# D7.2 VALIDATION METHODOLOGY AND PILOT ACTION PLAN

Definition of the baselines of the pilots and the action plan for community engagement, technical deployment, feedback gathering and KPI validation

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|---|---|
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| Project call | **EE-07-2016-2017 Behavioral change toward energy efficiency through ICT** |
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## History of changes

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# Table of Contents

# 1. Executive Summary

"D.7.2 Validation methodology and pilot action plan" is specified the enCOMPASS Description of Action as:

*"Methodology to conduct the three pilots. KPIs to be measured. Baselines to be employed in result evaluation. Strategies for integrating with the smart sensor and meter network, for collecting data from energy users, and delivering in-context, adaptive energy efficiency recommendations."*

This deliverable is one of the outputs of the project task "T7.2 Baseline refinement and validation methodology": main objective is design a methodology to conduct the pilot, based on state-of- art KPIs and the data collection and reporting best practices, with particular attention to experimental design. This task will design the methodologies for the case studies. The task delivers the methodology for both energy consumption measurement and the assessment of user acceptance and psychological energy behaviour determinants.

For an overall description of the dependencies among the above task T7.2 and the other project tasks and work packages, please refer to section 3.1.2 of the enCOMPASS Description of Action. D7.2 in particular is a main input for the task "T7.3 Pilot in the German case study", "T7.4 Pilot in the Greek case study" and "T7.5 Pilot in the Swiss case study" in WP7 (Pilots on behavior change for energy-saving). The task T7.3 deploys the pilot in Germany introducing enCOMPASS behavior change apps to a selected group of pilot users. Awareness dissemination will promote the participation among citizens, based on real world community events media campaigns and online social network promotion. The task T7.4 addresses residential and office buildings with both permanent staff and visitors, along with a private college building with students and personnel. The task T7.4 deploys the awareness apps in the Swiss pilot. The task will monitor use of the app over a time period long enough to exclude seasonal variations. The task T7.2 gets input form the task T5.1 „Behavioral determinants of consumption".

This document is structured as follows:

- Section 2 presents a review of the validation methodologies that have been applied in the past in similar studies.
- Section 3 describes the validation methodollgy to be applied in the enCOMPASS project, which is based on the eeMeasure methodology. First we recall the timeline of the trials, then we identify the KPIs to be measured, and finally we decline the eeMeasure methodology in the enCOMPASS project.
- Section 4 specifies the planning of the pilot validation, the baseline collection (both regarding quantitative electric energy consumption and qualitative energy behavior), the monitoring periods, the definition of control/intervention groups, the monitoring techniques of the KPIs.
- Section 5 details the plan for the integration of data coming from smart sensors in order to deliver context sensitive recommendations.

The relationships between this deliverable and other deliverables of the project are as follows:

- D2.2 FINAL REQUIREMENTS provides the details of how enCOMPASS will implement the strategy for energy users data collection, especially in the user story called "Completing the user profile".
- D6.2 PLATFORM ARCHITECTURE AND DESIGN provides the details of how enCOMPASS will implement the strategy for integration with smart meter and sensor data, especially in the section devoted on the Data Acquisition Layer.

# 2. Review of current methodologies for the validation of energy savings

This section reviews existing methodologies for energy saving that have informed the further development and refinement of the methodology to validate the enCOMPASS applications.

In D5.1 Behavioural change models and determinants for energy consumption, a systematic review has been presented, which has yielded 47 papers that assessed behavioural determinants of energy saving in public buildings and schools. In this sub section, the methodology that was employed in these studies is assessed. Additionally, we summarize the validation methodologies used in household settings, drawing on the same set of systematic reviews that were used for D5.1.

From the 47 studies, 37 focused on energy saving in public buildings. Schools were in focus of 10 papers only. These numbers show that energy saving in public buildings and schools have not been studied so often in comparison to residential buildings.

Methods of data collection for energy saving in public buildings are listed in the Table 1.

**Table 1: Data collection methods in public buildings**

| Method | Studies found |
|---|---|
| Questionnaire | Di Matteo et al. (2014), Tetlow et al. (2015), Loureiro & Lima (2009), Wells et al. (2016), Xu et al. (2017), Yun et al. (2012), Zhang et al. (2013), Zhuang & Wu (2014), Zierler et al. (2017), Azizi et al., (2014), Manika et al. (2015b), Ucci et al. (2014), Greaves et al. (2013) |
| Interviews | Jurin & Fox-Parrish (2008), Goulden & Spence (2015), Chung & Hui (2009), Schleich & Gruber (2008), Zhuang & Wu (2014), Schleich (2009), Coleman et al. (2013), Pellegrini-Masini & Leishman (2011), Ucci et al. (2014), Katzeff et al. (2013), Greaves et al. (2013) |
| Energy data collection/ energy data monitoring | Metzger et al. (2011), Murtagh et al. (2013), Handgraaf et al. (2013), Yun et al. (2015), Gustafson et al. (2008) |
| Survey | Stokes et al. (2012), Jurin & Fox-Parrish (2008), Di Matteo et al., (2014), Chung & Hui (2009), Zierler et al. (2017), Manika et al. (2015b), |
| Case study | Li et al. (2014), Karatas et al. (2016), Azizi et al. (2014), Coleman et al. (2013), Bull et al. (2015) |
| On line survey | Karatas et al. (2016), Sawang & Kivits (2014), Greaves et al. (2013) |
| Focus groups | Tolias et al. (2015), Murtagh et al. (2013) |
| Pre- and post- survey questionanire | Agha-Hossein et al. (2013), Handgraaf et al. (2013) |
| Pilot study | Yun (2014) |
| Observation | Stokes et al. (2012) |
| Electronic (on line) questionnaire | Nisiforou et al. (2012) |
| Pre- and post survey | Murtagh et al. (2013) |
| Pre- and post- test | Lee et al. (2013), |
| Game score | Tolias et al. (2015) |
| Portfolio analysis | Li et al. (2014) |
| Study | Gustafson et al. (2008) |
| Mixed methods | Di Matteo et al. (2014), Zhuang & Wu (2014), Zierler et al. (2017), Azizi et al. (2014), Manika et al. (2015b), Ucci et al. (2014), Greaves et al. (2013), Jurin & Fox-Parrish (2008), Chung & Hui (2009), Coleman et al. (2013), Murtagh et al., (2013), Handgraaf et al. (2013), Gustafson et al. (2008), Stokes et al. (2012), Li et al. (2014), Karatas et al. (2016), Tolias et al. (2015) |

The most popular data collection method for energy saving in public buildings is to apply some combination of methods (17 papers). Surveys, interviews, case analysis are often combined with questionnaires, as well as data collection is combined with pre- and post-questionnaires, etc. In order to collect data about occupants behavior towards energy saving (quantitative data), questionnaires or interviews are applied.

Quantitative data may be collected by meters or the changes in energy consumption may be self-reported. The methods for data collection in schools are presented in Table 2.

**Table 2 : Data collection methods in schools**

| Method | Studies found |
|---|---|
| Questionnaire | Scherbaum et al. (2008), Salleh et al. (2016), Mtutu & Thondhlana (2016), Kastner & Matthies (2014), Manika et al. (2015a) |
| Energy data collection/ energy data monitoring | Piselloet al. (2016), Fehr & Andrade (2016), Kastner & Matthies (2014), Whittle et al. (2015), Schelly et al. (2010) |
| Interviews | Salleh et al. (2016), Whittle et al. (2015), |
| Survey | Mtutu & Thondhlana (2016), Manika et al. (2015a) |
| Case study | Fehr & Andrade (2016), Schelly et al. (2010), |
| Focus groups | Scherbaum et al. (2008), Schelly et al. (2010) |
| Pilot study | Salleh et al. (2016), |
| Socio-economic data collection | Castleberry et al. (2016) |
| Mixed methods | Scherbaum et al. (2008), Salleh et al. (2016), Mtutu & Thondhlana (2016), Kastner & Matthies (2014), Manika et al. (2015a), Whittle et al. (2015), Fehr & Andrade (2016), Schelly et al. (2010), Castleberry et al. (2016) |

Table 2 above represents data collection methods in schools. In general, they do no differ much from methods used in public buildings. Most often the mixed methods were used to evaluate energy savings in schools: questionnaires were usually combined with surveys, focus groups, pilot studies and energy data collection; data collections were combined with interviews and case studies, etc.

Dependent variables in public buildings, analyzed in reviewed papers are presented inTable 3.

**Table 3: Dependent variables in public buildings**

| Dependent variable | Studies found |
|---|---|
| Behavioural determinants | Stokes et al. (2008), Jurin & Fox-Parrish (2008), DiMatteo et al. (2014), Agha-Hossein et al. (2013), Tetlow et al. (2015), Lee et al. (2013), Tolias et al. (2015), Loureiro & Lima (2009), Xu et al. (2017), Zhang et al. (2013), Zierler et al. (2017), Manika et al. (2015b), Handgraaf et al. (2013), Pellegrini-Masini & Leishman (2011), Greaves et al. (2013) |
| Energy consumption metered | Jáñez Morán et al. (2016), Li et al. (2014), Chung & Hui (2009), Schleich & Gruber (2008), Murtagh et al. (2013), Yun et al. (2012), Schleich (2009), Azizi et al., (2014), Katzeff et al. (2013), Schelly et al. (2010), Yun (2014), Gustafson et al. (2008) |
| Energy saving behavior | Metzger et al. (2011), Goulden & Spence (2015), Nisiforou et al. (2012), Wells et al. (2016), Zhuang & Wu (2014), Zierler et al. (2017), Karatas et al. (2016), Manika et al. (2015b), Ucci et al. (2014), Sawang & Kivits (2014), Bull et al. (2015) |
| Energy consumption (smart) metered | Coleman et al. (2013), Handgraaf et al. (2013), Yun et al. (2015) |
| Energy consumption self-reported | Pellegrini-Masini & Leishman (2011) |
| Technology acceptance | Bull et al. (2015) |
| No energy consumption measurement | Stokes et al. (2012), Jurin & Fox-Parrish (2008), DiMatteo et al. (2014), Lee et al. (2013), Tolias et al. (2015), Loureiro & Lima (2009), Goulden & Spence (2015), Schleich & Gruber (2008), Nisiforou et al. (2012), Wells et al. (2016), Xu et al. (2017), Zhang et al. (2013), Zhuang & Wu (2014), Schleich (2009), Zierler et al. (2017), Karatas et al. (2016), Azizi et al., (2014), Manika et al. (2015b), Pellegrini-Masini & Leishman (2011), Ucci et al. (2014), Sawang & Kivits (2014), Greaves et al. (2013), Bull et al. (2015) |

16 from 37 papers on energy saving in public buildings had behavioral determinants as dependent variables. Energy consumption metered was dependent variable in 12 reviewed papers. 11 reviewed papers used

energy saving behavior as dependent variables in their studies. Energy consumption data collection was not used in 22 papers.

Dependent variables in schools, analyzed in reviewed papers are listed inTable 4.

**Table 4: Dependent variables in schools**

| Dependent variable | Studies found |
|---|---|
| Behavioural determinants | Salleh et al. (2016) |
| Energy consumption metered | Pisello et al. (2016), Kastner & Matthies (2014) |
| Energy saving behavior | Scherbaum et al. (2008), Mtutu & Thondhlana (2016), Castleberry et al. (2016), Manika et al. (2015a) |
| Energy consumption (smart) metered | Whittle et al. (2015) |
| Technology acceptance | Castleberry et al. (2016) |
| Environmental performance index | Fehr & Andrade (2016) |
| Energy consumption No | Scherbaum et al. (2008), Salleh et al. (2016), Mtutu & Thondhlana (2016), Castleberry et al. (2016), Manika et al. (2015a) |

Energy saving behavior and meterded energy consumption were most often used as dependent variables in the studies, conducted in schools. Energy consumption data was not collected in five papers on energy saving in schools.

Following our approach in D5.1, our review of the methodologies employed in studies on residential energy consumption is based on the following review articles: Frederiks et al. (2015), Lopes et al. (2012), Bhattacharjee & Reichard (2011), Abrahamse and Steg (2013) and Murugesan et al. (2015) as well as a selection of articles cited by these authors as examples of the methodologies used that specifically relate to energy use in residential sector. The first three studies discuss the general energy consumption behavior, whereas the latter two relate to specific energy related interventions, such as providing users with social influence information and consumption visualization, respectively.

As can be seen from Table 5, studies on energy consumption in residential buildings employ a wide range of methodologies (Frederiks et al., 2015), and use both primary (e.g. questionnaire, interview, focus group) and secondary data (such as data collection through energy meters or socio-economic panels) to identify factors that influence household energy usage and changes in energy use over time. Studies exploring social influence in energy conservation aim to test different social influence approaches used in literature in an experimental design where an intervention's effect (e.g. comparative feedback or a social norm message) is compared to a control group or a group exposed to another intervention (Abrahamse and Steg, 2013). The visualizations, on the other hand, are usually tested in field trials, and in order to assess the behavior change mixed methods in form of log data from the software, interviewing and questionnaires are employed (Murugesan et al., 2015). Data collection methods applied in studies on energy saving in residential buildings is presented in Table 5.

**Table 5. Data collection methods in residential buildings**

| Method | Studies found |
|---|---|
| Energy data collection/energy data monitoring | Ueno et al. (2006) as cited in Lopes et al., 2012, Anker-Nilssen (2003) as cited in Frederiks et al., 2015 |
| Secondary data | Lenzen et al. (2004) as cited in Bhattacharjee & Reichard, 2011, Pachauri and Jiang (2008) as cited in Bhattacharjee & Reichard, 2011 |
| Interviews | Kennedy et al. (2004) as cited in Frederiks et al., 2015, Kim et al. 2010 (as cited in Murugesan et al. ,2015, Rodgers and Bartram (2011) as cited in Murugesan et al., 2015 |
| Focus group | Brandon and Lewis (1999) as cited in Frederiks et al., 2015 |
| Survey | Nair et al. (2009) as cited in Frederiks et al., 2015, McMakin et al. (2002) as cited in Frederiks et al., 2015, Barr et al. (2005) as cited in Frederiks et al., 2015, Kim et al. (2010) as cited in Murugesan et al., 2015, Rodgers and Bartram (2011) as cited in Murugesan et al., 2015 |
| Two-phase questionnaire–diary survey method | Tso et al. (2003) as cited in Bhattacharjee & Reichard, 2011 |
| Log data | Costanza et al. (2012) as cited in Murugesan et al., 2015, Igaki et al. (2010) as cited in Murugesan et al., 2005, Rodgers and Bartram (2011) as cited in Murugesan et al., 2015 |
| Experiment | Abrahamse et al. (2007) as cited in Lopes et al., 2012, Brandon and Lewis (1999) as cited in Frederiks et al., 2015, Katzev et al. (1981) as cited in Abrahamse and Steg, 2013, Nolan et al. (2008) as cited in Abrahamse and Steg, 2013, Siero et al. (1996) as cited in Abrahamse and Steg, 2013, Pallak et al. (1972) as cited in Abrahamse and Steg, 2013, Kim et al. (2010) as cited in Murugesan et al., 2015 |
| Review | Gynther et al. (2011), Abrahamse and Steg (2013), Frederiks et al. (2015), Murugesan et al. (2005), Lopes et al. (2012) |
| Simulation | Al-Mumin et al. (2003) as cited in Lopes et al., 2012 |
| Field study | Gatersleben et al. (2002) as cited in Frederiks et al., 2015, Costanza et al. (2012) as cited in Murugesan et al., 2015 |
| Comparative study | Kim et al. (2010) as cited in Murugesan et al., 2015 |

Usually studies focus on individual behavior of households, however sometimes their respondents are special user groups such as students or farmers. Social influence approaches are most successful for such target groups as employees, followed by students, and then households (Abrahamse and Steg, 2013). These studies use different approaches: qualitative approaches from social sciences trying to understand individual consumption behavior, quantitative approaches that try to model energy consumption on an aggregate level and combinations thereof (Lopes et al., 2012).

In Table 6, we provide a review of dependent variables that have been used in the studies on energy consumption in residential buildings. The target behavior in social influence studies are usually self-reported (or observed) energy savings or use behavior which is tested on a sample ranging from 80 to over 500 users, evenly distributed among treatments (Abrahamse and Steg, 2013). The target behaviors in the visualization studies are increases in energy related knowledge and awareness of energy use (Murugesan et al,. 2015).

**Table 6. Dependent variables in residential buildings**

| Dependent variable | Studies found |
|---|---|
| Energy consumption (actual) | Ürge-Vorsatz et al. (2009) as cited in Lopes et al., 2012, Anker-Nilssen (2003) as cited in Frederiks et al., 2015 , Brandon and Lewis (1999) as cited in Frederiks et al., 2015, McMakin et al. (2002) as cited in Frederiks et al., 2015, Kurz et al. (2005) as cited in Abrahamse and Steg, 2013, Nolan et al. (2008) as cited in Abrahamse and Steg, 2013, Katzev et al. (1981) as cited in Abrahamse and Steg, 2013, Pallak et al. (1972) as cited in Abrahamse and Steg, 2013 |
| Energy consumption (self-reported) | Abrahamse et al. (2007) as cited in Lopes et al., 2012, Barr et al. (2005) as cited in Frederiks et al., 2015 |
| Energy consumption (approximated) | Tso et al. (2003) as cited in Bhattacharjee & Reichard, 2011 |
| Behavioral change (energy savings) | Webb and Sheeran (2006) as cited in Frederiks et al., 2015, Abrahamse et al. (2007) as cited in Abrahamse and Steg, 2007, Midden et al. (1983) as cited in Abrahamse and Steg, 2007, Costanza et al. (2012) as cited in Murugesan et al., 2015, Igaki et al. (2010) as cited in Murugesan et al., 2005, Kim et al. (2010) as cited in Murugesan et al., 2015 |
| Adoption of energy saving actions | Dietz et al. (2009) as cited in Lopes et al., 2012, Ouyang and Hokao (2009) as cited in Lopes, 2012, Siero et al. (1996) as cited in Abrahamse and Steg, 2013 |
| Attitudes towards energy saving | Nair et al. (2009) as cited in Frederiks et al., 2015, Barr et al. (2005) as cited in Frederiks et al., 2015 |
| Energy knowledge and awareness | Kennedy et al. (2004) as cited in Frederiks et al., 2015, Costanza et al. (2012) as cited in Murugesan et al., 2015, Kim et al. (2010) as cited in Murugesan et al., 2015, Rodgers and Bartram (2011) as cited in Murugesan et al., 2015 |

Energy behavior studies in the residential sector are predominantly field experiments testing instruments to promote more efficient energy behaviors and trying to establish the behavioral determinants for energy use (Lopes et al., 2012). Studies recognize a wide range of factors to explain individual household energy consumption, and are most frequently subdivided into: socio-economic variables, psychological factors as well as external contextual and situational factors (Bhattacharjee and Reichard, 2011; Frederiks et al., 2015). Although some factors have been found to be better predictors of energy savings than others, they are still far from being consistent across time, context, as well as samples of participants and studies (Frederiks et al., 2015). Additionally, very few studies have found the interventions to be effective and achieve substantial behavioral changes (Frederiks et al., 2015). There are several reasons for this. First, as we have seen from Table 6 the dependent variable in the studies is differently conceptualized, operationalized and measured, for example as overall energy consumption (e.g. kW per hour of usage), changes in specific everyday practices (e.g. curtailment actions) or adoptions of certain energy-efficient technology (e.g. efficiency actions). Second, these differing results may be explained by the fact that very few studies have rigorously tested causal relationships using appropriate methodology such as randomized controlled trials, with many relying on non-experiential designs that can only uncover correlations between variables (Frederiks et al., 2015). Moreover, a lot of studies report methodological issues, relating the theoretical framing, target segmentation and the overall approach (Lopes et al., 2012). Therefore, in order to document behavioral change, it is essential to use validated instruments, as well as have a direct connection between theoretical model, the methodological approach and the context in which the intervention takes place. Design of the validation methodology to be used in the enCOMPASS project

In this section we describe the validation methodollgy to be applied in the enCOMPASS project, which is based on the eeMeasure methodology. First we recall the timeline of the trials, then we identify the KPIs to be measured, and finally we decline the eeMeasure methodology in the enCOMPASS project.

## 2.1 Timeline of the enCOMPASS trials

Timeline of the enCOMPASS trials in households, public buildings and schools has already been introduced in Deliverable D7.1. Since we will refer to it throughout the present Deliverable D7.2, we report it here as well, by means of Figure 1, Figure 2 and Figure 3.

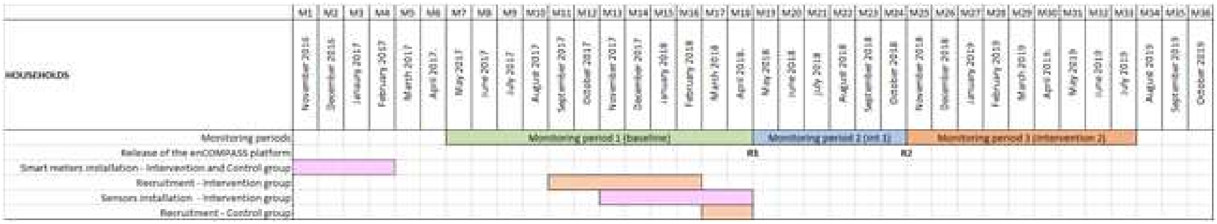


**Figure 1: Timeline of the enCOMPASS trial for households**

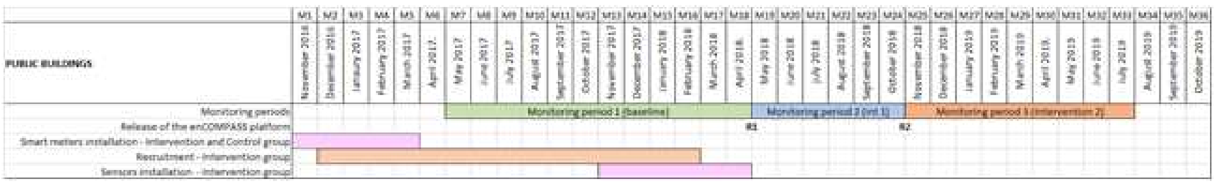


**Figure 2: Timeline of the enCOMPASS trial for public buildings**

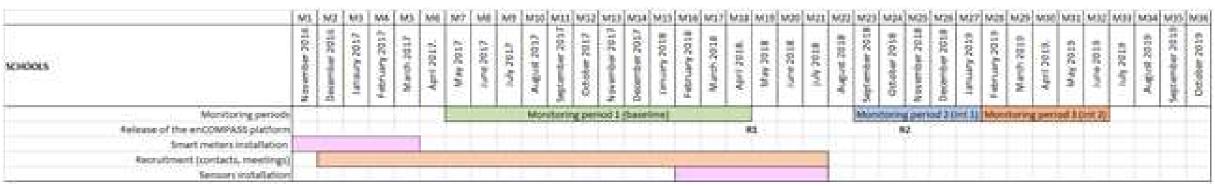


**Figure 3: Timeline of the enCOMPASS trial for schools**

## 2.2 KPI to be measured

In the Description of Action and in deliverable D7.1, preliminary key performance indicators (KPIs) have been defined to assess the objectives of the enCOMPASS project. Those KPIs were refined based on the outcomes of the requirements analysis and assessment of user needs with respect to energy behavior (preliminary results made available at M8 - June 2017 in deliverable *D2.1 Use cases and early requirements,* final version made available in M12 – October 2017, in deliverable *D2.2 Final requirements*). Furthermore, the state-of-the-art overview of (psychological) behavioral change research provided in D5.1 *Behavioral change models and determinants for energy consumption* and how such psychological factors can be assessed was used as input for the details of the validation methodology (D7.2 Validation methodology).

Based on such elements, Table 7 proposes the refined list of the KPIs and their target values, by directly relating them to the project objectives indicated in the enCOMPASS Grant Agreement (Description of Action), and their measurement instruments (KPIs assessment). In Table 7 instead we summarise the KPIs that will be monitored during the project.

**Table 7: enCOMPASS Objectives and related KPIs**

<table>
<tr><td colspan="2">Objective 1: Stimulate behavioural change for energy saving with a holistic approach integrating innovative digital tools with smart home automation and a full-cycle model of sustained behavioural change.<br>enCOMPASS extends and integrates existing technologies and product offerings of their partners' with innovative elements, such as user-friendly visualizations, context-awareness, adaptive gamification, context-aware energy saving recommendations to implement a holistic system for behavioural change.</td></tr>
<tr><td>KPIs and target values</td><td>KPI assessment</td></tr>
<tr><td>1. Energy savings (electricity consumption) & $CO_2$ emissions savings achieved through integrated enCOMPASS system:<br>~ 20-25%</td><td>Use of the eeMeasure methodology (see Section 2.3) to assess electricity consumptions.<br><br>This KPI will be assessed both for intervention period 1 (enCOMPASS release 1) and for intervention period 2 (enCOMPASS release 2), by comparing electricity consumption data with baseline data.<br>When available (residential buildings), data gathered for the control group will be considered.</td></tr>
<tr><td>2. User awareness of energy consumption:<br>1pt increase on a 5-points Likert scale (+20%)</td><td rowspan="3">Use of established behavioural change models (e.g. Ajzen, 1991; Schwarzer, 1997) to assess behavioural attitudes and perceptions of individual citizens involved in the pilot trials.<br><br>This KPI will be assessed both for intervention period 1 (enCOMPASS release 1) and for intervention period 2 (enCOMPASS release 2), by comparing behavioural variables with respect to the corresponding baseline data.<br>When available (residential buildings), data gathered for a control group will be considered.</td></tr>
<tr><td>3. User knowledge of energy saving actions:<br>1pt increase on a 5-points Likert scale (i.e. +20%)</td></tr>
<tr><td>4. Perceived impact of enCOMPASS system on intention to save energy:<br>1pt on 5-point Likert scale (20%)</td></tr>
<tr><td>5. Cost-effectiveness of the enCOMPASS system:<br>ROI <2,5 years<br>(residential: 1-1,5 years, public buildings: 1-2,5 years, schools: <1 years)</td><td>This KPI measures the cost sustained by a user who would subscribe to a pay per use version of the enCOMPASS system versus the savings s/he obtains over a period of 2.5 years. The subscription cost is computed simply as sharing the total platform cost across 10% of the utility customers, as we assume this as an average adoption rate.</td></tr>
<tr><td>6. Number of people involved in the pilots:<br>2000</td><td>Number of participants in each household (intervention groups) +<br>Average number of monthly customers in each public building * number of months of the trial +<br>Number of employees in each public building +<br>Number of teachers in each school +<br>Number of pupils in each schools * 2<br>[we make the hypothesis that each pupil talks about enCOMPASS activities in the classroom with at least one adult person]</td></tr>
</table>

<table>
<tr><td colspan="2"><u>Objective 2:</u> Make energy usage data accessible to consumers in a user-friendly, easy-to-understand way.<br>Electricity consumption data will be visualised in a way that translates the abstract, numeric consumption data into a semantically understandable format for the users, by applying visual metaphors that are easy to use, easy to understand and fun to explore. Interactive exploration of different levels of detail (time, usage by device) will support energy awareness and integrate contextualized advice for energy saving actions (from recommender).</td></tr>
<tr><th>KPIs and target values</th><th>KPI assessment</th></tr>
<tr><td>7. Usability of the energy visualisation for consumers:<br>4 or higher (on a 5-points Likert scale)</td><td rowspan="4">Assessment will be based on well-established user experience and technology acceptance frameworks, such as the Unified Theory of the Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003), which typically employ questionnaires for data collection. Apart from an assessment of user experience metrics, additionally the hedonic value (fun-of-use) of the enCOMPASS system must be assessed, as hedonic incentives (gamification mechanisms, and visually appealing consumption feedback) play an important role in the enCOMPASS behavioural change model. Additionally, user behavior data with respect to the usage of the enCOMPASS applications will be collected and analyzed, to complement the self-reported measures.<br>A mixed-method approach is used, drawing on:<br>• user behavior data collected by the enCOMPASS apps,<br>• questionnaires that elicit user feedback on technology acceptance of the app (Venkatesh, Morris, Davis, & Davis, 2003)<br>• individual features, such as the visualizations and recommendations.<br>Logs of user behavior are analyzed to relate the impact of using enCOMPASS features on electricity consumption levels. User logs are also analyzed with respect to the acceptance of recommendations for energy saving actions.</td></tr>
<tr><td>8. User experience of the energy visualisation:<br>4 or higher (on a 5-points Likert scale)</td></tr>
<tr><td>2. User awareness of energy consumption:<br>1pt increase on a 5-points Likert scale (+20%)</td></tr>
<tr><td>9. User comprehension of personal energy consumption:<br>4 or higher (on a 5-points Likert scale).</td></tr>
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<table>
<tr><td colspan="2"><u>Objective 3:</u> Demonstrate that individual comfort levels can be maintained while achieving energy savings.<br>Recommending targeted energy saving actions to users, based on their comfort profile, current context, activity, and best-fitting energy control profiles, will allow users to save energy while retaining personal comfort levels.</td></tr>
<tr><th>KPIs and target values</th><th>KPI assessment</th></tr>
<tr><td>10. User satisfaction with in-door comfort level during usage of enCOMPASS:<br>4 or higher (on a 5-points Likert scale)</td><td rowspan="2">Research on indoor climate perceptions will be used to obtain measurements for perceptions of in-door comfort levels, which will be elicited through the awareness app, for thermal and visual comfort on a seven-point scale ranging from very cold to very hot, and from very dark to very bright respectively. Additionally, on the same scales the desired comfort level at the moment of measurement is requested.<br>Objective data comes from explicit feedback on recommendations (e.g. the % of recommendations that is accepted by users), collected by logging and analyzing user-system interactions. The feedback options measure the behavioural intention to carry out the tip (e.g. Will do, already doing it), as well as negative relevance judgments ('Not suitable').<br>Perceived usefuleness will be measured through five-point Likert scale items, assessing both context-based and static recommendations (referred to in enCOMPASS as tips) for energy saving actions.</td></tr>
<tr><td>11. Perceived usefulness of context-based recommendations for energy saving:<br>4 or higher (on a 5-points Likert scale)</td></tr>
<tr><td colspan="2"><u>Objective 4:</u> Validate the relative effectiveness of different types of behavioural change interventions for different types of users, in different types of settings and in different climatic conditions.<br>Measuring the effectiveness of different interventions directly w.r.t actual consumption reduction would require too many different variations of treatment and control groups, not feasible in real-world pilots. As our approach is grounded in behavioural theory (TPB), we can measure user perception of the impact of different interventions on their intention to save energy. A number of studies have shown that this works well as a proxy for actual behaviour.</td></tr>
<tr><th>KPIs and target values</th><th>KPI assessment</th></tr>
<tr><td>2. User awareness of energy consumption:<br>1pt increase on a 5-points Likert scale (+20%)</td><td rowspan="3">Use of established behavioural change models (e.g. Ajzen, 1991; Schwarzer, 1997) to assess behavioural attitudes and perceptions of individual citizens involved in the pilot trials.<br><br>Data collection on these KPIs is done by questionnaires at key moments: before the trial starts (baseline, end of monitoring period 1) and at the end of monitoring periods 2 and 3.<br><br>Answers will be compared by user types, building type and climate condition.</td></tr>
<tr><td>3. User knowledge of energy saving actions:<br>1pt increase on a 5-points Likert scale (i.e. +20%)</td></tr>
<tr><td>4. Perceived impact of enCOMPASS system on intention to save energy:<br>1pt on 5-point Likert scale (20%)</td></tr>
</table>

| | |
|---|---|
| **12. Perceived impact of individual elements (energy visualisation / context-based recommendations / adaptive gamification / physical-digital game) on user intention to save energy:**<br>**1pt on 5-point Likert scale (20%)** | |
| **6. Number of people involved in the pilots:**<br>**2000** | Estimate of the indicator is performed as follows:<br><br>Number of participants in each household (intervention groups) +<br>Average number of monthly customers in each public building * number of months of the trial +<br>Number of employees in each public building +<br>Number of teachers in each school +<br>Number of pupils in each schools * 2<br><br>[we make the hypothesis that each pupil talks about enCOMPASS activities in the classroom with at least one adult person] |
| <u>**Objective 5:**</u> **Make the enCOMPASS platform, digital tools, services and acquired energy data available to designated third-parties (in privacy-preserving ways) initiating the creation of a business ecosystem for the development and provision of value-added services for smart energy demand management.**<br>**The enCOMPASS platform and its modules will be made available as platform-as-a-service (PaaS) and software-as-a-service (SaaS) with open APIs for developers of new extensions and value added services. Anonymized, privacy-preserving aggregates of energy consumption data from the pilots will be published as open data sets.** | |
| ***KPIs and target values*** | *KPI assessment* |
| **13. Number of open APIs for reuse of the enCOMPASS platform by third parties:**<br>**2** | These KPI's will be continuously monitored as part of WP8, within the consecutive exploitation plan deliverables (D8.1, D8.4, and D8.6). |
| **14. Number of third-parties making use of enCOMPASS apps and services during project:**<br>**>=3** | |
| **15. Number of data sets published as open data:**<br>**> 5** | |
| **16. Number of external parties engaged:**<br>**utilities (>=10), SMEs (>= 10), PAs (>=10)** | |

## 2.3 Design of the enCOMPASS validation methodology

As indicated in D7.1, impact of the enCOMPASS energy saving intervention will be assessed by considering both energy consumption data (electricity consumption monitored by the smart meters) and behavioural data (attitudes and perceptions monitored by means of a three-wave survey). Assessment of the impact on electricity consumption data will be performed by means of the eeMeasure methodology and software, which is presented in detail below (Sections 2.3.1, 2.3.2 and 2.3.3), and was selected since it will allow us to get comparable results with other energy saving projects and interventions developed throughout Europe. Assessment of the impact on behavioral data will instead be performed by comparing Likert-scale answers to the same questions across the three waves of the survey, and by accounting for their variations (see Section 2.3.4).

### *2.3.1 The eeMeasure methodology for the assessment of the impact on electricity consumption*

For the assessment of the outcomes of the pilot trials, we will rely on the eeMeasure methodology, developed by the Information and Communications Technology Policy Support Programme (ICT PSP) funded projects (Lohmann, Heilmann, Hacke, & Robinson, 2011). Since January 2012, such projects have made available online[1] an eeMeasure software, which is aimed at producing an accurate quantitative analysis on the energy savings potential of ICT based solutions in residential and non-residential buildings.

The eeMeasure software facilitates the evaluation of all kinds of energy saving effects produced by a variety of ICT-based solutions, including behavioural changes due to installed ICT solutions and improved public awareness through ICT-based services. It mainly targets the residential sector, where energy use is generally much less, and more difficult to predict, than in the industrial sector. The software also allows for estimating the amount of $CO_2$ emissions, principally from savings in heat and electricity consumption that may be achieved by carrying out Energy Saving Interventions (ESIs).

In particular, the Residential Methodology is applicable only to dwellings and generally assumes a monthly measurement period. It works under assumption of variable demand as a result of the Energy Saving Intervention (ESI) stimulated by an ICT application, which enables a before-after comparison for the whole facility/dwelling. As depicted in Figure 4, it first requires to define which is (are) the target dependent variable(s) that shall be affected by the ESI (e.g. energy consumption, behavior, awareness) and which are independent variables that can also have an (unwanted) impact on the dependent variable(s) (not part of the intervention, e.g. weather conditions). The net ESI impact is the effect that is solely resulting from the intervention and must be distilled from the gross impact, i.e. the impact resulting from the ICT application and other external independent variables.

[1] The ICT PSP Methodology for Energy Saving Measurement, Available at: http://eemeasure.smartspaces.eu/static/files/eemeasure_residential_methodology.pdf [accessed 12/09/2017]

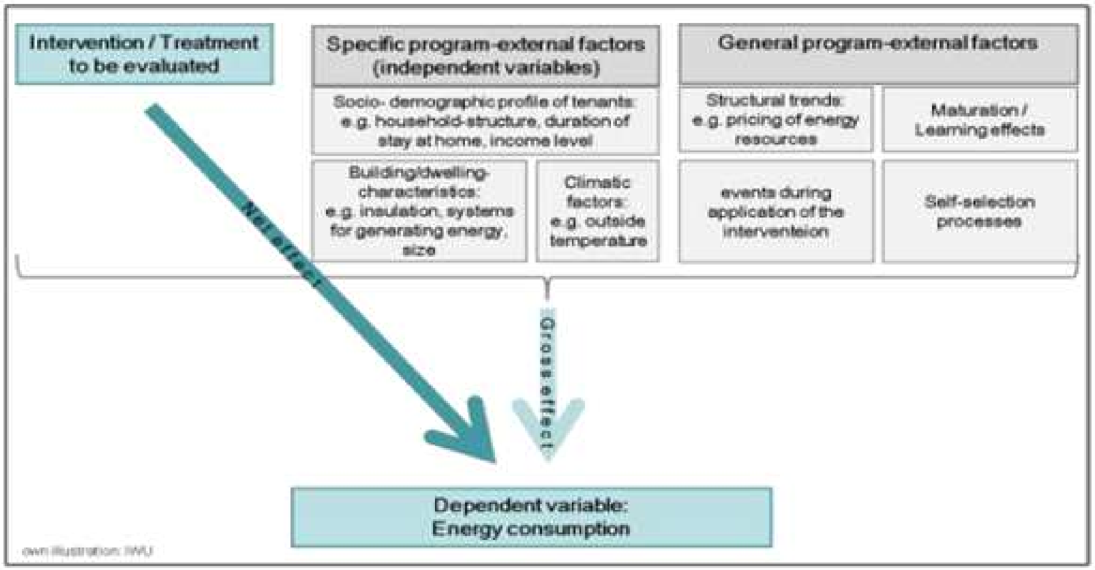


**Figure 4: Factors influencing gross vs net impact on energy consumption**

In before-after comparison, the actual energy saving caused by an ESI is estimated from the difference between consumption during the intervention and the consumption which would have taken place under the same demand conditions without the ESI. To estimate consumption levels without the ESI, consumption data prior to the intervention is used. This is known as baseline data.

When a control group is not available, to univocally attribute energy savings to the ESI, instead of other external factors, an "extended baseline" period is used. It represents the projection of consumption before the intervention into the period during the intervention. Estimation of such extended baseline can be based on prior consumption patterns (as discussed above) or on patterns of consumption in comparable settings unaffected by the intervention – "control buildings" – or on both. To this aim, the eeMeasure methodology proposes regression techniques to estimate projected energy consumption during the intervention ("extended baseline" data), based on values of the independent variables. The accuracy of such models is evaluated by metrics such as the squared multiple correlation coefficient $R^2$, which reflects the proportion of variance explained in the model. The correlation coefficient evaluates how well variations of an independent variable can predict changes in the dependent variable being examined (energy consumption data). If $R^2$ is low, further independent variables must be found to improve predictions. Also in such case, the net ESI impact is estimated by means of a "difference in differences" approach (ESI-period vs extended baseline period), though only referring to intervention group data.

Conversely, when control buildings are available, (i.e., buildings which match the characteristics of the experimental buildings in all known independent variables, e.g. type of building, location, energy equipment, insulation, heating system) , data are typically collected from the control group over the same intervention period, as done for experimental groups: therefore, possible variations in energy consumptions due to external variables take place both for the control and for the intervention group, so that they can be extrapolated and then discarded.

It follows that the "difference in differences" approach (Abadie, 2005) is used: differences between the "intervention consumptions" and "baseline consumptions" are assessed both for the intervention and the control group. Differences between such differences produces the net ESI impact.

In the following sections we explain in more details the procedure we will follow to validate impacts of the enCOMPASS energy saving intervention (enCOMPASS ESI).

### *2.3.2 Methodology for validation of impact on electricity consumption in schools and public buildings*

The enCOMPASS pilot trials for schools and public buildings do not envision a control group. Therefore, in such cases we will refer to the eeMeasure methodology exploiting "extended baseline data".

Estimation of the enCOMPASS ESI impact on energy consumption data will be based on:

- before-the-intervention ("baseline data") and during-the-intervention measures of the electricity consumption data,
- and "extended baseline data", namely estimates of the electricity consumption values that would have occurred in the intervention period without the enCOMPASS ESI.

More in detail, as stated by eeMeasure, we will refer to the following procedure, which is also shown in Figure 5 :

1. Nominate a time period for the baseline which captures all variation of immeasurable independent variables and can yield an average which can reasonably be expected to be repeated in the future; then, gather data for the energy consumption (dependent variable) and for all accessible independent variables (baseline period);
2. By means of regression analysis techniques, model the correlation between dependent and independent variables and calibrate the values of the related coefficients through the baseline data. Regression will be performed on weekly time steps.
3. Nominate a time period for the intervention, which is again long enough to capture all variation of immeasurable independent variables; then, gather data for the energy consumption (dependent variable) and for all accessible independent variables (intervention period).
4. Apply the regression coefficients estimated by the baseline data to the intervention period data for the independent variables, thus obtaining estimate values of the dependent variable, under the assumption that no intervention is performed (extended baseline data).
5. The impact of the intervention is obtained as the difference between estimated and measured values of the dependent variable, over the intervention period.

The baseline period has already been indicated in Deliverable D7.1 and in Section 0, and it consists of one full year, from May, 1 2017 to April, 30 2018. The independent variables measured during the baseline period are outdoor temperature and solar irradiation, measured by the meteorological monitoring network available in each pilot site. The dependent variable, instead, is electricity consumption; it is measured at the building level by means of a smart meter, with a frequency of fifteen minutes. The time step chosen to model correlation between dependent and independent variables (regression analyses techniques) is the week.

As indicated in Deliverable D7.1 and in Section 0, the intervention period for schools differs respect to the intervention period for public buildings, in order to take into account summer break of school activities. Intervention period for schools is in fact set as follows:

- enCOMPASS platform Release 1: September, 1 2018 – January, 31 2019 (intervention period 1);
- enCOMPASS platform Release 2: February, 1 2019 – June, 15 2019 (intervention period 2).

While intervention period for public buildings is set as follows:

- enCOMPASS platform Release 1: May, 1 2018 – October, 31 2018 (intervention period 1);
- enCOMPASS platform Release 2: November, 1 2018 – July, 31 2019 (intervention period 2).

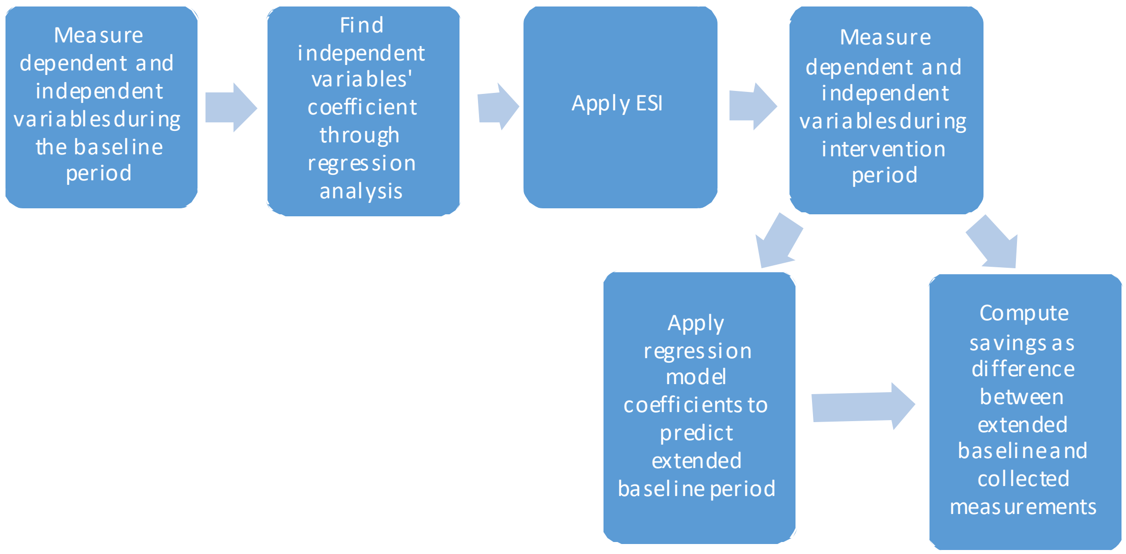


**Figure 5 : Steps to validate the impact of an energy saving intervention on energy consumption, according to the eeMeasure methodology in trials without a control group**

### *2.3.3 Methodology for validation of impact on electricity consumption in residential buildings*

In presence of control buildings (which is the case of the enCOMPASS pilot tests involving residential buildings), estimation of the enCOMPASS ESI impact on energy consumption data will be based on:

- before-the-intervention ("baseline data") and during-the-intervention measures of the electricity consumption data,
- both in the intervention and in the control group.

Accordingly, the following steps are executed (see Figure 6).

1. Select a group of buildings representative of the future exploitation potential of the energy saving intervention (ICT application).
2. Randomly divide the pilot buildings into 2 groups: intervention and control. Optionally, before dividing the buildings, a random stratification can be performed, identifying sub-groups of analogues cases respect to a certain number of criteria, so that the intervention and the control groups have a comparable composition respect to such criteria. If possible, establish pairs of analogues cases from both groups.
3. Measure dependent and independent variables during the baseline period in both control and intervention group
4. Implement the Energy Saving Intervention (ESI) in the intervention group
5. Measure dependent and independent variables during the intervention period, in both intervention and control group
6. Calculate energy saving (the impact of the intervention) as difference between
   - the difference in the measured energy consumption in the intervention group between the intervention period and the baseline period,
   - and the difference in the measured energy consumption in the control between the intervention period and the baseline period, (difference in differences), possibly using matched-pair statistical techniques.

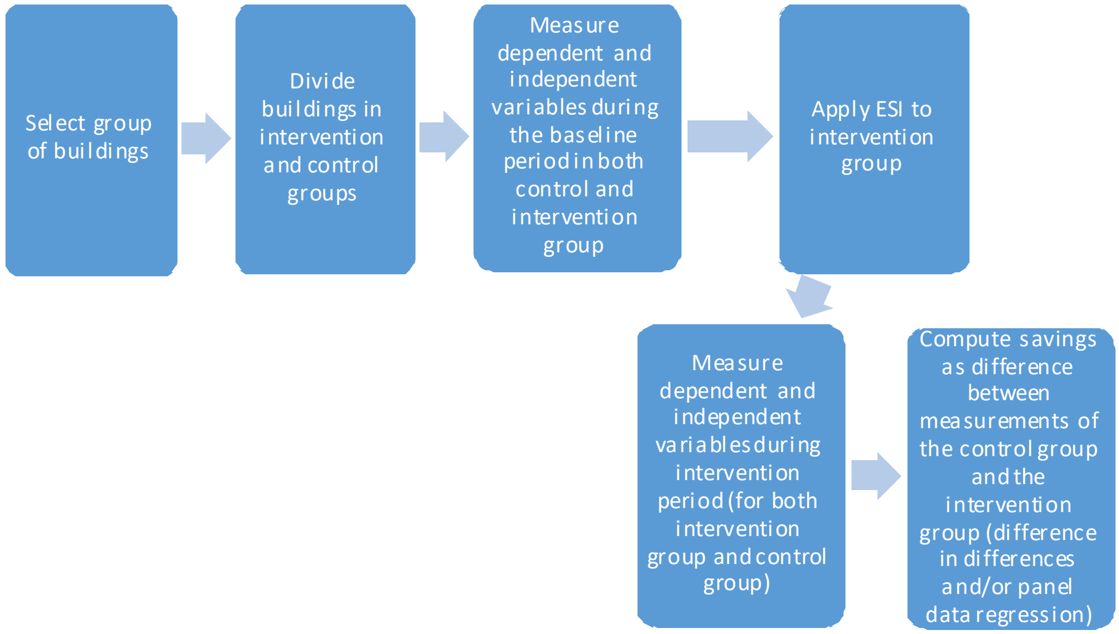


**Figure 6: Steps to validate the impact of an energy saving intervention on energy consumption, according to the eeMeasure methodology in trials with a control group**

The procedure to select the residential buildings (households) taking part in the trial is presented in detail in Deliverable D2.1. Here, we just highlight that stratification parameters we will refer to in the identification of the intervention and control groups will be taken from the following ones:

- Size: single-person/couple/more than two person households (family with kids).
- Type of house: single-family house (including terraced house)/apartment.
- Type of heating: electricity-fed (heat pump, direct electricity)/oil/gas/wood/other.
- Type of hot water boiler: electricity-fed/oil/gas/wood/other.

Depending on data availability in each pilot site, a sub-set of such parameters might be used.

The baseline period has alse been defined in Deliverable D7.1, and it consists of one full year, from May, 1 2017 to April, 30 2018. As for schools and public buildings, the independent variables measured during the baseline period is the outdoor temperature, measured by the meteorological monitoring network available in each pilot site. The dependent variable, instead, is electricity consumption; it is measured at the household level by means of a smart meter, with a frequency of fifteen minutes.
Intervention period for households has been set as follows:

- enCOMPASS platform Release 1: May, 1 2018 – October, 31 2019 (intervention period 1);
- enCOMPASS platform Release 2: November, 1 2019 – July, 31 2019 (intervention period 2).

### 2.3.4 *The methodology for the assessment of the impact on awareness*

Where interventions target user behavior regarding energy consumption, the awareness with regard to energy consumption must be measured in addition to the energy consumption itself, as the behavior has the function of a dependent variable. In addition to that, there are other behavior related aspects that can have an impact on the energy savings that have to be considered if the net effect of the intervention shall be uncovered. For the collection of data about these variables survey techniques can be used.

As has been shown in the methodology review in section 2.1, the value of many intervention studies is jeopardized by small sample sizes, and sub optimal experimental designs (e.g. missing control groups, missing ex-post vs. ex-ante comparisons). In enCOMPASS, a survey-based repeated measures approach will be adopted with measurements at multiple stages. To capture behavior and awareness change due to the intervention, questions referring to awareness and behaviour of the current time or immediate past will be used. Using a repeated measures approach that aims at the comparison of results in several stages, it must be ensured that the participating households can be identified, but data protection nevertheless is warranted. To achieve this, an ID that is related with the households will be used. By entering the IDs in the questionnaires of all stages (using a computer assisted instrument the ID can also be entered as password), the response rate will be known as well as the households that have participated in all stages. It is only on this basis that changes in the results of both stages can be identified.

As our intervention provides an information service, in order to assess behavioral change for the residential households a control group will be used. Pilot tenants will therefore be assigned either to the control or the intervention group, where the characteristics of the control group concerning living situation, household size, average age, ecological awareness or the like match those of the intervention group. The intervention group will use encompass user awareness apps, whereas the control group will not be exposed to this intervention. Additionally, as in the first release of the enCOMPASS platform for households the sensor infrastructure is the same across pilots (see *D2.2 Final requirements*), we will compare differences between the pilot locations, to the extent that influencing factors can be kept under control.

For the construction of the questionnaires, the KPI's related to awareness must be operationalized into measurable constructs with associated measurement instruments. The involved KPI's that were identified in the GA and in Section 2.2are:

- **User awareness of energy consumption:** 1pt increase on a 5-points Likert scale (i.e. + 20%)
- **User knowledge of energy saving actions:** 1pt increase on a 5-points Likert scale (i.e. +20%)
- **Perceived impact of ENCOMPASS system on intention to save energy:** 1pt on 5-point Likert scale

These three KPIs relating to behavior change are expected to differ between the control group which does not use an enCompass ESI and the intervention group that has been exposed to encompass ESI over a certain period of time. As mentioned in 2.1, in order to uncover the differences in behavior between the two groups, the process of operationalization of constructs is essential. As behavioral change is a complex process, the KPIs cannot be measured with a single construct, but needs to consider an array of constructs with corresponding items. Moreover, in line with the reviewed determinant models explained in D5.1, it is assumed that a set of psychological, social and other external variables (we call them control factors) impact the behavioral change and their impact on target behavior needs to be considered as well in order to be able to draw conclusions regarding the impact of the intervention.

The operationalization of the KPI's and the control factors is guided by the theoretical models regarding behavioral change and persuasive systems that have been presented in D5.1 and D5.2, addressing the determinants, processes, and incentives through which behavioral change can be induced. While the reviewed models and frameworks were assessed to support the definition of the focal points for the behavioral change incentives in the enCOMPASS ESI, they also give guidance to the operationalization of energy consumption awareness and help assess behavior change.

As mentioned in 2.1, the underlying theoretical model should determine the process of construct operationalization. Even though there is no unified model that is universally accepted by scholars as providing an all-inclusive explanation of energy consumption behavior or behavioral change (Frederiks et al., 2015), many attempts have been made at connecting different underlying theories. For the purpose of the validation, Stern's framework of environmentally significant behavior (Stern, 2000) is well-suited. The framework is founded on the propositions of the models that partially cover pro-environmental behavior (e.g. value-belief-norm (VBN) theory of environmentalism (Stern, 1999), Schwartz's (1977) norm activation model, and Guagnano et al.'s (1995) attitude-behavior-external conditions (ABC) model. The model considers that pro-environmental decision or behavior is a function of the four sets of factors: personal attitudes, habits and experience, as well as contextual factors such as individual capabilities and external conditions. Guided by this general framework, we adapt the proposed constructs to our context of energy use in order to measure behavioral change reflected in the KPIs resulting from using encompass ESI.

First, the **awareness of energy consumption** is a complex attitude formation process that involves understanding the impact of energy consumption not only on the individual behavior, but also that of other people. As such, we propose that the process of developing awareness is formed in line with the norm activation theory of altruism (Schwartz, 1977). This theory states that the result of increasing awareness is the formation of personal norm for energy conservation, which in turn is formed by increasing awareness of negative consequences of not saving energy and ascribing responsibility to oneself for bearing the consequences thereof (Guagnano et al., 1995). Additionally, Value-Belief norm theory (Stern, 1999) treats values as antecedents to the awareness formation process. It proposes that in order to increase awareness and form a personal norm, it is required that also relatively stable personality characteristics, such as personal values, should change as well. Some of our interventions in enCompass ESI are specifically designed to increase awareness of one's actions and understanding that already a small conservation behavior such as turning off the power when devices are not used, can cause reductions in energy consumption which translates into benefits for all individuals. Therefore, in order to assess change in awareness of energy consumption, we are going to measure four constructs with validated measurement instruments, which are adapted to the context of energy saving:

- **Personal norm** in line with Vining and Ebero (1992) by items such as "I feel strong personal obligation to save energy" or "I am willing to put extra effort into saving energy on a regular basis".
- **Awareness of consequences** in line with Hunecke et al. (2001) such as "I am aware that my energy consumption influences the change of climate caused by the greenhouse effect" or "I have a bad conscience towards the environment when I use too much energy"
- **Ascription of responsibility** in line with Harland et al. (2007) with items such as "Someone who does not save energy cannot be held responsible for the environmental consequences of that behavior"
- **Values** (hedonic, egoistic, altruistic and biospheric) will be measured in line with the goal framing theory (Lindenberg and Steg, 2013) by an instrument proposed by Steg et al. (2013)

Second, the **intentions to save energy** will be measured by two constructs. First, the intention variable that under favorable contextual conditions leads to actual behavior according to Theory of Planned Behavior (Ajzen, 2002). However, many studies have documented the so-called "attitude-action gap" in the context of energy conservation when positive values and attitudes lead to intentions, but have no impact on energy saving behaviors (Fredericks et al., 2015). This is often a result of not measuring other constructs that are indicative of behavior change or not taking into account the context in which behavior change occurs. As behavior change often requires breaking old habits and becomes established by creating new ones (Dahlstrand & Biel, 1997), habit strength is something that could provide indication of successful behavioral change. Habit is recognized by authors also a key factor in environmentally significant behavior (Stern, 2000). We are going to measure the following items:

- **Intentions to save energy** in line with Ajzen (2002) by items such as "I intend to save at least XX% energy next month" or "I plan to save at least XX% energy in the coming month"

- **Habit strength** will be measured by using a self-reported habit instrument, such as the Self-Report Habit Index (Verplanken & Orbell, 2000). Examples of items are "Switching the lights off when I leave the room is something I do automatically / I have no need to think about doing / that makes me feel weird if I do not do it".

Third, in order to measure the increase in **knowledge of energy saving actions**, the individual capabilities in the integrated model of pro-environmental behavior of Stern (2000) will be used. Applying the model to energy saving, increase in knowledge of energy saving actions is reflected in the increase in the belief about personal capabilities to save energy and the increase in the degree of environmental knowledge (Frick et al., 2004). Capabilities include knowledge and skills necessary to save energy, whereas environmental knowledge can be system-, action- and effectiveness related (Kaiser and Frick, 2002). Self-efficacy theory (Bandura, 1977) states that in order to effectively change behavior, incentives should be directed to increase the perception of ability of the person to perform actions. In the encompass ESI some of the interventions target especially the increase in knowledge about environmental saving and increasing person's capacity to perform energy saving actions. In order to assess the increase in the knowledge of energy saving actions, we are going to measure the following constructs:

- **Environmental knowledge** will be measured with an adapted scale from Kaiser and Frick (2002), and items relating to energy knowledge will be selected, such as: "Energy efficient light bulbs save about: 20% - 50% - 80% of electricity compared to conventional bulbs" and presented to users in form of multiple-choice answers.
- **Self Efficacy** in line with Bandura (2006) by items such as "To what extent do you feel capable of saving energy" on a scale: not at all confident – very confident. Alternatively, we could measure Perceived behavioral control as is operationalized in the TPB by Ajzen (2002) or ability as operationalized by Harland et al. (2007).

As mentioned above, behavior change is reflected not only in the KPIs, but also in an array of social and contextual indicators (control variables) that underlie the process of change. The Attitude-Behavior-External conditions theory (Guagnano et al., 1995) is the foundation of the external conditions part in the model of pro-environmental behavior of Stern (2000). The theory stresses that the attitude-behavior association is strongest when contextual factors are neutral, and approaches zero when contextual forces are strongly positive or negative (Stern, 2000). The more difficult, time-consuming and expensive the behavior, the more positive behavioral context is needed (by e.g. providing the incentives) to change behavior. In the model of Stern (2000) contextual forces include above others interpersonal influences (e.g. persuasion), community expectations, monetary incentives, and technological interventions. Clearly the incentives provided through the enCompass ESI are contextual forces which can increase the awareness of consequences of energy saving, as well as affect the conservation behavior directly. Moreover, numerous studies mention the impact of the broader social context on the behavior of individuals (Abrahamse and Steg, 2013). As a norm formation process underlies behavior change process, broader social norms can play an important role in influencing awareness and intention to save energy. We will measure the following constructs:

- **Social Norms** in line with Ajzen (2002) by items such as "Most people who are important to me think that I should – I should not (7pt Likert scale) conserve energy" or "It is expected of me that I conserve energy". Note that social norms are anchored in the environment, whereas personal norms come from individual's self (Kerr et al., 1997)
- **Behavioral response to incentives**, such as the impact of number of times the users viewed the visualizations, the position of the person in the ranking relative to others, the number of times the person took action based on the recommendation, the number of times the user logged in, etc. This

corresponds to the KPI Perceived impact of individual elements (energy visualisation / context-based recommendations / adaptive gamification / physical-digital game) on user intention to save energy.

The constructs proposed above will be measured with an array of validated items (for which examples have been demonstrated) adapted to the context of energy saving. The selected items will need to be aligned with the final incentive model for enCOMPASS, for which a draft version has been reported in *D5.2 Incentives, and engagement strategies*, and which will be finalized in *D5.3 First visualization and feedback interfaces and behavioral game concept*. For these reasons and also due to practical constraints such as the maximal length of the questionnaire, which can be expected from users to fill out, the final selection of items to measure the constructs will be done after the release of D5.3. The questionnaire and the first results will be reported in *D7.3 First validation report and data set*.

### *2.3.5 Methodology for the assessment of user behavior*

Finally, KPI's were identified that assess the perception of the enCOMPASS application by the users:

- Usability of the energy visualisation for consumers: 4 or higher (on a 5-points Likert scale)
- User experience of the energy visualisation: 4 or higher (on a 5-points Likert scale)
- User comprehension of personal energy consumption [visualization]: 4 or higher (on a 5-points Likert scale).

A mixed-method approach is used to assess these KPI's. Regarding the usability and user experience, a distinction is made between two levels: the level of the enCOMPASS application as a whole, and the level of individual features (e.g. visualizations, recommendations). At application level, we employ questionnaires, as is commonly done in technology acceptance research. At the level of individual features, both questionnaires and analyses of user-system interaction logs are used.

For the application level, we will make use of well-known frameworks for technology acceptance. More specifically, the following subscales from the Unified Theory of the Acceptance and Use of Technology (Venkatesh et al., 2012; Venkatesh et al., 2003) will be used:

- **Performance expectancy:** perceived usefulness of the enCOMPASS application
- **Effort expectancy:** perceived usability (e.g. ease-of-use) of the enCOMPASS application
- **Hedonic motivation:** perceived hedonic value of using the enCOMPASS application. This is important for enCOMPASS, as hedonic incentives (gamification mechanisms, and visually appealing consumption feedback) play an important role in the enCOMPASS behavioural change model.
- **Habit:** self-reported assessment of the extent to which the use of the enCOMPASS application has become habitual

On the level of individual features single-item Likert scale questions are asked, addressing the user experience and usability, with items on **ease-of-use**, **usefulness**, and **comprehension** for individual features (e.g. visualizations, recommendations).

Finally, in addition to the aforementioned self-reported measures, user behavior data is analyzed by assessing the logs of user-system interactions. The logging allows us to assess the frequency with which features are used, and the development of usage over time.

Additionally, user behavior data with respect to the usage of the enCOMPASS applications will be collected and analyzed, to complement the self-reported measures. The logs are analyzed with respect to the frequency with which the features are used, and the development of these frequencies over time. E.g. the number of times visualizations are viewed, the number of tips that has been read, or the share of the notifications that has been opened. User logs are also analyzed with respect to the acceptance of recommendations for energy saving actions, as derived from the explicit feedback to energy saving tips and context-aware recommendations. Additionally, to assess the impact of using enCOMPASS on achieved savings, correlational analyses will be used to relate the user behavior metrics to energy consumption levels.

# 3. Baselines and action plans of pilots

Here we update the action plans described in D7.1. This was requested in D7.1 but also in this deliverable, so we report it here, providing an updated version. In particular, we present the user engagement plan, the technical deployment plan for installation of sensors and smart meters and the baseline values gathered so far for both independent and dependent variables.

## 3.1 User engagement plan

In this Section, we present activities envisioned to guarantee appropriate user engagement and effective involvement of households, schools and public buildings.

In all pilot studies participants, and households in particular, are identified on a voluntary basis. Countermeasures will be taken to mitigate both a possible selection bias and the risk of participants dropping out before the end of the trial. Such countermeasures include physical rewards to be awarded at the end of the monitoring periods, virtual rewards in the enCOMPASS platform (e.g. points for participating in a survey) and randomized draws open to all active participants at the end of the trial.

### *3.1.1 German pilot*

All activities will take place in the city of Hassfurt: households, children attending the local school, civil servants and local decision-makers working at the municipal building “Altes Rathaus”. The presence of such tight relationships between the three levels of the pilot study creates positive synergies and is expected to stimulate higher commitment in the population, to favor active engagement in the project and to reduce drop-out rates over time.

The mayor of Hassfurt guaranteed involvement of the school and the municipal building in December 2016; smart meter electricity consumption data is available since 2009. Contacts have already been established with the school director and responsible for the technical sector to start planing the involvement in the pilots (e.g. for the sensor installation, information and education events for students, civil servants etc).

The involvement of households, the following activities are planned for the intervention group:

- SHF is placing articles on the introduction of enCOMPASS into the SHF customer magazine quarterly.
- The Hassfurt City council was already informed by SHF (in M4, February 2017).
- SHF did present the project and its aims at the 2nd Energy-Forum to inform the customers about the pilot in June 2017, where the first participants already signed up for the pilot.
- SHF will now create lists of typical types of households to be examined and benchmarked (M13, November 2017).
- Then out of the customer stock and based on the lists and experience out of former projects, SHF will invite up to 250 customers to gain 100 households for the pilot until end of M16 (February 2018).
- Prizes and rewards to stimulate the signups for participation in the pilots will be offered.
- The action on information campaign and pre-selection of customers is completed by the end of M16 (February 2018).
- Active recruitment activities will however be performed starting from M12 (October 2017).

All the above activities are aimed at selecting the intervention group households. Within the sign-up procedure, the subscribers are asked to give socio-economic and technical data, to support SHF in preparing the pilots and to guaranty the eligibility of the households:

- Number of persons living in the household: single/couple/more than two persons

- Type of the building: flat/other types of building
- Living space of the living room
- Number of doors/windows in the living room
- Type and number of heating devices in the living room

If needed, the Municipality of Hassfurt will be asked to provide further socio-economic data regarding the participating households and the buildings where they live.

This will allow us to stratify the sample and to compare it with the other pilot studies. Knowing the households and building types will also allow us to stratify the sample, so that we can then select a comparable control group, made of the same number of households, with similar proportions regarding number of persons and type of building.

All the above activities (see Figure 7) are aimed at selecting the intervention group households. For the selection of the control group households, instead, we plan the following steps (similar to the approach adopted for the Greek pilot):

- Recruitment of control group households will start directly after 100 intervention group households are selected.
- In M17 (March 2018) SHF will invite a set of up to 250 households to answer a set of two questionnaires over time, to investigate their energy behavior and whose composition is comparable to the intervention group.
- They will also be told that, by answering the questionnaires, they agree that their electricity consumption data from M7 (May 2017) to M33 (July 2019) are used within the enCOMPASS project, for research purposes only.
- Answers to the first questionnaire are expected to be gathered by the end of M18 (April 2018), to collect baseline behavioral data also for them. Answers will allow to identify the SHF customer number, which will allow us to start monitoring their electricity consumption during monitoring periods 2 and 3 and to gather their consumption during monitoring period 1.

Should more than 100 households answer the questionnaire, a selection among them will be made based on the household and building type, so that the control group is strictly comparable with the intervention group.

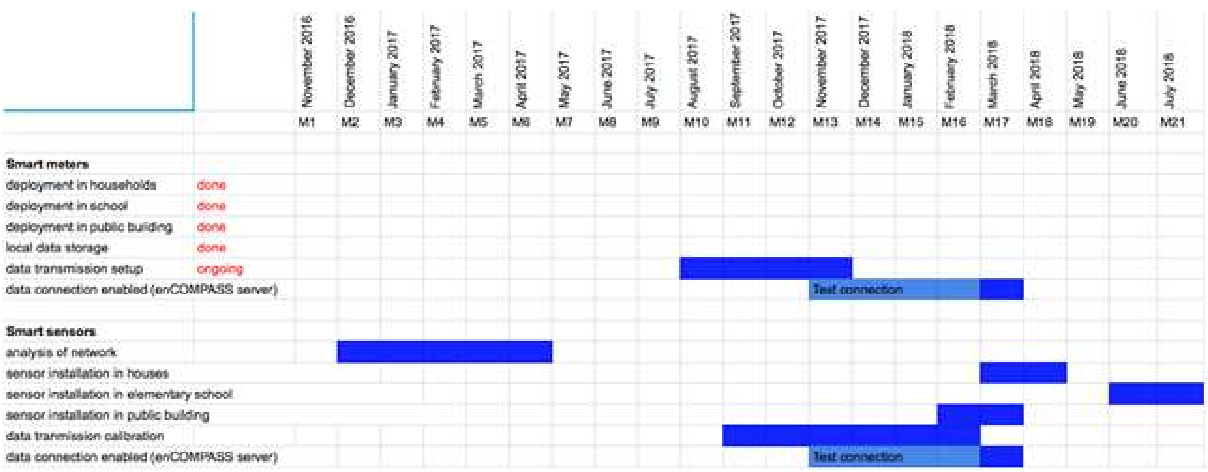


**Figure 7. The German pilot action plan**

***Reward and incentive based strategy for user involvement***

Countermeasures to mitigate a possible selection bias and the risk of participants dropping out before the end of the trial will be as followed in Germany:

In general, the participants get all Smart-Home devices for free and may keep them even after the end of the trail.

At the end of the monitoring periods the physical reward to be awarded is free entry into "Hassfurt Freizeitzentrum" for all members of each household. Depending on season and weather conditions, the families are invited to have fun with some outdoor activity. They may choose between the "adventure pools", where in summer as in winter a lot of water- and wellness-attractions are provided. In fall/winter/spring additionally the ice sports stadium is open, where skating for every age group is offered at diversified events.

At the end of the trial randomized draws open to all active participants will be arranged, where miscellaneous non-cash prizes can be won. SHF will especially honor winners of different encompass competitions.

### *3.1.2 Greek pilot*

All activities will take place using WATT+VOLT customer's portfolio in Thessaloniki and Athens. WATT+VOLT's Flagship Retail Store introduced and opened at 20/3/2017 in Thessaloniki city center is highly involved, engaging new customers to take advantage of the enCOMPASS approach, while the new flagship store customers will be taking advantage of acquiring the "smart watt" gateway and several sensors for free.

The Strategic Partnership between IEK DELTA and WATT+VOLT will involve students, parents and teachers gaining the "smart energy" privileges. IEK DELTA school presentations will be settled engaging at least 250 students to the enCOMPASS project and "smart energy" privileges, while it is planned a WATT+VOLT devices and sensors installation laboratory to be introduced, with lectures on the school building.

All the above activities (see Figure 8) are aimed at selecting the intervention group of households in Thessaloniki. Once such an intervention group will be completely recruited, WATT+VOLT is going to communicate the houses involvement in the enCOMPASS pilot, inviting them to the Retail Store for filling in the participation options. The final user group of 100 pilot houses will be selected based on WATT+VOLT's internal processes.

The following steps are envisioned for the selection of the control group households:

- Recruitment will start as soon as the intervention households are selected.
- A group of selected households (between 300 and 400) will be invited to answer a set of two questionnaires over time, to investigate their energy behavior; they will also be told that, by answering the questionnaires, they agree their electricity consumption data from M7 (May 2017) to M33 (July 2019) are used within the enCOMPASS project, for research purposes only.
- Answers to the first questionnaire will be gathered by M18 (April 2018), to collect baseline behavioral data also for them; answers will allow to identify the WVT customer number, which would allow us to start monitoring their electricity consumptions during monitoring periods 2 and 3 and to gather their consumptions during monitoring period 1.
- To stimulate them answering the questionnaire, prizes will be offered. Details are still to be defined; very likely, we will propose a random draw open to all the respondents, offering either discounts on electricity bills or vouchers for department stores or charity donations.

Should more than 100 households answer the questionnaire, we will stratify them based on the household, building and heating type, with the aim of selecting within them a set of at least 100 households that are overall comparable to the intervention group.


**Figure 8. The Greek pilot action plan**

***Reward and incentive based strategy for user involvement***

The enCOMPASS participants will receive the smart home package including a set of sensors for value of approximately 250 EUR.

### *3.1.3 Swiss pilot*

All activities will take place in the same community: we will involve households living in Contone (fraction of the Municipality of Gambarogno), children attending the pre-school and primary school in the close-by neighborhood of Cadepezzo, civil servants and local decision-makers working at the municipal building of Gambarogno, and even the household members themselves, in case they visit the municipality building.

The Municipality of Gambarogno, and especially the fraction of Contone, was chosen since in late 2016 SES had been appointed as the utility company covering this area, after an institutional aggregation between former municipalities. Curiosity towards the new utility company is expected to favor involvement in the enCOMPASS project and further retention throughout the whole pilot project. The only drawback related to such a choice is that smart meters were not previously available: SES installed them between M1 (November 2016) and M4 (February 2017); by M6 (April 2017) they became fully operational, and started gathering and storing electricity data, to build the related baseline data (see Section 3.3.1). In total, 614 smart meters were installed.

The original plan was to involve the primary school located in the fraction of Contone, in order to fully exploit positive synergies between families and the school attended by their children. However, since the second half of 2017, the building started undergoing a complete renovation, which would have compromised comparability between the monitoring periods. For this reason, the school in Cadepezzo was selected, which in any case is very close to the Contone residential area.

Involvement of the school and the municipal building was guaranteed by the mayor of Gambarogno in December 2016. In the following months, meetings with both the building managers, directors and employees have taken place, to plan sensors installation and first information events. Recently (end of

September 2017) the WP2 Requirements Workshops have been organized, respectively involving a group of employees in the municipal building and the director and teacher of the Cadepezzo primary school. Finally, smart meter electricity consumption data started being gathered from M6 (April 2017), coherently with the baseline monitoring period.

Involvement of households, instead, is not as straightforward, and requires a set of coherent communication actions, aimed at raising interest by citizens, who will be involved on a voluntary basis. enCOMPASS has been first introduced in a neighborhood assembly held in Contone on February 21st 2017, which had already been organized by the municipality of Gambarogno for other reasons. During the event, the new utility company SES was presented to the population and enCOMPASS was briefly introduced as well. Being mentioned during such an event was strategic for the project, since the assembly is attended by all types of population, not only by the small number of environmentally sensitive ones, who, instead, would have attended an enCOMPASS-only meeting. For the intervention group, the following activities have been envisioned:

- Active recruitment activities started in month M11 (September 2017), since the first activities within the pilot sites are expected to start at month M19 (May 2018), soon after the first release of the enCOMPASS platform.
- On month M13 (November 2017) a descriptive flyer presenting enCOMPASS and its advantages to the population will be sent by SES to all the households in Contone. The flyer will mention prizes, remark that participation is voluntary and invite all the interested households to communicate to SES their willingness to become engaged in the project.
- Since we do not expect to achieve the 100 households target by means of totally spontaneous applications, soon after 200 selected households will be explicitly invited by SES to engage in the project, by means of direct, written communication. Such communication will highlight benefits associated with participation in enCOMPASS and ask for a confirmation to take part in the project.
- These 200 households will be randomly selected respecting the composition of households of the whole Contone area (stratified random sampling, based on household composition, type of building and type of heating). Fallback solution is to randomly select 200 households from non-holiday houses, drawing on data from the SES database, in case the stratification data are incomplete.
- Besides such randomly selected households, participation in the pilot project will be open also to other interested households, in case they are triggered by the above-mentioned flyer.
- To favor positive responses by the 200 pre-selected households and to stimulate self-application by interested households, as indicated above, prizes to stimulate participation are offered (e.g. energy-saving gadgets, bill discounts and/or a prize draw).
- Selection of the participating households will be completed by the end of M16 (February 2018); electricity consumption data will have however been gathered (and stored) by SES for all Contone households since M6 (April 2017), so that the baseline data set will be regularly available from month 6 for the final selection of 100 participating households. As a final step to confirm their subscription to the project, we will ask them to answer an online questionnaire to gather their energy behavior (attitudes and perception) baseline data.
- Installation of sensors will be performed by the end of month M18 (April 2018), so that the full sensors and metering system will be activated in the Intervention group in time to start monitoring period 2 as soon as the R1 enCOMPASS platform is released.

All the above activities (see Figure 9) are aimed at selecting the intervention group households. For the selection of the control group households, instead, we envision the following steps:

- Recruitment will start as soon as the intervention households are selected (start of M17, March 2018).

- SES will contact all the remaining households in Contone (between 300 and 400 households) and invite them to answer a set of two questionnaires over time, to investigate their energy behavior; they will also be told that, by answering the questionnaires, they agree their electricity consumption data from M7 (May 2017) to M33 (July 2019) are used within the enCOMPASS project, for research purposes only.
- Answers to the first questionnaire will be gathered by M18 (April 2018), to collect baseline behavioral data also for them; answers will allow to identify the SES customer number, which would allow us to start monitoring their electricity consumption during monitoring periods 2 and 3 and to gather their consumption during monitoring period 1.
- To stimulate them answering the questionnaire, prizes will be offered. Details are still to be defined; very likely, we will propose a random draw open to all the respondents, offering either discounts on electricity bills or vouchers for department stores or charity donations.

In case more than 100 households answer the questionnaire, we will stratify them based on the household, building and heating type, with the aim of selecting within them a set of at least 100 households that are overall comparable to the intervention group.

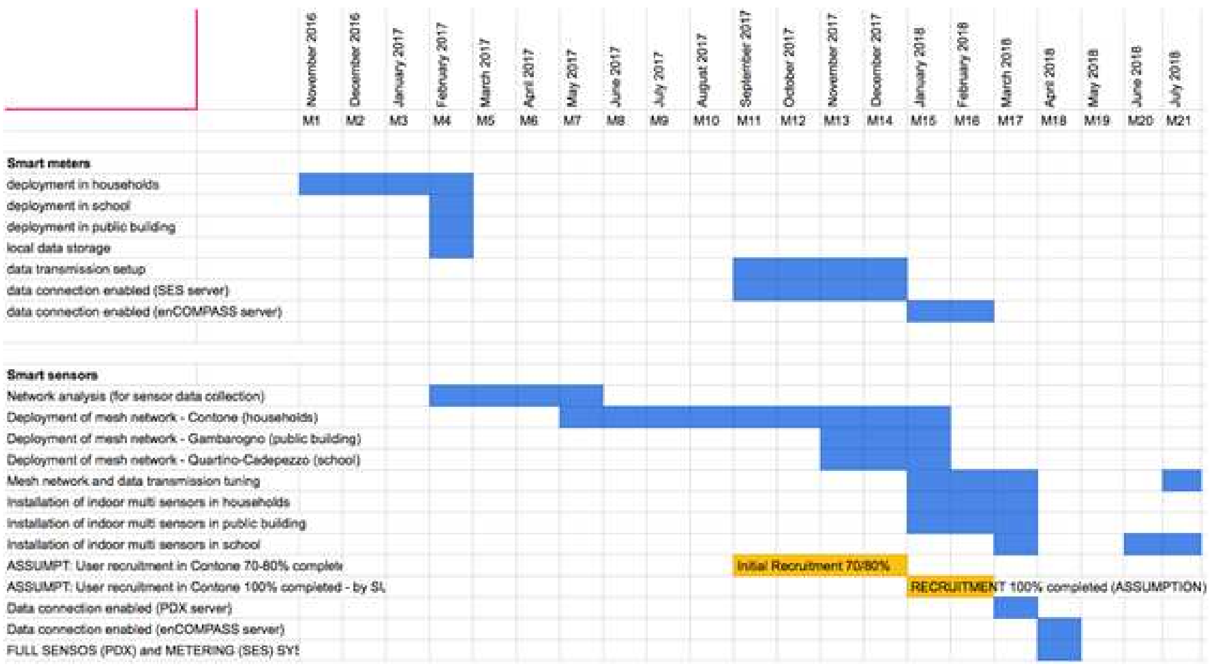


**Figure 9. The Swiss pilot action plan**

***Reward and incentive based strategy for user involvement***

A strategy to promote the enlisting of users in the intervention group of the enCOMPASS platform has been devised for the Swiss case study. In order to attract users, the following rewards will be announced:

- 100 vouchers each valued CHF 100.- for a discount on the electricity bill.
- 100 gadgets each costing CHF 10.- The gadgets are energy saving related.
- 3-5 "super-prizes" to be drawn out of the enCOMPASS participants. Each prize is worth approximately 700-1000 CHF (depends on total number).

## 3.2 Technical deployment plan: smart meters and sensors installation

In the German deployments, smart meters were already installed at the premises of the users. In the Greek deployments energy meters are already installed in the school building and the WATT+VOLT premises while smart meters exist in some of the Greek Pilot residential buildings. The smart meter installations for Germany and Greece will be included in the intervention/control groups, both for schools, public buildings and residential buildings. Differently, in the Swiss pilot, smart meters were installed during months 1-4 (November 2016 – February 2017) in all the households of Contone, as part of the enCOMPASS activities; they were instead already installed in the selected school and public building.

Besides electricity metering, the enCOMPASS platform will also collect data produced by a variety of sensors, monitoring humidity, indoor temperature, pressure, and presence of people in the room. Table 8 shows the full list of sensors used within enCOMPASS. However, the subset of available sensors will differ across building type and pilot trial. The specific list of sensors for each pilot has been presented in detail in the deliverable D2.1 based on the findings of the requirements analysis process.

Sensors will not be used in the first monitoring period, which is aimed at collecting baseline data. They will in fact be installed in all households, public buildings and schools of the intervention groups at the latest by the end of M18 (April 2018); in schools, they will be installed by M21 (July 2018). Apart from schools, where activities will start after the 2018 summer holidays, the full metering system for households and public buildings (electricity smart meters and sensors) will therefore be fully operating in Month 19 (May 2018), in occurrence of the release of the R1 enCOMPASS platform.

**Table 8 : Independent variables that will be measured and used within enCOMPASS (in households for intervention groups, schools and public buildings)**

| *Variable Name* | *Measurement Unit* | *Source of data* |
|---|---|---|
| Indoor Temperature | Celsius | Temperature sensors |
| Indoor/Outdoor Humidity | % | Humidity sensors |
| Indoor/Outdoor Luminance | Lux | Luminance sensors |
| Presence | [True/False] | Presence sensors |
| Door/Window Status | [Open/Close] | Magnetic contact sensors |

Additional data regarding outdoor temperature will be gathered in order to use them to model the “extended baseline data” (independent variable). Such data will be retrieved through local meteorological services, thus they will not require specific installations for the enCOMPASS pilot tests. In some cases, outdoor temperature sensors will also be installed, to get more accurate local measures. In each pilot test area, two outdoor temperature sensors will be installed, following the same time schedule as indoor sensors.

## 3.3 Baseline data collection

### *3.3.1 Electricity consumption data*

Baseline electricity consumption measurements of both the intervention groups and the control groups are being collected according to the time schedules indicated in Section 2.3. The baseline period started on May 2017 in all the sites and all the building types and will last until the end of April 2018, so that a full year of data will be collected. At the time of writing the present deliverable, we can therefore provide indication on the baseline values gathered so far (five months, from May 2017 to September 2017). The following Tables 9, 10, 11 present the baseline data available, comparing them to the historical electricity consumption data that were provided in deliverable D7.1 (i.e. electricity consumption measurements collected before the beginning of the enCOMPASS baseline period).

The final baseline will therefore include both factors that can display differences over time due to the use of the enCOMPASS application, as control factors that can explain differences between e.g. subsets of the user population and differences between the enCOMPASS treatment group and the control group. For an overview of factors that will be collected, please refer to the section 2.4.4.

**Table 9 : Details on electricity baseline data gathered so far for school buildings, compared with available historical electricity consumption data**

| *School buildings* | *Historical data* | | | | *Baseline data* | | |
|---|---|---|---|---|---|---|---|
| | *Number of monitored buildings* | *Data granularity* | *Time span covered* | *Average consumption* | *Number of monitored buildings* | *Data granularity* | *Average consumption (May – September 2017)* |
| Gambarogno (CH) | 1 | Year | 2014-2016 | 30'171 kWh/year (for electricity) +200'000 kWh/year (for heating) | 1 | Quarter of hour | 6'517 kWh/month |
| Hassfurt (DE) | 1 | Hour | 2011-2016 | 13'000 kWh/year | 1 | Hour | 883,35 kWh/month |
| Thessaloniki (GR) | 1 | Month | 2016 | 87.600 kWh/year | 1 | Quarter of hour | 7.300 kWh/month |

**Table 10 : Details on electricity baseline data gathered so far for public buildings, compared with available historical electricity consumption data**

| *Public buildings* | *Historical data* | | | | *Baseline data* | | |
|---|---|---|---|---|---|---|---|
| | *Number of monitored buildings* | *Data granularity* | *Time span covered* | *Average consumption* | *Number of monitored buildings* | *Data granularity* | *Average consumption (May – September 2017)* |
| Gambarogno (CH) | 1 | Year | 2014-2016 | 124'167 kWh/year | 1 | Quarter of hour | 7'528 kWh/month |
| Hassfurt (DE) | 1 | Hour | 2011-2016 | 8'000 kWh/year | 1 | Hour | 1755,36 kWh/month |
| Thessaloniki (GR) | 1 | Month | 2016 | 21'000 kWh/year (WVT Flagship Retail Store) | 1 | Quarter of hour | 1'750 kWh/month |
| Athens (GR) | 2 | Month | 2016 | 220'000 kWh/year (WVT Headquarters) | 2 | Quarter of hour | 18'200 kWh/month |
| | | Month | 2016 | 275'000 kWh/year (NHRF) | | | 22'600 kWh/month |

An important comment has to be made for baseline values of the household electricity consumptions. In fact, differently for public buildings and schools, which were selected at the start of the project, identification of actual households that will be involved in the enCOMPASS trial for residential buildings has not been performed yet, neither for the intervention nor for the control. Therefore, the baseline electricity consumption values we provide here are the average electricity consumption values of all the households located in the enCOMPASS pilot regions and equipped with smart meters. Once selection of the actual enCOMPASS households will be performed, baseline values will be updated in order to account for their specific electricity consumptions.

**Table 11 : Details on electricity baseline data gathered so far for residential buildings (households for both the intervention group and the control group), compared with available historical electricity consumption data**

| *Households* | *Historical data* | | | | *Baseline data* | | |
|---|---|---|---|---|---|---|---|
| | *Number of monitored buildings* | *Data granularity* | *Time span covered* | *Average consumption* | *Number of monitored buildings* | *Data granularity* | *Average consumption (May – September 2017)* |
| Gambarogno (CH) | 5'200 | Month | 2010-2016 | 5'200 kWh/year | 400 | Quarter of hour | 1'100 kWh/month |
| Hassfurt (DE) | 10'000 | Hour | 2011-2016 | 5'000 kWh/year | 100 | Hour | 223 kWh/month |
| Thessaloniki (GR) | 400 | Month | 2016 | 8'000 kWh/year | 100 | Quarter of hour | 660 kWh/month |

### *3.3.2 Outdoor temperature*

Outdoor temperature in the three pilot sites is displayed in the Table 12.

**Table 12 : Details on outdoor temperature data being gathered in the three pilot sites**

| *Outdoor temperature [°C]* | *Historical data* | | | *Baseline data* | |
|---|---|---|---|---|---|
| | *Data granularity* | *Time span covered* | *Average temperature per year* | *Data granularity* | *Average temperature (May – September 2017)* |
| Gambarogno (CH) | Annual | 2012-2016 | 12.1 °C | Semi-hourly? | 19.9 °C |
| Hassfurt (DE) | Annual | 1981-2010 | 9,1 °C | monthly | 16,34 °C |
| Thessaloniki (GR) | Annual | 2012-2016 | 15,7 °C | monthly | 29,30 °C |

The same data will be collected also during the intervention monitoring periods. SHF will provide outdoor temperature during the intervention monitoring periods with daily granularity at least.

### *3.3.3 Behavioural data*

Baseline data regarding energy consumption awareness will be collected by means of online surveys. For the treatment group questionnaires will be administered towards the end of monitoring period 1 (Baseline), monitoring period 2 (Intervention period 1) and monitoring period 3 (Intervention period 2). For the control group, questionnaire data will be collected for towards at the baseline and at the end of monitoring period 3. The baseline measurement draws on Stern's framework of environmentally significant behavior (Stern 2000) described in Section 2.3.4. and its relation to the awareness KPIs. The following constructs will be measured with validated items (the items will be finalized and reported in D7.3): awareness of consequences, personal norm, ascription of responsibility, pro-environmental values, environmental knowledge, self-efficacy (capability), social norms, intention to save energy, habit strength in energy saving and behavioral response to incentives. These measures are described in detail in Section 2.3.4.

# 4. Strategies for integration with smart sensor and meter network and energy efficiency recommendations

## 4.1 Integration with smart sensors and smart meter data

Integration with smart meters and sensors is a technical topic treated in D6.2 PLATFORM ARCHITECTURE AND DESIGN, especially in the sections about the Data Acquisition Layer of the enCOMPASS Platform.

In this section we briefly recall the strategies available for integrating with smart sensor and meter networks and the motivations for the choice made in the project.

**Smart meter data** handled by the project are a distributed replica of the metering data collected by the smart meter infrastructure managed by the utility companies.

**Sensor data** handled by the project are a distributed replica of the sensor data collected by the smart home infrastructure managed by the utility companies. As long as consumption data, in an aggregated format, reaches the Platform End User, the sensor data is only used by the intelligent Platform back-end components that disaggregates these data and applies various inference algorithms to determine indicators like: User Comfort level, Activity Level

Essentially, two alternative strategies have been taken into account to manage the data cached in the enCOMPASS Data Acquisition Layer:

- PULL: the enCOMPASS Data Acquisition Layer calls the native server of the utility company on demand, to extract the smart meter and sensor data. For example, the PULL strategy could be implemented with the following workflow:
  - Platform component responsible for consumption and sensor data processing periodically requests these data from certain end-poins exposed by Utility company.
- PUSH: the native server of the utility company uploads the smart meter data to the Platform. For example, the PUSH strategy could be implemented with the following workflow:
  - At deployment time of the enCOMPASS the origin server of the utility company uploads the consumption baseline data into the enCOMPASS Data Acquisition Layer. Such a push can be implemented in two ways
    - By secure file transfer with a protocol such as Secure FTP.
    - By secure web service call, e.g., with Restful services invoked under a secure protocol such as Secure HTTP
  - Periodically, the origin server of the utility company uploads into enCOMPASS Data Acquisition Layer the new consumption and sensor data acquired from the smart meter and sensor network since the last processing time
- HYBRID: a mix of PUSH and PULL. In this strategy, a PULL strategy can be employed at sign-up, to transfer the baseline data of a new consumer; then a PUSH strategy can be applied to align periodically the smart metered data of the enCOMPASS Platform with the origin server.

The enCOMPASS platform the adopted strategy to manage smart metering and sensor data relies on the PUSH approach, for the following reasons:

- Simplification of the interaction with three different utility company origin servers, each one endowed with its own IT architecture.

- Easy standardization of the data transfer format. The smart meter and sensor data can be simply serialized by each utility company into a common format used for ingestion by the enCOMPASS Data Acquisition Layer.
- In transit security: using secure data transfer protocols, the in transit security of the data can be properly safeguarded.

## 4.2 Strategies for collecting data from energy users

Besides smart meter and sensor data, enCOMPASS will also collect from energy consumers' data about the essential characteristics of their house or building and about their activities, in order to support the disaggregation process and consumer clustering algorithms.

The strategy to foster the collection of such data is based on the gamification approach of enCOMPASS. At the sign-up page, users are asked to provide the most essential information that is required for the underlying components (e.g. for the disaggregation, the devices the user is using are asked).

Furthermore, the Awareness Application will contain a section dedicated to the "User profile", where the consumer will be engaged to provide additional information about the household. This page contains questions that provide additional data for the indoor climate detection, and recommender, with questions about the room, about the users, and about the occupancy. Users get points for answering questions. Users get bonus points after answering all questions in a section, to encourage the most important information for the application to work to be collected first.

The specification of the user story for implementing this strategy is specified in D2.2 Final Requirements (Section 5.1.2).

## 4.3 Adaptive energy efficiency recommendations

Recommendation for energy saving actions differ from regular recommendation scenarions, such as recommendations in e-commerce settings. The key differences compared to such scenarios: (1) the recommendable items are actions performed on devices, (2) the user's behavior is not observed directly, instead it has to be inferred from the context produced by smart meters and sensors, (3) recommendations are triggered (instead of recommendations being requested) when energy wasting behavior is noticed by the system. In the case of the pilots (4) the user set is also much more limited. Similarly, to other recommendation scenarios, explicit feedback from users is expected to be limited, but in addition implicit feedback will be also less reliable, since there is an additional step in the inference of this feedback, since the user behavior can not be monitored directly. This required the project to develop a new recommender scenario to match the specifics of the energy context. This enCOMPASS recommender is developed in WP4.

For the first release, a rule-based recommender is implemented that evaluates the user context against pre-defined rules. The rule consists of so called primitives and the suggested action to be taken by the user. A primitive is a certain behaviour pattern or state of device/consumption. The combination of primitives can describe energy wasting behaviors that are matched with a suggestion how to avoid them, as shown in the example below:

**Not in the building for a long time & heating is on → turn off heating.**

- *P1: Not in the building for a long time: motion sensor is inactive for at least X hours*
- *P2: Heating is on: the temperature outside is (much) lower than inside, yet the temperature inside increases or stays around the same value for a longer time*

The precision of the recommendations is improved by employing the user profile data explained in the previous section. Additionally, explicit feedback is collected where users can indicate the intention to take action on the recommendation ('Ok, will do', 'Already doing this', 'Won't do it'), and the relevance of the recommendation (e.g. 'I'm not able to do this'). Finally, machine learning approaches are employed to improve the connection between context to primitives. This includes the inference of implicit feedback from the context. For example, if a user always leaves the heating on when leaving the building, despite being recommended not to that several times, the system can infer that the user is not interested in undertaking this particular recommendation, thus it will be slowly phased out. The primitives in the rules can also be refined by both the explicit and implicit feedback. The approach is summarized in Figure 10.

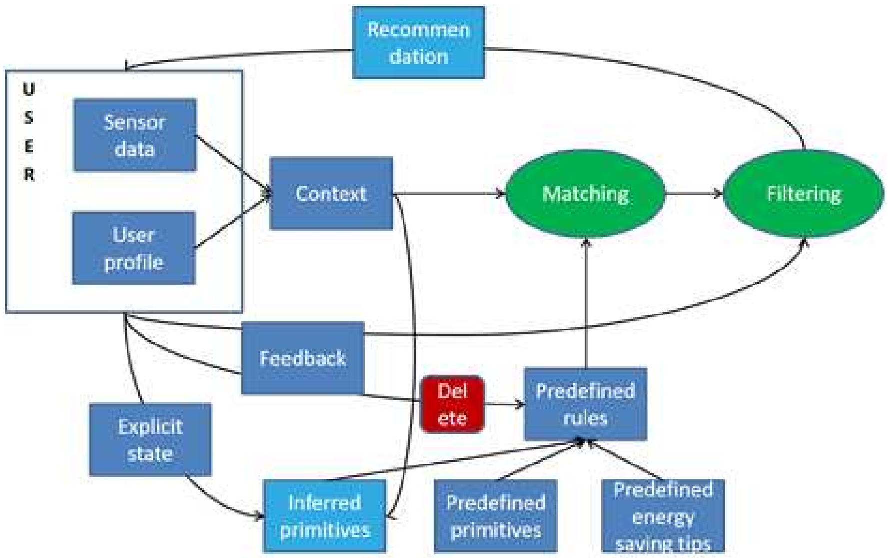


**Figure 10. Rule-based recommender approach**

Additionally, following the sensor infrastructure set-up described in *D2.2 Final requirements*, in the second release recommendations are made available to the user for a set of actions that can be automatically executed by the home automation system. Before such actions are executed, the user is asked for approval (see the associated user story in D2.2).

For both releases recommendations are made available in two ways: first, the mobile app contains a dedicated page where all recommendations are displayed that have been released by the recommender. On this page, users can also give their feedback. Second, when a new recommendation has become available, a notification is sent to the user at a moment in time defined by the scheduler component. In D2.2 mock-ups and a more detailed description of the recommendations can be found.

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