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Development of a web based energy management system for University Campuses: The CAMP-IT platform

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ABSTRACT

University campuses can be considered as small towns due to their size, number of users and mixed and complex activities, including numerous actions usually met in urban environments. The energy and environmental impact of universities could be considerably reduced by applying organizational, technological and energy optimization measures. The aim of the present paper is to present an efficient web based energy management system for Campuses which manages in an energy efficient way the Campus buildings and spaces of public use, monitors the energy load and performs energy analysis per building and for the Campus as a whole, as well as it interacts with each building's BEMS and each user through questionnaires, e-mails and forms. The existing Campus IP infrastructure is exploited by using sensor networks, where nodes communicate their information using Web services, allowing direct integration in modern IT systems. To guarantee the system scalability and respect consolidated and diffused standards, the logical/architectural level of the whole Campus Energy Management System is linked with the existing infrastructure based on Internet Protocol (IP). The overall installation is tested via on line questionnaires to the building users showing a significant increase of the occupants' satisfaction. Finally, the energy efficiency achieved by the proposed system is almost 20%.

1. Introduction

Universities' campuses can be considered as small cities due to their size, users and mixed complex activities. The energy and environmental impact caused by universities via activities and operations in teaching and research, as well as provision of support services, could be considerably reduced by an effective choice of organizational and managerial measures [1]. Since the natural land of University campuses is replaced by artificial surfaces and buildings with undesirable thermal effects, the overheating by human energy release and absorption of solar radiation on dark surfaces and buildings is possible. Energy wastage in various space types, such as teaching auditoriums, working areas (offices, laboratories, computer rooms, etc.) or residential buildings (dormitories) can be encountered. All these thermal gains create an urban – kind climate in campuses [2]. The energy and environmental impact of universities could be considerably reduced by applying organizational, technological and energy optimization measures.

To design and operate a sustainable campus, it is necessary to holistically and strategically integrate the indoor – outdoor environment parameters and information into the planning and operational process. Since the post-modern era, when scientists and designers realized the disadvantages of the continuously growing artificial environment, the improvement of the outdoor environment and its impact on the indoor environmental quality has gained a substantial attention. Open urban spaces can contribute to the quality of life within cities, or contrarily, enhance isolation and social exclusion. The major factor that determines the quality of the open urban spaces is the climate conditions that occur in the micro scale environment. The strategies to improve urban environment include the use of smart materials, the increase of vegetation, ventilation, shading and evaporation [3–5]. Accurate and detailed simulation models should be integrated and interconnected to allow more sophisticated and, at the same time, more efficient calculations which take into account the impact of the microclimatic conditions on the energy demand for buildings. Various researchers have performed similar efforts. A simulation tool

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for the prediction of the effect of outdoor thermal environment on building thermal performance (heating/cooling loads, indoor temperature) in an urban block consisting of several buildings, trees, and other structures is proposed by [6]. External surface temperature and mean radiant temperature is used to estimate the impact of the outdoor environment. As underlined by [7] the evaluation of policy measures in district level requires the effective combination of the building geometry with possible canyon formation, along with local weather conditions and energy load prediction, in order to effectively manage the available resources. The energy load, as well as local meteorological parameters' prediction on campus level can be performed by Artificial Neural Networks (ANN). Neural networks are used due to their adaptive nature to acquired measurements [8,9]. Similar works have been performed for the energy demand prediction in microgrid level [10], in hospitals [11,12] as well as in various energy systems [13].

Furthermore, the increasing use during the last decades of the building services management systems and control has led to the gain of significant experience. Simulation and application of artificial intelligence control techniques (such as fuzzy logic and artificial neural networks), has indicated that they have the potential to make significant energy savings in buildings [8,14]. Regarding the University Campus level, the main challenge in the design of control systems is to find the balance between implementation costs, operation costs, energy consumption, indoor environmental quality, users' satisfaction and contribution to sustainable living. Intelligent Campuses are those involving environmentally responsive design, taking into account the surroundings and building usage, and enabling the selection of appropriate building services and control systems to further enhance the blocks of buildings operation with a view to the reduction of energy consumption and environmental impact over its lifetime. This procedure requires advanced control techniques to establish a balance among user comfort requirements, energy consumption, passive solar design concepts and solar heating/cooling technologies. Therefore, control and optimization algorithms [14,15] based on efficient and accurate built environment models are required in order to obtain efficient and nearly-optimal operation on Campus level.

In addition, sensors, actuators and interfaces are essential components for the successful implementation and real-time operation of a web based energy management system. The evolution of the specific components was quite rapid during the last decades leading to the intelligent buildings' concept derived from artificial intelligence and information technology. While ICT infrastructure networks are seen as an important part in emerging building and community energy management systems through i.e. Metropolitan Area Networks, the integration of sensor networks with future energy management systems is still an open problem [16].

Based on the above analysis, there is a considerable room for improvement and research potential in energy management for group of buildings in a Campus context, where different buildings and outdoor spaces are considered. Towards this integrated approach the interrelation between the indoor and outdoor environment, smart meters and distributed intelligence on building and campus level should be considered.

To this end, the aim of the present paper is to present an efficient web based energy management system for Campuses which: (a) Manages in an energy efficient way the Campus buildings and spaces of public use. (b) Monitors the energy load and performs energy analysis per building and for the Campus as a whole. (c) Interacts with each building's BEMS and each user through questionnaires, e-mails and forms. (d) Optimizes of the overall strategy based on historical data. (e) Focuses on the Campus as a district and creates a holistic methodology for buildings and outdoor spaces of public use.

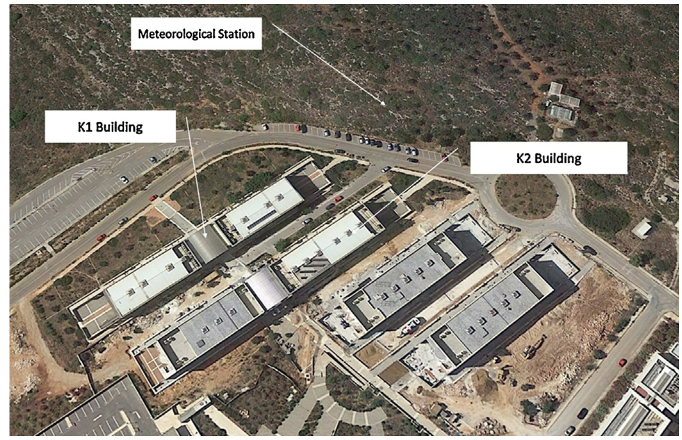

Fig. 1. Aerial photo of campus buildings K1 and K2.

The specific system, called hereafter Camp-IT, is installed in the Technical University of Crete Campus. The paper includes a description of the case study campus in Section 2. The description of control procedure is included in Section 3 and the overall infrastructure in Section 4. Finally, Sections 5 and 6 comprise the discussion of the results and conclusions.

2. The case study campus

The Campus of the Technical University of Crete hosts five University departments, two libraries, administrative buildings and student dormitories. The Campus is one of the major energy consumers in the electricity grid of Crete with a peak power demand of 1.2–1.5 MW. It should be noted here that Crete is supported by an autonomous energy system, not interconnected with Greece's mainland power network [17,18]. In the Campus, 19 smart energy meters have been installed to monitor the energy consumption for electricity in the various building blocks. The area selected for the CAMP-IT implementation are the buildings K1 and K2 of the Environmental Engineering Department, including the outdoor area.

Fig. 1 depicts the buildings under study, the exterior spaces around them and the topography of the area. The building K1 is located at the northern end of the campus with its main façade facing north-west. The distance between K1 and K2 is approximately 16.20 m, with K2 sited to the south of K1. Each floor of K1 is divided in two wings, connected through an atrium. The main characteristics of the selected buildings, as well as their structural materials, are tabulated in Table 1.

3. Modelling procedure

3.1. Development of thermal models of the institutional buildings

The ESP-r energy-modelling tool is employed for simulation of the conditions inside the University buildings. ESP-r can simulate complicated elements of the building envelope and any electrical/mechanical equipment available [19]. The computational subroutines exchange information (interaction between the parameters of the various thermal zones) in order to accurately calculate the interactions between the systems of the building. One of the most important characteristics of ESP-r is that it co-operates with other simulation tools to provide a wider range of very accurate results. Moreover, ESP-r was selected for the specific study as it can model all the electric devices and the systems producing and storing energy from renewable energy sources, it includes a very wide range of control algorithms for the various systems, including fuzzy logic algorithms, it uses airflow networks which enable the

Table 1
Main characteristics of the selected buildings.

Characteristics of K1	
General Dimensions (m)	(Length/Width/Height): 86.40/15.20/12.00
Number of Floors	3
Facilities on Ground floor	14 laboratories, 3 offices, 2 mechanical rooms, elevators, stairs, WC
Facilities on 1st floor	17 offices, 1 meeting room, 2 mechanical rooms, elevators, stairs, WC
Facilities on 2nd floor	Laboratories & mechanical rooms
Characteristics of K2	
General Dimensions (m)	(Length/Width/Height): 48.00/15.20/11.00
Number of Floors	3
Facilities on Ground floor	5 computer rooms, 1 printer room, 1 office, 1 mechanical room, elevators, stairs, WC
Facilities on 1st floor	3 laboratories, 14 offices, elevators, stairs, WC
Facilities on 2nd floor	Mechanical rooms
Characteristics of Exterior spaces	
Exterior spaces	Soil, marble, stone, tiles (cotto), plants, trees
Structural materials of K1 & K2	
Exterior walls	Ground and first floors ceilings
a) Double plasterboard (width:18 mm each)	a) Uncoated concrete: 2 cm
b) Insulation: 5 cm rockwool, d = 80 kg/m^3	b) Insulation: 5 cm rockwool, d = 80 kg/m^3
c) Cement board: 12 mm	c) Ceramic tiles: 10 mm.
Second floor ceilings	Windows (104 windows in B1 & 68 windows in B2)
a) Uncoated concrete: 2 cm	a) Double pane windows.
b) Insulation: 10 cm	b) Aluminum frames.
c) Asphalt membrane: 10 mm	c) Exterior lamellas.
Floor top coating	
a) Ceramic tiles: 10 mm (in all spaces)	
b) Industrial flooring: 20 mm (Chemistry lab)	

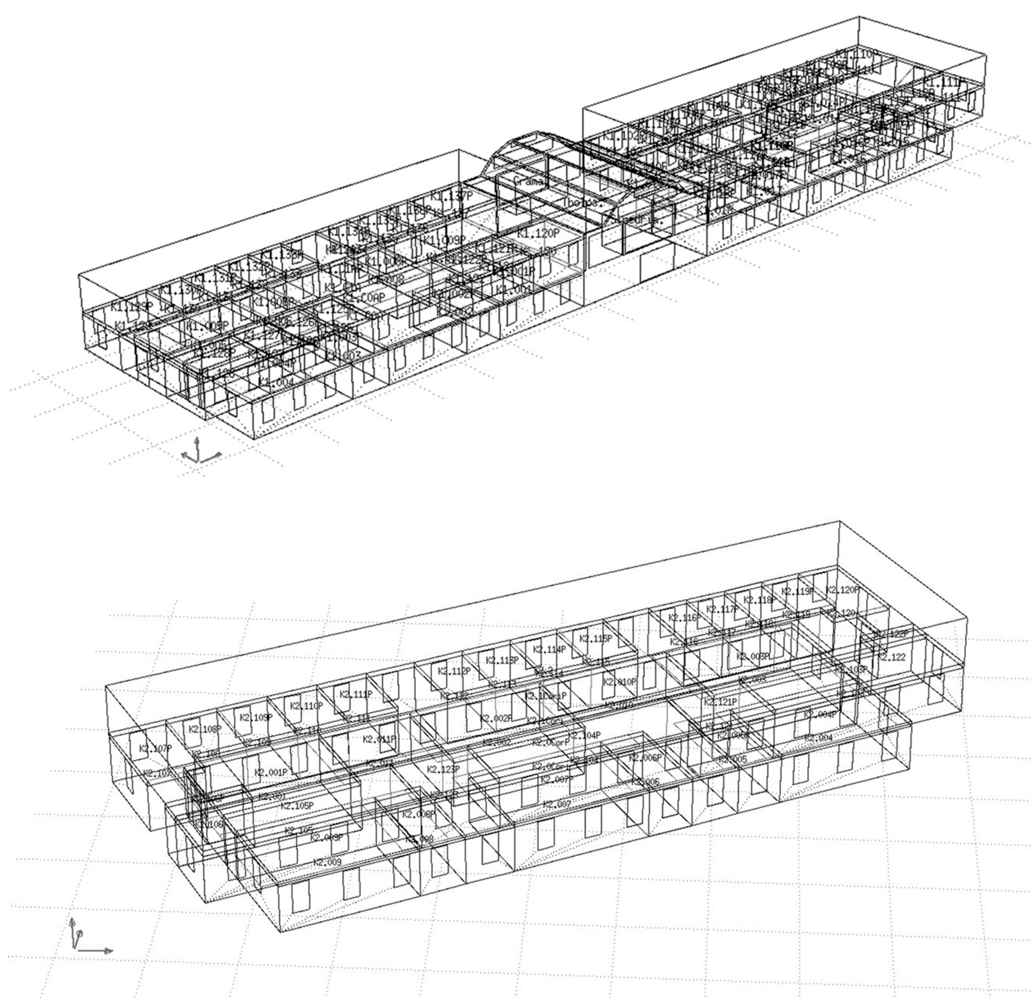

Fig. 2. Building Models using ESP-r.

calculation of the movement of air masses inside or outside buildings, etc. The developed models using ESP-r are depicted in Fig. 2. One very important function of ESP-r is that features execution of scripts to further manage and automate the modelling procedures. This eases interconnectivity with other models. A feature not supported by ESP-r is the import of 3D building models. Especially in buildings with complicated shapes and forms, the import of 3D models in ESP-r may be time consuming. For that reason, a specific plugin is developed to simplify the process. The plugin, developed in the programing language Ruby [20], allows the export from SketchUp to ESP-r. Along with the creation of the geometry in ESP-r, the plugin also connects the various surfaces of the building model, either between each other or with the ground. Moreover, the plugin has the ability to transform the floor 2D diagram into thermal zones. With this functionality, the time for the development of the model is drastically reduced. The plugin also provides for the storage of the coordinates, edges, surfaces and material names for every different thermal zone of ESP-r in a single text file with the extension ".geo".

3.2. Modelling of exterior spaces of the campus

Artificial surfaces of urbanized areas tend to generate large amounts of heat and modify the microclimate and air quality [21,22]. The simulation of outdoor environmental conditions enables the design of urban areas that have the minimum environmental and energy impact on the surrounding constructions. Moreover, this type of simulations may have effect on the energy management of the neighbouring buildings. Exterior environmental conditions can be predicted by complex microscale or mesoscale computer models (CFD, OpenFoam, MIST, ENVI-MET, WW5, etc.). For the simulations of the conditions in the exterior area between the buildings of the Technical University of Crete, the three-dimensional microclimate model ENVI-metENVI-met is used [23–26]. ENVI-met ENVI-metis a three-dimensional non-hydrostatic microclimate model including a simple one dimensional soil model, a radiative transfer model and a vegetation model. ENVI-met uses a uniform mesh with a maximum of about $300 \times 300 \times 35$ cells with the horizontal extension ranging between 0.5 and 10 m and a typical vertical height of 1–5m. The materials and the sizes of the buildings, the exterior surfaces and the trees/plants were as accurately reproduced as possible. The weather parameters that were used as input (air temperature and relative humidity) were acquired by the University's weather station and the parameters that were simulated, are: a) Surface temperature (°C); b)Air temperature at a height of 1.80 m above ground level (°C) and c)Wind velocity (m/s).

The results for 12:00 are depicted in Figs. 3 and 4. The modelled surface temperature is quite high, i.e. between 40 and 43° C, in the area between the K1 and K2 building and in all areas covered with asphalt, as expected. The areas covered with soil and grass have a surface temperature of around 35° C and 29° C respectively. The average air temperature in the region is around 26° C with a variation of 2° C around the various areas.

3.3. Coupling of indoor-outdoor models

The various simulation tools for buildings cannot take into account the microclimatic conditions of the buildings' outdoor area, while usually they use weather files that contain statistically processed meteorological data. The use of real weather data requires a meteorological station installed in the surrounding area of the building, which is not always available. Moreover, the wind velocity is considered constant at all points of the building elevation and possible variations due to the geometry of the buildings and other obstacles is not taken into account.

The most important parameter when coupling indoor and outdoor models is the convective heat transfer coefficient between the outdoor air and the building envelope [27]. The convective heat transfer coefficient is influenced by several factors, such as the geometry of the building and building surroundings, the position at the building envelope, the building surface roughness, wind speed, wind direction, local airflow patterns and surface to air temperature differences [28]. In urban areas, local airflow patterns around a building strongly depend on the arrangement and geometry of neighbouring buildings [29,30] which drastically influence convective heat transfer coefficient. Terrain type influences the mean wind speed and turbulence intensity profiles [30,31], which also affect the convective heat transfer coefficient values [28]. There are different methods to obtain values for the specific coefficient which can be categorized in analytical, numerical and experimental ones [32]. Analytical methods are only applicable for some specific flow regimes and simple geometries, e.g. flat plates and cylinders [33]. Numerical methods, namely Computational Fluid Dynamics (CFD), are powerful tools to calculate the convective heat transfer coefficient [34,35].

Most building simulation programs including ESP-r are using McAdams model [36] for the h_c factor calculation which is based on measurements using wind tunnel [37]. In order to avoid the use of sensors' installation in the buildings' external surfaces, a coupling of the buildings' thermal models with the external ENVI-metENVI-met models is performed. The methodology followed for the coupling is described below:

1. The two models, i.e. the ENVI-met external area model and ESP-r geometry representation of the buildings are deeply examined in order to avoid inconsistencies and support the exchange of information between them.
2. A 3D representation of the buildings is performed in Python Programming Language [38] based on ESP-r models. Then the ENVI-met grid is integrated in the 3D representation using Python. The results of the ESP-r and ENVI-met grid interconnection is depicted in Fig. 5.
3. The air temperature, wind speed and direction on each outer cell of the buildings K1 and K2 grid areextracted from ENVI-met.
4. The convective heat transfer coefficient (h_c) on each outer surface of the grid is calculated on hourly basis. On the other hand, ESP-r cannot accept changes of h_c on hourly basis but only for seven time periods per day. For that reason, the 24 h are split in seven slots: 1) 0:00–8:00, 2) 8:00–10:00, 3) 10:00–12:00, 4) 12:00–13:00, 5) 13:00–15:00, 6) 15:00–17:00, 7) 17:00–24:00 following the occupancy schedule. For each time slot the average convective heat transfer coefficient is fed into ESP-r.
5. The weather files of ESP-r are updated with the outputs from ENVI-met, i.e. air temperature, wind velocity, relative humidity and solar radiation.
6. The buildings' simulation is then performed via ESP-r with the ENVI-met weather files and the extracted convective heat transfer coefficients.

3.4. Development of prediction models for the energy load and exterior conditions

During the last decades there has been a substantial increase in the interest on artificial neural networks and their applicability in energy applications [39]. The artificial neural networks are advantageous in tasks and problems that involve incomplete data sets, fuzzy or incomplete information, and for ill-defined problems, where humans usually decide on an intuitional basis. They can learn from examples, and are able to deal with non-linear prob-

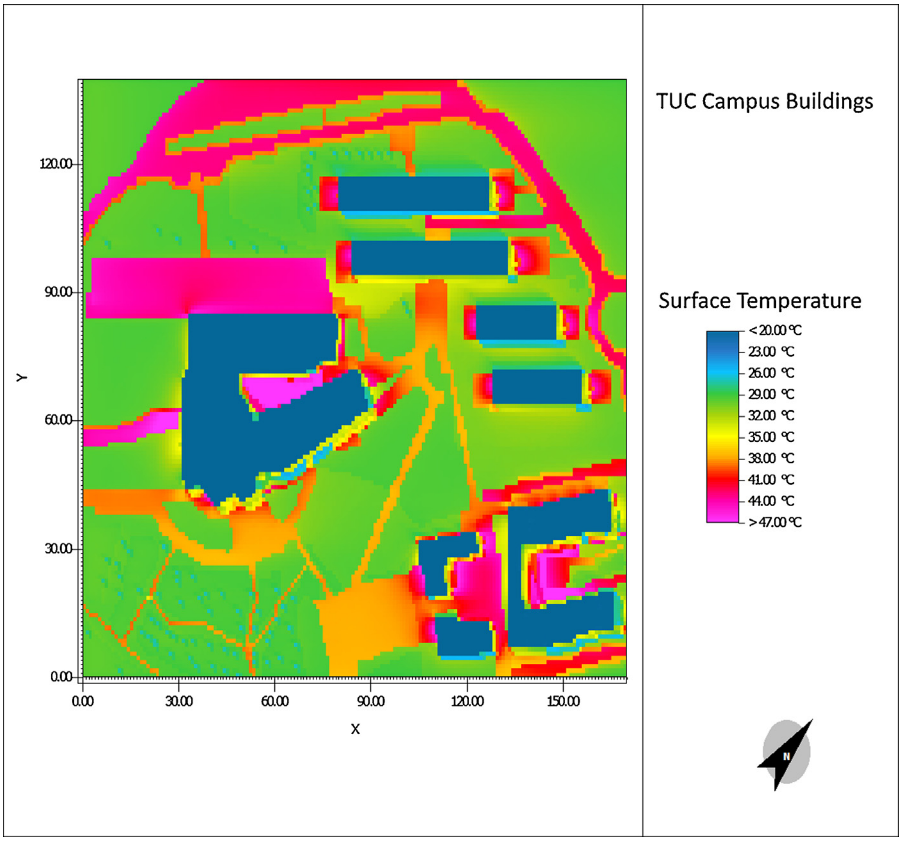

Fig. 3. The surface temperature of the TUC Campus on 23/6/2015 at 12:00.

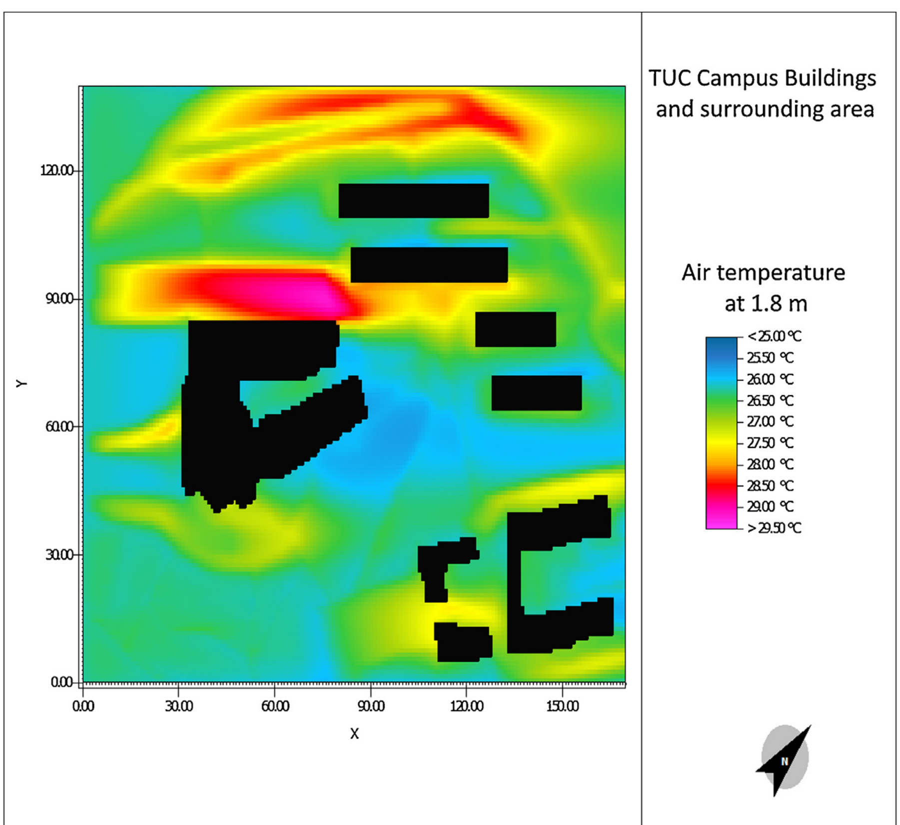

Fig. 4. The air temperature around the TUC Campus Buildings on 23/6/2014 at 12:00.

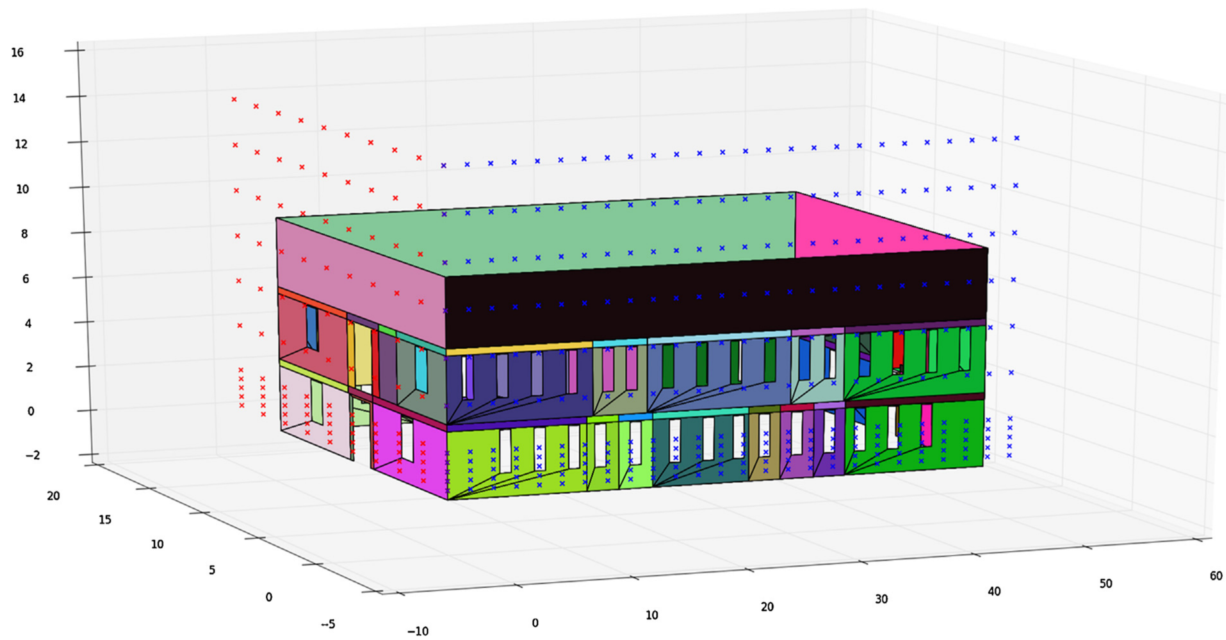

Fig. 5. 3D representation of K1 building and outdoor environment using Python.

Table 2
Characteristics of the ANN used for the energy demand prediction in the TUC Campus buildings.

ANN properties	Description
ANN type	Elman Neural Network
Model	Feed Forward
Number of inputs	3
Inputs	Ambient Temperature “db”Day of the week: “weekdays”Minutes: “minutes”
Number of outputs	1
Output	Buildings energy load “power”
Number of Hidden Layers	3
Size of Hidden layers	[322]
Performance function/indicator	Run Mean Square Error (RMSE)
Initial training dataset	1000
Epochs	3000
Number of maximum fails	3000
Transfer function	Tangent sigmoid function

lems, while they offer robustness and fault tolerance. In the specific paper neural networks are used for the prediction of the energy loads of buildings K1 and K2 and for the prediction of the exterior environmental parameters affecting the energy consumption and user comfort. The input parameters for the neural network predicting the energy load of the buildings are the exterior temperature, measured by a weather station positioned opposite to the studied buildings, the day of the week and minutes of the day. Also, the energy demand, recorded every five minutes, by smart meters, is used. The training of the neural network is repeated every day in order to avoid possible errors’ accumulation from the weather conditions of the previous day. The weather data are then forwarded to the neural network to be used as input. The comparison of the predicted energy load with the load measured by the smart meters, shows that the neural networks predict the load with acceptable accuracy. Accordingly, the parameters used as inputs for the network predicting the exterior temperature for the 24 h following a specific moment are the exterior temperature, the total horizontal radiation, relative humidity, wind speed and direction, as well as the time of day. The weather data also come from the weather station positioned opposite to the studied buildings. The properties of the ANN are tabulated in Table 2 [8].

The neural networks ‘training is repeated in regular intervals (i.e. on daily basis) in order to adapt to the various changes .

3.5. Models’ testing and validation

The validation of the building models is performed using a series of measurements based on the infrastructure installed in the TUC Campus Buildings (see Section 5). The monitoring devices, tabulated in Table 4 are installed in different rooms of the two buildings in order to cover all orientations, room types (PC rooms, laboratories, offices, etc.) and floors. The monitoring period started on March 2014 and ended on June 2014. For the validation of the building models the period of 20–30 April 2014 was used because the buildings were under free floating conditions during that specific period. The measured versus the modelled indoor temperatures for one representative area is depicted in Fig. 6. The difference between the measured and modelled temperatures is less than 10% for all cases and ranges between 0.6 and 1.5 K.

The coupling mechanism is verified using the following procedure: The measurements acquired by the meteorological station that is close to buildings K1 and K2 (Fig. 1) are compared with the ambient temperature extracted by ENVI-met and for the same height. The ENVI-met model results versus the measured ones for the ambient temperature and for 23/6/2014 are illustrated in Fig. 7. From the regression analysis it is concluded that ENVI-met simulates the microclimatic conditions around the buildings quite accurately. By using the microclimatic conditions in the building

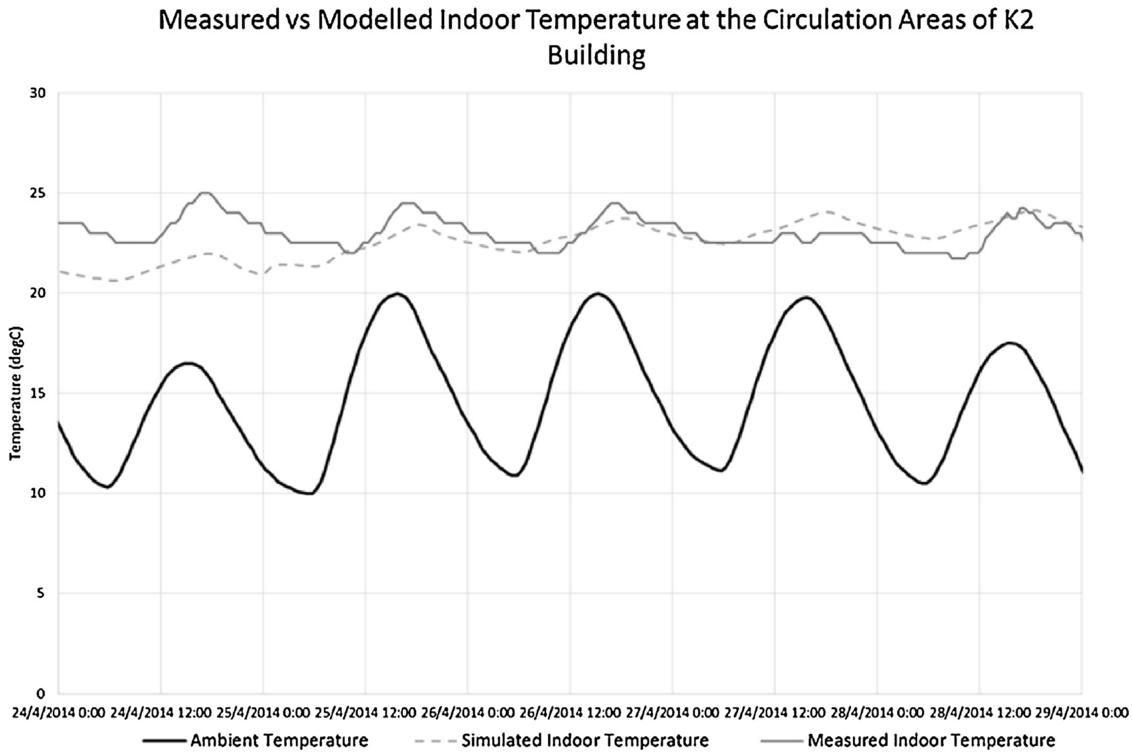

Fig. 6. Monitoring versus modelled indoor temperature for circulation areas of K2 building.

thermal models (i.e. ESP-r), the differences in the energy demand calculations can be up to 12% depending on the outdoor climatic conditions.

The values predicted by the developed neural networks have been compared with the data collected from the smart energy meters (Fig. 8).

4. Development of control and optimisation algorithms

4.1. Control algorithms for the indoor environmental quality

The developed control algorithms are based on fuzzy logic techniques [12,40]. The characteristics of the fuzzy logic algorithms for

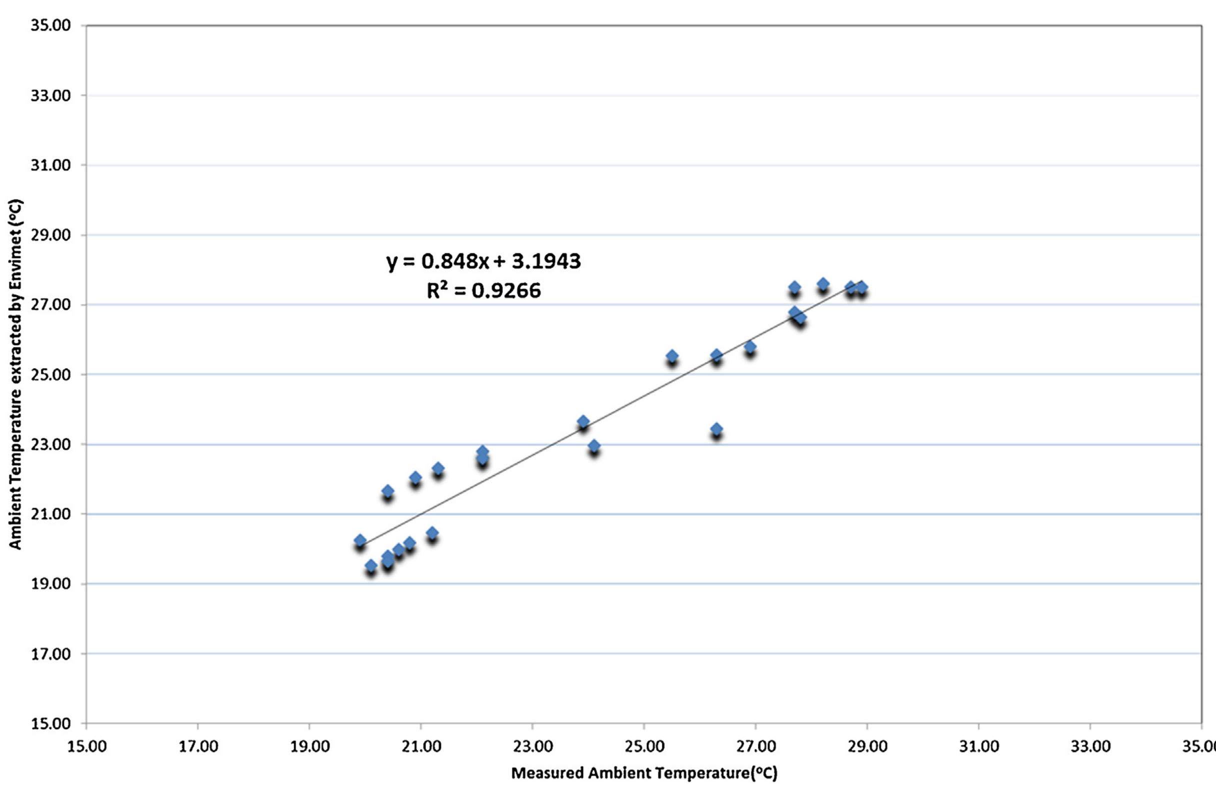

Fig. 7. Measured versus simulated ambient temperature: regression analysis.

Table 3
The fuzzy control algorithms characteristics.

Thermal Comfort and Indoor Air Quality		
Fuzzy logic type	'Mamdami'	
Inputs	PMV_{error} ($PMV - PMV_{setpoint}$) CO_2 concentration $_{error}$ ([$CO_2 - CO_{2Setpoint}$] Ambient temperature	
Outputs	On/Off of the heating/cooling system	Ventilation flow rate
Parameters of the Mandani fuzzy logic algorithm	And Method: 'min' Implication Method: 'min' Defuzzification Method:'centroid'	Or Method: 'max' Aggregation Method: 'max'
Visual Comfort		
Fuzzy logic type	'Sugeno'	
Inputs	Difference between desired and actual illuminance	
Outputs	On/Off of the electric lighting system	
Parameters of the Sugeno fuzzy logic algorithm in Matlab	And Method: 'prob' Implication Method: ' prod ' Defuzzification Method:'wtaver'	Or Method: 'probor' Aggregation Method: 'sum'

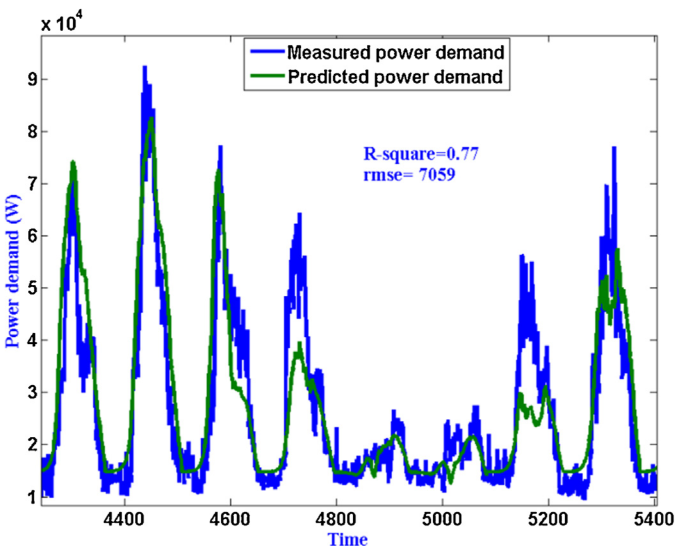

Fig. 8. Comparison of the Measured (blue line) and the Predicted power demand (green line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the indoor environmental quality and visual comfort are tabulated in Table 3.

The algorithm for the control of the lighting can dim or turn on/off the luminaires, depending on the available daylight and the desired lighting levels. The algorithm for the indoor environmental quality, controls the Heating Ventilation and Air Conditioning System (HVAC) using the difference of the PMV index parameters (temperature, humidity, radiation, air velocity, metabolic rate and clothing) and the difference of the CO_2 concentration level from the required ones, in order to change the heating/cooling system or increase/decrease the flow of fresh air through the ventilation system.

The algorithm for the thermal comfort uses the PMV index parameters (temperature, humidity, radiation, air velocity, metabolic rate and clothing), in order to adjust the heating/cooling system or increase/decrease the flow of fresh air through the ventilation system.

The development of these algorithms is made using Matlab, since it provides the appropriate libraries and graphical representation of the controls behaviour. The performance of the control algorithms in reducing the energy consumption and in providing comfortable indoor conditions has been assessed, by linking the control algorithms with the simulation models for the interior and exterior environment (Fig. 9).

The control algorithms in Matlab environment exchange data in real-time with the thermal models and ENVI-met, through the Building Control Virtual Test Bed (BCVTB) software.

The algorithm controlling the illuminance levels in the interior spaces, should keep the lighting levels stable at 500 lx from 8:00 until 18:00, regardless the exterior illuminance, while the lighting levels should be kept 0 during the rest of the day. The energy saved by the use of the control algorithm is calculated by comparing the prior energy consumption and the energy consumption after the regulation of the artificial lighting with the use of the control algorithm. The prior energy consumption for lighting is 31.5 kWh/m^2, while the energy saved is 6.9 kWh/m^2 per year, which is translated into 22% reduction of the energy use for electric lighting.

Concerning the system for the control of thermal comfort and air quality, the minimum requirements have to be met even in extreme cases. During winter, the thermostat is set at 20 °C, from 8:00 until 16:00, while during the rest of the day the heating is turned off. During summer, the thermostat is set at 26 °C from 8:00 until 16:00, and the cooling system is turned off for the rest of the day. The maximum CO_2 concentration is 800 ppm.

Comparing the prior energy demand for heating and cooling using the thermal models developed in Section 3 with the energy demand after the application of the developed algorithms, the annual energy savings for heating and cooling are calculated. The savings are calculated to 30.22% for the heating and cooling of the entire building under study for one year. The following Fig. 10 shows the relation between the power demand (kW) and the ambient temperature (°C) before and after the application of the control algorithms. The energy efficiency achieved is verified by the decrease of the power demand gradient versus the ambient temperature after the application of the control algorithm [41].

4.2. Optimisation techniques

The optimisation technique is developed using genetic algorithms. The specific technique is selected as it provides near optimal solution in nonlinear problems [42,10,43].

The objective function is expressed as:

$$\min\left(w_1\cdot\sum_{i=1}^{32}\left(\frac{Energydemand}{9\cdot 10^5}\right)+w_2\cdot\sum_{i=1}^{32}\left(\frac{|PMV|}{3}\right)+w_3\cdot\sum_{i=1}^{32}\left(\frac{[CO_2]}{2000}\right)\right) \tag{2}$$

s.t.

$$|PMV|\left\{\begin{array}{l}\leq 3 during nonoccupancy hours\\ \leq 0.5 during occupancy hours\end{array}\right\}$$

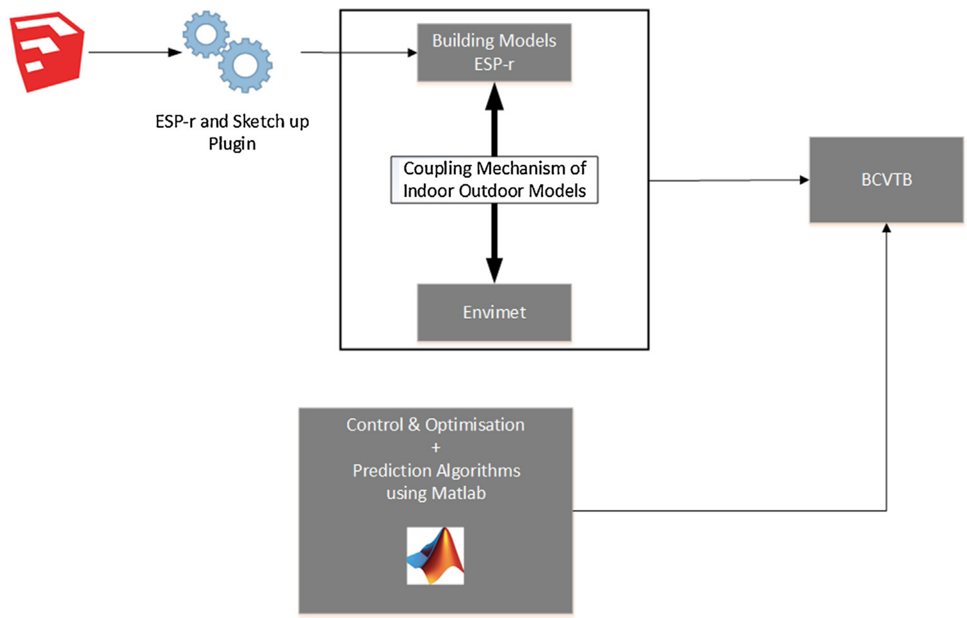

Fig. 9. The connectivity of the various models.

$$[CO2]\left\{\begin{array}{l}\leq 2000 during non-occupancy hours\\ \leq 800 during occupancy hours\end{array}\right.$$

where:

PMV corresponds to the thermal comfort index [44].

$[CO_2]$ corresponds to the concentration of carbon dioxide indoors

w_1, w_2, w_3 are the weights of the decision variables defined by the decision maker. The weights are defined in the range [0,1] and $w_1 + w_2 + w_3 = 1$.

The objective function is described graphically in Fig. 11 under 3 different scenario of weights. In parallel in Fig. 13.

The decision variables are the PMV index set point for the next 8 h in steps of 15 min (32 variables) and the relevant $[CO_2]$ concentration values that will drive the ventilation system (32 variables). The total number of decision variables is equal to 64. All decision variables including the energy demand are normalised in the range [0,1] by dividing them with its maximum value. The output of the optimization algorithm depends on the weight of the decision variables. An example of the output of the PMV index decision variable is presented in Fig. 12 the energy demand for the HVAC system of the selected area is depicted.

In the first scenario ($w_1 = 0.7$, $w_2 = 0.1$, $w_3 = 0.2$) priority in the objective function is given to the energy saving of the HVAC system and the PMV set-point is not within the required values ($|PMV| \leq 0.5$). Comparing the first scenario with the second one ($w_1 = 0.1$, $w_2 = 0.7$, $w_3 = 0.2$) where priority is given to the comfort of the occupants different outputs are calculated. Comparing Figs. 12 and 13 it can be seen that in the second scenario PMV set-point is within the comfort level but the required energy is higher compared to scenario one. Finally, in scenario three ($w_1 = 0.1$, $w_2 = 0.2$, $w_3 = 0.7$), the selected weights provide priority to the ventilation comfort. The output of the optimization algorithm in the 2 aforementioned figures illustrates that and the PMV set-point, as well as energy demand is between the 2 other scenarios covering partly the requirements for energy saving and the satisfaction of the occupant's thermal comfort. The decision variables ($PMV_{setpoint}$ & $CO2_{setpoint}$) are extracted by the genetic algorithm are then fed into the control algorithms until the next execution of multi-objective optimization.

The decision variables are strongly related to each other, since they affect the overall energy consumption of the HVAC system for the selected areas over the optimization period (8 h), while they are used to describe the satisfaction of indoor environmental quality through their application in the defined cost function. A potential distributed optimization approach, which uses less decision variables might not take under consideration, for example, the effect of fresh intake air to the thermal comfort and thus the energy required to achieve good comfort during the next steps.

5. The web based campus energy management infrastructure

5.1. The hardware infrastructure

The existing Campus IP infrastructure is exploited by using sensor networks where nodes communicate their information using Web services, allowing direct integration in modern IT systems. To guarantee the system scalability and respect consolidated and diffused standards, the logical/architectural level of the whole Campus Energy Management System is linked with the existing infrastructure based on Internet Protocol (IP). The IP choice leads to wired networks realization in combination with Wi-Fi networks. Another advantage of the Ethernet protocol is its capability to integrate networks even in already existing buildings. The system is exposed towards the external part of the network by means of Web Services, enabling the XML information exchange through communications on Internet channels.

The overall infrastructure is installed in the Campus in the following phases:

1. Changes and preparatory work in the existing Building Energy Management Systems
2. Wiring and power supply installation
3. Installation of controllers
4. Installation of sensors/actuators
5. Installation of electricity meters
6. Integration and testing

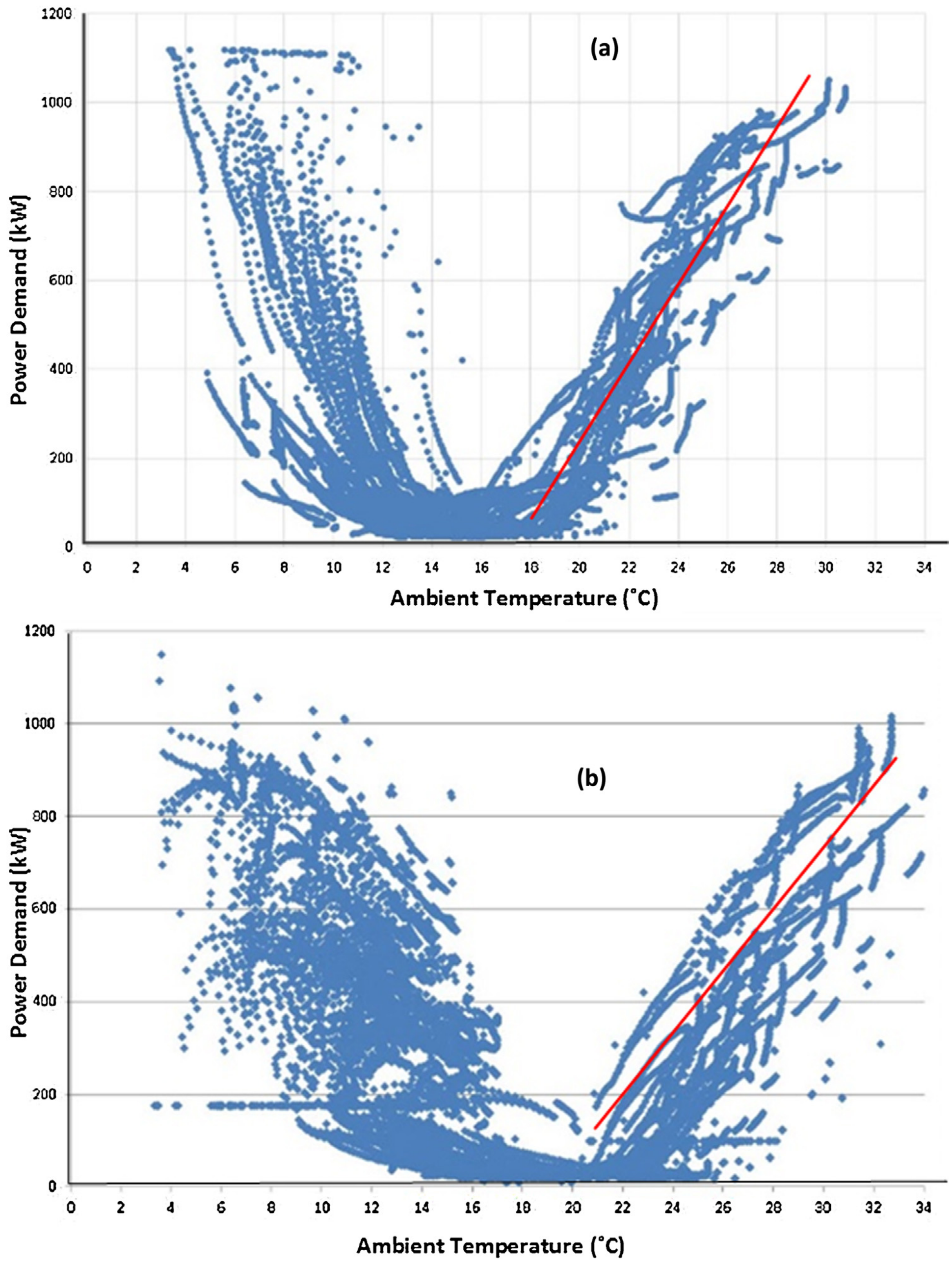

Fig. 10. Power demand vs ambient temperature (a) without and (b) with the control algorithms.

The changes in the overall hardware architecture is depicted in Fig. 14. All devices are tabulated in Table 4. A floor plan of the various devices positioning is included in Fig. 15.

The hardware system operation is constantly monitored due to the fact that its characteristics may change in time. The hardware parts whose operational characteristics change mainly over time are the sensors. The computers, energy meters, HVACs, relays, cabling, etc. have self-diagnostic procedures for faulty operation and are monitored using the software.

The sensors operation drifts in time (a) due to dirt or dust deposited on the sensor, or (b) due to inherent degradation of the sensor behaviour. In the case of dirt, a regular annual maintenance is foreseen to restore the sensor's operation. To cope with the sensors' functionality degradation, a yearly recalibration of the sensors characteristic, using reference measurements, is applied. After the recalibration, the appropriate parameters in the control algorithm are adjusted accordingly.

More specifically:

- The presence detector and the wired door/window switches may operate for several years without noticeable problems.
- The relative humidity sensor's long-term stability, according to its specifications, is 1%/year.
- The temperature sensor long-term stability, according to its specifications, is 0.1 °C/year.
- The Carbon dioxide CO_2 sensor long-term stability, according to its specifications, is 5%/5 years.

The maintenance and recalibration described above, ensure the reliable operation of the overall system.

Table 4
List of Web based Campus Infrastructure.

Description	Quantity	**Picture**
Multi-Purpose Management device (MPM) enables the control, monitoring, and management of entire sites. They can also be used for wired and wireless zone control in larger buildings.	12	
Room controllers (temperature – relative humidity, presence detection sensors)	39	
CO_2 concentration measurement	25	
Wireless Door Switches	39	
Wireless Window Switches	96	
The sensor SLR 320 converts the illuminance measurement (lux) in 4–20 mA or 0–10 V.	25	
Remote switches	50	
Presence detector which detects human presence in a range of angles from 0 to 360° versus the horizontal plane and with maximum radius of the 7m. ARGUS	35	
Electricity meter iEM3150	2	
Electricity meter iEM3155	1	
Electricity meter iEM3350	15	
Electricity meter iEM3250 + current transformation	21 + 1	
Modbus RTU to Modbus TCP/IP EGX100 Gateway	3	

5.2. Integration of control and optimisation algorithms

The integration of the control and optimisation algorithms described in Section 3 in the overall infrastructure is performed using the Lua programming environment [45]. Lua is a programming language which can be embedded in different platforms. Lua is also based on ANSI C. For the incorporation of the control algorithms in the Multi-Purpose Management device, two different software architectures are used. The first software architecture is the Composite Design Pattern which treats a group of objects in similar way as a single object. Composite pattern composes objects in term of a tree structure to represent part, as well as whole hierarchy [46]. The developed source code is easily understood by other software developers and can be amended or extended with no extra effort. For the Campus energy management system, a number of extra functions are developed. Some of them are:

- *Addrule*: for adding a fuzzy rule.
- *Addinp*:for adding an input value for the fuzzy algorithm
- *Addout*: for adding an output value for the fuzzy algorithm
- *Addlingvar*:Inserting the membership functions (trapezoids and triangles)
- *Solvefuzzy*:for the calculation of the defuzzifcation results

For example PMV is read by the fuzzy algorithm using the list below:

```
local PMV_value = fuzzy:addinp('PMV_value',-3,3)
PMV_value:addlingvar('NE', trapmf, {−9.35,−5.15,-2.5,−1.65})
PMV_value:addlingvar('SNE',trapmf, {−2.85,−1.85,−0.95,−0.15})
PMV_value:addlingvar('ZERO',trapmf, {−1.35,−0.5,0.5,1.35})
PMV_value:addlingvar('SPO',trapmf, {0.15,0.95,1.85,2.85})
PMV_value:addlingvar('PO',trapmf, {1.65,2.85,3.15,4.35})
```

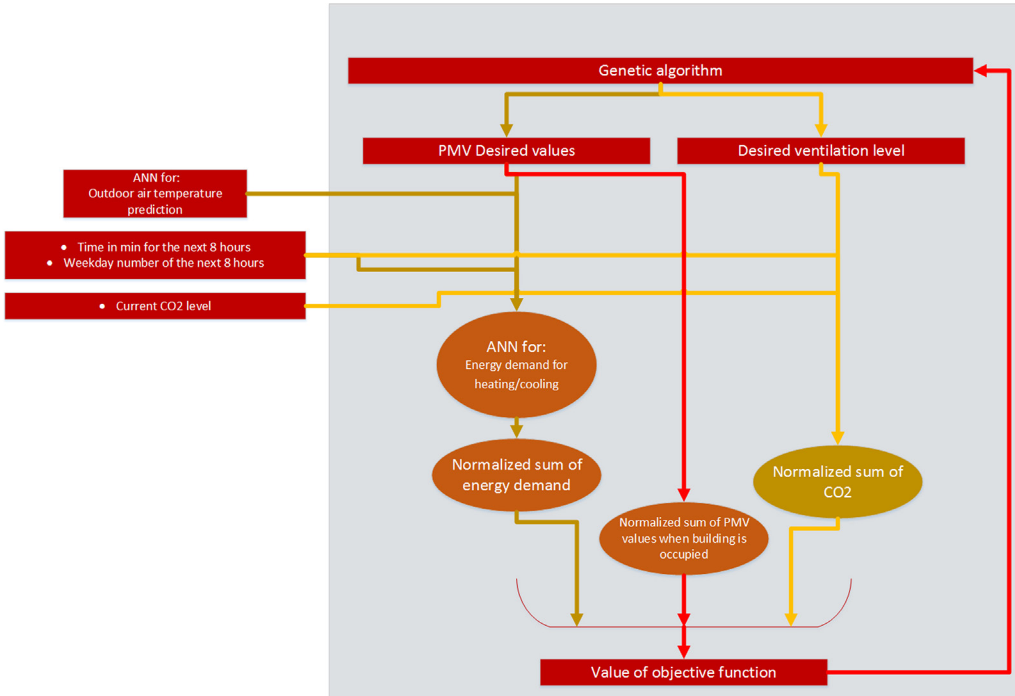

Fig. 11. Graphical representation of the optimisation procedure.

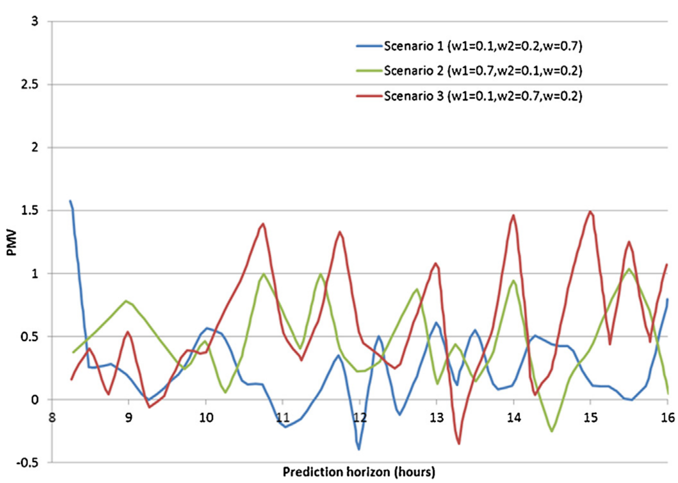

Fig. 12. The PMV index extracted by the optimisation procedure.

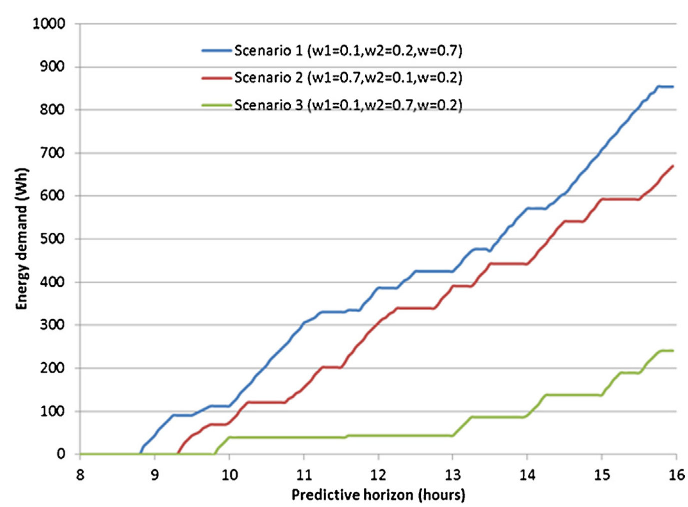

Fig. 13. The energy demand for the HVAC system.

The second architecture used is based on matrices development for the storage of the rules and variables. This architecture is used in order to minimise the needs for extra RAM. The following matrices are developed:

- Input tmatrix ***g_fisInput***
- Output matrix, ***g_fisOutput***
- Rules 'matrices, ***fis_gRI***, ***fis_gRO,***
- Membership functions for inputs and outputs ***fis_gMFICoeff, fis_gMFOCoeff***
- Names and indices matrices ***fis_gMF***, ***fis_gMFI***

Moreover, various functions are included:

- The function ***loadFuzzy() for loading all matrices in the MPM***
- The ***fis_evaluate()*** that calculates the fuzzy output and transfer it in Lua to be read by the MPM.

With this implementation the control algorithms are run locally in the MPM while information is exchanged via IP with the Automation server, as depicted Fig. 14.

After the completion of the installation, the verification in order to ensure the proper functionality of the system in the campus site is performed, i.e. the data collection and processing software, the sensors, Actuators & User-Interfaces, as well as the interconnection with smart metering and with the power substations is checked.

6. Results and discussion

The overall Internet based energy management system for Campuses was installed in March 2015. The evaluation of the overall work is based on:

- The indoor environmental quality assessment of the buildings under study. The assessment is performed via on-line question-

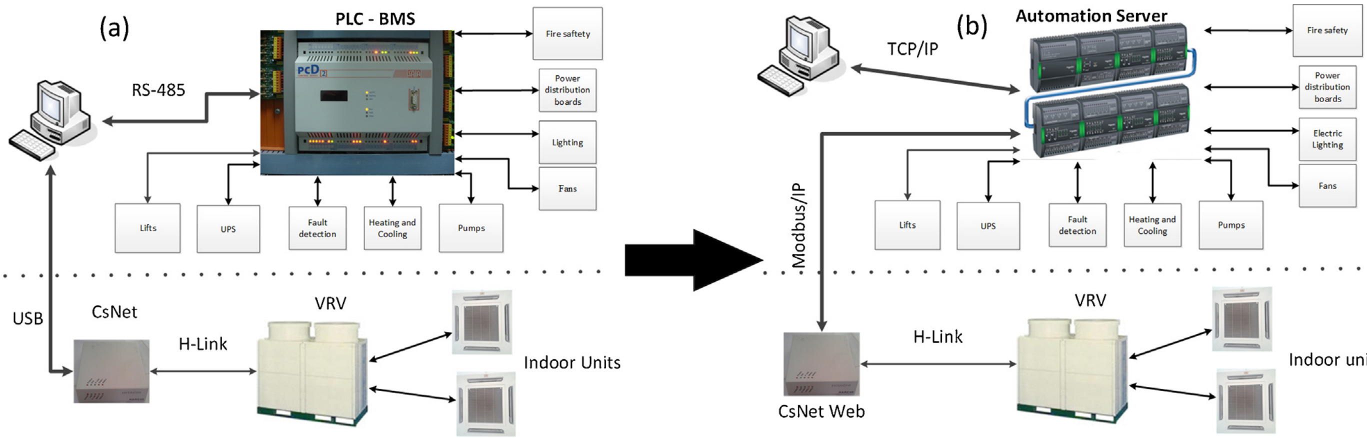

Fig. 14. The hardware architecture (a) before and (b) after the installation of the web based Campus Energy Management.

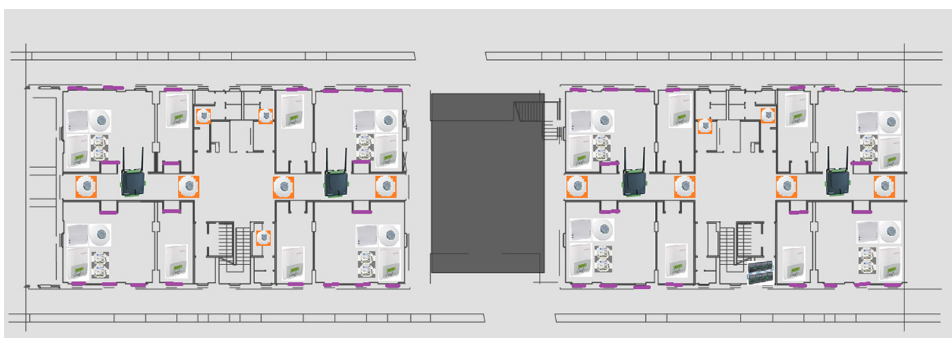

Fig. 15. The floor plan of the buildings with the positioning of the various devices.

naires that were distributed to the buildings' users via e-mails every day from November 2014 until June 2015. A total number of 381 questionnaires were collected. The users' responses to the questionnaires are then linked with the indoor environmental conditions monitored via the sensors of the Camp-IT infrastructure.

- The monitoring of the energy consumption via the smart meters of the Camp-IT infrastructure.

6.1. Indoor environmental quality assessment

In the Camp-IT project, users and their preferences were given a leading role in the development of the monitoring and control system, as well in the assessment and evaluation of the energy management system. The interconnection of the user's preferences with the energy management system is performed recording daily their preferences and comfort levels with the help of questionnaires. A set of 143 questionnaires were collected by six spaces where users responded on regular basis. Alongside, they were informed by e-mail, brochures and site visits to ensure their consensus and support throughout the whole effort.

The assement of the indoor conditions is based on the comparision of the building users' responses before and after the installation of the web based energy management system during February, March and April 2015. The assement results are illustrated in Fig. 16–18 for February, March and April 2015 respectively.

Regarding the thermal comfort conditions, the percentage of the satisfied people has increased from February to April 2015. During Ferbruary 2015 the percentage of satisfied (including very satisfactory and satisfactory) was 73% and has increased during March 2015–82% and April 2015–85%. Moreover, the percenage of the very satisfied people has also increased from 28% on February 2015–41% and 52% during March and April respectively. In addition, through the correlation of the users' responses with the corresponding indoor temperatures measured (see Fig. 19) it is observed that for the 25% of the time the non-satisfied users have indoor temperature which is less than 21 °C in their rooms. The same percentage for the "very satisfactory" group is 7%.

Concerning the visual comfort, the percentage of the satisfied people has decreased from February to March 2015 and has increased during April. More specifically, the percentage of satisfied people during Ferburay 2015 was 62% while during March was decreased to 42%. Moreover, during March 2015 the number of rooms that the users turned on the electric lightning during the day was increased to almost 20%, showing that the people were dissatisfied while the electric lights were on. During April 2015 the percentage of the satisfied people was increased and reached 82% while the use of electric lighting during the day was dramatically decreased.

The indoor air quality assesment shows that 57% of building users are satisfied during Februay 2015, while during April 2015 this percentage was increased to almost 91%. This is due to the fact that the web based energy management infrastructure required the maintenance of the ventilation system which was put in operation independantlly from the heating and cooling mode of the buildings.

6.2. Energy consumption of the buildings

The energy consumption of the buildings before and after the overall installation is monitored via the smart energy meters. The

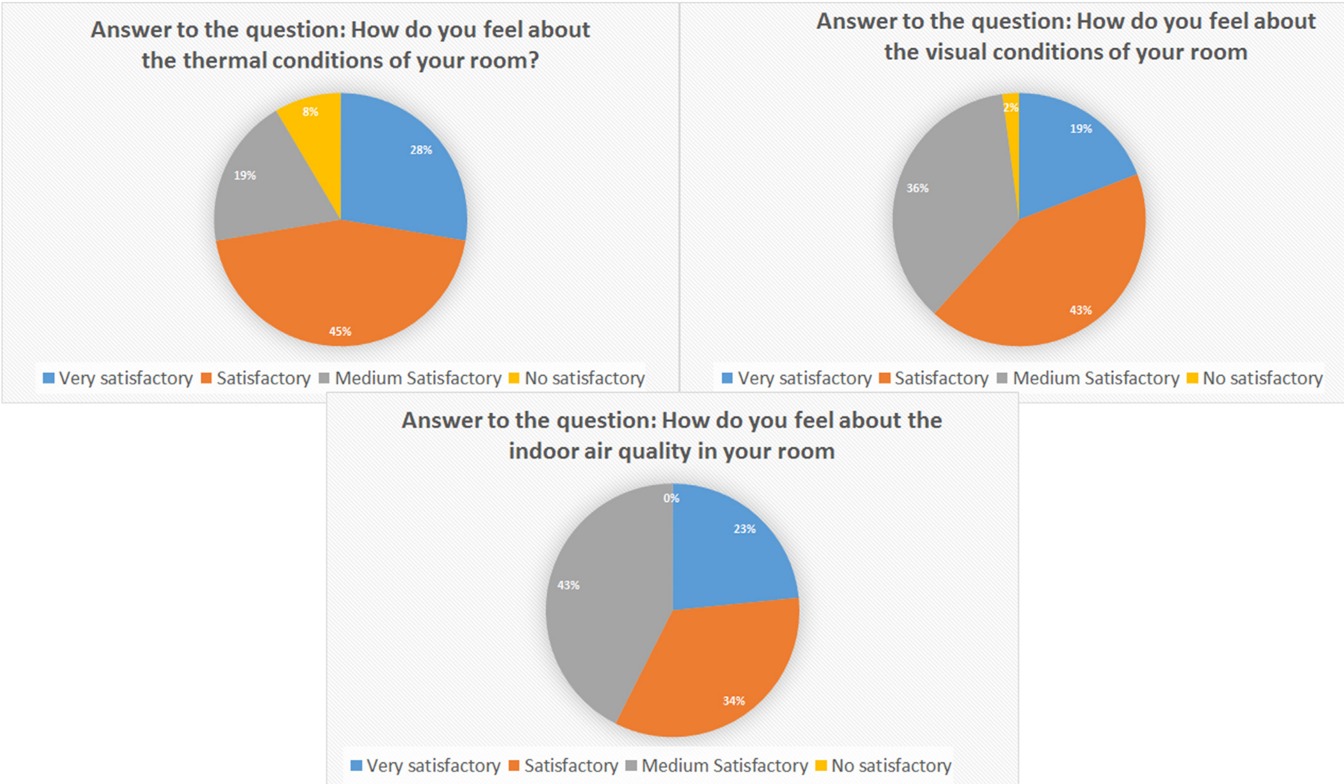

Fig. 16. The indoor environmental quality assessment during February 2015 before the Camp-IT installation.

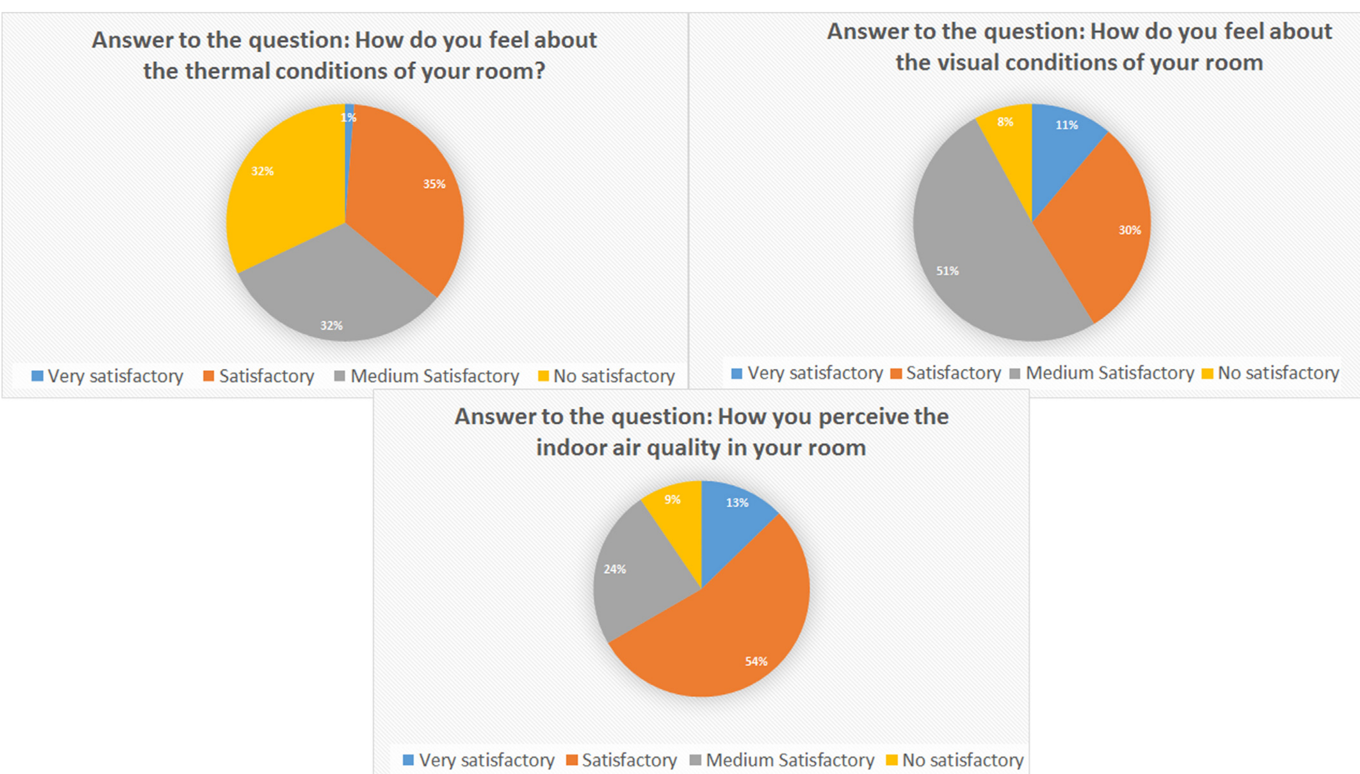

Fig. 17. The indoor environmental quality assessment during March 2015 after the Camp-IT installation.

reduction of the energy use is analysed on monthly basis. The energy consumption of the 2014 corresponding months versus the 2015 ones are tabulated in Table 5.

Moreover, the cooling degree days of the specific months for 2014 and 2015 are calculated. The energy consumption is then normalised with the number of the cooling degree days in order

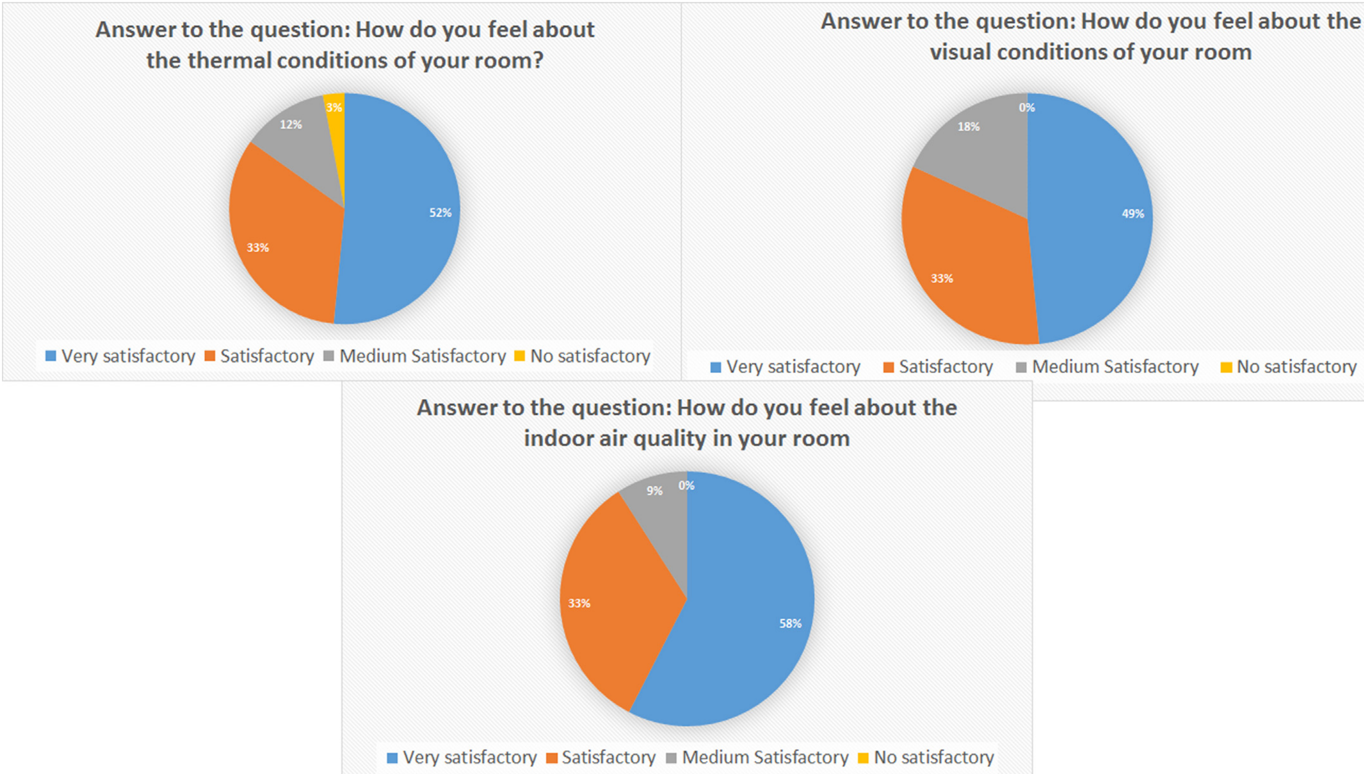

Fig. 18. The indoor environmental quality assessment during April 2015 after the Camp-IT installation.

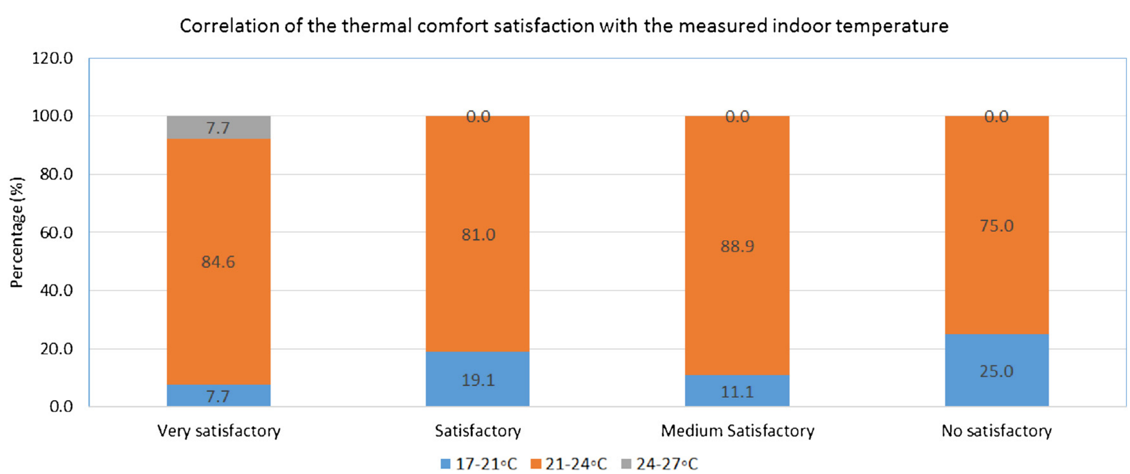

Fig. 19. The indoor temperatures versus the buildings users 'responses.

Table 5
Monthly energy consumption for the years 2014 and 2015.

Months	Energy Consumption (kWh) 2014	Energy Consumption (kWh) 2015	Cooling Degree Days (2014)	Cooling Degree Days (2015)	Energy consumption per Cooling Degree Day for 2014	Energy consumption per Cooling Degree Day for 2015	Percentage of change (%)
May	17188	17340	84	85	205.4	204.7	0%
June	22770	21239	188	173	120.9	122.8	−2%
July	33765	29695	257	252	131.3	117.9	10%
August	22313	18756	288	282	77.4	66.5	14%
September	31117	24592	193	205	161.3	120.1	26%
October	19458	17344	71	91	272.6	190.3	30%

to compare the energy requirements of the two consecutive years without the weather conditions' influence. As it is observed in Table 5 the energy requirements' reduction ranges from 10% to 30% depending on the month of the year. The reduction of 20% as an average, is considered satisfactory due to the fact that the overall energy efficiency is mainly attributed to the optimal operation and management of the various buildings' facilities and systems. Also, the energy demand in the Campus buildings cannot be reduced more than 20%, since some laboratory equipment operate constantly and cannot be switched off. A further considerable improvement would be achieved by closely monitoring the overall performance of the Heating Ventilation and Air Conditioning Systems' operation by means of the Camp-IT monitoring platform. The use of Web based platform operation has reduced the system's failure and the maintenance efforts of the Campus technical services. The additional overall cost of the Camp-IT platform is almost €8/m^2, while the energy cost reduction is estimated to €1.5/m^2. Moreover the Camp-IT installation is used as a Living Lab for the energy related educational activities of the University.

7. Conclusions

The present paper analyzes the design and implementation of the CAMP-IT innovative web based energy management system for University Campuses. This system aims to reduce the Campus energy consumption by optimal use of the energy systems, while simultaneously improves the indoor environmental quality (air quality, thermal and visual comfort).

An integrated approach for coupling the building models with the outer spaces is developed to support the evaluation of advanced control and optimization algorithms used in the Camp-IT project. The modelling procedures coupled with the control and optimization procedure proved that the energy efficiency potential can be up to 30%.

The installation of the Camp-IT system in the TUC University Campus and its interconnection with the existing building services provided the necessary knowledge and methodology to exploit existing IP infrastructures and connectivity to uptake the Campuses 'energy performance while ensuring interoperability, expandability and flexibility.

The interaction with the building users results in a significant improvement of the indoor environmental quality, while the energy consumption reduction ranges from 15% to 30%, depending on the period of the year.

Acknowledgements

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