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WP1 Trial Results

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Abstract:
The WP1 Trial Results is WP1's seventh deliverable in the FINESCE project. The purpose of this deliverable is amongst other to describe and report WP1's final trial results within the FINESCE project.

The deliverable is split into the following results sections: usage of Generic Enablers and FIWARE, Energy optimization, Simulations, and Other.

Keyword list:

Generic Enablers, FIWARE, API, Results, Simulation, Data processing, Analyses, FPL Visualization

Executive Summary

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1. Introduction

The purpose of this deliverable is amongst other to describe and report WP1's final trial results within the FINESCE project.

The scope of the trial has been to execute Demand Side Management and Demand Side Response tests with external buildings in, Malmö, Sweden. The solution should be capable of testing activities of an integrated approach of energy carriers in order to demonstrate Demand Side Management and Demand Side Response tests based on either price or energy mix (CO2) for both heat and electrical loads.

The desired outcomes are stated here below.

- Understanding of how Future Internet technologies can contribute to an efficient and robust Demand Side Management system
- Proof of concept and evaluation on solution which architecture is based on distributed energy management capability and centralized portfolio management capability
- Proof of concept regarding cost optimization on price signals for heat and electricity based on different business model(s)
- Increased knowledge on future potential for Demand Side Management and Demand Side Response as well as ideas on customer's potential to act as balancing power
- Evaluation of the thermal load shifting potential by different heating systems, e.g. under floor heating and radiators, while leveraging the building's thermal inertia
- Definition of a scale-up strategy for the trial, e.g. ability for other towns, regions or business sectors to use the results and functionality

All of the desired outcomes for WP1 have been met and documented in different FINESCE deliverables.

The deliverable is split into the following results sections: usage of Generic Enablers and FIWARE, Energy optimization, Simulations, and Other.

Different results and conclusions have also been reported in previous deliverables. See for example the below deliverables for more information.

- WP1 Analysis of Generic and Specific Enablers Integration (D1.4)
- WP1 Trial Demonstration (D1.5)
- WP1 Innovation and Business Report (D1.8)

1.1 Trial architecture

The below figure illustrates the architecture developed in WP1.

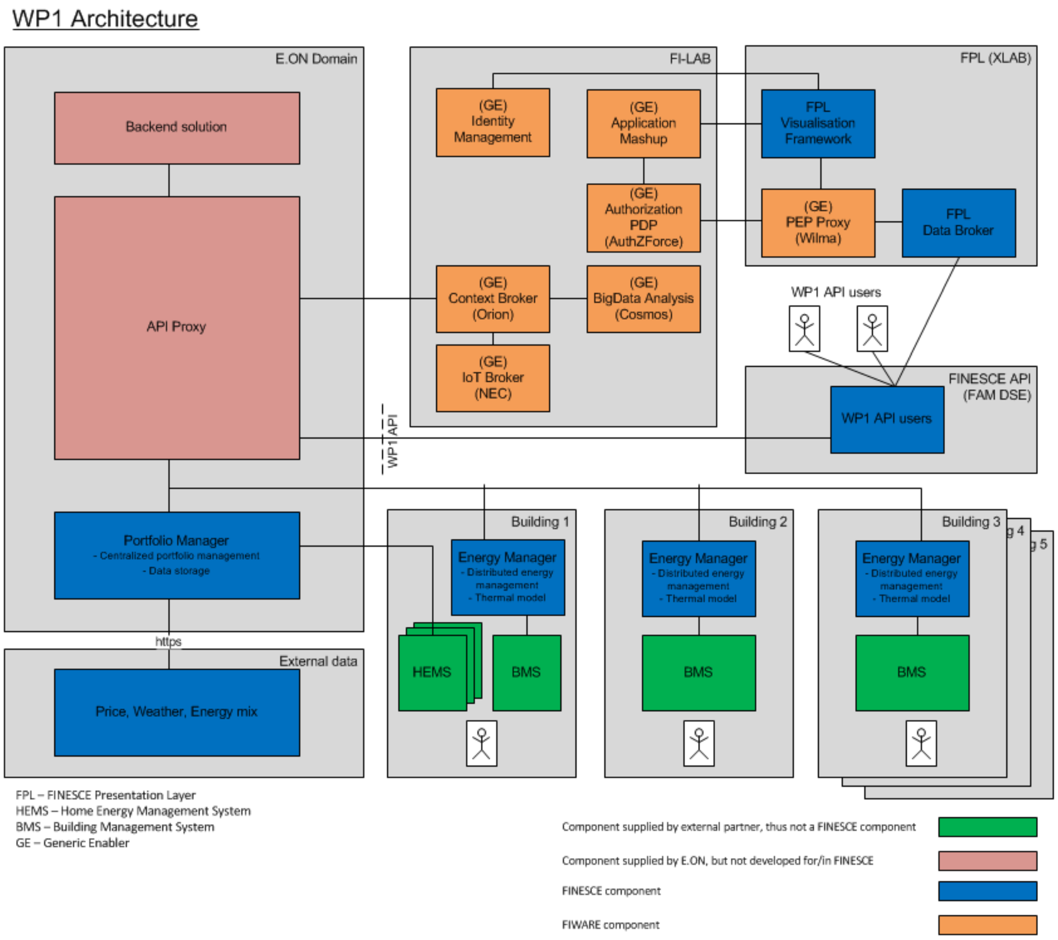

Figure 1-1 WP1 trial architecture

2. Trial results on usage of Generic Enablers and FIWARE

2.1 XLAB's view on the FIWARE platform and Future Internet capabilities

The FIWARE proved highly beneficial in the trial development both in terms of the offered infrastructure and the GE's readily available for the integration. From the perspective of XLAB as a SME in the consortium, this means less time and effort spent on technology, and more attention given to the actual content of the bigger Smart Energy projects.

Of the GE's available and integrated into the trial, we found the greatest use in the ones from the Security chapter of the FIWARE Catalogue. The GE Identity Manager KeyRock has been serving as the Single Sign-On solution for the visualisation applications. It also serves as the go-to place for authenticating users and machine clients, who access the data handling and serving layer of the visualisation services in the trial. To implement the authorization functionality, we use the GE Authorization PDP AuthZForce, and to complement the two services, we also use the GE PEP Proxy Wilma. By deploying the services in a topology where the PEP Proxy serves as a gate keeper to the data service, we have a stack where data is protected from unauthorized accesses.

The benefit of the FIWARE's whole package of the two of the three As (Authentication, Authorization, Accounting) is that the trials and their applications can take advantage of the accounts of the stakeholders already registered in the FIWARE. This means that both the Phase II and the Phase III projects' participants can use a unified and safe approach in presenting their user credentials. At the same time, the GEs employ open standards (e.g., the XACML for the Authorization PDP), so using FIWARE does not represent any vendor lock-in.

Thanks to this open design, the solutions currently working in FIWARE could be adapted to work with other solutions mandated by the potential customers (e.g., a utility or a DSO) due to their strict administrative policies. Of course this customisation requires a minor amount of effort and some overhead.

2.2 Lessons learned with FIWARE and GE's

Details concerning lessons learned with FIWARE and GE's are documented in the below deliverables. Those deliverables include example of concrete feedback given to GE developers as well as a comparison between the Generic Enabler BigData Analysis (Cosmos) and a similar service (Hortonworks).

- WP1 Mid-term Analysis of Generic and Specific Enabler Integration and Trial Impact (D1.3.2)
- WP1 Analysis of Generic and Specific Enablers Integration (D1.4)

3. Trial results on energy optimization

The developed trial infrastructure has proven to be a very flexible system with regard to handling different use cases and business models. One of the infrastructure's many strengths is the ability to deliver benefits both on a local level, optimization in the building, and at the same time on a global level, system optimization.

The infrastructure can handle all types of energy carriers, and we have been controlling electrical loads, district heating loads and district cooling loads.

Currently five buildings are connected to the infrastructure. All originally identified use cases have been implemented, investigated and proven. These use cases include amongst others tests for load curtailment and load shifting. Even additional use cases have been added. New use cases are found as spinoff when developing and investigating, resulting in new future opportunities. See previous deliverables (D1.1 and D1.2) for more information concerning energy optimization.

Further, some of the use cases have been found to have a commercial potential and plans are made to progress towards a commercial phase, post the FINESCE project. This concerns for example system optimization of district heating and district cooling. As for the previously reported district cooling case in the Western harbour, Malmö, the current status is that a rollout of the WP1 infrastructure to circa 25 buildings in 2016-2017 (i.e. post the FINESCE project) would have a positive NPV compared to a "conventional" case. The "conventional" case includes investments in additional production capacity (MW). This rather expensive production capacity would not be required to the very same extend thanks to the load curtailment use case.

3.1 Results

The infrastructure is capable to shift load according to defined use cases. The potential for shifting loads without significant impact on the customer's comfort has been shown to be bigger than initially expected. All this is of course very positive as it indicates good opportunities for leveraging the loads' flexibility.

Therefore E.ON is now further exploring how the flexibility can be used to enable system optimization of district heating and district cooling grids. For example, provided that desired flexibility is available, that could enable avoidance of firing up peak production units which usually have higher operational costs and CO_2 emissions. Thus, rolling out the infrastructure to the wider Malmö (here 5 buildings would not be enough, 50+ are required) could enable benefits to the whole City of Malmö.

In order to quantify the potential, different analyses and simulations have been activated, in addition to planned FINESCE activities, to identify a potential return of investment given the costs to set up a commercial operation of the infrastructure and rollout of required technology (compared to today's pilot operation with 5 buildings). These promising aspects would not have been this far without E.ON's involvement in the FINESCE project.

3.1.1 Dynamic district heating prices

E.ON has been testing so called dynamic district heating prices together with 3 of the buildings in the WP1 trial. The prices varied on hourly basis. The test is referring optimization of heating for the complete building, i.e. on building level, not necessarily individual apartment level.

There are many different possibilities to build dynamic price models for district heating with different advantages and drawbacks. The selected price model for this project was based on the Nord Pool electricity prices.

Moreover, Nord Pool is the Nordic electricity market, hence not at all district heating market. However, when it is cold outside, the electricity prices increase. The same concerns district heating. When it is cold outside, more district heating production is required. Hence there is a correlation between electricity prices and district heating production. Still there is not at all a perfect correlation. This correlation is relevant over hours and days, however it is not as strong over longer periods of time, for example over months and years.

The tests of using dynamic district heating prices based on Nord Pool electricity prices have been successful in general, but also resulted in a number of learnings for the future.

As the building's heating system should not be turned off completely (to avoid physical stress in the building), a 50% maximum curtailment capacity was set. It means that when the BMS system in the building requires 60kW of heat power at a given moment, for example, the WP1 optimization algorithm reduced the heat consumption to 30kW during the that period. This 50% maximum curtailment cap limits as well the capacity of monetizing the price differences within the day by half.

The dynamic district heating price based on Nord Pool has periods with very low variations, and periods with higher variations. See below figure.

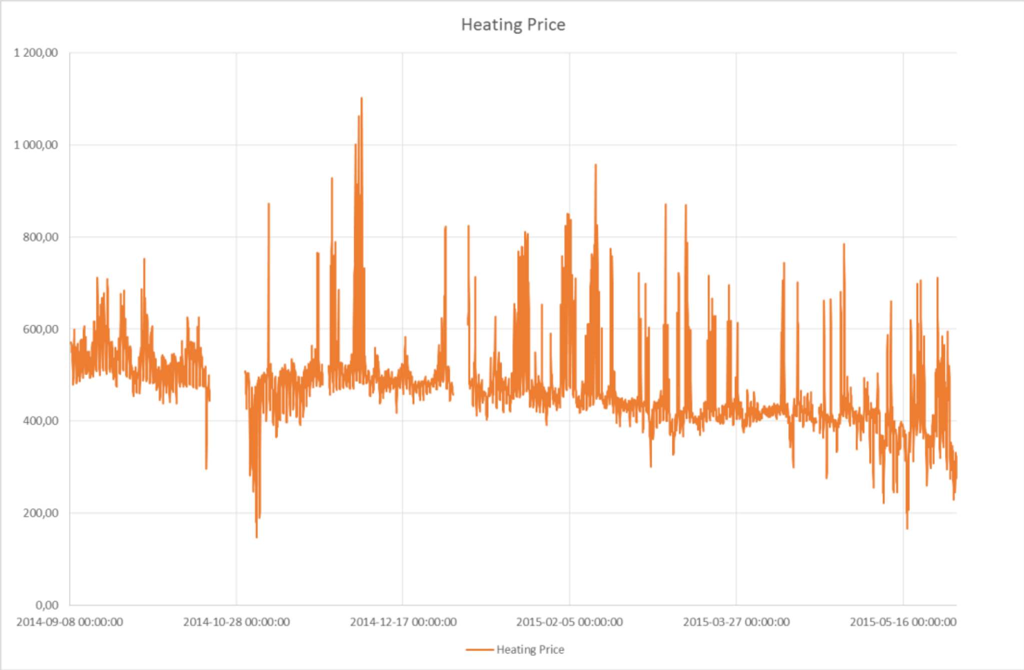

Figure 3-1 Prices over 2014-2015

It can be seen that there are periods of high variations and periods with low variations. Periods with high variations generally have peak price changes close to double the price of the lowest price of the day.

The uncertainty of these factors makes it very difficult to state an overall saving potential for the customer. However using the chosen price model, for a selected period of time, and estimated flexibility, calculations indicates savings around 5% (compared to doing no optimization at all). The figures of 5% derive from a so called baselining process. Calculating the baseline is very complex. It is very difficult – if not impossible – to know for certain how the load behaviour would have looked like without optimization.

Moreover, it is also important to be aware of that some days have a very flat price profile, which indicates a low possible to lower the costs. On the other hand some days have a more extreme variation which indicates a high possible to lower the costs. That is one of the reasons why it is impossible to define an exact percentage concerning the reduction potential.

4. Trial results on simulations

4.1 Simulation

4.1.1 Introduction

In district heating grids, the conventional operation of heating plants is demand oriented. As a result, peak units that are generally characterized by a high cost and CO2-footprint, and specific generation costs are operated to ensure the security of supply in periods of large demand.

Residential and commercial buildings account for up to 38% of the total end energy consumption worldwide and hence provide a large potential for energy savings and Demand Side Management (DSM) [1]. The embedded thermal mass of a building may be actively used as structural thermal storage capacity. Therefore intelligent control strategies can be used to optimize the use of this capacity by taking into account the thermal characteristics of the building. This is realized by a dynamic control of the indoor temperature to flatten the buildings' heat demand profile maintaining or even improving thermal comfort. Such dynamic control strategy would preheat the building and activate the storage capacity by increasing the indoor temperature setpoint in times of low demand that correspond to low CO2 emissions.

Alternatively, the heating setpoint could be lowered in high load periods which induce the operation of peak units that result in high CO2 emissions. Consequently the thermal mass releases the stored energy thereby reducing the energy demand allowing for avoiding CO2 emissions.

The most crucial barrier of estimating the building inertia is the lack of knowledge about the building physical properties. A detailed investigation of these factors requires extensive monitoring and analysis which is, in practice, applicable only on a small fraction of the total existing building stock. The aim of this work is to develop a method for the identification of the building thermal flexibility, described by the parameters of a simplified building model with a clear physical interpretation. The parameter identification process involves optimization of the model fitting using a few input variables measured at the building and very basic information about the building. The determined thermal flexibility will describe the capability of the building to act as short term heat storage and will therefore represent its load shifting potential for district heating networks. The development of the method aims its applicability on different building types without significant adjustments.

4.1.2 Approach

This work is based on a systematic approach that will allow for a straightforward future application of the method on other buildings. The below figure gives an overview of the applied approach. First the input data measured at the building is filtered and completed in order to be usable for the model fitting. The model parameters are initialized and constrained based on basic building information combined with specifications from norms and standards. The estimation of the model parameters is performed by fitting the simulation output to the available measurement data. An optimization algorithm is used for the parameter approximation based on an interior point optimization method for solving linear and non-linear convex optimization problems.

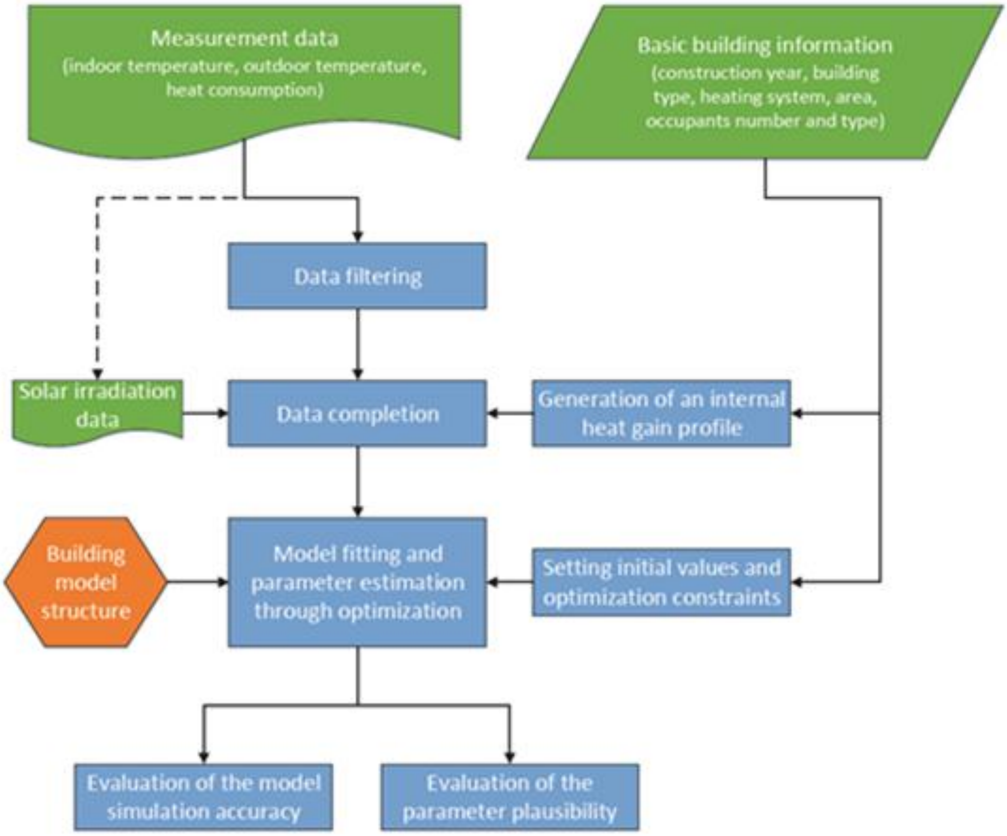

Figure 4-1 Flow chart of the building modeling and input data estimation

4.1.3 Models

The estimation of the model parameters through optimization of the model fitting is tested for different model structures. The six models tested in the study include different building components and vary regarding their complexity and accuracy to represent the real physical interrelationships in a building. The below table gives an overview of the presented building models and the physical effects they regard. The test parameter estimation approach on the different building models will reveal which ones are simple enough to be parametrised through fitting of measured data but complex enough to reproduce the building thermal response accurate enough for the use in DSM measures.

Table 4-1 Overview on the building models considered in this work

Separate consideration of:	**Building models**					
	I	**I-H**	**I-E**	**I-E-A**	**I-H-E**	**I-H-E-A**
interior component	✓	✓	✓	✓	✓	✓
exterior component	✗	✗	✓	✓	✓	✓
heater component	✗	✓	✗	✗	✓	✓
indoor air temperature node	✗	✗	✗	✓	✗	✓
transmission heat losses	✓	✓	✓	✓	✓	✓
infiltration heat losses	✗	✗	✓	✓	✓	✓
radiative heat exchange between interior and exterior	✗	✗	✓	✓	✓	✓
convective heat exchange	✗	✗	✗	✓	✗	✓
convective and radiant contribution of the heat gains	✗	✗	✗	✓	✗	✓
heat gains on interior and exterior	✗	✗	✓	✓	✓	✓

4.1.4 Case study

The presented approach was tested on a residential apartment building in Malmö, Sweden connected to a district heating grid operated by E.ON. The observed residential building includes 53 apartments and a total floor area of 4740 m². As shown in the below figure, the building integrates three blocks - two consisting of 5 floors and a third block with an additional penthouse floor. The construction year 2013 suggests a good insulated building envelope.

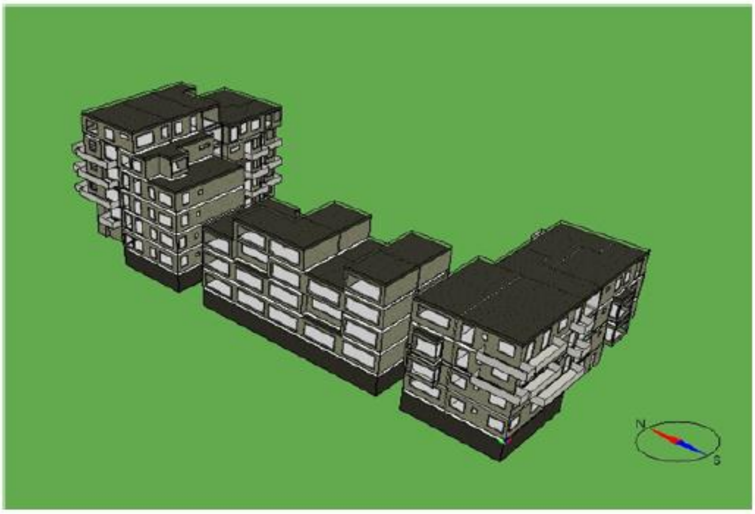

Figure 4-2 of the test building in Malmö, Sweden

The input data for the model simulation is presented by times series of measurements extracted from the building management system (BMS) and the thermostat system of the test building for the period between end of January and beginning of March 2014. The collected data includes hourly values of the indoor temperature (average value for the building), the heat consumption and the outdoor temperature. Additionally, values for the solar irradiation on horizontal surface for the area of Malmö could be obtained by the Swedish Meteorological and Hydrological Institute.

4.1.5 Results

The parameters of the simplified building models were identified using the monitored data of 14 consecutive days from the 14th to the 28th of February. Subsequently, the models were simulated for the whole available period from the 14th of February to the 3rd of March. The most suitable building model is identified by comparing the simulation output accuracy and the parameter plausibility of the different models.

a. Quantitative analysis

The quantitative accuracy of the model regarding their ability to represent the indoor temperature fluctuations are evaluated based on the root mean squared error (RMSE) of the residuals between the simulated temperature and the measured indoor temperature of the building. The results show that simulation error decreases slightly with the rising complexity of the models. Still, the absolute differences between the RMSE of every two models does not exceed 0,03 K - an insignificant value considering the sensitivity of the temperature sensors in the rooms.

b. Qualitative analysis

Considering the similar RMSE values of the different models, the qualitative analysis of the temperature prediction presents a better way to evaluate the accuracy of the model simulations. The models I-E-A, I-H-E and I-H-E-A give a better representation of the building cooling rate in the night hours, even if the average absolute residuals to the measured temperature do not differ significantly.

c. Plausibility of the estimated parameters

The below figure gives an overview over the estimated model parameters regarding their physical plausibility. Most of the models have several parameter assessed to their boundary values. Only the I-E-A-model provides a parameter set which is completely within the physically plausible range.

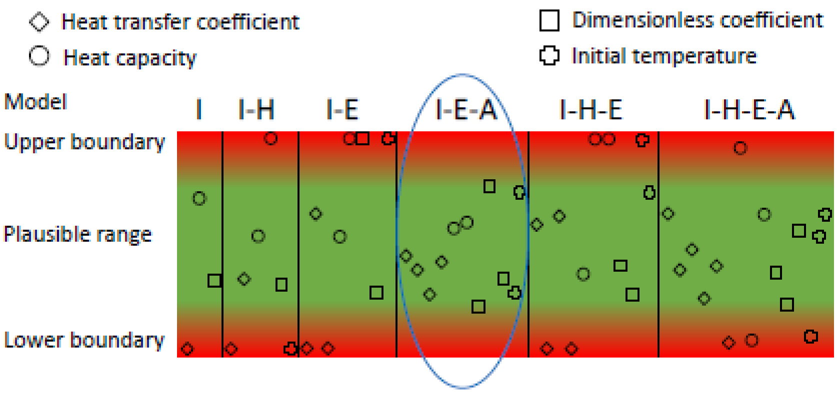

Figure 4-3 Physical plausibility of the estimated model parameters

In conclusion, the only building model that presents a whole parameter set with reasonable physical interpretation and reproduces accurately the indoor temperature dynamics is the I-E-A-model. This model is used further for the estimation of the thermal flexibility of the test building.

4.1.6 I-E-A-model

The below figure presents the model structure of the I-E-A model. All interior and exterior building components are summarized in one respective capacity. Additionally the indoor air is observed as massless temperature node. The model distinguishes between infiltration heat losses, connecting the indoor air directly to the environment, and transformation heat losses, which transfer the heat first to the exterior and then to the ambience.

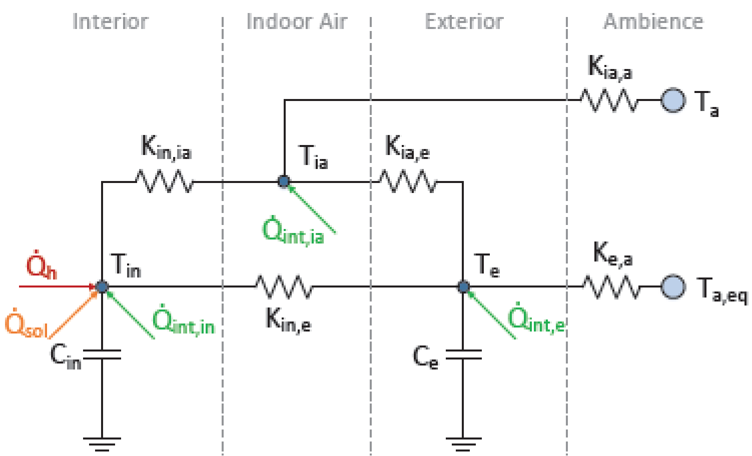

Figure 4-4 Simplified building model: I-E-A

As presented in the below figure, the model fitting gives a good match of simulated and measured temperatures. It must be noted that the recorded temperature drops are reproduced by the model simulation in a very accurate way.

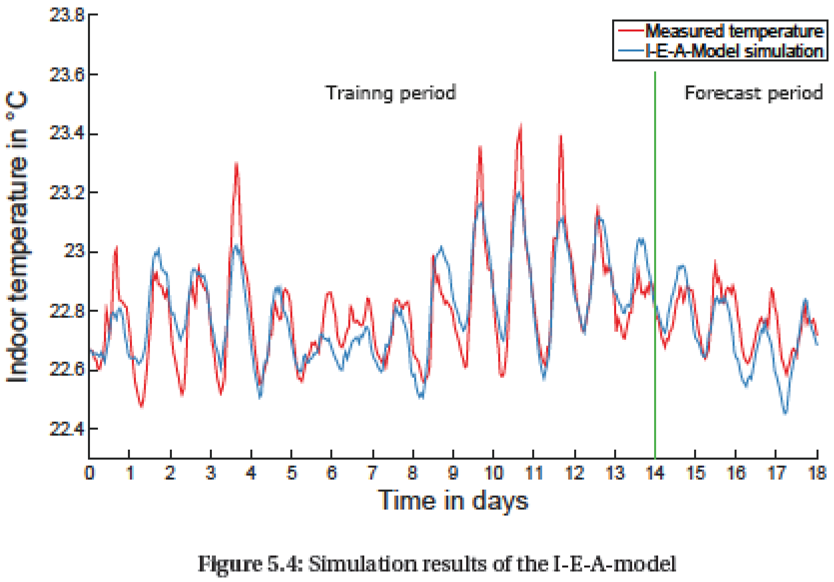

Figure 4-5 Simulation results of the I-E-A model

4.1.7 Thermal flexibility estimation

District heating network operators need information about the thermal flexibility of the heat consumers in order to plan demand side management measures. Therefore, the practical application of the developed method involves the derivation of the building thermal flexibility from the estimated model parameters. In this sense, the potential of a building for demand side management is defined by its thermal flexibility.

The below figure presents an estimation of the thermal flexibility of the case study building as a function of the permitted indoor temperature decrease and the heat load reduction performed using the I-E-A-model.

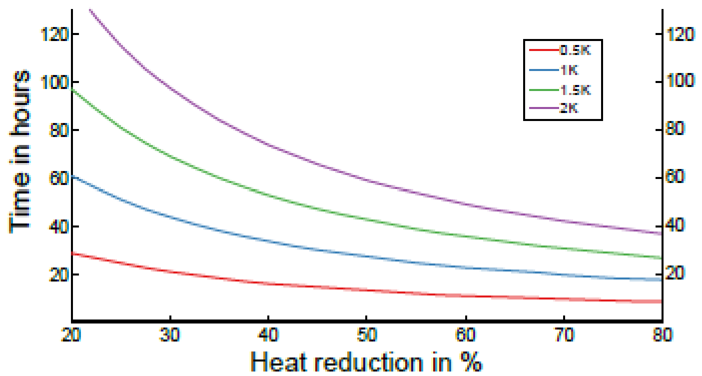

Figure 4-6 Maximum time of building wall mass heat storage discharge for preset indoor temperature drops

Each curve corresponds to the allowed temperature drop in the building. High offsets of the building heating reduce the influence of the various indoor temperature drop constraints on the maximum cool down times. For the observed building, the heat stored in the building mass is sufficient to keep the indoor temperature in a comfortable range (less than 1 K temperature drop) for 20 hours with a heating reduction of 70%. These results are observed for an average outdoor temperature of 3°C, present at the period of the simulated heat reduction.

A step test was performed by E.ON at the real building in Malmö to verify the calculated results. On the 12th of December at 1:00 am in the morning the heating system operation of the test building was reduced by 30% for 14 hours. As a result, the average indoor temperature of the building decreased by less than 0,2 K. This confirms the high thermal flexibility of the building assessed by the building model simulation.

4.1.8 Conclusion

This work has presented a method for assessing the building thermal characteristics based on collected measurement data and basic building information. For this purpose, the building was represented through a lumped capacity model using a grey-box modelling approach. After a process of filtering and completion of the input data, an optimization algorithm was applied to fit the simplified building model to the available measurement data. The initial parameter values and the optimization constraints were derived from norm and standard specifications as well as basic principles of the building physics and were defined to be generally valid for different building types. The model parameters estimated by the optimization algorithm allow for the direct derivation of the building thermal flexibility, the building time constant and therewith the potential of the building for Demand Side Management measures. The wide applicability of the building model structure and the parameter constraints for the optimization, developed within the method, allows for an implementation on different buildings types. The qualitative analysis of the model temperature prediction and the evaluation of the estimated model parameters revealed that only the two capacity building model with an additional consideration of the indoor air as a massless node (I-E-A-model) combines an accurate qualitative reproduction of the indoor temperature fluctuations and a clear physical interpretation of the estimated parameters.

An evaluation of the building thermal flexibility using the I-E-A-model determined that the building can maintain a comfortable indoor temperature (less than 1 K temperature decrease) over 20 hours for an average outdoor temperature of 3°C and a heating reduction of 70%. The high thermal flexibility of the building was confirmed by step tests performed at the real building.

4.2 Modelling a CO2-steering signal for Demand Side Management in district heating grids

4.2.1 Introduction

Usually the operation of combined heat and power plants for district heating grids follows the demand. Peak units are used to cover the demand in times of higher demand periods. In general those units have higher CO2 emissions and in particular are most cost intensive. Hence, Demand Side Management or Demand Side Response concepts for district heating grids can be sufficient solution for an optimized operation of the heating plants. Firing up the peak units could be avoided.

Such concepts could make use of the thermal flexibility on the building side given by the thermal inertia of the building or thermal water storages. The flexibility could shift the demand from times with high CO2 emissions into times of lower CO2 emission to support a more sustainable operation of the heating grid.

This work derives a CO2 steering signal based on generation data from the district heating plants in Malmö of the years 2011 and 2012. The CO2 steering signal is the same as the CO2 emissions prediction. This data plus hourly outdoor temperature and the corresponding CO2 emission factor per power plant is provided by the district heating grid department. The derived signal is applied to the customers to give incentives for shifting demand.

Both an artificial neural network (ANN) and a regression based method are applied to the data for modelling the CO2 signal.

4.2.2 Modeling

First, the provided data is used to calculate the CO2 emissions for all heating plants and the total amount in every hour of the years 2011 and 2012 according to the outdoor temperature. We filter the data according to the outdoor temperature with a resolution of 0,5°C and the corresponding hour of the day. This results in information of the CO2 emissions for each hour of a characteristic day depending on a certain outdoor temperature. For taking into account inaccurate information an exponential robust fitting is applied to each hour. This results in 24 different fitting curves offering the opportunity to calculate the emissions at a certain hour depending on the temperature during this hour h.

$E_{\mathrm{CO2}}(h)=a(h)\cdot e^{b\cdot T_{\mathrm{out}}(h)}+c(h)$ Eq. 1

Eq. 1 applied to each hour of a day is then used to derive a 24hour CO2-emission forecast implied that the outdoor temperature forecast is available. Due to the fact that if the daily outdoor temperature is higher than 15°C there is no heating required within the building we set the CO2 emissions to zero during those time periods. An example for the robust fitting of one hour in the one-day model is pictured in the below figure.

For covering the disadvantage that those days can appear also in winter and transition periods, we extend the model to a three-season model. This represents, using the VDI 4655, the different weather periods, such as winter, transition and summer period. Studies showed that a linear fitting approach, given in equation 2 fits best here.

$E_{\mathrm{CO2}}(d_s,h)=a(d_s,\mathrm{h})\cdot T_{\mathrm{out}}(d_s,h)+c(d_s,\mathrm{h})$ Eq. 2

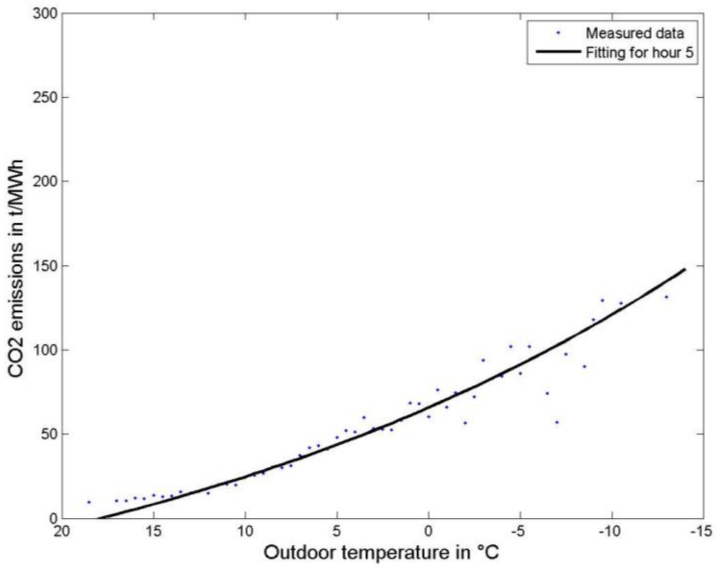

Figure 4-7 Example of the robust fitting approach for hour 5 using the one-representative day model

The below figure shows an overview on the work flow for the modelling of the three-day representative model. The distinction between these periods is based on the average day temperature. If the average temperature is less than 5°C it is considered to be a winter day, whereas an average temperature higher than 15°C refers to summer period. Other average temperatures lead to transition period.

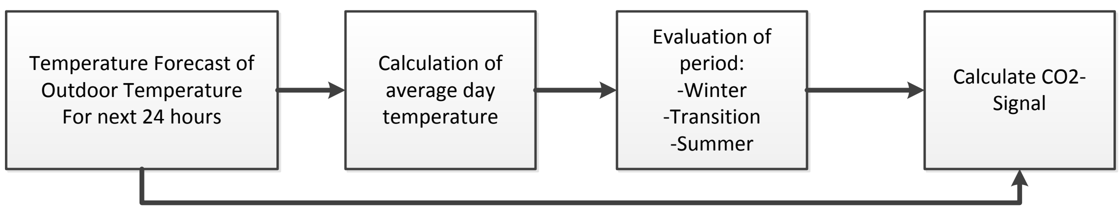

Figure 4-8 Work Flow of CO2-Signal Modelling

4.2.3 Results

For the evaluation of the model both the one representative and the three-seasonal model are analysed. The fitting results for the measurements of two years data are considered. In addition, we also apply a nonlinear autoregressive network with exogenous inputs (NARX) artificial neuronal network model. It contains 20 neurons and 2 layers. The data of 2011 and 2012 is used to forecast the CO2 emissions of the year 2013.

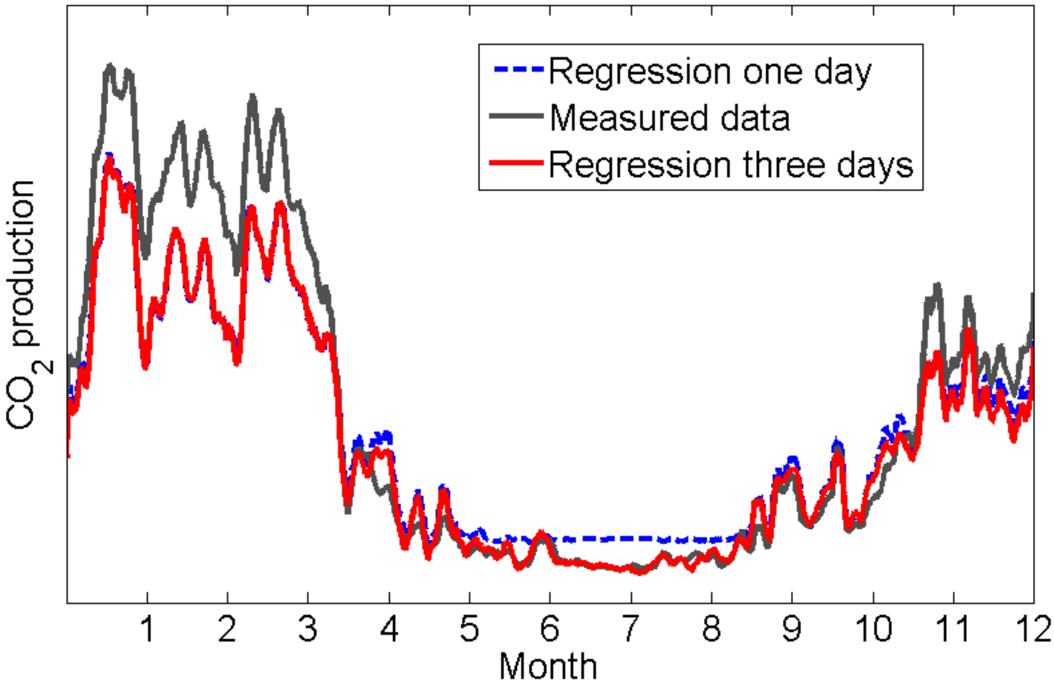

Figure 4-9 Comparison of results taken from

As evaluation criteria we mainly focus on the sum of squared error (SSE). The analysis shows that the ANN model has the biggest SSE and is hence neglected for further comparison. Looking into the two other models shows that the three-seasonal model has a slightly smaller SSE than the one-day model and hence gives a better performance. In general both models show that the dynamic behaviour of the CO2-emission profile can be captured by both approaches. The below table provides an overview on the SSE per model. In general a lower SSE is related to a higher performance.

Table 4-2 Overview on SSE per Model Approach

Model Approach	Sum of Squared Error (SSE) * 10^5
Artificial Neuronal Network	5.00
One-day Approach	3.98
Three-day Approach (VDI 4655)	3.75

4.2.4 Conclusion

This analysis showed that the model trained with historic production from two years can be used to evaluate a CO2 signal. This signal is able to be used for DSM concepts in district heating grids to give incentives to move consumption into times of lower CO2 emissions. In general the three-seasonal model according to VDI 4655 should be preferred due to a lower SSE meaning a better performance. However, further training data is desired to reduce the SSE.

5. Other Trial Results

Results linked to WP1 customer engagement and partner interaction was presented in deliverable WP1 Trial Demonstration (D1.5).

5.1 Visualization

The Demand Side Management trial involves the tenants of the buildings and the staff working in the commercial buildings. The amount and the dynamics of heating directly affects the comfort levels of the people. At the same time, the consumption of energy is associated with cost, which the consumers wish to minimise. One of the better ways of controlling the energy consumption is by monitoring it in a Smart Energy graphical application.

In FINESCE, XLAB used the FINESCE Presentation Layer (FPL), developed in the WP3, to create an application, which visualises the energy consumption of the smart building. The architecture of the FPL is presented in a greater detail in D3.7, but in short, it is composed of the Data Broker for collecting and enriching the Smart Energy data, a visualisation framework and visualisation widgets. Using these components, end-user applications are created. The aim in the design of these applications was to present the data to the users with a pleasing appearance, but at the same time also to offer crucial visual information on the current and past energy consumption.

The application is suitable for a number of use cases. Principally it is aimed at the owners of the building, and the operators of the heating and electricity service, such as E.ON. However, it is also possible to extend its use to include individual tenants in the use cases where the energy consumption meters are installed at the individual consumer's apartment.

A single installation of the application supports all three use cases. The users will see the data and functionality suitable for their assigned role. The role system also enables various granularities of the data accessible to the users, protecting the data from the unauthorised views and operations.

The design of the application follows the principles of the responsive interfaces. This assures that the visualisation is suitable for a wide range of displays, starting at the largest panels used in the operating centre to the small screens of the smart phones. The choice of the underlying technology also enables portability of the application, and assures compatibility with the great majority of modern and popular web browsers.

The FPL is also designed to respond quickly to the requests, making sure that the users do not perceive the delay between the requesting a view and receiving it on screen. This includes the views, which display the Smart Energy data on a wider time scale. The quick responses are possible because FPL's Data Broker aggregates the data at various levels and stores the aggregations to be quickly displayed.

5.1.1 Energy Service Providers

The first use case of the Smart Building application assumes that the energy providers or the DSO's need to monitor the ongoing energy consumption by their customers. For these users, the administrator must have created an account, and has also created the users in the application, assigning then the role of the providers. When a user with this role logs into the application, they first receive the Overview view. The below figure shows an example of the view, which contains the following elements:

- the latest readings of the aggregated electricity and heat consumption,
- a chart showing the history of the energy consumption readings starting at the beginning of the day, both for the heating and the electricity as the energy source,
- the history of the outside temperature readings from the beginning of the day,
- the history of the energy prices, both for electricity and heating.

The purpose of this view is for the operator to have it always open and visible, thus being able to perform continuous monitoring of the network status. By showing the live data and the chart that periodically updates to display the history between the beginning of the current day and the current time, it enables a view that requires no input parameters.

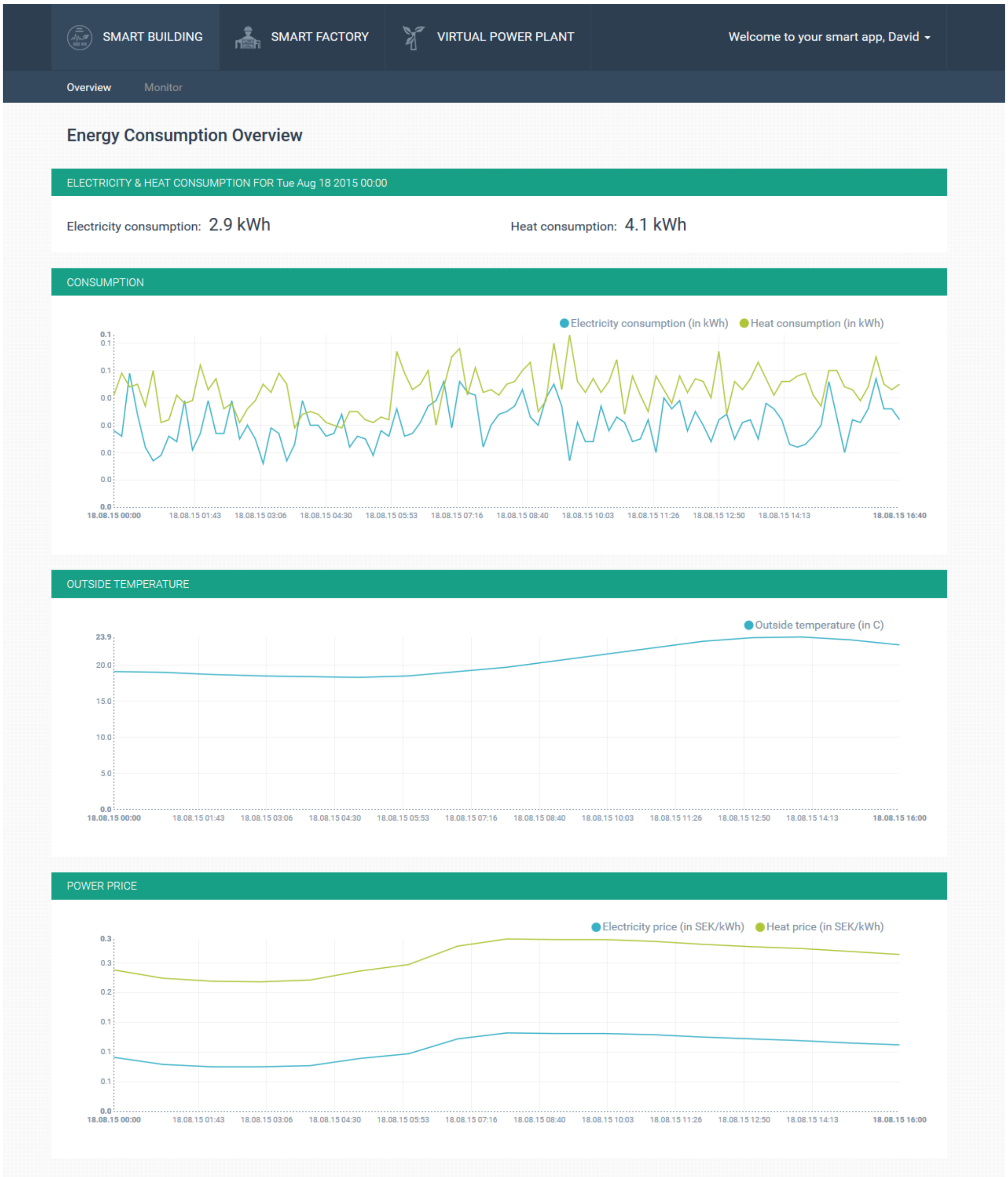

Figure 5-1 The Smart Building application's Overview displays the data relevant for continuous monitoring of the Smart Factory's energy consumption

To access a view where the user has much more control over the range of the data shown, the user can switch to the Monitor view. There, a provider user obtains a list of all the meters registered in the system, with each meter placed in a building and a region. The user can then select from this list a region, a house or a meter, and the widgets on the rest of the view will show the data applicable for the selection. Additionally, the user can adjust a start time and an end time of the range of data used in this view. The data shown on the visualisation widgets will therefore represent a relevant aggregation of the data if the user selects a building or a region. . The Figure 5-2 shows an example of this view.

The data display at the Monitoring view includes the following:

- a chart showing the history of the heating and the electricity power consumption
- an aggregation of the heating and electricity energy consumed in the selected time range
- a chart showing the history of cost of the energy consumed

- a chart showing the history of prices of the energy as it has been readjusted in time
- a chart showing the history of the outside temperature

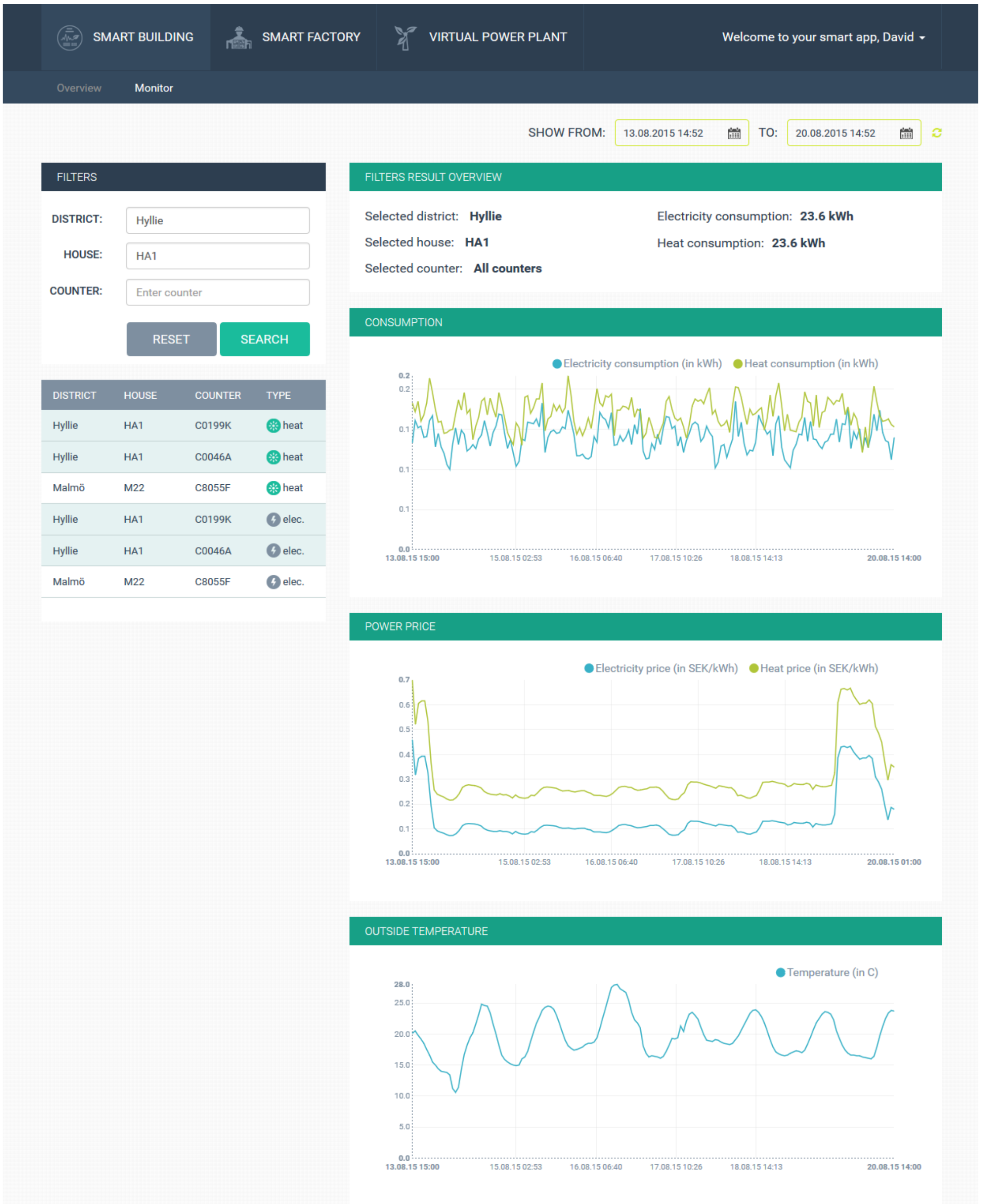

Figure 5-2 The Smart Building application's Monitor view for the energy provider's operator shows data at various levels of aggregation

5.1.2 Customers and consumers

The second major role in the application represents the recipients of the energy, who are the direct customers of the energy provider (e.g., the building owners) or the end consumers (e.g., tenants in the house or the building). We assume that they purchase the energy and pay at a monthly interval for the energy metered and consumed in the previous month. The prices are set by the market and possibly the provider, and they can be flat or can dynamically change throughout the day. The consumer's interest in the metered data is therefore the history of the energy consumption and the cost accumulated so far.

Following this rationale, the users upon logging in receive the **Overview** view (Figure 5-3), which visually summarises the following:

- live power currently consumed according to the most recent reading
- a chart showing the electricity and heating power consumption history since the beginning of this month (or since the start of the accounting month)
- accumulation of the energy consumed since the start of the month
- the cost of the energy consumed
- the grade of the energy consumption efficiency in this month as compared to the metered consumption in the previous month
- a chart showing the outside temperature since the beginning of the month
- the current weather

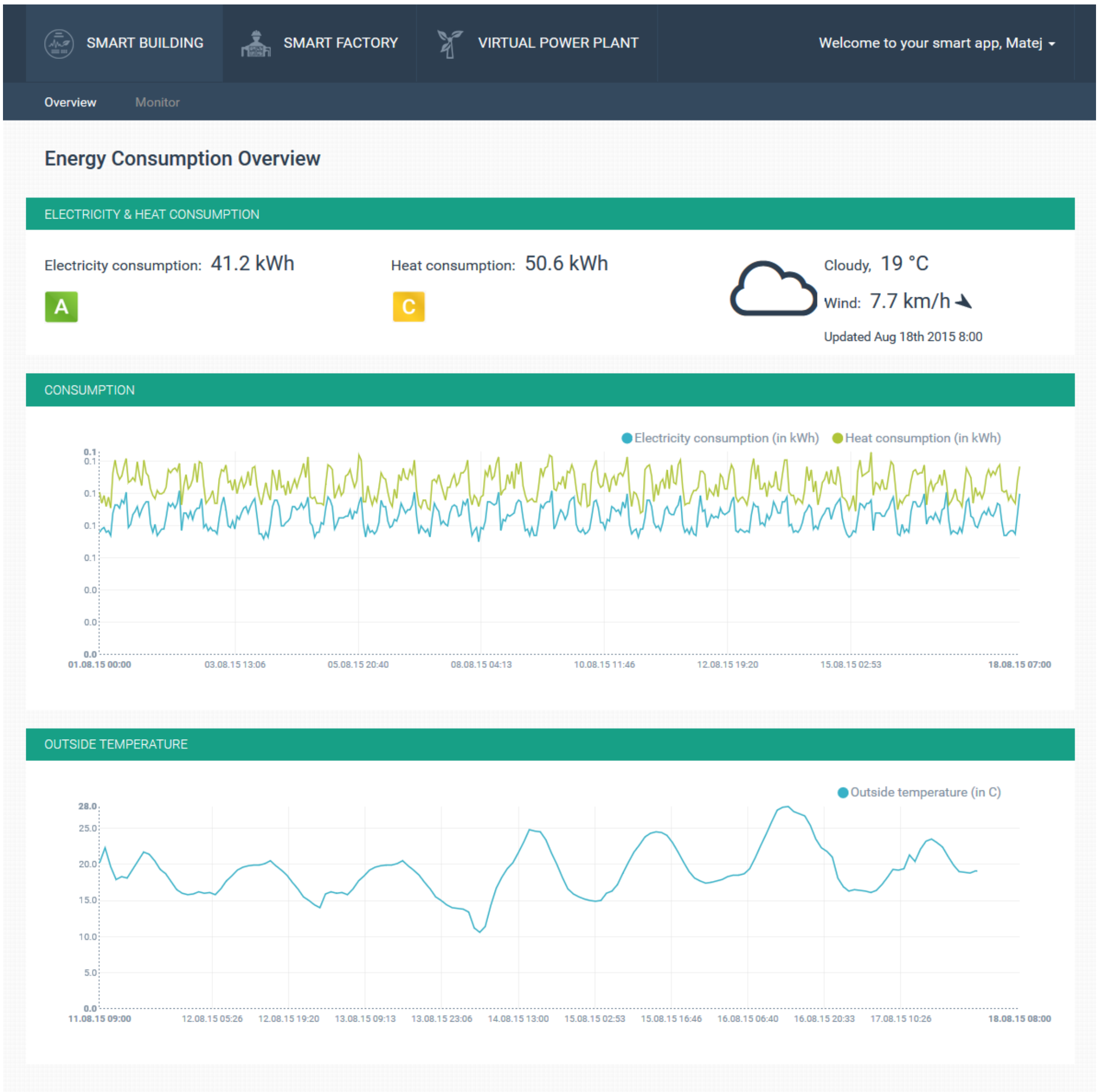

Figure 5-3 The Smart Building application's Overview tab for the customers and consumers displays the data relevant for monitoring the consumption in the current

The consumers may also switch to the Monitor view for the ability to select a custom time range for the visualised data. The Figure 5-4 shows an example, which consists of the following widgets:

- a chart showing the history of the heating and electricity power consumed during the selected time
- a chart showing the history of the cost of the energy consumed in the selected time range
- a chart showing the history of the outside temperature in the selected time range,
- a weather history

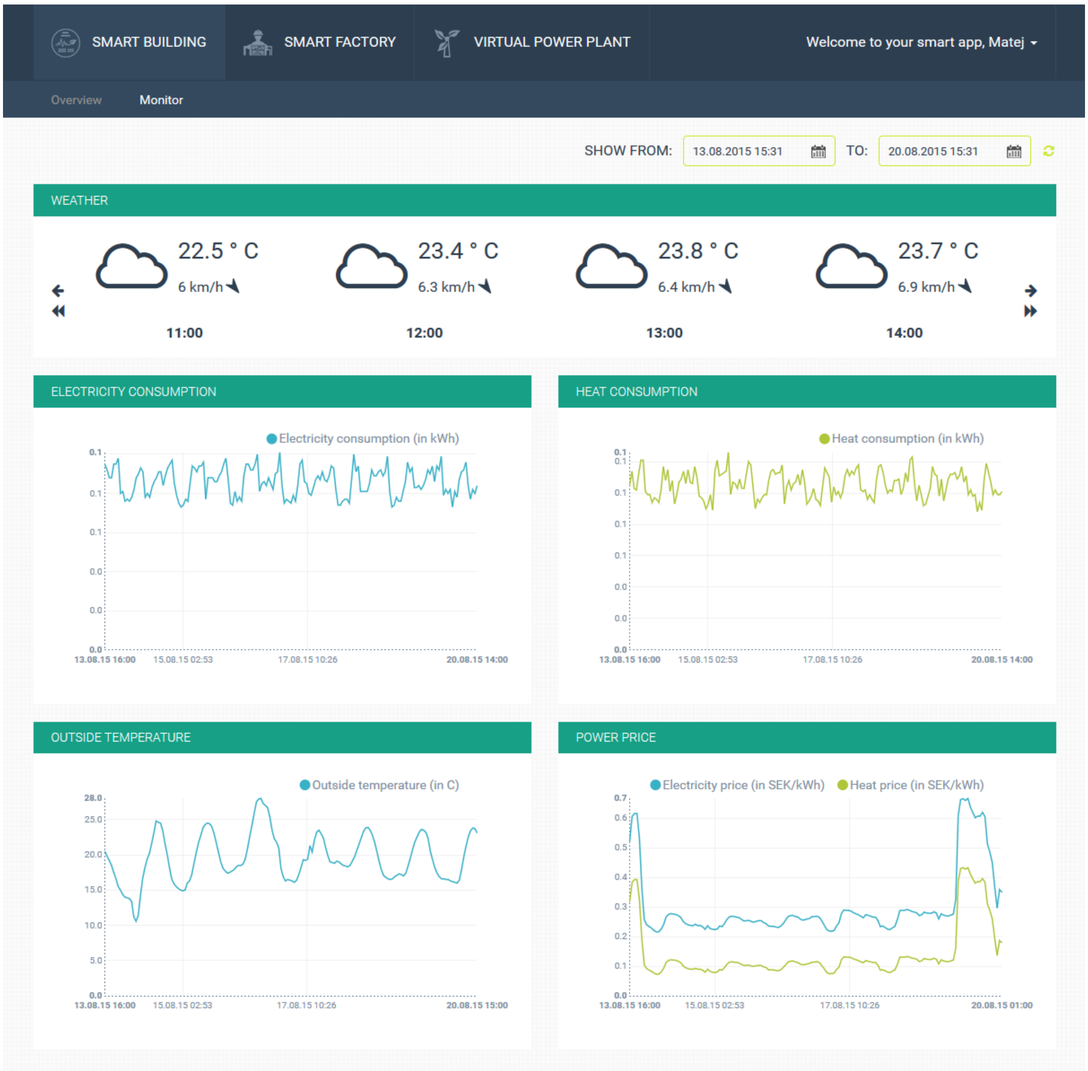

Figure 5-4 The Monitor view for a consumer user shows the data related to a single building or apartment

5.1.3 Visualization security

The heat consumption data of a building are considered sensitive data. When produced by tenants, the data is private, because it could be used to discern a deeper insight into the habits of the consumers. For the whole buildings, they could represent a business secret. In either case, we wanted to build into the application the ability for the users to only access the data when they are logged in. Therefore we integrated with the application the use of the GE Identity Manager KeyRock. In practice this means that the users need to provide their FIWARE credentials (user name and password). The application supports Single-Sign-On protocols such as OAuth2, therefore the user's password goes to the Identity Manager directly, never to be intercepted by the application.

The application keeps the access policies encoded in an XACML format, compatible with the GE Authorization PDP AuthZForce. The GE PEP Proxy Wilma serves as a gatekeeper for the Data Broker service, permitting access only to the requests, which come from authorized and properly logged-in users, and which the AuthZForce grants the access to. The access policies base the conditions to grant access on the user's known attributes, which include the user's assigned role, the account (e.g., a household or a company) that the user belongs to, and a list of the meters owned or rented by the user. To support this functionality, we complemented the KeyRock's features by implementing our own **Attribute Manager**.

In the trial, the application's deployment relied on the FIWARE Lab's instances of KeyRock and AuthZForce. Thanks to the two GEs' source availability and well-written documentation, we are also able to deploy and use our own instances of the GEs. Additionally, our Attribute Manager can also be used in other contexts and applications, including other FINESCE use cases such as the ones from WP3.

6. Conclusion

The deliverable includes extended results for the following results sections: usage of Generic Enablers and FIWARE, Energy optimization, Simulations, and Other.

WP1 has a gained a positive experience with FIWARE, mainly linked to data processing and security chapters.

The developed trial infrastructure has been to proven to be a very flexible system with regard to handling different use cases and business models. One of the infrastructure's many strengths is the ability to deliver benefits both on a local level, optimization in the building, and at the same time on a global level, system optimization.

Concerning the CO2 model simulations, the analysis showed that the model trained with historic production from two years can be used to evaluate a CO2 signal. This signal is able to be used for DSM concepts in district heating grids to give incentives to move consumption into times of lower CO2 emissions. In general the three-seasonal model according to VDI 4655 should be preferred due to a lower SSE meaning a better performance. However, further training data is desired to reduce the SSE.

Lastly, all of the desired outcomes for WP1 (mentioned in the Introduction) have been met and documented in different deliverables.

7. References

[1] International Energy Agency. Technology roadmap energy-efficient buildings: heating and cooling equipment. Tech. Rep 2011.

8. List of Abbreviations

B2B	Business to Business
BMS	Building Management System
CAPEX	CAPital EXpenditure
CENELEC	European Committee for Electro technical Standardization
CEP	Complex Event Processing
COTS	Commercial off-the-shelf
CPMS	Charge Point Management System
CSA	Cloud Security Alliance
DER	Distributed Energy Resources
DMS	Distribution Management System
DMTF	Distributed Management Taskforce
DSE	Domain Specific Enabler
EAC	Exploitation Activities Coordinator
EMS	Energy Management System
ERP	Enterprise Resource Planning
ESB	Electricity Supply Board
ESCO	Energy Service Companies
ESO	European Standardisation Organisations
ETP	European Technology Platform
ETSI	European Telecommunications Standards Institute
GE	Generic Enabler
HEMS	Home Energy Management System
HV	High Voltage
I2ND	Interfaces to the Network and Devices
ICT	Information and Communication Technology
IEC	International Electro-technical Commission
IoT	Internet of Things
KPI	Key Performance Indicator
LV	Low Voltage
M2M	Machine to Machine
MPLS	Multiprotocol Label Switching
MV	Medium Voltage
NIST	National Institute of Standards and Technology
O&M	Operations and maintenance
OPEX	OPerational EXpenditure
PM	Project Manager
PMT	Project Management Team
PPP	Public Private Partnership
QEG	Quality Evaluation Group
S3C	Service Capacity; Capability; Connectivity
SCADA	Supervisory Control and Data Acquisition
SDH	Synchronous Digital Hierarchy
SDN	Software defined Networks
SDOs	Standards Development Organisations
SET	Strategic Energy Technology
SET	Strategic Energy Technology
SG-CG	Smart Grid Coordination Group
SGSG	Smart Grid Stakeholders Group
SME	Small & Medium Enterprise
SoA	State of the Art
SON	Self Organizing Network
SS	Secondary Substation
TL	Task Leader
TM	Technical Manager
VPP	Virtual Power Plant
WP	Work Package
WPL	Work Package Leader