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Energy Demand Aware Open Services for Smart Grid Intelligent Automation

SmartHG

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Contents

Executive Summary

Objectives SmartHG second year evaluation activity focussed on assessing all SmartHG services in a stand-alone fashion. This third and final evaluation focuses on assessing how the whole SmartHG Platform (i.e., all services cooperating together) addresses the project objectives: (a) Support the Distribution System Operator (DSO) in optimising Electric Distribution Network (EDN) operations; (b) Reduce energy costs for residential users; (c) Reduce CO2 emissions.

Retrospect In the second year we focussed on two *reference scenarios*, one from Kalundborg test-bed and one from Central District (Israel) test-bed. Data from such test-beds were provided by sensors deployed in the homes and by historical data about Plug-in Electric Vehicle (PEV) charging/discharging provided by our networking with the "Test-an-EV" Danish project. All SmartHG services were deployed and run on their intended hardware platforms, namely a Raspberry Pi for Energy Bill Reduction (EBR) and workstations for all other services. On our test-bed scenarios we performed *technical*, *economic* and *environmental* evaluations. Our technical evaluation showed that computation time and memory usage of all SmartHG services (Intelligent Automation Service (IAS)) and communication services (Database and Analytics (DB&A), Home Energy Controlling Hub (HECH)) are compatible with their intended use. Our economic and environmental evaluations showed that SmartHG services flatten the aggregated demand (*peak shaving*) without increasing CO2 emissions.

Achievements In the third year we extended our scenarios with data from new sensors in Kalundborg and Central District as well as with historical data from our Minsk test-bed. Using such data, our third year evaluation shows the following.

The benefits provided by SmartHG individualised price policy technology to the EDN, and thus to the DSO are: 1) increase of the *demand load factor* of more than 18% with respect to a flat price policy and of more than 35% with respect to to a global price policy (because of *rebounds*), thereby providing a *peak shaving* effect considerably better than the one offered by a *global* price policy; 2) reduction of low-voltage violations in the grid; 3) reduction of network line thermal MVA limit violations; 4) reduction of network line losses (e.g., of about 2% with respect to a global price policy).

The benefits provided by SmartHG to electricity retailers mainly consist in the possibility of effectively exploiting distributed home energy storage to buy energy when its price is low in the day-ahead market (*arbitrage*). When only a PEV is present the energy cost saving ranges from 7% (Kalundborg test-bed) to 13% (Minsk test-bed), whereas when both a PEV and a home battery are present the energy cost saving ranges from 11% (Central District test-bed) to 19% (Kalundborg test-bed). Such results show that, as a side effect, SmartHG technology fosters PEV uptake by enabling residential users to exploit their PEV to save on energy cost.

Finally, SmartHG can bring benefits also to the environment, by allowing electricity retailers to buy energy when its CO2 footprint is small. When only a PEV is present CO2 emissions reduction ranges from 7% (Kalundborg test-bed) to 13% (Minsk test-bed) whereas when both a PEV and a home battery are present CO2 emissions reduction ranges from 12% (Central District test-bed) to 15% (Kalundborg test-bed).

Impact Our evaluation results, together with the booming of home energy storage systems (e.g., Tesla Power Wall, Enphase AC Battery) and the expected uptake of PEVs show *economic viability* of SmartHG approach and identify electricity retailers and DSOs as main customers for SmartHG technology. Our evaluation results indeed form the basis for a commercial exploitation of SmartHG technology by ICT companies providing software services *orchestrating* home devices so as to provide economic and/or environmental benefits to electricity retailers, DSOs, and residential users.

Chapter 1

Retrospect

In this section we briefly recall the main achievements obtained (and the main shortcomings identified) in the second year evaluation of SmartHG services, described in Deliverable D5.2.1 and presented at the second review meeting held in May 2015. The detailed list of all advancements of the third year evaluation (described in this deliverable) with respect to the second year evaluation is reported in Section 5.

In the second year iteration of WP5 we evaluated all SmartHG Services (IAS), i.e., Demand Aware Price Policies (DAPP), Price Policy Safety Verification (PPSV), EDN Virtual Tomography (EVT), DB&A, EBR, Energy Usage Reduction (EUR) and Energy Usage Modelling and Forecasting (EUMF) in a stand-alone fashion.

Evaluation was carried out on two *reference scenarios*, one from Kalundborg test-bed and one from Central District (Israel) test-bed. The latter was not present in the first year. Data from such test-beds are provided by sensors deployed in the homes and historical data on PEV charging, acquired from our networking with the "Test-an-EV" Danish project. All our services have been run on their intended hardware platforms, namely a Raspberry Pi for EBR and workstations for all the others.

On our test-bed scenarios we performed *technical*, *economic* and *environmental* evaluations.

Our technical evaluation showed that computation time and memory usage of all SmartHG services are compatible with their intended use. In particular, EBR (time-wise the most critical one) runs in a few seconds on a Raspberry PI.

Our economic evaluation showed that SmartHG services are *economically viable*. Namely, by using them, *both* residential users and DSOs obtain an economic benefit.

In particular, if the EDN is *congested enough* to justify the DSO offering a reasonable discount on electricity distribution costs to residential users contributing to *peak shaving* by following DAPP suggested power profiles, then residential users can reduce their electricity bill by about 5% (the DSO benefits being Transmission and Distribution (T&D) investment deferral).

Energy cost and CO2 emissions both depend on the electricity demand time distribution. Accordingly we ran simulation on historical data in order to verify that DAPP suggested shifting of the aggregated demand (to attain peak shaving) does not lead to an increase in energy cost or CO2 emissions.

Finally, the following limitations to the second year were identified. First, a few planned sensors were not yet installed. Second, evaluation of EBR at IMDEA micro-grid did not address communication delays.

Chapter 2

Introduction

The main objective of the SmartHG project is to develop software services (IASs) that are *economically viable* for both residential homes and DSOs. This is achieved using a hierarchical control approach (see Figure 2.1) where the high level control loop (steered by the DSO) sets price policies for the electrical energy for each residential user, and the low level control loop (steered by residential users) manage home devices in order to minimise home energy bill. SmartHG Grid Services (Grid Intelligent Automation Services, GIASs) support the DSO in computing price policies whereas SmartHG Home Services (Home Intelligent Automation Services, HIASs) support residential users in managing home devices. IASs (i.e., GIASs + HIASs) communicate via the DB&A service with the architecture summarised in Figure 2.2.

SmartHG Home Services (HIASs) comprise the following services: EUR, EUMF, EBR. EUR and EUMF are used by EBR for short term (a few hours) forecasting of user demand and have been evaluated in a stand-alone fashion during our second year evaluation. Since this year we are focusing on evaluation of SmartHG Platform as a whole, we will focus, as for SmartHG Home Services, on EBR being understood the EUR and EUMF are part

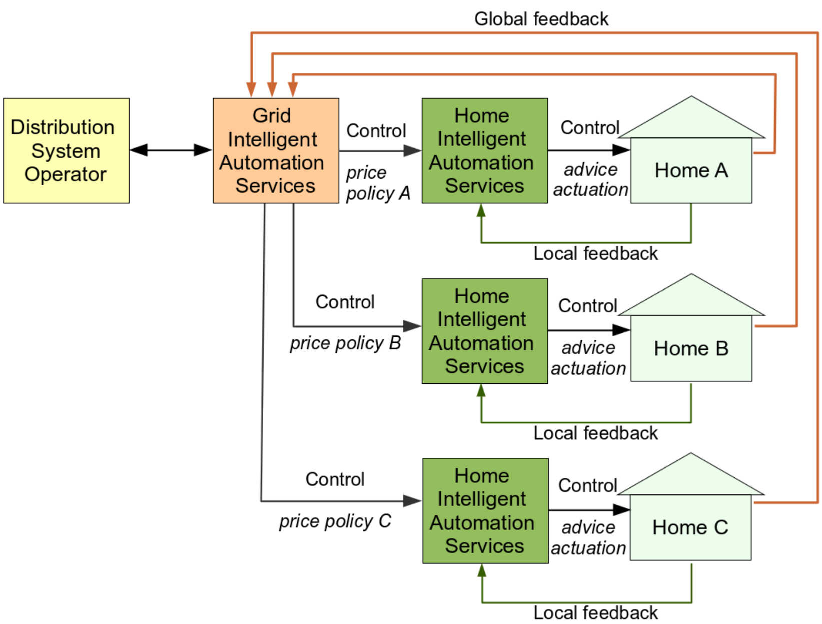


Figure 2.1: Functional schema of SmartHG IASs.

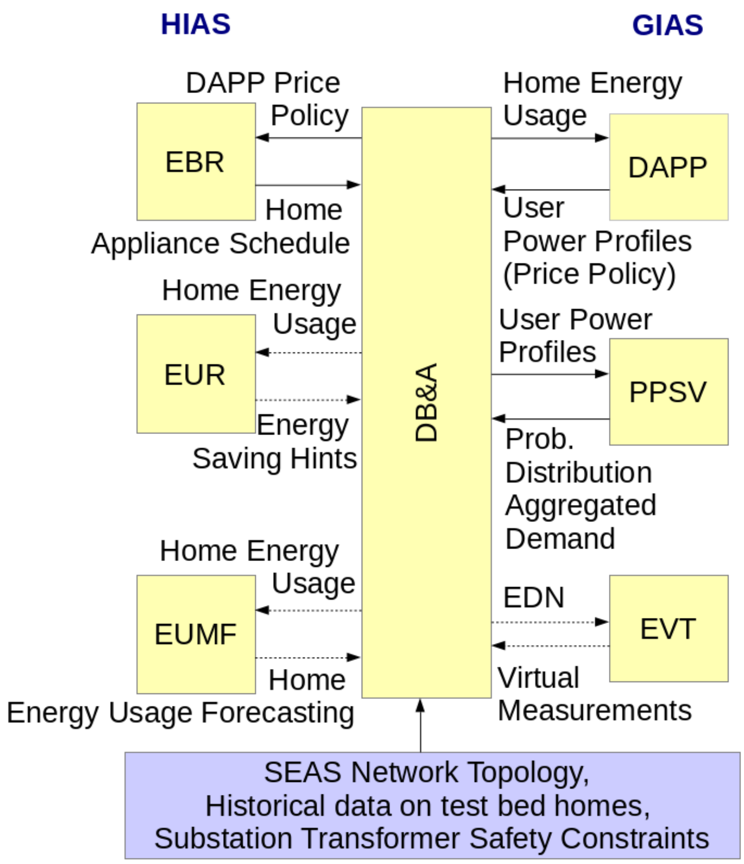


Figure 2.2: SmartHG IASs architecture.

of it.

SmartHG Grid Services (GIASs) comprise the following services: EVT, DAPP, PPSV, DB&A. DB&A and PPSV have been evaluated in a stand-alone fashion in our second year evaluation. PPSV is an ancillary service used by DAPP to verify robustness of the solution proposed. DB&A is part of the communication infrastructure and is thus used, basically, by all services. Again, since this year we are focusing on evaluation of SmartHG Platform as a whole, we will focus, as for SmartHG Grid Services, on EVT and DAPP.

2.1 Objectives

Our main goal in this final evaluation activity is to assess how the whole SmartHG Platform (i.e., all services cooperating together) addresses the project objectives:

1. Support the Distribution System Operator (DSO) in optimising Electric Distribution Network (EDN) operations;
2. Reduce energy costs for residential users;
3. Reduce CO2 emissions.

2.2 Main Achievements

In the project third year we extended our second year scenarios with data from new sensors in Kalundborg and Central District as well as with historical data from our Minsk test-bed. Using such data, our third year evaluation shows the following.

The benefits provided by SmartHG individualised price policy technology to the Electric Distribution Network (EDN), and thus to the Distribution System Operator (DSO), are:

1. Increase of the *demand load factor* of more than 18% with respect to a flat price policy and of more than 35% with respect to to a global price policy (because of *rebounds*), thereby providing a *peak shaving* effect considerably better than the one offered by a *global* price policy;

2. Reduction of low-voltage violations in the grid;

3. Reduction of network line thermal MVA limit violations;

4. Resuction of network line losses (e.g., of about 2% with respect to a global price policy).

SmartHG provides electricity retailers with the possibility of effectively exploiting distributed home energy storage to buy energy when its price is low in the day-ahead market (*arbitrage*). When only a Plug-in Electric Vehicle (PEV) is present the energy cost saving ranges from 7% (Kalundborg test-bed) to 13% (Minsk test-bed). Finally, when both a PEV and a home battery are present the energy cost saving ranges from 11% (Central District test-bed) to 19% (Kalundborg test-bed). Such results show that, as a side effect, SmartHG technology fosters PEV uptake by enabling residential user to exploit their PEV to save on energy cost.

Finally, SmartHG can bring benefits also to the environment, by allowing electricity retailers to buy energy when its CO2 footprint is small. When only a PEV is present CO2 emissions reduction ranges from 7% (Kalundborg test-bed) to 13% (Minsk test-bed). Finally, when both a PEV and a home battery are present CO2 emissions reduction ranges from 12% (Central District test-bed) to 15% (Kalundborg test-bed).

2.3 Outline

This deliverable is organised as follows.

Chapter 3 outlines our evaluation results as for using SmartHG services to support the Distribution System Operator (DSO) in optimising operation of the Electric Distribution Network (EDN).

Chapter 4 outlines our evaluation results as for using SmartHG services to support electricity retailers and residential users in reducing electrical energy cost and CO2 emissions.

Finally, Table 2.1 maps SmartHG WP5 tasks to sections of this deliverable.

Task	Task Name	Sections
T5.1	Evaluation of EUMF service	Chapter 4
T5.2	Evaluation of EBR service	Chapter 4
T5.3	Evaluation of EUR service	Chapter 4
T5.4	Evaluation of DAPP service	Chapter 3
T5.5	Evaluation of EVT service	Chapter 3
T5.6	Evaluation of PPSV service	Chapter 3
T5.7	Evaluation of DB&A service	Chapter 3

Table 2.1: Mapping between SmartHG WP5 tasks and sections of this document.

Chapter 3

Optimising EDN Operations

The main goal of SmartHG Grid Services is to optimise EDN operations as described below.

First, supporting the DSO in computing a *power profile* (i.e., lower and upper limits to the average power in each 1-hour time slot) for any EDN substation, so that operation of the whole EDN is optimised.

Second, supporting the DSO in computing an *individualised price policy* (defined using a *power profile*) for each residential user, so that in each time slot the aggregated demand of all users connected to the given substation is within the substation power profile computed above.

In this section we outline the benefits provided by SmartHG to the EDN, whereas the following sections will focus on the economic benefits provided to electricity retailers and residential users as well as on the environmental benefits (as CO2 emissions reduction) provided to the society as a whole.

3.1 Introduction

Distribution networks have traditionally been designed as unidirectional links between transmission network bulk supply points and end-users. Typically they have been operated as passive systems, in which power flows are relatively easy to predict and manage. Recently, distribution networks have seen increasing penetrations of Distributed Energy Resources (DER), such as small to medium-sized Distributed Generation (DG), demand-responsive loads, electric vehicles, devices with storage capability, and microgrids.

All relevant studies suggest that such trends towards more actively-managed distribution systems are set to continue, and that the integration of these technologies will lead to more frequent occurrences of problems in the distribution network, such as congestions and excessive voltage variations [1, 2]. This has led to interest in adapting network management techniques, previously only used at the transmission level to distribution systems, such as state estimation and short-term operational planning [3, 4, 5, 6].

Given this context, EDN Virtual Tomography (EVT) activities have focused on developing services and tools aimed at assisting the network operator (Distribution System Operator (DSO)) in the operation and management of active distribution networks. In most Electric Distribution Networks (EDNs), only few measurements are taken due to technical or economic limitations. This scarcity of measurements leads to a lack of situational awareness which complicates proper supervision and control of the EDN. However, detailed simulation models can be used to estimate current, voltages and other physical variables in the network. State Estimation (SE) has already been employed in many transmission networks, but is rarely used in distribution networks. The employment of estimators helps to get valuable information even from locations without sensors. The use of virtual sensors in form of estimators allows a closer supervision and control of the EDN. The main goal of this service is to estimate the grid state, generate warnings and alarms when the physical variables exceed certain limits and give recommendations to avoid the detected problems. A significant amount of work was carried out in improving the performance and reliability of this service, making the SE robust to noise and bad data in the input measurements, and developing algorithms which would allow the DSO to predict potential technical problems in the EDN and suggest appropriate corrective actions.

3.1.1 Objectives

The main objectives for the third year were to improve upon several aspects of the EVT service developed in years 1 and 2, to better integrate the EVT the other Grid Intelligent Automation Service (GIAS) services, and to demonstrate the potential benefits of these services to the DSO.

Several aspects of the EVT service were investigated further, with the following specific aims:

- To develop suitable demand forecasting techniques to support the EVT service in the generation of intelligent warnings, alarms and recommendations for the DSO;
- To improve the algorithms for bad input data detection and increase the robustness of the Distribution System State Estimation (DSSE) solver so that it can function correctly even in the presence of noisy or missing input data.;
- To integrate the EVT service more closely with the other GIAS services, namely Demand Aware Price Policies (DAPP) and Price Policy Safety Verification (PPSV);
- To demonstrate, where possible, the benefits of these services to the DSO, using data from the SmartHG test site electricity networks.

3.1.2 Achievements

The main achievements of the third year are as follows:

- We developed demand forecasting models to support advanced EVT service functions, such as the generation of intelligent warnings, alarms and recommendations for the DSO, and implemented several improvements to the DSSE algorithms to improve the robustness and accuracy of the estimator;
- We developed a number of scenarios designed to demonstrate the benefits of EVT and other GIAS services to the DSO;
- We designed models for the interaction of EVT with the other GIAS services and the Database Service (DBService), and proposed a suitable Common Information

Model (CIM) for the communication between EVT service and the DSO network monitoring and control systems;

- We published a number of journal and conference papers from this work, including two international journal papers (one published and one in review) and four international conference papers. In addition, a joint journal publication is in preparation which aims to demonstrate the benefits of the GIAS services to the DSO.

3.1.3 Outline

Section 3.2 discusses the evaluation of the advanced EVT functions developed in the third year, including the demand forecasting and DSSE. Section 3.3 discusses the evaluation of the EVT services in the context of the rest of the GIAS services, and several scenarios used for demonstrating the potential benefits of GIAS to the DSO.

3.2 Evaluation of Advanced EVT Functions

In this section we outline the main results from the evaluation of advanced EDN Virtual Tomography (EVT) functions, namely: Demand Forecasting (Section 3.2.1) and Advanced Distribution System State Estimation (DSSE) Functions (Section 3.2.2).

3.2.1 Evaluation of Demand Forecasting Approaches

The following presents results which evaluate the performance of the short-term demand forecasting, which is used to support the EVT service. The Non-linear Auto-Regressive eXogenous (NARX) model was selected, since it provided the best results for short-term forecasting (e.g.,, forecasting from several hours to a few days ahead) of substation-level demands.

An important aspect of this work was to quantify the level of uncertainty which could be expected in this forecasting, since this has important implications for the the EVT, in terms of its ability to provide load estimates to support the DSSE, and to accurately predict network issues and generate suitable alarms, warnings and recommendations for the Distribution System Operator (DSO).

3.2.1.1 Evaluation of NARX Forecasting Model

The results in Figure 3.1 provide the *mean* prediction errors at each level of aggregation. In order to provide results illustrating the *distribution* of the load forecasting error, boxplots of the prediction errors are given for each month of the year for the Kalundborg test site, Figure 3.2. The results show that at all levels of aggregation the prediction accuracy is relatively consistent across the year, but with slightly higher forecast errors in the summer (low demand) months. It is also clear that at the Low Voltage (LV) feeder and individual user level the errors are much more widely distributed, with large outlier values occurring, Figure 3.2.

3.2.1.2 Variation of Errors with Forecasting Horizon

The forecasting errors obtained vary according to the forecasting horizon used in the model. The demand prediction is made using the NARX model and the forecasting

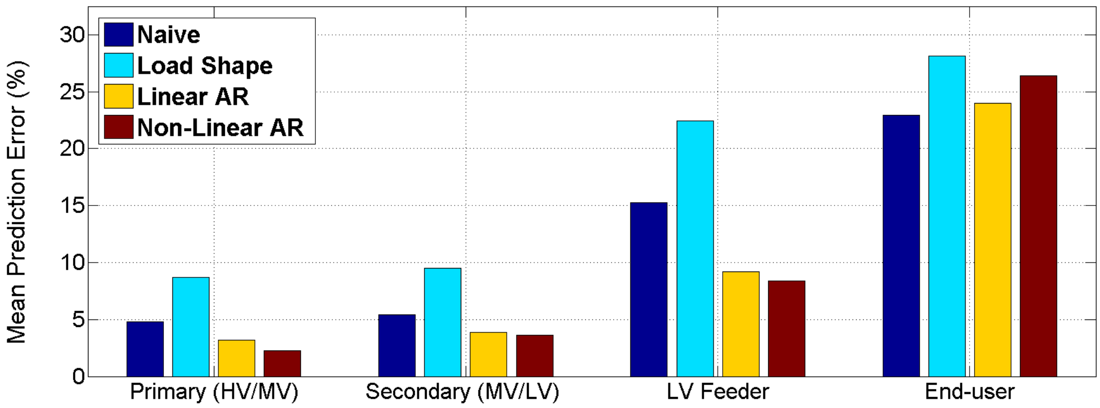


Figure 3.1: Comparison of demand forecasting model mean prediction errors, at various levels of load aggregation: (i): Primary HV/MV substations (hundreds to thousands of customers); (ii) Secondary MV/LV substations (few hundreds of customers); (iii) LV feeder level (few to tens of customers); (iv) End-user level (single customer).

horizon h is varied from 1 hour ahead to 48 hours ahead. In addition to providing a point estimate of the predicted demand at each time instance, a probabilistic estimate is made, which takes into account the historical error distribution of the demand forecasting. The demand forecasting error vector at forecasting horizon h is given by:

$$\mathbf{e}_h = A_t - F_t \qquad for \;\; t = 1, 2, ..., T \tag{3.1}$$

where T is the total number of available actual and forecasted data points in the data set. This demand forecasting error varies according to the demand forecasting horizon. In order to create confidence intervals for each forecasting horizon from 1 hour ahead to 48 hours ahead, the *percentile errors* for each error vector $\mathbf{e}_1$ to $\mathbf{e}_{48}$ are calculated. For example, the 90% confidence interval for a single point demand forecast at 48 hours ahead y_{t48} is given by:

$$C_{90} = -\pi_{95} \leq \mathbf{e}_{48} \leq \pi_{95} \tag{3.2}$$

where π_{95} is the 95^{th} percentile of $\mathbf{e}_{48}$. The advantage of using a non-parametric approach with percentiles is that the method is independent of the probability distribution of the demand forecasting errors. A sample of the results at the secondary (MV/LV) substation level are shown in Figure 3.3 for the Kalundborg test site data set.

3.2.1.3 Discussion

These results validate the performance of the selected short-term demand forecasting model using data from the Kalundborg test site. There is a clear trend in the results showing a decrease in accuracy at the lower levels of demand aggregation, as expected, since at lower levels of aggregation the demand profiles are more volatile. However, it is shown that, with appropriate forecasting techniques, good accuracy (< 5% Mean Absolute Percentage Error (MAPE)) can be achieved at the primary and secondary substations. This work was important in defining the limitations and the expected levels of accuracy of the demand forecasting.

There are important implications for both the DSSE and the generation of alarms, warnings and recommendations in the EVT service. In an Electric Distribution Network

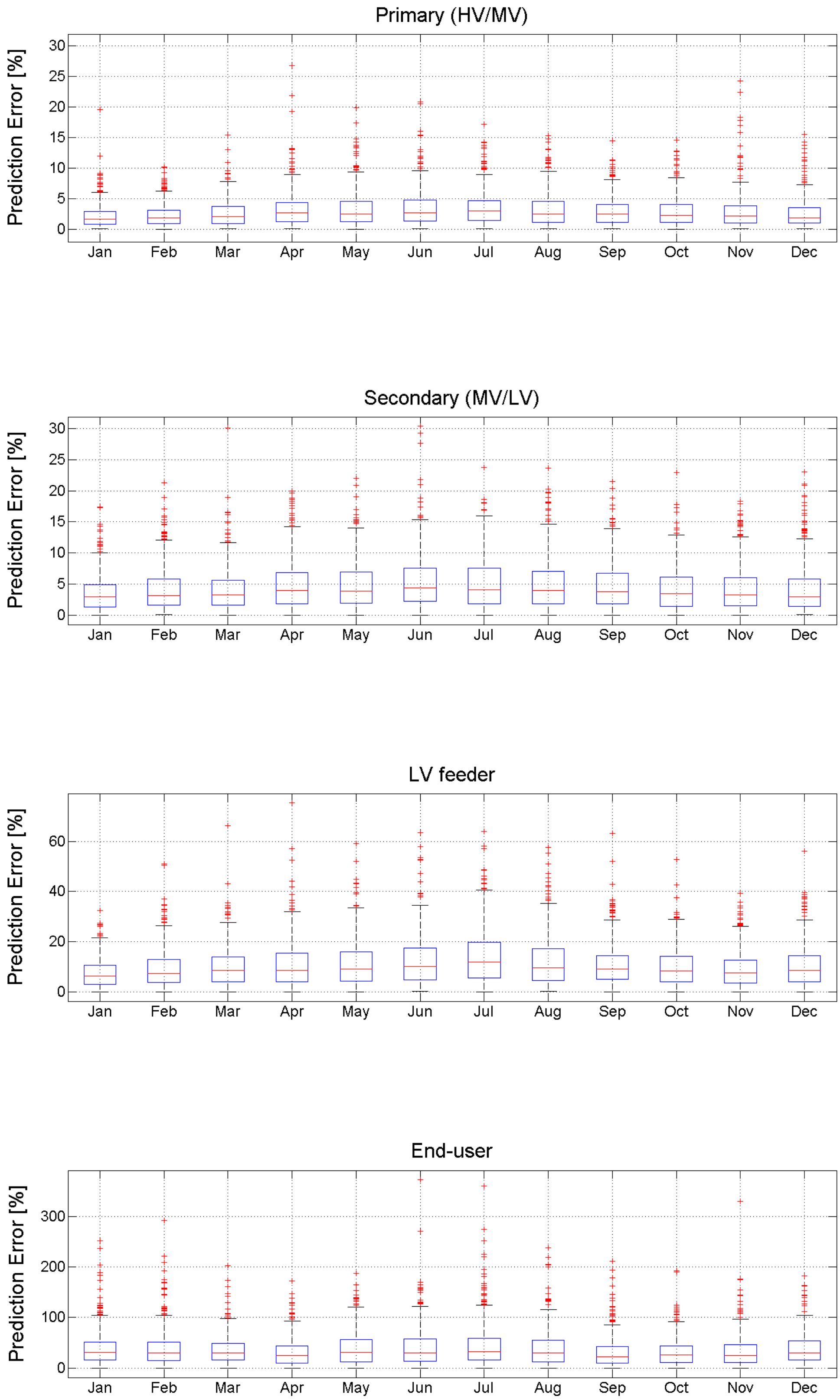


Figure 3.2: STLF error boxplots by month, using NARX model at each level of aggregation: primary substation; secondary substation; LV feeder; individual user. Outlier values are indicated by crosses (+).

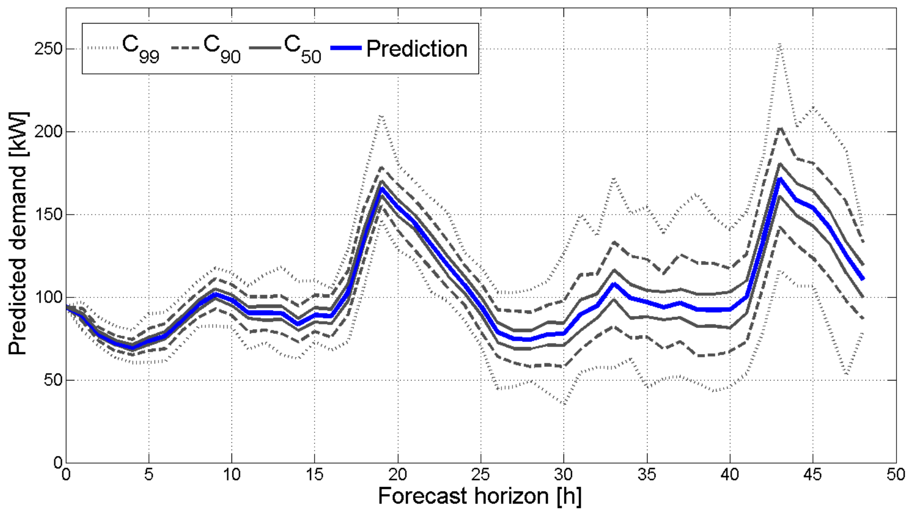


Figure 3.3: Load forecasting at the secondary (MV/LV) substation level, where the forecasting horizon is varied from 1 hour ahead to 48 hours ahead. Confidence intervals are shown at 50% (solid lines), 90% (dashed lines), and 99% (dotted lines).

(EDN), where the number of direct measurements from the network is typically very limited, the DSSE depends on load estimates, i.e., forecasts of the demand at substations to fill in for missing, delayed, and/or bad data in the input measurement data set. The Weighted Least Squares - Robust (WLS-R) estimator was capable of tolerating noise levels of 15–20%, which is with the limits of the demand forecasting capabilities.

The demand forecasting is also very important in supporting the EVT in generating advice and recommendations for the DSO. With accurate predictions of the demand at each EDN substation in the short-term, it is possible for the EVT to correctly identify constraints and congestions in the network, simulate various potential solutions, and advise the DSO accordingly. Some examples of this are provided in Section 3.3.1.

3.2.2 Evaluation of Advanced DSSE Functions

We outlined an approach to link the demand forecasting and the State Estimation (SE) solver algorithm to create a closed-loop DSSE. This is particularly useful for distribution networks, which typically have a limited quality and quantity of real-time measurements provided to the DSO by the EDN telemetry system. The demand forecasting at each substation provides the DSSE with estimates, or *pseudo-measurements* of the power injections in the network, which can be used to supplement real measurements (e.g., from Supervisory Control And Data Acquisition (SCADA)), and replace bad, missing and/or delayed measurements from the EDN. It has been shown in [7] that this can improve the DSO's observability and situational awareness in the EDN. Some results illustrating the closed-loop DSSE approach, using data from the Kalundborg test site are given below.

3.2.2.1 Metering and Communication Errors

The following results show the response of the DSSEto a monitoring issue which occurred in the Kalundborg test network at one individual MV node. Figure 3.4 shows a sample of

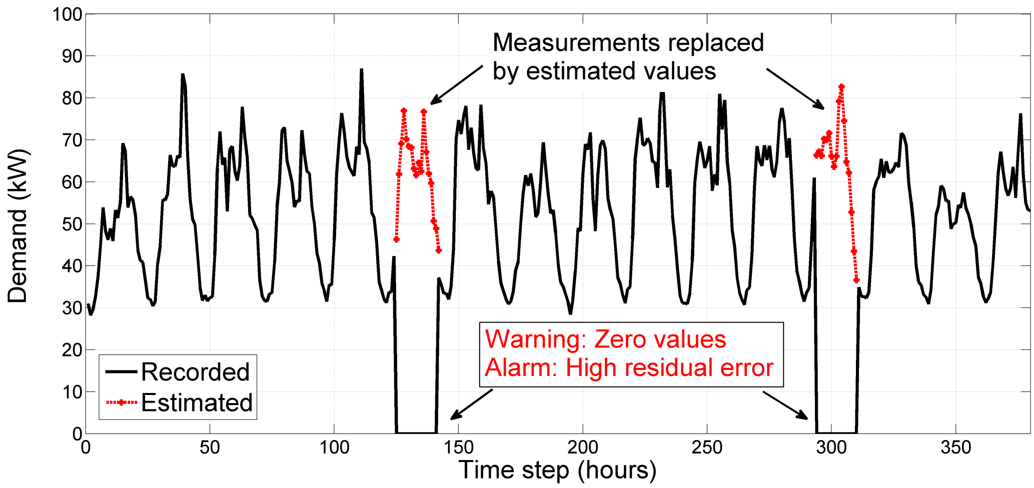


Figure 3.4: Example showing DSSE response to intermittent monitoring issue.

the active power demand measurement at one MV node, where there is an intermittent issue with the monitoring system that results in the input measurements equalling zero at certain times. It is likely that this issue was caused by a temporary metering or communication system failure at this node. This analysis provides a means for highlighting suspect or erroneous values, and replacing these with high-quality estimated values.

When the monitoring error occurs, the DSSE issues a “warning” to the network operator, notifying that zero values have occurred in the input measurement data, and also an “alarm” for high residual error values at this node, indicating a gross error in the input data. The bad input data are detected by the DSSE, and replaced with estimated values from the load estimator, Figure 3.4. This ensures that gross input data errors do not have a significant impact on the DSSE calculation.

3.2.2.2 Simulation of Closed-Loop DSSE Tool

The overall performance of the closed-loop DSSE tool was evaluated by carrying out a simulation on the Kalundborg EDN. The results are compared below for two simulation cases:

- **Case (i):** The network state (e.g., voltages, active/reactive power flows) is estimated using power injections calculated from a NAIVE demand model, where the DSSE load estimates are based on the corresponding hour of the previous day. No feedback loop is applied in this case.

- **Case (ii)** The network state is calculated using load estimates from the NARX model, applying feedback to the DSSE.

In each case, the performance of the tool is measured by comparing the accuracy of the *estimated* day-ahead network voltages and active/reactive power flows, with the “actual" values for the network state, once the measurements at all MV nodes throughout the network have become available from the smart metering system. The simulation was run over a time period of approximately 4 months. Figure 3.5 shows some samples of time series of the output obtained from the simulation, illustrating the maximum absolute

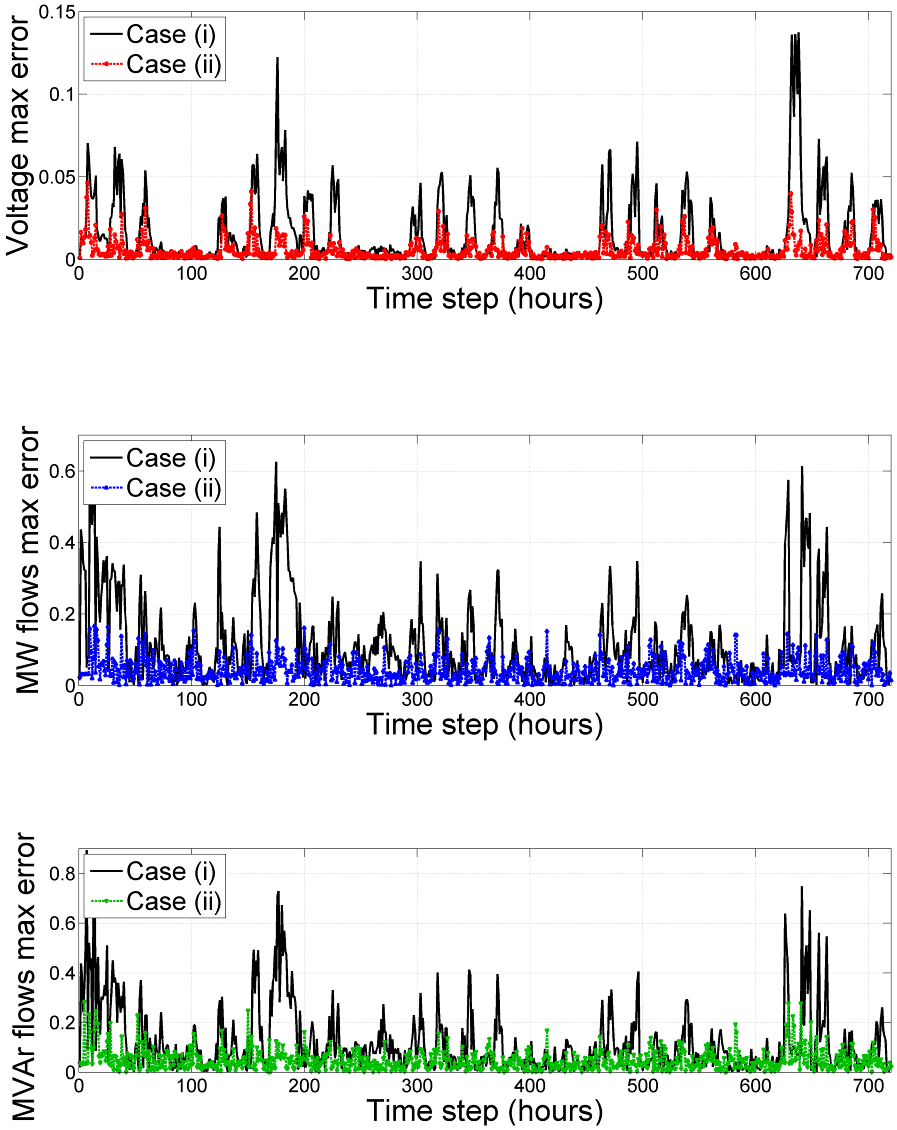


Figure 3.5: Sample showing maximum absolute percentage errors from DSSE: system voltages; system active power flows; system reactive power flows.

percentage errors for per unit voltages and MV/MVAr flows (considering all buses and lines in the MV network).

The mean and maximum absolute percentage errors obtained over the entire simulation period are summarised in Table 3.1. The results illustrate the importance of providing accurate load estimates to the DSSE. The absolute percentage errors in Case (i) are significantly larger, with mean voltage errors around 1% and mean MW/MVAr flow errors of 7%. However, it is shown that the maximum errors which occurred in Case (i) can reach 60–90% (column 3, Table 3.1), which is clearly unacceptable for any practical application. In Case (ii), the mean errors are relatively low (0.3% for voltage and 3-3.5% for MW/MVAr flows), and the maximum errors obtained are in a more acceptable range (6-28%, column 5, Table 3.1).

	Case (i) mean error (%)	Case (i) max error (%)	Case (ii) mean error (%)	Case (ii) max error (%)
Voltages	0.9	14.6	0.3	6.6
MW flows	7.0	62.9	3.1	16.7
MVAr flows	6.9	89.5	3.4	28.3

Table 3.1: Summary of results from closed-loop DSSE tool simulation.

3.2.2.3 Computational Requirements and Practical Considerations

Most of the computational effort in the proposed approach is required in the initial model development stage, where the NARX estimation models for each network node are created. The NARX model training time (which includes validation check of the trained model) averaged 1.3 seconds for each MV network node. For the entire MV network considered (approximately 1600 customers in total, located at 46 MV nodes) the total NARX training time required was 59.8 seconds. However, it is expected that this work can be carried out off-line. Once the NARX models at each MV node have been trained, they are only re-trained/updated when there is a significant change in the baseline performance of the load estimation model. In the presented analysis, the re-training frequency is limited to 30 days. In practice, most MV nodes will have a lower re-training frequency (e.g., 1 or 2 re-trains per year).

The other parts of the methodology are much less computationally expensive than the NARX model training. The WLS-R solver takes on average 0.15 seconds to complete for the entire network, including the time taken to read the input data and output the SE results. All of these computation times are based on running MatLab on a standard PC. This is expected to be within the capabilities of practical distribution utilities, even for much larger networks than the Kalundborg test site EDN.

3.3 Integration of GIAS Services and Scenarios for Final Evaluation

The following section discusses the evaluation of the EDN Virtual Tomography (EVT) services in the context of the rest of the Grid Intelligent Automation Service (GIAS) services, and several scenarios used for demonstrating the potential benefits of GIAS to the Distribution System Operator (DSO).

3.3.1 Proposed Service Architecture and Previous EVT Evaluation

The proposed architecture for the GIAS services is illustrated in Figure 3.6, taken from [8]. The main role of the EVT is to use all of the available measurements and sensor data from the Electric Distribution Network (EDN) provide an accurate estimate of the system state. This is designed to improve the DSOs visibility of the Medium Voltage (MV) part of the network, through providing “virtual" measurements even in parts of the network where

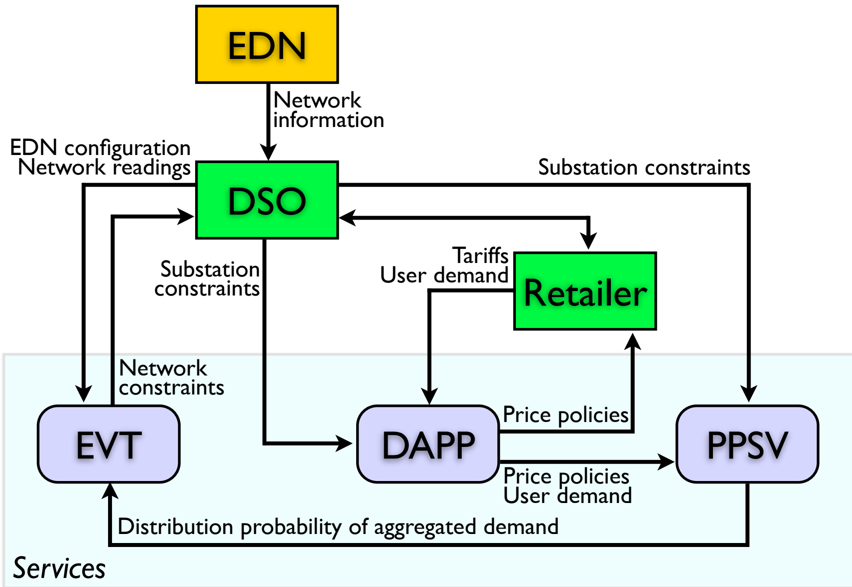


Figure 3.6: Proposed GIAS architecture [8].

no sensor data is available. This is achieved through computer modelling of EDN and using the forecasting and state estimation techniques outlined in Sections 3.2.1 and 3.2.2.

The EVT is also used to support the other GIAS services by computing the EDN operational constraints, which are a required input to the Demand Aware Price Policies (DAPP) service, and by verifying (in combination with the Price Policy Safety Verification (PPSV) service) that the proposed price policies do not cause adverse effects in the EDN.

Previous evaluation of the EVT in the second year demonstrated the key functions of the EVT service using the Kalundborg test network. One of the scenarios simulated demonstrated a low voltage issue at the most electrically distant part of the Kalundborg network (Logtved). According to the EU standards for public distribution systems (EN50160 and EN61000), voltage magnitude limits throughout all points in the Low Voltage (LV) and MV networks should remain within ±10% of nominal (taken as 10 min average of the Root Mean Square (RMS) voltage). There are also other specific limits around temporary under- and over-voltages that are not considered here.

Due to the fact that there may be considerable voltage drop along LV feeders, particularly on long lines in rural areas, the DSO may wish to tighten the limits at the feeder head, or secondary (10:0.4kV) substation to e.g. ±3%, since voltage is generally worse at the feeder extremities. In general, the DSO will set nominal voltages higher than $1.0 p.u.$ particularly at full-load, in order to provide more headroom for voltage drop and to reduce network RI^2 losses. In this example, the primary substation voltage set-point is $V = 1.02 p.u.$ and tap ratio is 1.0125 (+2 taps).

Figure 3.7 shows the PowerWorld Simulator output for the above described scenario, where low voltages occur in parts of the network which are further from the primary substation. The warnings/alarms and corrective actions generated by the EVT are given below:

- **Warning/alarm**: Voltage below $0.97 p.u.$ at Bus 46, Bus 47 and Bus 48.
- **Recommendation**: Adjust transformer taps at primary transformer (50:10kV) by +2 ($2 * 0.00625$) to increase voltage throughout the network.

Figure 3.8 shows the PowerWorld Simulator output for the above described scenario, after the corrective action recommended by EVT has been taken, where the voltage has reached a normal level throughout the system.

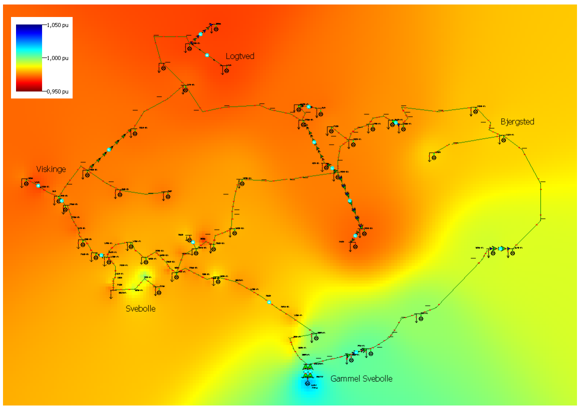


Figure 3.7: EVT technical evaluation: before corrective actions on Kalundborg scenario.

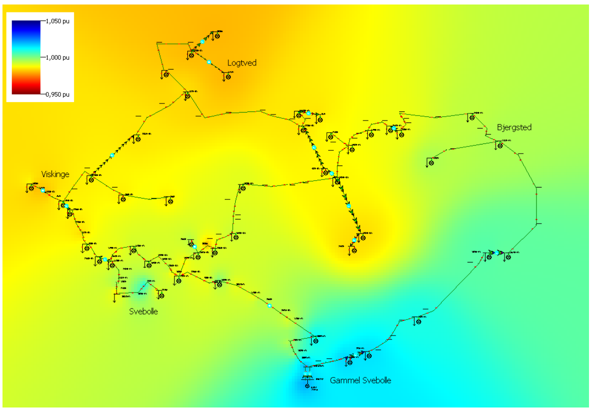


Figure 3.8: EVT technical evaluation: after corrective actions on Kalundborg scenario.

3.3.2 Demonstrating the Benefits of GIAS Services to DSO

In order to show the applicability of the GIAS services introduced in SmartHG, and to demonstrate the benefits of these services to the DSO, several evaluation scenarios have been developed in the third year. One of the unique aspects of the approach introduced in the SmartHG project is that the price policies are "individualised", e.g., each individual user receives a separate electricity pricing scheme designed to incetivise demand management in order to optimally manage flexible demands. These pricing schemes (see DAPP service for details) are designed to achieve several objectives, with the primary objective to reduce the peaks in overall EDN demand (with obvious benefits for the network and DSO). This is achieved in such a way that the average electricity price each individual user receives is fair and non-discriminatory, and the pricing policy is designed to shape the demand without reducing the overall demand volume, which is undesirable from the DSOs point of view.

One of the drawbacks of traditional approaches to Demand Side Management (DSM), where all users are subject to the same price (i.e., a "global" price policy), is the peak-shifting schemes may result in undesirable "rebound" effects, e.g., simply shifting the demand peaks from the peak hour to the off-peak hours, and creating new demand peaks. An example of the rebound effect is shown below, using real data from a SEAS-NVE study carried out on residential DSM [9]. In this study, residential users were given a time-varying price policy with three distinct pricing periods, designed to test the flexibility of residential demand to economic peak-shifting incentives, Figure 3.9. The prices provided strong incentives to shift residential electricity consumption from the peak "cooking" hours (17:00-20:00) to the night period (20:00-06:00), where the price is zero. The values are provided below in Danish Krone (DKK):

- **Day:** 1.50 DKK / kWh (06:00-17:00)
- **Peak:** 8.00 DKK / kWh (17:00-20:00)
- **Night:** 0.00 DKK / kWh (20:00-06:00)

The above price policy was applied to a "Test group" of 350 households, with a "Reference group" of 349 households receiving a fixed price of 2.25 DKK / kWh at all hours during the day (as per the standard residential pricing scheme currently used in the SEAS-NVE networks). The study was carried out over a full year from 1 October 2013 to 30 September 2014. The results of this study showed that with these price incentives, a significant amount of residential demand (up to 19%) was shifted away from the peak hours, compared to the reference group. The price incentives had little effect on the overall demand consumption, i.e. the total volume of consumption remained almost constant, only the times at which consumption occurred was changed by the pricing scheme.

Figure 3.10 shows a sample of the results from the SEAS-NVE study [9] for the month January 2014. All months of the year showed a similar pattern, but the amount of demand shift from the peak hour was largest during the winter months. Moving demand from peak hours to off-peak hours is typically a primary objective of DSM schemes.

However, the results in Figure 3.10 are a good example of the "rebound" effects which can result from global time-varying price policies. There is a significant increase in demand at the beginning of the off-peak period for the "Test group", and this pricing scheme has created a new demand peak at 21:00, which is slightly large than the demand peak in the "Reference group", Figure 3.10. These effects are undesirable, since typical DSM

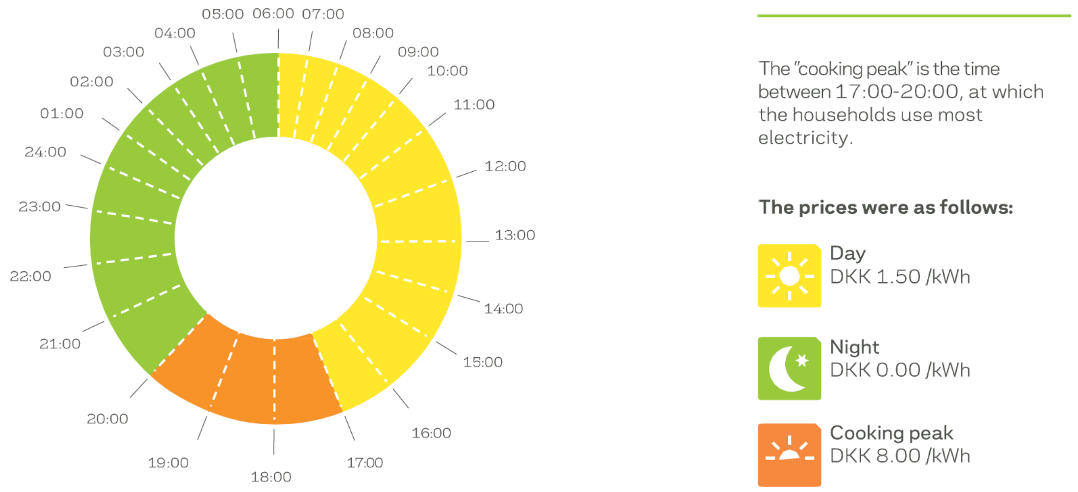


Figure 3.9: Price policy applied in SEAS-NVE residential demand flexibility study [9].

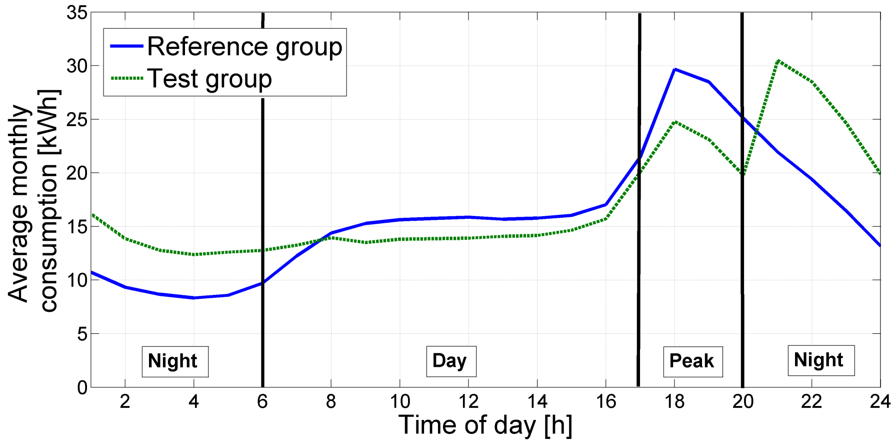


Figure 3.10: Sample of the results from the SEAS-NVE study, showing peak shifting in the Test group compared to the Reference group during January 2014 [9].

objectives are to smooth the load profile, increase the load factor, and reduce demand peaks, all of which have benefits for the EDN, such as improving the utilisation of network assets and potentially allowing the DSO to defer costly network upgrades.

An alternative solution is proposed in this work: to provide an "individualised" price policy using DAPP, which is designed to maximise the benefits of demand response actions for both the user and the DSO. Previous work in the second year of the project (e.g., [8] applied this approach at a single network substation. In the third year, the individualised price policies proposed in DAPP are tested using the entire MV network from the Kalundborg test site. The effects on network operation and the potential benefits to the DSO in using such an individualised price policy are to be evaluated using the scenarios presented in the following section.

3.3.2.1 Final Evaluation Scenarios

In order to evaluate the individualised price policy approach and the GIAS services introduced in SmartHG, and to demonstrate the potential benefits to the DSO, a number of scenarios were developed. These used recorded smart meter data from the Kalundborg test site, along with information from the SEAS-NVE demand flexibility study [9], and a Danish study on Electric Vehicle (EV) integration [10]. These scenarios apply both "global" and "individualised" price policies to each of the 1400 residential users connected to the Kalundborg MV network, and compare the results in terms of the ability of each Time of Usage (ToU) price policy to reduce demand peaks and improve the network load factor (e.g. the overall ratio of average demand to maximum demand).

It should be noted that even with very strong price ToU incentives for demand-shifting, such as those used in the SEAS-NVE study (Figure 3.9 and [9]), the amount of demand flexibility from residential users is limited.

However, two technologies which are expected to grow significantly and influence future electricity distribution networks, electricity storage and EVs, are also examined in the scenarios. Energy storage technologies offer much greater possibilities for shifting the electricity demand, and it is widely expected that the cost of such technologies will continue to decrease in the near future, making storage accessible to a wide range of users, including domestic consumers. In addition, Plug-in Electric Vehicle (PEV)s can significantly alter the demand profiles, and create significant congestions in the EDN if not managed appropriately.

Hence, scenarios have been developed in which the residential homes are equipped with batteries and PEVs, allowing us to examine potential future scenarios with greater user flexibility in response to ToU pricing. The final scenarios used in the analysis are provided below.

- **Base Case** The results calculated using the actual recorded data from the network for the two-year period from September 2012 to September 2014. All users received a fixed (i.e.,, flat) electricity price during this period.
- **Scenario 1a** All residential users in the case study network receive the same ToU price designed to shift demand away from the peak hours (e.g. a "global" price policy). Households do not have energy storage or PEV.
- **Scenario 1b** All residential users receive the individualised ToU price policy proposed by the DAPP service. Households do not have energy storage or PEV.
- **Scenario 2a** All residential users receive the same "global" ToU price policy designed to shift demand away from the peak hours. 50% of the households (randomly-selected) are equipped with both energy storage in the form of a Tesla PowerWall battery (with 7 kWh capacity and 2 kW power rate). and a PEV (with 16 kWh capacity and 13 kW power rate). The PEV data used in this study was taken from actual vehicle charging data from the "Test-an-EV" project [10].
- **Scenario 2b** All residential users receive the individualised ToU price policy proposed by the DAPP service. 50% of the households (randomly-selected) are equipped with both energy storage and a PEV as in Scenario 2a.

The results demonstrated that the use of global DSM price policies can cause synchronisation of user demand patterns, reducing load diversity and creating undesirable

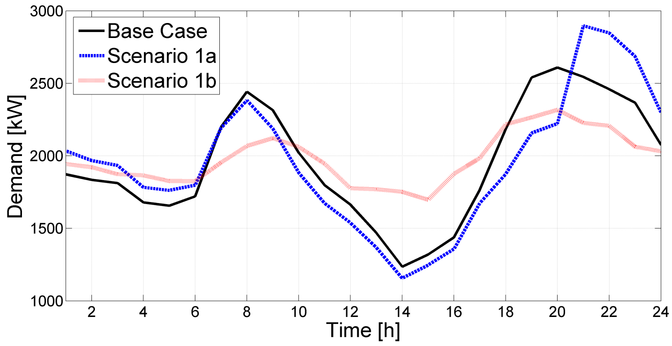


Figure 3.11: Scenario 1 - Time series of aggregate residential demand profiles showing Base Case, global price policy (Scenario 1a), and individualised price policy (Scenario 1b) for winter peak.

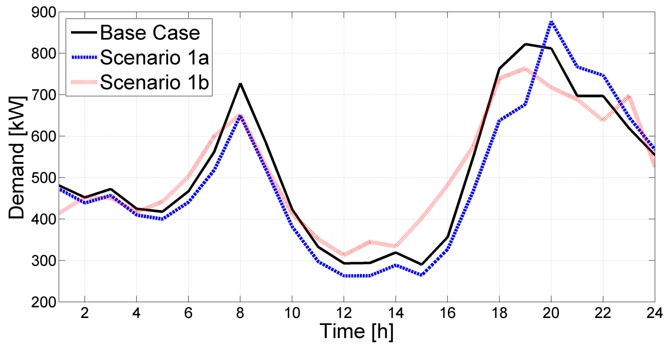


Figure 3.12: Scenario 1 - Time series of aggregate residential demand profiles showing Base Case, global price policy (Scenario 1a), and individualised price policy (Scenario 1b) for summer minimum.

"rebound" effects. It was shown that the individualised price policy approach proposed in SmartHG has several advantages over a global policy approach, in that it can reduce the magnitude of the demand peaks, and flatten the overall system demand profile. Some of the practical benefits of this are simulated in a distribution network operations context, where it was shown that the individualised price policy can increase the load factor, and improve voltage and line loading conditions, and reduce network losses, compared to a global DSM price signal.

3.3.2.1.1 Simulated Impact of Price Policies We describe the impact of individualised price policies on demand profiles, network voltages, network power flows, network line losses.

3.3.2.1.1.1 Impact on Demand Profiles This section shows the impact on load profiles at each substation calculated by simulation of each of the above scenarios. Figures 3.11 and 3.12 show a sample of the load profiles for the Base Case, Scenario 1a and Scenario 1b. These are shown for the winter peak and Summer minimum demand cases respectively.

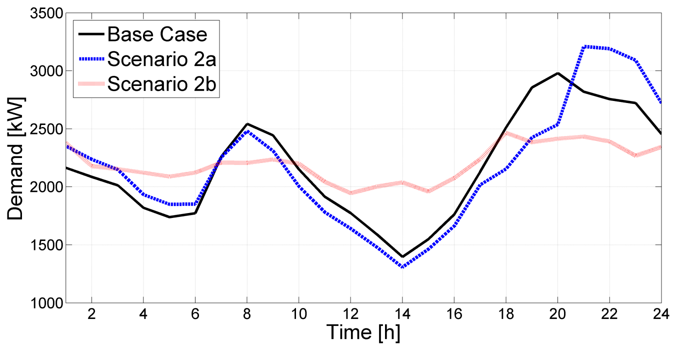


Figure 3.13: Scenario 2 - Time series of aggregate residential demand profiles showing Base Case, global price policy (Scenario 2a), and individualised price policy (Scenario 2b) for winter peak

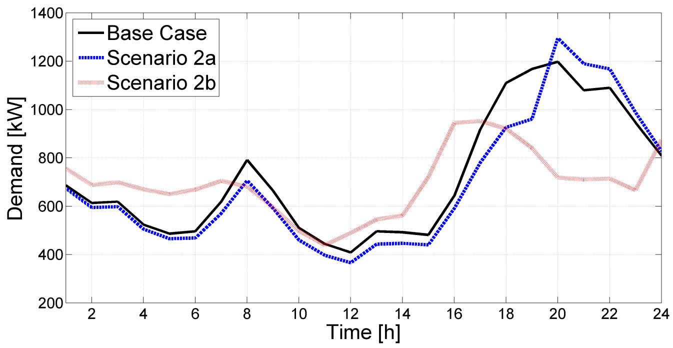


Figure 3.14: Scenario 2 - Time series of aggregate residential demand profiles showing Base Case, global price policy (Scenario 2a), and individualised price policy (Scenario 2b) for summer minimum.

It can be seen from Figures 3.11 and 3.12 that the global price policy (dashed line, Scenario 1a) results in a rebound demand peak similar to that recorded in Figure 3.10, Section 4.1 and [9]. For the individual price policy case (dotted line, Scenario 1b, Figure 3.12), the demand peaks are much reduced due to the effect of the DAPP algorithm. This significantly improves the load factor (the ratio of average to maximum load).

For Scenario 2 (Figures 3.13–3.14), the overall demand is increased due to the influence of PEV load, with larger peaks in the evening hours. The global price policy results show a large demand rebound at hours 20:00 – 22:00 (dashed lines, Scenario 2a). The proposed individual price policy results in a much flatter demand profile (dotted lines, Scenario 2b in Figure 3.12).

The aggregate load factors, calculated across all residential customers, are provided in Tables 3.3 and 3.4. These were calculated for typical "Winter peak" and "Summer minimum" days, and also for the "overall" case, which calculates the total load factor over the two years of the simulation. These results reflect the pattern shown so far. The global price policy (Scenarios 1a and 2a) increases the magnitude of the demand peaks, reducing load factors, whereas the individualised price policy flattens the demand profiles and increases load factors (Scenarios 1b and 2b). The load factors in the "Overall" case (final rows of Tables 3.3 and 3.4 are much lower than the Winter peak/Summer minimum

Scenario	Price policy	PEV	Energy Storage System (ESS)
Base Case	flat rate	No	No
1a	global	No	No
1b	indiv	No	No
2a	global	50%	50%
2b	indiv	50%	50%

Table 3.2: Scenarios characteristics summary

Load Factor	Base Case	Scenario 1a	Scenario 1b
Winter Peak	0.7054	0.6164	0.8017
Summer Min	0.6205	0.5794	0.6257
Overall	0.3327	0.2897	0.3933

Table 3.3: Scenario 1 Aggregated Load Factors

Load Factor	Base Case	Scenario 2a	Scenario 2b
Winter Peak	0.7116	0.6176	0.8124
Summer Min	0.5927	0.5280	0.7038
Overall	0.3471	0.3084	0.4415

Table 3.4: Scenario 2 Aggregated Load Factors

day cases, since the “Overall” values represent the average load factor calculated over the entire two year period, considering all of the seasonal variations during this time.

This simulated increase in load factors due to the application of individualised price policies would have clear benefits for the DSO. This would reduce the amount of energy to be purchased from the wholesale market during expensive peak hours, and the flatter load profiles would result in less instances where network is overloaded, potentially reducing network maintenance and upgrade costs and allowing deferral of network investments. In the following section, some of the impacts of the proposed price policies on the distribution network operation are examined in more detail.

3.3.2.1.1.2 Impact on Network Voltages The minimum voltages which occur in the MV distribution network case study are shown in Figures 3.15 and 3.16 for Scenarios 1 and 2, respectively. These voltages are expressed in per unit on a 10kV base, and displayed sorted in descending order, for each of the 730 days considered. In this network, the only automatic means of voltage control is by on-load tap-changing transformer in the primary substation. The minimum allowed voltage “Voltage Limit” in Figures 3.15–3.16 is considered to be 0.97 p.u.[1]

[1]MV network voltage limits are set tighter than the typical statutory voltage limits of 1.1 – 0.9 p.u., since it is expected that there will be significant further voltage drops on the LV feeders downstream of the MV substations, particularly along the longer lines.

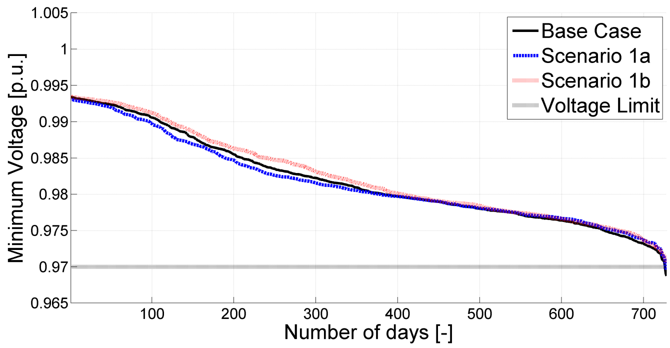


Figure 3.15: Daily minimum voltages for Scenario 1.

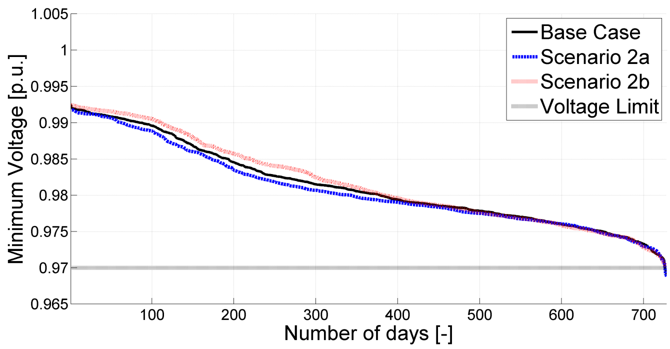


Figure 3.16: Daily minimum voltages for Scenario 2.

No. Low Voltages (> 0.97 $p.u.$)	Base Case	Global Price Policy	Individual Price Policy
Scenario 1	2	2	0
Scenario 2	2	2	0

Table 3.5: Summary of Low Voltage Violations.

Any voltages lower than 0.97 were recorded as voltage violations. High voltage events are not considered in the study, nor are events involving network faults and planned/unplanned outages, which would affect the voltage profiles. The voltage violations are summarised in Table 3.5. These results show that several voltage violations occur in both the Base Case and Scenario 1a and 2a (global price policy) cases. These low voltages occur during time of peak loading, in the parts of the network with the greatest electrical distance from the primary substation. In the individual price policy simulations, Scenario 1b and 2b, there were no violations, due to the reductions in peak loading.

3.3.2.2 Impact on Network Power Flows

The impacts on power flows throughout the MV network were also analysed. Figures 3.17-3.18 show the results for Scenarios 1 and 2, using the maximum thermal MVA flow expressed as a percentage of the line rating. The thermal MVA flow is calculated for all of

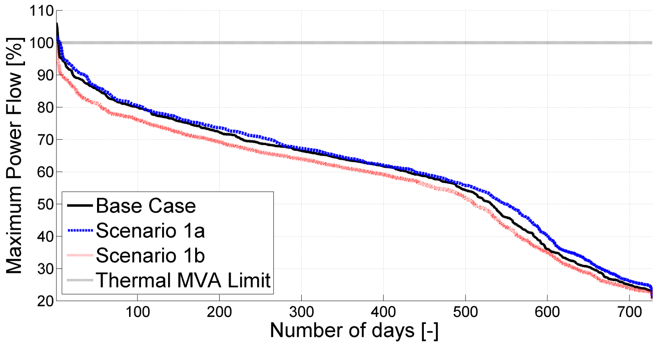


Figure 3.17: Daily maximum loading as a percentage of the line limits for Scenario 1.

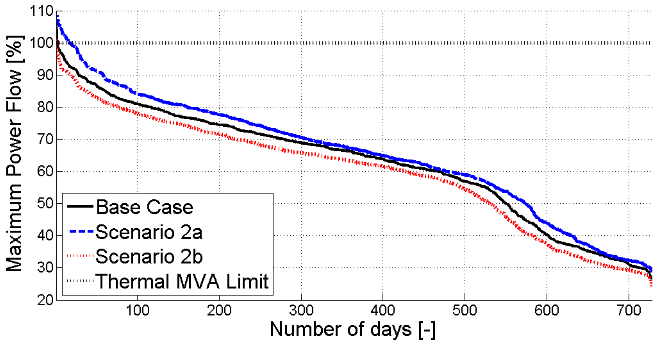


Figure 3.18: Daily maximum loading as a percentage of the line limits for Scenario 2.

No. Overloads (> 100 %)	Base Case	Global Price Policy	Individual Price Policy
Scenario 1	3	6	0
Scenario 2	3	18	2

Table 3.6: Summary of Line Thermal MVA Limit Violations

lines and transformers in the MV test case distribution network, and the maximum value value for each day in the 2-year period is shown. From both Figures 3.17 and 3.18, it is clear that the global price policy (Scenario 1a and 2a, dashed lines) results in heavier line loading values, whereas the individualised price policy (Scenario 1b and 2b, dotted lines) results in reduced line loading. This result is expected, since it is shown in Section 3.3.2.1.1.1 that the individualised price policy reduces the magnitude of the demand peaks and improves the load factor. Table 3.6 shows the results for the number of overloads (MVA flow > 100 % of line rating) in each case.

3.3.2.2.1 Impact on Network Line Losses The analysis of the total losses in the MV test case network showed some differences in network losses as a results of applying the global and individualised price policy scenarios:

- **Scenario 1**: Typical cumulative losses in the MV network are 142 MWh/year and 68 MVAr/year. The individualised price policy produced 1.5 – 1.6% lower line losses compared to the global price policy case.

- **Scenario 2**: Typical cumulative losses in the MV network 162 MWh/year and 78 MVAr/year. The individualised price policy had 2.2 – 2.3% lower line losses.

Chapter 4

Reducing Electricity Costs and CO2 Emissions

In this section we present (Low Voltage) substation level evaluation results on using SmartHG services to reduce energy cost and CO2 emissions.

4.1 Introduction

Economic viability of SmartHG Platform rests on its ability to provide value to the main actors involved. While Chapter 3 focused on showing how SmartHG Grid Services (EDN Virtual Tomography (EVT), Demand Aware Price Policies (DAPP), Price Policy Safety Verification (PPSV), Database and Analytics (DB&A)) can provide benefits to the Distribution System Operator (DSO) (by optimising Electric Distribution Network (EDN) operation), in this section we focus on showing how SmartHG Home Services (Energy Bill Reduction (EBR), Energy Usage Modelling and Forecasting (EUMF), Energy Usage Reduction (EUR)) along with DB&A can provide benefits to electricity retailers by reducing electricity cost and CO2 emissions.

We note that we envision a fully automated Demand Response (DR) approach, where home energy storage is used to modulate user demand towards the substation. Accordingly, SmartHG Home Services are needed even if we only aim at steering user demand to flatted the aggregated demand.

On the other hand, if our goal is only to reduce energy cost or CO2 emissions then we may just use SmartHG Home Services, along with DB&A running on the Home Energy Controlling Hub (HECH).

4.1.1 Objectives

Our main objectives are:

- To compare SmartHG distributed control approach with a centralised one (e.g., at substation level one) as for efficiency in exploiting the available battery capacity.
- To evaluate the energy cost reduction capability of SmartHG services.
- To evaluate the CO2 emissions reduction capability of SmartHG services.

4.1.2 Main Achievements

Our main achievements can be summarised as follows.

- The SmartHG hierarchical distributed control of energy storage is about as effective as a centralised control of the storage.
- The benefits provided by SmartHG to electricity retailers mainly consist in the possibility of effectively exploiting distributed home energy storage to buy energy when its price is low in the day-ahead market (*arbitrage*). When only a home battery is present the energy cost saving ranges from 3% (Minsk test-bed) to 13% (Kalundborg test-bed). When only a Plug-in Electric Vehicle (PEV) is present the energy cost saving ranges from 7% (Kalundborg test-bed) to 13% (Minsk test-bed). Finally, when both a PEV and a home battery are present the energy cost saving ranges from 11% (Central District test-bed) to 19% (Kalundborg test-bed). Such results show that, as a side effect, SmartHG technology fosters PEV uptake by enabling residential user to exploit their PEV to save on energy cost.
- SmartHG can bring benefits also to the environment, by allowing electricity retailers to buy energy when its CO2 footprint is small. When only a home battery is present CO2 emissions reduction ranges from 3% (Minsk test-bed) to 8% (Kalundborg test-bed). When only a PEV is present CO2 emissions reduction ranges from 7% (Kalundborg test-bed) to 13% (Minsk test-bed). Finally, when both a PEV and a home battery are present CO2 emissions reduction ranges from 12% (Central District test-bed) to 15% (Kalundborg test-bed).

4.1.3 Outline

The scenarios we will be considering are outlined in Section 4.2.

We then present (Low Voltage) substation level evaluation results on using SmartHG services to reduce: residential user demand peaks (Section 4.3), electrical energy costs (Section 4.4), CO2 emissions (Section 4.5).

Finally, Section 4.6 presents results on combining such possibly conflicting objectives.

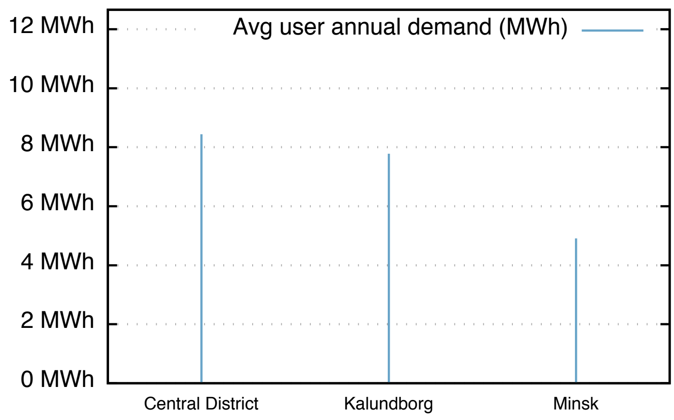
4.2 Evaluation Scenarios

In this section we describe the scenarios we will use to evaluate reduction of energy cost and of CO2 emissions enabled by SmartHG services.

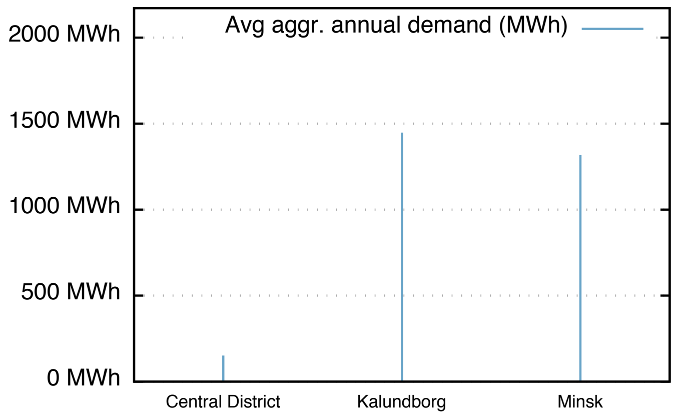
4.2.1 Test Beds

We consider three test beds: Kalundborg, Central District and Minsk, consisting of, respectively, 18, 186 and 268 households.

We add, to the electricity demand of each home, the electricity consumption due to one of the Plug-in Electric Vehicles (PEVs) from the data gathered through the Danish project *Test-an-EV* (https://www.clever.dk/test-en-elbil). The resulting average annual electricity demand (in MWh) in each test bed is shown in Figure 4.1a. For example, from



(a) Average annual demand in MWh of households.



(b) Aggregate annual demand in MWh.

Figure 4.1: Annual electricity demand in our test beds.

Figure 4.1a we see that the average home in our Kalundobrg test bed consumes about 7.78 MWh per year. Figure 4.1b shows, for each test bed, the aggregate annual electricity demand.

4.2.2 Electricity Prices

In our evaluation we use, as day-ahead electricity prices, those from DK2 area of Nord Pool Spot (http://www.nordpoolspot.com) in all test beds, thus simulating the condition in which all users from our test beds are in Denmark (but have different electricity demand patterns from those in Kalundborg). This allows us to evaluate SmartHG services on user demands with different characteristics.

On such a basis we can compute the average (over one year, among test bed households) energy cost per MWh. For Central District, Kalundborg and Minsk we have, respectively, 77.54 EUR/MWh, 102.70 EUR/MWh and 88.61 EUR/MWh, as shown in Figure 4.2.

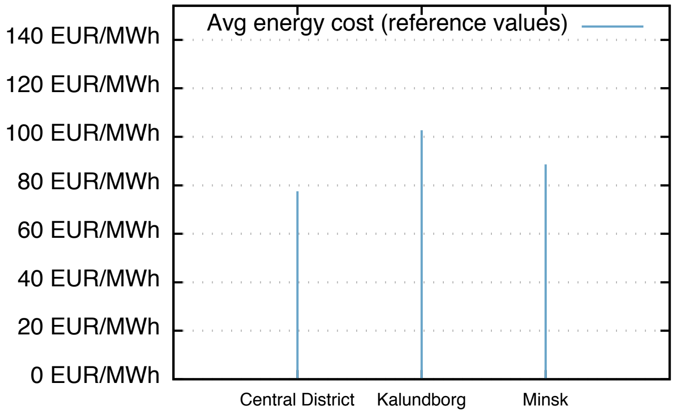


Figure 4.2: Reference energy costs in our test beds.

4.2.3 Home Storage

In this third year evaluation, battery capacities and power rates are computed, for each user, by the SmartHG Home Services (namely, Energy Bill Reduction (EBR)) so as to maximise user saving on energy cost. To that end we refined the battery cost model with respect to the one used in the second year evaluation. Here we describe our battery cost model (Section 4.2.3.1) along with the resulting (from EBR) battery values (Section 4.2.3.2). Finally, in Section 4.2.3.3 we describe the home energy storage configurations we will consider in our evaluation.

4.2.3.1 Storage Cost Model

SmartHG Home Services (namely, the EBR service) computes the optimal home battery dimensioning taking into account battery prices, day-ahead market electricity cost and historical data about user electricity demand.

We focus on lead-acid batteries and estimate the cost in EUR of a battery having capacity c (in kWh) and power rate p (in kW) as:

$$90c + 200p \tag{4.1}$$

Figure 4.3 shows the error percentage of the estimated cost over several home lead-acid batteries by Trojan (www.trojanbattery.com). In particular, for each battery model b (having capacity c and power rate p), the figure shows ratio $\frac{est(b)-cost(b)}{cost(b)}$, where $cost(b)$ is the current commercial cost of b (from www.elebatt.com) and $est(b)$ is the cost of b as estimated by our cost formula (4.1) above.

From Figure 4.3 we see that our cost model is safe, meaning that it (slightly) overestimates the actual cost of commercial lead-acid batteries (except for one single battery, whose actual cost is 1% less than our estimated cost).

We amortise the battery cost over a 10 year period. Thus, for example, a battery whose cost is 1000 EUR will cost for us 100 EUR per year.

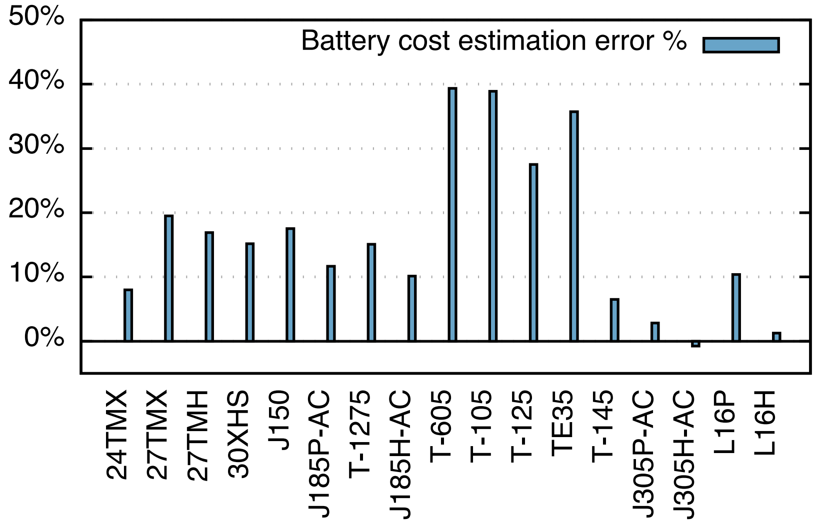


Figure 4.3: Error % in battery cost estimation made by our linear battery cost model for lead-acid batteries by Trojan.

4.2.3.2 Storage Capacity and Power Rate

In our evaluation, we assume that users are endowed with batteries having capacity and power rate values as computed by EBR.

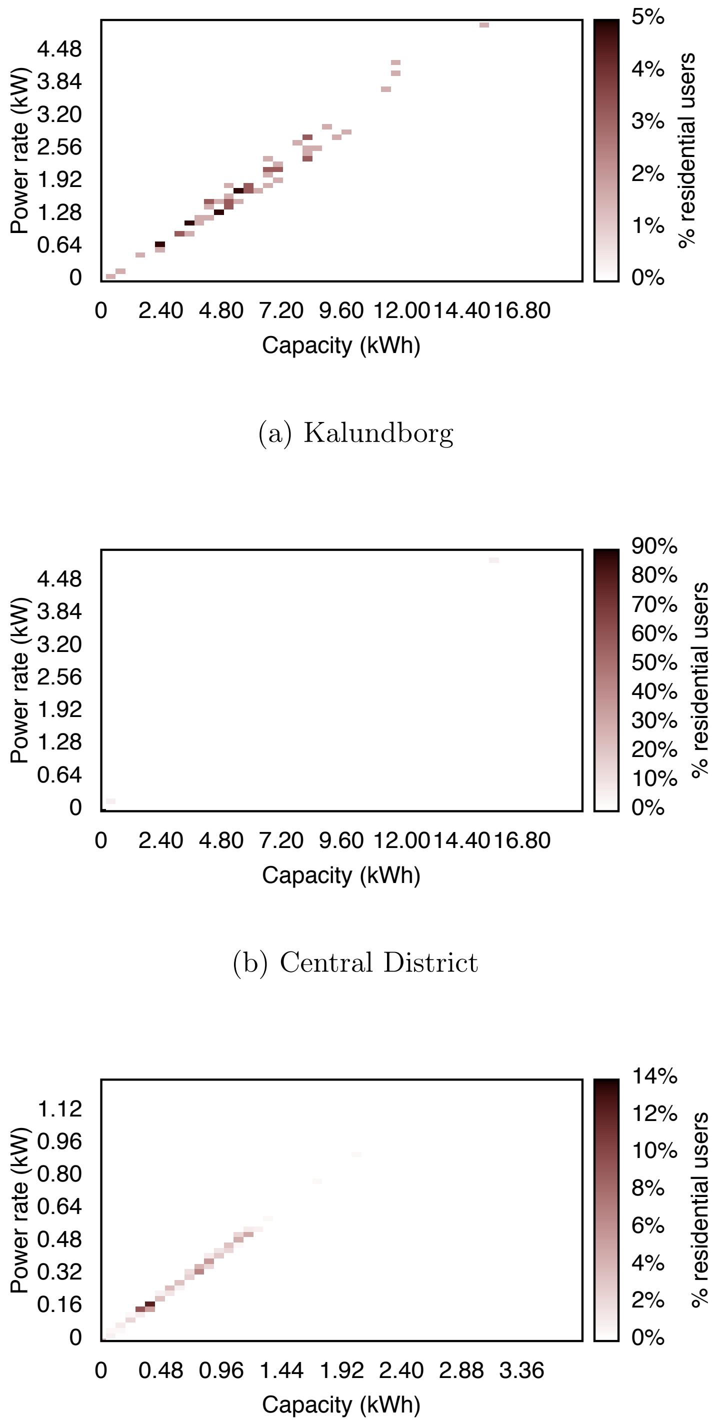
Figure 4.4 shows, for each test bed, the percentage of users endowed with a battery of any given capacity and power rate. Note that, notwithstanding the fact that the energy consumption in the Central District test bed is larger than in Kalundborg or Minsk test beds, installing battery is economically rewarding only for 2 houses in Central District (for all others EBR suggests to put no battery).

Figure 4.5 shows, for each test bed, the percentage of users endowed with a battery of any given cost per MWh of annual electricity consumption. Battery costs are based on the battery cost model of Section 4.2.3.1.

Figures 4.6a, 4.6b and 4.6c show, respectively, the average battery capacity (in kWh), power rate (in kW), and amortised (over 10 years) cost (in EUR), for each MWh of household annual consumption. For example, we see that, on average, batteries (as chosen by SmartHG Home Services) in a household of our Kalundborg test bed have average capacity of 0.71 kWh/MWh, average power rate of 0.16 kW/MWh, and average cost 9.60 EUR/MWh for each MWh of of annual consumption.

4.2.3.3 Storage Configurations

For each test bed we consider five energy storage configurations as outlined in Table 4.1. Note that scenarios BD and PD in Table 4.1 both use PEVs as *home energy storage* devices (e.g., as in the project Storage4All http://www.smartgridrendement.nl/nieuwe-diensten/dienst-7).

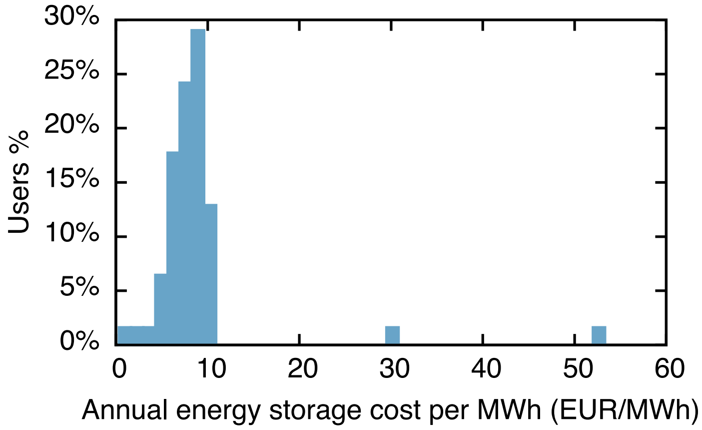


(a) Kalundborg

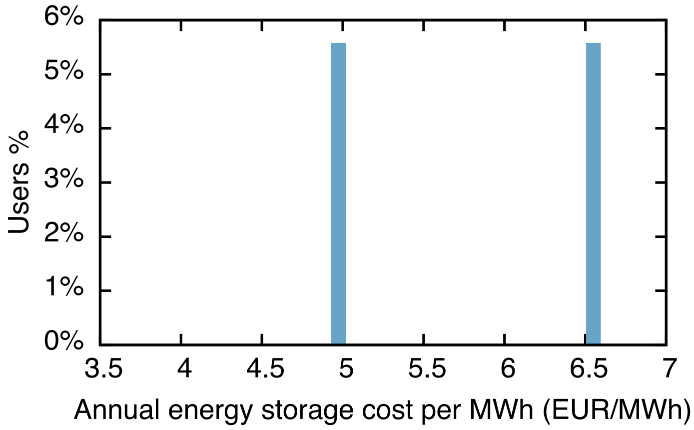
(b) Central District

(c) Minsk

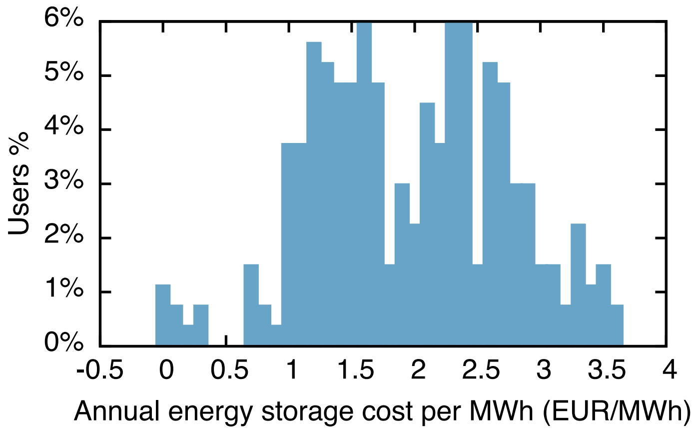
Figure 4.4: Percentage of users endowed with storage of any given capacity and power rate.



(a) Kalundborg

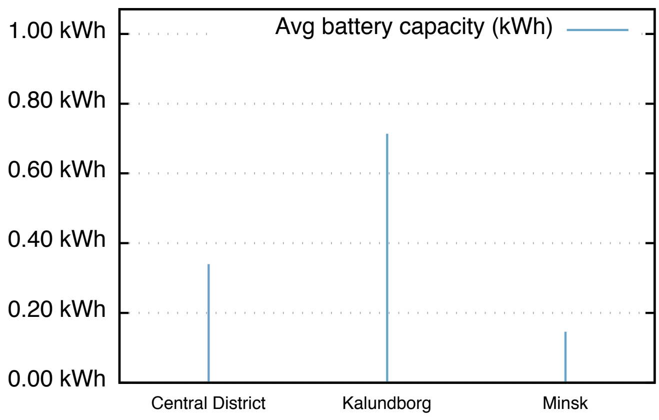


(b) Central District

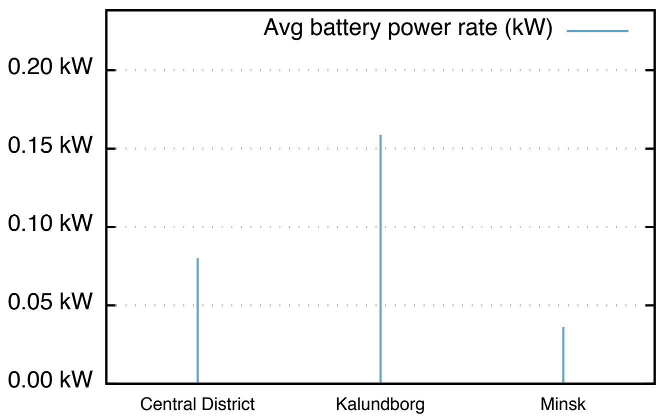


(c) Minsk

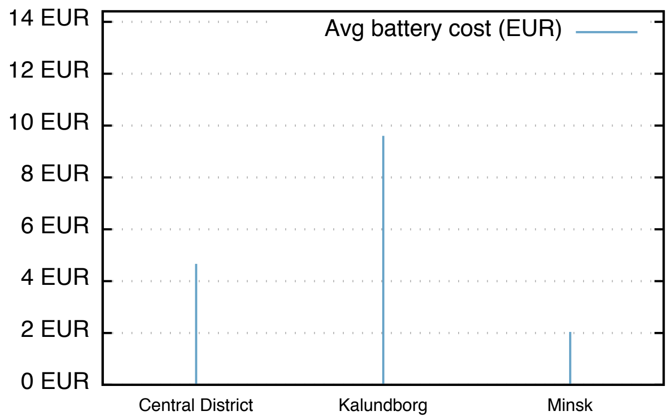
Figure 4.5: Percentage of users in of our test-beds endowed with a battery of a given cost per MWh of annual consumption.



(a) Average battery capacity per MWh of annual consumption (kWh/MWh)



(b) Average battery power rate per MWh of annual consumption (kW/MWh)



(c) Average battery cost per MWh of annual consumption (EUR/MWh)

Figure 4.6: Energy storage dimensioning for each test bed.

Configuration ID	Description
BU	Home Battery, PEV at home can only be charged and charge is not controlled by SmartHG services.
BC	Home Battery, PEV at home can only be charged and charge is controlled by SmartHG services.
BD	Home Battery, PEV at home can be charged and discharged and both are controlled by SmartHG services.
PC	No home battery, PEV at home can only be charged and charge is controlled by SmartHG services.
PD	No home battery, PEV at home can be charged and discharged and both are controlled by SmartHG services.

Table 4.1: Energy storage configurations considered in our evaluation for electricity cost reduction.

4.3 Reducing Demand Peaks

The benefits to the Electric Distribution Network (EDN) provided by SmartHG Grid Services have been discussed in Chapter 3. Our goal here is to show computation times (Section 4.3.1) and to compare the peak shaving effectiveness of the distributed SmartHG approach with that of a centralised one (Section 4.3.2)

4.3.1 Technical Evaluation

The SmartHG Grid Service computing *power profiles* for all users connected to a substation (on the basis of constraints provided by the DSO through SmartHG Grid Service EVT) is Demand Aware Price Policies (DAPP).

On the basis of historical data, DAPP computes power profiles for the day after. Accordingly, DAPP will be run once a day for each substation of interest. It is thus important to verify that, notwithstanding the big size of the optimisation problem the DAPP has to solve, its computation time is acceptable for the intended application.

Figure 4.7 shows the average, minimum and maximum execution times for the DAPP service, when computing power profiles for a period of one year. Such execution times are perfectly compatible with the intended DAPP execution frequency.

4.3.2 Peak Shaving Efficiency

Of course, peak shaving yields an economic saving (as investment deferral) that the Distribution System Operator (DSO) may harvest by distributing electricity through a less congested (thanks to peak shaving) EDN. However, the exact amount of such an economic saving strongly depends on the EDN characteristics and its congestion level.

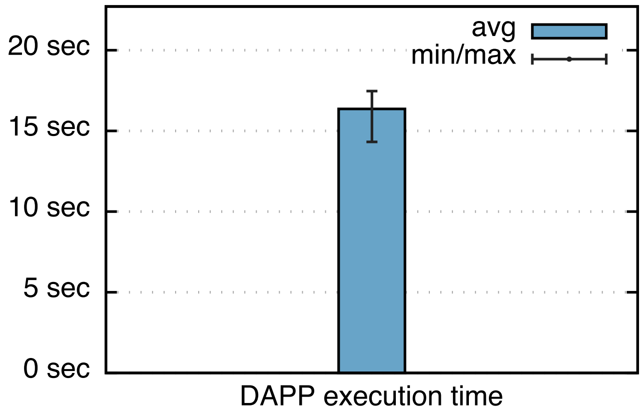


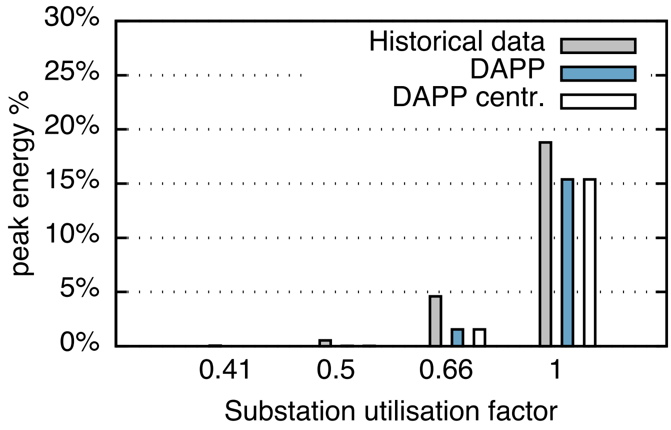
Figure 4.7: DAPP execution time.

We measure the congestion level of a given substation through the *substation utilisation factor* defined as the ratio between the annual aggregated energy demand from users and the energy that the substation can provide in one year without ever exceeding its nominal power.

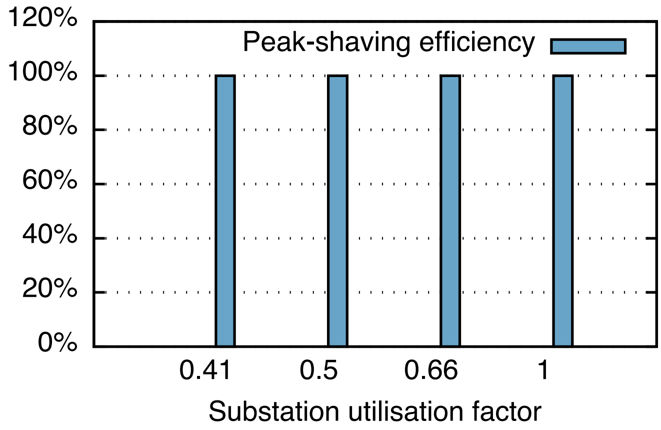
The following figures show statistics about effectiveness of SmartHG Grid Services.

Figure 4.8a shows how the peak shaving effectiveness changes with the substation utilisation factor. For each substation utilisation factor value considered we have a group of 3 vertical bars. The first bar in each group shows historical data about the percentage of annual energy consumption that *exceeds* the substation power limit (*peak energy percentage*). The second bar in each group shows the same data when SmartHG Grid Services (namely DAPP and Price Policy Safety Verification (PPSV)) are used to manage user demand so as to keep, as much as possible, the substation power level below its nominal value. Finally, the third bar in each group shows the same data when centralised storage (with capacity and power rate equal, respectively, to the sum of capacities and power rates of the energy storage devices installed at homes) is used to flatten the aggregated demand. Although a distributed storage approach has many advantages with respect to a centralised one (e.g., a *pay-as-you-go* schema is possible and there is no *single-point-of-failure*), it will always be as most as effective as a centralised one. From Figure 4.8a we can see that, as for flattening user demand, thanks to the control strategy provided by SmartHG Grid Services, SmartHG distributed storage is only slightly less effective than a centralised energy storage approach.

Another important measure of effectiveness for peak shaving approaches based on distributed storage is the *peak shaving capacity*, that is the ratio between the energy moved away from the peak and the storage capacity used to achieve such a peak shaving. Finally, the *peak shaving efficiency* is the ratio between the peak shaving capacity when using SmartHG and (as a reference) the peak shaving capacity when using centralised storage (as described above). Figure 4.8b shows the peak shaving efficiency attained under 4 different values for the substation utilisation factor. It can be observed that, in all cases, the achieved peak shaving efficiency is about 1, which means that the SmartHG distributed storage approach is basically as effective as a centralised energy storage approach.



(a) SmartHG peak shaving effectiveness with respect to a centralised approach.



(b) SmartHG peak shaving efficiency.

Figure 4.8: SmartHG distributed energy storage vs. centralised storage.

4.4 Reducing Electrical Energy Cost

In this section we summarise our results about electricity cost reduction for residential users enabled by SmartHG Home Services, namely Energy Bill Reduction (EBR).

4.4.1 Technical Evaluation

EBR runs on the Home Energy Controlling Hub (HECH) which is a a Raspberry PI running Linux and GNU GLPSOL in order to solve EBR Mixed-Integer Linear Programming (MILP). For this computation, EBR calls the other SmartHG Home Services (namely, Energy Usage Reduction (EUR) and Energy Usage Modelling and Forecasting (EUMF)) to make a short-term prediction of the user electricity demand.

Figure 4.9 shows the average, minimum and maximum time need by EBR to compute a schedule for the batteries installed in the household. We note that the observed com-

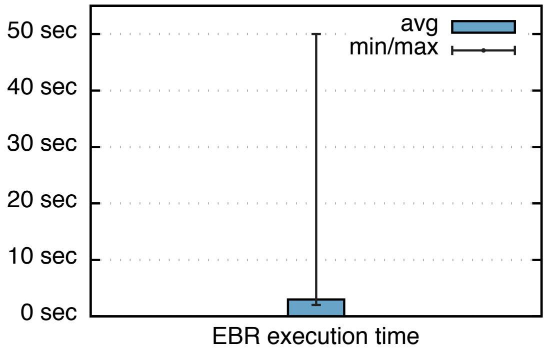


Figure 4.9: EBR execution time on the HECH.

putation times are adequate for EBR, as this service never needs to run more often than once every minute or so in our setting.

4.4.2 Attained Electricity Cost Savings

In this section we summarise the economic benefits enabled by the SmartHG Home Services technology.

The SmartHG platform enables saving on the energy costs by leveraging on price differences during the day. That is, we can buy electricity when its price is low, store it and then use it when the electricity price is high (*arbitrage*).

Using as a reference the energy costs described in Section 4.2.2, Figure 4.10 shows, for each test bed and for each home storage configuration in Section 4.2.3.3, the average energy cost saving percentage (among all test bed users) enabled by SmartHG Home Services.

In the following we comment the results in Figure 4.10.

First, we observe that cost saving opportunities stem from the relationship between the patterns of home energy usage and energy cost. If electricity demand is high when energy cost is low and vice versa, then, unsurprisingly, energy cost saving opportunities are limited. This is the case in Minsk and Central district test-beds, where a battery alone (BU configuration) yields a modest energy cost saving (respectively, 3% and 5%). The opposite holds in Kalundborg where a battery alone (BU) yields a 13% cost saving.

As for Plug-in Electric Vehicle (PEV) usage, we see that, in all test-beds, configurations BC and BD (battery + PEV) yield very similar savings. The same holds for the configurations PC and PD (just PEV). This means that because of the interaction between home energy usage pattern, energy cost pattern and PEV availability at home, in all test-beds controlling just the charging of the available PEV (configurations BC and PC) and controlling both PEV charging and discharging (configurations BD and PD) lead to similar cost savings. Thus, each user should carefully evaluate if it is indeed economically advantageous to invest in the equipment needed to use his PEV as a battery (BD or PD) or just focusing on suitably controlling PEV charging (BC or PC).

If we just have a PEV without home battery, then the saving goes from about 7% (PC configuration in Kalundborg) to 13% (PD configuration in Minsk). Furthermore we see that in Central District test-bed a PEV alone (PC, PD) yields basically the same saving (about 11%) than a home battery with a PEV (BC, BD).

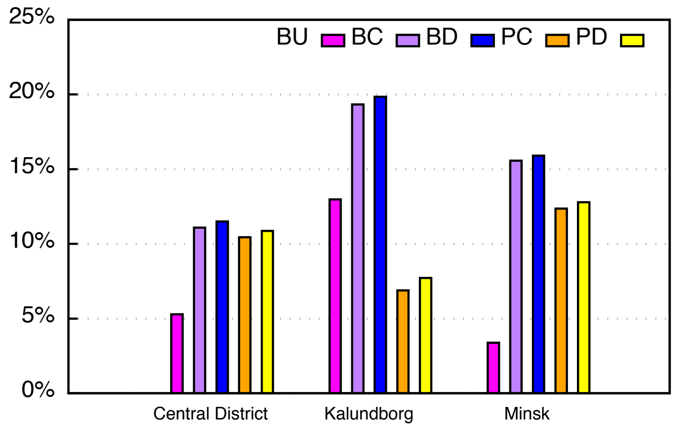


Figure 4.10: Average energy cost saving percentage among users in each test bed.

In Minsk and Central District test-beds a PEV alone (PC, PD) yields greater cost savings (10%–12%) than a battery alone (BU: 3%–5%), whereas in Kalundborg the opposite holds, since a PEV alone (PC, PD) would yield a 6%–7% cost saving whereas a battery alone (BU) would yield a 13% cost saving.

As to be expected, using a PEV along with a battery (BC, BD configurations yields the best results with saving ranging from 11% (Central District) to 19% (Kalundborg).

Summing up, our evaluation shows that suitably controlling PEV charging yields energy cost saving ranging from 7% (Kalundborg test-bed) to 13% (Minsk test-bed). Using a home battery along with a PEV yields energy cost savings ranging from 11% to 19%. Such results show that, as a side effect, SmartHG technology fosters PEV uptake by enabling residential users to exploit their PEV to save on energy cost.

4.5 Reducing CO2 Emissions

Using SEAS data for Denmark market, we can compute the CO2 emissions from historical data. On such a basis, in this section we summarise the environmental benefits provided by the SmartHG Home Services technology.

The following figures show, for each test bed and for each home storage configuration in Table 4.1, statistics about the attained CO2 emissions reduction.

Figure 4.11a shows the average (among all test bed users) reduction in CO2 emissions for each MWh of annual electricity consumption. Figure 4.11b shows the average (among all test bed users) percentage reduction in CO2 emissions.

As done for energy cost savings, in the following we comment the results in Figure 4.11b.

First, we observe that CO2 emissions reduction opportunities stem from the relationship between the patterns of home energy usage CO2 emissions. If energy demand is high when CO2 emissions due to electricity production is low and vice versa, then, unsurprisingly, CO2 emissions reduction opportunities are limited. This is the case in Minsk and Central District test-beds where a battery alone (BU configuration) yields a modest CO2 emissions reduction (respectively, 3% and 5%). Kalundborg offers more opportunities, since there a battery alone (BU) yields an 8% CO2 emissions reduction.

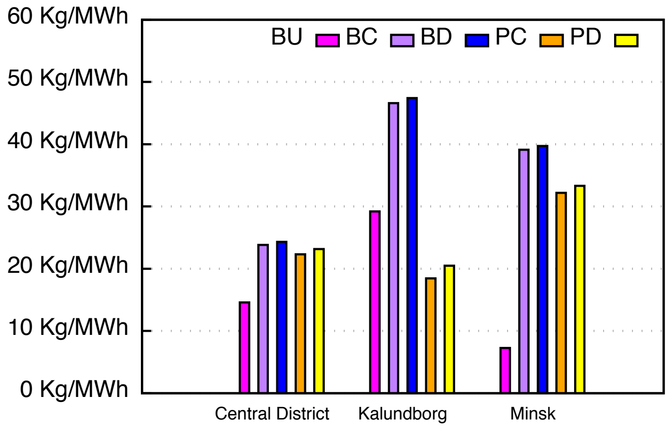
As for Plug-in Electric Vehicle (PEV) usage, we see that, in all test-beds, configurations BC and BD (battery + PEV) yield very similar CO2 emissions reduction. The same holds for the configurations PC and PD (just PEV). This means that because of the interaction between home energy usage pattern, CO2 emissions pattern and PEV availability at home, in all test-beds controlling just the charging of the available PEV (configurations BC and PC) and controlling both PEV charging and discharging (configurations BD and PD) yield very similar reductions in CO2 emissions.

If we just have a PEV without home battery, then the CO2 emissions reduction goes from about 7% (PC configuration in Kalundborg) to 13% (PD configuration in Minsk). Furthermore we see that in Central District test-bed a PEV alone (PC, PD) yields basically the same reduction (about 12%) than a home battery with a PEV (BC, BD).

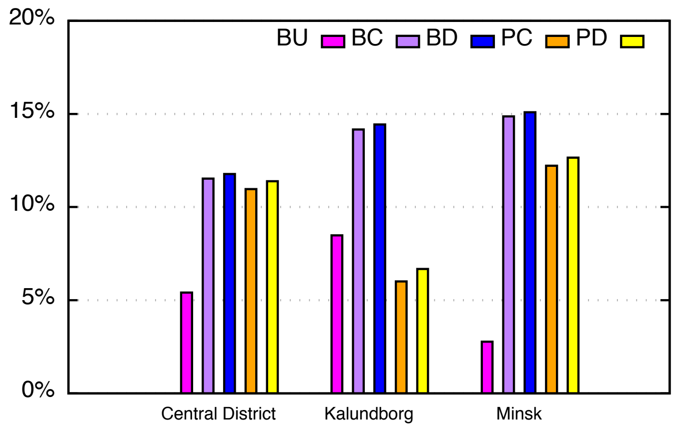
In Minsk and Central District test-beds, a PEV alone (PC, PD) yields greater reductions (12%–13%) than a battery alone (BU) whereas in Kalundborg the opposite holds, since a PEV alone (PC, PD) yields a 6% reduction whereas a battery alone (BU) yields a 9% reduction.

Of course, using a PEV along with a battery (BC, BD configurations) yields the best results, with CO2 emissions reduction ranging from 12% (Central District) to 15% (Kalundborg).

Summing up, our evaluation shows that suitably controlling PEV charging yields CO2 emissions reductions ranging from 7% (Kalundborg test-bed) to 13% (Minsk test-bed). Using a home battery along with a PEV yields CO2 emissions reductions ranging from 12% to 15%.



(a) Average CO2 emissions reduction per MWh of annual household electricity consumption.



(b) Average percentage CO2 emissions reduction.

Figure 4.11: Statistics about CO2 emission reduction for each scenario in our test beds.

4.6 Pursuing Peak Shaving along with Energy Cost Reduction

This section evaluates effectiveness of SmartHG services in pursuing the following conflicting objectives:

1. Flatten the energy demand according to the requirements received by the SmartHG Grid Services;
2. Decrease energy cost (by using energy when it is less expensive);
3. Reduce CO2 emissions (by using energy when its production requires less CO2).

Figure 4.12 shows effectiveness (with respect to the substation utilisation factor) of SmartHG Home Services in attaining peak shaving. For each considered value of the substation utilisation factor, we have a group of 7 bars. The first bar shows the percentage of peak energy when SmartHG is not used (i.e., historical data). The second bar, shows

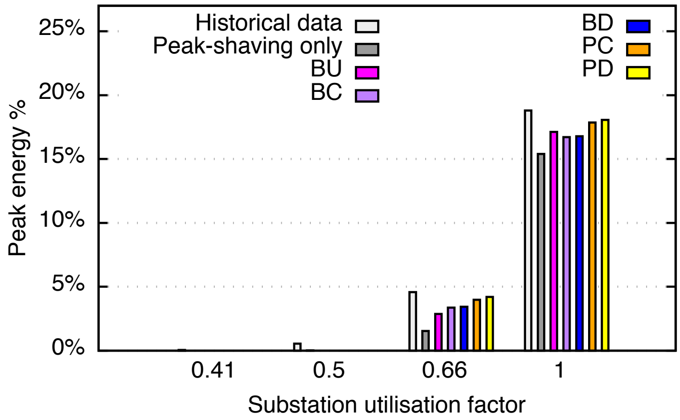


Figure 4.12: Peak shaving entailed by SmartHG services.

the percentage of peak energy when SmartHG Home Services only pursue the objective of flattening energy demand. The remaining 5 bars show the percentage of peak energy when SmartHG Home Services take into account all objectives (flattening energy demand, minimise energy cost, minimise CO2 emissions) under the 5 home storage configurations described in Section 4.2.3.3.

Figure 4.13 shows effectiveness (with respect to the substation utilisation factor) of SmartHG Home Services in reducing electrical energy cost when also pursuing the goal of keeping demand within the power profile provided by SmartHG Grid Services (namely, Demand Aware Price Policies (DAPP)). We focus on scenarios where the substation is moderately-to-heavily loaded (namely, utilisation factor having values 0.66 and 1). For each considered substation utilisation factor value we have a group of bars showing the average energy cost saving percentage as entailed by SmartHG Home Services (when taking into account all objectives) under the 5 home storage configurations described in Section 4.2.3.3.

Figure 4.14a shows effectiveness (with respect to the substation utilisation factor) of SmartHG Home Services in reducing CO2 emissions. For each substation utilisation factor value considered we have a group of bars showing the average CO2 emissions (kg) per MWh of annual consumption, as entailed by SmartHG (when taking into account all objectives), under the 5 home storage configurations described in Section 4.2.3.3.

Finally, Figure 4.14b shows the average percentage of CO2 emissions reduction as entailed by SmartHG (when taking into account all objectives), under the 5 home storage configurations described in Section 4.2.3.3.

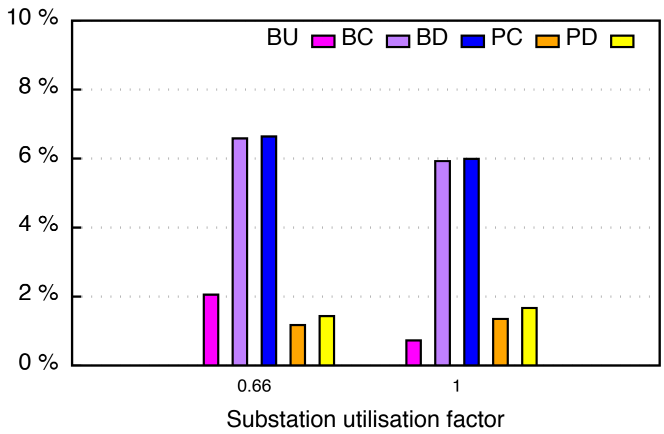
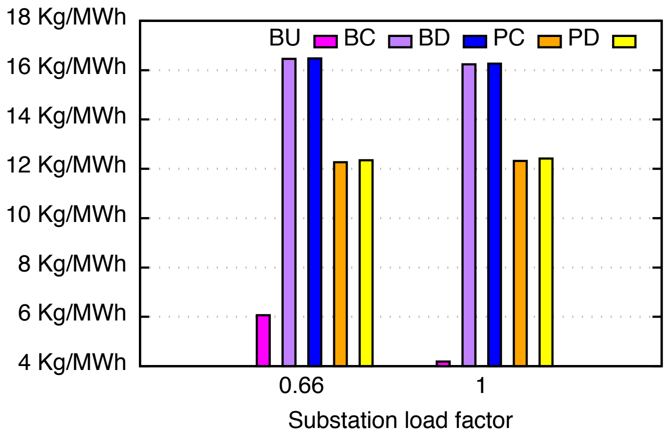
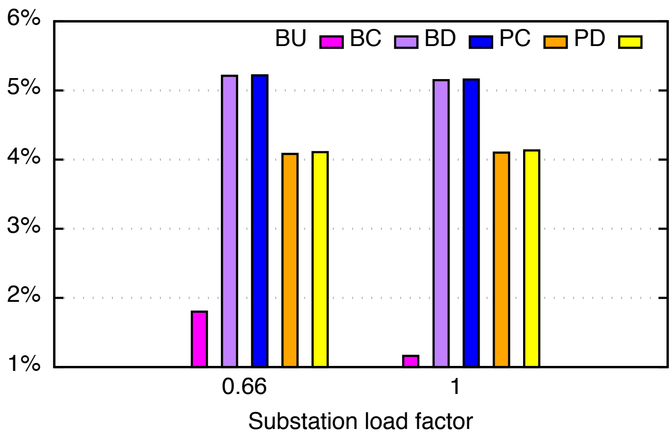


Figure 4.13: Average energy cost saving percentage entailed by SmartHG Home Services.



(a) Reduction of CO2 emissions entailed by SmartHG Home Services.



(b) Percentage reduction of CO2 emissions entailed by SmartHG Home Services.

Figure 4.14: Pursuing peak shaving along with energy cost and CO2 emissions reduction using SmartHG services.

Chapter 5

Conclusions

In the third year evaluation we overcame the limitations of our second year evaluation by taking into account all 607 sensors (providing about 293 544 measurements so far) deployed in Kalundborg and Central District and of historical data (about 3 409 132 measurements) from Minsk and by addressing estimation of computational and communication delays for the Energy Bill Reduction (EBR).

SmartHG third and final evaluation focussed on assessing how the whole SmartHG platform (i.e., all services cooperating together) address the project objectives: (a) Support the Distribution System Operator (DSO) in optimising Electric Distribution Network (EDN) operations; (b) Reduce energy costs for residential users; (c) Reduce CO2 emissions.

Our evaluation results show the following.

First, SmartHG individualised price policy technology provides the following benefits to the EDN (and thus to the DSO).

1. Increase of the *demand load factor* of more than 18% with respect to a flat price policy and of more than 35% with respect to to a global price policy (because of *rebounds*), thereby providing a *peak shaving* effect considerably better than the one offered by a *global* price policy;

2. Reduction of low-voltage violations in the grid;

3. Reduction of network line thermal MVA limit violations;

4. Reduction of network line losses (e.g., of about 2% with respect to a global price policy).

Second, SmartHG hierarchical control approach to energy storage management is almost as effective as a centralised one. This opens up the possibility of deploying energy storage with a *pay-as-you-go* approach thereby avoiding massive investments that may be too risky in such a rapidly changing market.

Third, the benefits provided by SmartHG to electricity retailers mainly consists in the possibility of effectively exploiting distributed home energy storage to buy energy when its price is low in the day-ahead market (*arbitrage*). In fact, suitably controlling Plug-in Electric Vehicle (PEV) charging yields energy cost saving ranging from 7% to 13%. Using a home battery along with a PEV yields energy cost savings ranging from 11% to 19%. Such results show that, as a side effect, SmartHG technology fosters PEV uptake by enabling residential users to exploit their PEV to save on energy cost.

Fourth, SmartHG can bring benefits also to the environment, by allowing electricity retailers to buy energy when its CO2 footprint is small. In fact, suitably controlling PEV charging yields CO2 emissions reductions ranging from 7% to 13%. Using a home battery along with a PEV yields CO2 emissions reductions ranging from 12% to 15%.

5.1 Impact

Our evaluation results show *economic viability* of SmartHG approach and identify electricity retailers and Distribution System Operators (DSOs) as main customers for SmartHG technology. Such results form the basis of SmartHG exploitation plan which sees Information and Communications Technology (ICT) companies providing software services *orchestrating* home devices so as to provide economic and/or environmental benefits to electricity retailers, DSOs and residential users.

Finally, a number of publications have resulted from this work. These include:

- 2 international journal papers: (one published [7] in IEEE Transactions on Smart Grid, and one currently in review)
- 4 international conference papers: one on demand forecasting approaches [11], one on Distribution System State Estimation (DSSE) techniques [12], and 2 joint papers on EDN Virtual Tomography (EVT) and the other Grid Intelligent Automation Service (GIAS) services (to be presented).

In addition to this, a joint paper, outlining the potential benefits of EVT and the other GIAS services, namely Demand Aware Price Policies (DAPP) and Price Policy Safety Verification (PPSV) has been submitted to IEEE Transactions on Smart Grid. This paper demonstrates the applicability of the *individualised price policy* concept introduced in the SmartHG project in real-world contexts based on SmartHG test-beds. It discusses several scenarios, which demonstrate the coordination of the GIAS services, and compares the solution proposed in SmartHG to Demand Side Management (DSM) approaches with the traditional global price policy, quantifying the potential benefits to the DSO.

Chapter 6

List of Acronyms

CIM Common Information Model 9

DAPP Demand Aware Price Policies 47

DB&A Database and Analytics 28

DBService Database Service 9

DER Distributed Energy Resources 8

DG Distributed Generation 8

DR Demand Response 28

DSM Demand Side Management 47

DSO Distribution System Operator 47

DSSE Distribution System State Estimation 47

EBR Energy Bill Reduction 46

EDN Electric Distribution Network 46

ESS Energy Storage System 24

EUMF Energy Usage Modelling and Forecasting 38

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