MODELS FOR THE REAL-TIME CONTROL OF SUBWAY STATIONS

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ABSTRACT

This paper discusses the role of models and simulations in the perspective of the real-time control of complex buildings. It describes the approach used in the model engineering of the SEAM4US EU research project, concerned with the optimal control of the *Passeig De Graçia* metro station systems in Barcelona. The paper introduces the model predictive control (MPC) architecture and the main features of the large Modelica station model, made of over 80000 variables. It then details the statistical model reduction methodology adopted either for mapping the large station model into a deployable sensor network, and for embedding the model into the main control loop.

INTRODUCTION

In the last 10 years Model Predictive Control (MPC) spread over the building domain (Henze et al., 2005) (Coffey et al. 2010) (Oldewurtel et al., 2010) (Ma et al., 2010) (Hailemariam et al., 2011). MPC is an advanced control technique (Maciejowski, 2002) which, when applied to buildings, employs a model of the building dynamics to solve an optimization problem aimed at determining the optimal control inputs.

The MPC approach is being used in the EU-funded research SEAM4US (Sustainable Energy mAnageMent for Underground Stations). Its objective is the development of an advanced control system for subway stations capable of setting up the internal environment in an optimal way, based on the forecasts regarding the external environment, the passenger flow and according to energy efficiency, comfort and regulation requirements (Figure 1).

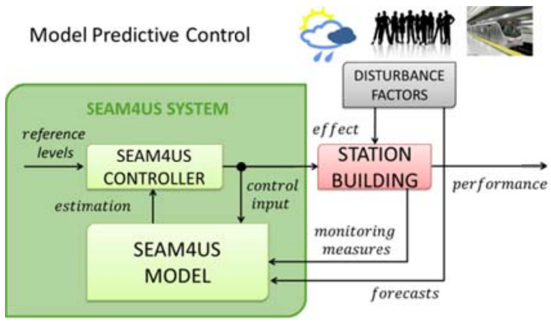

Figure 1 - SEAM4US MPC architecture

The particular application domain raises a number of modelling issues that make the development of the integrated station model a challenging engineering task (Ansuini et al., 2012). In fact, the modelling process involves multi-physics models with multiple time scales, different levels of detail and large spatial dimensions. The real-time management of the metro station underground space requires that models are able to support the human controller with scenario analysis, which means they must be robust, invertible and able to propagate uncertainty throughout the computational chain (Giretti et al., 2012). Finally, the run-time deployment of the models into the control loop imposes that models are computationally efficient, that they have a manageable size, and, most important, that they could be mapped into a deployable sensor/actuator networks. This last requirement deserves a specific attention because, in our case, it drove the development of a tailored model reduction methodology. The real-time control of the metro station systems requires that the model input and output variables correspond to physical parameters that can be either measured or controlled. In real-world applications this fact imposes a number of exogenous constraints, like for example the size of the sensor network, the cost of the sensor equipment, their robustness to vandalism, etc. that cannot be easily represented in a pure analytical model reduction procedures (Antoulas et al., 2001; Moore, 1981; Sandberg, 2006; Stykel, 2004, Vandendorpe et al., 2004). In addition, the highly nonlinear event-based Modelica model made the application of such procedures practically unfeasible. Therefore a specific multi-stage model reduction methodology, based on statistical cluster analysis, has been developed.

This paper describes the approach used in the model engineering of the SEAM4US EU research project, concerned with the optimal control of the *Passeig De Graçia* (PdG) metro station systems in Barcelona. The paper introduces the modelling workflow used to develop the MPC system and the main features of the large Modelica station model. It then details the statistical model reduction methodology adopted and discusses the structure and the performances of the resulting Bayesian Networks models. This research has been funded under EU grant n. 285408.

THE MODELING WORKFLOW

The SEAM4US model engineering foresees two modelling cycles (Fig. 2), starting from the findings of a preliminary modelling phase, a sensor network is designed and deployed in the environment. In parallel the models are developed: a Whole Building Model, including airflow, heat transfer and lighting physics, is developed and validated against standard reference simulation tools and probabilistic models for the real-time control. The main role of the Whole Building Model is to provide support for the development of the stochastic Bayesian Network Model through a model reduction process. The stochastic model will be the core of the control system (Oldewurtel et al. 2010; Choudhary, 2011), providing performance forecast, adaptivity and decision support.

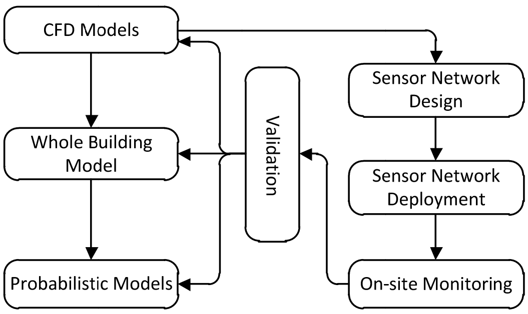

Figure 2 - Phases of one of the two modelling cycles of the SEAM4US environmental model engineering process.

Both the whole building and the stochastic models will be fine-tuned as soon as the sensor data is available. Finally, the whole cycle is repeated, updating components and systems, until a satisfying performance grade is reached.

THE WHOLE BUILDING MODEL

The Whole building model (WBM) of the *Passeig De Graçia* station was developed in the Dymola (Modelica-based) simulation environment, using the Buildings Modelica library (Wetter et al, 2009; Wetter et al. 2011; Nouidui et al. 2012). The building library has been extended in order to represent underground spaces and subway stations equipment. The top level block of the Dymola model of the PdG north (N) station (Figure 3) is composed by the transit spaces (platform (P), hall (H), corridors (C)) and building and systems components of the station (entrances, doors, equipments). The main space is the platform of Line 3 (PL3), as it contains the main disturbances (trains and high number of people) and the equipment to be controlled (fans, lights and escalators).

Extension of the Buildings Modelica library

In order to suit the simulation of underground spaces, the Buildings Modelica Library was extended by developing some new components and by customizing some existing components.

The development of new components involved:

- *horizontal openings* to simulate airflows across large horizontal openings with the possibility of two-way flow by combining forced and buoyancy airflows together an horizontal opening component has been developed, mainly inherited from a NIST report presented by (Cooper, 1989). The sloping plane (Bolmqvist and Sandberg, 2004) portion of the model was added to represent staircase;
- *internal gains*, managing the heat gains due to people, lighting, specific equipment and the trains;
- *train manager*, aimed at include the train effects in terms of airflow, heat and pollutants, combining a set of schedules to other components (differential pressures, trace substance sources, heat gains).

Furthermore some customizations were needed, mainly in relation to airflow components, such as airflow tolerances (as the subway station has higher value of mass flows than a common building, the tolerance must be kept higher), initial values and the enhancement of the component modelling wind pressure (OutsideCp), including specific input data for wind pressure coefficients.

The WBM Model

The actual release of the WBM is composed by 7206 components and 86397 variables of which 1443 are constants, 62902 are parameters and 22052 are unknowns.

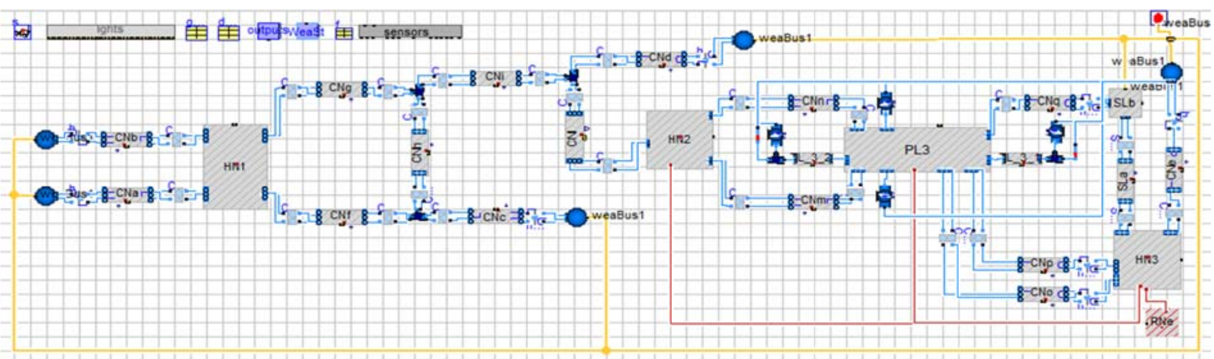

Figure 3 - Top Level of the Dymola WBM of PdG North Station: Platform(PL3), Halls (HNx), Corridors (CNx)

The platform component (PL3) of the Modelica model has 398 components and 4947 variables of which 70 are constants, 3472 are parameters and 1405 are unknowns. The WMB model was preliminarily calibrated through a set of data collected in a two-day survey. The sensor network was deployed in December 2012 and the extensive calibration phase is on-going. The preliminary simulation results have been used to guide the definition of the stochastic models in the first iteration cycle of the model engineering workflow.

The simulation results pointed out that the platform PL3 showed the worst environmental condition and energy consumption, and that consequently it can be used as the reference environment for the initial development of the model. The simulations showed also that the temperature trend is clearly dependent on the previous states (due to inertial process), and that the airflow process can be considered practically instantaneous.

THE WBM MODEL REDUCTION

After the preliminary calibration phase, the Modelica model was able to simulate all relevant physical processes with acceptable accuracy, so it was used as the basis for the development of the preliminary stochastic model through model reduction. As we have already annotated the pure analytic techniques for model reduction do not apply to our case for a number reasons:

- the extremely reduced number of deployable sensors, which imposes a significant cut on the number of model inputs and outputs;
- the high nonlinearity of the event based Modelica model of the station, which let the matrix change possibly at each simulation step, hindering the practical possibility of computing the Gramians (Sandberg et al., 2008; Stykel, 2004);
- the exogenous and qualitative constraints imposed by practical aspects like costs and vandalism, which strongly influence the selection of the input and output variables.

Therefore, a two-step procedure, combining a knowledge-driven and a data driven model reduction phases, was defined, using respectively two sources of information: the model structure and the results of large simulation sets. In both cases, the rationale of the reduction procedure was to minimize the information loss due to variable reduction by clustering variables that correlate and to select a representative (i.e. synthetic variable) for each group. The variable clusters are computed in the first case based on the model structure, and in the second case by means of statistical clustering techniques. The representative of each class is selected based on its compliance to the exogenous qualitative constraints.

Knowledge-driven reduction

Since the scope of the project is mainly focused to the platform and the preliminary simulation results showed that the physical processes in the platform are quite representative of the behaviour of the whole station; the initial variable reduction process was limited to the set of variables related to the platform. The platform component (PL3) has 4947 variables of which 1405 are unknowns.

The knowledge-driven phase used the model structure as its clustering mean. Almost every component of the Modelica model has a hierarchical structure, thus each variable is computed with nested variables. For instance, the variable "mean air temperature of the room" (heaPorAir) is the result of combined physical processes consisting of heat transfer (conduction, convection, infrared radiation, etc.) and of fluid dynamics (air balance) components (Figure 4). Therefore, a topmost variable is necessarily correlated to a number of inner variables, and it is consequently representative of their combined behaviour.

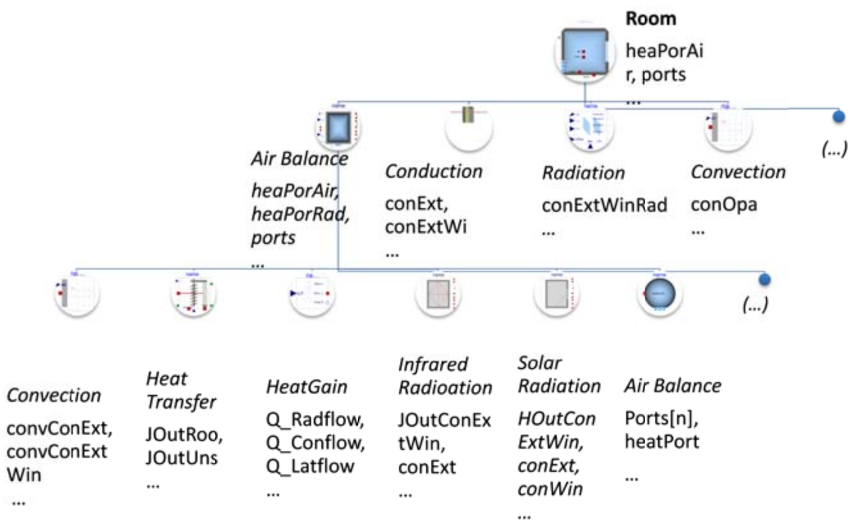

Figure 4 - Example of model structure in relation to the variable heaPorAir (air temperature)

The selected topmost variables have been arranged according to the fact that they were:

- *input variables*, representing the driving features of the specific system (weather, trains, number of people, fan control inputs);
- *state variables*, in relation to the main physical processes: heat transfer (air temperature, surface temperature, heat gains), fluid dynamics (airflows, pressure drops related to airflow resistance, geometrical features and buoyancy), pollutant diffusion (CO2 and PM10 concentrations);
- *output variables*: energy consumptions, air change rates, comfort.

At the end of the first phase a set of 97 variables were selected. Despite the extremely severe reduction rate, this set is still too large for being completely coupled with a monitoring sensor network. Furthermore some of these variables cannot be directly and easily measured such as the local pressure drop due to geometrical features of the space. So a further phase of variable reduction was performed through a statistical clustering.

Statistical Clustering

Statistical clustering was used to find out 'far' correlations among variables, that is, correlation that cannot be induced from the equation structure of the model and that can be identified only by means of simulation results. Several steps of statistical clustering were performed using the ClustOfVar (Chavent et al., 2011) package of the R software (R-project, 2012).

In this package, two methods are used for the clustering of variables: a hierarchical clustering algorithm and a k-means type partitioning algorithm. A cluster of variables is defined as homogeneous when the variables in the cluster are strongly linked to a central quantitative synthetic variable. This link is measured by the squared Pearson correlation for the quantitative variables and by the correlation ratio for the qualitative variables. Using this aggregation measure, the algorithm builds a hierarchy, called dendrogram. In a dendrogram, the height (y axis) is the dissimilarity, measuring the loss of homogeneity observed when two clusters are merged.

The statistical computations are based on a dataset consisting of simulation results of the Modelica station platform model run for one month (April) and a time step of one hour. The weather conditions were derived from the IWEC weather file (ASHRAE, 2001), internal gains were set to typical values achieved from the station manager and a random schedule was used as control input for ventilation equipment, in order to excite the relevant process dynamics.

Figure 5 shows the cluster dendrogram for the initial set of 97 variables, which manifests a clear separation in two groups of variables. The two groups are related to the two main physical processes: *thermal* (cluster on the right of figure 5) and *airflow* (on the left of figure 5). The left side of the cluster dendrogram is composed by variables related to the airflow and to the fans, like pressure drop, volume flow rate, net flow and air change rate and fan power. The right hand of the dendrogram contains variables related to the thermal process, like internal heat gains, mean air temperature and surface temperature, comfort related variables and the weather variables (dry bulb temperature, relative humidity, wind speed, etc.). It also contains the variables representing the pressure drops related to the different heights (that is the driving mechanism of the buoyancy effect is included in the reduction).

The clustering process proceed iteratively. At each step, the resulting clusters were analysed and some variables were deleted or replaced with synthetic ones when a cluster contained:

- variables of the same *physical quantity* (e.g. all the pressure drops due to buoyancy);
- variables contributing to the same *physical process* (e.g. airflow and pressure drops through an opening);
- variables correlated by the *spatial topology* of the building.

The two sub-clusters were analysed separately. Figure 6 represents the last step of "thermal cluster", consisting of 17 variables. There are three groups of variables well correlated each other and that can be quite easily connoted. In fact, all the variables related to temperature are grouped ("temperature differential" zone in Figure 6): buoyancy pressure, Fanger Comfort Index (PMV and PPD), zone temperature and outdoor temperature. This is quite interesting because it points out that the buoyancy process and weather condition are related to the zone temperature and to the thermal comfort. This suggests that outdoor and indoor temperature variables are sufficient to represent these aspects. A further group emerging is the one called "heat gains" in Figure 6. This group contains variables representing the trains, the people and the gains from the other equipment. The PM10 concentration is contained in this group as well. This variable is not considered so far, as the pollutant model will be developed during the next project year. The last group of variables refers mainly to external weather. Finally, the first branch on the left is weakly correlated to the others and contains the surface temperature, the external pressure and the static pressure of the platform.

Concerning the "airflow cluster" (Figure 7) it can be noticed that all the variables related to the tunnel are grouped and are not strongly correlated to the other variables. The other variables are mainly divided in two groups, related to the station fans (only exception

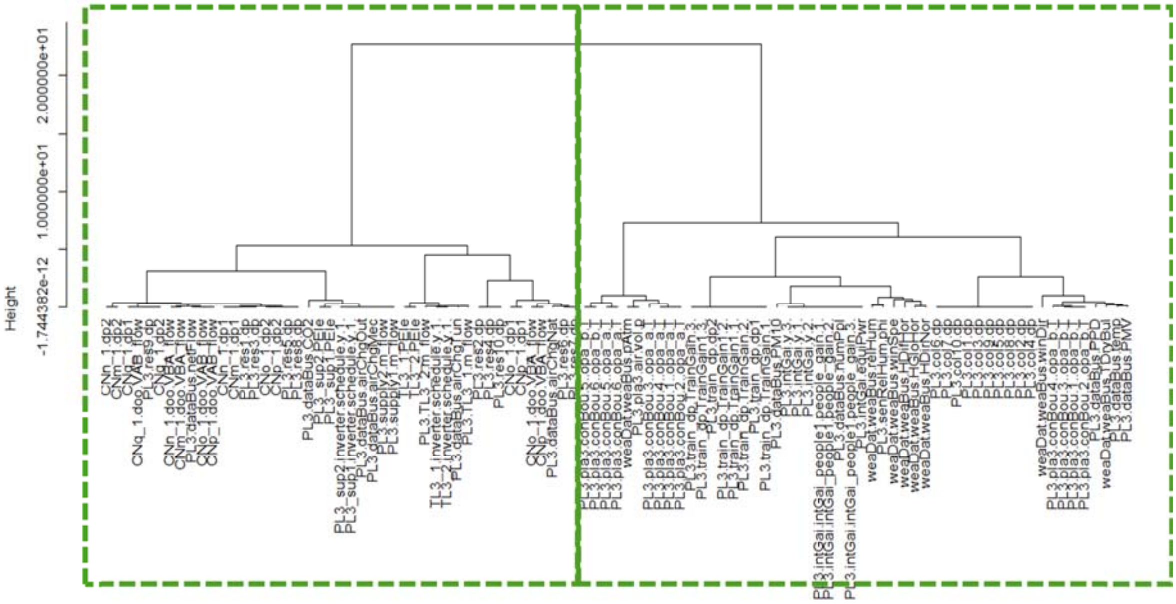

Figure 5 – Bird-eye view of the dendrogram of the initial set of 97variables

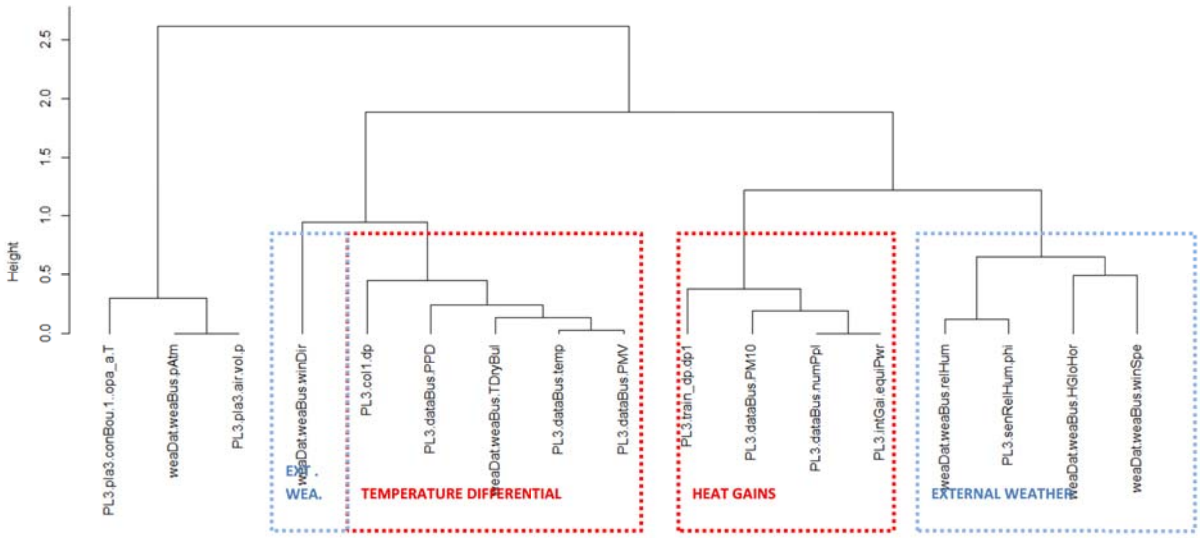

Figure 6 - Final Thermal Cluster (17 variables)

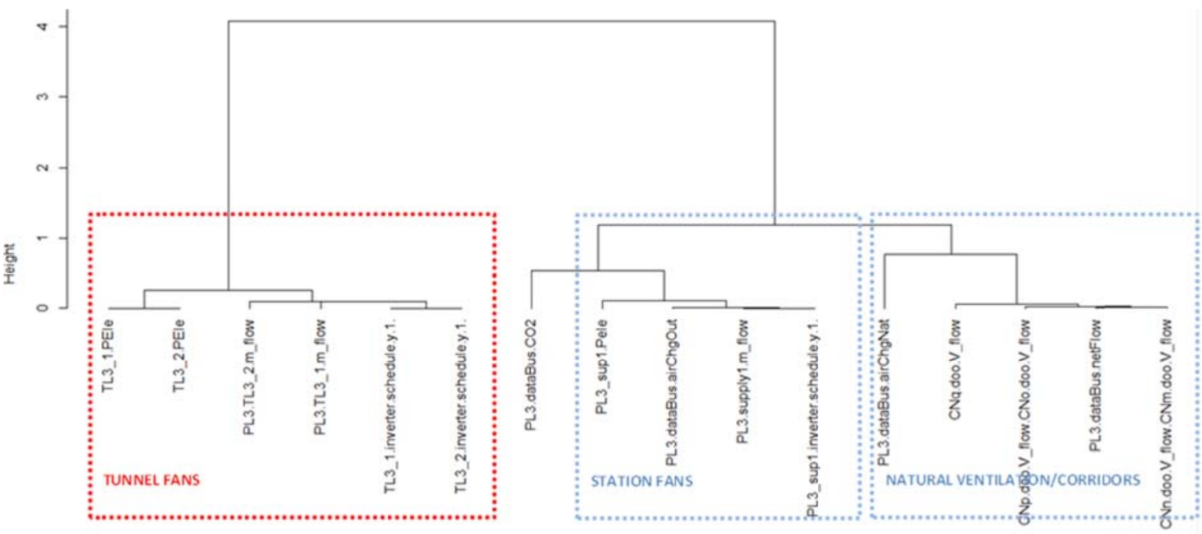

Figure 7 - Final Airflow Cluster (16 variables)

is CO2, not being considered at this stage) and "natural ventilation" considering the airflow passing through the corridors. Among them, the variable airChgNat, as it is the sum of the airflows from the corridors, will be omitted.

THE PROBABILISTIC MODELS

The last stage of the model-engineering phase consisted in the development of PdG-L3 station's stochastic models, in particular Bayesian Networks (BNs) (Murphy, 1998) (Korb, 2004), which natively provide uncertainty management, machine-learning capabilities and, consequently, offer a good basis for adaptivity and decision support have been adopted. The clustering process guided the development of the Bayesian models.

Theoretically, a unique Bayesian model could have been developed including all the physics and dynamics occurring in the station. However, the clustering clearly showed the possibility of considering separately the two main physics (heat transfer and fluid dynamics). Since these various physics have different time-scales, in order to reduce the structural complexity of the single model, two different BNs are used.

Since the simulation results showed that there is a correlation between instantaneous values of temperature and airflows, thus the Bayesian Models, are connected by shared variables during simulation.This correlation is physically explained also by the fact that in PdG subway station the mechanical ventilation system, is in charge of both air quality requirements and thermal comfort.

For this reason, both networks share five variables: three variables for the Outdoor Weather (Temperature, Wind Speed and Wind Direction), Platform Air Temperature (*T0PL3, TemPL3*) and Platform Net Flow (*NFlPL30, NFlPL3*).

The Thermal Bayesian Network

The thermal Bayesian Network is depicted in figure 8. The thermal clustering set suggests that the variables related to the differential temperature between the indoor and the outdoor spaces (*TOuMet0*), and one single variable representing the cluster of the overall internal heat gain (*NPeSta0* - number of people, in this preliminary release) capture the main thermal gains of the station. Furthermore, the WBM simulation results confirmed that the thermal state of the station dynamically depends on previous states. Therefore nodes for three previous time steps, each lasting 1 hour, were added (*Tm3PL3, Tm2PL3*, etc.). Finally, considering that WBM simulation showed in some cases different trends of the temperatures in the platform and in the other main halls, the actual and previous temperatures for the four other main halls were added (*T1HN1, Tm3HN1*, …, *T1SLb, TM3SLb*, etc.).

The resulting Thermal BN is able to predict the temperature in the platform, halls and critic spaces with a time step of one hour.

The Airflow Bayesian Network

The airflow Bayesian Network is depicted in figure 9. The Air Flow clustering shows that both mechanical ventilation variables and airflow path variables must be considered. Thus, the current airflow DBN estimates the Air Change Rate (NetFlow in PL3 – *NFlPL3*) in the platform and the Fan Energetic Consumption (for 2 Tunnel Fan and 1 station fan – *PElTFa1, PElTFa2, PElSFa1*) at the current time *t*. The estimation is carried out on the basis of the external weather conditions (*WiDMet, WiSMet, TOutMet*) , the temperature in the platform (*TemPL3*), and the Fan Input Frequency (*freTFa1, freTFa1, freSFa1*). The combination of these seven inputs defines the state of the four outputs (*PEiTFa1, PElTFa2, PElSFa3, NFlPL3*).

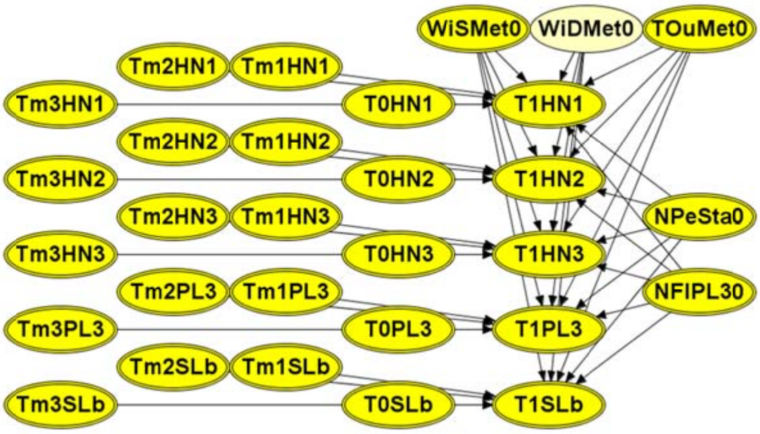

Figure 8 – The thermal dynamic BN

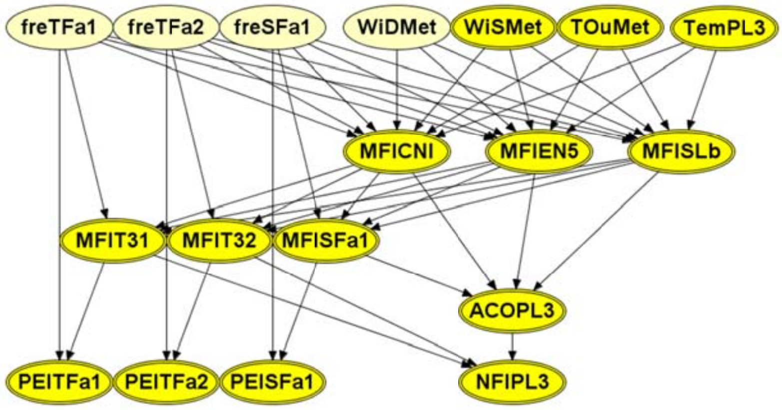

Figure 9 – the Airflow static BN

The BN Learning Phase

The current BNs have been trained on a data-set made of a one year simulation (amounting at 52392 cases) of the Modelica model, run with a time step of 600s, considering weather retrieved from the DOE-US weather file and fan inputs derived by the actual schedule of the pilot station. The resulting data set was split in two parts, the assessment dataset (with 13098 cases, about 25% of the data) and the training data set (with 39294 cases, about 75% of the data).

The Prediction Process

When the monitoring network will be deployed and integrated into the control system, the actual state will be retrieved in real time from the measured value obtained by the sensors. The BN models can then predict the state of the station one hour later (*t*+1) on the basis of the actual state (*t*) and of previous recorded states (*t*-1, *t*-2, *t*-3). If the prediction requested by the controller lasts more than 1 hour, an iterative prediction process with one hour time step is employed.

BN Preliminary Assessment

A preliminary assessment of the Bayesian Models was performed by evaluating the mean error of the prediction. The *error relative to a typical value [%] (TypValErr)* is computed as the mean value of the absolute error (Res_{BN} - Res_{WBN}) with respect to a typical nominal value (*TypVal*) calculated as the mean of the value set. The following equation was used:

$$TypValErr = \frac{avg(|Res_{BN} - Res_{WBN}|)}{TypVal} \text{ [\%]}$$

The particular choice of the performance index was necessary because the range of some variables is quite large (mostly order of thousands), therefore high percentages in low absolute values are not relevant to the aim of the energy saving estimation. The typical value TypValErr was computed as the mean absolute value of a data set composed by 13248 cases (3 months).An automatic procedure was implemented using the HUGIN API Active X Server for Visual Basic (HUGIN Expert A/S, 2012). The developed script instantiates the Bayesian Network, propagates evidences for each record of the data set and returns the estimated values and the related variances. Then the error, the relative error, and the standard deviation (*StDev*) are computed. The average values among the errors of the whole set are reported in Table 1 for the two BNs. The mean percentage errors are between 2-7% for the main output variables, that is, considering we are at a preliminary stage of the process, an appreciable result.

Table 1 - Performance Data about Thermal and Airflow BNs

THERMAL	T1 PL3	T1 HN3	T1 HN2	T1 HN1	T1 SLB
TypValEr	5.92	4.84	3.93	2.19	5.52
TypVal	22.0	19.1	22.0	17.3	21.3
StDev	2.16	1.66	1.40	0.72	1.91

AIRLFOW	PEL TFA1	PEL TFA2	PEL SFA1	NFL PL3
TypValEr	5.85	6.81	3.44	5.65
TypVal	5920	6178	3999	22.35
StDev	2758	2958	1670	3.98

CONCLUSION

This paper described the approach used in the model engineering of the SEAM4US EU research project, concerned with the optimal control of the *Passeig De Graçia* metro station systems in Barcelona. The paper detailed the statistical model reduction methodology adopted and discussed the structure and the performances of the resulting Bayesian Networks models. The preliminary assessment reported that the first release of the hardly reduced Bayesian Network models introduce an average error of about 5% with respect to the Modelica model simulation results, allowing on the other side uncertainty management, model inversion and adaptivity. In next months the first release will be improved, working on the optimization of the Bayesian Models either in term of the model structure and variable domain discretization. The overall structure will be completed introducing the pollutant representation, and will be calibrated with measured data as soon as data from the sensor network will be available.

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