RESPOND

DEMAND RESPONSE FOR ALL

Integrated Demand REsponse SOlution Towards Energy POsitive NeighbourhooDs

WP4 ICT enabled cooperative demand response model

T4.3 OPTIMAL ENERGY DISPATCHING AT HOUSEHOLD AND NEIGHBOURHOOD LEVEL

D4.3 Optimal energy dispatching at neighbourhood level

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 768619

PROJECT ACRONYM	RESPOND
DOCUMENT	**D4.3 Optimal energy dispatching at neighbourhood level**
TYPE (DISTRIBUTION LEVEL)	☐ Public ☒ Confidential ☐ Restricted
DELIVERY DUE DATE	30.09.2019.
DATE OF DELIVERY	30.09.2019.
STATUS AND VERSION	FINAL, v1.0
DELIVERABLE RESPONSIBLE	IMP
CONTRIBUTORS	DEXMA
AUTHOR (S)	Marko Jelić, Nikola Tomašević (IMP)
OFFICIAL REVIEWER(S)	Iker Esnaola (TEK) Lisbet Stryhn Rasmussen (AURA)

DOCUMENT HISTORY

Version	ISSUE DATE	CONTENT AND CHANGES
V0.1	15.8.2019.	Draft version
V0.2	24.9.2019.	First reviewer comments
V0.3	25.9.2019.	Second reviewer comments
V1.0	26.9.2019.	Final version with reviewer comments integrated

EXECUTIVE SUMMARY

This deliverable presents an extension to the methodology developed in D4.2 with which the single-user Energy Hub models are extended to form aggregate neighbourhood models of the Aarhus, Madrid and Aran Islands pilot sites of the RESPOND project. The production and demand are scaled up and real-world demand curves are generated from IoT sensor data that is registered in the InfluxDB time-series database. All three pilot models are employed in optimizations with either load decreases or load increases facilitated by time-of-use tariffs which include implicit DR events. Finally, it is described the usage of the optimization outputs for the communication with end users.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS AND ACRONYMS

DR	Demand response
LP	Linear programming
MILP	Mixed-integer linear programming
RES	Renewable energy source
DHW	Domestic hot water
STC	Solar thermal collector
PV	Photovoltaic
EL	Electric
ToU	Time-of-use

1. INTRODUCTION

In its core, at the feasible level, rather than dealing with individual users, the RESPOND project tackles aggregated sets of users, at the so-called neighbourhood level. This concept essentially represents a theoretical aggregation of different households, their daily habits, energy consumption curves, etc. into one single model which represents a whole set of users summed up into one. By performing this scaling from a single user to a neighbourhood, individual users' habits are averaged out. The resulting aggregate profile possesses the key feature of load flexibility, that is, the ability to shift load values in time and value between different users.

With related literature [1] citing load flexibility values of around 25% using communication with end users, this flexibility can be exploited for the purposes of running Demand Response (DR) programs. As the RESPOND control loop contains elements for monitoring, analysis and communication with users, the results of the cloud-based platform are passed on to end-users to exploit the aforementioned flexibility.

With the core mixed-integer linear programming models for optimizations already described in D4.2, what remains to be done is to adapt these models through minor modifications, parameter adjustments and Energy Hub interlinking in order to be able to model the neighbourhood scale of the pilot's systems. In order to provide as close to real-world results as possible, these scaled-up models are to be fed with real-world measurements of aggregated demand for all possible domains (electric, thermal, domestic hot water) and the optimization results will be analysed for these new batches of data. Finally, with these models ready and developed at the end of this deliverable, the applications of the optimization engine are discussed within the context of the RESPOND control loop.

2. ENERGY HUB MODELING

2.1 MODEL OVERVIEW

The core methodology that is employed for optimal energy dispatching at a neighbourhood level is essentially the same as was the case with single-user demand response management, described in D4.2. Owing to its versatility and flexibility, the Energy Hub can be employed at both the residential single-households scale as well as the somewhat larger neighbourhood scale.

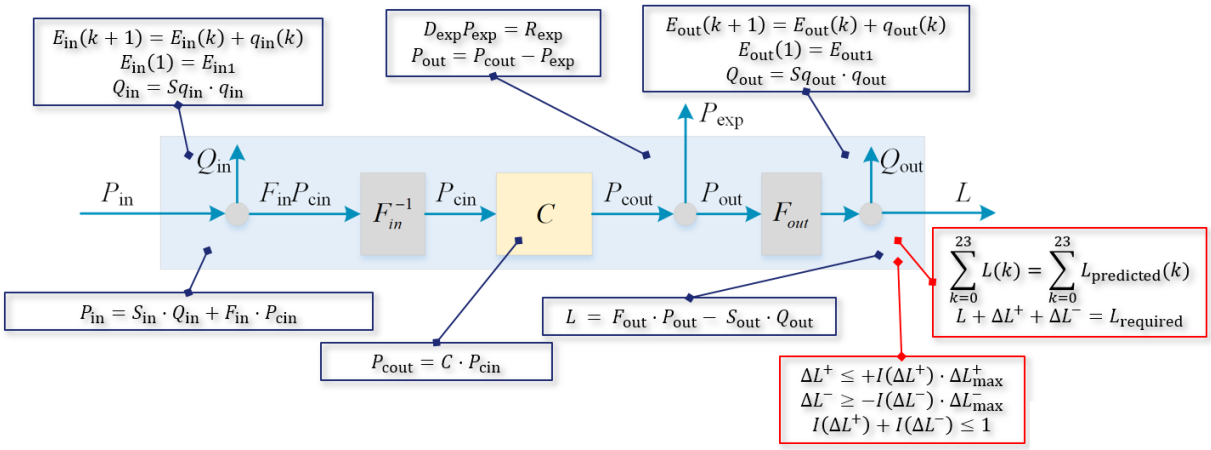

FIGURE 1 – ENERGY HUB STRUCTURE WITH OVERLAID CONSTRAINTS (VARIANT 2)

To properly model energy dispatching at the neighbourhood scale, the hub should be instantiated with a topology that accurately depicts all possible energy transformations that may occur within the neighbourhood. The general structure of the Energy Hub with overlaid constraints regarding energy transformations, dispatching and load management is given in Figure 1. Since the users are viewed from a neighbourhood perspective, the individual load monitoring methodology is not considered in this deliverable with only aggregate load management being discussed. Therefore, this so-called "Variant 2" of load management will be briefly recapitulated in the following subsections.

2.2 LOAD MANAGEMENT CONSTRAINTS

In order to add specific penalization to load deviations from a predefined required profile, an additional variable called the load deviation variable must be introduced. The deviation is defined as the difference between the realized load value L and a predefined load profile L_{required}, as is given by

$$\Delta L = L_{\text{required}} - L.$$

The main purpose and intention of introducing this variable into the model is that at certain times when a demand response is to be activated, a required load profile should be followed by the realized profile as closely as possible. Therefore, the introduction of penalization of differences between the actual load L and the required one into the objective function should lead to the

minimization of this difference, and hence force the output load to follow the required load. However, at time when the criterion is defined which is before the optimization process takes place, it is not known beforehand whether such deviations will be positive or negative and therefore it cannot be inferred with which sing the load deviations should be penalized. Namely, if the load deviation tends to be positive, a criterion that should be minimized should penalize such deviations with positive values. Conversely, if the load exhibits a negative deviation, it should be penalized with negative values. Nevertheless, since it cannot be guaranteed when the deviation will be positive and when it will be negative, it is separated into a positive and negative part. This is done by formulating the rightmost equality of the following equation as a constraint

$$\Delta L(k) = \Delta L^{+}(k) + \Delta L^{-}(k) = L_{\text{required}}(k) - L(k).$$

However, this condition by itself does not guarantee that the positive deviation will really be positive and that the negative deviation will really be negative. This additional feature can be obtained by introducing two additional variables that indicate whether the respective deviations are currently active or not. Since the load deviations are limited by the maximum and minimum difference between the predicted and the output optimized load. These two newly introduced binary variables are tied to the load deviations with constraints

$$\Delta L^{+}(k) \leq +I\big(\Delta L^{+}(k)\big) \cdot \Delta L^{+}_{\max}(k)$$
$$\Delta L^{-}(k) \leq -I(\Delta L^{-}(k)) \cdot \Delta L^{-}_{\max}(k).$$

Finally, these three constraints by themselves allow for both positive and negative deviations to coexists at the same time. Therefore, an additional inequality constraint is added to force only one of these indicators to have a non-zero value at a given timestep. This is obtained by

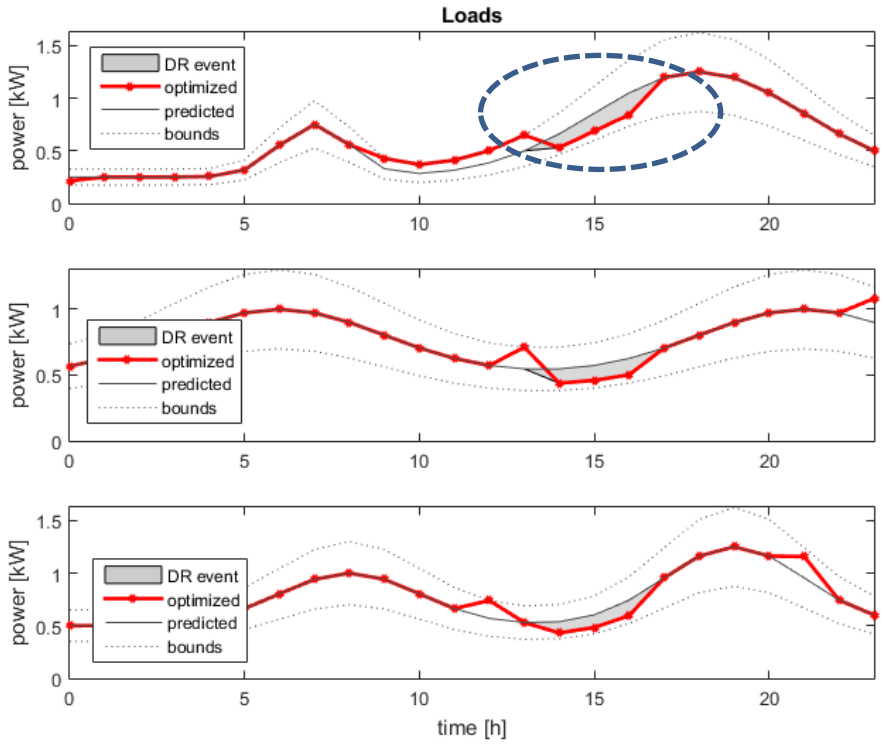

FIGURE 2 - ILLUSTRATION OF A DR EVENT LOAD DEVIATION FOR ELECTRIC (TOP), HEATING (MIDDLE) AND DHW (BOTTOM) LOADS

$$I(\Delta L^{+}(k)) + I(\Delta L^{-}(k)) \leq 1.$$

Another key constraint regarding the load management process is the integral constraint of the load. Namely, without an integral constraint, the optimizer would inherently drop all the load values to their lowest possible values. Therefore, in order to keep a load level that fulfils the energy demand, a period of time is preselected with a requirement that during this period, the total energy consumed must equal that of the predicted profile within the same time span. This constraint, in its general form, is written as

$$\sum_{k=k_1}^{k_2} L(k) = \sum_{k=k_1}^{k_2} L_{\text{predicted}}(k)$$

where k_1 and k_2 represent the beginning timestep and ending timestep of the window for which the constraint is to be applied. This constraint will be employed on a daily basis for a 24-hour long window, however, it can also be used to maintain the integral load of peak-hour times (for example during the morning and the evening), as will be demonstrated in one of the optimization use-cases.

An illustration of an explicitly defined DR event using load deviation penalization is given in Figure 2. Here, all three types of loads are penalized during a window that lasts from 14:00 to 16:00. As can be observed in this example, the requested profile (under the red line) that in this case equals 80% of the predicted load (full black line) is realized during the DR event. However, because of the reduction in energy consumption during the aforementioned time window, loads are increased during the rest of the day when the system deemed that such behaviour is optimal.

2.3 LOAD MANAGEMENT BOUNDS

As for the case in which the load is managed through its aggregated profile, a load tolerance limits are imposed in form of two margins (upper and lower margin) between which the loads can be adjusted. This is obtained by enforcing a limiting constraint as

$$(\forall k)\left((1+\text{tol}^{-})L_{\text{predicted}}(k) \leq L(k) \leq (1+\text{tol}^{+})L_{\text{predicted}}(k)\right).$$

In this regard, the load tolerance is mentioned in literature [1] to be in the range of $-\text{tol}^{-} = \text{tol}^{+} = 20\%$, however as research related to this topic is relatively scarce, other load tolerance values will be tested within the RESPOND platform as well. Having in mind that the load difference between the optimized profile and the required one is modelled using positive and negative load deviations, these variables must also be limited using

$$(\forall k)(\Delta L^{+}(k) \geq 0) \quad \text{and} \quad (\forall k)(\Delta L^{-}(k) \leq 0).$$

Finally, the indicator variables that depict the activity of the aforementioned load deviations must be equal to either one or zero thus rendering this problem also to be classified as MILP rather than LP, as set by

$$(\forall k)(I(\Delta L^{+}(k)), I(\Delta L^{-}(k)) \in \{0,1\}).$$

After adequate transformations, the given expressions can be morphed into the A_{eq}, and A_{ineq} matrices and b_{eq}, b_{ineq}, l_{b} and u_{b} vectors defining the constraints from the MILP problem

definition. What remains to be set in order to complete the model used for optimization is the objective function f.

2.4 OBJECTIVE FUNCTION

The main objective that is being considered within the RESPOND optimization process is the minimization of costs that would ultimately fall on the end users. Therefore, the most beneficial factor to the cost function are the costs of individual energy types. These values are modelled by setting the objective function f's values to the corresponding energy import/export prices. Since the energy import (P_{in}) usually costs money if it is being imported from the grid, the corresponding values of those elements of f are set to positive values that depict electricity prices at the given time. Also, if the local legislative allows for renewable energy generation subsidies, the elements of f that correspond to energy imports from renewable sources are set to negative values that are given by the acting generation tariff. Furthermore, the user can also receive monetary gains by exporting excess energy back to the grid (P_{exp}) and so the corresponding values should also be set to negative values dictated by the acting feed-in tariff program. If i and j represent import and export power energy carriers, α represents the costs of importing energy and β represents the costs of exporting energy, the overall operational cost can be obtained as

$$C = \sum_i \sum_k \alpha_i(k) P_{\text{in}}(i,k) + \sum_j \sum_k \beta_j(k) P_{\text{exp}}(i,k)\,.$$

However, to enable simultaneous optimizations that include specific DR events in order to force the load to uphold the requested profile, the mentioned cost function is extended with the addition of load deviation penalization as is given by

$$C' = \sum_i \sum_k \alpha_i(k) P_{\text{in}}(i,k) + \sum_j \sum_k \beta_j(k) P_{\text{exp}}(i,k) + \sum_k (w_{\text{d}}^{+}(k)\Delta L^{+} + w_{\text{d}}^{-}\Delta L^{-})\,.$$

In this mixed criterion, the penalization factors w_{d}^{+} and w_{d}^{-} are supposed to have non-zero values only when a specific DR event is active, with w_{d}^{+} being strictly positive and w_{d}^{-} being strictly negative in those cases in order to force the deviations into their minimum optimal value. When defining these values, a balance should be made between the raw operational costs as given by C and the additional factor introduced in C', i.e. the load penalization should not be significantly greater or smaller than the operational costs.

Another interesting indicator of the ecological impacts of running the system are the effective CO_2 emissions of running the system. This value can be estimated using the corresponding grid power fuel mix and life cycle emissions provided by [2] through the expression

$$\text{CO}_{2\ \text{emiss}} = \sum_k \sum_i c_i P_{in}(i,k)$$

where c_i represents the carbon footprint value of the i-th energy carrier. These values can even be included within the cost criterion in order to create a multi-criteria optimization function that would include multiple factors.

3. NEIGHBOURHOOD PILOT MODELS

The RESPOND project is deployed in three pilot sites: Aarhus (Denmark), Madrid (Spain) and Aran Islands (Ireland). As opposed to the process of modelling individual users using the Energy Hub structure that was described in D4.2, this deliverable depicts modelling of greater scale, at the neighbourhood level. Having in mind that one of RESPOND's goals is to tap the DR potential of residential loads through monitoring the aggregated load of multiple users simultaneously, the neighbourhood approach to the optimization process is the one that will be implemented as a service within the RESPOND loop.

There are two distinct types of model that will be employed within the RESPOND project for the purposes of energy flow modelling: one where the pilot consists of homogeneous units, i.e. where each apartment or house within the neighbourhood has the same topology, input carrier types, pricing scheme, etc. and one in which the pilot consists of heterogeneous households and therefore to depict it truthfully, multiple interconnected Energy Hubs must be employed to obtain a good enough model for simulation. Figure 3 and Figure 4 provide appropriate illustrations of the modelling process for both the homogeneous as well as the heterogeneous use case.

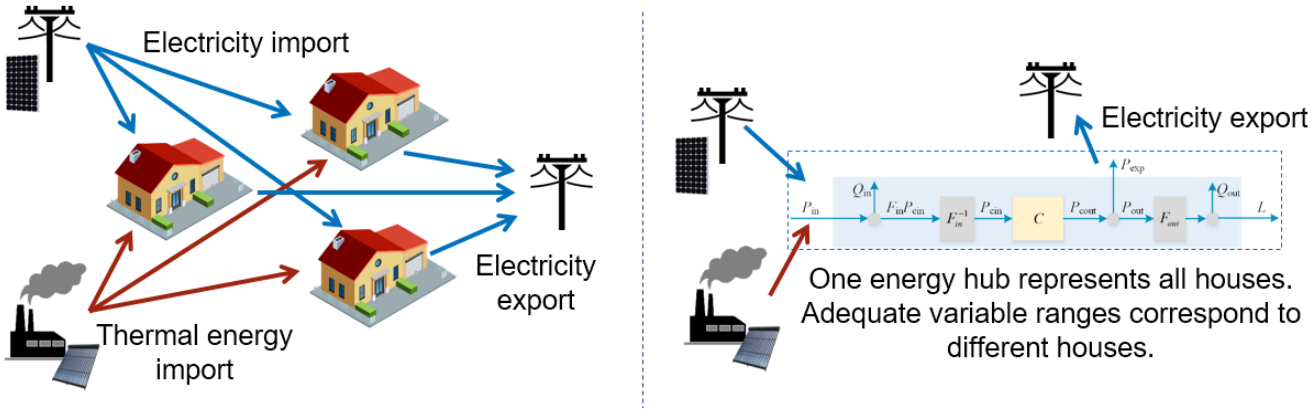

FIGURE 4 – AN EXAMPLE OF MODELING A HOMOGENEOUS HEIGHBOURHOOD USING A SINGLE ENERGY HUB

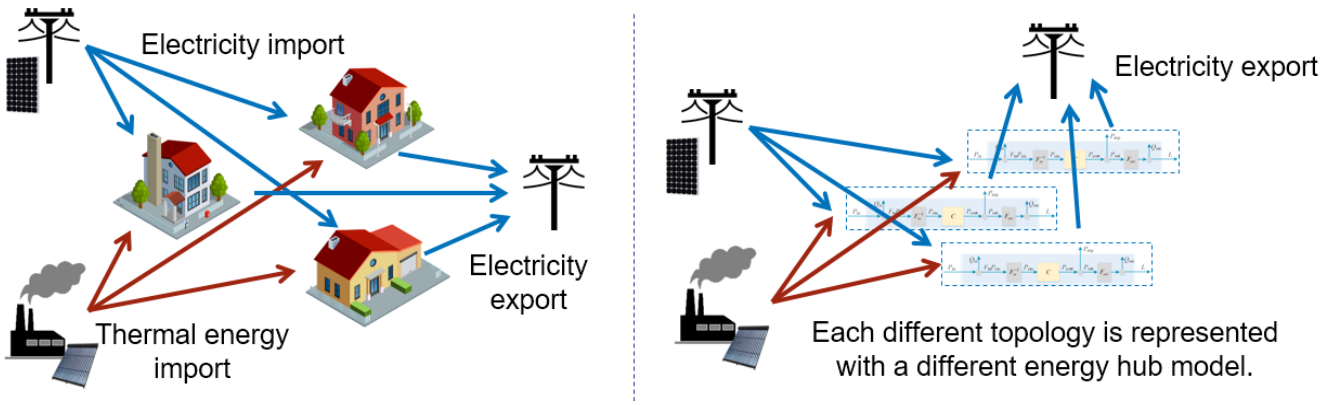

FIGURE 3 – AN EXAMPLE OF MODELING A HETEROGENEOUS HEIGHBOURHOOD USING MULTIPLE ENERGY HUBS

Having in mind that the Aarhus (Denmark) pilot site consists of multiple buildings that contain apartments that are supplied with electricity and hot water in the same way and that the Madrid

(Spain) pilot site consists of several apartments within the same building where all the tenants are supplied with electricity, gas and hot water in the same way, it is clear that these two pilots sites are candidates for the first mentioned modelling approach using a homogeneous model. These models have several benefits over heterogeneous ones, mostly because they have a smaller number of variables and are hence optimized quicker and are easier to manage. On the other hand, as described in D4.2, the Aran Islands (Ireland) pilot site consists of three different types of houses of whom some have PV generation, and some do not, and also some do have battery storage, while others do not. Therefore, this pilot must be modelled as a heterogeneous system using multiple Energy Hubs. However, to maintain the neighbourhood perspective even in this case, the loads of different hubs are aggregate to once again form a single neighbourhood profile that can be optimized.

3.1 AARHUS

Given that the Aarhus pilot in Denmark consists of apartments that have the same structure, the entirety of this pilot site can be modelled using a single hub. Namely, of the considered apartments, each one of them is supplied electric energy from one of two sources: on the one hand, the centralized PV array that is placed on top of the ALBOA buildings and that the residents can share, and on the other, the grid. Although the total size of the PV array is reported to be $622\ \mathrm{kWp}$, not all of that capacity can be attributed to the apartments participating in RESPOND and will therefore have to be scaled down when the service is instantiated in accordance with the total number of participating households. Also, the apartments' domestic hot water and heating

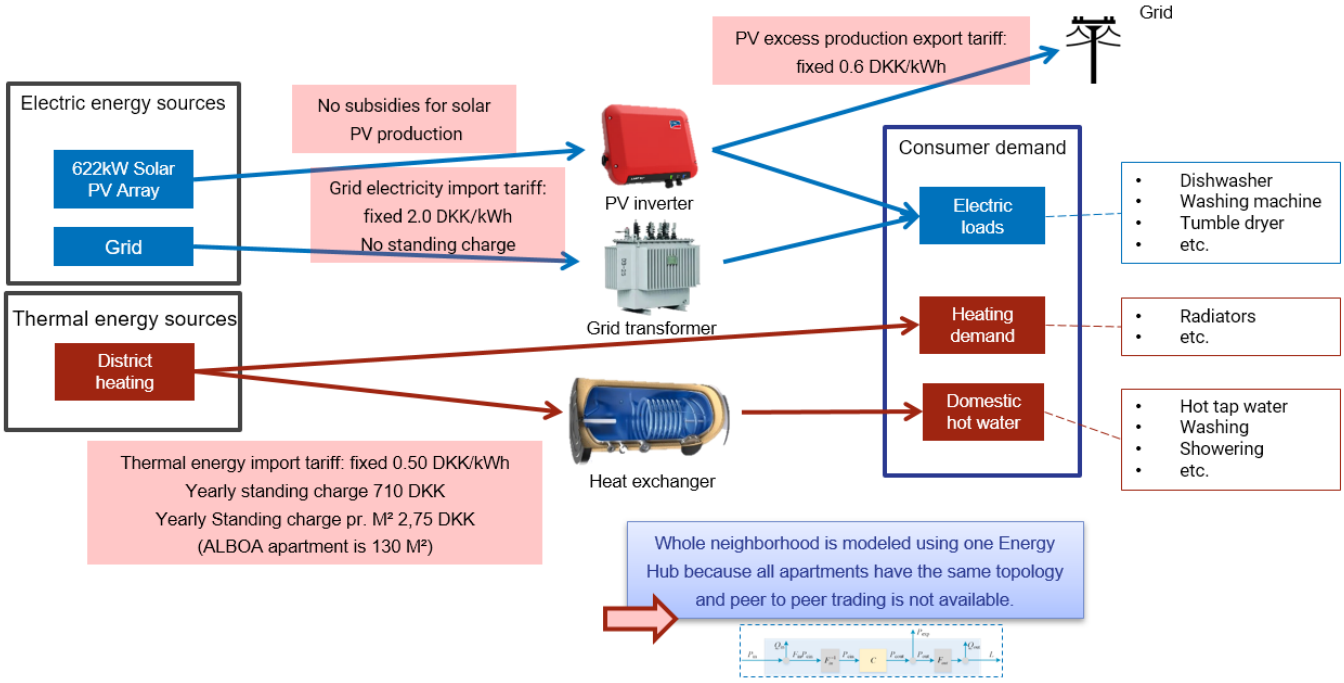

FIGURE 5 - AARHUS PILOT NEIGHHBOURHOOD PERSPECTIVE TOPOLOGY

demands are fulfilled using the district heating system that is very prominent in Denmark. The only difference between the ways in which these two load types are fulfilled is that an additional heat exchanger is employed in the domestic hot water loop. Having in mind that overproduction from the PV array is possible, and that no storage facilities are present to store the excess electric

energy for later use, the PV array has the ability of selling the excess energy back to grid at a given tariff.

Since the prices of energy supply are changing constantly based on a contract that is formed with the tenants, it is difficult to accurately depict current prices. Therefore, for the initial simulations within this service, the current prices as of writing this document were selected with their values and the associated Energy Hub model depicted in Figure 5. There is no generation tariff for the electricity produced by the PV panels, however, the excess energy can by exported at a rate of $0.6\ \mathrm{DKK/kWh}$. Electricity from the grid is imported at a rate of $2.0\ \mathrm{DKK/kWh}$ whilst the thermal energy from the district heating system can be obtained at $0.5\ \mathrm{DKK/kWh}$. From the standpoint of the optimization engine, fixed costs such as standing charges do not affect the end results, and therefore, they are not taken into consideration when evaluating the criterion function. However, they can be added at the end to illustrate the effective cost of the system's operation that will fall on the end user.

Having in mind that from the neighbourhood perspective, this pilot site is a homogeneous system made up of the same households with regards to energy flow topology, the neighbourhood model can be created by using an Energy Hub of a same structure as was the structure of a single apartment in D4.2. This Energy Hub is created using a model that correspond to the previous description, as depicted in Figure 5, and is defined by

$$S_{\mathrm{qin}} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, S_{\mathrm{in}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, F_{\mathrm{in}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}, C = \begin{bmatrix} 0.98 & 0 & 0 & 0 \\ 0 & 0.95 & 0 & 0 \\ 0 & 0 & 1.00 & 0 \\ 0 & 0 & 0 & 0.98 \end{bmatrix},$$

and

$$D_{\mathrm{exp}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, R_{\mathrm{exp}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, F_{\mathrm{out}} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, S_{\mathrm{qout}} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, S_{\mathrm{out}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

with all storage capacities set to zero as no storage facilities are present within this pilot. The aforementioned matrices are populated with multiple efficiency factors $\eta_{\mathrm{transformer}} = 0.98$, $\eta_{\mathrm{inverter}} = 0.95$ and $\eta_{\mathrm{heatexch}} = 0.98$, whose value ranges can be found in related literature [3], [4], [5] and [6].

As opposed to the single-user model formulated within D4.2, when employing the Energy Hub for neighbourhood-level energy dispatching, although the structure of the hub is unchanged, the corresponding demand forecasts and input energy availability are scaled up from the single-household level to a greater, neighbourhood, level. The concrete use case optimizations will be discussed in the following sections where different types of DR events will be showcased.

3.2 MADRID

The Madrid pilot in Spain focuses on a preselected set of apartments within a residential building. Each household fulfils its electric load using the energy supplied from only the grid. As opposed to the Aarhus pilot, the Madrid pilot does not have distributed electric energy generation, and therefore the grid is the only supplier of electric energy. On the other hand, the thermal domain is significantly more complex. There are two distinct types of thermal demand: heating demand and

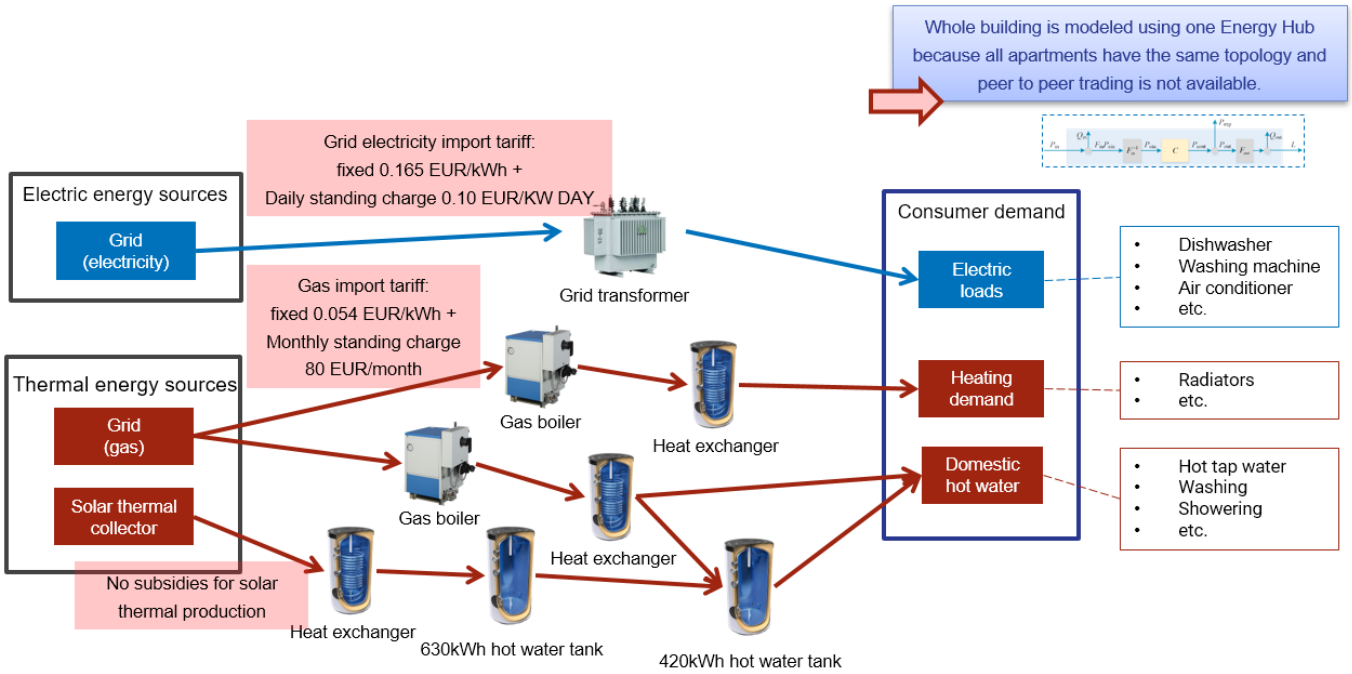

FIGURE 6 - MADRID PILOT NEIGHHBOURHOOD PERSPECTIVE TOPOLOGY

domestic hot water demand. Before the RESPOND project began, both were supplied using only gas that is obtained through the grid supply. However, during the project, a solar thermal collector system was installed to supplement gas as a means of fulfilment of domestic hot water needs. The gas from the grid can be burnt in one of two boilers with one being solely designated for the heating demand whilst the other one is combined with energy provided from the STC in order to fulfil the hot water load. Both loops include heat exchangers to separate subloops of these supply systems. The DHW loop also includes two hot water tanks, one with capacity of $630\ \mathrm{kWh}$ that is designated just for hot water obtained from the STC and one with capacity of $420\ \mathrm{kWh}$ which can store both hot water from the STC and from the gas boiler.

The current price scheme as of writing this document allows for the electricity from the grid to be imported at $0.165\ \mathrm{EUR/kWh}$ while the gas from the grid can be imported at a cost of $0.054\ \mathrm{EUR/kWh}$. Since there are no distributed energy generation devices there are no export potentials, and there are no substitutes for the STC system's production.

As was the case with the Aarhus pilot that also consist of a homogeneous set of apartments, this fact also applies for the Madrid pilot and therefore the schema of the appropriate Energy Hub that models one of the households actually models the entirety of the neighbourhood and is presented in Figure 6 with the model being instantiated using the following structural matrices

$$S_{\text{qin}} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, S_{\text{in}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.98 \end{bmatrix}, F_{\text{in}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0.97 & 0.97 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, C = \begin{bmatrix} 0.98 & 0 & 0 & 0 \\ 0 & 0.98 & 0 & 0 \\ 0 & 0 & 0.98 & 0 \\ 0 & 0 & 0 & 0.98 \end{bmatrix},$$

and

$$D_{\text{exp}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, R_{\text{exp}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, F_{\text{out}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix}, S_{\text{qout}} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, S_{\text{out}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0.98 \end{bmatrix}$$

with relevant DHW reservoir storage limits set to the appropriate capacities mentioned earlier. The aforementioned matrices are populated with multiple efficiency factors $\eta_{\text{transformer}} = 0.98$, $\eta_{\text{inverter}} = 0.95$, $\eta_{\text{boiler}} = 97\%$, $\eta_{\text{heatexch}} = 0.98$, whose value ranges can be found in related literature [3], [4], [5], [6] and [7].

Again, alike the Aarhus pilot, at the neighbourhood scale, the demand profiles are scaled up from those that were mentioned in D4.2 and can be obtained by aggregating multiple individual profiles of different households that participate in the project. These examples are also discussed in the following section.

3.3 ARAN ISLANDS

Arguably the most complex pilot for energy flow modelling is the Aran Islands pilot in Ireland. This pilot site consists out of houses distributed over an island, and even though there are not geographically too much apart to require different models for renewable production, there are significant differences in energy flow topology between different houses that, as opposed to Aarhus and Madrid pilots where the system was homogeneous, call for a heterogeneous model

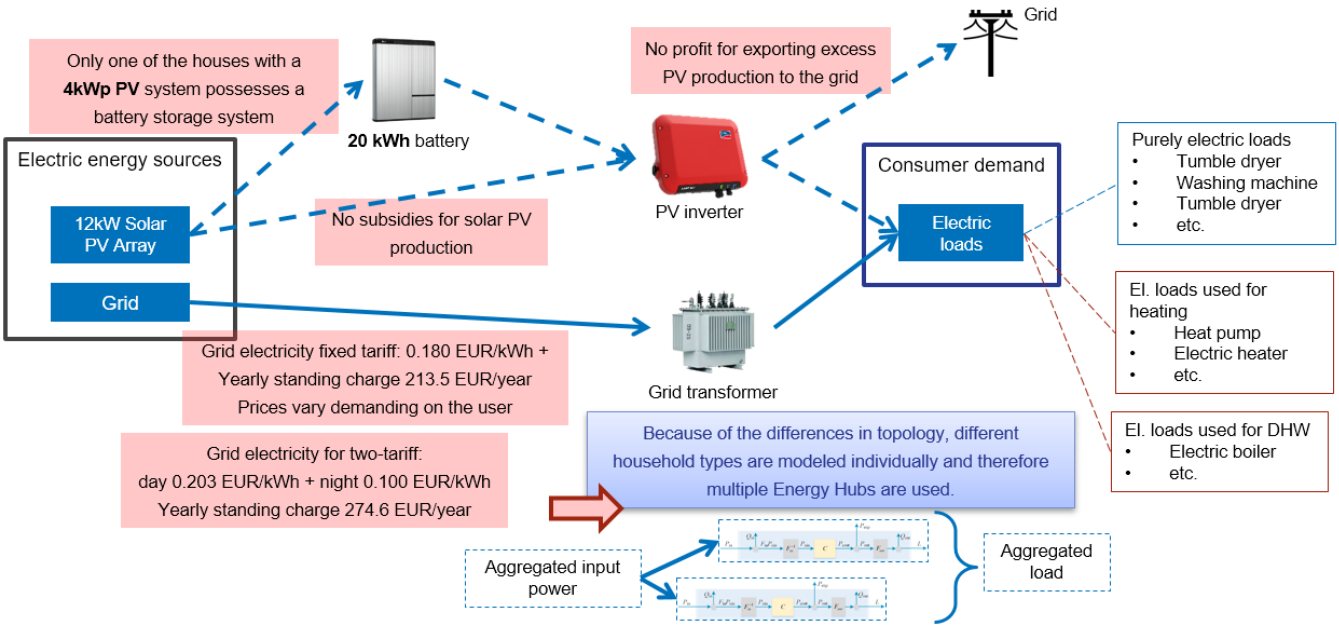

FIGURE 7 - ARAN PILOT NEIGHHBOURHOOD PERSPECTIVE TOPOLOGY

to be employed. In such a model, each different topology is represented using a single Energy

Hub with an appropriate structure. The neighbourhood level model is illustrated in Figure 7. As was mentioned in D4.2, there are three different types of houses within this pilot site:

- Type 1: Electric energy is obtained either by importing from the grid or by utilizing the distributed PV generation (with installed capacity of $4\ \mathrm{kWp}$) and PV energy can be locally stored in a battery with of $20\ \mathrm{kWh}$ capacity (house internally referred to as H2 is of this type);
- Type 2: Electric energy is obtained either by importing from the grid or by utilizing the distributed PV generation (with installed capacity of $2\ \mathrm{kWp}$) (house internally referred to as H1 is of this type)
- Type 3: Electric energy is only obtained by importing from the grid.

The corresponding Energy Hub structures of these three household types adhere to the structures that were given in D4.2. These hubs can be instantiated using

$$S_{\mathrm{qin}} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, S_{\mathrm{in}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, F_{\mathrm{in}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, C = \begin{bmatrix} 0.98 & 0 \\ 0 & 0.95 \end{bmatrix},$$

and

$$D_{\mathrm{exp}} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, R_{\mathrm{exp}} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, F_{\mathrm{out}} = \begin{bmatrix} 1 & 1 \end{bmatrix}, S_{\mathrm{qout}} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, S_{\mathrm{out}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

and the storage limit set to the aforementioned value for type 1,

$$S_{\mathrm{qin}} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, S_{\mathrm{in}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, F_{\mathrm{in}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, C = \begin{bmatrix} 0.98 & 0 \\ 0 & 0.95 \end{bmatrix},$$

and

$$D_{\mathrm{exp}} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, R_{\mathrm{exp}} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, F_{\mathrm{out}} = \begin{bmatrix} 1 & 1 \end{bmatrix}, S_{\mathrm{qout}} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, S_{\mathrm{out}} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

for type 2 and finally

$$S_{\mathrm{qin}} = [0], S_{\mathrm{in}} = [1], F_{\mathrm{in}} = [1], C = [0.98],$$

and

$$D_{\mathrm{exp}} = [1], R_{\mathrm{exp}} = [0], F_{\mathrm{out}} = [1], S_{\mathrm{qout}} = [0], S_{\mathrm{out}} = [1]$$

for type 3. The aforementioned matrices are populated with multiple efficiency factors $\eta_{\mathrm{transformer}} = 0.98$, $\eta_{\mathrm{inverter}} = 0.95$, whose value ranges can be found in related literature [3], [4] and [5].

In order to stay true to the neighbourhood perspective, input, exported and other power variables as well as the loads of different architectures must be aggregated in order to obtain the total levels that correspond to the entire neighbourhood. For example, if the three aforementioned topologies are denoted with 1, 2 and 3, the aggregated values of some of the hub's variables for each time step are simply obtained by enforcing the following constraints

$$(\forall k)\left(P_{\mathrm{in}}(k) = P_{\mathrm{in}_1}(k) + P_{\mathrm{in}_2}(k) + P_{\mathrm{in}_3}(k)\right)$$

$$(\forall k)\left(P_{\mathrm{exp}}(k) = P_{\mathrm{exp}_1}(k) + P_{\mathrm{exp}_2}(k) + P_{\mathrm{exp}_3}(k)\right)$$

$$(\forall k)\big(L(k) = L_1(k) + L_2(k) + L_3(k)\big)$$

where P_{in}, P_{exp} and L are essentially newly introduced variables that depict the energy being transmitted into and from the holistic hub from the neighbourhood perspective and the enumerate variables depict individual hub's internal variables in accordance with the model defined in D4.2 and briefly covered in the beginning of this deliverable.

Finally, the holistic neighbourhood model should be instantiated with aggregated demand and production forecast profiles as will be demonstrated in the following section. The model will internally dispatch adequate shares of the available energy to models of different topologies, process them, and return the aggregate profile.

4. DATA AGGREGATION

Using the datapoint lists for all three pilot sites, queries for individual pilot sites can be made in order to obtain the needed data. A snipped of the datapoint list for the Madrid pilot is presented in Table 1. Here, each measurement is associated with a device id that defines the specific sensor which reports measurements. Also, each sensor is associated with a gateway id which corresponds to the ID of the gateway that the sensor is connected to. Each sensor also corresponds to a location space id that defines which apartment or shared space the sensor belongs to with a detailed description of the sensor's position given in the location in the space column. Finally, two key fields that describe the sensor type and reported measurement type are the device type and measurement/control id.

TABLE 1 - DATA POINT LIST SNIPPED FOR MADRID PILOT

Nr.	Device id	Gateway id	Location space id	Location in the space	Device type	Measurement id / Control id
1	ENE-75A97E556184E76E-0-12	ENE-75A97E556184E76E	Madrid_00	whole_apartment	meter_demand	demand
2	ENE-75A97E556184E76E-0-12	ENE-75A97E556184E76E	Madrid_00	whole_apartment	meter_demand	energy
3	ENE-75A97E556184E76E-0-12	ENE-75A97E556184E76E	Madrid_00	living_room	meter_demand	demand
4	ENE-75A97E556184E76E-0-12	ENE-75A97E556184E76E	Madrid_00	living_room	meter_demand	energy
5	ENE-75A97E556184E76E-0-12	ENE-75A97E556184E76E	Madrid_00	kitchen	meter_demand	demand
6	ENE-75A97E556184E76E-0-12	ENE-75A97E556184E76E	Madrid_00	kitchen	meter_demand	energy
7	ENE-0F00000B	ENE-75A97E556184E76E	Madrid_00	bedroom_1	sensor_temperature	temperature
8	ENE-0F00000B	ENE-75A97E556184E76E	Madrid_00	bedroom_1	sensor_humidity	humidity
9	ENE-0800046B	ENE-75A97E556184E76E	Madrid_00	kitchen	sensor_temperature	temperature

Using the data given in the datapoint list, queries can be generated to obtain different measurements. For example, the first sensor's data can be queried through an URL request defined by the following expression

```
https://147.91.50.171:8086/query?q=SELECT value FROM "iot"."autogen"."demand" WHERE time > now() - 1h AND "deviceID"= 'ENE-75A97E556184E76E-0-12'
```

in conjunction with the appropriate credentials that protect the sensitive user data from unauthorized access. With minor modifications, these queries can be transformed in order to obtain only total electricity, total thermal demand and total domestic hot water energy consumption.

First of all, from the datapoint list, electricity meter sensors are selected, and through appropriate queries, each apartment's individual electricity consumption was obtained for the selected day for this showcase (which is selected to be June 27th, 2019). Examples of these raw profiles is given in Figure 8. Then, each of these profiles is converted into an hourly profile by calculating the average power demand for each one-hour time span during the given day. These hourly profiles

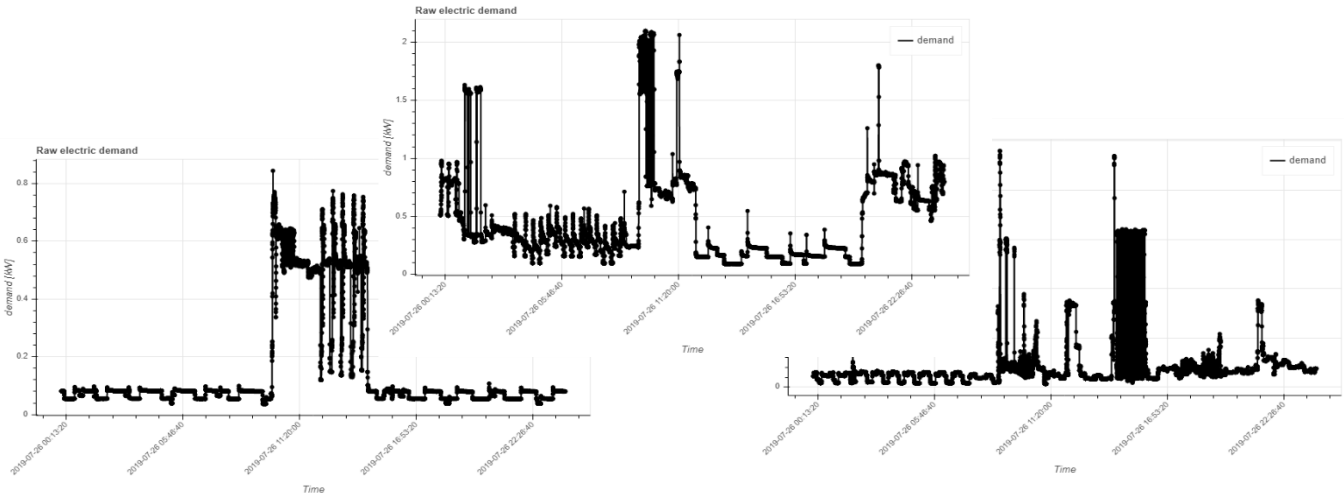

FIGURE 8 - EXAMPLE OF RAW ELECTRIC DEMAND PROFILES FOR MADRID PILOT

are then aggregated into a neighbourhood profile by simple addition. The resulting neighbourhood profile is illustrated in Figure 10 for the electricity domain of the Madrid pilot site. A similar process is also applied where thermal supply measurements are available to obtain the aggregate thermal

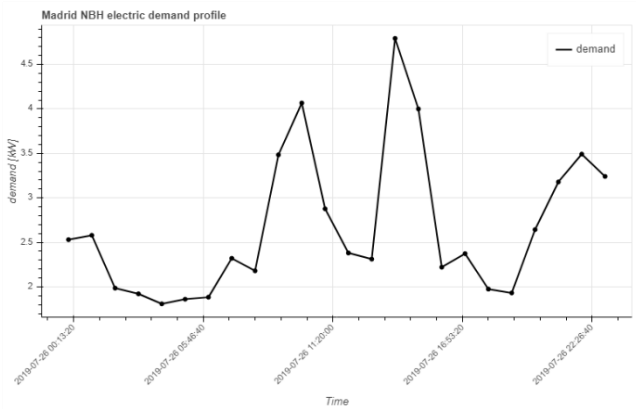

FIGURE 10 - AGREGATE NEIGHBORHOOD ELECTRICITY DEMAND PFORILE FOR MADRID PILOT

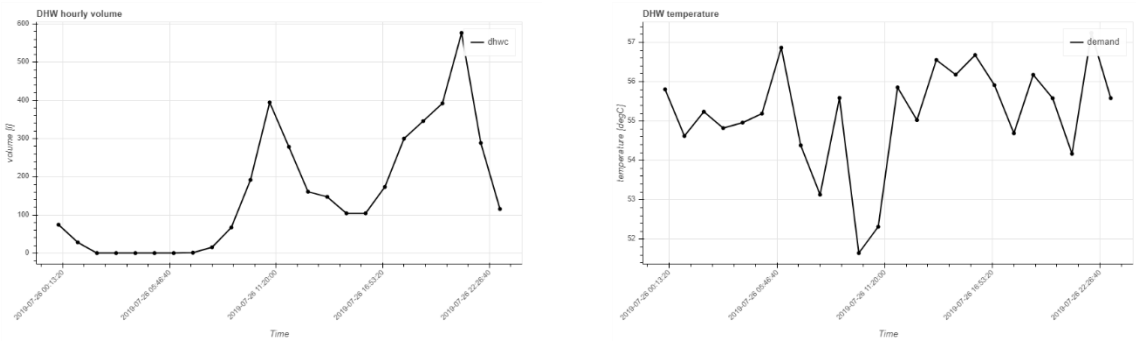

FIGURE 9 - DHW FLOW/VOLUME AND TEMPERATURE PROFILE FOR MADRID PILOT

demand.

Although the DHW profile for the Madrid is estimated using a predefined daily consumption profile that is scaled in accordance with the total consumed, a similar approach can also be employed

to obtain the neighborhood demand curve for this type of load. However, direct measurements of energy contained within the hot water supplied to the end users is not available, with hot water flow (or hourly volume to be more precise) being measured instead. Using the available measurements, aggregate volume of DHW can be obtained as well as the temperature supplied to the dwellings, with the profiles for the selected showcase day being displayed in Figure 9. Since the energy contained within how water can be calculated using

$$Q = mc\Delta t = \rho V c \Delta t$$

where m is the mass of water, c the specific heat capacity of water, Δt the temperature difference between the considered water and water which is considered to hold "no useful energy" (which could in this case be tap water at $t_t = 15\,°\mathrm{C}$), ρ the density of water and V its volume, the DHW demand profile which is essentially power, is obtained from

$$P = \frac{Q}{\tau} = \frac{\rho V c \Delta t}{\tau}$$

where τ is the time in which Q is consumed. Since hourly profiles are used, this time value can be fixed at $\tau = 1\,\mathrm{h}$ where the aforementioned constants are set to $\rho = 1000\,\mathrm{kg/m^3}$ and $c = 0.00111\,\mathrm{kWh/(kg \cdot K)}$. When the volume and temperature profiles are applied to this equation, the estimated DHW profile is obtained and displayed in Figure 11.

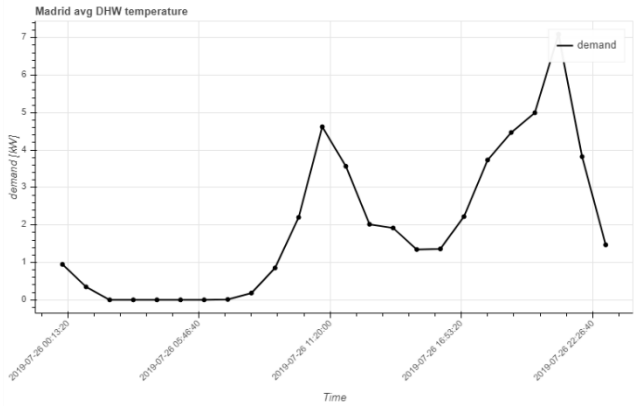

FIGURE 11 - AGREGATE NEIGHBORHOOD DHW DEMAND PFORILE FOR MADRID PILOT

Because different aggregate profiles can be obtained using a different number of total sensors (for example, the neighbourhood electric demand can be obtained from 7 different electric meters whilst the thermal demand is obtained from 14 measuring stations), all domains for a given pilot

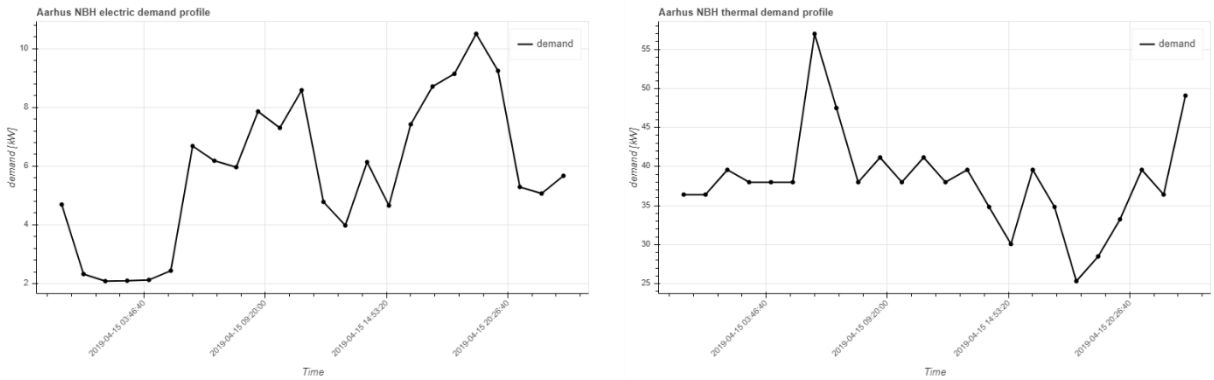

FIGURE 12 - NEIGHBORHOOD ELECTRIC AND THERMAL DEMAND PROFILES FOR THE AARHUS PILOT

site are always normalized for either the maximum of minimum of these number. That means that in the given example, the either the thermal demand is scaled down with a factor of 7/14=0.5 or the electric demand is scaled up by a factor 14/7=2. Whether scaling up or down is performed is determined on a case-by-case basis depending on the number of sensors that have reported valid measurements.

Using similar techniques as the abovementioned algorithm, the aggregate profiles are determined for the other two pilot sites as well. The figures for the Aarhus pilot are given in Figure 12 while the figures for the Aran Island pilot are given in Figure 13. Since the Aran Island pilot only has electric demand measurements, thermal and DHW loads can only be synthetized using predefined profiles. However, heat pump consumption is measured independently, and can be used for thermal demand estimations in the future. Nevertheless, for the purposes of developing the optimization engine, this deliverable will only focus on the electric domain as reported by electricity meters. It is also worth mentioning that at the time of writing this deliverable, it is unclear

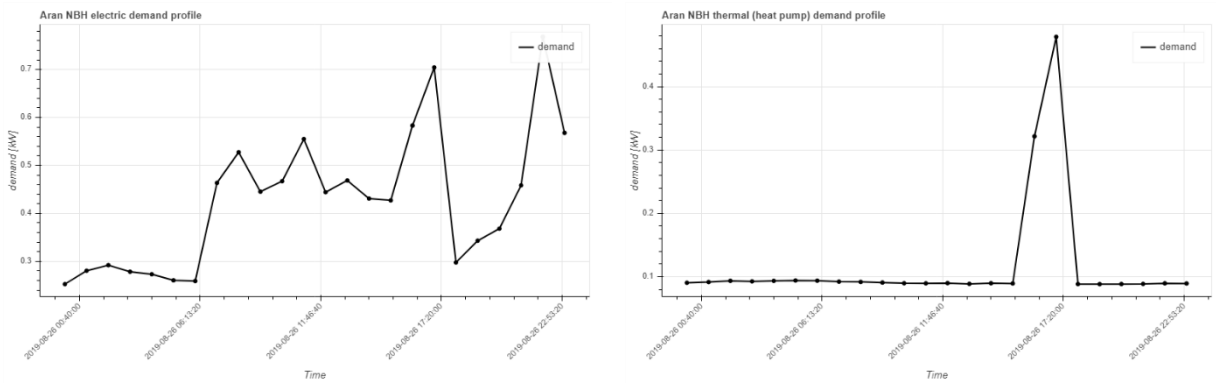

FIGURE 13 - NEIGHBORHOOD ELECTRIC AND THERMAL DEMAND PROFILES FOR THE ARAN ISLAND PILOT

whether the measurements from electricity meters includes the amount of energy consumed from the PV panels. That means, that in addition to the given profiles, the houses that have PVs have additional consumption that is not (yet) taken into consideration because of the technical issues regarding the installation of the required equipment.

5. OPTIMIZATION USE CASES

Power plants, generators, distribution systems, powerlines, transformers and all the other equipment in the path of electric energy from raw fuels to the end-users must be sized accordingly to be able to cope with peak demands. However, if these peaks can be even slightly reduced, the system which could otherwise be unnecessarily oversized (in context of the maximum power flow capacity), when the system is optimized, major cost savings can be achieved with regards to both equipment and maintenance. Arguably the most prominent way in which these peaks are reduced (colloquially referred to as “peak shaving”) is through DR strategies.

The traditional way in which DR is utilized for maintaining grid stability considers the possibility of load reductions through interactions with users. The most common applications of DR programmes are in the industrial sector. Here, the DR aggregator forms individual contracts with large consumers like factories that specify exactly how often, at which times, and by which amount the load can be lowered. This methodology is used at times when demand is generally very high, in order to lighten the burden that falls on the power plants that generate electricity. Furthermore, it plays a key role in balancing the generation with the demand. In this regard, the DR aggregator has the capabilities to directly control a set of preselected appliances in the industrial facilities. These most commonly include chillers, large fluid heaters and similar high-consumption equipment.

As for the residential sector, obtaining direct control over individual household appliances is considered to be too invasive and too impactful on the perceived comfort of residential users. Here, the system’s acceptance rate is highly influenced by user habits. For making any DR solution widespread and accepted amongst residential users, such a system must at least somehow incorporate the option for users to perform final acknowledgement before any actions are taken.

Given the previous considerations, the best way to enforce DR programmes amongst residential users is through indirectly creating so-called DR events. DR events are windows of time in which the price of an energy carrier is higher or lower than at other times, which in turn motivates users to increase or decrease their demand. For example, if the price of electricity is increased by 10% during peak-hours (i.e. from 16:00 to 21:00), the users are motivated to lower their demand at those times in favour of other times of day in which the prices are lower. Such a result is also the main motivation behind time-of-use (ToU) tariffs where, for example, the day price of energy is significantly higher as opposed to the night prices. Such a schema provides a basis for implicit load shifting whereby the users will most probably use the lower price for large consumers like space heaters, radiators, water heaters, washing machines, dishwashers, etc. and activate them during the night-time, whilst only the necessary appliances will be active during the day. By allowing for these price differences, the utility company creates a steadier aggregate demand curve where the day is populated by mostly necessary appliances and activations of users that are unwilling to adjust their habits, while the night is populated by non-crucial activations. This also has the side effect of lowering peak demand values, which in turn provides a more stable electric grid and lower running costs.

The following chapter considers several theoretical scenarios in which the developed methodology is showcased and applied for all three pilot sites.

5.1 LOAD DECREASE EVENT

Since load decrease events are more common as they are a key factor in peak-shaving, these will be demonstrated first. In order to provide a simulation during development that will stay true to the tasks that the optimization service will perform within the RESPOND control loop, actual neighbourhood-level data was extracted to form aggregate electric, thermal and domestic hot water profiles. Namely, the sensor data from the pilot sites is sent and stored in an InfluxDB time-series database. From there, individual measurements are made accessible.

5.1.1 ARAN USE CASE

The methodology for performing implicit load decreases will be implemented for the Aran Islands pilot site as an example. As it was previously described, a neighbourhood Energy Hub is formed using three individual Energy Hubs that model three houses with different energy flow structures. In order to faithfully represent real-world optimization scenarios, the aggregate neighbourhood load profile is separated into three equal demand profiles that are set as forecasted load for each of the houses. Then, each house (with the option of multiple houses with the same topology to also be included) is individually optimized, and the results are aggregated into a neighbourhood profile. In this way, each topology makes full use of the resources that are available to it (PV generation and export as well as storage systems).

To facilitate load decreases, the baseline price profile is slightly modified, with an increase of 5% in price during afternoon hours over the rest of the day. This way, using time-of-use pricing, users are motivated to reduce their loads while the prices are high. However, the average price for the entire day is fixed to the amount before the modification, meaning that the values are adjusted accordingly as not to provide significant changes to the energy provider and to present a basis for a real-world scenario. The price profile for this use case is given in Figure 14.

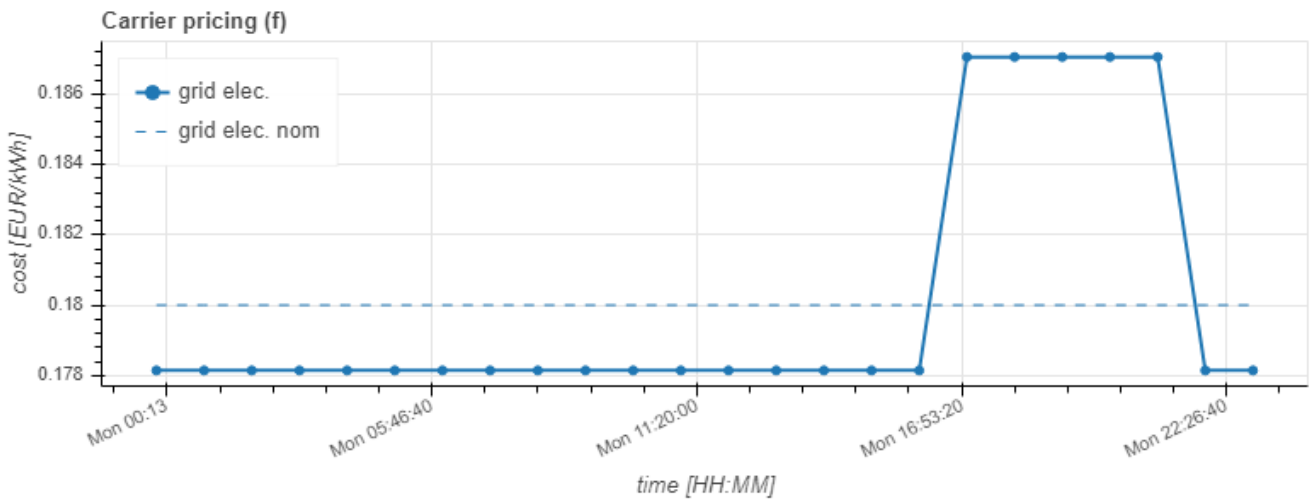

FIGURE 14 - MODIFIED PRICE PROFILE FOR LOAD REDUCTION

When the modified carrier pricing profile is used within the Energy Hub, the effects on the load profiles if a load flexibility of 30% is assumed, can be observed in Figure 15 and the imported power profiles can be observed in Figure 16.

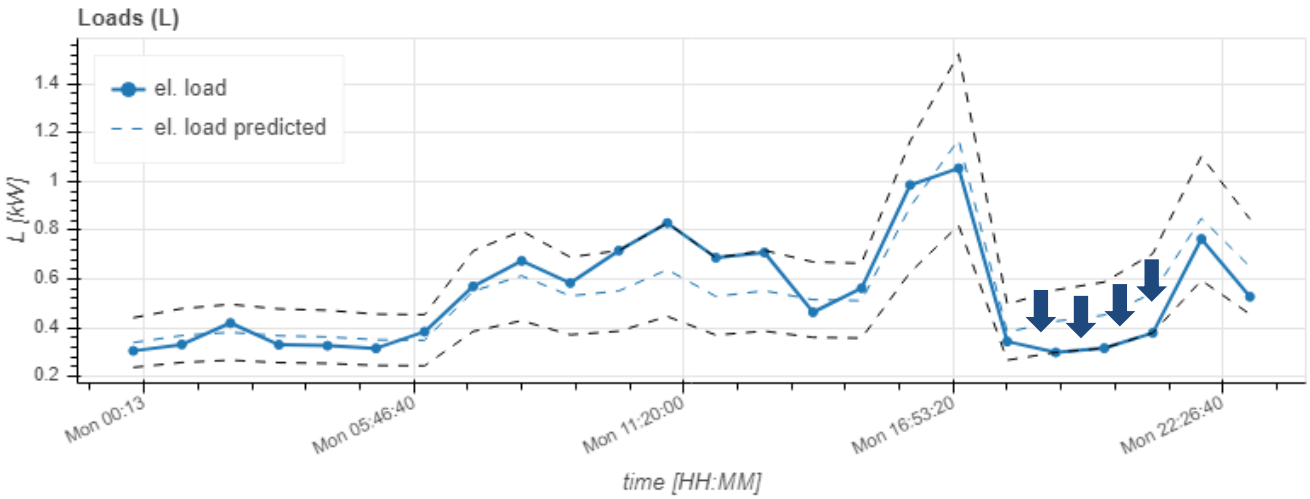

FIGURE 15 - LOAD PROFILE WITH LOAD REDUCTION

As it can be observed in the mentioned figures, the optimization engine manages to utilize the difference in electricity price between the implicit DR event and the rest of the day and lowers the load accordingly. However, due to the integral energy constraint, loads are essentially shifted to times when the electricity has a lower price with the utilization of the assumed load flexibility. However, from the grid's point of view, the difference in price also affected the imported power profile, with the demand in peak hours being significantly lowered that the baseline (forecasted) profile. This phenomenon is considered to be the most important result of applying DR programmes in the residential sector and is essentially the main goal of the optimization process.

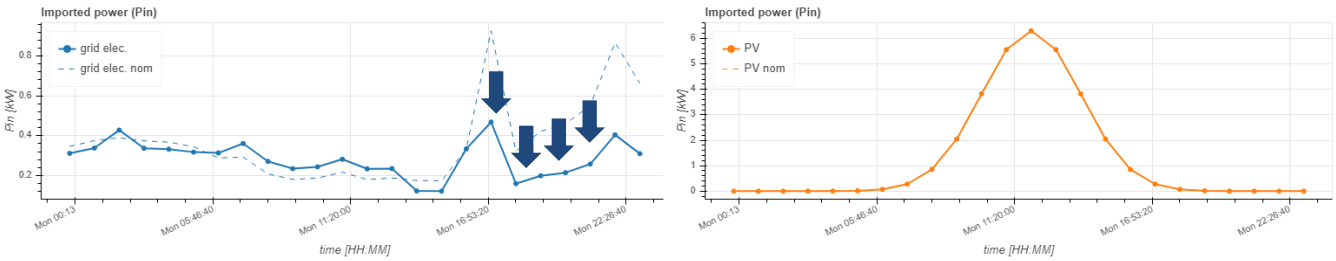

FIGURE 16 - IMPORTED POWER PROFILES WITH LOAD REDUCTION

Having in mind the integral energy constraint that maintains that the energy consumed within the simulated day must be the same in both the nominal case and the optimal one, major energy savings cannot be expected to be returned by the simulation engine. However, the results for this case show that around 5% of energy imported from the grid can be saved with the optimal use of PV energy dispatching and smart utilization of the battery system. Savings are more significant with regards to the cost, with the solution being reported as 20% cheaper in this case that the baseline output. Finally, mainly due to the savings in energy imported from the grid, the carbon footprint is reduced by around 13%.

Since the optimization engine incorporates a set of specific constraints that are necessary for proper mathematical modelling, it should be noted that real-world savings in cost, energy and CO2 emissions may significantly differ from what the model reports. Namely, specifics of user behaviour are not modelled in the Energy Hub, and therefore if the users comply with most of the suggestions, the obtained savings may even be greater that what the model predicts (for example, the total energy consumed may be less that what is forecasted because the users may decide that some appliance activations are not necessary). However, if the users refuse most of the suggestions, poor results are to be expected. Therefore, user acceptance and communication are considered key factors with regards to the savings performance indication.

5.1.2 MADRID USE CASE

The Madrid pilot also presents a potential scenario in which the loads can be manipulated through implicit DR. However, in this case, the domestic hot water domain is also made available and can be used for potential load adjustments. First of all, energy carrier price profiles are assumed in

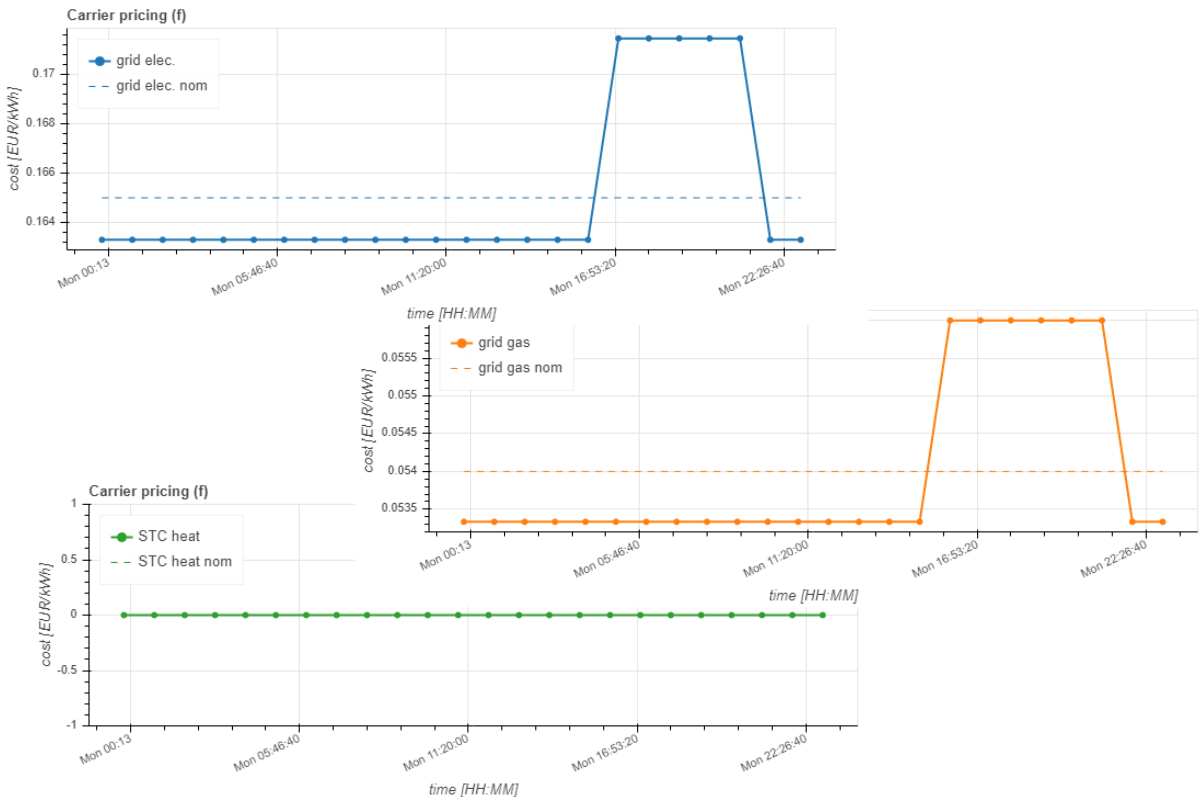

FIGURE 17 - PRICE PROFILES FOR LOAD DECREASE

accordance with a time-of-use scheme where the prices are increased by 5% during the evening hours when demand is generally very high, as given in Figure 17. After employing these profiles in the Energy Hub, the load curves are obtained and displayed in Figure 18. Since there are no available measurements for the thermal domain as of writing this document, the thermal domain is temporarily disregarded, and the focus is placed on the electric and domestic hot water loads. As it can be observed, once again the difference in price forces the loads to decrease during peak times. However, in this case, the baseline consumption is simulated using only a gas baseline (no STC system). Furthermore, it should be noted that since production from the STC system is

not directly subsidized, there is no way to influence DHW loads by price manipulations because the modelled STC is capable of completely fulfilling the DHW load, especially given the fact that both hot water tanks are assumed to be filled with $50\,\mathrm{kWh}$ of hot water at the beginning the

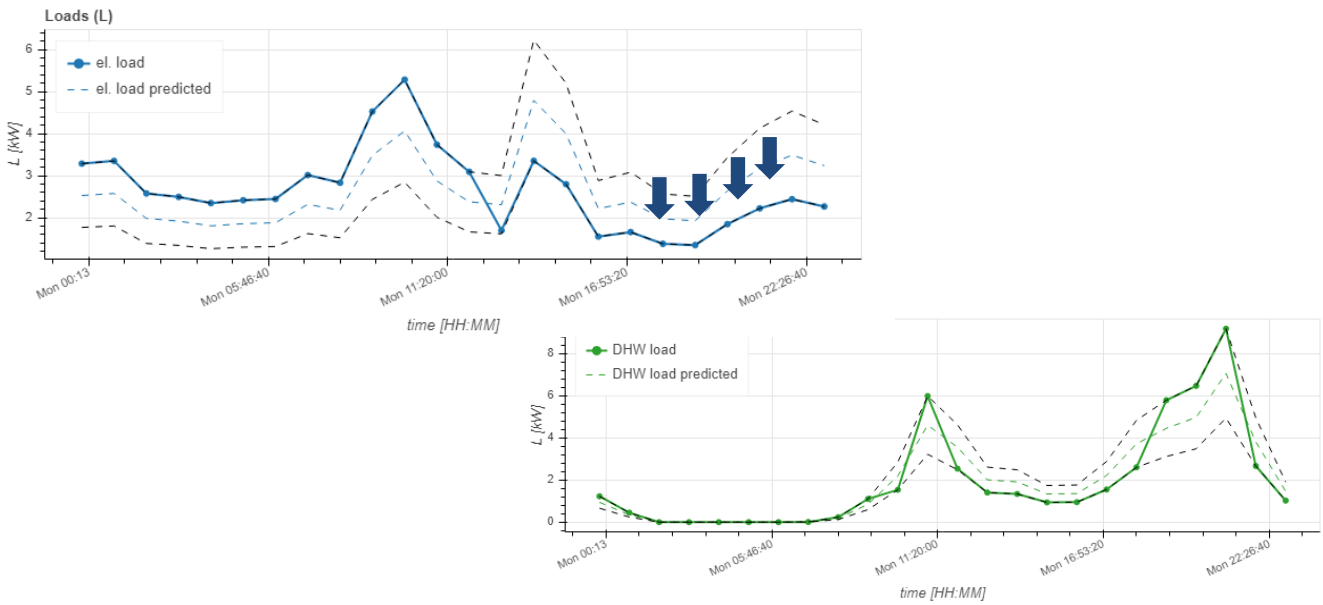

FIGURE 18 - LOAD PROFILES WITH LOAD DECREASE

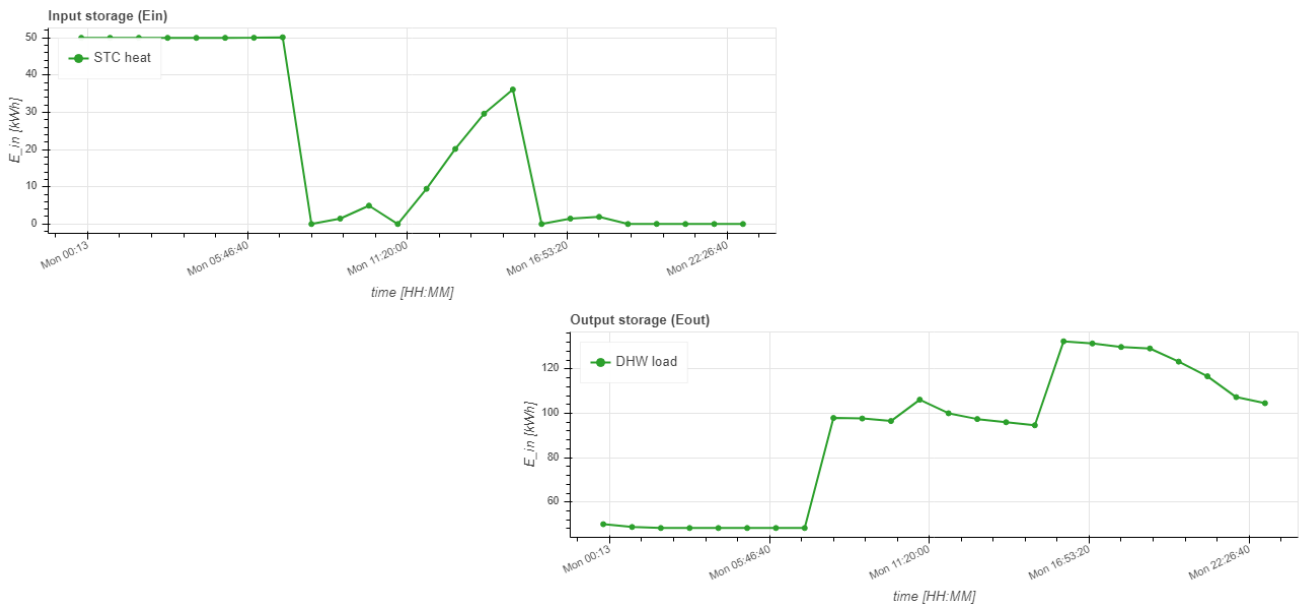

FIGURE 19 - AVAILABLE ENERGY IN HOT WATER TANKS

simulation (thus modelling left over energy from the previous day), as shown in Figure 19. This means that the Madrid pilot presents a potential use case for explicitly defined DR events where the cost criterion is extended beyond the monetary factors and explicit penalties are included for load deviations. Alternatively, recommendations for the DHW consumption may be issued to end users without regarding the optimization in this aspect in order to experiment with load flexibility and test if the users are willing to adjust these types of loads in addition to electrical appliances.

Finally, when the imported power profiles are analysed, it can be observed that the price increase in the electric domain has a similar effect as was the case for the Aran pilot. This reduction can be seen in Figure 20. When compared with the gas-only baseline, the inclusion of the STC system in conjunction with the optimization process yield significant savings in cost (around 20%), energy from the grid and gas imports (around 40%) and in the carbon footprint (around 64%). However, since the thermal/heating domain is not simulated, it must be noted that these values only represent potential theoretical savings in the considered case and will most certainly be offset with the real-world consumption of gas as the only source of heating demand fulfilment. Also, when more data is available for colder periods, more detailed simulations may be conducted on this demand to formulate a more realistic baseline.

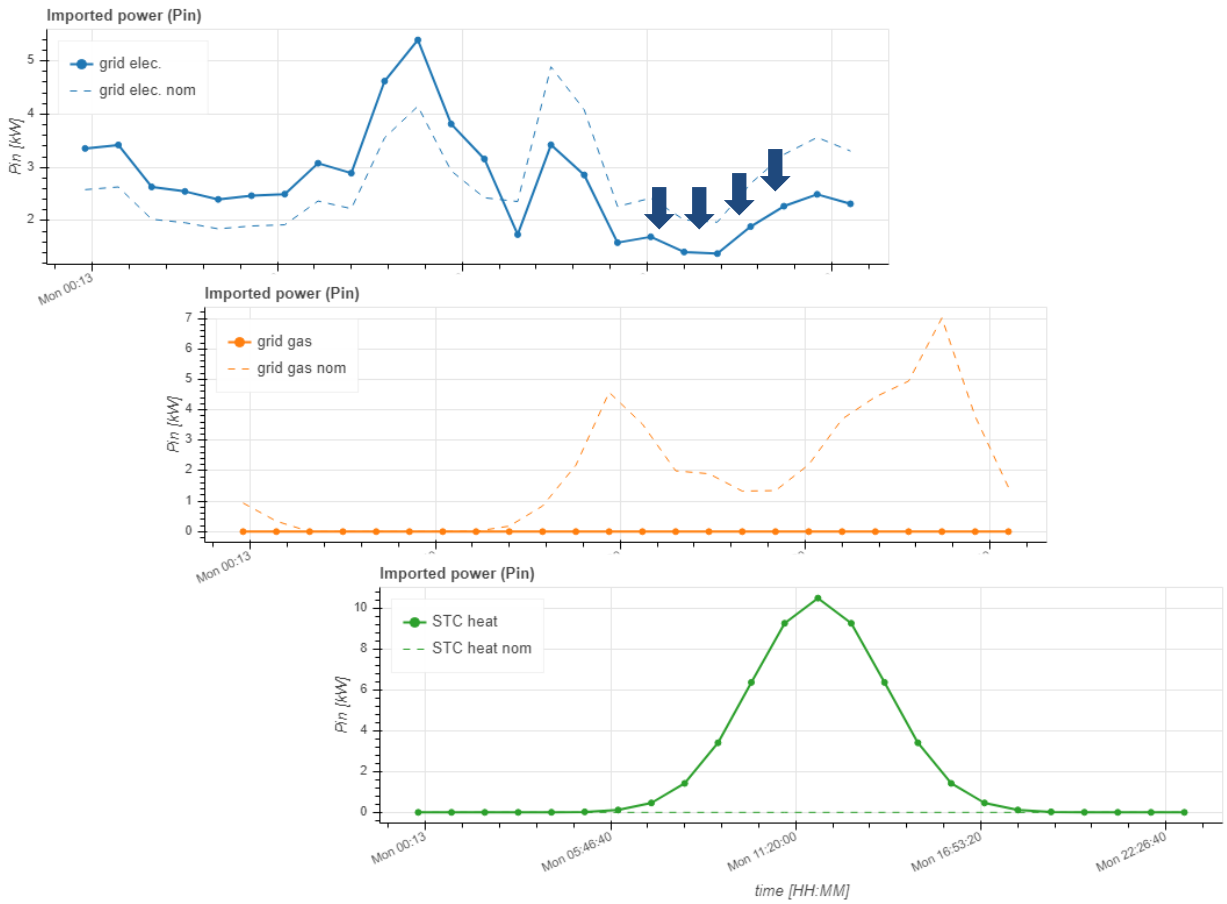

FIGURE 20 - IMPORTED POWER PROFILES WITH LOAD DECREASE

5.2 LOAD INCREASE EVENT

Even though the most common implementations of DR events impose load decrease requests, DR can also be used to facilitate load increases at times when there more energy is produced (for example during mid-day hours when the sun is shining bright and there is overproduction from the PV cells) than required by the load. In a similar way in which the stability of the grid is compromised when the loads exceed the total available amount of power, grid stability is also at jeopardy when the total available amount of power exceeds the total load by a significant margin. Both positive and negative load to available power disbalances compromise the grid stability.

One of the ways in which a load increase event can be implicitly induced, is using a time-of-use tariff where the price of energy is significantly lower at times when the load is to be increased, and significantly greater at times from which the load is to be shifted to the designated load increase period. This concept is essentially the inverse of what it was presented in the last section, where high energy prices are used to motivate load decreases.

5.2.1 AARHUS USE CASE

The Aarhus pilot is selected to showcase how loads can be increased using implicit DR events and time-of-use pricing. Analogous to the former case with load increase, 5% of difference in price of electric energy is enforced during the mid-day period when there should be ample energy produced by renewable sources, whilst a 5% increase of district heating price is enforced during

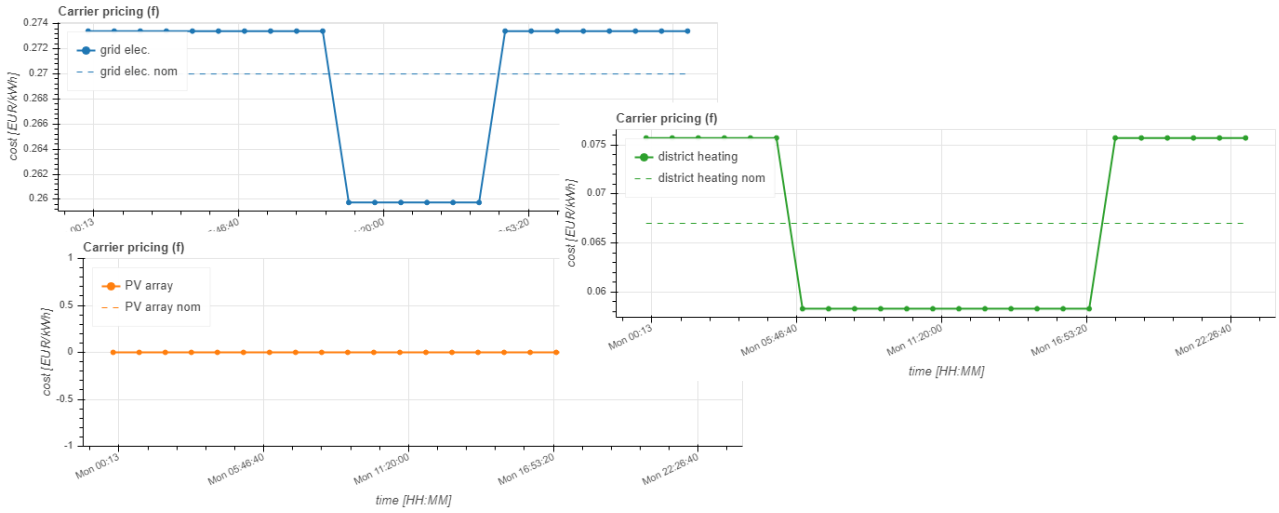

FIGURE 21 - PRICING PROFILES FOR LOAD INCREASE

the night and evening hours, when it is most likely that many of the users will activate their heating systems and pose a burden on the supply system. These profiles are illustrated in Figure 21.

When these profiles are employed in the Energy Hub model for the neighbourhood of the Aarhus pilot, the loads are adjusted as well as the imported power profiles. The effects of the

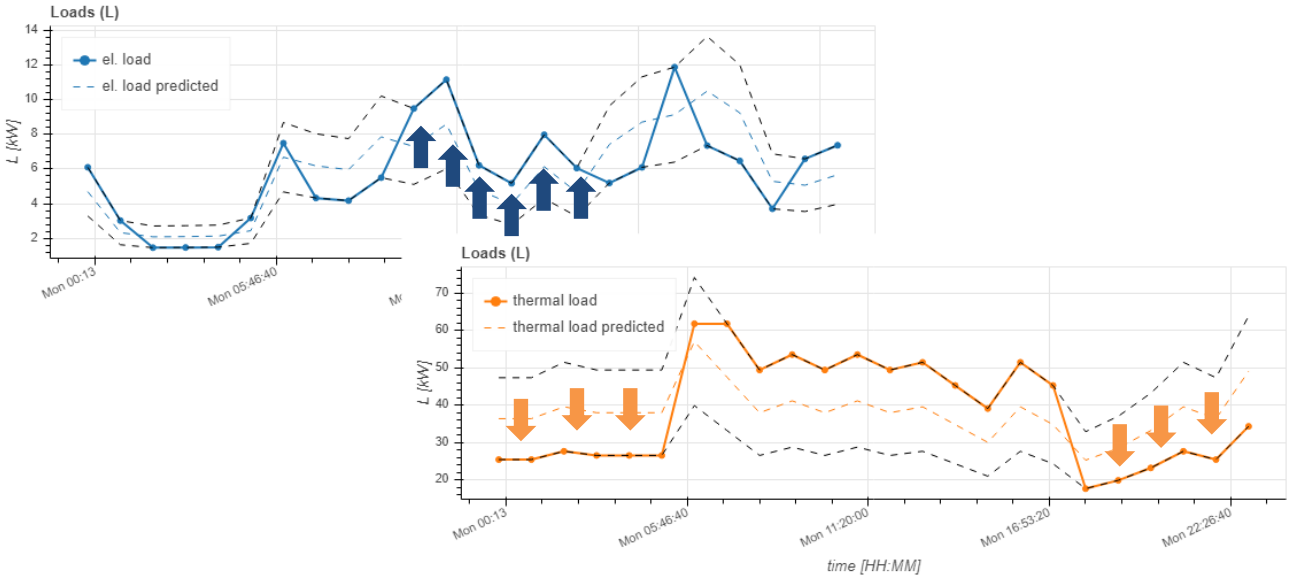

FIGURE 22 - LOAD PROFILES WITH LOAD INCREASE (ELECTRIC) AND LOAD DECREASE (THERMAL)

aforementioned time-of-use pricing profiles on electric and thermal (district heating) loads are illustrated in Figure 22 with the domestic hot water domain being disregarded in this case because there are no available measurements. As it can be observed here, the electric load is maximized during mid-day to make use of the lower price, whilst the thermal load is minimized during the night and evening when the price is high (or conversely, the thermal load is increased during daytime when the price is lower).

Once again, more important effects of this methodology should be observed in the imported power profiles that are given in Figure 23. Since the simulated size of the PV system is sufficient to fulfil the entire load amount during the mid-day period, the load increase results in the maximization of renewable usage while the imported energy in hot water from the district heating system is adjusted in the same way in which the thermal load is adjusted. Even though the optimal solution incorporates a load increase event, the model reports cost savings of around 6%, around 9% of savings in electric energy imported from the grid and a reduction of carbon footprint of roughly 8% because the main goal of the optimization remains the minimization of costs and the integral energy of the whole day has remained the same.

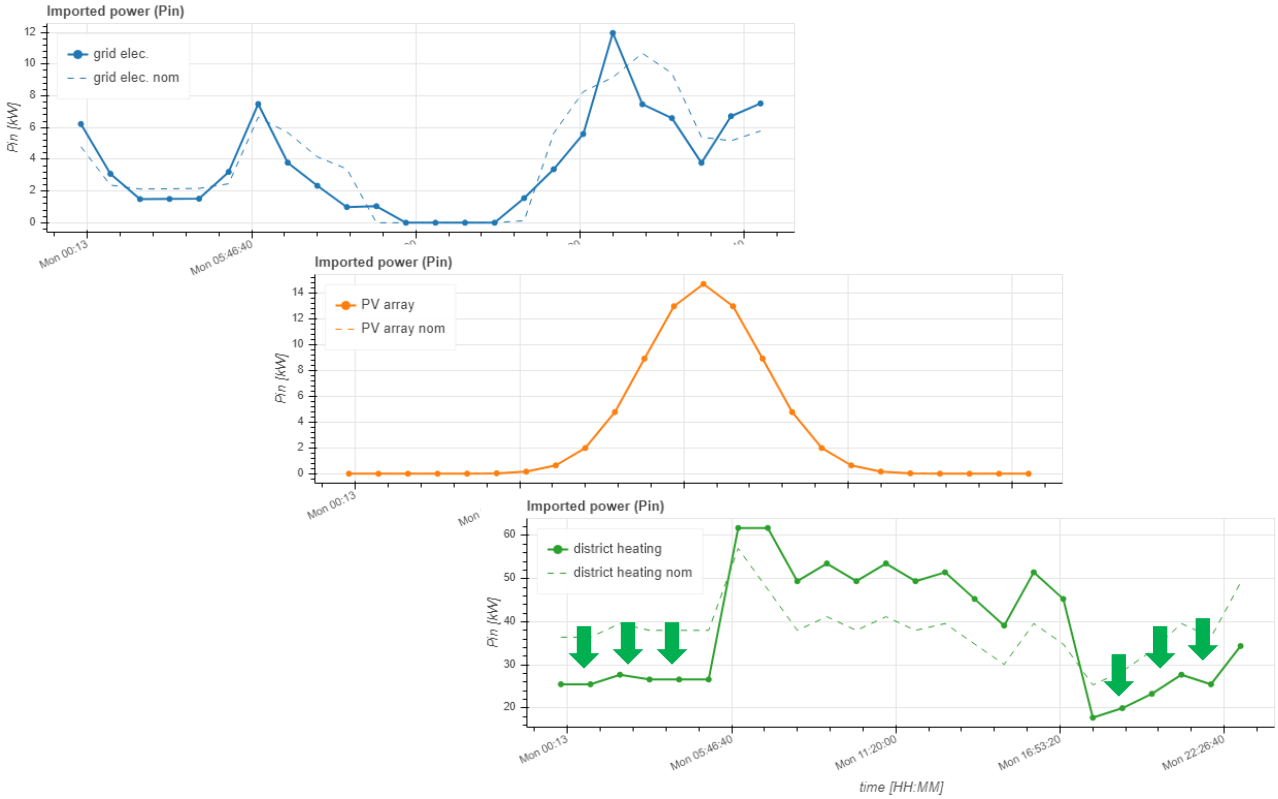

FIGURE 23 – IMPORTED POWER PROFILES WITH LOAD INCREASE (ELECTRIC) AND LOAD DECREASE (THERMAL)

6. RECOMMENDATION TRANSLATION

In order to complete the RESPOND control loop, the optimization output is further used in the analysis of the current state of user's consumption and to facilitate and adjust notifications to be issued. Figure 24 illustrates the RESPOND control loop in detail from start to finish. In the beginning of the loop, data is collected from individual houses and a neighbourhood profile is formed. This profile is optimized using the data from the demand forecasting service, renewable production service and the day-ahead price profiles. When the optimized profile is made available, it can then be compared with either the forecasted profile or the actual (measured) profile of users during the following day. When a deviation between the optimized and the reference (forecasted or measured) profile is noticed, a notification should be issued to end-users suggesting the

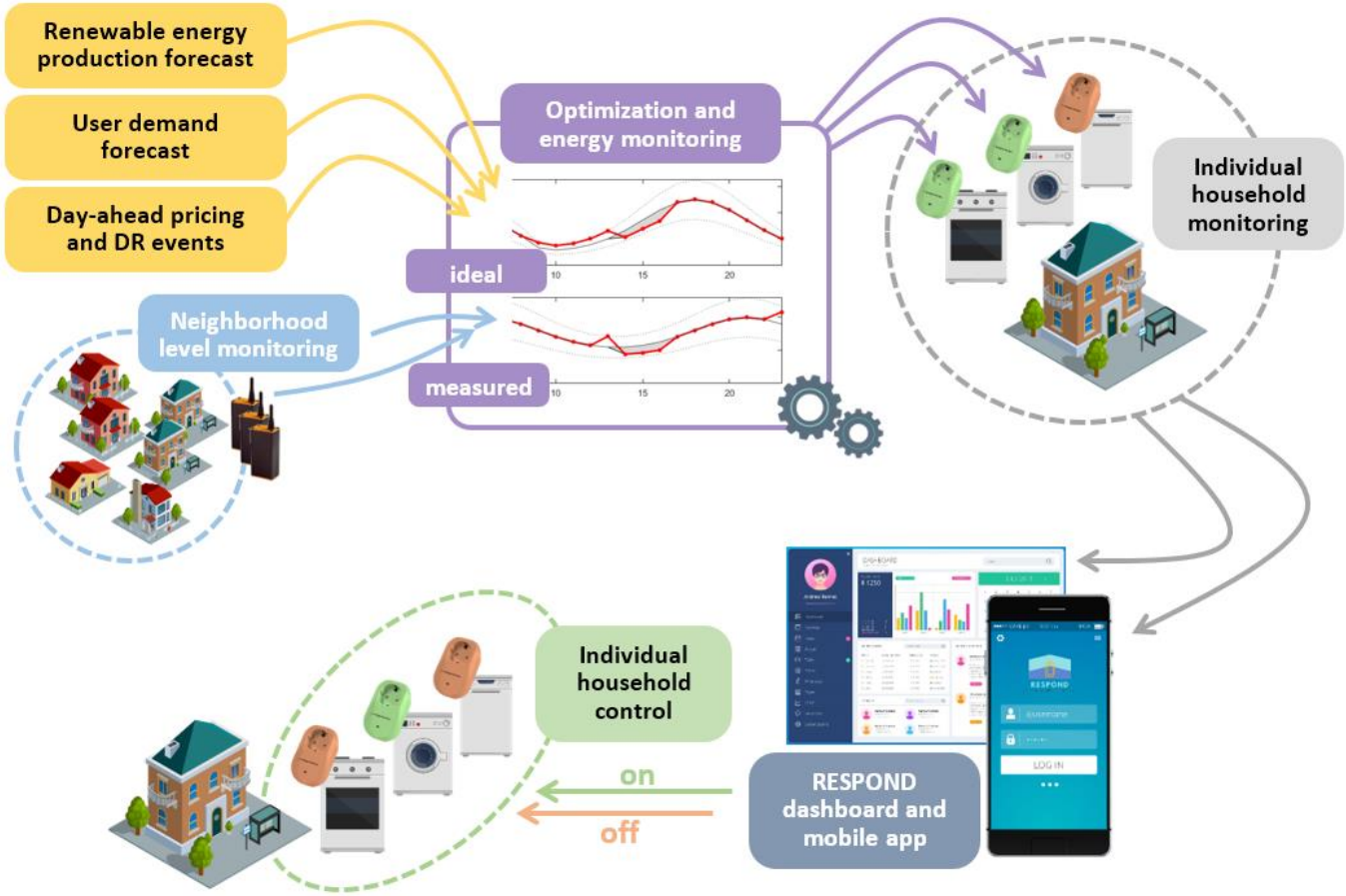

FIGURE 24 - RESPOND CONTROL LOOP

appropriate course of actions. The types of these messages are discussed in earlier deliverables and they should essentially consider either basic generic recommendations (i.e. increase demand or decrease demand) or appliance-specific recommendations (e.g. turn off the dishwasher and use it later).

If the predicted demand is used as a reference profile, these messages can be scheduled in advance because when the optimization output is made available there is ample time to analyse the given results and recommend the appropriate reactions. However, in this way, a lot of potentially useful information regarding individual appliance activations is lost. In contrast, if the

measured profile is used as a reference, messages cannot be scheduled in advance because the measured values are obtained in real-time and therefore, messages must be generated also in real-time. However, when working in real-time, current measurements from devices are available and therefore, custom, user and appliance-tailored messages can be generated to target specific apartments and specific appliances. For example, if the measured profile is significantly larger than the optimized one, the InfluxDB database is queried, and currently active appliances are singled out. Then, these appliances' users are determined, and they are issued notifications in which it is suggested that specific appliances' activations should be altered if possible. In order to facilitate high customer adoption, the RESPOND app should also provide the ability of automatized actions by which the user can deactivate an appliance connected to a smart plug

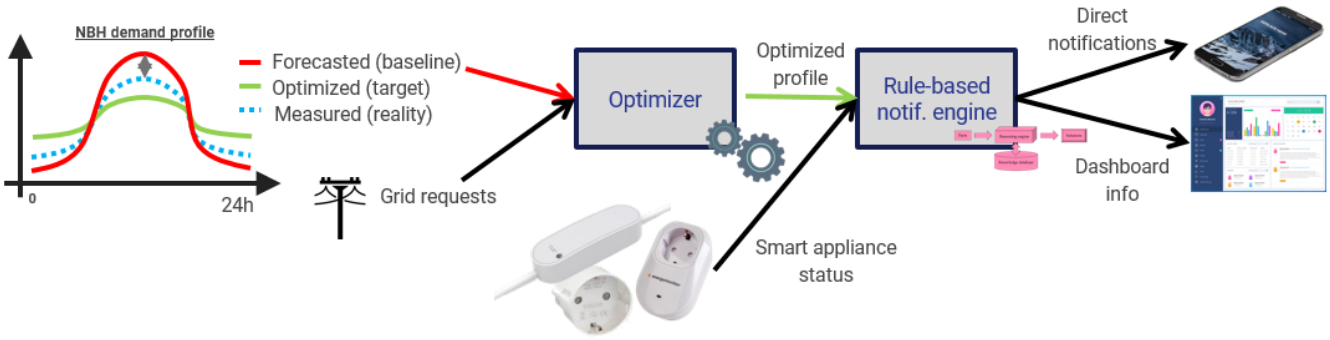

FIGURE 25 - NOTIFICATION TRANSLATION SERVICE WORKFLOW

just using one click of a button. The notification translation workflow, as described above, is illustrated in Figure 25. Since both methods have their respective merits and drawbacks, the best possible implementation should incorporate a hybrid system where both the forecast and measured profiles are used in conjunction with the optimized curve, in order to provide the most detailed analysis of user behaviour and allow its adjustments. The forecast profile should be used for rough assessment of potential deviations and bulk actions where multiple users are sent the same notification with a basic description of what the best course of action is. On the other hand, as sensor data becomes available, the rough instructions should be extended with detailed information regarding specific appliance activations and suggestions.

The key aspect of this translation procedure is the RESPOND mobile app, as it presents a unique bridge between the raw data, cloud services and the end users in the pilot sites. As the residential domain is the main focus of the RESPOND project, the highest priority should be assigned to the minimization of any additionally introduced user discomfort.

7. CONCLUSION

This deliverable extends and builds upon the results presented in D4.2, where the Energy Hub modelling concept with its modifications for load management applications is implemented for single-user use cases for the RESPOND's pilot sites, by introducing the demand management from the neighbourhood perspective. In the cases discussed in this deliverable, different households are not viewed independently of each other, but rather as a whole. This concept allows for some of the individual habits of different users to be averaged out and also presents a more suitable testbed for the load flexibility mechanism that is assumed to be the core of the demand management scheme.

In accordance with the layout of D4.2, first a short recapitulation of the key load management mechanism of the Energy Hub are discussed. Afterwards, the single-user models are extended and scaled up to form their respective neighbourhood representatives. Additionally, the simulations presented in this deliverable include real-world aggregate demand profiles from the pilot sites that are used to model the output of the demand forecasting service that provides inputs to the optimization engine. In conjunction with the synthetized renewable generation profiles, these aggregate systems are optimized in one of two scenarios: implicit load reduction and implicit load increase. All three pilot sites are used in these demonstrations with some of their unique characteristics being pointed out. Finally, it is described how the outputs of the optimization engine are to be used later in the RESPOND control loop to close the process and provide feedback and reactions from the users.

8. REFERENCES

Illustrations from freepik.com

[1] "Achieving energy efficiency through behaviour change: what does it take?," *European Environment Agency*. [Online]. Available: https://www.eea.europa.eu/publications/achieving-energy-efficiency-through-behaviour. [Accessed: 12-Aug-2019].

[2] Intergovernmental Panel on Climate Change, "Technology-specific Cost and Performance Parameters," in *Climate Change 2014: Mitigation of Climate Change: Working Group III Contribution to the IPCC Fifth Assessment Report*, Cambridge University Press, 2015, pp. 1329–1356.

[3] T. Kubo, H. Sachs, and S. Nadel, "Opportunities For New Appliance and Equipment Efficiency Standards: Energy and Economic Savings Beyond Current Standards Programs," p. 116.

[4] H. De Keulenaer, "The scope for energy saving in the EU through the use of energy-efficient electricity distribution transformers," in *16th International Conference and Exhibition on Electricity Distribution (CIRED 2001)*, Amsterdam, Netherlands, 2001, vol. 2001, pp. v4-27-v4-27.

[5] "Inverter Efficiency - an overview | ScienceDirect Topics." [Online]. Available: https://www.sciencedirect.com/topics/engineering/inverter-efficiency. [Accessed: 13-Aug-2019].

[6] "Elge Shell & Coil Heat Exchanger| WasteEnergy Recovery| AR MAC| GS Dunham." [Online]. Available: http://www.gsdunham.com/heat.html. [Accessed: 13-Aug-2019].

[7] "hvac-factsheet-boiler-efficiency.pdf." .