PRELIMINARY IMPLEMENTATION OF A PREDICTIVE CONTROL FOR VENTILATION SYSTEMS IN METRO STATIONS

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ABSTRACT

In this paper a possible methodology to supplement a predictive control approach is reported. The benefits deriving from the application of a predictive control on complex buildings lay on its capability of adapting in advance to the conditioning needs of indoor environments. In fact, the mere reactive control is usually affected by response delays, mainly determined by latency intrinsic in systems and by the massive nature of buildings, which slows down their response to changeable inputs. Hence, systems are too often solicited at their maximum power to recover against comfort deficiencies, and high consumptions are had. This paper reports on the application of a predictive approach to the Passeig de Gracia (PdG) metro station in Barcelona, which is a considerably high energy demanding building and where ventilation systems are used to control both comfort and air quality. Although an extensive simulation for estimating energy savings obtainable through that approach is currently ongoing, in this paper we detail the several components which make up a "predictive control framework" and we perform a preliminary demonstrative simulation. In particular, the whole setup is formed by: a detailed model of PdG, which simulates the station's "real state"; a control model, which optimizes a given cost-function; probabilistic predictive models to infer the future state of the systems, given the assumptions on the control actions by the control module. The outcomes of this paper show that the procedure is applicable and preliminary results over a short simulation horizon of half a day are reported.

KEYWORDS

Energy efficiency, predictive control, building systems, metro stations.

INTRODUCTION

The development of a novel adaptive control of HVAC based on the use of predictive models is part of a wider ongoing research project, funded by the EU Commission and called "Seam4us" (http://seam4us.eu/). The pilot of such a project is the "Passeig de Gracia" station in Barcelona (Spain). Seam4us aims at overcoming the traditional homeostatic short-term feedback mechanisms which are applied singularly to each equipment type. Current building systems are often inefficient in their energy usage for maintaining occupant comfort as they operate according to predetermined schedules and maximum design occupancy assumptions, and they rely on code defined occupant comfort ranges. The new approach will exploit the availability of pervasive sensor networks, which accurately monitor dynamics of the indoor environment, and will implement anticipatory optimal control policies. Their development is conditioned upon the elaboration of integrated models capable of predicting the future behavior of controlled environment. In this paper we will rely specifically on the predictive control of the mechanical air supply equipment and will present a methodology to implement and simulate such a control.

COMPARISON BETWEEN NON-PREDICTIVE AND PREDICTIVE ADAPTIVE CONTROL

The concept of adaptive (but non-predictive) and predictive control was already studied in one previous contribution (Gyalistras et al., 2010). The authors showed that predictive control guarantees higher performances over other conventional approaches, which include: allowing for room temperature set-backs during nights and weekends; general reduction of thermal comfort due to a widening of the room temperature comfort range; use of indoor air quality controlled ventilation; adjustment of the control such that it is optimized for energetic rather than monetary cost; use of advanced, non-predictive control. All results were derived from whole-year, hourly time step simulations of an office building, with a physically based, single zone, twelfth order, time discrete bilinear building model of coupled thermal, air quality and light dynamics (Gyalistras and Gwerder, 2010), (Lehmann et al., 2010). In particular, Figs. 1-a and 1-b compares energy savings deriving from an adaptive and a predictive control policies (D. Gyalistras et al., 2010): percentage energy savings are plotted against average solar gains on the x-axis. The savings are expressed in terms of NRPE (Non-Renewable Primary Energy) reduction with respect to the reference building, conditioned through the use of standard pre-determined temperature and air quality thresholds. It can be noticed that the adoption of adaptive control (Fig. 1-a) determines energy reductions up to 25%, while predictive control increases energy savings up to 60%, when referred to the same kind of buildings.

In this paper we present our framework for implementing a predictive control in the case of very complex buildings, where environmental models can hardly be reduced into linear models. Then we describe a very preliminary implementation of the whole control loop.

THE CONTROL APPROACH

The case study: “Passeig de Gracia” metro station

The PdG metro station in Barcelona is a 3-line connection station between metro lines no. 2, 3 and 4. Line 3 (L3) is located in the northern hub. The station includes spaces devoted to different activities: commercial, transportation, people movement, public and technical services, staff reserved rooms. Fig. 1-b shows entrances (E), halls (H), corridors (C), platform (P) and rooms (R), including technical rooms, restrooms, vestibules and other areas whose access is restricted to the staff. The public access area is mechanically ventilated. The whole station is lit by means of regular, auxiliary and emergency light fittings controlled by several power circuits. People movement is favored by upward escalators.

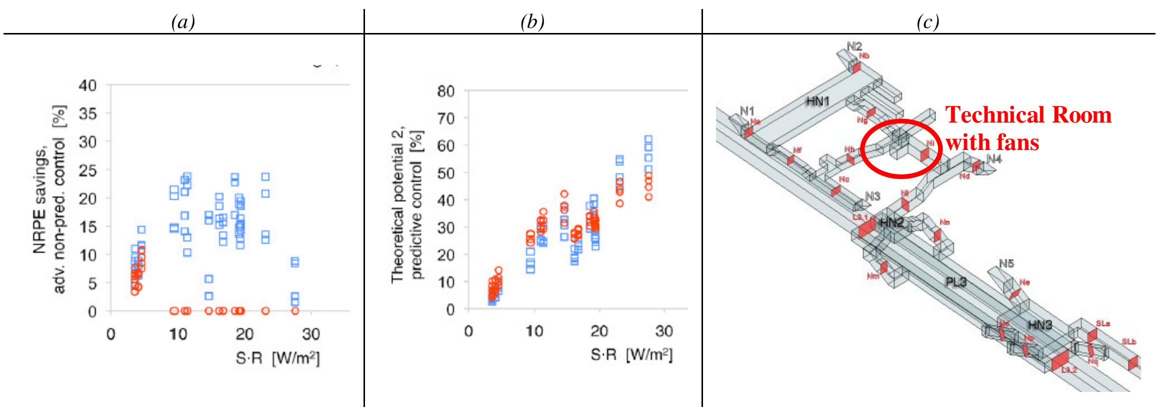

Figure 1 – Comparison of energy savings deriving from the use of adaptive and predictive control (source: (D. Gyalistras et al., 2010)) (a-b); 3D view of PdG-line 3 (c).

The fans are located in the station’s technical room, which lays between sections Nb and Nl in Fig. 1-c. The main ventilation ducts leave from here to convey outdoor fresh air into the platform (PL3) through air intakes located on the ceiling. Two CONAU V1080 injection fans (object of our control) are placed in the station’s technical room, while two fans are extracting air through ventilation shafts in the tunnels adjoining PdG-L3. The current daily summer ventilation schedule keeps injector fans on during the day (from 5 am to 10 pm) at their highest rate. They are switched off in the night. Similarly is valid in winter, but the fans’ input frequency is halved. Also, outdoor ventilation is induced through its five entrances and corridors leading to the platform.

The adaptive/predictive control framework

The control problem is targeted to minimize power consumption while keeping the comfort level and guaranteeing robustness of the solution. In order to fit these specifications, the control system must comply with several features. It must be optimal, i.e. it finds out the values of a vector of design parameters that yield optimal system performance evaluated by a so-called cost function. Furthermore, the control system must be adaptive, which is "a special type of nonlinear control system which can alter its parameters to adapt to a changing environment. The changes in environment can represent variations in process dynamics or changes in the characteristics of the disturbances. […]" (McGraw-Hill, 2002). Finally, predictive control is necessary for achieving high energy efficiencies: prediction gives the capability of taking soft control actions in advance, thus, saving energy. Robustness is also required, thus implying that the models used for designing the controller should consider all process dynamics and must be able to adapt to unknown conditions.

We are implementing a predictive control based on the “Receding Horizon strategy”, that is the control action is designed by running the model of the process over a given prediction horizon and evaluating the control sequence that gives the minimum value of the cost function (Qin et al., 2003). From the controller point of view, PdG-L3 is represented as a block with inputs and outputs (Fig. 2-a). Inputs (u) to the system are the variables that can be manipulated: frequency that drives injector fans in this case. The outputs (y) are the power consumption and indicators for comfort and health, that must be controlled in order to reach certain reference levels. The relation between inputs and outputs is also significantly affected by a set of disturbances (d), such as weather, train arrival, passenger flows and fans external to the station: they cannot be manipulated but only “accounted for” by using direct measures, whenever possible, together with a Disturbance Model.

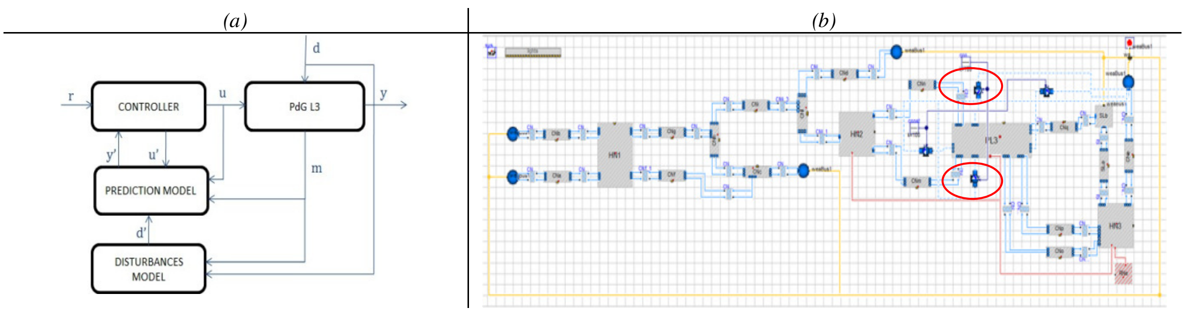

Figure 2 – Adaptive/predictive control strategy applied in PdG (a) and the Dymola™ PdG-L3 model (b).

As better explained in previous papers (Ansuini et al.,2012), one PdG prediction model is used as a model for guiding the predictive controller (Fig. 2-a). At each control step the state estimator (“prediction model”) receives candidate input sequences (u’) picked out by the controller, disturbance predictions come from disturbances model (d’), measured outputs (m) from PdG-L3 and the state estimator predicts the output sequence (y’). The optimal control sequence (u) is that array which minimizes a given cost function while complying to preset constraints. Once the optimization problem has been solved, the optimal sequence is applied as the best control action. The overall procedure is repeated at each step thus closing the control loop. In our simulation the “model-in-the-loop” approach was applied, i.e. the PdG-L3’s state is not measured by sensors, but based on the outcomes of the PdG-L3 Dymola™ model (Ansuini et al., 2012).

SETUP OF THE FRAMEWORK USED TO IMPLEMENT THE ADAPTIVE/PREDICTIVE CONTROL

The whole framework is made up of several components: the station model; the disturbances model; the predictive models (which are in charge of estimating the future state of the station in advance, thus allowing the application of control policies in advance and resolving the response delay typically experienced by non-predictive adaptive control approaches), and the control function.

The models of the station and of disturbances

The *station model* (i.e. “PdG-L3” in Fig. 2-b) was based on Dymola^{TM} environment and was used to simulate the station’s behavior once control inputs are applied to the domain. In the final implementation, the state of PdG will be tracked by means of sensor networks, which are currently under installation. However, the Dymola^{TM} model will be kept to simulate the state of those parts of the station which are not directly monitored. In addition, it will be used to generate datasets useful to learn the predictive Bayesian models. The Dymola^{TM} environment allowed the development of a “lumped parameter model”, which deals with the main challenges imposed by the case at hand: the multiple (and) different time scales (e.g. weather and train passage); the station’s large size; multi-physics and control logics integration. The developed model is based on the open source Modelica “Buildings” library (Wetter et al., 2009). The classes which make up a whole model allow to consider both spatial continuity and many physical phenomena typical of the station (Giretti et al., 2012): heat transfer, airflow, lighting, HVAC systems. The components of the “Buildings” library have been properly customized to build the overall model of the station, whose graphic representation is given in Fig. 2-b. The two red circled components in Fig. 2-b mark the location of the two fans in the technical room of PdG-L3, whose importance is given by their duty of providing fresh air into the platform. The developed fan model includes two instances of class “fixedResistanceDpM” which consider inlet and outlet pressure drops determined by the fan and the distribution piping, and the main hydraulic component represented by “FlowMachine” class” which actuates flow motion given certain rotational speed and pressure drop. Then it implements the thermal transfer to and from the fluid. The efficiency and characteristic curves (also dependent on the rotational speed) of the fans were given as parameters. This fan is driven by a new asynchronous inductance motor class “AIM” that does not explicitly consider exact sinusoidal signals (that would introduce too fast dynamics) but its phasor representation that is still capable of catching its unsteady behavior, according to the approach proposed by (Beaty and Kirtley, 1998). Given a three-phase symmetrical and balanced supply system with frequency f and RMS line voltage V, the slip of the rotor w.r.t. the rotating field for an electric motor with p pole pairs rotating at mechanical speed Ωm is $s=(2\pi f-p\Omega_m)/\ 2\pi f$. The torque originates from this slip and can be expressed as:

$$T_e = 3/2\cdot p\cdot(\lambda_{ds}i_{qs}-\lambda_{qs}i_{ds}) \tag{1}$$

which is linked to the relations:

$$\begin{bmatrix}\lambda_{dS}\\ \lambda_{dR}\end{bmatrix}=\begin{bmatrix}L_s & M\\ M & L_r\end{bmatrix}\cdot\begin{bmatrix}i_{dS}\\ i_{dR}\end{bmatrix} \quad \text{and} \quad \begin{bmatrix}\lambda_{qS}\\ \lambda_{qR}\end{bmatrix}=\begin{bmatrix}L_s & M\\ M & L_r\end{bmatrix}\cdot\begin{bmatrix}i_{qS}\\ i_{qR}\end{bmatrix} \qquad \text{(2) and (3)}$$

where λ is the magnetic flux, i is the electric current flowing through the excitation coils, subscripts d,q denote the real and imaginary parts while subscripts S,R indicate stator or rotor reference frames. With these definitions in mind, dynamics of motor is described by the following equations (Beaty and Kirtley, 1998):

$$V = \sqrt{3/2}\cdot(d\lambda_{ds}/dt-2\pi f\lambda_{qs}+R_s i_{ds}) \tag{4}$$
$$0 = d\lambda_{qs}/dt + 2\pi f\lambda_{ds}+R_s i_{qs}) \tag{5}$$
$$0 = d\lambda_{dR}/dt - 2\pi fs\lambda_{qR}+R_R i_{dR} \tag{6}$$
$$0 = d\lambda_{qR}/dt - 2\pi fs\lambda_{qR}+R_R i_{dR} \tag{7}$$
$$d\Omega_m/dt = 1/j\cdot(T_e-T_m) \tag{8}$$

where T_m is the mechanical resisting torque generated by “FlowMachine” object. Model parameters are stator and rotor resistances per phase R_R,R_S, stator and rotor inductances L_S,L_R and main field inductance M. The inverter class was used to emulate the actual inverter that drives the motor according to the inputs generated by the controller. It takes in an input frequency and it gives back total absorbed electric power along with frequency, voltage and delta-star connection flag of the motor’s three-phase supply system. Fig. 3-a shows the correspondence between the model’s classes and real components of the ventilation system. Its parameters were validated through comparison with energy consumption data collected during on-site surveys and shown below in Table 1 (Giretti A. et al., 2012).

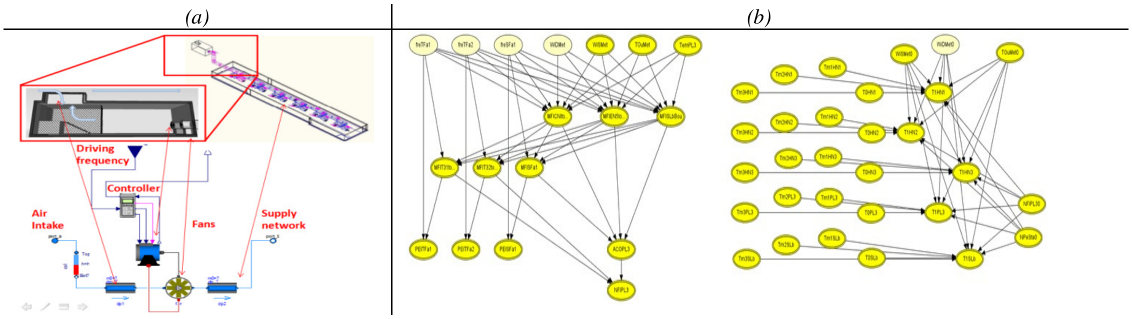

Figure 3 – Class of the three-phase asynchronous fan model (a) and Bayesian predictive models (b).

The predictive models and the control function

Predictive "*disturbances models*" (e.g. weather, thermal gains based on occupation) will be provided by modules, which are partly already available by specialized services (i.e. weather forecasts) and partly under development by some members in the seam4us consortium, other than Univpm, to which the authors of this paper belong to. Once the current state is known (m) and prediction on disturbances are given (d'), the domain's future state is inferred by prediction models, which have been developed in the form of Bayesian Networks, and interfaced to the controller.

The choice of Bayesian Networks was determined by their capability of dealing with uncertain knowledge, even as inputs (B. Naticchia et al., 2007), of managing both continuous and discrete casual variables, and of expressing complex relationships in the form of lumped conditional probability tables, relying on the Bayesian theory (Heckerman, D., 1996). In order to form a database useful for learning Bayesian Networks through the EM algorithm (Heckerman, D., 1996), the aforementioned PdG-L3 model was run on a randomly generated wide set of weather and occupancy combinations. The results of these simulations were used to extract time series pertaining to all the relevant variables describing the station's behavior. Then, they were organized into two Bayesian Networks, one relative to "Airflow" and the other one relative to "Temperature" prediction, as depicted in Fig. 3-b. The former accepts as inputs the fans' mechanical frequencies, outside temperature and wind direction and speed, and the platform temperature in order to estimate, as outputs, net air change renewal per hour in the station. The latter is a dynamic Bayesian network over four time steps (current time step plus three previous lags), which accepts as inputs spatial temperature profile (platform, halls and station links) over time, outdoor temperature and wind speed and direction, current time step's air flow through the platform, occupancy, so as to predict expected temperature profiles throughout the station in the next time step. So the combination of the two networks provided future estimations needed to implement the predictive control approach.

A cost function was prepared in order to take into account all the contributions regarding comfort conditions:

$$CF = \sum i\ \alpha[PElTF\alpha 1(t)+PElTF\alpha 2(t)+PElSF\alpha 1(t)] + \beta\cdot[1/(ACOPL3(t)+d)] +\gamma\cdot[TemPL3(t)-T_{ref}] \quad (9)$$

where two terms of the kind "PElTF" accounts for energy consumption of adjoining tunnel fans; while "PElSF" is the energy consumption of the two injector station fans. The former are not directly driven by the control system, but their consumption is someway dependent on the way the latter are driven (i.e. when station fans slow down, friction pertaining to the air extracted by the tunnel fans increases: this effect never determines consumption swings higher than 10%). The second term accounts for air changes from outdoor air had in the station and it is put at the denominator because this term should be maximized and never drop below the minimum admissible value. The last term keeps the platform temperature (PL3) as close as possible to the wished value (T_{ref}). The three members contribute to the cost function according to some tunable parameters or weights (α, β, γ). The output of this control model is an optimal frequency input to the injector station fans. In our simulations the wished temperature (T_{ref}) was set equals to the outdoor one, because in summer the PdG metro station is comfortable in case it is not warmer than outside.

METHODOLOGY USED FOR THE PRELIMINARY IMPLEMENTATION OF THE PREDICTIVE CONTROL

The weighting coefficients of the cost function (CF) in eq. (9) were calibrated in order to balance the influence of all the terms in the summation. They are measured using different units (i.e. electric power in the order of thousands, inverse of air changes per hour in the order of one tenth, temperature in the order of tens). So the coefficients were set: $\alpha = 1/30{,}000$; $\beta = 1$; $\gamma = 100$. The time unit was set at 1 hour and fan frequencies were allowed to vary between 1 and 50 (although actually they cannot drop below 20Hz for technical reasons). The block diagram shown in Fig. 2-a was implemented by means of a procedure which allowed to preliminary go through the steps which will be part of an algorithm for automatic implementation of the control. As our procedure was implemented manually on the morning of July 1st, just the first few steps were accomplished, which were useful to demonstrate that the control methodology is feasible and ready to be fully implemented. The main steps of the algorithm are the following ones:

1. the current domain state at 5 a.m. was evaluated by running the Dymola^{TM} model;
2. data from bullet 1 were integrated with temperature profiles until three time steps earlier and the other inputs in the network, in order to run the predictive "Temperature" Bayesian network and infer station's temperature profile in the next time step;
3. the "Airflow" Bayesian network was run based on the temperature inputs predicted by bullet 2 along with the other required inputs, so as to create 50 possible scenarios deriving from the 50 potential injector fan frequency values available to drive ventilation;
4. hence a new database containing all the outdoor air changes according to frequency was created, and per each of these values indoor station's temperature were updated repeating the instruction in bullet no. 2 per each of the 50 frequency combinations;
5. finally, the cost function given below by eq. (9) was minimized and the optimum fan frequency input for the next time step was determined.

In the first iteration, the CF's minimum was found at min(CF) = 28 Hz, and this fan frequency was inputted to the injection station's fans (Fig. 4-a).

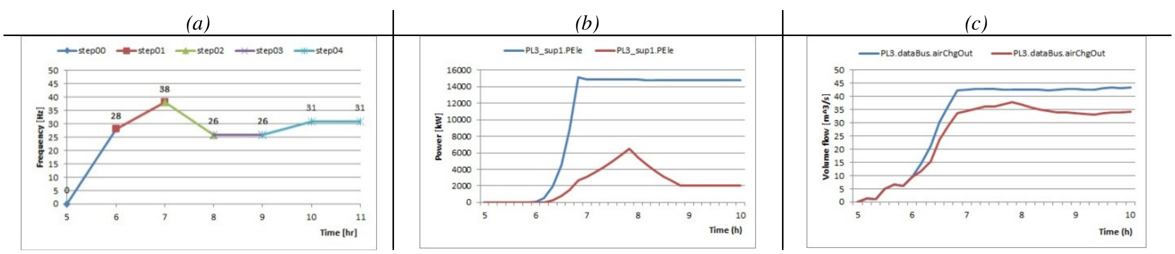

Figure 4 – Optimal frequency array over the control horizon (a), corresponding reduction of electrical power consumption (b) and overall air changes in the station (c).

In practice, at step 1 the relevant variables were extracted as outputs of the Dymola PdG-L3 model; inferences at steps no. 2 and 3 were done by running the corresponding Bayesian Networks through HuginTM software program; the database and the CF at steps 4 and 5 were implemented by means of an ExcelTM spreadsheet, which did not only help manage the data, but also graphically solved the CF minimization problem. Such iterations gave back the frequency profile as shown in Fig. 4-a. Presently the PdG's mechanical system is not controlled. In summer, it's turned on at 5 am at its highest frequency (50 Hz) and turned off at midnight. This shows there is room for big energy savings. A comparison between energy consumption due to the current fan schedule (50 Hz) and the one suggested by our control policy is shown in Fig. 4-b. The overall savings over a period of just 5 hours (from 5 am to 10 am) made energy consumption lowered as much as 38 kWh, which means cutting down 77.5% on electric consumption in the early morning on July 1st . Yet, this did not make air flow to be reduced too much, as shown in Fig. 4-c, probably thanks partly to the contribution from outdoor ventilation and partly to the unvaried mechanical air supply provided by the tunnel's ventilation shafts.

Finally, also the difference between domain predictions provided by the Bayesian models in Fig. 3-b and the real domain behavior calculated through the Dymola^{TM} lumped parameter model were listed in Table 1:

predictions in temperature, air flow and fan power consumption were affected by small average errors, also the maximum ones did never overcome 7.6%, thus showing the validity of the approach using Bayesian probabilistic networks as prediction models.

Table 1 – Accuracy of the prediction models as compared to the reference Dymola™ model

	Temperature [°C]	Air changes [m^3/h]	Fan power [kW]
Average error	2.0 %	3.9%	-0.38%
Maximum error	3.15%	7.58%	1.13%

CONCLUSIONS

This paper was able to preliminarily implement an adaptive and predictive control to a rather complex case study. In order to make that, an accurate model of the domain was needed, along with predictive models of the same domain and a control policy managed through the definition of a cost function. Such a research led to the conclusion that the approach is ready to be automatically implemented: it will also allow the inclusion of variable constraints, which could not be considered within this manual simulation. Interestingly enough, the results coming from this preliminary work showed that there is high potential for energy savings thanks to an intelligent dynamic management of mechanical ventilation in PdG station, which in turns accounts for a rather high fraction out of the overall consumption of the whole station and these results will be extended through further simulations covering the whole year.

REFERENCES

D. Gyalistras, M. Gwerder, F. Oldewurtel, C.N. Jones, M. Morari, B. Lehmann, K. Wirth, V. Stauch, (2010) Analysis of Energy Savings Potentials for Integrated Room Automation, Clima - RHEVA World Congress, Antalya, Turkey, May 2010.

Gyalistras, D., Gwerder, M. (2010), Use of weather and occupancy forecasts for optimal building climate control (OptiControl): Two years progress report, Terrestrial Systems Ecology ETH Zurich, Switzerland and Building Technologies Division, Siemens Switzerland Ltd., Zug, Switzerland.

Lehmann, B., Wirth, K., Carl, S. et al. (2010) Modeling of buildings and building systems. 10th REHVA World Congress Clima 2010, 9-12 May 2010, Antalya, Turkey

McGraw-Hill, (2002) Concise Encyclopedia of Engineering. The McGraw-Hill Companies, Inc.

Ansuini R., Larghetti R., Vaccarini M., Carbonari A., Giretti A., Ruffini S., Guo H., Lau S.L.. (2012) Hybrid Modeling for Energy Saving in Subway Stations. In: Jonathan Wright and Malcolm Cook, (Editors), Proceedings of the 2012 Building Simulation and Optimization Conference; 10-11 September 2012, Loughborough, Leicestershire, UK; ISBN 978-1-897911-42-6.

Wetter, M. A (2009) Modelica-based model library for building energy and control systems, Proc. of the 11th IBPSA Conf., Glasgow, Scotland, 2009.

Giretti A., Lemma M., Larghetti R., Ansuini R. (2012) Energy control of subway stations, 29th ISARC Proceedings, in special issue of Gerontechnology "ISG*ISARC 2012 World Conference", vol. 11 (2), pag. 168, 2012.

Beaty H. Wayne, Kirtley James L. (1998) Electric Motor Handbook, McGraw-Hill Professional.

Giretti A., Carbonari A., Vaccarini M., Pescatori G. (2012) Predictive control of ventilation systems in large underground public buildings, in "The missing brick: towards a 21st century built environment industry", Maggioli ed., Milano, ISBN: 8838761647.

B. Naticchia, A. Fernandez-Gonzalez, A. Carbonari (2007) Bayesian Network model for the design of roofpond equipped buildings, Energy and Buildings, Vol. 39(3), p. 258-272.

Heckerman, D. (1996) Bayesian Networks for knowledge discovery, in Fayyad, U.M., Piatetsky-Shapiro, G., Smyth, P., Uthurusamy, R., Advances in knowledge discovery and data mining, AAAI Press/MIT Press.