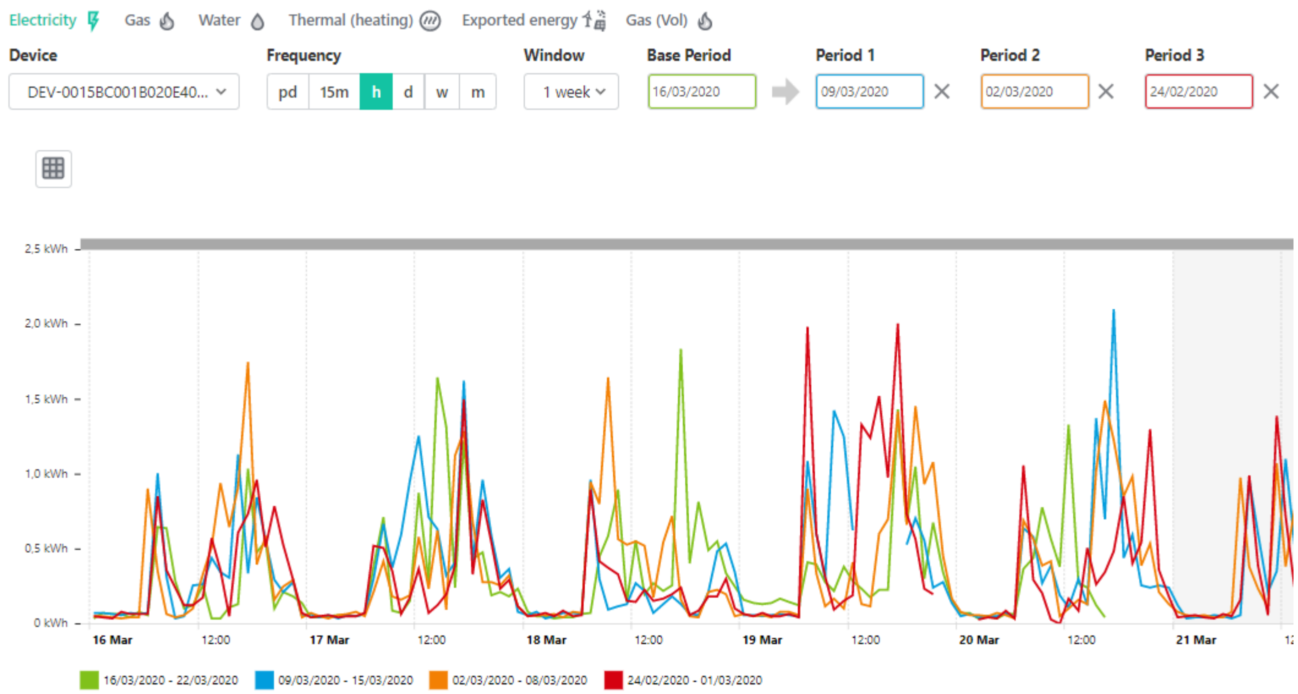

Figure 30: Comparison section in DEXMA Analyse

Under the chart, a summary table can be found, just like in the Consumption section.

Table 7: Summary tale under chart in Comparison section

Period		Total	Difference	Difference [%]
16/03/2020 - 22/03/2020		36,82 kWh	-- kWh	-- %
09/03/2020 - 15/03/2020		36,20 kWh	-0,62 kWh	-1,69 %
02/03/2020 - 08/03/2020		40,15 kWh	+3,33 kWh	+9,04 %
24/02/2020 - 01/03/2020		35,23 kWh	-1,58 kWh	-4,30 %

In order to calculate the energy savings, a device and 2 time periods must be selected (period where savings must be calculated and the same period for the previous year, for example). A frequency and time window must also be indicated.

4.3.2 CO_2 KPIs

Reduction of greenhouse gas emissions

This KPI is very similar to the previous one, Energy savings. Once the energy savings have been calculated, the only input needed is the CO_2 emission factor [22] of electricity for the country the building is in. The energy savings have to be multiplied by the emission factor.

4.3.3 Demand KPIs

Peak demand

In order to obtain the reduction in the peak demand during a DR event, the maximeter during that period must be obtained and compared to the baseline maximeter. Power readings can be obtained in Peak demand section:

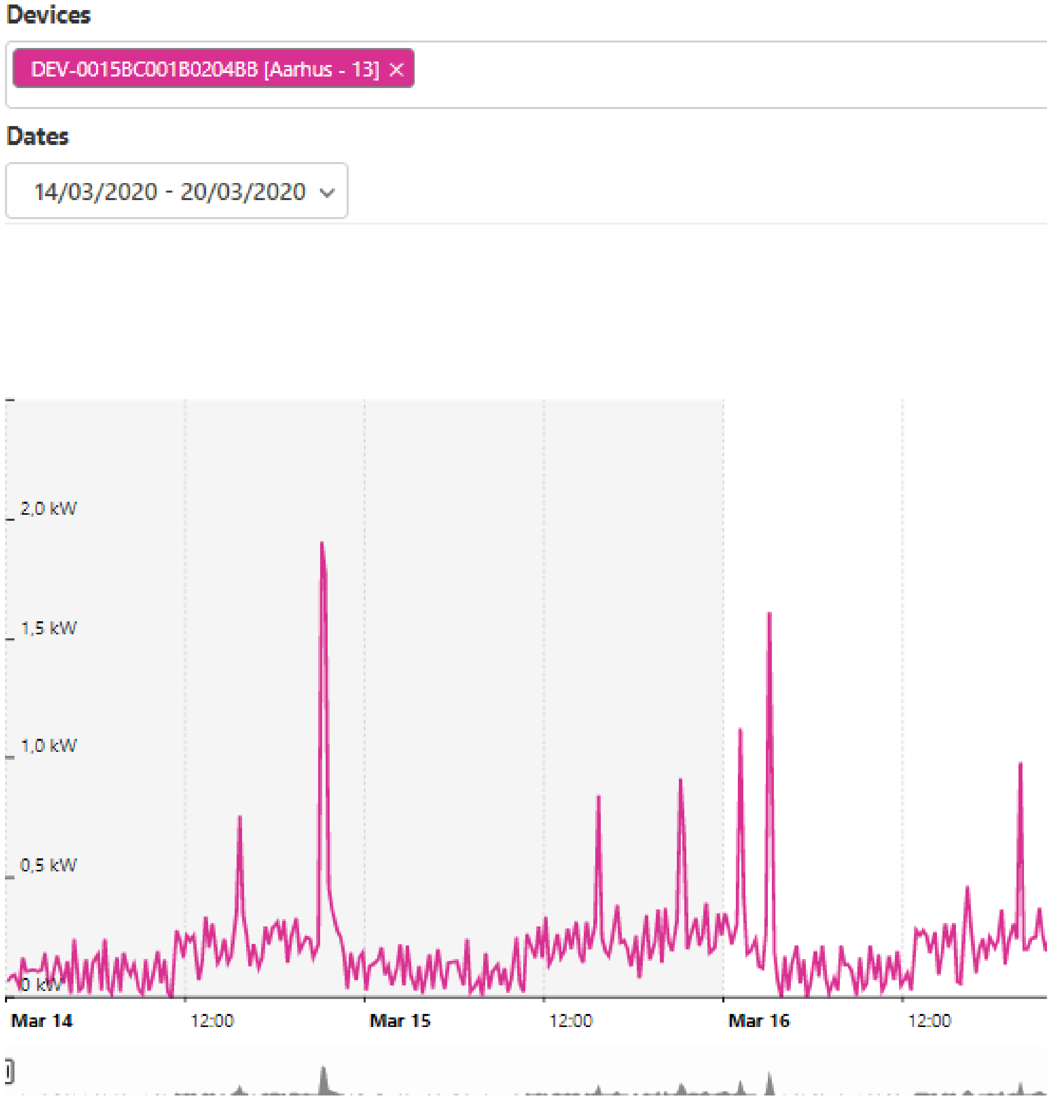

Figure 31: Peak demand section in DEXMA Analyse

Note that in this section the DR events cannot be seen, but both in Comparison and Consumption section the DR events are visible.

Rescheduled demand

The rescheduled demand is the amount of energy saved during the DR event that is used during another period of the day. In order to obtain the necessary inputs for this KPI, it is best to use the Comparison section (which is also used to obtain Energy savings KPI), where the savings during the DR event and outside the DR event can be obtained and compared.

4.3.4 Economic KPIs

Rescheduled demand

The main inputs in order to calculate this KPI are:

- Energy costs during the DR event
- Baseline energy costs

Both these parameters can be obtained in the Cost section in DEXMA Analyse. However, the location to be analysed needs to have an active Price, Contract and Supply, which can be configured in Settings > Supplies and Prices.

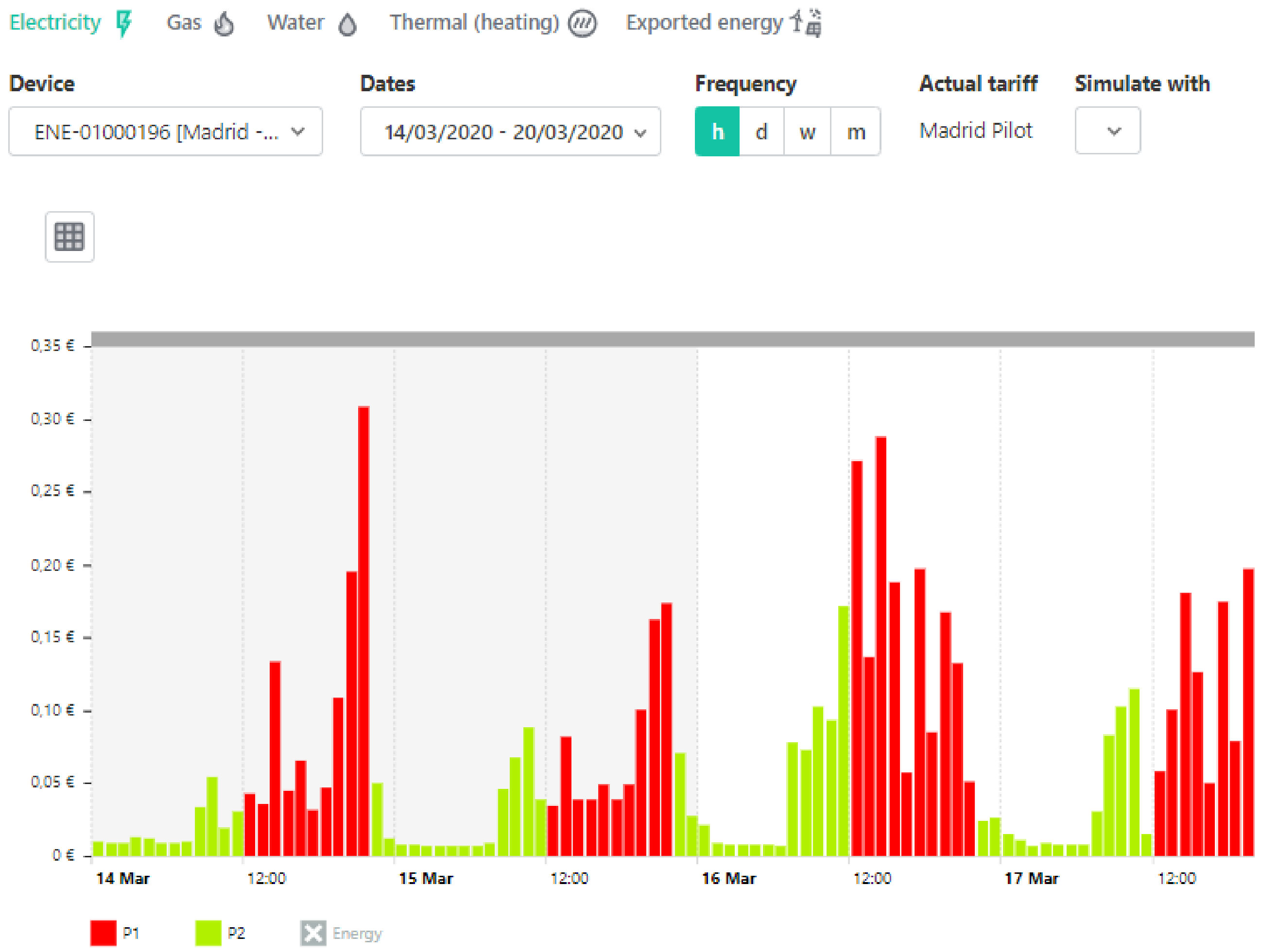

Figure 32: Cost section in DEXMA Analyse

Under the chart, a summary table can be found, like in Comparison and Consumption sections. Also, DR events are displayed as comments just below the summary table.

Table 8: Summary table in Cost section

		Compare with	Previous period (07/03/2020 - 13/03/2020)	
Periods	Tariff	Consumption	Cost	Average
P1	0,166212 €/kWh	43,62 kWh + 16,8 %	7,25 € + 16,8 %	0,11 € + 15,0 %
P2	0,094916 €/kWh	35,50 kWh + 4,7 %	3,37 € + 4,7 %	0,04 € + 6,9 %
TOTAL	**0,134225 €/kWh**	79,12 kWh + 11,1 %	10,62 € + 12,7 %	-- -- %

4.3.5 Comfort KPIs

Indoor air quality (IAQ)

The level of CO_2 concentration during a DR event in ppm can be obtained in DEXMA Analyse, provided there is a CO_2 sensor in the location at study. In Advanced Analytics section the readings from CO_2 sensors can be visualized graphically. In this section, the parameter (in this case, CO_2 concentration) and device must be selected.

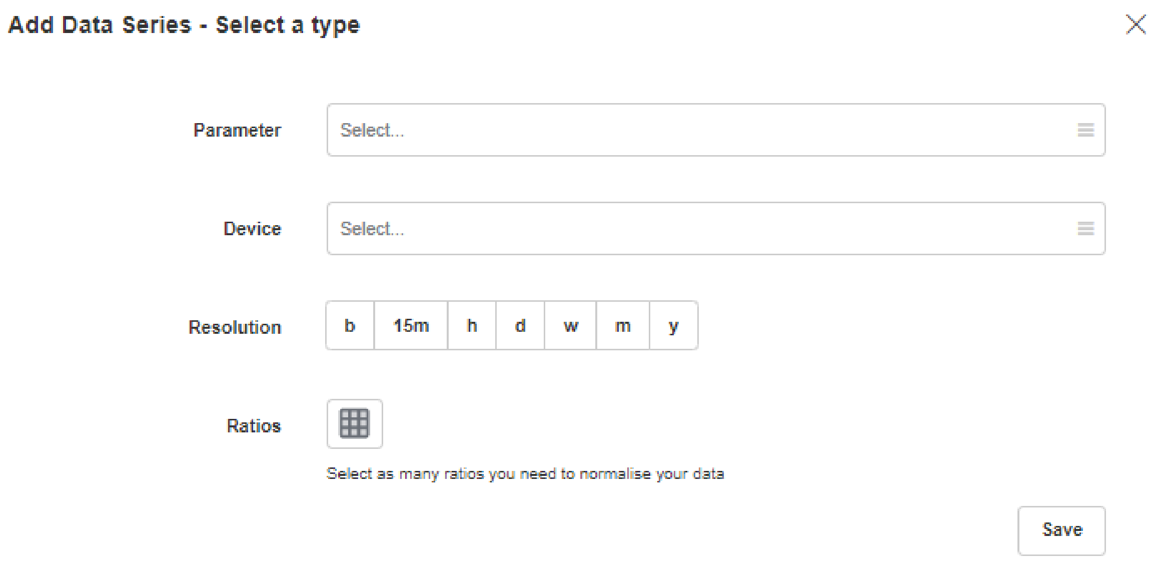

Figure 33: Parameter and device selection in Advanced Analytics section

Once this has been selected, the data is displayed in the following manner:

Figure 34: CO2 concentration chart in Advanced Analytics section

Several devices and parameters can be added to the existing one.

5. CONCLUSIONS

Data analytics and optimized control have been implemented in the RESPOND platform by means of multiple services developed by different project partners. The orchestration of services following the optimization loop has provided the needed functionalities required from the platform to support the implementation of DR strategies.

The developments have implemented a complete set of smart services that brings to the platform advanced functionalities regarding DR with respect to the existing energy management systems.

This document shows the different steps of the data flow where the data is acquired, stored, processed and displayed in order to offer the adequate information to the corresponding user at the best time. To achieve this objective, the work of four developer partners has been coordinated to reach the integration level that could maximize the advantages of the individual services.

This deliverable shows the different approaches used to satisfy the functionalities and requirements of each service. This variety demonstrate the use of different techniques to solve different problems finding always the excellence.

This successful integration would have not been possible without the important work done in WP2 and WP5, which allows the interoperability of the developed services for creating a complete DR platform.

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