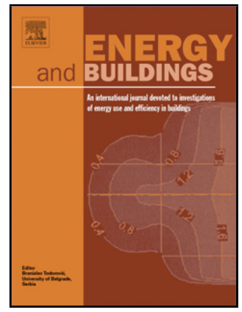
Model predictive energy control of ventilation for underground stations



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Highlights

- An underground station is a very harsh environment but also highly demanding in terms of energy consumption.
- A Model-based Predictive Control algorithm is used together with a permanently installed monitoring platform.
- Predicitons about the future are exploited by a Bayesian prediction model and a weather forecast web service.
- The proposed control architecture is implemented in the Passeig de Gràcia metro station in Barcelona.
- More than 30% of energy savings in the ventilation system, while maintaining the pre-existing comfort levels.

Model Predictive Energy Control of Ventilation for Underground Stations☆

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Abstract

Smart building systems are opening up new markets, nevertheless the implementation of these novel technologies still lacks suitable and proven whole engineering solutions in complex buildings. This paper presents a detailed approach for the ventilation control of an underground space, as an example of application of the developed solution to a very harsh environment but also highly demanding in terms of energy consumption. The underground spaces are characterized by a particular thermal behavior, because of the continuous and huge thermal exchange they have with the outside, via the openings and the ground surrounding the majority of the building. The main objective of the developed methodology is to reduce energy consumption of ventilation control while maintaining acceptable comfort levels: succeeding in achieving this twofold goal in a real station and the generalization of the approach are the most relevant contributions of the paper. The developed solution is based on a Model-based Predictive Control algorithm used together with a proper monitoring platform. The model predictive control is based on a Bayesian environmental prediction model, which works in cooperation with a weather forecast web service, schedule-based predictions about trains and external fans and an occupancy detection system to appraise the real amount of people. The prediction model develops scenarios useful to allow the controller acting in advance in order to adapt the system to the current and future conditions of use, taking profit of the knowledge of the real ventilation demand. Finally, the proposed control architecture is applied to the Passeig de Gràcia metro station in Barcelona as a case study, validating the usefulness of the proposed approach and obtaining more than 30% of energy savings in the ventilation system, while maintaining the pre-existing comfort levels. The saving percentage values estimated by simulation are confirmed by the direct measures continuously taken on site through energy-meters.

Keywords: Energy savings, Energy-efficient buildings, Building climate control, Model predictive control, Underground station

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1. Introduction

1.1. Energy control of buildings

The general objectives of the energy control of buildings, usually given as specifications, are to minimize energy consumption while guaranteeing acceptable comfort and health and safety (H&S) levels [1]. Energy needs can be minimized by using natural sources as much as possible (such as natural ventilation, solar radiation when overground, etc.), by avoiding energy waste (e.g. using sensors and/or user models) and by improving maintenance policies (e.g. suggesting replacement of inefficient components). Comfort can be guaranteed by dynamically accommodating the final user needs regarding lighting (e.g. by using light gradients in order to accommodate human perception), temperature (e.g. by using temperature gradients) and air quality (e.g. by maintaining CO2, PM10, humidity under certain comfort limits) [2]. H&S requirements usually involve the support/integration of fire detection and suppression systems as well as respect for air quality standards (e.g. limiting CO2, PM10, Radon concentrations, etc.).

All these requirements must be satisfied by maintaining the robustness of the control system with respect to uncertainties, noise and component faults or failures. Moreover, the control solution must be sustainable during the whole life-cycle, thus requiring systematization of the control design approach to efficiently integrate the classical building design stages (as happens for the synthesis of industrial controllers), and the possibility to upgrade, downgrade and maintain the hardware without significant intervention.

Commercial Building Energy Management Systems (BEMS) are the current state-of-the-art technology for advanced energy management in buildings. Although different control strategies are used in the wide variety of commercial BEMS, in general demand-driven control strategies are adopted, and often the demand is not measured but simply schedule-based. This approach suffers from the uncertainty that affects the surrounding environment due to weather conditions, internal loads caused by the occupancy dynamics, or external factors such as energy grid dynamics. A more effective control strategy must be considered in order to address the complex domain of building energy control. This need has recently encouraged research efforts for the development of intelligent buildings [3].

A comprehensive review, reflecting the terminology and conceptualizations largely adopted in the control community, has recently been published [4]. Focusing mainly on the controller structure, the control methods for HVAC systems are divided into classical control (P, PI, and PID control), hard control (gain scheduling, nonlinear, robust and optimal control and MPC), soft control (Fuzzy Logic and Neural Network control), hybrid control (fusion of hard and soft control techniques).

Among the hard control approaches, Model-based Predictive Control (MPC) [5, 6] is one of the most promising techniques because of its ability to integrate disturbance rejection, constraint handling, and dynamic control and energy conservation strategies into controller formulation. In fact, for complex constrained multi-variable control problems, MPC has become the accepted standard in the process industries [7]. MPC computes the optimal control policy by minimizing a proper cost function subject to certain constraints on input, output or state variables. Its success is largely due to its unique ability to optimally control either linear or nonlinear MIMO processes by using a predictive model and explicitly considering constraint in its formulation. Explicit consideration of uncertainty is discussed in a number of contributions [8, 9, 10, 11] and can be achieved by using stochastic models and by minimizing the probability of constraint violation. Due to these reasons, it has been successfully implemented in various research on buildings over the last years. A review of the representative studies about MPC can be found in [12], that also exploits the Building Controls Virtual Test Bed (BCVTB) for running a building energy simulation with real-time BEMS data as inputs.

An operational way of classifying MPC methodologies applied to building energy management is provided in [13]. By limiting the MPC conception to cost function minimization using a receding horizon mechanism, a generalization of the overall vision is obtained, which includes, under the same MPC umbrella, modeling technologies based on linear systems theory, as well as on soft computing technologies, and on black and grey-box approaches. Assuming this perspective, the main issues concerning MPC for building energy efficiency can be grouped into three classes:

1. Comfort indexes. An MPC problem is adopted in [14, 15, 16, 17] to minimize energy consumption while maintaining the indoor thermal comfort criterion (PMV) at an adequate level [18, 19]. Simpler yet descriptive comfort indexes have recently been used as a set of linear constraints on the zone temperatures, CO2 concentrations, and relative humidity [14, 15, 20, 21].
2. Models used in predictive control. The models reported in literature can be categorized into three groups: detailed models based on the numerical solution of differential algebraic equations (DAE); simplified DAE and grey box models; black box models. A number of early studies demonstrated the successful design of optimal MPC controllers using detailed DAE models [22, 23], but the identification and validation of these models are often computationally intractable because of the large number of parameters required for tuning and simulations. As shown in [24, 25, 26, 27], the complexity issues affecting the detailed DAE models, have been partially solved by using gray box models where the unknown parameters of a simplified physics are estimated by fitting historical measurements.
3. Control implementation. The implementation of the control actions depends on the problem complexity and on the available computational power. In the literature, two major implementation methods are reported, either computing the control signals in real-time (online), or using look-up tables for accessing off-line pre-computed solutions (offline) [6]. In order to reduce the computation time for the optimal control actions, and enable real-time implementation, offline methods attempt to solve an optimal solution set parameterized over initial states offline [28]. Since, in order to be stored, the optimal solution set needs excessive memory, several approximation methods are proposed to reduce the use of memory in offline methods [29].

1.2. Energy savings for underground stations

Efforts to reduce the energy consumption of public buildings and spaces have recently received increasing attention. Metro operators suffer from the high energy consumption of their facilities. While the lighting, ventilation and vertical transport systems are crucial for the safety and comfort of passengers, they represent the most of the non-traction energy required in underground stations. Hence, as shown in [30], the intelligent control of these subsystems can significantly reduce their energy consumption without impacting the passenger comfort or safety or requiring expensive refurbishment of existing equipment.

Differently from the buildings above ground, the environmental conditions (temperature and humidity) are quite stable in underground spaces and, usually, there is no need for heating in winter but just for cooling in summer. Since no air conditioning plant is usually installed in underground spaces, the air change becomes a key requirement that must be guaranteed by means of forced ventilation that compensates for lacks of natural ventilation. Therefore, in this domain, both the natural and the forced air flows are relevant and produce thermal effects that cannot be neglected. Nevertheless, it has to be remarked that a specific norm about air change in underground spaces has not been drawn up yet.

Underground stations are also characterized by a large number of output variables (temperature, air exchange, CO_2 and PM_{10} concentrations in platform and energy consumption of actuators) but by a small number of input variables (usually just one fan): this reduces the controllability and the possibility to simplify the control task by coupled sub-problems decomposition. The decomposition into simpler (eventually coupled) sub-problems, in fact, is possible when different output variables are mainly affected by different control inputs: since usually the control input is just the speed of the station fan for controlling many output comfort and air quality variables, there is no chance for decomposition. Therefore, the problem is handled with a cost function formed by a weighted sum of conflicting objectives and subject to appropriate constraints, while the control task is faced through an optimization problem.

This severe controllability issue means that a *whole building control strategy*, such as MPC, is much more effective. Energy savings define a clear objective: *minimize energy consumption* in the presence of uncertainties. Thus, uncertainty must be explicitly considered by including *adaptation capabilities* in order to adjust the control strategy to changing conditions. Comfort and H&S requirements define operative constraints that can be either hard or soft: this implies that *constraints must be explicitly considered* in the control strategy.

The complex morphology of the station and the severe security and safety issues make difficult to install a widespread sensor network and some particular measures have to be taken. First of all, the need for cabling must be reduced as much as possible thus simplifying the installation phase. Wireless communication systems must be capable of working in presence of channel failures and must require a reduced maintenance. Finally, for handling unexpected events and faults, the control system must be capable of implementing some safe policy when needed.

Within the recently concluded EU-funded research project SEAM4US (Sustainable Energy mAnageMent for Underground Stations [31]), a system was developed for the intelligent energy management of this type of public underground space, integrating systems for the monitoring of the physical state of the station, passenger flow and energy consumption of all the subsystems, with systems for the control of lights, fans and escalators. The result of this project is a complete prototype for the intelligent energy management of public underground spaces that integrates both existing and new infrastructures, deployed at the metro station Passeig de Gràcia–Line 3 (PdG-Line3) in Barcelona. While the standard approach adopted by the station operator is to drive the devices solely based on a time schedule, SEAM4US tackles the problem in a dynamic way: it uses the information coming from the monitoring network and from the models to decide, via MPC, on the optimal control to be applied at any given time for the ventilation control of the station.

1.3. Contribution of the paper

In this paper, the MPC strategy for the energy control of underground spaces is formulated and developed: the architecture and deployment of the system, its components, and the design principles followed during its development are presented here and formulated as a general approach for controlling the ventilation of underground stations.

The effectiveness of the developed approach, has been validated within the SEMA4US project, where this control architecture was successfully applied to the Passeig de Gràcia metro station in Barcelona. The control objective of SEAM4US was to minimize energy consumption while maintaining the environmental comfort perceived by the occupants. Succeeding in achieving this twofold goal in a real station can be considered as one of the greatest and most innovative contributions of the project. The prediction model was built by training a Bayesian Network (BN), described in the following Section 3.3, with a set of experimental data. Multiple step predictions were obtained by iterative runs of a BN over a fixed prediction horizon. The model predictive control approach allowed the control time horizon to be extended for hours into the future: yet one-hour ahead prediction returned good results in the pilot station. This means that the station not only reacts to current events (number of passengers, weather conditions, current thermal status etc.) but also prepares itself to take the most appropriate action in the near future. In order to develop, test and tune such a complex control system without affecting the real station, a comprehensive simulator of the station was built, as described in Section 3.5. Since it embeds a thermal/airflow model of the station, a control system and disturbance models, it was possible to create the whole control system before having access to the real data and to implement the fine-tuned control algorithm in the real station. The ASHRAE guidelines [32] were adopted in terms of temperature, humidity and pollutants in order to evaluate the soundness of the model calibration regarding the required comfort levels.

This paper begins with a discussion on goal of the controller and the requirements that are imposed by regulations, by the station operator and by the particular environment in which the control system must operate (Section 2). Regulation and commitment requirements are translated into constraints on the process variables. The resulting system architecture is presented in its overall view in Section 3, which also describes in details the sensor network adopted, the monitoring software, the prediction model used by the controller, the disturbance handling and, finally, the control block. Operative requirements enforce specific technological solutions for the adopted actuator/sensor network. In particular, the sensor network must require a reduced cabling need and some safe control strategy must be foreseen in order to allow unexpected events to be handled. The control problem is then formulated in Section 4, in which a real time solution method is also provided. The case study of the EU-funded research project SEAM4US is then presented in Section 5, by detailing the pilot station, the system set-up and the achieved control performance and savings.

1.4. Nomenclature

The notations used in Table 1(a) will be adopted throughout the paper. For the sake of generality, parameters and variables are normalized in the control problem formulation (see Section 4.2) with respect to a proper normalization factor. Denoting the control instant with the integer value $t \in \mathbb{Z}$ and using notation defined in Table 1(a), allows to introduce for a measured variable $\tilde{x}$ a corresponding dimensionless normalized variable x defined as $x \doteq \frac{\tilde{x}(t)}{x^{max}}$. The normalization factors x^{max} for each variable are defined in Table 1(b).

2. Goal and system requirements

Since the control of ventilation is considered here, the main purpose of the control system is to minimize the energy consumption of the controlled fans while maintaining an acceptable comfort level inside the station. The thermal climate parameters, their influence on the occupants and the influence of buildings and systems on these parameters are relatively well-known nowadays and are set down in international standards such as ISO EN 7730 (2005), CR 1752 (1998) and ASHRAE Standard-55 (2004-2013). The comfort criteria usually assessed for residential and similar buildings (PMV, PPD) cannot be applied to very specific buildings such as underground stations. Therefore the metro operator is responsible for providing an adequate and safe environment, based on the most suitable interpretation of the regulations.

In energy retrofitting of underground stations, the general aim, as required by the metro operator in the SEAM4US project, is to ensure that the environmental comfort after energy retrofitting is not worse than the levels registered during normal operation. Considering that, as confirmed by our preliminary measures, underground infrastructures are characterized by almost constant environmental variables (such as radiant and surface temperatures of walls, ceilings and floors and air humidity)[33], and that other individual variables (such as clothing and activity level) are too uncertain and difficult to be dynamically measured at each instant, the remaining significant comfort and air quality variables are: air speed, air temperature and pollutants (for which CO_2 and PM_{10} concentrations are good indicators). For these variables, some limits (defined by requirements, law, standards or regulations) must be imposed when dynamically controlling environmental comfort. Moreover, in order to explicitly consider comfort variations due to energy retrofitting, a set point value must be established for each of these criteria. These two kinds of requirements produce two kinds of constraints: hard constraints (bounds) and soft constraints (preferred values).

Set point levels are defined through measured data acquired during normal operation. Bound constraints, for establishing minimum IAQ levels, are defined as follows:

- Air exchange level on platform greater than a minimum threshold: $\tilde{M}(t) > \tilde{M}^L \tilde{O}(t)/O^{max}$
- Difference between inside and outside Carbon Dioxide level lower than a maximum level: $\tilde{C}_{CO2}(t) - \tilde{C}^O_{CO2}(t) < \tilde{\Delta} C^U_{CO2}$
- Particulate level lower than a maximum threshold: $\tilde{C}_{PM10}(t) < \tilde{C}^U_{PM10}$
- Temperature lower than a maximum threshold: $\tilde{T}(t) < \tilde{T}^U$

Note that there is not heating system installed but just a ventilation system, since there is no need for heating due to the high internal gains of the station. Unlike the

Table 1: Main notations used throughout the paper (a) and normalization factors and normalized variables involved in MPC formulation (b). For each physical variable $\tilde{x}$ in the first column, a corresponding dimensionless normalized variable x (denoted with the same name without tilde) is computed as $x(t) \doteq \tilde{x}(t)/x^{max}$, where x^{max} is the normalization factor reported in the last column.

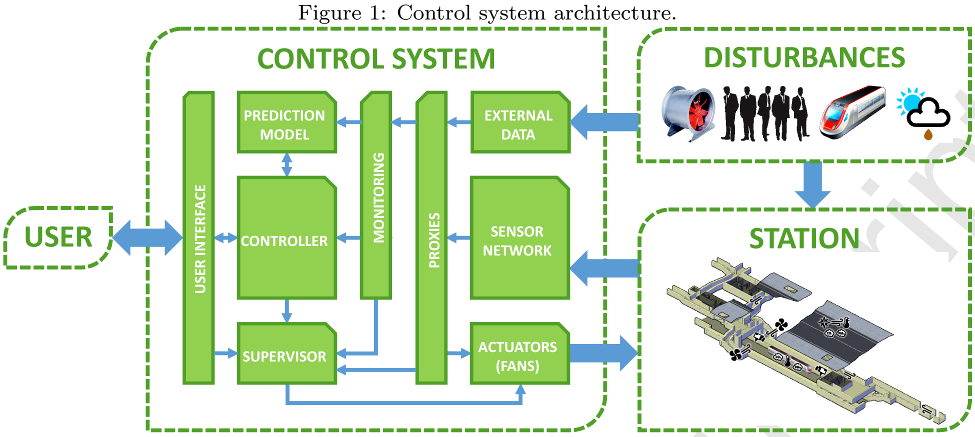
(a) Nomenclature

Symbol	Unit	Description
$\tilde{P}_{T_i}$	W	Power of the i-th tunnel fan
$\tilde{P}_{S_i}$	W	Power of the i-th station fan
$\tilde{T}$	$^\circ C$	Mean temperature on platform
$\tilde{T}^O$	$^\circ C$	Mean temperature outside
$\tilde{\bar{T}}$	$^\circ C$	Set point temperature on platform
$\tilde{M}$	kg/s	Air exchange with outdoor air
$\tilde{\bar{M}}$	kg/s	Set point air exchange
$\tilde{C}_{CO2}$	ppm	CO2 concentration on platform
$\tilde{C}^O_{CO2}$	ppm	CO2 concentration outside
$\tilde{C}_{PM10}$	$\mu g/m^3$	PM10 concentration on platform
$\tilde{C}^O_{PM10}$	$\mu g/m^3$	PM10 concentration outside
$\tilde{F}_i$	Hz	Frequency driving i-th station fan
$\tilde{F}_{T_i}$	Hz	Frequency driving i-th tunnel fan
$\tilde{O}$	N° people	Number of people in platform
$\tilde{S}$	m/s	Wind speed
$\tilde{D}$	deg	Wind direction
$\tilde{R}$	N° trains	Number of trains in interval δ_r
$\tilde{x}(t)$	$[x]$	Raw measured value for variable x
$x(t)$	-	Normalized value for variable x
x^L	-	Lower bound for general variable x
x^U	-	Upper bound for general variable x
y^{max}	-	$\max[y(t)] \doteq \arg\{\max_t [y(t)]\}$
p	-	Prediction horizon

(b) Normalization factors

Raw	Normalized	Normalization factor
$\tilde{P}_{T_i}$	P_{T_i}	$P_T^{max} \doteq \max[\sum_{i=1}^{N_T} \tilde{P}_{T,i}(t)]$
$\tilde{P}_{S_i}$	P_{S_i}	$P_S^{max} \doteq \max[\sum_{i=1}^{N_S} \tilde{P}_{S,i}(t)]$
$\tilde{T}$	T	$\Delta T^{max} \doteq \max[\tilde{T}^O(t) - \tilde{T}(t)]$
$\tilde{T}^O$	T^O	ΔT^{max}
$\tilde{\bar{T}}$	$\bar{T}$	ΔT^{max}
$\tilde{M}$	M	$M^{max} \doteq \max[\tilde{M}(t)]$
$\tilde{\bar{M}}$	$\bar{M}$	M^{max}
$\tilde{C}_{CO2}$	C_{CO2}	$C^{max}_{CO2} \doteq \max[\tilde{C}_{CO2}(t)]$
$\tilde{C}^O_{CO2}$	C^O_{CO2}	C^{max}_{CO2}
$\tilde{C}_{PM10}$	C_{PM10}	$C^{max}_{PM10} \doteq \max[\tilde{C}_{PM10}(t)]$
$\tilde{F}_i$	F_i	$\Delta F_i^{max} \doteq \max[\tilde{F}_i(t) - \tilde{F}_i(t-1)]$
$\tilde{O}$	O	$O^{max} \doteq \max[\tilde{O}(t)]$

Figure 1: Control system architecture.



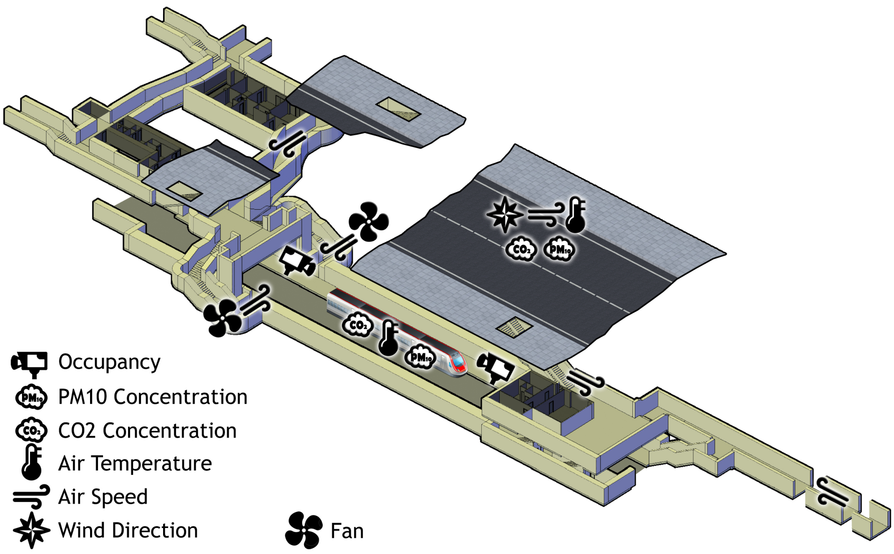
conservative approach in which the ventilation system is designed to address the nominal conditions that may occur in the considered space, the lower bound for the air change $\tilde{M}^L$ is modulated by the actual number of people on the platform $\tilde{O}(t)$: this dynamic modulation based on the real occupancy level, avoids wasting energy by ventilating even when no people are present and also determines the required air exchange.

In order to feed the control system, a proper sensor network is needed, consisting of a number of sensor nodes installed in several areas that provide information about the outdoor and the indoor climate [34]. The sensor node placement is driven by a combination of several different requirements, conditions and limitations of the environment itself.

3. System architecture

The overall control scheme is depicted in Figure 1. The energy manager is in charge of enabling or disabling controller functionalities. A supervisory subsystem is in charge of checking the correct operation of each subsystem and alerting the energy manager in the case of failures, faults or constraint violations. It is also in charge of detecting unreliable sensory data and to switch to a safe control policy (the original one) when needed. A set of software proxies, one for each sensor or external data or actuator, acts as middle-ware, thus making information available to and from the control system independently from the specific hardware or external service adopted. A monitoring subsystem (see Section 3.2) collects information about station status (via sensor network detailed in Section 3.1), and predictions about disturbance factors that affect the dynamic behavior, such as external uncontrolled fans, people, trains and weather (Section 3.4). This information is then processed and made available for use by the controller subsystem (Section 4). The prediction model (described in following Section 3.3), fed with all the available information, is used to carry out a scenario analysis and to select which control policy ensures the best predicted performance in terms of energy consumption and comfort. The corresponding optimal solution is applied to the station as control action and the process is repeated at each control step. In order to support the control system development, test

Figure 2: 3D view of the station with indication of sensors and actuators used for control.



and tuning, the overall control scheme depicted in Figure 1 is implemented and tested in the MATLAB® Simulink® simulation environment described in Section 3.5.

3.1. Sensor network

The sensor network is of paramount importance for each control system since it determines the ability of the system to reject disturbances and unpredictable events.

One of the most important design choices is to deploy a wireless network, as the need for wiring all the nodes can easily limit the installation options. Therefore, some nodes are battery powered and other nodes have their own power supply. The nature and position of the sensors was identified during SEAM4US project in order to get the smallest set of measures that better represents the overall monitored space. As described in details in [35], by means of a calibrated lumped parameters model developed in Dymola™Modelica simulation environment, a rich data-set was generated for clustering analysis. The clustering process, together with the Hugin™software tool for exploiting the relations among the state variables, allowed reducing the number of representative measurable variables to the minimum set depicted in Figure 2. The final WSN is made by occupancy sensors (CCTV), PM_{10} and CO_2 sensors, air temperature sensors, air speed sensors (anemometers) and one wind direction sensor.

Since the real building is a complex system with distributed parameters and the sensors retrieves just local information, the sensor placement is relevant for the casual relation among the sensed variables. As discussed in [34], sensor placement, operation and communication reveal a set of problems to consider, such as the complex rambling morphology of the station, the presence of a big amount of obstacles affecting the radio signal propagation and the potential damage and vandalism. In order to solve problems linked to the needed reliable connectivity of the sensing nodes to the central server and limit the installation costs, an ultra low power Wireless Sensor Network (WSN) has been installed and the network architecture was built in order to provide multi-hop paths from all nodes to the gateway. Maintenance is an expensive task in this kind of environment for many reasons: the difficulty to reach the location where several sensors were installed, the permission to operate only in a few night hours and so on. Due to the above-mentioned limitations, it is often necessary to choose a trade-off between requisites for monitoring, wireless communication and building morphology. However, the main issue consists in keeping the passageways and corridors free: no interference between the final users and the WSN are allowed. The sensors, should therefore be placed as close as possible to the locations for which the model is designed; a calibration process can subsequently be used for estimating to what extent the measurements are affected by the sub-optimal locations and, when feasible, applies correction factors. However, since the prediction model is, at the final implementation, trained on real data, eventual misplacements of the sensors are compensated by the model adaptation process which implicitly implements the calibration process.

Summarizing, with reference to Figure 2, occupancy sensors must be placed, as usual, in order to detect the widest possible area of the platform, pollutant and temperature sensors must be placed in the location that usually is more crowded (i.e. the center of the platform) and air speed sensors are placed close to the walls or roof [36], but far from corners and conjunctions of spaces in order to avoid turbulence.

Clearly, in this kind of harsh environment, redundancy is often needed or desired, as it contributes to increasing the reliability of the system.

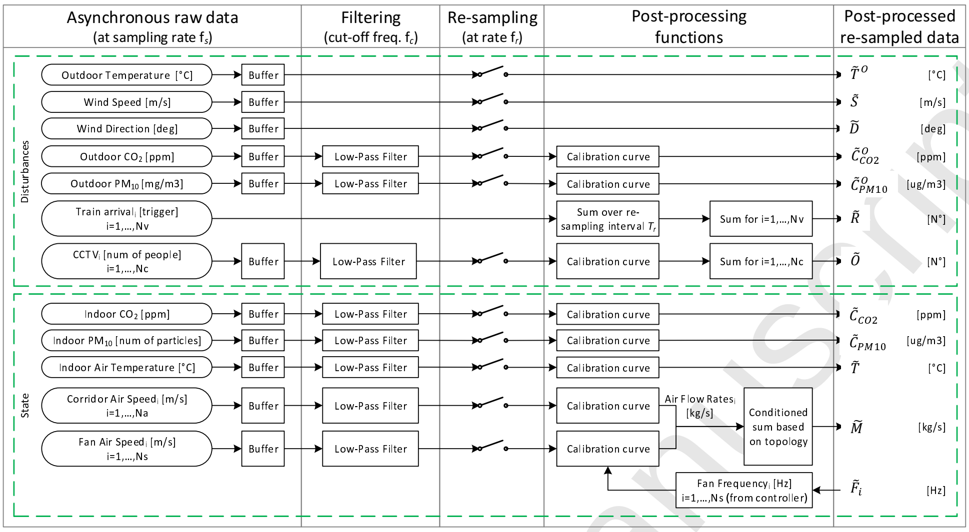
3.2. Monitoring

A fundamental issue in the implementation of MPC is the interface between the model used to drive the control logics and the data gathered by means of the sensor network. Models used in the MPC control loop are based on a somewhat idealized representation of the environment: clean data, perfect time alignment, direct measures of all the necessary physical quantities, etc. Of course, this is not the case in real systems [24]. Therefore, specific modules must be developed to recover a data flow from the sensor network that is suitable for feeding the model predictions. In SEAM4US this is called the Monitoring Component.

The main task of the monitoring subsystem is to act as an interface between the model used to drive the control logics and the data gathered by means of the WSN described in section 2. In fact, the control model accepts as input both synchronized clean data and complete records at regular time intervals. However, this is not the case of raw data sent by the WSN. For that reason, the monitoring subsystem was made up of a set of units developed to recover a data flow from the WSN and convert it into a suitable form for feeding the control model computations. As a consequence, three main steps are accomplished by this component: 1) filtering in order to reduce the aliasing and the noise of raw data; 2) re-sampling to perform time alignment; 3) post-processing (i.e. unit conversion, calibration, estimation of indirect measurements).

Raw data are asynchronously acquired by the sensor network with sampling frequency f_s (subject to some drift due to network latency), therefore they have to be aligned in time before entering the controller. This task is carried out by a re-sampling centralized process that, at a fixed rate f_r, captures the updated value for each sensor and stores

Figure 3: Data processing performed by the monitoring component.



it. In order to avoid aliasing, according to Shannon's theorem [37], this process requires input data to be low-pass filtered with a cut-off frequency greater than half the re-sampling frequency $f_c \leq f_r/2$. Re-sampled data are then processed in order to provide all necessary measures and estimations to the control system.

Filtering is used to smooth data, however it introduces a delay that, when too long, could make the information useless for control purposes. The delay introduced by the filter depends on filter order, type and cutoff frequency (i.e. frequency at -3dB of attenuation) with respect to sampling frequency f_s. An IIR filter type was selected and used as the best compromise between complexity, selectivity and phase shift. Once the cutoff frequency is given, the filter parameter can be computed as $a = e^{-2\pi f_c/f_s}$ and a filter recursive form for implementation is:

$$y_n = (1-a)x_n - a y_{n-1} \tag{1}$$

A sampling frequency f_s must be established in order to avoid, or limit, aliasing noise in the digital signal. Again, according to Shannon's theorem, this is done based on the spectrum occupancy band of the continuous signal to be sampled. In order to determine the spectrum occupancy of each sensor type, a data collection campaign was performed in the real station. Data were acquired for a whole week with a high sampling rate in order to obtain an oversampled dataset. The sampling rate was 1 minute for temperatures, wind speed and wind direction and 10s for air speed and concentration of pollutants. The sampled data were then re-sampled and aligned in time every 10s. A Welch mean-square spectrum was then estimated and analyzed. The results are reported in Figure 8, where for each category, only the sensor with the widest band occupancy is reported, since it requires the highest sampling frequency.

Defining B_{-20dB} as the frequency at which power attenuation is at least $-20dB$ between the amplitude of the lower harmonics in the spectrum and the amplitude of the spectral components beyond spectrum occupancy band B_{-20dB} itself, its value can be graphically determined from the spectrum plots. Shannon's theorem states that, given a signal with occupancy band B, in order to keep all the original information in the sampled signal and to avoid aliasing, the sampling interval must be $f_s > 2B$. In our case, the sensors are much more reactive than the system dynamics and much of the original information contain noise that can be removed by post-process filtering with cut-off frequency $f_c \ll f_s$. Thus, a small amount of aliasing can be tolerated if it falls in the part of the spectrum that is cut by the post-process low-pass filter, i.e. when $f_c < B$, a less restrictive relation can be applied: $f_s > B + f_c$. In other words it is necessary to have $f_s > f_s^L$, where:

$$f_s^L \doteq \begin{cases} B + f_c & \textit{when } f_c < B \\ 2B & \textit{otherwise} \end{cases} \tag{2}$$

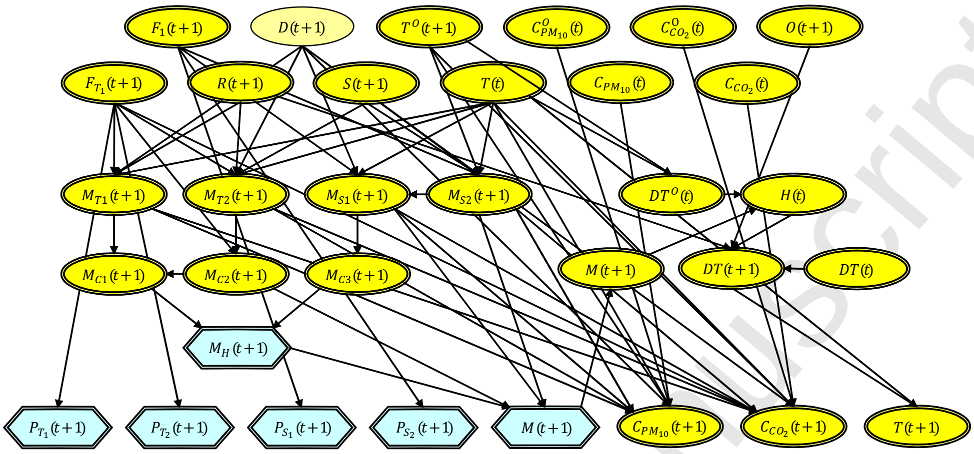
3.3. Prediction model

Deploying an efficient white box model of the station running in real time to support control decisions is unfeasible, due to the huge complexity that would cause problems in the use of memories and computational resources. Furthermore, the alignment of the initial state of such a large model with the actual state of the station is problematic in terms of both computational time and the stability of the solution. Therefore, the prediction model has to be compact and efficient: this is the reason for the increasing use of grey box prediction models [24, 27, 38]. A diffuse and very promising approach is based on the use of reduced lumped parameters models estimated after on site data acquisitions. However, this approach allows achieving satisfying results, under the assumption of linear building with Gaussian process and measurement noises. In the presence of large uncertainties due to the great number of human and external factors affecting the system, as in the case studied, the uncertainty must be considered explicitly by the model which must be able to provide the uncertainty of predictions together with their expected values. Moreover, online model adaptation could be needed in order to match the prediction model with changing conditions. This can be done recursively either as the data are captured by the sensor network, or in batch mode at scheduled intervals (e.g. every day or every week).

An efficient way to combine all these capabilities is the use of Dynamic Bayesian Networks [39, 40] which offer a good basis for adaptivity and decision support thanks to their native uncertainty management and machine learning capabilities. Bayesian networks are graphical representations of probabilistic models. In a Dynamic Bayesian Network, single events, or a sub-group of events, are described through random variables, which are represented as nodes. Each node is characterized by a domain and probability distribution. The relationships between events are represented through a set of conditioned probability distributions. These are presented graphically by means of an oriented arc from the parent to the child (i.e. conditioned) variables.

The most appropriate structure for the BN is established here based on simulated data, then the BN is trained on data collected from the real station, validated and used in MPC. Unmeasured disturbances affecting the process and the measurements are tackled by the BN during the learning process performed on-line data acquisitions: the

Figure 4: Bayesian Network model: the top most two layers represent the input nodes, the bottom nodes represent the output nodes.



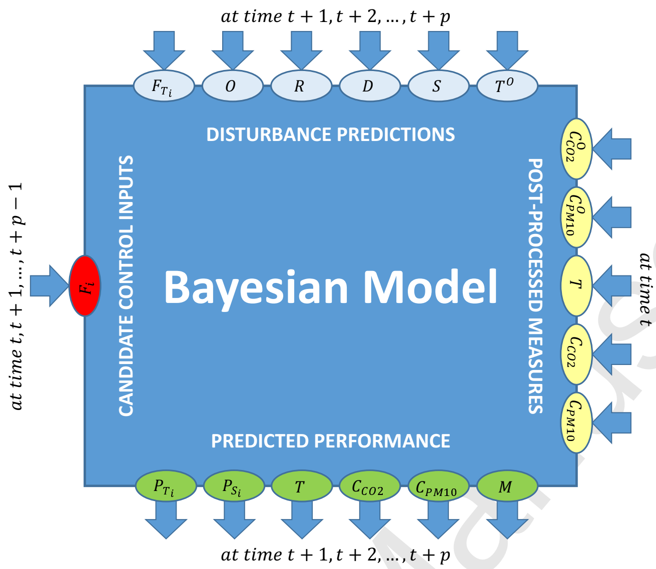
probability distribution of each node of the network will include all the noises included in the training dataset.

The method used in this paper to build a compact BN model for the pilot station has been developed and presented in [35, 36]. Basically, the development of BNs is not an easy task and usually consists of multiple iterations. A detailed lumped parameters model of the station (see Section 3.5 was used to produce a large set of control cases that were analyzed to determine the minimum set of parameters for the effective control of the target performance. This was deemed necessary because for such complex domains eliciting expert knowledge to learn conditional probability tables is not feasible. Hence several sets of data were generated through simulations prior to the application of the EM learning process. The reduced case set was then fed into the BN, through statistical clustering, structural and EM learning algorithms, in order to obtain the Bayesian predictor for the MPC control. Once the most appropriate structure of the BN was identified, a large set of data was collected from the station itself and fed into the EM learning process in order to fit the model on real data.

The prediction model was built by means of two Bayesian Networks, each relative to a different physical phenomenon: a temperature prediction dynamic Network and an air flow prediction Bayesian network that, when merged together, form the overall dynamic Bayesian Network represented in 4.

The one-step ahead prediction of the temperature in platform $T(t+1)$ is predicted starting from the current temperature $T(t)$, the predicted number of people in the station at the next step $O(t+1)$, the predicted internal gains supplied by trains at the next step $R(t+1)$, the predicted outdoor temperature $T^O(t+1)$ and the predicted air changes $M(t+1)$. These air changes, in turn, are generated by the other part of the BN based on the candidate control frequencies $F_i(t+1)$, the predicted control frequencies of tunnel fans $F_{T_i}(t+1)$, the predicted rate of arrivals for trains $R(t+1)$, the predicted wind direction $D(t+1)$ and speed $S(t+1)$, the outdoor temperature $T^O(t+1)$ and current temperature

Figure 5: Bayesian Network model for computing p step-ahead predictions based on disturbance prediction, measures and candidate control policy.



$T(t)$. Together with the air changes, the power consumption of station fans $P_{S_i}(t+1)$ and tunnel fans $P_{T_i}(t+1)$ are predicted by the BN. The intermediate state variables of the BN denoted with M followed by some subscript are air flows through connected spaces, the variables denoted with symbol DT represent temperature differences and that one denoted with H is the heat flow entering the platform.

The one-step ahead BN depicted in Figure 4 can be iterated in order to arrive at a prediction over an arbitrary prediction horizon p. As expected, the greater the prediction horizon, the greater is the uncertainty of the prediction. An input-output block representation of the resulting BN model is reported in Figure 5. Each input node (entering arrow) in the network corresponds to a data source provided by the monitoring subsystem or by the optimization algorithm. Each output node (outgoing arrow) is used by the controller in order to evaluate the control performance and to select the best control policy to apply.

The size of this predictor is small enough and its computational time is short enough to suit the model embedding requirements. The statistical nature of the predictor avoids any problems concerning the estimation of the initial state. The prediction accuracy achieved by the reduced model is good enough to ensure a reliable control of the station: the normalized root mean square error for the one-step ahead prediction of temperature in platform (T) was 4% and for the station fans power (P_{S_1}, P_{S_2}) was 2.3%.

3.4. Disturbance models

The main disturbances that affect station dynamics are weather, people, trains and external fans (i.e. not controlled fans). These disturbances have to be measured and, if possible, predicted by a model that provides the future behavior of non-controllable factors.

For trains and external fans the station operator can always provide schedules that may be reasonably used as a measure or prediction: any slight variation from the schedule can be addressed by the disturbance rejection capability of the feedback control scheme (Figure 1). When available, these schedules or the current status of trains and external fans can be accessed in real time through the SCADA system already installed in the station, thus improving the reliability of the measures of these disturbances.

A large-scale simulation study performed in [41] showed a potential for the energy savings and/or improvements in thermal indoor environment when using the weather forecasts in a predictive control strategy compared to a simple rule-based control, despite the uncertainty in the weather forecasts. Weather conditions and forecasts can be obtained by means of free online web-services, such as wunderground.com©. A software proxy must be developed embedding the functionalities for communication with this service and periodically providing weather conditions and forecasts. When no weather station is sufficiently close to the webservice, the quality of the weather conditions can be significantly improved by installing a local weather station connected to the Wireless Sensor Network.

People can be detected in different ways: via GSM/GPRS detectors, via CCTV, via CO2 levels, etc. The CCTV-based crowd density estimator is used here, since it is the main source of data for modeling passenger behavior and it is based exclusively on the video streams of the CCTV surveillance system which already exists in a station. Monitoring the density of passengers and their flow patterns can provide additional information in environmental models and transportation facilities and make the energy consumption controllers aware of the occupancy behavior. Thanks to the great amount of literature available concerning computer vision algorithms and an accurate design of video processing, it is possible to achieve sufficient accuracy in estimating the crowd (see e.g. [42]). Some work has already been carried out specifically for crowd density estimation in underground stations [43] using feed-forward Neural Networks that, when applied to crowd estimation in this type of building, show very promising results.

There are many different approaches to solve the problem of predicting passenger occupancy. For instance, in the context of station control, the availability of occupancy measures and historical data can be exploited by means of time series prediction algorithms ([44, 45]). Moreover, Bayesian Networks are exploited in [46] for forecasting pedestrian distribution under emergency evacuation, that is very similar to the movement of people in underground stations. However, as shown in [47], a large part of the energy savings potential can already be captured by taking into account instantaneous occupancy information. In addition, when only the mean occupancy level is needed for control, the estimation of the current occupancy alone may be sufficient to have a good estimation of future building dynamics.

3.5. Simulator

The SEAM4US simulator is a co-simulation architecture that has been developed to design and test the control strategies without affecting the pilot station. The simulator adopts MATLAB® Simulink® as a master controller and a slave Dymola instance embedded in a co-simulation FMI structure or loosely coupled by Dynamic Data Exchange. It has all main components depicted in Figure 1: the virtual station model, a passenger flow simulator and the ventilation controller.

The virtual station model is a comprehensive lumped parameter calibrated model of the building equipped with sensor network and ventilation system [48]. It has been developed via the Dymola/Modelica simulation environment and it has been proved, by extensive tests, to provide a very accurate model of all relevant aspects of the pilot site. This model includes all the physical details of the whole PdG-L3 station relevant to study the thermo-fluid dynamical behavior of the station [36]. The virtual station model receives as inputs a weather file of Barcelona that provides the hourly external weather parameters, the passenger occupancy levels in each ambient from the passenger flow simulator and the fan control frequencies both from not controlled (from the metro operator schedules) and controlled fans (from the ventilation controller). It then outputs all the calculated environmental parameters, like air temperature and humidity, the pollutants levels, and the energy consumption of the fans. These parameters are all fed to the controller for scenario analysis.

The passenger flow simulator reproduces the flows of passengers and the consequent occupancy distribution of people among the areas of the station. It is regulated by the train schedule and by the time of the day (rush vs non-rush hour) and is based on the BondLib Modelica library, that implements the methodology of modeling physical systems using bond graphs (a technique that had been developed in 1960 at M.I.T. by Henry Paynter). The passenger flow is modeled as continuous mass flow from the sources (entrances and trains) to the sinks (trains and exits respectively) and is calibrated based on the crowding data provided by the station operator. This allows to have plausible occupancy levels in each space at each time of the day in order to correctly estimate internal gains of heat and pollutants.

The ventilation controller replicates the actual MPC algorithm that is then applied to the real station: the best control policy is selected and used as control action according to what is discussed in Section 4 and the system components represented in Figure 1.

Although the simulator was of paramount importance for the first implementation, when no information about the suitable predictive model structure were available and some energy saving estimations were already needed, it required a significant developing effort that should be avoided in future implementations. In fact, when the structure of the predictive model (described in Section 3.4) has been established thanks to the results of the SEAM4US project, its proved ability to learn from real data makes the solution self adaptive.

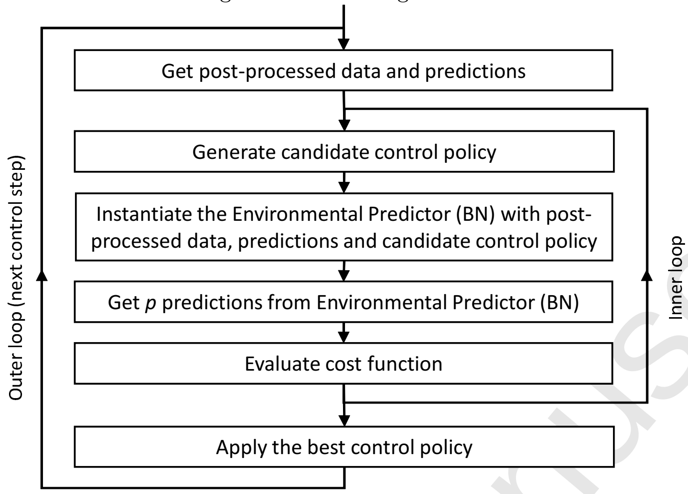
4. Control problem

4.1. Control algorithm

Based on what was stated in Section 3.2 and is shown in Figure 6, at each re-sampling instant (i.e. every $1/f_r$ seconds), the MPC algorithm collects information about the station by taking re-sampled data from the monitoring, evaluates the best control action by using hourly predictions over a predefined prediction horizon p and applies it to the station. Data acquisition is carried out by waiting a maximum defined time-out interval after each re-sampling instant: when time-out is reached, MPC proceeds to compute the control action corresponding to that interval and applies it via the actuator proxy.

The generation of the candidate control policy is strongly related to the adopted searching technique. Many searching techniques for finding the optimal solution of either

Figure 6: Control algorithm.



constrained or unconstrained MPC problems have been studied and developed in the literature (e.g. [49, 50]). However, in case of a single actuator with discrete frequency values and short control horizon, an almost exhaustive case generation can be used as a simple solution for determining the optimal control action to be applied among the possible discrete values defined by the resolution of the DAC connected to the inverter.

In the case study, since the controlled actuators have the same input values that are discretized from 0Hz to 50Hz with a resolution of 1Hz $\{0, 1, \ldots, 49, 50\}$ and the prediction horizon is set to $p = 1$, an exhaustive case generation is used as a simple solution for determining the optimal control action to be applied.

The choice of the control step for the pilot station, together with the sampling interval and the prediction interval, is discussed later on in Section 5.2.

4.2. Control problem formulation

For the sake of generality, parameters and variables are normalized here with respect to the maximum value of the related term in the cost function. Therefore, all the physical variables reported in Table 1(a), will be represented in the MPC problem formulation with their normalized versions (same name without tilde) as reported in Table 1(b).

In order to achieve the multiple conflicting objectives specified in Section 2 over a fixed prediction horizon p, the single objectives are combined in a global objective by arbitrary weighting factors α_{P_T}, α_{P_S}, $\alpha_{\Delta T}$, α_T, α_M, α_{CO2}, α_{PM10}, $\alpha_{\Delta F}$. The total absorbed electric power have to be minimized while keeping thermal comfort and air quality parameters as close as possible to the desired values (soft constraints). Moreover, the thermal comfort and air quality parameters must be kept strictly inside the bound constraints defined in Section 2.

The selection of the most appropriate MPC problem formulation for buildings has recently gained attention [51]. Due to the energy saving objective, the 1-norm of the total energy consumption has to be minimized, and this allows, under certain assumptions, to formulate and efficiently solve the control problem by using linear programming [52].

However, as stated in [51] and verified in the pilot station, the 1-norm formulation of MPC is highly sensitive to model mismatch and inaccuracies in weather predictions, often resulting in a bang-bang control that is undesirable for buildings. Moreover, the energy consumption should be balanced with the effects in terms of comfort and air quality parameters: the relative weight of energy with respect to the other terms comes from a subjective evaluation of the station operator and could also vary over the operative range. In this paper the square of energy is adopted as final choice, resulting in a smoother control action and a small importance of energy with respect to the comfort and air quality parameters at low regimes and a predominant importance of energy at high regimes. The drawback of this approach is that, in general, the control problem requires bigger computational efforts to be solved.

With reference to the normalized variables (Table 1(b)), the sum of squares of the absorbed electric power of tunnel fans P_{T_i} and station fans P_{S_i} have to be minimized. The temperature in platform T should be as close as possible to the outside temperature T^O and to the desired value $\bar{T}$ and it must be lower than the upper bound T^U. The air change rate with outdoor air M should be as big as possible and it must be bigger than the lower bound M^LO, that takes into account for the current occupancy also. Pollutant concentrations in platform C_{CO2} and C_{PM10} should be minimized, moreover C_{CO2} must be lower than the outdoor concentration C^O_{CO2} plus an allowed increase ΔC^U_{CO2} and C_{PM10} must be lower than the upper bound C^U_{PM10}. Therefore, the following cost function is defined and evaluated over the prediction horizon p:

$$\begin{aligned}
J^O(t) \doteq \sum_{k=1}^{p} \Bigg[& \alpha_{P_T} \left(\sum_{i=1}^{N_T} P_{T_i}(t+k) \right)^2 + \alpha_{P_S} \left(\sum_{i=1}^{N_S} P_{S_i}(t+k) \right)^2 + \\
& + \alpha_{\Delta T} \left(T^O(t+k) - T(t+k) \right)^2 + \alpha_T \left(\bar{T} - T(t+k) \right)^2 + \\
& + \alpha_M \left(1 - M(t+k) \right)^2 + \alpha_{CO2} \left(C_{CO2}(t+k) \right)^2 + \alpha_{PM10} \left(C_{PM10}(t+k) \right)^2 + \\
& + \alpha_{\Delta F} \sum_{i=1}^{N_S} \left(F_i(t+k-1) - F_i(t+k-2) \right)^2 \Bigg]
\end{aligned} \tag{3}$$

The last term in cost function has been added for considering the amplitude of change in frequency F_i that drives the actuators: it is a stability objective that could be useful to smooth the control movements.

Denoting with superscripts $\cdot^L$ and $\cdot^U$ lower bound and upper bounds respectively, the previous minimization is subject to the following comfort constraints $\forall t \in \mathbb{Z}$:

$$M(t) > M^L O(t) \tag{4a}$$

$$C_{CO2}(t) - C^O_{CO2}(t) < \Delta C^U_{CO2} \tag{4b}$$

$$C_{PM10}(t) < C^U_{PM10} \tag{4c}$$

$$T(t) < T^U \tag{4d}$$

and to the following operative constraints $\forall t \in \mathbb{Z}, \forall i = 1, \ldots, N_S$ that considers the physical limits of the actuators:

$$F_i^L < F_i(t) < F_i^H \tag{5}$$

The control sequence of length p is defined by:

$$u_p(t) \doteq \begin{bmatrix} F_1(t) & \cdots & F_1(t+p-1) \\ \vdots & \ddots & \vdots \\ F_{N_S}(t) & \cdots & F_{N_S}(t+p-1) \end{bmatrix}. \tag{6}$$

At each control step t, the MPC problem consists in finding the optimal control sequence $u_p^*(t)$ among candidate control policies $\hat{u}_p(t)$ so that:

$$u_p^*(t) = \arg\left\{ \min_{\hat{u}_p(t)} J^O(t) \right\} \tag{7}$$

subject to, $\forall k = 1, \dots, p, \forall i = 1, \dots, N_S$:

$$M(t+k) > M^L O(t+k) \tag{8a}$$

$$C_{CO2}(t+k) - C_{CO2}^O(t+k) < \Delta C_{CO2}^U \tag{8b}$$

$$C_{PM10}(t+k) < C_{PM10}^U \tag{8c}$$

$$T(t+k) < T^U \tag{8d}$$

$$F_i^L < F_i(t+k-1) < F_i^U \tag{8e}$$

Once the bounds M^L, ΔC_{CO2}^U, C_{PM10}^U, T^U, F_i^L, F_i^U are derived from regulations or operative limits and set point $\bar{T}_I$ is fixed by comfort requirements, the remaining degrees of freedom for tuning the controller are the weights of the different cost terms α_{P_T}, α_{P_S}, $\alpha_{\Delta T}$, α_T, α_M, α_{CO2}, α_{PM10}, $\alpha_{\Delta F}$ and the prediction horizon p.

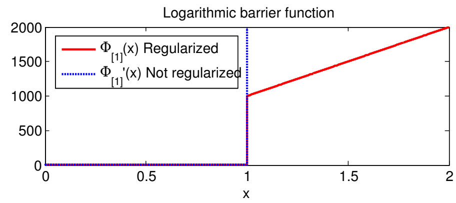
4.3. Real-time solution of the constrained MPC problem

In order to dynamically control the station in real time, a lightweight solution algorithm must be used. This can be done by considering the principle that motivates the common choice of sub-optimal solvers for MPC problems: "do something sooner" leads to better control than "do the optimal thing later" [53]. The approach proposed here includes the constraints in a generalized cost function in order to transform the constrained problem into an equivalent unconstrained minimization problem, and to implement some efficient optimization algorithms to solve it.

Operative constraints regarding manipulated variables, such as $F_i(t), i = 1, \dots, N_S$ in our case, are explicitly considered in the optimization algorithm when generating cases to be evaluated as candidate control policies.

The other constraint can be written as an upper bound constraint, which means that we are interested in keeping the target variable x smaller than an upper bound x^U. As reported in literature [54, 55, 56], barrier functions can be used to transform the constraints into objectives. In constrained optimization, a barrier function is a continuous function whose value increases to infinity when approaching the boundary of the feasible region. It is used as a penalizing term for the violations of constraints. The two most common types of barrier functions are inverse barrier functions and logarithmic barrier

Figure 7: Logarithmic barrier function for constraint $x < 1$: original version (dashed blue line) and extended version with $K = 10^3$ (continuous red line). The extended version provides a constraint violation level that may help the solver to find a feasible solution starting from an unfeasible one.



functions. The logarithmic barrier function, used here to implement an upper bound constraint $x \leq x^U$, is defined as follows:

$$\Phi'_{[x^U]}(x) \doteq \begin{cases} -\log(x^U - x) & x \leq x^U \\ +\infty & otherwise \end{cases} \tag{9}$$

An upper bound (lower bound) constraint $x \leq x^U$ ($x \geq x^L$) is then implemented by adding $\Phi'_{[x^U]}(x)$ ($\Phi'_{[-x^L]}(-x)$) to the cost function. A simple optimization problem formulated as Minimize min $J = f(x)$ subject to $x \leq x^U$, becomes the new unconstrained problem of finding the minimum of a unified cost function $\min[J + \beta\Phi'_{[x^U]}(x)]$, where beta is a meta-parameter that gauges the preference weight between the main objective and the constraints.

When constraints are not satisfied, their cost goes to infinity, thus making it impossible to detect which of the unfeasible candidates is closest to a feasible one or which is the best in terms of unified cost: this would produce a stall in the solution algorithm. In order to preserve the strong penalization of constraint violation and the ability to compare different unfeasible solutions, an extended version of the logarithmic barrier function is used. A simple linear interpolation is proposed here outside the constraint bound based on a defined threshold $K = 10^3$ over which the logarithmic function is truncated and extrapolated by a straight line (see Figure 7):

$$\Phi_{[x^U]}(x) \doteq \begin{cases} \min\left(-\log(x^U - x), \left|x - (x^U - x)\right| K\right) & x \leq x^U \\ \left|x - (x^U - x)\right| K & otherwise \end{cases} \tag{10}$$

With this approach, constraints (8a)-(8d) can be reformulated as:

$$-M(t+k) < -M^L O(t+k) \tag{11a}$$
$$C_{CO2}(t+k) - C^O_{CO2}(t+k) < \Delta C^U_{CO2} \tag{11b}$$
$$C_{PM10}(t+k) < C^U_{PM10} \tag{11c}$$
$$T(t+k) < T^U \tag{11d}$$

and imposed on the control problem by adding the following functional to original cost function:

$$
\begin{aligned}
J^C(t) \doteq &\beta_M \Phi_{[-M^L O(t+k)]} \left(-M(t+k)\right) + \\
&+ \beta_{CO2} \Phi_{[\Delta C^U_{CO2}]} \left(C_{CO2}(t+k) - C^O_{CO2}(t+k)\right) + \\
&+ \beta_{PM10} \Phi_{[C^U_{PM10}]} \left(C_{PM10}(t+k)\right) + \\
&+ \beta_T \Phi_{[T^U]} \left(T(t+k)\right)
\end{aligned} \tag{12}
$$

The unification of constraints with the objective is achieved by defining the following unified cost function:

$$
J(t) \doteq J^O(t) + J^C(t) \tag{13}
$$

and the optimization problem now becomes unconstrained:

$$
u_p^*(t) = \arg \left\{ \min_{\hat{u}_p(t)} J(t) \right\} \tag{14}
$$

5. Case study

5.1. Pilot station

The SEAM4US project involved the northern part of Passeig de Gràcia Station, serving Line 3 of the Barcelona Metro Network (Spain) as the pilot station. It consists in a historic central station with one platform served by two railways in two opposite directions. The air exchange and thermal comfort is achieved by two fans located in the station and two fans situated in the middle of the two tunnels.

The sensor network was designed to be totally based on wireless communication, in order to reduce wiring needs (see [57] for details). For the same reason, most of the sensor nodes are battery powered, whereas all the sensor gateways have a power supply, in order to guarantee continuous operation. As far as power saving is concerned, an energy efficient MAC protocol was implemented leading to a cross-layer mechanism able to allow nodes to stay in sleep mode most of the time, according to the application's data sampling and delay requirements. In this way, battery replacement periods of many years were achieved. Data reliability was strengthened by implementing a mechanism that periodically verifies the data received at the gateway server and requests data retransmission in the case of missing values. In practice, real-time monitoring is stricter in terms of delay requirements, hence the mechanism parameters must be tuned according to the specific requirements. The data delivery requirement can be summarized by specifying the maximum allowed packet loss as 20%. In fact, the system was able to satisfy this requirement as the average packet delivery ratio over the entire network during the evaluation period was 13%.

The original control policy, hereafter referred to as *baseline* (BSL), requires the station fans to inject air into the station in the daytime, and the tunnel fans to extract air from the platform in the daytime (between 07.00 and 22.00) and inject air at night (between 22.00 and 07.00 of the next day), when the station fans are switched off. All the fans are driven by an inverter based on the input frequency on the basis of a day/night schedule and a seasonal schedule set by the station operator as follows (the sign of the frequency input represents the air flow direction: positive when entering platform):

Table 2: Control parameters used in the SEAM4US system.

Symbol	Value			
	Winter	Spring	Summer	Autumn
$F_{S,i}^{L}, i = 1, 2$	$20Hz$	$25Hz$	$25Hz$	$20Hz$
$F_{S,i}^{U}, i = 1, 2$	$25Hz$	$45Hz$	$45Hz$	$25Hz$
T^{U}	$31°C$			
M^{L}	3.93 kg/s			
ΔC_{CO2}^{U}	370 ppm			
C_{PM10}^{U}	140 $\mu g/m^3$			
ΔT^{max}	$20°C$	$10°C$	$5°C$	$10°C$
P_S^{max}	13600 + 13600 W			
P_T^{max}	20000 + 70000 W			
M^{max}	50 kg/s			
C_{CO2}^{max}	530 ppm			
ΔC_{CO2}^{max}	200 ppm			
C_{PM10}^{max}	80 $\mu g/m^3$			
$\Delta F_i^{max}, i = 1, 2$	50 Hz			
O^{max}	20			
$\bar{T}$	$22°C$	$24°C$	$27°C$	$25°C$

- Winter (Jan, Feb, Mar) and Autumn (Nov, Dec) modes: tunnel fans at -25Hz in the daytime and +25Hz at night, station fans at +25Hz only in the daytime;
- Spring (Apr, May, Jun) and Summer (Jul, Aug, Sep, Oct) modes: tunnel fans at -50Hz in the daytime and +25Hz at night, station fans at +50Hz only in the daytime;

5.2. System setup

Since the tunnel fans serve different contiguous stations, their control must be implemented at a higher level in order to coordinate multiple stations on the same line. On the contrary, the station fans can be controlled locally (even if they must be driven in parallel in order to avoid falling into stall conditions) and are driven by the MPC agent in the SEAM4US pilot station. Therefore, the ventilation controller has to manage power consumption and indoor comfort by acting on only one actuator that is the driving frequency of the two station fans.

SEAM4US control is active only when the fans are active for the baseline, therefore MPC is ON between 07.00 and 22.00 (daytime).

All the *parameters* used in SEMA4US are summarized in Table 2. The maximum levels for normalization and reference values have been defined by analyzing data acquired from the sensor network, while four bound constraints have been defined in order to establish minimum indoor air quality levels.

The *cut-off frequency* for post-process low-pass filter f_c and the *re-sampling frequency* f_r are chosen so that reasonable values for raw sampling frequency f_s and residual aliasing are achieved. The results reported in Figure 8 and Table 3 are achieved with $f_r = 1/600Hz$ and $f_c = f_r/2 = 1/1200Hz$. The filter cutoff frequency is chosen as large as possible (equal to its upper bound) in order to limit the consequent phase delay and hence to make the controller more reactive.

Figure 8: Spectral analysis performed on data coming from the PdG-Line3 pilot station.

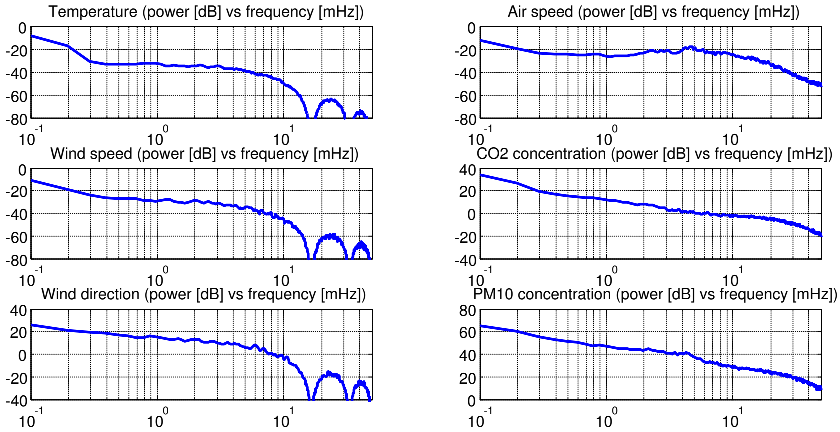


Table 3: Results of the spectral analysis. For each sensor category, given some aliasing noise limit (%) and a post-process low-pass filter with cut-off frequency $f_c = 0.8mHz$, the occupancy band B_{-20dB} is identified and the minimum sampling frequency f_s^{min} and maximum sampling interval δ_s^{max} are determined.

Sensor	Occupancy band	Aliasing	f_s^{min}	δ_s^{max}
Temperature	$B_{-20dB} = 0.3mHz$	1%	$0.6mHz$	$1667s$
Wind speed	$B_{-20dB} = 3.0mHz$	1%	$3.8mHz$	$261s$
Wind direction	$B_{-20dB} = 6.0mHz$	1%	$6.8mHz$	$146s$
Air speed	$B_{-15dB} = 10.0mHz$	6%	$10.8mHz$	$92s$
CO2 concentration	$B_{-20dB} = 0.7mHz$	1%	$1.4mHz$	$714s$
PM10 concentration	$B_{-20dB} = 2.0mHz$	1%	$2.8mHz$	$353s$

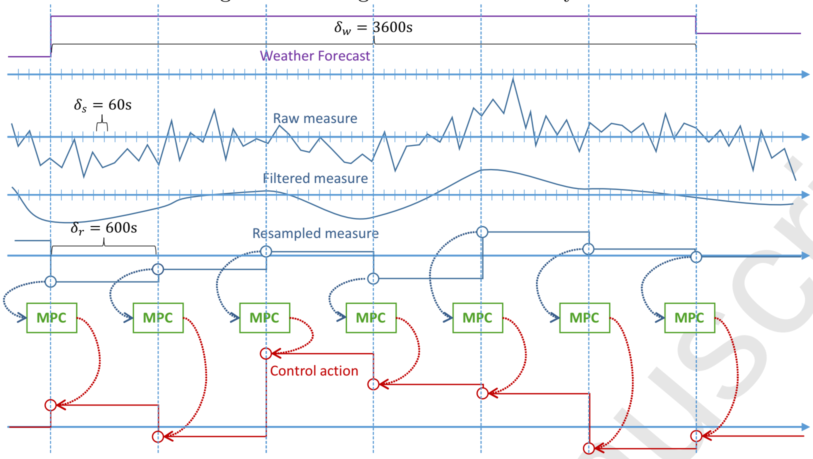
Based on the spectrum analysis, a *sampling interval* $\delta_s \doteq 1/f_s = 60s$ is selected as the final value for all the sensors involved in the control. In this way the sampling interval is large enough to limit the network traffic and the storage requirements, but it is also small enough to avoid significant aliasing in acquired information.

In order to exploit the disturbance rejection capability of the closed loop, the *control interval*, that is the interval used for updating the control action, is selected as the fastest synchronous data update rate available, that is the re-sampling rate $f_r = 1/600Hz$ ($\delta_r \doteq f_r = 600s$).

Finally, the *prediction interval*, that is the step used for updating predictions, is selected as the slowest available prediction update rate, which is the Weather Forecast update rate $\delta_w = 1hour$. This allows prediction horizons of hours to be used without introducing excessive computational burden and with better prediction accuracy (lower propagated uncertainties). Since, as will be shown in following Section 6, satisfactory control results and energy savings have been obtained with a prediction horizon of one step $p = 1$, a prediction horizon of one hour is finally adopted.

This selection of the timing is schematically represented in Figure 9 which shows how a raw asynchronous variable is sampled, filtered and re-sampled before being used by

Figure 9: Timing of the SEAM4US system



MPC. Even if predictions are made over multiples of hours, control action is updated at the same rate as the re-sampling process in order to allow for a better disturbance rejection.

Weather conditions and forecast data were provided by the free web service Weather Underground (www.wundreground.com) for location LEBL, that is relative to Barcelona Airport El-Prat. The sensors/actuators network was interfaced with the control system using a Linksmart middle-ware.

A prediction model was implemented in the control system by means of a java library that wraps the Hugin™reasoning engine and also allows for other high-level functionalities, such as multiple network iterations and interconnection between different networks that share the same variables. This library initializes the model with the set of variables describing the current state of the station and then, performs probabilistic inference by running the Hugin™ reasoning engine. This is iterated p times with any available prediction about system variables in order to obtain the whole performance prediction over the specified prediction horizon. Expected values and corresponding uncertainties are then extracted for use by the controller.

5.3. Tuning

Once cost function, prediction horizon and constraints are defined, the control algorithm is parameterized with respect to the relative weights of the different terms of the cost function which have to be tuned in some way in order to achieve good performance. A simulation platform was developed for this purpose as explained in Section 3.5. The Model In the Loop (MIL) strategy was exploited for testing the controller before implementing it in the real station, thus allowing many runs to be made in a short time, without affecting the real station. Detailed models of the station, the monitoring network and the disturbances were developed and embedded under MATLAB® Simulink® co-simulation platform, in which the control algorithm and the prediction model library were also integrated.

Table 4: Final weights used in the SEAM4US system.

Symbol	Value	Symbol	Value	Symbol	Value
α_{P_T}	92/1000	α_M	4/1000	β_M	8/1000
α_{P_S}	10/1000	α_{CO2}	36/1000	β_{CO2}	88/1000
$\alpha_{\Delta T}$	134/1000	α_{PM10}	8/1000	β_{PM10}	1/1000
α_T	531/1000	$\alpha_{\Delta F}$	0/1000	β_T	88/1000

By running the simulator for many alternative scenarios and comparing the resulting control performance in terms of energy consumption, comfort and air quality, a set of parameters was selected. Then, a second tuning phase focused on refining these parameters in order to achieve the expected behavior of the controller in specific conditions. The final set was used for implementation in the real station for the third tuning phase. During the first month of running, in fact, some adjustments were required in order to adapt the Bayesian Networks and, consequently, the control parameters to the real station. However, after this short start-up phase, the system started to control properly and to produce the expected results in terms of power savings and comfort.

The final set of parameters reported in Table 4 was selected and implemented as final choice for the SEAM4US system. Note that the PM10 constraint was almost relaxed since its value is barely controllable in the short-term by acting on the station fans. Its instantaneous value is mainly determined by the frequency of trains passing through the station. The controllability of PM10 could be improved by adding filters in the ventilation ducts in order to inject clean air in the stations. For this reason, the constraint on particulate cannot be rigorously satisfied by MPC but it can be kept as small as possible in the long term. The stability constraint was relaxed since the feedback system proved to be stable without other precautions.

6. Control performance

The described MPC strategy was successfully applied to control the forced ventilation of the PdG-Line3 station for five months (from August to December 2014). Some relevant measures collected by the monitoring system, representing filtered, re-sampled and post-processed quantities, are depicted in Figure 10.

Figures 10(a) and 10(b) refer to the system operating in the summer mode during a working day (when the station opens at 05:00 and closes at 24:00) and during a weekend (when the station remains open all the time). Similarly, Figures 10(c) and 10(d) refer to the system operating in the winter mode during a working day and during a weekend.

Note that, during the working days, irrespective of the summer or winter modes, the higher number of people and trains passing through the station makes the indoor climate less comfortable and the savings margins become smaller, albeit still relevant w.r.t the weekend. In winter mode, since the operative constraints for the fans are quite tight and the power consumption of the fans depends on the square of frequency, the savings margins are much smaller than in the summer mode. The comfort indexes all remain acceptable: temperature is kept stable and at acceptable levels while pollutants comply with constraints.

Permanently installed energy meters where used for monitoring energy consumption before and after the installation of the SEAM4US system. The total energy saving

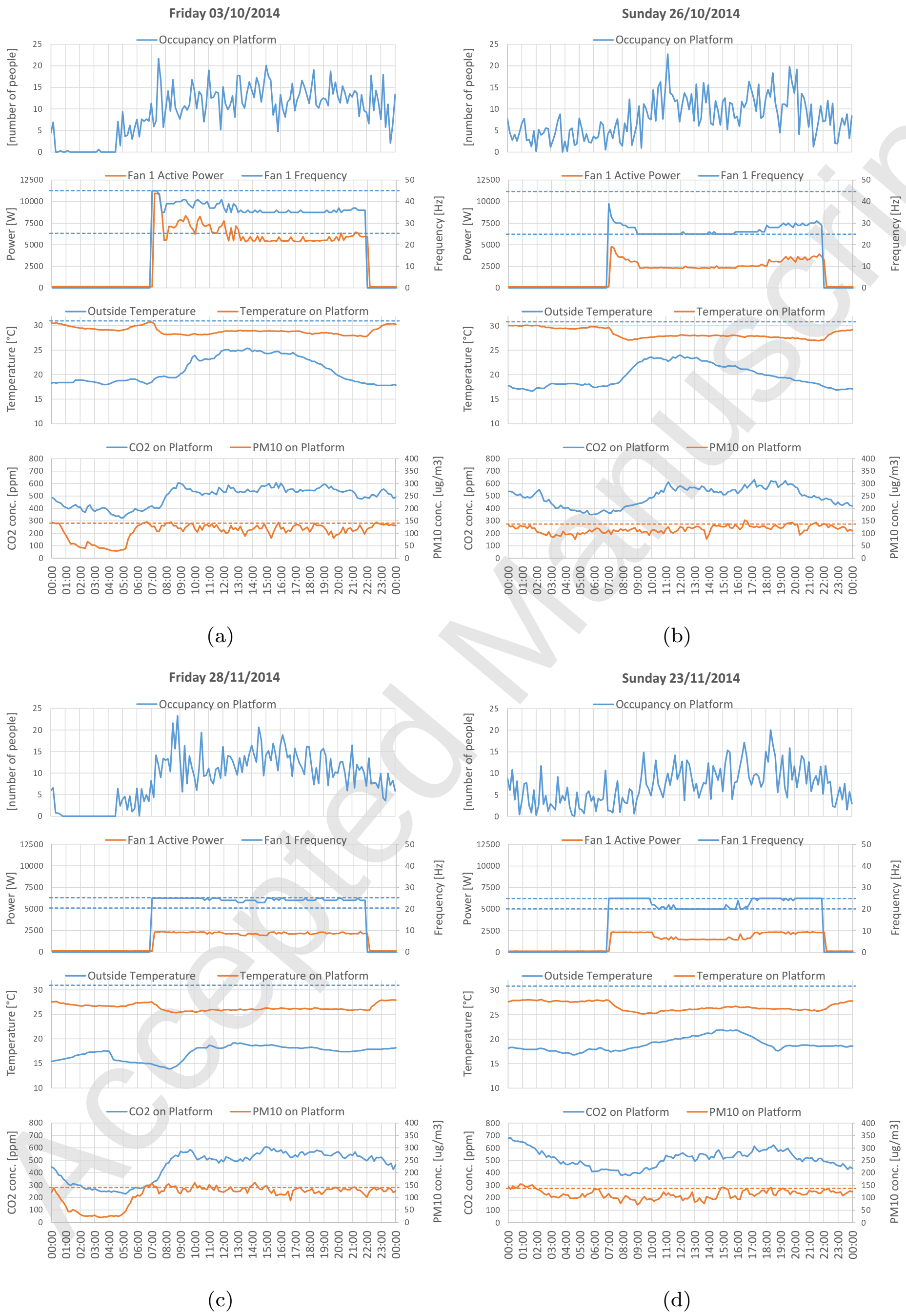


Figure 10: Control performance on two days in October 2014 (summer mode) (a)-(b) and in two days in November 2014 (winter mode) (c)-(d). Dashed lines represent bound constraints.

Table 5: Absolute (S) and percent ($S_{\%}$) energy savings achieved during year 2014 thanks to the SEAM4US system.

Month	S	$S_{\%}$
September	2304 kWh	30 %
October	3859 kWh	48 %
November	240 kWh	11 %
December	297 kWh	14 %
Total	6701 kWh	33 %

with respect to the baseline $S \doteq E_{MPC} - E_{BSL}$ is defined as the difference between the energy consumption achieved with the MPC strategy E_{MPC} and the energy consumption obtained with the baseline strategy E_{BSL}. The percent energy saving $S_{\%} \doteq S/E_{BSL}$ is the same value S divided by the baseline energy consumption E_{BSL}. The resulting values for energy saving relative to the direct and continuous measures taken during the four months of full operation are reported in Table 5. These periods are representative of the different operating conditions occurring in PdG-Line3 station and produce global savings of about 33% without significantly affecting passenger comfort.

7. Conclusions

The problem of controlling the ventilation of underground stations has been considered in this paper and a complete solution based on MPC has been developed. Hardware, software and algorithmic requirements are specified and translated in a real implementation of the presented approach at Passeig de Gràcia metro station in Barcelona. Control performance over a period of four months, showed almost unchanged comfort for passengers with respect to the original condition, while achieving mean energy savings of 33%. This proves the effectiveness and soundness of the developed approach for controlling underground spaces. A big effort was required here for developing the detailed model to be used for establishing the BN structure and for testing and pre-tuning the MPC controller. However, in future applications such an effort is no more needed: the Bayesian model can be directly tuned on measurements and the MPC controller adjusted online for achieving the desired performance.

In view of the good results achieved, it would be interesting to test the developed solution also for other kinds of buildings, whether common residential or more complex structures, such as public or facility buildings. Thanks to the learning capability of the Bayesian model, an online automatic learning procedure can be implemented and should be also investigated and tested, since it would avoid the need for human intervention at start-up or when important changes occur in the building model. Since the sensors are difficult to be installed and maintained on such a harsh environment, a further reduction on the required monitoring platform could help the proposed architecture to be more cost-effective. Additional benefits in terms of performance and robustness could be achieved by adding uncertainty to the constraint formulation, by adopting a more efficient optimization algorithm and improving disturbance forecasting. This would allow for better exploiting the prediction capabilities of the proposed approach over longest time horizons, and for further improving the yet satisfying control performance in terms of comfort and energy savings.

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