HYBRID MODELING FOR ENERGY SAVING IN SUBWAY STATIONS

Roberta Ansuini¹, Roberto Larghetti¹, Massimo Vaccarini¹, Alessandro Carbonari¹, Alberto Giretti¹, Sara Ruffini¹, Hongliang Guo², and Sian Lun Lau³

¹Department of Civil and Building Engineering and Architecture, Università Politecnica delle Marche, Ancona, Italy
²Almende, B.V., Rotterdam, the Netherlands
³Chair for Communication Technology (ComTec), University of Kassel, Germany

ABSTRACT
The development of a new class of energy control systems for underground public environments, is one of the main objectives of the EU-funded R&D project called Sustainable Energy Management for Underground Stations (SEAM4US). It aims at developing a fully featured pilot system for the dynamic control of energy consumption in Barcelona’s “Passeig de Gracia” subway station. This paper will outline the model engineering of the integrated environmental models of the subway station’s Energy Control System, which involves the development of natural and forced ventilation, thermal models, and their integration into a Dynamic Bayesian Network.

INTRODUCTION
Underground transportation systems are significant energy consumers, hence even a small fraction of non-traction energy savings in underground transportation scenarios, will produce a relevant energy saving figure in absolute terms (Anderson et al., 2009). A metro station is a very complex system. It involves, among others, multi-storey underground spaces having multifaceted thermal behaviour, e.g., intricate air exchange dynamics with the outside, heat conduction with the surrounding soil and high variable internal gains due to travelling passengers and trains. Furthermore, a metro station is usually serviced by various equipment involving cooling, ventilation, safety and security, lighting, vertical transportation and horizontal passenger transfer, gates and selling machines, information and auxiliary systems. Control systems applied to public underground environments, like metro 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 (Mahdavi et al., 2009). The implementation of these 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 (Wetter, 2009).

The objective of the SEAM4US research is the development of an advanced control system for the “Passeig De Gracia” metro 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. In the following paragraphs, we will briefly outline the difficulties.

Multiple time scales and large spatial dimensions. Processes occurring in subway stations, such as the arrival and departure of trains, passenger transit, commercial activities, surface traffic, the weather, buildings’ physics, have their own dynamics and time scale. This makes modelling a quite complex and delicate task especially when discrete time models have to be integrated into a single framework (Wetter et al., 2006). Furthermore, a typical metro station is a large environment, with linear dimensions amounting to hundreds of meters, and the modelling of the environmental conditions requires analysis at the urban blocks scale, which means dimensions up to thousands of meters. It is well known that at this dimensional scale fluid dynamics finite element models (FEM) are pushed to their limits (Franke et al., 2004).

Multi-physics and control logics integration. Different processes characterizing metro station dynamics have different natures. Discrete time process, such as train arrival, multi-physics involving thermal airflow and pollutants, stochastic processes such as the weather which, in addition to the integration of sensor-actuator networks and control logics, 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 (Wetter et al., 2006).

Decision Support. The management of public environments is subject to severe operational and safety constraints. Most of the time, the management
system operates in support of human decision makers. This kind of operation requires that the model can be inverted.

**Uncertainty.** Most of the data defining model’s 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 (Russel et al., 2009).

**Adaptivity.** 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 (Kinshuk et al., 2009).

The general hybrid architecture of the SEAM4US control system is shown in Figure 1. In control theory hybrid systems are generally understood as systems that intermix discrete and continuous components (Antsaklis et al., 1995) (Curtis, 1996). The discrete part of the system makes the decision for the whole system to switch to another set of control rules if conditions are favourable. As a result, the continuous part works according to the new rules. In building control, the discrete part of the system is generally a model driven decision maker, itself controlled by a set of rules which are based on the predictive capability of the model (Mahdavi, 2006).

The problem of defining the initial model is a critical one in the SEAM4US modelling framework because the sensor network will be designed on the basis of the insights provided by the preliminary modelling phase. Therefore, the main goal of the preliminary modelling phase is granting the greatest possible accuracy. Section 3 will outline the strategy adopted for granting modelling accuracy of the airflow through Computational Fluid Dynamic (CFD) FEM modelling, and section 4 will discuss the main modelling issues faced concerning the sensor network design. Further issues concern the development of the stochastic model. The main problems faced pertained to the definition of the case set for pre-training the stochastic model, and the preliminary validation of the stochastic model before deployment. To this aim a specific lumped parameter model, based on the Modelica framework, was developed. This model was used by means of Montecarlo sampling to calculate the pre-training set, and through a model-in-the-loop approach to validate it before deployment. Section 5 outlines the development process of the lumped parameter model (LPM) defined on the basis of the findings of the

**MODEL ENGINEERING FRAMEWORK**

This paper will outline the model engineering of the environmental model of the “Passeig De Gracia” metro station and the main features of the hybrid modelling solution undertaken to fulfil the stringent functional requirements. The SEAM4US model engineering foresees two modelling cycles (Fig. 2), starting from the findings of a preliminary modelling phase, a sensor network will be designed and deployed in the environment. In parallel, a lumped parameters model, including airflow, heat transfer and lighting physics, will be developed and validated as much as possible against standard reference simulation tools. The main role of the lumped parameter model is to provide support for the further development of the stochastic Bayesian Network Model which will be the core of the control system, providing performance forecasting, adaptivity and decision support. Both the lumped parameters and the stochastic models will be fine-tuned as soon as the sensor data is available. Finally, the whole cycle is repeated updating every component.

![Figure 1 The general SEAM4US control architecture](Chang, 1999) used a neural network based hybrid model to control lighting comfort in buildings with promising results. Neural network approach is not well suited to support human decision makers because it is not capable of furnishing certainty factors or explanations to the figures provided, hence providing scarce support to decision making. The SEAM4US approach adopts Dynamic Bayesian Networks (DBN) (Murphy, 1998) which provides native uncertainty management, machine learning capabilities and, consequently, offers a good basis for adaptivity and decision support.

![Figure 2 Phases of one of the two modelling cycles of the SEAM4US environmental model engineering process](image-url)
preliminary CFD analysis and points out the results of the validation which, in this preliminary phase, have been compared to reference E+ results. Finally section 6 details the development of the Dynamic Bayesian Network model.

PRELIMINARY CFD MODELLING

Literature concerning underground environments CFD FEM modelling is not much extended. Many studies are design-oriented, evaluating the effects of specific technological solutions (Ke et al., 2002) (Yang et al., 2011) or focused on modelling dynamics occurring in case of fire (Hu et al., 2008). 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 et al., 2007) 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.

The preliminary natural-forced ventilation CFD modelling phase was mainly intended to investigate airflow dynamics in the various spaces of the indoor environments as functions of the outdoor weather.

The evaluation of the underground space’s natural ventilation potential was carried out in order to justify the relevant effort for the advanced fan control system development on this basis. 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. Critical parameters, like dimensions of the computational domain, have been determined on the basis of the literature (Franke et al., 2004). Furthermore, to determine the appropriate geometric detail level, a sensitivity analysis was carried out concerning the presence of tall trees, balconies and recesses in the building facades. To this aim, an on site measurement campaign was conducted using a weather station placed on top of one of the entrances. Subsequently, a sample of eight simulations were carried out combining the wind speeds and directions which occurred during the on-site survey, using a detailed block model representing roof geometries, trees, cars and people in proximity of the station entrances (Fig. 3). Once completed, the simulation results for the simple and detailed models were compared, showing that the detailed model produced much more reliable results; wind speed error, at the entrances, was lowered on the average, from 54% to 17%. The simulations were carried out by means of COMSOL Multi-physics 4.2, 3D steady state analysis (Comsol, 2011), using a mesh size ranging from 2.5m to 16.7m. Following the sensitivity analysis, 81 scenarios were defined combining the average speeds of the first 10 intervals in the Beaufort scale with the 8 wind directions, plus one high speed present in the historical series. The 81 scenarios provided the estimated boundary conditions at the station entrances that allowed a more detailed analysis set of the indoor environment, with a mesh ranging from 0.35m to 3.26m. 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 the speed of 60000m³/h and the ones imposed by the tunnel fan coils extracting air at the speed of 90000m³/h. The definition of these boundary conditions required specific CFD modelling of the fan and ventilation ducts. Finally, the train air inflow-outflow induced at arrival-departure time (referred to as piston effect) was modelled as further boundary conditions according to (Kim et al., 2007), and combined with the other scenarios, extending the whole set of scenarios to 243 (i.e. 81 scenarios for two train directions plus 81 scenarios without trains). A typical streamline map concerning one of the scenarios is depicted in Fig. 4.

The evaluation of the urban canyon simulation of the city blocks surrounding “Passeig de Gracia”.

In the end, the evaluation of the flow in the “Passeig De Gracia” metro station pointed out that winds...
occurs in Barcelona 7421 hours per year (85%), on the average and that, even in the worst condition, natural ventilation contribution is relevant and should be used to reduce forced ventilation.

Furthermore, the streamline scenario showed that in a typical year, 2932 hours out of 8760, the forced ventilation system, as it has been designed, works in opposition to natural ventilation, allowing, in principle, for considerable gains in the efficiency of the forced ventilation system under adaptive control.

Further development of the preliminary CFD analysis phase concerned the determination of the distribution of pollutants in the various scenarios. The results of the steady state analysis was used to set up a dynamic mass transfer model to evaluate the zones having the major concentration of pollutants. Literature concerning contaminants in underground spaces are mainly focused on CO₂, PM₂.5 and PM₁₀. Much experimental data on subway stations worldwide is available (Fridell et al., 2010; Cheng et al., 2010; Kim et al., 2010) concerning the nature of particles and average levels. As these are transit spaces, the measurement of the average exposure of passenger and workers requires specific procedures and equipment (Nieuwenhuijsen et al., 2007). Few are the works which consider modelling CO₂ concentration on subways stations (Liu et al., 2009).

On this basis, we approached the modelling of contaminant concentration, in this preliminary phase, using standard literature data (Salma et al., 2007) combined with available measured data (EEA, 2011), with the only purpose to calculate the distribution patterns of the contaminants and to identify potential critical zones. The qualitative analysis carried out pointed out that there are two types of high concentration zones in terms of contaminants, one zone regards low airflow which accumulates pollutants, and the other is in proximity to the source and subject to high flow rates, so that large amounts of contaminants are continuously brought into the station.

![Figure 5 Yearly average air change per hour in the pilot station’s main spaces](image)

Finally, the preliminary CFD analysis led to the estimation of the natural ventilation potentials in each of the underground station’s indoor spaces. Figure 5 reports the histogram of the yearly average air change per hour in the main spaces of the pilot station, illustrating how even in the worse conditions the flows are sufficient enough to presuppose exploiting them through adaptive control.

**SENSOR NETWORK DESIGN**

Identifying the most effective sensor arrangement (i.e. number, type and position) capable of capturing all the relevant station dynamics is of paramount importance for the success of the modelling process and, later, for the closed-loop control performances. Therefore, particular attention was devoted to the preliminary environmental sensor network design. The streamline and contaminant maps were used to qualitatively evaluate turbulence zones and to provide a general initial insight regarding airflow speed, pressure and contaminant sensor placement and sizing (i.e. accuracy, ranges, etc.). In particular, a specific study was conducted for each measurement point implemented, in order to correlate the point measure provided by the sensor with the spatial average behaviour in each related spatial section or volume. A 3D measurement point grid was defined for each room and the correlation between the simulated measurement data among each couple of points was calculated (Fig. 6). The same process was applied to the 2D sections. In fact, points having a high correlation factor provide the same kind of data and, therefore, they can be merged in order to choose the one having minor impact on passenger movement as the actual measurement point. This strategy allowed the selection of the measurement points while minimizing their number and nonetheless maintaining the necessary accuracy.

Finally, since the sensor arrangement was to be totally reflected in the Bayesian Network model, the overall sensor network topology was double checked in order to verify that the chosen topology would not induce high numbers of links converging on a single node, causing unmanageable complexity in the DBN.

**LUMPED PARAMETERS INTEGRATED MODEL**

The second major step in the SEAM4US model engineering involves the development of the station’s multi-physics lumped parameter model (LPM). This vast effort is necessary for a number of reasons. First of all, although the station’s CFD modelling provides a lot of qualitative insights regarding the behaviour of the station’s airflow and pollutants under different environmental conditions, it doesn’t offer the necessary flexibility for integration with other models of different nature and for being included in complex control algorithms. Therefore, a new modelling paradigm is required; one providing a higher level of abstraction and modularisation in order to manage the domain complexities. Secondly, the development of the 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. A challenging set of requirements drives the Lumped Parameter Modelling framework.

A number of further customisations 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. Concerning the airflow network, a horizontal opening component model was introduced and a further customisation of the outside-Cp component, involving the calculation of the wind factors for the station’s recessed entrances, was defined. This aspect is worthy of further discussion because it shows how the combined hybrid CFD-LPM approach provides complementary information.

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 (Swami et al., 1988) 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. It is noteworthy that the station link boundary condition, easily inserted in the Modelica LPM, cannot be inserted in any of the EnergyPlus models. Therefore, only partial validation of the customised components was possible within the Energy Plus simulation environments, Modelica’s expressiveness is, in fact, much higher. Consequently, a number of partial models for underground spaces were developed in both of the simulation environments and their performance was compared. For example, Figure 8 shows the comparison among mean air temperatures during a typical winter week (February, 1-7) for three, adjacent, underground zones with internal gains due to 0.2 person/m². An in depth validation of the Modelica LPM will be conducted with experimental data in the upcoming months.

In particular, a number of key representational features are required such as knowledge encapsulation, topological interconnection, hierarchical modelling, and object orientation, as well as the availability of certified libraries that could grant both for the necessary expressiveness and flexibility and moderate the development effort. The Modelica framework, with the Buildings library in the current release (Wetter, 2011) 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. 7) was built using the room model of the Buildings library customised for underground spaces (e.g. windows have been deleted) to reduce the number of variables and improve efficiency, making the large station model manageable.

![Figure 6 Regression line between two highly correlated points of the measurement grid.](image)

![Figure 7 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.](image)
THE DYNAMIC BAYESIAN NETWORK

The last stage of the model engineering consisted in the development of the station’s Dynamic Bayesian Network model. This last development was necessary for two main reasons. First of all, DBN natively supports adaptivity, uncertainty management and model inversion, which cannot be easily implemented using a standard LPM approach. Furthermore, the LPM cannot be easily embedded into the SEAM4US control system due to the fact that, apart from the issues related to the estimation of the initial state, the very large number of sensors required to keep the model updated would have caused an extremely large, expensive and unmanageable sensor network. On the other hand, the LPM 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.

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.

Three different networks were developed, concerning weather (Fig. 12), airflow (Fig. 10) and indoor temperature dynamic (Fig. 11). 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 three networks was obtained by running the LPM for one week.

Assuming 30min sampling interval, 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. 9). 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 node refers 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. 9(b)). Figure 10 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. 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.

**Figure 10 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. The estimated temperatures are then used as inputs to the station airflow network allowing for the estimation of air exchange rates. The prediction of wind speed and direction are provided to both airflow and temperature network by the weather model. The weather model is shaped as a fourth order Markov chain. Three chains representing air temperature, wind speed and direction were implemented as shown in Figure 11.

**Figure 11 Weather Prediction Model**

The data provided by the Barcelona weather files were used to initially define the structure and the preliminary network CTP. 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). The estimation accuracy of these preliminary weather networks is reported in Table1. The results are quite satisfying considering that the model engineering process is only in the first cycle and validation has to be done.

More specifically, the external temperature uncertainty is adequate for managing comfort parameters in transit spaces such as subway stations. Analogously, the uncertainty concerning wind speed and direction are acceptable for the purposes of estimating air exchange potentials on the station platform.

**Table 1**

<table>
<thead>
<tr>
<th>TIME</th>
<th>WIND SPEED m/s</th>
<th>WIND DIRECTION Degrees</th>
<th>AIR TEMP °C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1st Hour</td>
<td>0.55 , 0.58</td>
<td>15.5, 32.3</td>
<td>0.48 , 0.60</td>
</tr>
<tr>
<td>2nd Hour</td>
<td>1.02 , 0.95</td>
<td>24.2, 41.0</td>
<td>0.98 , 1.01</td>
</tr>
<tr>
<td>3rd Hour</td>
<td>1.31 , 1.10</td>
<td>27.3, 42.3</td>
<td>1.34 , 1.19</td>
</tr>
</tbody>
</table>

**CONCLUSIONS**

This paper describes the modelling process of the EU funded SEAM4US project, aimed at energy saving through dynamic control of the Passeig De Gracia subway station in Barcelona. 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 details the hybrid modelling solution involving FEM CFD, lumped parameter in conjunction with stochastic modelling and their role in the overall modelling process and in the run-time phase. 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.

**ACKNOWLEDGEMENT**

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