Environmental Modeling for the Optimal Energy Control of Subway Stations

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Purpose Underground transportation systems are big energy consumers and have a significant impact on energy consumption at regional level. One third of the networks' energy is required for operating the subsystems of metro stations and surroundings, such as ventilation, vertical transportation and lightning. Although a relatively small percentage of energy can be saved with optimal management of these subsystems, in absolute terms this means large energy savings are obtained. Furthermore, optimal management is a big opportunity for energy efficiency since it involves much smaller investments than those usually applied to transportation by providing new ways for sustainable energy saving solutions. In this perspective, the EU-funded R&D project SEAM4US (Sustainable Energy Management for Underground Stations) is aimed at defining a technological and methodological framework for optimized energy management in public underground spaces, which will be applied to the dynamic control of the energy consumption in Barcelona Passeig de Gracia subway station. **Method** The development of a new class of predictive control logics, behaving consistently in changing environments is at the core of the optimal energy management approach and it is one of the main objectives of this research. This class of control systems is based on advanced environmental models, directly coupled with an environment monitoring sensor network, that is capable of interpreting the sensed data (both indoor and environmental) and of forecasting future states. In order to achieve the necessary level of robustness these models must be able to learn from previous states so they can adapt to the varying environment. The development of this class of environmental models for large underground environments like subway stations involves the elaboration and the integration of different simulation models concerning natural and forced ventilation, passenger movement, lighting systems, and their integration in a unique formals statistical framework, which is able to manage the uncertainty affecting the sensed data and to learn from the data flow. **Results & Discussion** We will outline the methodological approach to the development of the Passeig de Gracia environmental models for the optimal control of its energy consumption. The adopted hybrid modeling solutions, integrating different classes of simulation means in a unique Bayesian framework4, and a preliminary architecture of the overall control system will be presented.

Keywords*: information technology, management and social issues, realities or application systems, energy efficiency*

INTRODUCTION

Control systems applied to public underground environments, like subway stations, have been traditionally based on suboptimal homeostatic short-term feed-back mechanisms which are applied singularly to each equipment type. Recently, the availability of pervasive sensor networks, allows us to accurately monitor dynamics of the indoor environment and to implement complex anticipatory optimal control policies[1]. The implementation of optimal control policies 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[2].

The objective of the SEAM4US research is the development of an advanced control system for the "Passeig de Gracia – Line 3" (PdG-L3) subway station in Barcelona capable of setting up the internal environments opportunistically, in the optimal way, on the basis of forecasts regarding the external environment, according to energy efficiency, comfort and regulation requirements. This application domain raises a number of issues which make the development of a station's integrated model a challenging engineering task.

Application domain

First of all, the integration of dynamics and scales at different levels, both in time and space domain. In fact modelling environmental processes that are time-continuous (weather, building physics) and typical events of a subway station (train arrival, people activities) into a single framework is quite complex[3]. Furthermore, the analysis of occurring environmental dynamics often requires dimensional scales moving from the decimetres of a fan vent to the thousands of meters of urban canyons.

Second, different processes characterizing subway station dynamics have different natures. Discrete time events, quite random processes such as passenger flows, multi-physics involving thermal, airflow and pollutants, stochastic processes such as the weather should need very different type of models. Their integration in a unique model requires the adoption of a rather articulated modelling approach, in order to study each process with the most effective computational tool available, and to subsequently use a very flexible modelling mechanism to integrate each single model in the overall framework[3].

These models must also be capable to integrate advanced control processes, in terms of sensor-actuator networks and control logics. This is far from usual, as common building simulation environments are mainly procedural and offer only quite basic control scenarios[4].

Furthermore, most of the data defining models' boundary conditions is affected by uncertainty to some degree. Therefore, the models should be capable of propagating this uncertainty throughout the computational chain, in order to support the decision maker with certainty factors qualifying the estimated performances[5].

A final noteworthy aspect concerns system adaptivity. As the model supports management decisions taken by the human controller, the proposed scenario must reflect changing reality as much as possible. To this objective, the models must be capable of improving their performance by adapting their behaviour on the basis of the measured environmental data[6].

CONTROL FRAMEWORK

Subway stations are nonlinear, multivariable non-stationary, **stochastic** and constrained processes even with hybrid dynamics (with mixed continuous, discrete, on-off variables). Despite the complexity of the process and interested domain, the control objective in the SEAM4US research is clear: minimize power consumption. Therefore, in order to maximize its efficiency, the control system needs to have some features.

First of all, the control policy has to be **optimal**, in the sense that it attempts to find the values of a vector of design parameters that yield optimal system performance, subject to some architectural and comfort constraints. The system performance can be measured by a so-called cost function[7].

The identification of control **constraints** is a challenging and key step: it could mean also considering a hierarchy of constraints and control functions. In fact, the economic operating point of a typical process unit often lies at the intersection of constraints[8], and often significant benefits do not come from simply reducing the variations of a controlled variable but dynamic controlling variable set-point to be moved closer to a constraint without violating it[9]. Control constraints derive directly from implicit and explicit system/process requirements, such as comfort (thermal, lighting, acoustic…), health (e.g. air quality) and safety, but from the operational requirements of the equipment also.

Furthermore, the control system has to be **adaptive**. In fact, even if most current techniques for designing control systems are based on a good understanding of the system under study and its environment, in cases like subway stations, the system to be controlled is too complex and the basic physical processes in it are not fully understood. Thus, control design techniques need to be augmented with an identification technique aimed at obtaining a progressively better understanding of the plant to be controlled[10]. Adaptive control is a technique of applying some system identification technique to obtain a model of the process and its environment from input-output experiments and using this model to design a controller. The parameters of the controller are adjusted during the operation of the system as the amount of data available increases through on-line learning.

Finally, **predictive** control is necessary for achieving high energy efficiencies: prediction gives the capability of taking soft control actions in advance, thus, saving energy. Predictive control is 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[11,12] .

All these control features suit perfectly but require the development of integrated models capable of:

- achieving adaptation feature by recursive online identification (or tuning) of process model,
- fully exploiting stochastic models by including both predicted values and uncertainties in the cost function formulation, thus modulating the reactivity of the controller based on the reliability of the obtained predictions,
- predicting the near future behaviour of the controlled environment under specific conditions.

The SEAM4US approach adopts Dynamic Bayesian Networks (DBN) [13]which provide native uncertainty management, machine learning capabilities and, consequently, offer a good basis for adaptivity and decision support.

MODELLING FRAMEWORK

In this perspective, a hybrid modelling framework was defined, aimed at integrating different types of models in an overall Bayesian model in order to efficiently support control logics.

Operationally, different types of models are needed:

- a set of **predictive models** that can represent the stochastic variables such as weather. They also have been modelled through Bayesian Networks;
- the development of the overall DBN requires the definition of a training set and a number of fine tunings that can be accomplished only via a running model which closely resembles both the environmental physics and the control policies. It must be a **Whole Building model** and the SEAM4US approach develops it in the Modelica-Dymola simulation environment;
- various models are needed for the **detailed analysis and modelling of the thermal and airflow processes**. They are aimed at investigating a number of specific conditions that will be modelled coherently in the whole building model, through boundary conditions and specific components. They have been modelled through Finite Element Method (FEM) multi-physics models.

This section briefly presents the models developed so far and the structure of the preliminary Bayesian network that will support the controller. All models presented are a first version and need to be validated through experimental data in the following months.

Weather Predictive Models

The prediction of wind speed and direction are provided to both the airflow and temperature networks by the weather model. The weather model is a probabilistic Bayesian model, shaped as a fourth order Markov chain. Three chains representing air temperature, wind speed and direction were implemented as shown in Fig. 1.

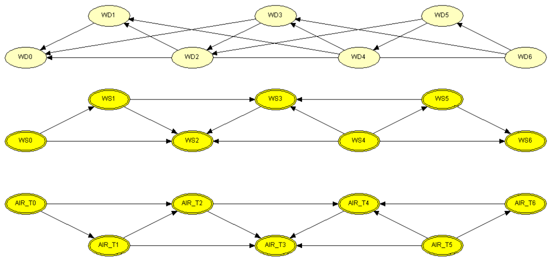

Fig.1. Weather Prediction Model

The data provided by the Barcelona weather files were used to initially define the structure and the preliminary network conditional probability tables. The analysis led to a second order Markov chain for air temperature and wind speed and to a third order Markov chain for wind direction. Further refinements will be performed on the basis of the forecasting data provided by on-line weather services such as (WWO, 2012[14]).

Whole Building Models

The Whole Building Model is fundamental in the overall model engineering process because it provides support to the development of the stochastic model through four main points:

- the definition of the pre-training set used to learn the conditional probability tables of the Bayesian Network;
- the integration of the devices' operational constraints in the forecasting process;
- the definition of the optimal fading rate of the Bayesian Network learning algorithm which optimizes the adaptive behaviour;
- the overall assessment of the stochastic system before its deployment.

Although, as already said, it cannot be developed efficiently in the common building simulation environments, as they do not support features such as advanced control integration, multi-physics in many cases and the integration of specific components and/or boundary conditions. Specifically, for modelling the "Passeig de Gracia (PdG) - Line 3" it is necessary to insert specific boundary conditions for modelling the terminal sections of tunnels and corridors linking to other stations (station link in Fig. 2). At these boundaries, specific conditions in terms of Heat Flow, air flow and Mass Transfer (water and pollutants) have to be assigned in order to model the actual dynamics occurring.

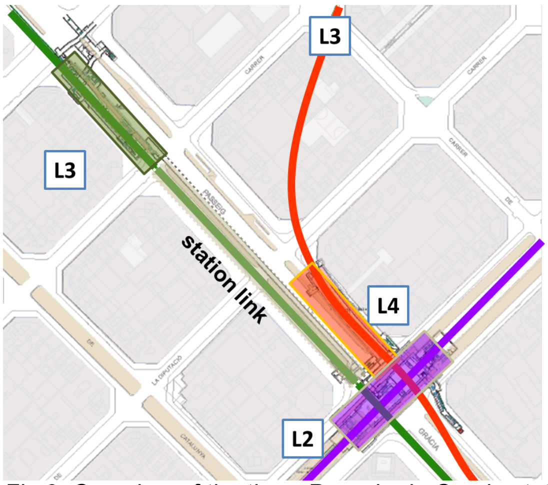

Fig.2. Overview of the three Passeig de Gracia stations, belonging to Line 2, Line 3 and Line 4.

As common simulation software do not provide these key representational features, the Modelica framework, with the Buildings library in the current release[15] and the Dymola© environment were chosen as the SEAM4US development platform.

In the current development state, the implemented physics are heat transfer and airflow. Lighting, passenger flow and trains will be implemented in future releases. The Modelica station model (Fig. 3) was built using the room model of the Buildings library customized for underground spaces (e.g. windows

have been deleted) to reduce the number of variables and improve efficiency, making the large station model manageable.
A number of further customizations were required in order to match the particular equipment present in the station (i.e. fan coils models, lighting models, etc.) and, most importantly, to link their behaviour with actual energy consumption.

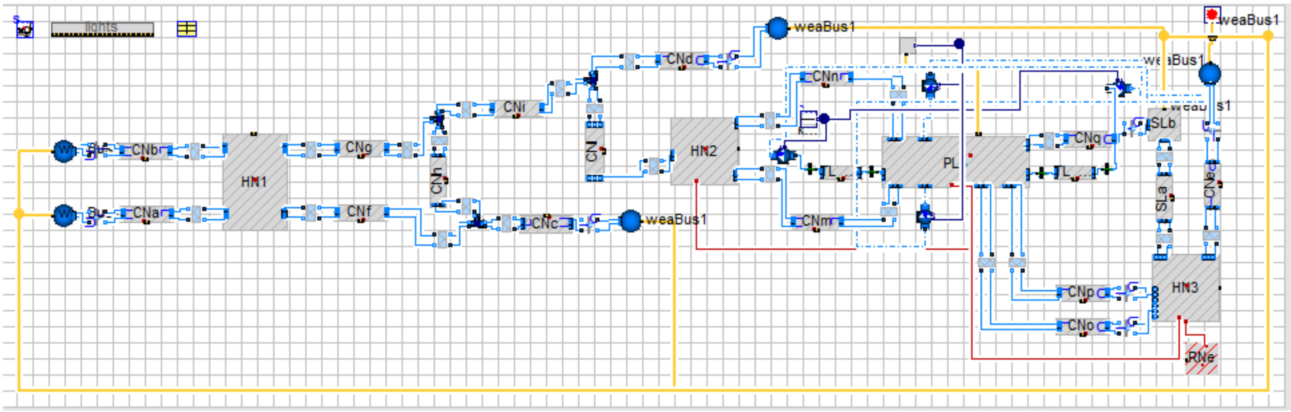

Fig.3. The top level blocks of the "Passeig De Gracia" subway station Modelica model. Each top level block corresponds either to a main ambient or to a connection.

The data derived from the CFD scenarios were used for modelling the airflow in a number of pilot station boundaries such as lengthy pedestrian corridors leading to other stations (station link) and station entrances. In particular, Wind Pressure Coefficients for each entrance, were specifically computed for our case since, literature[16] provides values and formulas for calculating the wind factor for low rise buildings which cannot be applied in this case.
An in situ survey is, of course, required in order to validate data obtained from CFD models. However, this approach allows estimating the overall thermal-fluid dynamics occurring in the pilot station before the deployment of the sensor network.

Boundary and Specific Conditions through FEM Models

The PdG whole building model contains a number of specific boundary conditions and specific spatial components that were modelled using data derived from FEM models. All FEM models developed represent airflows, using Computational Fluid Dynamics (CFD) methods and some of them combine it with heat transfer and transport of diluted species.
Literature concerning underground environments CFD FEM modelling is not much extended. Many studies are design-oriented, evaluating the effects of specific technological solutions[17] or focused on modelling dynamics occurring in case of fire[18]. Other studies are more oriented on discussing a methodology for an effective CFD modelling of subway stations. As usually, they are large volume, some simplifications have to be adopted. Yuan[19] reports that simplification of the airflow to steady process and presumption of the transient velocity to the time-averaged velocity are applicable to simulate the distribution of temperature and air velocity of subway platform in the pulling-in cycle.
Two types of FEM models were developed so far.

CFD models for Wind Pressure Coefficients

Whole Building Models use Wind Pressure Coefficients for Computing airflows entering in the building (Fig. 5). An outdoor urban canyon model, encompassing the eight city blocks surrounding the station entrances, was developed to determine the pressure and velocity maps at the station entrances for each main wind reported in the Barcelona weather file. The model contains both the outdoor blocks and the underground environments (Fig. 4).

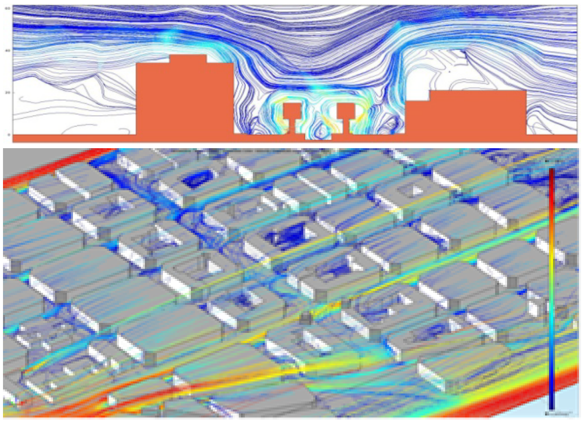
Fig.4. Typical streamline map resulting from an urban canyon simulation of the city blocks

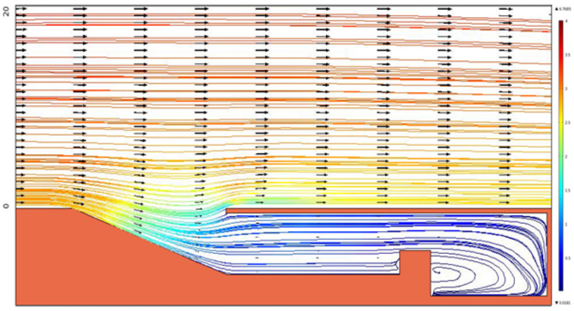

Fig.5. Section view of streamlines in an entrance

Critical parameters, like dimensions of the computational domain, have been determined on the basis of the literature[20]. In any case, sensitivity analysis was carried out concerning the presence of tall trees, balconies and recesses in the building facades in order to determine the right detail level in terms of the geometric model. The simulation was carried out with COMSOL Multi-physics 4.2, 3D steady state analysis[21], with a mesh size ranging from 2.5m to 16.7m. In the end, 81 scenarios, distinguished for wind direction and speed at 200m altitude, were defined.

FEM models for Specific Spaces

A number of detailed FEM model for evaluating the airflow-thermal behaviour of specific spaces are needed, for instance for coherently modelling alternative corridor-spaces that in the nodal perspective of whole building software could be equivalent, but are not, in fact, because of their spatial features (Fig. 6).

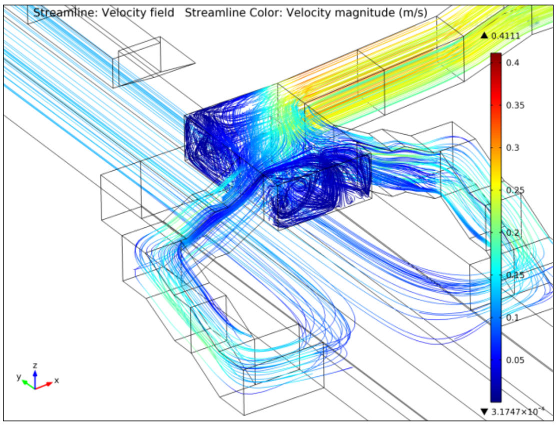

Fig.6. Example of spatial configuration where the presence of alternative paths needs to be investigated through FEM analysis in order to be modelled coherently with the nodal approach.

In order to have more detailed airflow boundary conditions for the specific space models, a further set of 81 scenarios for a more detailed analysis of the overall indoor environment, with a mesh ranging from 0.35m to 3.26m was developed. This more detailed indoor analysis also integrated the boundary conditions imposed on the ventilation shafts by the two fan coils pumping air inside the station at a speed of 60000m3/h and the ones imposed by the tunnel fan coils extracting air at a speed of 90000m3/h.

The development of the specific spatial portion models is on-going. They combine heat transfer, CFD and transport of diluted spaces.

PASSEIG DE GRACIA-LINE 3 BAYESIAN MODEL

The last model engineering stage consisted in the development of the PdG-L3 station's Dynamic Bayesian Network model. The development of the Dynamic Bayesian Network, consists in three phases:

1. definition of the network topology; both static and dynamic (usually called structural learning),
2. preparation of the training set and the learning of the conditional probability tables,
3. final assessment of the network using the LPM as the reference before deployment, in a model-in-the-loop architecture.

The sampling time chosen was 30 minutes because of actual fan coils control time constant, which is about one hour. The training set for the network was obtained by running the Whole Building Model for one week. Assuming 30min sampling intervals, in this preliminary release, airflow dynamics was considered nearly instantaneous, since any pressure impulse from the outside is capable of propagating inside and is exhausted within one sampling interval. Hence, a simple static Bayesian Network was used to represent airflow (Fig. 7). The static network topology was directly derived from the station layout, and it completely reflects the sensor network topology. In other words, each DBN node corresponds to a sensor and the links reflect the physical connection among the indoor spaces. Three further nodes were added representing environmental conditions: outdoor air temperature, wind speed and wind direction (white nodes). The links between the indoor air temperature in each hall and the correspondent airflow capture the buoyancy phenomenon, while the links among the connections and the halls reflects airflow induced by the dynamic pressure gradients.

The yellow node (PL3_NET) accounts for the net flow passing through the platform and it was used for control strategies. Grey nodes refer to forced ventilation directly on the platform (PL3_F) and from the tunnels (TL3_F). In order to estimate air temperature inside the station, given that the station envelope time constants exceed six hours, the envelope's past thermal states must be taken into account (orange nodes in Fig. 7(b)). Figure 8 shows the Bayesian Network for estimating indoor air temperature in the station halls and in the platform. The network has been shaped and has been learned from a training set produced by the LPM.

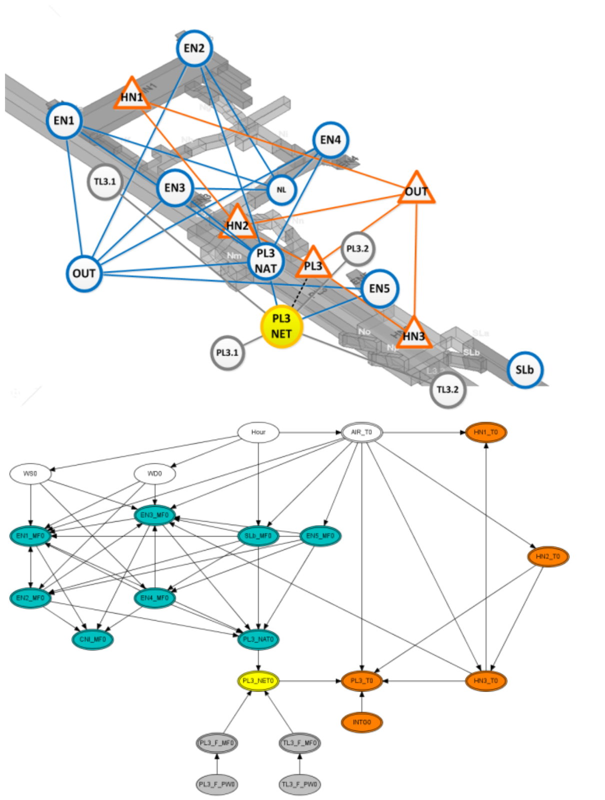

Fig.7. Airflow Static Network (a) the Bayesian Network structure mapped on the station model,(b) the network portion related to the platform

The temperature nodes chosen for estimation (e.g. HN1_T4, HN2_T4, HN3_T4, PL3_T4) depend on the corresponding temperatures measured during the previous four hours (i.e. HN1_T4 depends on HN1_T0, HN1_T1, HN1_T2, HN1_T3) and from the outside temperature wind speed and direction, WT, WS, WD respectively.

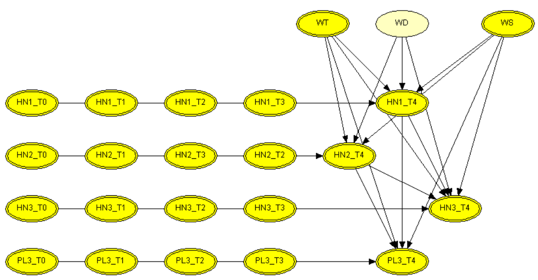

Fig.8. Indoor Temperature Dynamic Network

This network is capable of predicting temperature with an average error of 0.3 and a standard deviation of 0.32, by selecting the expected value of the platform output distribution.

These networks will be integrated into other networks modelling other physics and events of the Passeig de Gracia station.

Control Strategy

From the controller point of view, *PdG-L3* is represented as a block with inputs and outputs (Fig. 9). Inputs ( ) to the system are the variables that can be manipulated: Fans (frequency), Lights (level) and Signalling (for Passenger Paths). The outputs ( ) are the Power consumption and indicators for Comfort and Health States 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 ( ), 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, when possible, together with a *Disturbance Model*. The internal state dynamics (is function of the actual state ( ), inputs, disturbances and time ( ), thus it is a non-stationary system.

The *PdG-L3 Bayesian Model*, that also include a state estimator, is used as model for guiding the predictive controller. The *Disturbance Model* is composed by different types of models (e.g. schedules for trains, predictive model for weather), and so far, some of them are still under development by other research groups, such as the users/passengers model. By connecting these continuous-time models to a discrete-time controller which samples the signals, the preliminary architecture of the SEAM4US control system can be represented at each time step as in Figure 10.

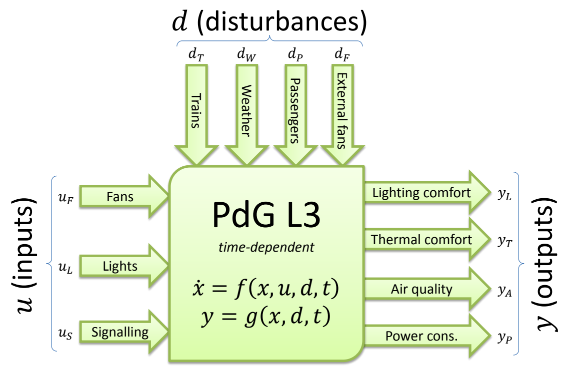

Fig.9. Block diagram representation of PdG-L3 station.

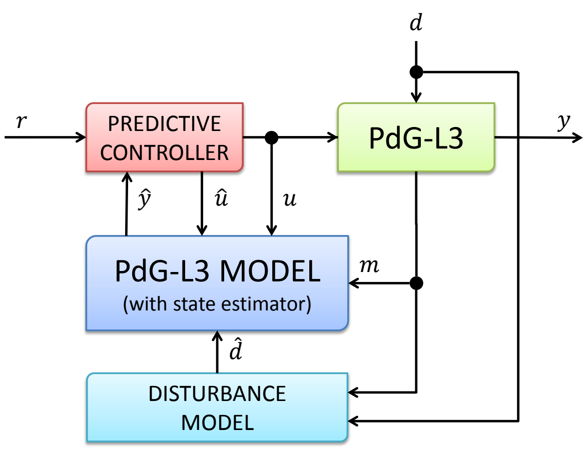

Fig.10. Architecture of the model based adaptive predictive control system.

At each control step, the state estimator internal to the *PdG-L3 Model* receives data about the given input ( ) and measured output ( ) (through the sensory system) from *PdG-L3* station and computes an estimate for each significant state variable (. The *PdG-L3 Model* uses them, together with measured values, candidate input sequence (coming from the *Predictive Controller* and predicted future disturbances (obtained from the *Disturbance Model* for computing the predicted output sequence (and gives it back to the *Predictive Controller*. The optimal control policy ( ) is the sequence that minimizes a given performance index subject to a set of given operative constraints. Once the optimization problem has been solved, the first element of the optimal sequence (is applied as control action. The overall procedure is repeated at each step thus closing the control loop.

CONCLUSIONS

This paper reports the modelling methodology and control architecture being developed for the optimal energy control of the "Passeig de Gracia – Line 3" subway station in Barcelona, in the ambit of the EU funded SEAM4US project. The paper outlines the main issues faced during the modelling of the extremely complex environment, and shows how large scale civil engineering applications involve a number of stringent requirements that cannot be satisfied if not with a complex model engineering approach. The paper gives an overview of the hybrid modelling solution involving probabilistic Bayesian modelling in conjunction with FEM CFD and Whole Building and their role in the overall modelling process and in the control framework. The project's current development stage leaves a number of issues open, such as passenger flow modelling and integration and assessment after deployment on the basis of measured data.

ACKNOWLEDGMENTS

This research is funded by the European Commission through the 7th Framework Programme: Project SEAM4US, Grant agreement no. 285408.

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