Energy in Time Project: summary of final results

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ABSTRACT

This paper presents the main results achieved during the "Energy IN TIME", a project funded by European Commission, started in October 2013. The project is developing an integrated control and operational approach, that combines state of the art modelling techniques with the development of an innovative simulation-based control technique with the overarching objective of automating the generation of optimal operational plans tailored to the actual building and users' requirements. The methods are based on the prediction, according to weather forecast and building historical data of indoor comfort conditions and user behaviour performance, to improve the lifetime and efficiency of energy equipment and installations through continuous commissioning and predictive maintenance.
The main results and benefits of the implementation and testing of this innovative approach in the energy management systems of four demo buildings to be automatically and remotely operated are included in this paper.

KEYWORDS

Tertiary buildings, simulation based control, optimal operational plan, model based control, predictive maintenance, continuous commissioning, fault detection diagnostic.

INTRODUCTION

According to the 2010 Energy Performance of Buildings Directive (EPBD) and followed by the 2012 Energy Efficiency Directive, the European legislation aims to reduce the energy consumption of buildings [1, 2]. In fact, since then, the European Commission has recently proposed the update of this regulation with the aim of promoting the use of smart technologies in buildings. Prior to the EPBD publication, some European projects worked on the development of techniques or methodologies about the Continuous Commissioning (CC) of buildings as one of the best methods for evaluating and monitoring their energy performance. One of the most important is the "Building EQ" project, within the "Intelligent Energy Program", which ended in December 2009. In the same way, different EU projects related to smart technologies in buildings have been approved and carried out along these years[3, 4].

Within these topics, the "Energy IN TIME" project (EiT), within the 7th Framework Programme, addresses both Smart Technologies and CC going beyond existing building control techniques through the development of a solution that combines control and operation of a building [5, 6]. Throughout this paper, the main and final results of this project are presented with the aim of explaining the challenges achieved, as well as the conclusions gathered from the development of the project. This project, which started in October 2013, finishes after four years of work. The results have been gathered from the implementation of the EiT system in four demonstration buildings, being all of them non-residential or tertiary buildings. Due to the typology of these kind of buildings, the Faro's Airport in Portugal, an office building and a hotel in Finland, and an office building in Romania, the EiT system allows obtaining a higher impact than in residential buildings because of their variety and quantity of facilities, level of occupancy, uses and management. Different tools and applications have been developed and will be enounced below as the main results of the project. According to the variety of tertiary buildings, the applications and tools that constitute the modules of the EiT system, have been developed in a way that is adapted to the needs and requirements of each building. In each of the following section will be analysed the six key tools of the EiT system:

- Virtual Auditing App (VAA): is a smart tool used to gather data from the building on its systems, the equipment availability and condition, in a very easy and fast way.
- Simulation Reference Model (SRM): is a thermodynamic and energetic building simulation model that accurately reflects the building performance.
- Predictive Maintenance Module (PMM): is an application that applies the predictive maintenance approach in an innovative way since the system reconfiguration and/or the maintenance scheduling have an on-line character.
- Automated Fault Detection and Diagnostics (FDD): is a tool that will improve the current state of service by making decision on parts replacement and specify the manufacturers of components that have failed and furnish other details such as part numbers.
- Medium and long-term building and equipment Decision Support System (DSS): is a new user-friendly tool for mid-term investment analysis that also improves trend analysis by data mining techniques.

- Intelligent Daily Operational Plan Generator (OPG): a tool that generates operational strategies to be provided to the simulation engine.

The results of the development and implementation of this tools within the EiT are shown throughout the following pages.

VIRTUAL AUDITING APP

The traditional process of gathering data from the buildings on its systems, the equipment availability and condition can be quite onerous, time-consuming and involve data being collected and tracked in a number of different documents or software tools. In addition to this, there is a typically large range of building components and parameters in commercial buildings, making it difficult to identify or prioritise the key parameter information to be audited. The VAA aims to overcome these issues through the development of a smart tool to gather data in a very easy and fast way. This is achieved through the design of a virtual app-based framework which minimises the effort and requirements in gathering data from buildings, and prioritises relevant information required, based on a per building basis to optimise the data collection process.

The principal unique and differentiating features of the VAA tool to the user are:

- Identification and prioritisation of energy parameters to be audited based on a number of building specific questions.
- Ability to pre-load building drawings (plans, elevations and schematics) to the VAA.
- To gather data from the building on its systems, the equipment availability and condition, in a very easy and fast way.
- Tagging of information to specific locations on the pre-loaded drawings with high level Drawing Tags as the user moves around the building.
- Ability to take pictures using the VAA which can be allocated as linked resources to the Drawing Tags.
- Resource Tags can be added for different Tag Types to record specific information on lighting, equipment, Heating Ventilation and Air Conditioning (HVAC) and renewables, as well as related schedules to create a linked hierarchy of information for a specific location.
- The VAA allows for full reportage of the data collected to be output in a clear and structured format.
- All information can be stored digitally in one place in a structured format.
- The same project/audit can be open in Desktop (for pre-loading Drawings and for detailed analysis) or Tablet (or portable collection of information while on-site).
- Information can be input/updated at any time (pre-audit, during audit, post audit).

Given the different building types involved in the project, and the potential building's that could utilise the EiT system in future, the VAA framework was devised in such a way that it could be deployed for the majority of commercial building stock and that the resulting information can be used to develop an energetic model in any selected model simulation environment. Figure 1 below shows the VAA workflow and high level description for all of the Tabs available in the app itself. As illustrated in the figure, all of the information gathered in each tab is output to the Reporting Tab, which collects and presents all of the information gathered back to user to be used in the model creation and calibration process.

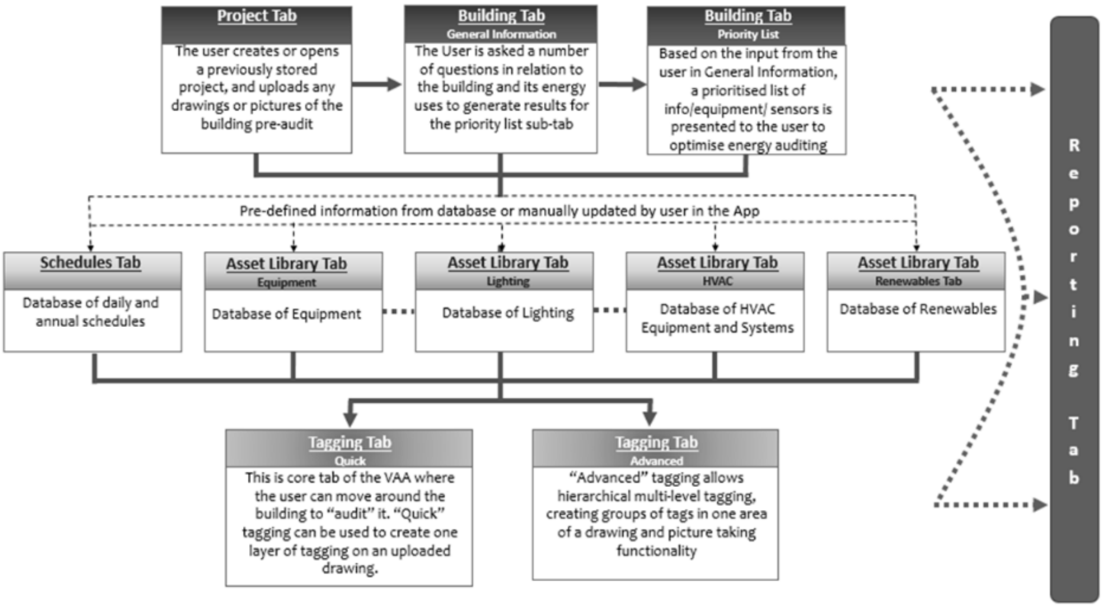

Figure 1: VAA workflow and Tabs description

As an example of the novel functionality in the VAA, Figure 2 (left) below shows how the user can answer high-level building questions in the app, and Figure 2 (right) shows the updated estimated energy breakdown for the building with an associated priority list of data to be collected based on the user's answers. The energy breakdown is based on 1,000s of pre-run simulations for a range of building types and locations, with the aim of ensuring that the user focuses on the areas that consume the most energy during the audit in order to minimise the amount of data that needs to be collected.

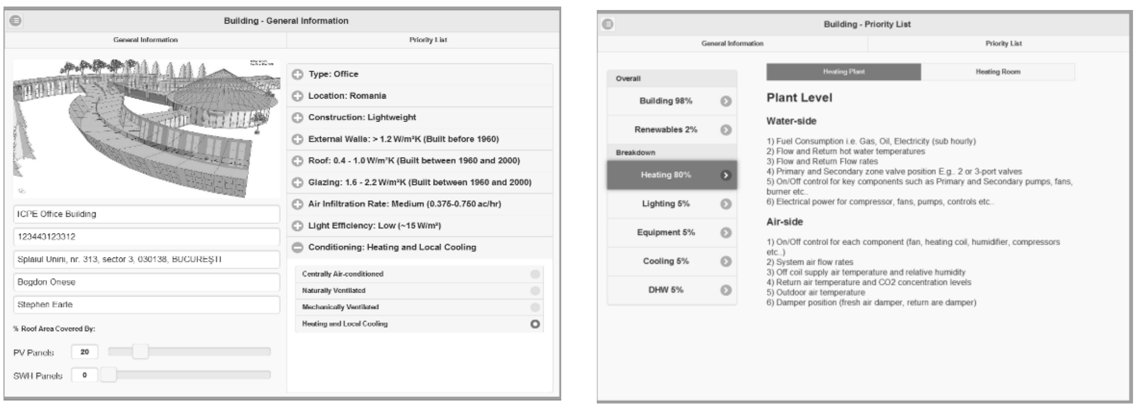

Figure 2 General Building Information (left) and Generated Priority List

In terms of the EiT, the VAA (currently defined at TRL 7) was a key development in order to minimise the effort and requirements in gathering data from buildings in respect to relevant information on building components and systems required for developing energy models in a simulation environment. It was used in each of the EiT demo buildings in the early stages of the model creation process to gather the key building audit information from the building, which was then updated in the building simulation models to ensure they further reflected the actual operational performance of a building (as opposed to models being based on the building *design* information only, which is often mismatched from the *actual* operation) [7]. Due to the complexity of the building and its operation, the VAA was used extensively in a three-day audit of the Faro building which greatly enhanced the speed, auditing capabilities and increased the amount of information that would have otherwise been collected on-site using traditional auditing approaches. This in-turn improved the accuracy of the SRMs, which are described in more detail in the next section.

SIMULATION REFERENCE MODEL

In optimising a buildings operational performance, determining the actual detailed performance breakdown, predicting performance and assessing the impact of any changes to a buildings operation is a complex undertaking. This difficulty is compounded even more so when attempting to continuously assess and optimise a building's performance due to dynamic nature of buildings, their use and the effect of user behaviour (which can be difficult to measure directly). The SRMs developed in the EiT will contribute to overcome these issues through the incorporation of a thermodynamic and energetic building simulation model that accurately reflects all aspects of a building dynamic performance. The SRMs are developed in the IESVE software platform, which is a suite of building performance-modelling tools incorporated into a single integrated data model [8]. The SRMs are calibrated and verified to reflect buildings actual operation, and are updated with "live" Building Energy Management Systems (BEMSs) and building data to continuously adapt to the building as it evolves. The latter allows for accurate and dynamic forecasting incorporating actual and forecast weather data enabling advanced optimization and decision making to improve the buildings operational performance. The software model is uploaded to the cloud, where it can be continuously updated with new data or accessed by 3rd party tools to simulate the model and download results. The SRM also allows accurate energy conversation measure and retrofit analysis. The key unique and differentiating factors of the developments include:

- Use of the IESVE which is a proven building simulation software product.
- Automated calibration process to create better calibrated models.
- Cloud based access through the IES SCAN platform to continually update and access the models [9].
- More accurate building performance prediction using simulation models, which results in improved building control optimisation.

During the EiT, four SRMs (currently at TRL 7) were developed for each of the demo sites which accurately reflected the actual buildings performance. The following Figure 3 shows an image of the SRM created for Sanomatalo's office building.

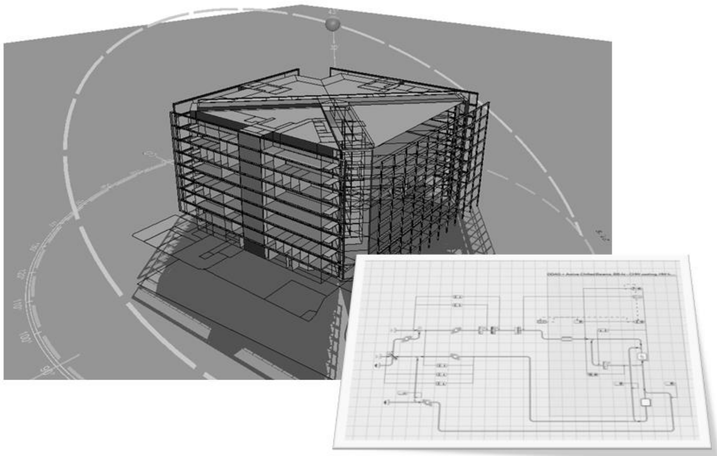

Figure 3 Sanomatalo's office building SRM

In order to create the final SRM for the project, each SRM was developed through the following stages:

1) Passive model which includes modelling all passive (or static) elements of the building such as building constructions, framework, façade, claddings, location, orientation, etc.
2) Active model which involves modelling all active (or dynamic) elements of the building such as its HVAC systems, occupancy, weather, infiltrations, etc. Information collected from site-audits carried out using the VAA (previous section) was also updated at this stage.
3) Operational model where steps were undertaken to automatically acquire operational data from the BEMS to further improve the accuracy of the models.
4) Model Calibration where a semi-automated procedure was developed to further fine-tune the final building model parameters to match the actual building performance to within ±5% accuracy (which was achieved for all four demo buildings).
5) Variant Model which enables other EiT modules and tools (e.g. OPG and PMM) to connect to and use the SRMs for automated analysis and decision making.

The final SRMs were uploaded to the cloud and used by the OPG (discuss in further detail in a later section) to optimise the control plan of the buildings for the following day through the prediction of all aspects of the buildings performance (weather, occupancy, lighting, infiltration etc.) and test the impact of a range of scenarios under the EiT system.

PREDICTIVE MAINTENANCE APPLICATION

The maintenance costs represent a significant percentage of the expenses in most of facilities and in most of cases account for almost the same facility's operating budget as the energy expenses. Thus, they can be an important problem in the building management and is therefore worth optimizing. Usually, the maintenance budget is spent inefficiently with a reactive "wait till it breaks" approach (i.e. corrective maintenance, leading to system unavailability and unplanned resource management) or with a systematic maintenance (i.e. preventive maintenance) that leads to replace a facility even if its useful life remains. On the other hand, predictive maintenance promises beyond traditional approaches (corrective and preventive), to reduce downtime and maintenance costs as well as to enhance system performance efficiency, availability and sustainability. Furthermore, predictive maintenance is one of maintenance strategies that has been widely addressed in the literature by various authors since years 2000. It consists in three processes: Monitoring and diagnostic, Prognostic and Decision-making [10]. In the EiT, the first process was considered in the FDD and CC modules (discuss in a later section), while the other two has been considered during the development of the PM. The aim of Prognostic is to provide the remaining useful life of facilities while the Decision-making has to provide the scheduling proposition to the maintenance manager.

The predictive maintenance has been applied mainly for complex system like factories [11], nuclear power plant [12], rotary machinery [13], electronic systems [14] and wind turbine [15]. On the other hand, the building domain has received only little attention. The main work has been focused on the Prognostic process of various components such as heat exchangers [16, 17], pumps [17, 18] and filters [19,20]. For Decision-making the work has been mainly focused on facility control [21, 22].
Based on the state of the art, the main innovative work done in the EiT has been for Decision Making process, in particular in its application in chaining with Prognostic. In the following Figure 4 can be seen the workflow of the PMM.

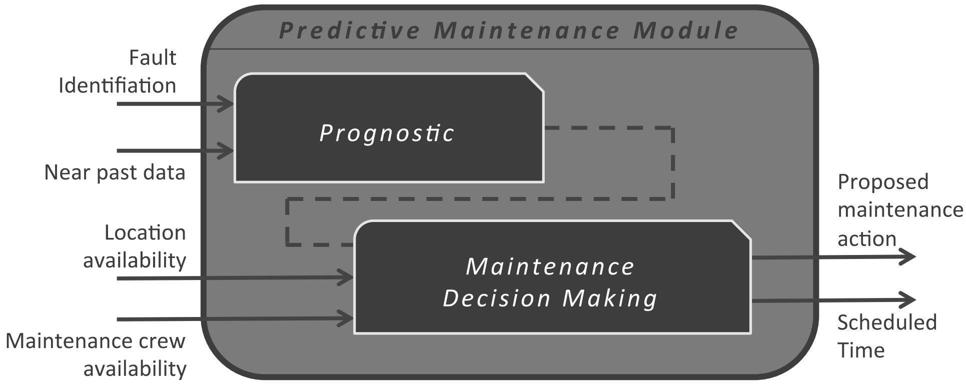

Figure 4: PMM workflow

As can be seen in the Figure 4 the Prognostic part of the module uses the information about critical system of the building coming from the FDD and CC modules to estimate their Remaining Useful Life (RUL) which represents the remaining time that an item, component, or system should be able to function in accordance with its intended purpose before warranting replacement. This information is transferred to the Decision Making part of the module that uses it, together with the information about the availability and location of the Operation and Maintenance (O&M) personnel, to propose and schedule the maintenance of items. In this way, the O&M personnel is provided with timely information in order to assess the energy efficiency and the risk of premature facility outages and to schedule and plan future maintenance activities. Therefore, compared to corrective and systematic maintenance strategies, the PMM allows to anticipate appliances failure since it includes a prognostic of the degradation. Moreover, it allows to maximize O&M personnel working time. The main benefits that this module offers are:

- A tool that gives the RUL for critical systems in the building.

- A list of best instants to carry out a predictive maintenance action, for critical systems in the building, according to the RUL and the operation profile of the building.
- Maintenance costs reduction thanks to a "just in time maintenance" approach.
- Risk reduction (on service continuity, on maintenance actions for maintenance operators).

The PMM will be well fitted with building maintenance where a BEMS is available (in order to collect information from monitoring) and when the O&M crew is not always on site but performs inspection/maintenance tour (in order to maximize O&M personnel resources). In the EiT the PMM was implemented to the Levi's Hotel demo site. Main aspect was to collect the actual HVAC data from the BEMS. Based on the data there was made analysis on how the components behave. Because the active life time and fouling of the HVAC components usually takes a long time, there were performed "simulated faults". With these simulations there were modelled the following faulty situations: fouled filter, leaking valve, false temperature readings.

The effect of a fouled filter has been considered for prognostic purpose. Based on a literature review an exponential model coupled with a stochastic process has been chosen [23]. Real tests have been conducted in Levi's Hotel demo site in order to get data to validate and adapt the model. The test was performed by using different size of cardboard sheets to cover a certain percentage in the filters (from 5% to 50%). With the sheets, the pressure difference over the filter was increased and this was used to illustrate the natural fouling in the filters. With these results there was create a pattern that could be followed in the future in the filter replacement. Thanks to this test there should be known the exact time of filter replacement interval and over-maintenance should be avoided.

A leaking valve was simulated by switching the heating coils valve on manual control. The valve was placed in certain position (25%, 50% or 75% open) and left in that position. With that way the valve was constantly in "wrong" position: either giving too much heat or not enough. This data was analysed and there was created a pattern to detect this effect in the future. By realising the leaking valve as fast as possible, it will give great energy savings and allow a fast reaction of the maintenance crew, improving also the satisfaction of building users.

False temperature readings were simulated by purposely calibrating wrong reading in the supply air temperature (false reading was usually -2°C, -1°C, +1°C or +2°C of the actual reading). This causes wrong set point that that has as effect an increased energy consumption or lowest indoor comfort conditions. Benefits for realising the false readings in time is similar that in leaking valve test.

Currently, results achieved are hard to present because a running of the module in the building for few years is needed. And even in that case, there is the possibility that system works perfectly. Nevertheless, by analysing the existing data from Levi's Hotel, there was made an observation that at least the filter replacement was made so frequently that there was not seen an increased pressure difference. This indicates that the replacement interval was too frequent in comparison with the optimal. On the other hand, concerning maintenance decision making, it was implemented to Levi's Hotel in accordance with the maintenance subcontractor which is in charge of two others buildings in the Levi's Hotel area. The decision algorithm was based on adapted for maintenance by Levrat [24, 25]. The main originality lies in the consideration of crew availability. It was noticed that predictive maintenance actions are integrated in systematic preventive maintenance actions and corrective maintenance actions, thanks to the concept of opportune decision which is a Decision Making approach that take profit of the corrective maintenance (needed as soon as possible for critical components) to plan a maintenance action for another component This approach can be considered well suitable in the context of building exploitation and concern critical components.

CONTINUOUS COMMISSIONING AND AUTOMATED FAULT DETECTION AND DIAGNOSTICS OF BUILDING HVAC SYSTEMS

The preventive or corrective strategies, as commented in the previous section, do not guarantee the optimal functioning and the cost effective maintenance of building facilities. In order to avoid facilities faults that will also worsen the indoor comfort conditions, is recommended to perform the building system maintenance, in particular those related to critical systems, using a predictive strategy. The latter was implemented during the EiT adopting three approaches. Prognostic and Decision-making are part of the PMM (commented before) while the Monitoring and Diagnostic approach was implemented by CC and FDD modules that will be explained at following.

Continuous commissioning

The CC aims to have continuous monitoring for some building equipment or HVAC systems and to detect indicators for high energy use, unexplainable increase in energy consumption, constant failure of building equipment or systems and continuous occupant complaints about indoor temperature, air flow and indoor air quality. The target of CC is to see their errors in advance and find the reason why systems are not working as designed. With CC it is expected to have savings for energy consumption and maintenance actions and also increase the quality of the indoor air. CC was implemented in the Sanomatalo demo site where was followed the function of the Variable Air Volume (VAV) units. In this case, CC had three functions:

1) Comparing Air Handling Unit (AHU) air flows to the sum of the VAV air flows.
2) Comparing individual VAV air flow to the design air flow.
3) Weekly testing for whole range of motion for each VAVs.

The 1) was used to detect possible fault in the system. In case the difference was too much, it gave an alarm meaning that a fault was occurring in the AHU flow sensor or in some of the VAVs. With the 2), was possible to detect individual faults. The reason for these faults was usually in the jamming. Finally, the 3) drives the VAV plates in all of the positions once a week and was used to prevent the jamming. The CC operated two years and there was around ten alarms detected. None of these was recurring, indicating that the weekly testing program expelled the emerging faults. There were a lot of faults in Sanomatalo’s VAV units in generally causing extra maintenance, even though some of the units were perfectly fine. By expanding the CC methodology to every VAV units, can be achieved a lot of savings both in energy and maintenance cost, and also in indoor comfort conditions.

Automated Fault Detection and Diagnostics of Building HVAC Systems

The building HVAC equipment, which is badly maintained, degraded and inefficiently controlled, can waste an estimated 15-30% of the energy consumed in a commercial building. In addition, a faulty HVAC system failing to maintain air quality and zone temperature to the prescribed level in a building can be critical for the occupants’ health, cognitive abilities and productivity. For many common faults, HVAC energy efficiency decreases before there is a noticeable change in occupant comfort and the building operator does not perceive an issue with the HVAC system, since is applied a corrective and not a predictive maintenance strategy. A FDD can facilitate early detection of HVAC health issues in a building by preventing waste of energy while maintaining occupants’ comfort level. A robust, efficient and scalable automated FDD technology was developed in a pilot building HVAC system with the following objectives: (a) Real-time (continuous) monitoring: relevant sensor data are continually fed into the models and the FDD generates alarms through a user-friendly graphical user interface, whenever a fault is detected. (b) On demand health analysis: a methodology to group equipment by failure modes to produce a report consisting of information, based on which corrective actions can be initiated.

Both methodologies were tested using the sensor data from a demonstration building containing 71 Fan Coil Units (FCUs) and 1 AHU. The on demand health analysis methodology was further validated using data from a test building containing 218 VAV units and 18 AHUs. The detected faults by both the methods were physically verified. Development of an optimal maintenance schedule and prioritization of the maintenance action depend on the criticality of the detected faults in terms of its impact. An analysis framework was developed to perform a detailed study of the impact of the commonly occurring faults in a building HVAC system. Injecting faults and analysing their impact in hardware set up is challenging mainly due to: safety issues, difficulty in the choice of magnitude of the faults, risk of permanent damage to the system etc. To mitigate these risks, a detailed simulation model was developed in the Dymola environment, for studying the impact of the faults in energy consumption of the system and the comfort level of the occupants.

The differentiating factor of the FDD is the fact that is envisioned to be an integrated part of the BEMS and will support and provide improved decision support in the context of building HVAC commissioning and maintenance.

MEDIUM AND LONG-TERM BUILDING AND EQUIPMENT DECISION SUPPORT SYSTEM AND DATA MINING TOOL

This component of the EiT system relies on two different tools: a DSS that helps to decide which improvement package(s) to apply among a list of possible/available energy related actions/works. Complementary, the Data Mining Tool (DMT) implemented in the project does not need a priori knowledge about the options to implement. It is an explorative tool that discovers new insights about how the established energy system behaves by finding trends or anomalies. In the following, both tools are described in more detail.

Decision Support Systems

DSSs are software products that help users apply analytical and scientific methods to decision making. They work by using models and algorithms from disciplines such as decision analysis, mathematical programming and optimization, stochastic modelling, simulation, and logic modelling. DSS products can execute, interpret, visualize, and interactively analyse these models over multiple scenarios. In recent years, the growing popularity of online analytical processing, data warehousing, and supply chain management has led to an increased interest in the development of DSS. DSS tools could assist decision-makers in problems involving risk management, the allocation of scarce resources, and the need to balance conflicting objectives. When well implemented and used wisely, DSSs can significantly improve the quality of an organization's decision making. Input of data process represents a real challenge today, as data are not easy to collect and represent a quite complex process. Reliability is also another question to be considered.

The DSS has been tested to the terminal building of the FARO airport pilot site. The prototype of DSS has been developed to help facility managers in designing and assessing mid-long term building energy renovation scenarios for the pilot site. The methodology used in the DSS includes: a) a dynamic energy simulation model (COMETh), b) a Life-Cycle Analysis method which reads Energy Product Declaration of construction products, c) a Life-

Cycle Costing algorithm, and d) a module dedicated to scenarios ranking. These 4 models and methods exploit inputs extracted from a BIM file (quantities and metrics).
The DSS is developed in both C# and Python languages [26]. The first one targets facility managers with an easy-to-use Graphical User Interface (See Figure 5), the second targets R&D applications such as mono-objective optimization algorithms.

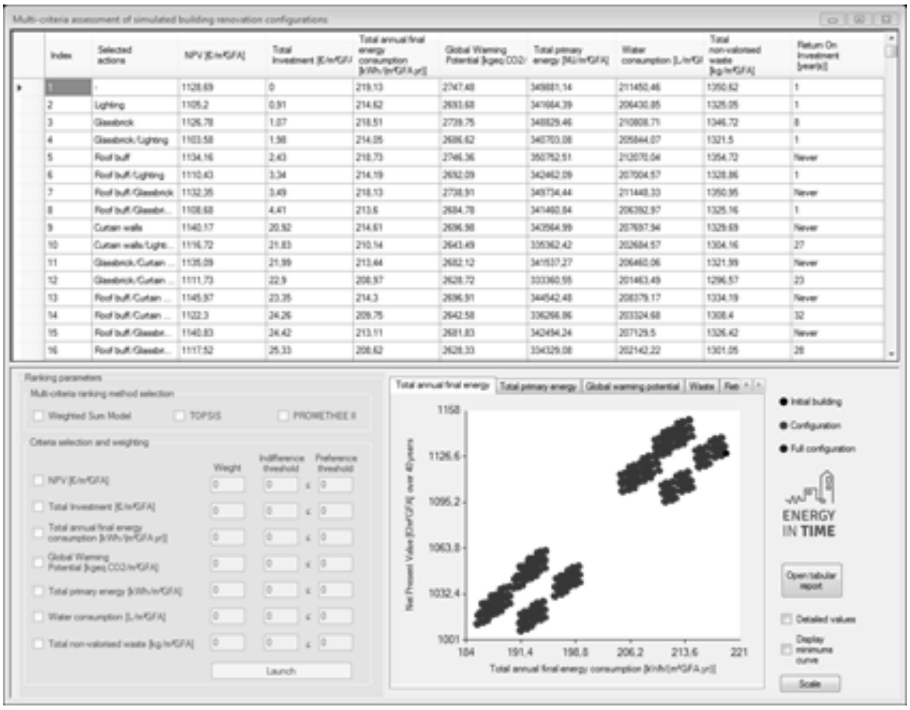

Figure 5. Graphical User Interface of the DSS tool

The DSS improve the current state of service by processing various input data to retrieve different options relevant to building retrofitting and aims to:

- Offer a new tool for investment mid-term analysis
- Introduce reliability instead of inaccuracy
- Perform extensive comparisons of renovation sub-sequences
- Gather experience and knowledge in appropriate databases
- Gather experience and knowledge in analysis/filtering techniques of energy-related big databases
- Introduce focus on lifetime, in addition with energy and cost
- Train people in asset management and energy performance

The Expected level of development for the result (TRL) is 7.

Data Mining Tool

Data mining aims to build systems and algorithms to discover knowledge, detect patterns, and generate useful insights and predictions from large-scale data [27, 28]. It encompasses the whole data analysis process, which begins with data extraction and cleaning, and extends to data analysis, description, and summarization. The result is the new information gathered from data which may turn out in sets of classified data, behavioural trends or future predictions, which will be conveniently visualized. Thus, Data Mining involves mathematical and statistical analysis, combined with information technology tools. However, deriving insights from data is not only achieved by using such techniques. The expert must also manage and interpret the data in order to obtain valuable knowledge. There are different aspects of Energy Efficiency and Management that Data Mining techniques can support and improve [29]:

- Predicting the energy demand required for the efficient operation of a building.
- Optimizing building operation.
- Verifying the operational status and failures of building equipment and networks.
- Analysing the economic and commercial impact of user energy consumption.
- Detecting and preventing energy fraud.

The DMT developed within EiT includes different stages: it starts with the collection of streaming raw data which is stored in the information repository. After that, it is necessary to clean the data and to select the segment that might have interesting information for the analysis. For that purpose, the expert must apply filters to the data or formulate queries that will remove irrelevant information. Once data are prepared for use, an exploratory analysis (including visualization tools) can help to decide which methods or algorithms are the most effective to obtain the desired knowledge. Finally, the application of such tools will lead to a set of results that will guide decision-making.

The DMT has been developed in Python within a Big Data architecture framework that enables to process massive data, retrieved from multiple sensors during a time period [30]. The final result consists on a set of trends and relations among the selected data that can be conveniently visualized using several graphical tools. The generated output produces valuable information that is important by itself and also can serve as input for the Decision Making process.

INTELLIGENT DAILY OPERATIONAL PLAN GENERATOR

Energy costs of daily operation are a problem that building managers face since are not easy to reduce. The OPG is an intelligent sub-system that automatically computes a plan including the actions (i.e. set points) that should be applied during the next day to optimize energy consumption while guaranteeing comfort in the building. To do so, the OPG evaluates the expected energy consumption of many possible equipment configurations by running simulations (thanks to the online connection with the SRM) that consider the forecasted state of the building (weather, occupancy, etc.), and selects the best of these configurations. The OPG system performs the following tasks:

1) Information collection: OPG retrieves weather forecasts, user occupancy, building status and other information about the expected building operation conditions from a specific-purpose database containing weather data, occupancy estimations, energy tariffs, etc.
2) Simulation execution: OPG runs simulations testing different operating actions on the simulation engine in order to reproduce the expected building behaviour (in terms of energy consumption and comfort). Accordingly, simulations use as input the building

conditions (collected in the previous step) and the operation actions (suggested by the OPG algorithm), and produce as output the values of energy consumption and temperature inside the buildings according to these conditions and actions.

3) Plan selection: OPG selects an appropriate plan (ideally, the optimal plan) from the large number of possible plans simulated in step 2) such that: (a) can be applied on the equipment; (b) are compliant to the comfort requirements; (c) minimize energy consumption.

4) Plan storage: The OPG stores the generated operational plan and the associated context (i.e., which external conditions led to the plan) to make it available for later justifications and data analysis procedures.

The process flow of OPG tool is represented at following in Figure 6.

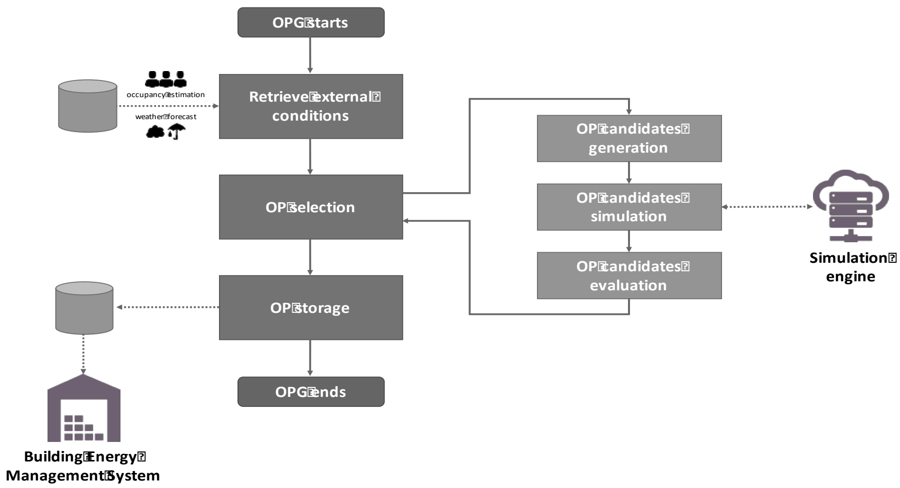

Figure 6: OPG process flow

The OPG tool provides unique features compared with typical planning solutions since it optimizes the operation for the whole day rather than performing minor real-time adaptation, which makes it possible to better address the inertial nature of HVAC systems. Furthermore, the use of Artificial Intelligence techniques and the capability to incorporate expert knowledge to the OPG allows reducing the time required to evaluate all the large amount possible equipment configurations. The OPG can be automatically applied to the BEMS by using a setpoint writing component, and/or presented to the building operator for further inspection and application. All data about successful plans, influencing conditions, etc. is stored in the system, and can be afterwards manually and automatically analysed. Besides, the OPG is agnostic of the underlying building equipment, and can be adapted to any scenario provided in a simulation model.

Demonstration in the project demo sites have shown significant energy savings, while keeping comfort (up to 15% in some cases). It is particularly effective in the mid-seasons, when it is not necessary to use the heating/cooling equipment at full and allows to automatically adjust the operation, adapting to daily weather forecasts, without the need of continuous supervision by the building operators. End of heating/cooling seasons can be anticipated, and at the same time, the software can react to particularly cold/warm days.

The Expected level of development for the result (TRL) is 5.

CONCLUSION

The EiT system can be integrated in the BEMS of different type of non-residential buildings with multiple facilities and maintenance strategies for the reason that its modules can work as separated from each other. The implementation of the EiT system in the four demo sites of the project has allowed energy savings between 2% and 26% that have been demonstrated thanks to the data collected from the monitoring systems installed in the pilots and due in particular to the adoption of the OPG tool. Furthermore, has been also demonstrated that important economic savings and improving in indoor comfort conditions can be reached thanks to the optimization of the maintenance strategies and of the O&M personnel management as well as to the shortening of times required for a first building information analysis and collection.

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NOMENCLATURE

AHU: Air Handling Unit
BEMS: Building Energy Monitoring System
CC: Continuous Commissioning
DMT: Data Mining Tool
DSS: Decision Support System
EC: European Commission
EiT: Energy IN TIME project
EPBD: Energy Performance of Building Directive
FCU: Fan Coil Unit
FDD: Automated Fault Detection and Diagnostics
HVAC: Heating Ventilation and Air Conditioning
OPG: Intelligent Daily Operational Plan Generator
O&M: Operation and Maintenance
PMM: Predictive Maintenance Module
R&D: Research & Development
RUL: Remaining Useful Life
SRM: Simulation Reference Model
TRL: Technology Readiness Level
VAA: Virtual Auditing App
VAV: Variable Air Volume

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