Development and First Testing of a Framework for Predictive Energy Control of Underground Stations

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Abstract -

Building Energy Management Systems consist of hardware and software components. The hardware set-up of BEMS is typically made up of a set of computers in charge of building control and sensor-actuator networks. The software side of BEMS is usually made up of a number of functional layers that implement standard management functionalities. This paper will present an application of Model based Predictive Control (MPC) targeted to energy management of the "Passeig de Gracia" metro station in Barcelona. This approach uses the predictions of future building status, obtained by means of a set of Bayesian Networks, in order to determine the optimal control policies. First the predictive Bayesian Networks were developed through the following steps: structural learning based on a simulated dataset; improvement of the network's topology through enhanced datasets derived from the previous one; final refinement and validation based on experimental data collected through a pervasive wireless monitoring network. Then those networks were integrated within a control framework, including control algorithms, a Dymola™ based virtual model of the station to simulate its evolvement and, on top of them, a user graphic interface to manage the system. The results about energy savings estimation determined by the application of model based predictive control to the station's mechanical ventilation showed that as much as 35% can be saved on average.

Keywords -
BEMS; predictive control; real-time control

1 Introduction

The development of an innovative adaptive control of HVAC based on the use of predictive models is part of an 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). This approach will overcome the traditional homeostatic short-term feedback mechanisms which are applied singularly to each equipment type. This paper concerns the design and the development of a new type of intelligent building energy management system (which is usually referred to as BEMS), that is able to optimise the operation of the mechanical air supply systems of the Passeig De Gracia metro station in Barcelona. To the purpose of this application, predictive models were developed to support the optimal control of indoor environmental conditions in the station, which was necessary due to the many interacting variables of the domain.

BEMSs usually consist of hardware and software components. The hardware set-up of a BEMS is typically made up of sensor-actuator networks that accurately monitors the indoor-outdoor environment and the building plants state and drive the systems accordingly. The software side of a BEMS consists of a number of functional layers that implement standard management functionalities like plant status monitoring, alarm management, demand driven plant management, reporting, etc.. [1]. Still plant and building set-points follow prescribed schedules and are rarely optimized in response to changing dynamic conditions, including weather, internal loads, occupancy patterns, etc. Nonetheless, there are significant opportunities for optimizing control set points and modes of operation in response to dynamic forcing functions and utility rate incentives. A number of studies [2] have shown potential savings for optimized controls in the range of 10% to 40% of the overall cooling cost.

Model Predictive Control (MPC) may be used to enhance BEMSs so that they can improve their control performances getting close to optimal behaviour. MPC is an advanced control technique [3] that uses the predictions of future building status, obtained by means of a model of the building's dynamics, in order to solve the problem of determining the optimal control policies in advance and anticipate its reaction to external forces. But this requires the development of integrated models capable of predicting the near future behaviour of the controlled environment under specific conditions, so that the optimal solution can be sought through scenario analysis. Furthermore, MPC models must interoperate with real sensor/actuator networks that usually, for cost reasons, cannot be larger than few tenths of devices and whose deployment is constrained by a number of external factors. Nevertheless, the model accuracy must be granted despite the reduced representation of the physical model and the suboptimal selection of the parameter set. The fulfilment of such competing requirements compels the definition of a modelling framework that, by guiding the MPC modeller through a set of methodological steps, will contribute to design accurate and robust models, which are sufficiently light to be embedded in real control systems. Thus far the model part was usually left to statistical models and it was usually targeted to quite simple domains. In this paper, a new probabilistic approach was tested, suggesting that Bayesian Networks can provide the means to manage very complex domains. In particular, they are shown to be able to make correct inferences in the case of a metro station, whose behavior is affected by a number of variable and interacting physical phenomena. Hence they supported the development of a MPC scheme.

2 The case study: underground station PdG

The PdG metro station in Barcelona is a 3-line connection station between metro lines no. 2, 3 and 4 (Fig. 1). Line 3 (L3) is located in the northern hub of the station, which includes spaces devoted to different activities: commercial, transportation, people movement, public and technical services, staff reserved rooms. A spatial survey in the station led to the identification of the following types of spaces: 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. Internal comfort is managed by means of several systems. 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. Other systems (e.g. split units, communication) are installed in commercial, technical and staff only rooms.

In this paper we will show how MPC can optimally regulate comfort by means of a dynamic control strategy, instead of by a set of predefined design constraints. To that purpose, the station must be capable of dynamically accommodating the user needs, by driving the fans located in the station’s technical room. The main ventilation ducts leave from here to convey outdoor fresh air into the platform (PL3). Air intakes are located above both platform’s sides and they supply air changes. Two CONAU V1080 injection fans (that are the main object of our control) are located in the station’s technical room, and other two fans are extracting air through ventilation shafts in the middle of the tunnels adjoining PdG-L3 (which are not controlled instead). 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, and their air flow rate is reduced at about one third, as a consequence. Also, outdoor ventilation is conveyed through its five entrances and corridors leading to the platform.

(a) (b)

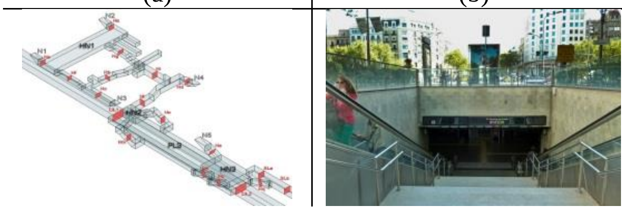

Fig. 1 – Spatial layout of the PdG underground station (a) and pictures (b).

3 MPC control

As mentioned in the Introduction, the Bayesian networks developed in this chapter were used to provide forecasts about the future state of the PdG-L3 in Barcelona, given the knowledge about their current state. Any control in buildings is targeted to minimize power consumption while keeping required comfort level and guaranteeing robustness of the solution. To this purpose, the control system must be optimal and 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 […]" [4]. Reliability is also required, and the predictive feature is another opportunity for achieving high energy efficiencies: prediction gives the capability of taking soft control actions in advance instead of suddenly reacting to unexpected deviations from the required state, thus saving energy. MPC takes into account the (measured) current state of the system, future weather conditions and other disturbances (e.g. internal gains), in order to control actuators (e.g. HVAC, lighting and blind systems), so that energy and money usage are minimized. At the current point in time, a heating/cooling plan is formulated for the next several hours to days, based on predictions of the upcoming weather conditions. 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 [5].

One remarkable survey about the effectiveness of

MPC was carried out by means of simulations and applied to office buildings [6]. First, the authors considered and compared a list of potential adaptive approaches, among which we cite reduction of the thermal comfort when the building is not used, widening of the room temperature comfort range, use of Indoor Air Quality controlled ventilation. Those preliminary simulations showed that the highest energy savings were determined by predictive control [7].

In the case of large underground buildings, like PdG-L3 metro station in Barcelona, interaction with the outdoors is very complex and occupancy figures result someway difficult to predict. Hence, the dynamics of the station cannot be solved –and predicted– though a simplified thermal model. Bayesian Networks will be shown to work well when it is necessary to reduce a complex building model into a more manageable one. In fact, they gave back a lumped representation of a complex system, involving thousands of variables.

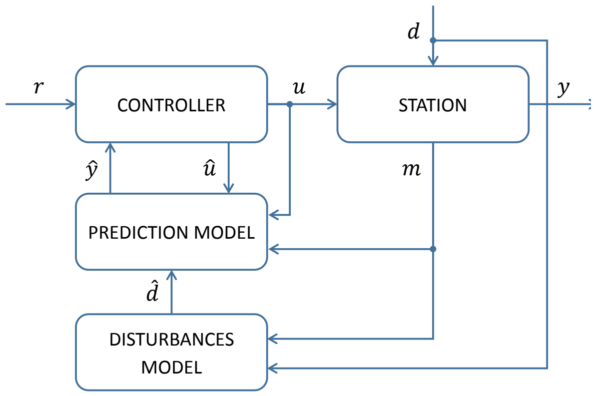

Fig. 2: predictive model based control framework defined for the metro station PdG-L3.

The overall MPC control framework applied to the station is represented in Fig. 2. Inputs u to the system are the variables that can be driven by the controller (e.g. frequency that drives injector fans). The outputs y are the power consumption and indicators for comfort and health that must be controlled in order to reach certain desired reference level r. 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. At each control step, the prediction model receives candidate input sequences $\hat{u}$ picked out by the controller; disturbance predictions come from disturbances models $\hat{d}$, measured outputs m from PdG-L3 and the prediction model estimates the future output sequence $\hat{y}$. The optimal control sequence u^* is that one which minimizes a given cost function while complying with given constraints. Once the optimization problem has been solved, the first step u of the optimal sequence is applied as the best control action. The overall procedure is repeated at each step, thus closing the control loop. The implementation of those systems asks for the development of devices and services:

- monitoring systems and intelligent algorithms to interpret occupant's behaviour, as deeply explained by the authors in [8];
- high-level control systems capable of solving optimization problems in real-time;
- accurate and fast dynamic models of buildings' behaviour and their systems (which is object of this paper);
- accurate modelling of disturbances.

4 Development of predictive models

Indeed, Bayesian Networks may be thought as a directed acyclic graphs that encodes assertions of conditional independence [9]. In fact, it orders the variables in a domain U. They are suitable to reduce complex domains into computationally manageable models, which is a key feature when computations must be performed in real-time. Also, they are capable of managing incomplete (e.g. one or a few data are not available because the corresponding sensors are broken) and uncertain information (e.g. if we include uncertainty in sensor measurements or if inputs are relative to forecasts of disturbance actions).

They implement inference algorithms, thanks to the conditional probability relationships defined among the variables of the domain under analysis [10, 11]. In other words any node can be conditioned upon new evidences. This feature is particularly important in case a control system must work in real-time, because in that case evidences acquired about a state variable (i.e. from sensor measurements) must be propagated to update the state of the rest of the domain. When it is run in the MPC framework, the controller will make queries to a set of nodes belonging to the networks, whose probability distributions are computed from the state of other nodes, upon which observations (or evidences) are already available. In the case of PdG-L3 presented in this chapter, the Bayesian Networks were built in the Hugin™ software environment. The conditional probability tables were learned from datasets put together through numerical simulations, by means of the "EM learning" algorithm [9].

In order to validate their performances, different kinds of indices were developed. The difference between the predicted value $\hat{X}_i$ and the actual value X_i is defined as error $E_i \triangleq \hat{X}_i - X_i$. The absolute error is $AE_i \triangleq |E_i|$ and its squared error is $SE_i \triangleq E_i^2$. Percentage error will be: $PE_i \triangleq 100 \cdot E_i / X_i$. In order to have a global performance index to be evaluated over the whole validation dataset made up of K samples, these instantaneous indices must be combined into global indices, such as the mean absolute error:

$$MAE \triangleq \frac{1}{K}\sum_1^K \left|\hat{X}_i - X_i\right| \tag{1}$$

and the root mean square error is:

$$RMSE \triangleq \sqrt{\frac{1}{K}\sum_1^K \left(\hat{X}_i - X_i\right)^2}. \tag{2}$$

As indices of the predicted variables are related to different physical quantities with different units, they should be normalized with respect to their typical range of variation, by means of:

$$NMAE \triangleq \frac{\frac{1}{K}\sum_1^K |\hat{X}_i - X_i|}{|X_{max} - X_{min}|} \tag{3}$$

and:

$$NRMSE \triangleq \frac{\sqrt{\frac{1}{K}\sum_1^K (\hat{X}_i - X_i)^2}}{|X_{max} - X_{min}|}. \tag{4}$$

ASHRAE Guideline 14-2002 [12] establishes that for calibrated simulations, the CVRMSE and NMBE of energy models shall be determined for each calibration parameter by comparing simulation-predicted data to the utility data used for calibration. The proposed indices are the coefficients of variation of the root mean square error (CVRMSE) and normalized mean bias error (NMBE). Following this guideline, the RMSE has been selected as the main performance index for evaluating the accuracy of a BN. The range of the considered variable has been taken as a normalization factor and the NRMSE has been selected as final index for the design process of the BN because it includes information about both bias and variance of the error.

4.1 Predictive models

Basically, the development process of both Bayesian Networks consists of three main phases:

1. definition of the network topology;
2. preparation of the training set and learning of the conditional probability tables;
3. final assessment of the network.

In the case object of this chapter, the behaviour of the metro station Passeig de Gracia was first simulated through whole building analyses, which provided datasets encompassing all the possible environmental conditions, such a knowledge was transferred into Bayesian Networks then. Three datasets were generated:

- the first one was made up of randomly generated data, which means that the inputs (e.g. weather, heat gains, occupancy figures etc..) were allowed to vary without additional constraints in their range;
- the second sample, called “likely” dataset, was generated through simulations whose inputs were allowed to vary within their same ranges cited above, their differential variations being constrained, so that the difference between the value of each variable at the present time step and the value of the same variable at the previous time step was limited by a threshold;
- the third “typical” sample was built through simulations, whose inputs were taken from real measurements, such as real weather conditions, number of people etc ...

The use of the random dataset was targeted to provide to the networks information about any kind of combination of events possible, including the less likely ones. Then, more information about the more likely scenarios included in the second and third datasets was added. These two last datasets were constrained by setting input variables within those values which were measured in past years (e.g. weather conditions, occupancy, driving frequencies of ventilation systems). The whole building model used for running simulations was developed as a lumped parameter model in the Dymola™ simulation environment, that is based on the Modelica language [13]. Starting from a validated library for building simulation developed by the Lawrence Berkeley National Laboratory [14], a specific library for underground stations was developed. However, such a model cannot be run in real-time when the controller needs to determine the best candidate control strategies, so it was reduced into the less computationally demanding form of Bayesian Networks. The PdG-L3 predictive model was split into two Bayesian Networks:

1. temperature prediction dynamic Network (TP-DBN), which is in the form of a DBN, because it forecasts expected temperature in the station given inputs about current and past time steps;
2. air flow prediction Bayesian network (AF-BN), which is in the form of a regular BN, because it estimates variables relative to air flow in the station and energy consumption of the fans, given its current status.

Once available, the two networks were run according to the scheme outlined in Fig. 3. At every iteration the controller will opportunely query the two networks to get future estimations about the variables relevant to select the most opportune control policy to be adopted at each running step. To this aim, the networks need to be instantiated first: the current temperature in the station’s platform (PL3) and weather conditions will be provided by the permanent monitoring network installed in the station, along with candidate fan frequencies. Given these inputs, the controller is allowed to query the AF-BN in order to estimate fans consumption and air changes in the station at each time step. Such a prediction step takes a few seconds and is performed by the software Hugin™ through algorithms for belief propagation. Then, the TP-DBN will take these variables as inputs, along with other state variables (e.g. current PL3 temperature, temperature difference between inside and outside and forecasted weather, people, train arrival etc..) in order to predict PL3 temperature at the next time step. Again, belief propagation is performed with this second network. Then, the same loop will be repeated at each iteration. Both the networks were built following the same methodology:

- first structural learning: it was determined first by the a-priori knowledge from the researchers and cluster analyses;
- improvement of the network's structure: this was carried out through analysis of its performance indices, after learning conditional probability tables from the random dataset;
- final refinement using the two additional datasets: adding more datasets allowed the developers to quantify even probabilistic relationships among the variables;
- final evaluation of the networks.

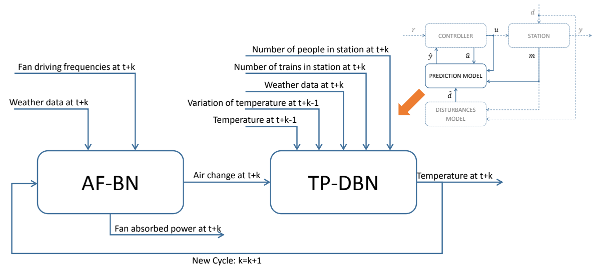

Fig. 3: The basic loop of the predictive cycle adopted for PdG-L3 which involves both Bayesian Networks.

The first step started from the analysis of 81 variables included in the Dymola^{TM} dataset. Iterative cluster analyses [15] were useful to group those variables into clusters and determine those which were redundant [16]. Finally, the number of variables was cut down to 25. This final set's variables were naturally grouped into two sub-clusters of variables: one of them including those related to air flow processes, and the other one including those related to the temperature dynamics.

The second step helped in several tasks: meaning and dependencies between nodes have been reviewed according to the relationships suggested by physical laws; the number of intervals for discretizing the state space pertaining to every node, with the final purpose of minimizing the errors of the output variables given by the performance indices; a few links have been rearranged.

Fig. 4-a depicts the final structure of the dynamic Bayesian network (i.e. TP-DBN), which was used to predict PL3's temperature in PdG station in the next step (node TemPL3_p01), starting from inputs such as: forecasted number of people in the station at the next step (NPeSta_p01), forecasted internal gains supplied by trains at the next step (GaiTr_p01), current PL3's temperature (TemPL3), forecasted outdoor temperature (TouMet_p01), forecasted air changes per hour (ACOPL3_p01) and deviation of temperature from the past time step (DtePL3). The network's intermediate variables are useful to perform computations and simplify conditional probabilistic relationships among variables. Similarly holds with the AF-BN network (Fig. 4-b), whose inputs are: forecasted frequencies of fans in the station and tunnels at the next time step (DfreTF1_p01, DfreTF2_p01, DfreSF1_p01), forecasted internal gains by trains (GaiTr1_p01), forecasted wind direction and speed (WiDMet_p01, WiSMet_p01), outdoor temperature (TouMet_p01) and current temperature (TemPL3). The main outputs are the power consumption of fans – in the station (PelSF1) and in the tunnels (PelTF1, PelTF2) – and air flow rates expected across the corridors leading to PL3: AflCNl_p01 (corridor CNl), AflCNop_p01 (sum of corridors Cno and CNp), AflCNq_p01 (corridoio CNq) and AflSlb_p01 (station link). These estimated airflows are then summed up coherently to the Air Mass Balance for computing the overall air change in PL3 (ACOPL3), needed as input from the TP-DBN.

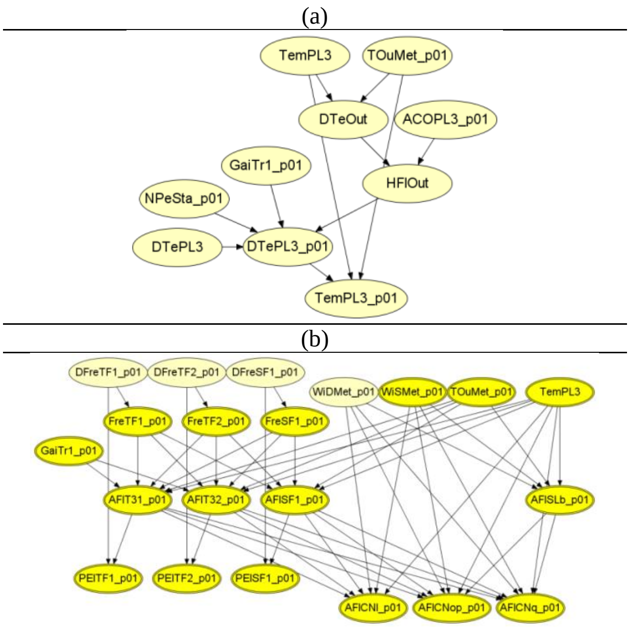

Fig. 4: Predictive and dynamic Bayesian Network relative to temperature in PL3 (a) and predictive Bayesian Network relative to air flow changes in the station (b).

The third step was aimed at performing further refinement using the "typical and "likely" datasets. Technically, that means that the EM learning algorithm was implemented by adding the information included in these two datasets to the information already derived from the "random" dataset. This process allowed to include information about those scenarios which are likely to occur more often. The refinement was mainly performed in terms of tuning the subdivisions into intervals of all the nodes and in terms of converting discrete variable into continuous variables.

The steps no. 2 and 3 required many iterations of learning, refining and validating. On the whole, 140 cycles were made with the TP-DBN (Tab. 1), which was useful to reduce the error from 4.98 to 0.72 °C (in the RMSE case) and from 17% to 4% (in the NRMSE case). The trend during the refinement process led to a continuous increment of performances, as shown in Tab. 1. In addition, 82 cycles were needed to optimize the AF-BN: for the control variable, Station Fan Power (PelSF1) RMSE fell down from 1858 W to 377 W, whereas NRMSE fell from 10.3% down to 2.3%.

In the TP-DBN all the nodes were represented by discrete variables. In the AF-BN all the variables were continuous except the following ones: frequencies of fans (DfreTF1_p01, DfreTF2_p01, DfreSF1_p01) and wind direction (WiDMet_p01).

Tab. 1: Gradual improvement of performances during continuous refinement of the TP-DBN network.

Cycle no.	TemPL3_p01	
	RMSE (°C)	NRMSE (%)
1	4.98	17
....		
54	3.32	12
...		
98	1.81	6
...		
114	1.00	4
...		
140	0.72	4

4.2 Cost function

The controller unit passes a candidate control policy to the BNs and uses resulting predictions in order to compute a cost function, which must select the best output to be used as an input in the next time step. The degrees of freedom (outputs) of the controller for PdG-L3 station are the frequencies of the station fans ($FreSF1, FreSF2$). The predictions that the controller queries to the Bayesian Networks are the absorbed powers of tunnel fans and station fans (PelTF1, PelTF2, PelSF1, PelSF2) and the air temperature in the platform (TemPl3). The future outdoor temperature (TouWS) is retrieved from a weather forecast service and the air change in the platform (ACOPl3 = amount of clean air entering the platform) is computed as a proper combination of the air flows predicted by the BNs. The objective of MPC is to minimize the following cost function with respect to station fan frequencies (the variables marked with “tilde” (~) are the normalisation coefficients that corresponds to the typical values of the corresponding variable while the weights of each single objective in the cost function is determined by $\alpha_{...}$):

$$
\begin{aligned}
J &= \sum_{k=1}^{H} \alpha_{PT}\left(\frac{|PElTF1(k)+PElTF2(k)|}{2\widetilde{PT}}\right) \\
&+ \alpha_{PS}\left(\frac{|PElSF1(k)+PElSF2(k)|}{2\widetilde{PS}}\right) \\
&+ \alpha_{DT}\left(\frac{TOuWS(k)-TemPl3(k)}{\widetilde{DT}}\right)^2 \\
&+ \alpha_{T}\left(\frac{\overline{TemPl3}-TemPl3(k)}{\tilde{T}}\right)^2 \\
&+ \alpha_{AC}\left(\frac{\overline{ACOPl3}-ACOPl3(k)}{\widetilde{AC}}\right)^2 \\
&+ \alpha_{DF}\left(\frac{FreSF1(k)-FreSF1(k-1)}{\widetilde{DF}}\right)^2
\end{aligned}
\tag{5}
$$

The inclusion of temperature in PL3 (*TemPL3*) and air changes per hour (*ACOPl3*) were used to control comfort conditions. The respective coefficients of eq. (5) can be tuned to weigh the importance of the several concurrent factors.

4.3 Validation of the predictive models

Finally the performances of the two networks were verified also through simulations. Fig. 5 shows the good agreement between the real temperature simulated by Dymola™ in PL3 and the forecasted plot of PL3 as predicted by TP-DBN. The simulations performed by the Bayesian Networks in this case were carried out according to what already described. The input values at the first time step were instantiated as evidences taken by the Dymola™ model. Then, the outputs from the networks were used as inputs for the next time step in the networks and the simulations were iterated in the same way all over the period shown in the diagram. It’s clear that the predictive and dynamic Bayesian networks (BN) are able to accurately model the temperature plot sin PL3 and to give the right inputs to the controller, in order to evaluate the best control policy.

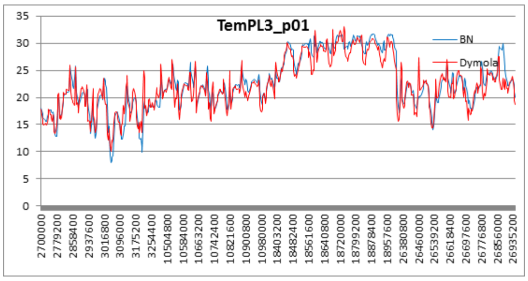

Fig. 5: Qualitative comparison between the real temperature plot computed by Dymola™ and forecasts by the Bayesian Network TP-DBN.

5 The Simulator

The Bayesian predictor and the MPC logics have been embedded in a simulation environment that accurately reproduces the thermal and air-flow dynamics of the outdoor and indoor environments, and the trains and passenger flows.

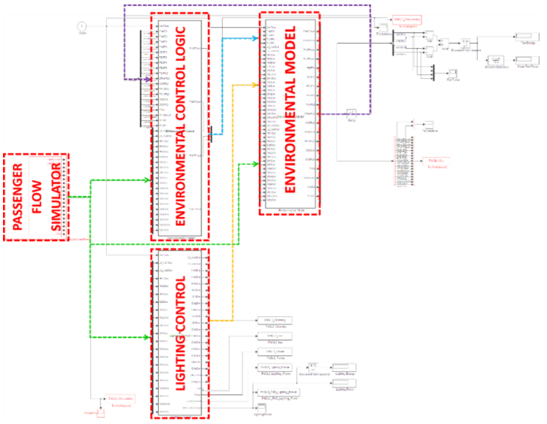

Fig. 6. The Simulink SEAM4US Simulator architecture: occupancy (green), fan frequencies (blue), dimming level of lights (orange), measures (purple).

The Simulink (Mathworks©) architecture of the SEAM4US simulator is shown in Fig. 6. The simulator is made of four main components: the PdG environmental model, the passenger flow simulator, the lighting control simulator and the environmental MPC. In this paper we are showing the potentials of MPC applied just to environmental control. The PdG Model is that one developed in Dymola™. At compile time the PdG environmental model results in a matrix with tenths of thousands of unknowns. The PdG Model is interfaced with a weather file of Barcelona that provides the hourly external weather parameters, including wind speed and directions. The PdG environmental model receives as inputs passenger occupancy levels, lighting level of the appliances in each space, and fan control frequencies. It then outputs all the environmental parameters (e.g. air temperature and humidity, pollutant levels, energy consumption). These parameters are then fed back to the control logics as the basis for the next control step. In the SEAM4US simulator the large PdG Environmental model acts as the real station. The Bayesian models reported in sub-Section 4.1 support the controller by means of predictions on the future status of the station. The size of this predictor is small enough and its computational time short enough to suit the model embedding requirements.

The control logics implemented in the SEAM4US simulator is based on a particle filtering mechanism. The controller randomly generates a number of different control options that are sent to the predictor. The predictor updates the model with the control parameters and by means of Bayesian inference calculates the environment and energy consumption parameters. Then the controller ranks the predictor outcomes according to the cost function in eq. (5). The best performer is then selected and used in the next control step. Fig. 7 shows an example of a simulation results of three days of operation, which is relative to the environmental control. The simulation time is represented along the x axis, while the y axis represents the fan frequencies in Fig. 7-a Negative frequencies means that the fan direction is inverted (extracting air instead of supplying). Three curves are reported. The dashed curve (i.e. baseline) depicts the current policy used for fan control. The fan is driven at maximum speed for all the station opening time and it is turned off during the closure time. The second dash-dot curve represents MPC constrained to only two driving frequencies, while the third (continuous) curve is related to a continuous frequency driving. In addition to the fact that MPC control provides an energy saving rate that can rise up to 35%, it is noteworthy to realize why this happens. Comparing the baseline curve with the MPC controlled, it appears that in many cases the driving frequencies and the baseline have opposite signs. This means that in the standard baseline driving the station fans very often are opposed to the air flow induced by the external sources, and therefore contribute negatively to the air exchange. This is reflected by the temperature curves that are slightly lower – i.e. more comfortable - for the MPC controlled environment despite the huge energy saving (Fig. 7-b). Summarizing, these results show how the effectiveness of the MPC control of complex environment relies on the power and on the flexibility of the Bayesian predictor and of the Bayesian Inference paradigm.

(a)
(b)

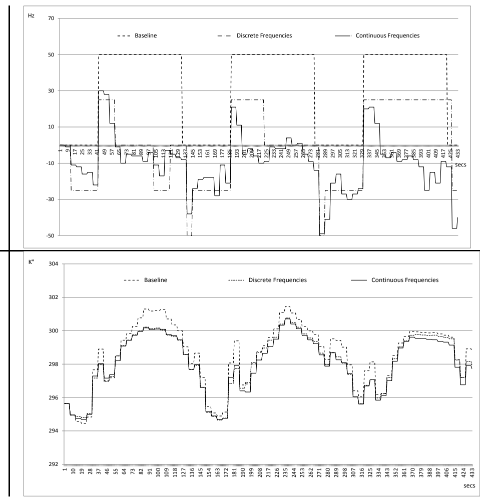

Fig. 7 - Plots from the simulations in search of optimal control strategies.

6 Conclusions

Predictive control of buildings is one of the most effective ones currently being developed by researchers. However, it cannot be applied without a reliable predictor of the expected state of the controlled domain. Computationally demanding software programs cannot be used to produce predictions at run time, but they can be run to generate datasets and these datasets may be used to transfer knowledge into Bayesian Networks. In fact, inputs by the controller are instantiated in Bayesian Networks in the form of a set of evidences; then, inference algorithms are propagated and expected future values describing the energy and thermal state of the domain might be estimated. This procedure can be repeated thousands of times at each control step and it makes the implementation of MPC feasible.

When implemented in a real case, the results from inferences were shown to be very accurate with low deviations from the values estimated by means of more complex numerical models. In addition, our testing of the use of predictive Bayesian Networks embedded in a wider MPC framework to support the ranking of concurrent control policies was successful, too. So Bayesian Networks proved to be able to solve the problem of reducing complex models into more manageable tools for performing cumbersome inferences through limited computational efforts, while getting highly accurate results.

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