

The Overall Architecture of a Decision Support System for Public Buildings

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# The overall architecture of a Decision Support System for public buildings

Alfonso Capozzoli<sup>a</sup>, Fulvio Corno<sup>b</sup>, Vincenzo Corrado<sup>a</sup>, Alice Gorrino<sup>a,\*</sup><sup>a</sup> Department of Energy, Politecnico di Torino, corso Duca degli Abruzzi 24, Torino 10129, Italy<sup>b</sup> Department of Control and Computer Engineering, Politecnico di Torino, corso Duca degli Abruzzi 24, Torino 10129, Italy

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## Abstract

Building energy monitoring and real time control strategies can decrease energy consumption on one hand, and improve comfort on the other hand, by increasing the understanding of the control system. A decision support system for building energy management can be a proper tool for supporting the measurement and management of energy usage and costs of public buildings.

The aim of the paper is to describe the architecture of the Decision Support System (DSS), that is being developed within the FP7-Smartcities Project OPTIMUS (OPTimising the energy Use in cities with smart decision support system). The architecture of the system is described considering both the energy related and the information technology aspects. An example of action modeling is also presented and the first results are discussed.

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**Keywords:** Smart building, Decision Support System, Energy efficiency, Energy monitoring, Energy management

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## 1. Introduction

Smart cities are characterized by networks of sensors, to better manage and control the city systems by collating ever-detailed information about real time operation, and to optimize decision making in the immediate, short and long term.

Several literature works demonstrate that building energy monitoring and control strategies can decrease energy consumption and improve comfort, by increasing the understanding of the control system.

In this context, there are different kinds of tool to be used to better manage a building: on one hand a Building Energy Management System (BEMS), or BACS (Building Automation Control Systems) as described in ISO 16484 [1,2], is able to automatically control the technical systems (heating, cooling, DHW, etc.) using real time monitored data. On the other hand, new kind of more advanced tools, like Decision Support Systems (DSS) for building management, enable building owners and energy manager to take advantage of the monitored data: a DSS does not act autonomously and automatically, but it is designed to give suggestions to the building manager regarding actions to be carried out in a long/short period (e.g. a week).

A DSS needs the intervention of the building manager who chooses whether to accomplish the suggested action or not. Although it could appear a less efficient system than an automation system, the request for human intervention makes the building manager more aware of the building behavior, and may stimulate the adoption of more effective actions. The building

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\* Corresponding author. Tel.: +390110904549; fax: +390110904499.

E-mail address: [alice.gorrino@polito.it](mailto:alice.gorrino@polito.it)

manager becomes an integral part of the building management itself, able to critically evaluate the energy/comfort/cost/performance trade-offs, with the help of the expert advice given by the DSS system on the basis of collected data.

Many decision support systems for building energy management have been developed during the last few years. Doukas et al. [3] describe a DSS based on intelligent rules aimed at ensuring both the appropriate level of comfort and the energy saving; Kuo-Hao Chang [4] developed a DSS to manage the hybrid renewable energy systems; several work focused on the thermal mass control strategies [5,6,7,8]. Moreover, in recent years, few decision support tools were designed for a cluster of buildings rather than for a single building [9].

This paper describes the first results of the FP7-Smartcities Project OPTIMUS (OPTimising the energy Use in cities with smart decision support system), where the DSS concept is experimented at the level of public buildings (managed by municipalities), by running 4 pilots in different countries. The paper is structured into three main sections: first a general description of the DSS is presented; then the DSS general architecture both from the energy related and the Information System aspects is described; finally the first results of a DSS action to the town hall in Sant Cugat, Barcelona are shown.

## 2. Purpose and general description of the OPTIMUS DSS

The DSS is a web based tool addressed to city authorities, aimed at assisting them in the decision making process. The aim of the DSS is to minimize both energy use and CO<sub>2</sub> emissions in public buildings through a set of suggested actions that contribute to the weekly management of the energy systems, while maintaining adequate comfort levels. In the buildings equipped with BEMS, the DSS integrates with existing energy management strategies.

The suggested actions are mainly applicable to 1) the management of the HVAC technical systems, 2) the management of the building occupancy, 3) the planning of the Renewable Energy Sources. The actions are classified according to EN 15232 [10].

Typical actions related to the management of the HVAC systems include the optimal start/stop time of the space heating/cooling system considering the building thermal capacitance, the schedule of the indoor set point temperature according to the adaptive comfort, the optimization of the time using an air-side economizer.

The actions related to the management of the building occupancy are aimed at reducing peak loads by optimizing the exploitation of the free heat gains or by better managing the technical systems control.

The planning of the RES includes consumption/selling according to energy prices and weather forecasting.

All actions suggested by the DSS are based on prediction models and logic inference rules.

The actions are referred either to the whole building or to the different zones in which the building can be partitioned. The partitioning process is an integral part of the action modeling and it is performed according to FprEN 15603 [11]. According to this Technical Standard, the building can be partitioned according to different criteria (different energy uses, different technical subsystem, etc.): for the DSS purpose, a zone is related both to the monitored zones as well as to the actions.

## 3. Architecture of the OPTIMUS DSS

### 3.1. Energy and energy related aspects

The DSS is fed by building and context information, both static and dynamic: building static data refer to building and technical systems features while building dynamic data are mostly collected from sensors (either already existing in the BEMS, or newly installed). The DSS can interact with many types of existing building monitoring systems.

The DSS architecture has been designed in a general structure, to be adaptable to different specific cases. In the project use cases, it is considered that the DSS is composed of five data capturing modules that collect dynamic data from different domains:

- Weather forecasting: data concerning upcoming weather conditions as well as weather data from climate control units
- De-centralized sensor-based: gathers inputs on the energy and environmental performance, through sensors that will be installed in the buildings and through data extracted from existing BEMS variables
- Social media: input from end-users through social media (e.g. aspects related to the occupants opinion about comfort)
- Energy prices: data concerning energy prices available from energy producers, on the current and next days
- Renewable energy production: data concerning the production of energy from any renewable energy sources.

According to Figure 1, for each monitored variable the raw data are collected and pre-processed through pre-processing modules.

The main output of the DSS consists of the suggested actions and of a set of general indicators, that allow to quantify the expected impact of the actions on building performance. The observed indicators are the first outputs of the DSS as visualized by the DSS user. They are aimed at quantifying the performance of the building before the suggested actions are implemented.

Since the DSS is a tool aimed at supporting the decision making process within a week time, in addition to the observed building performance indicators, the DSS supports the decision maker with the predicted indicators, synthetic indices coming from a data mining process.

The methodology focuses on the construction of prediction models for every-day of the next week with energy consumption related to different end energy uses (space heating, cooling, etc.) and energy carrier. Both steady state and dynamic inverse

models are used in relation to the available data and to the building features: the simplest steady-state regression model correlates monthly actual energy consumptions with average outdoor air temperature, or in general outdoor climate parameters; robust and efficient methods including multiple linear regression (MVR), change-point linear regression etc.

The predicted indicators are also classified into ante and post actions indicators. The first ones come from predictive modules themselves while the second ones come from the elaboration process through data mining techniques and data correlation through an intelligent rules process.

The inference rules are built using as input both the elaborated data through data mining techniques, pre-processed and static data. They are based on a sequence of logical propositions consisting of premises (involving propositional variables) and a conclusion. An argument form is valid if the truth of all its premises implies that the conclusion is true. The premises consists of proposition involving elaborated dynamic and static data and the conclusion is the suggested action itself.

It is supposed that the actions derived from the processing of inference rules process will feed the data mining process, together with the other variables.

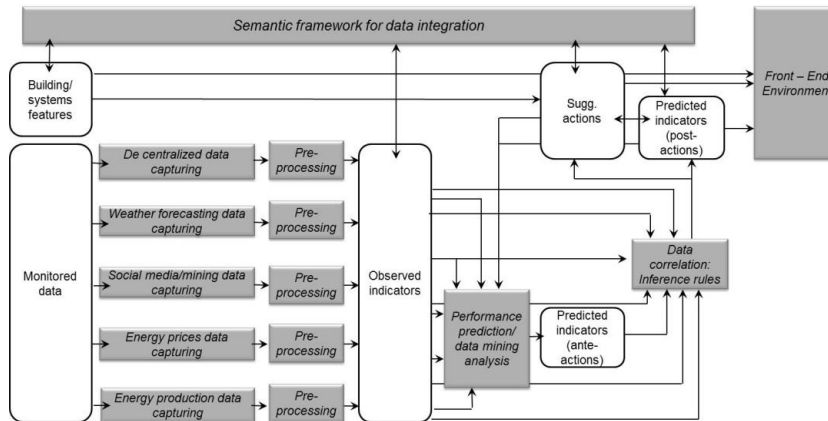


Fig. 1. General architecture scheme of the OPTIMUS DSS.

A period of training and testing of each model based on inference rules will be defined in order to better adapt the general rule to the specific DSS object. Finally, each inbound and outbound information flow will be modelled and integrated using semantic technologies. The DSS engine will be part of a front-end environment, namely, a web-based environment adapted to the needs and knowledge of different types of stakeholders.

### 3.2. Design and architecture of the Information System

Figure 2 shows the general software architecture of the DSS system, where both data capture modules (on the left) and the computational and front-end modules (top right) are represented. All data collected by the capture modules is sent to the DSS, that stores it into a semantic data store (encoding it as RDF triple, according to Semantic Web standards). The front-end modules essentially consist of a set of web applications, used to visualize the current state of the system (raw data, inferred data, DSS suggestions, and various indicators).

The diagram also focuses on the communication infrastructure and the software integration: the high variability of number of types of modules, whose nature depends on the type of building features, suggested the adoption of a semantic-based representation of data and information, coupled with a flexible communication protocol based on the publish/subscribe pattern.

From the point of view of information technology, it is a distributed architecture, with modules running on different locations and interacting over the Internet. The design process of the OPTIMUS DSS distributed architecture followed a set of guidelines and processes. Above all, we aimed at exploiting the hardware-software patterns that currently lie at the state of the art of sensor-based networks and of Internet-of-Things architectures. In particular, two main pillars have been identified as drivers for system integration: semantic representation and publish-and-subscribe communication.

#### 3.2.1. Semantic representation

Concerning the first pillar, i.e., *semantic representation*, it has been adopted to enable the generality (i.e., ease to adapt and reconfigure to the different pilots, or even to different projects) and the interoperability with current and future services (thanks to the self-describing nature of the representation).

Semantic techniques are used both for describing characteristics of the pilot sites, and for encoding live real-time data exchanged. A suitable ontology, based on the W3C standard Semantic Sensor Network Ontology (SSN) [12] has been defined and is adopted

by all the modules in the DSS system. Such encoding allows to represent any type of sensor with a uniform language; an example is shown in Figure 3, where the sensor `sunnyportal_solar_radiation` has measured, at time instant `2014-10-03T00:10:00Z`, the value of `123.45`.

### 3.2.2. Publish and subscribe communication

Concerning the second pillar, i.e., publish-and-subscribe communication, it allows fast and reliable exchange of messages (that mainly consist of data collected from the modules and sent to the DSS), and at the same time allow for very easy reconfiguration of the layout of communications, which is essential during the incremental development of the whole Optimus system.

A publish-and-subscribe platform, based on the Zstreamy [13] open source software (developed by UC3M), has been deployed and configured, and hosts all data exchange towards the DSS.

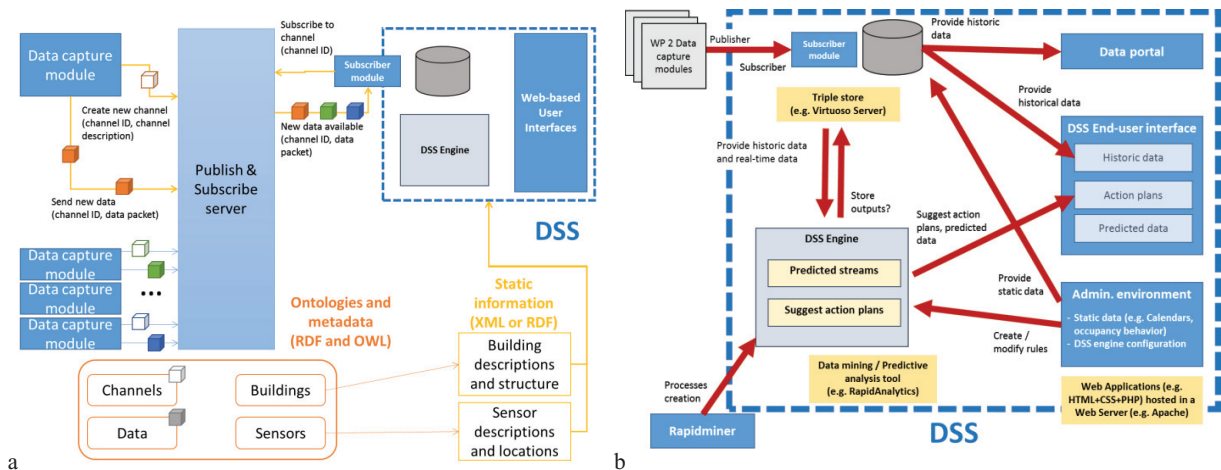


Figure 2. (a) General DSS architecture; (b) internal architecture of the DSS Engine - zoom on the top-right box of left side

The architecture includes the definition of the internal structure of the “core” module of the DSS system, i.e., the DSS engine that is responsible for gathering all input information and elaborating outputs and suggestions based on the predictive modules, whose details are sketched in Figure 2 (b). The figure highlights the main processing components, i.e., the semantic data base (triple store), and the DSS engine in charge of processing data streams and predicting values and/or computing suggested actions plans.

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<http://www.optimus-smartcity.eu/resources/sant_cugat/observation/sunnyportal_solar_radiation1> ssn:observedBy
<http://www.optimus-smartcity.eu/resources/sant_cugat/sensingdevice/sunnyportal_solar_radiation>.
<http://www.optimus-smartcity.eu/resources/sant_cugat/observation/sunnyportal_solar_radiation1> ssn:observationResult
<http://www.optimus-smartcity.eu/resources/sant_cugat/sensoroutput/sunnyportal_solar_radiation1>.
<http://www.optimus-smartcity.eu/resources/sant_cugat/observation/sunnyportal_solar_radiation1>
ssn:observationResultTime <http://www.optimus-smartcity.eu/resources/sant_cugat/instant/201410031620>.
<http://www.optimus-smartcity.eu/resources/sant_cugat/sensoroutput/sunnyportal_solar_radiation1> ssn:hasValue
"123.45"^^xsd:decimal.
<http://www.optimus-smartcity.eu/resources/sant_cugat/instant/201410031620> time:inXSDDateTime "2014-10-
03T00:10:00Z"^^xsd:dateTime.
```

Figure 3. Example of a semantic representation of a sensor measurement

## 4. Example of action modeling

In order to clarify the general framework of a DSS action, an HVAC system management action is briefly described and first results are presented. The action is related to the optimization of the boost time ( $t_1$ ) and to the duration of the cut-off period ( $t_2$ ) taking into account occupant thermal comfort through the reaching of the optimal set point temperature ( $\theta_{set,point}$ ) (Fig. 5 (a)) [14].

In Fig. 4 the whole action modeling process is described. The procedure is theoretically split into three main sections: the capturing data procedure (related to each zone), the performance prediction and the inference rules. The process is firstly applied to the Town Hall of Sant Cugat (Barcelona), whose typical floor is shown in Fig. 4. The following variables have been collected: outdoor/indoor air temperatures, schedule of the heating system operation, occupancy profile, maximum heating power. Moreover input from social media will be collected to have real time feedback from the building users about thermal comfort.

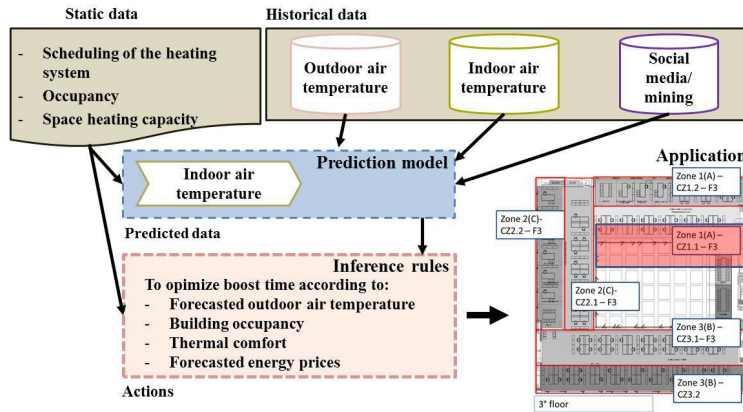


Fig. 4. Action modeling procedure scheme applied to the Town Hall of Sant Cugat, Barcelona, Spain.

The method used for both the prediction and the inferencing rule process is based on a grey box approach. The model is characterized by a node whose temperature is equal to the indoor air temperature. It is in contact to the internal thermal inertia through a capacitance and to the external environment through an heat resistance. (Fig. 5 (b)).

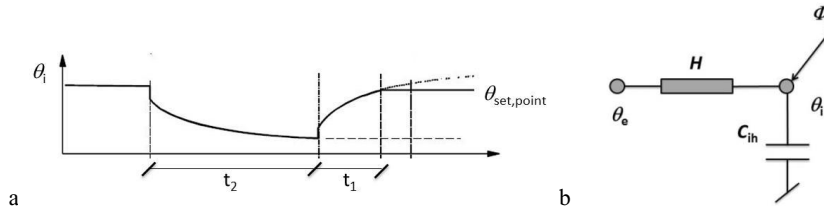


Fig. 5. (a) Indoor air temperature trend for the heating system cut-off mode (EN ISO 13790:2004); (b) Capacitance-resistance building model.

The indoor air temperature trend is predicted by applying equation 1, which considers the data monitored in the previous week.

$$\left[ \theta_i - \left( \theta_e + \frac{\Phi}{H} \right) \right] / \left[ \theta_{i,0} - \left( \theta_e + \frac{\Phi}{H} \right) \right] = e^{-\frac{t}{\tau}} \quad (1)$$

where  $\theta_i$  and  $\theta_e$  are the monitored indoor and outdoor air temperatures;  $\theta_{i,0}$  the indoor air temperature at time  $t = 0$ ;  $\tau$  is the time constant of the building;  $\Phi/H$  is the ratio between the heat gains and the heat loss coefficient. Both  $\tau$  and  $\Phi/H$  are nonlinear regressors of the equation:  $\tau$  is only calculated for the cut off mode, while  $\Phi/H$  is calculated both for boost and for cut-off mode.

Once the time constant and the  $\Phi/H$  ratios are evaluated, the inverse model is used for predicting the indoor air temperature trend during the cut-off and the boost period of the week after as well as for calculating the optimal boost time.

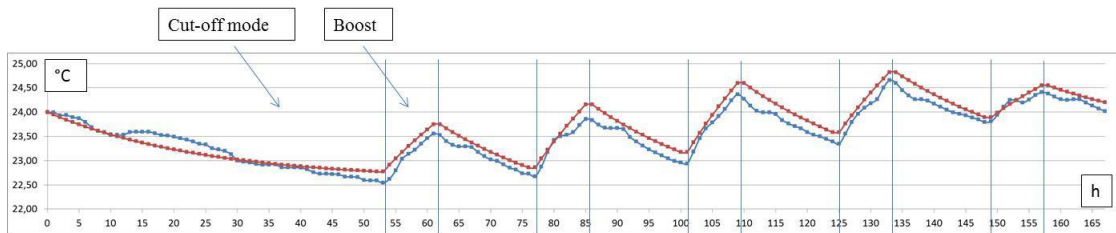


Fig. 6. Comparison between monitored and predicted indoor air temperature during cut-off and boost period (Sant Cugat, 1 – 7 November 2014)

In Fig. 6 the monitored (blue) and calculated (red) indoor air temperature are shown for one zone of the Town Hall of Sant Cugat (Fig. 4, red zone) for the first week of November 2014. The indoor air temperature trend is divided into cut-off mode and boost, since no normal heating mode occurs. Equation 1 has been applied and the regressors have been calculated. The average deviation between the monitored and calculated data is  $0,2^{\circ}\text{C}$ .

The procedure is applied each week of the heating period and the regressors are used for the inferencing rule process of the week after. The optimal boost time is defined according to occupancy and outdoor air temperature predicted for the week after.



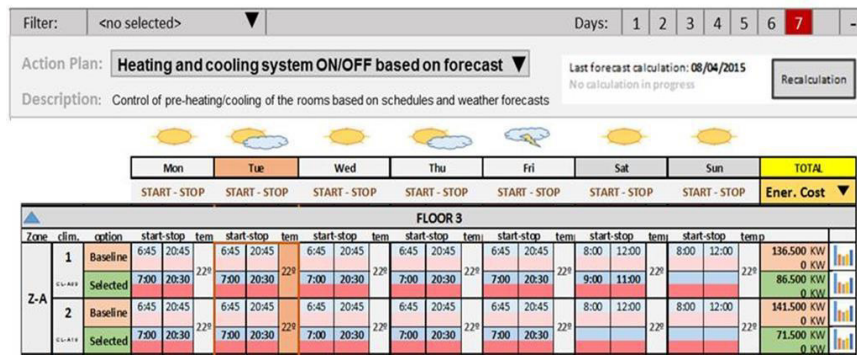


Fig.7. Front-end environment related to the optimal start and stop of the heating system

In Fig. 7 the front end-environment to manage the start/stop of the heating system is shown. For each day of the week after, the scheduling of the start/stop of the heating system is provided for a zone of the building.

## 5. Conclusion and future work

The decision support systems are becoming innovative tools that allow the decision makers to better understand the performance of a building or group of buildings in term of comfort, energy saving, cost saving etc. and to be supported in the decision making process. In this contest, the first phase of development of the OPTIMUS DSS has been described together with its potentialities. Both energy related aspects and the architecture of the information system have been taken into account.

The main innovation of the developed DSS consists of the use of predictive grey box models coupled with real time data capturing. Moreover, these data are taken from various sources and processed through a semantic framework.

The overall architecture of the OPTIMUS DSS has been designed considering both the energy related and the information technology aspects. The research activity is going on during the second and third years of activity following the steps as below:

- definition and implementation of data mining techniques and inferencing rules
- implementation of methods and tools to provide an integrated access to the data captured and modelled using semantic technologies
- designing of a web-based environments which will provide access to different types of stakeholders
- application of the OPTIMUS DSS to four public pilot cases: a primary and secondary school located in Savona, the town hall in Zaanstad, the town hall and the theatre in Sant Cugat.

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