PERFORMANCE IMPROVEMENT OF A HYBRID VENTILATION SYSTEM VIA PREDICTIVE CONTROL

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ABSTRACT

Accurate and responsive ventilation control is of primary importance in the airflow management in tunnels, especially in the case of fire events. This is even more critical in long single-tube, two-way road tunnels such as the Mont Blanc Tunnel, where the ventilation system is hybrid (longitudinal and transverse), and smoke must be confined and conveyed to suitable ceiling vents connected to an extraction shaft, while stratification must be kept as stable as possible. Jet fans are employed to realize the confinement, coupled with a PID controller which acts on the velocity excess in the position of the fire event, with the aim of nullifying it in the shortest possible time. The action of the controller is crucially subject to the action of several different factors: (i) the barometric pressure difference between portals, (ii) the accuracy and frequency of the reconstruction of pointwise velocity, and (iii) the delays related to the operation of the extraction system. All these factors, and especially the last one, can hinder the correct performance of the controller, by introducing perturbations leading the system to unwanted oscillatory behavior, potentially disrupting smoke stratifications and delaying smoke extraction and intervention of firefighting squads. To this aim, in this work we propose a novel approach based on predictive control, aimed at improving the performance of the Mont Blanc Tunnel ventilation system. The method is based on an a priori analysis of the ventilation transients and asymptotic conditions for a wide range of scenarios, using both field data and a 1D numerical model. Results of the analysis are then used to construct corrective factors for the PID input signal. The constants for the corrected PID are then optimized using a DOE approach. Preliminary numerical assessments indicate a significant improvement of the system response and a drastic reduction of oscillations.

Keywords: tunnel ventilation, predictive control, PID, 1D CFD model, airflow management.

1. INTRODUCTION

Ventilation control in road tunnels plays a fundamental role in ensuring operational efficiency and safety during emergency events such as fires. Long bi-directional tunnels such as the Mont Blanc Tunnel (11.6 km) pose further challenges, since they require a fine balance between longitudinal and transverse ventilation, to continuously feed fresh air across large distances while being able to manage and extract smoke at any location. The existing hybrid ventilation system of the TMB employs jet fans for confinement and extraction ducts for smoke removal [1-3]. The operation of jet fans is managed by a PID controller that reacts to sensor data in real time. During a fire, the control system aims to establish a zero-velocity zone around the event to confine smoke spread.

Since the reopening of TMB in 2002, TMB-GEIE, the concessionary binational company of the infrastructure, has continuously refined its control logic to improve stability and responsiveness. However, systematic analyses of events occurred between 2015 and 2024, where the control logic was activated to manage and extract smoke, highlighted recurring non-conformities between the actual and target time to attain the zero-velocity conditions. In most cases, this occurred under specific combinations of barometric pressure difference (Δp) and event position (PM_{event}). The underlying issue was identified as the time delays between sensor readings, control actuation, and the activation transients of the extraction system. The durations of these transients are far from negligible, and their action significantly modifies the aeraulic conditions around PM_{event}. These conditions can cause transient sign inversions of the measured velocity, leading to counterproductive control actions.

Therefore, while keeping the basic operation of the control system unchanged, a corrective predictive modification was proposed, based on a pre-mapping of the effects of extraction on the velocity profile. This logic, which effectively constitutes predictive control [4-6], operates exclusively during the initial phase of event management and then gradually returns to the current PID logic after an appropriate time interval. The development of this control logic exploits the previous comprehensive physical and digital characterization of the TMB ventilation system operated through multi-point airflow measurements [1], continuous longitudinal profile acquisition [2], and a 1D numerical model [3]. In the following, the novel algorithm and its calibration are presented, alongside preliminary 1D CFD assessments.

2. METHODOLOGY

2.1. Current TMB Control Logic

The baseline TMB control algorithm reconstructs the longitudinal airflow velocity profile along the tunnel using an array of 20 ceiling anemometers [1]. The average velocity at the fire location, v_{event}, whose target value is zero, is fed into a PID controller that determines the number of jet fans to activate:

$$\mathrm{n_{fan}}(\mathrm{t}) = \mathrm{K_P} v_{event}(\mathrm{t}) + \mathrm{K_I}\int_0^{\mathrm{t}} v_{event}(\mathrm{t})\mathrm{dt} + \mathrm{K_D}\frac{\mathrm{d}v_{event}(\mathrm{t})}{\mathrm{dt}}$$

where n_{fan} is the number of jet fans to activate (positive or negative depending on the required direction of thrust), and K_P, K_I, K_D are the proportional, integral, and derivative gains, respectively. While efficient and robust, this logic reacts only to *current* measurements, while airflow perturbations induced by the system transient may invert v_{event}, temporarily driving the PID in the wrong direction. In fact, when the algorithm is triggered (at time t_I), the extraction system simultaneously ramps up to full capacity and the dampers in the event area open. As shown in Figure 1, these actions cause a rapid evolution of the longitudinal velocity profile during the initial phase of the event. Under normal ventilation mode, the longitudinal profile is monotonically increasing, since air is injected into the tunnel by the fresh-air system. When the extraction system is activated – i.e., air is removed from the tunnel – it introduces a decreasing segment in the velocity profile whose amplitude depends on the extraction rate. The final profile stabilizes only once the extraction system has reached steady-state operation (approximately 2–2.5 minutes). From a control standpoint, this means that the current logic is systematically delayed, as it corrects a condition that is rapidly evolving.

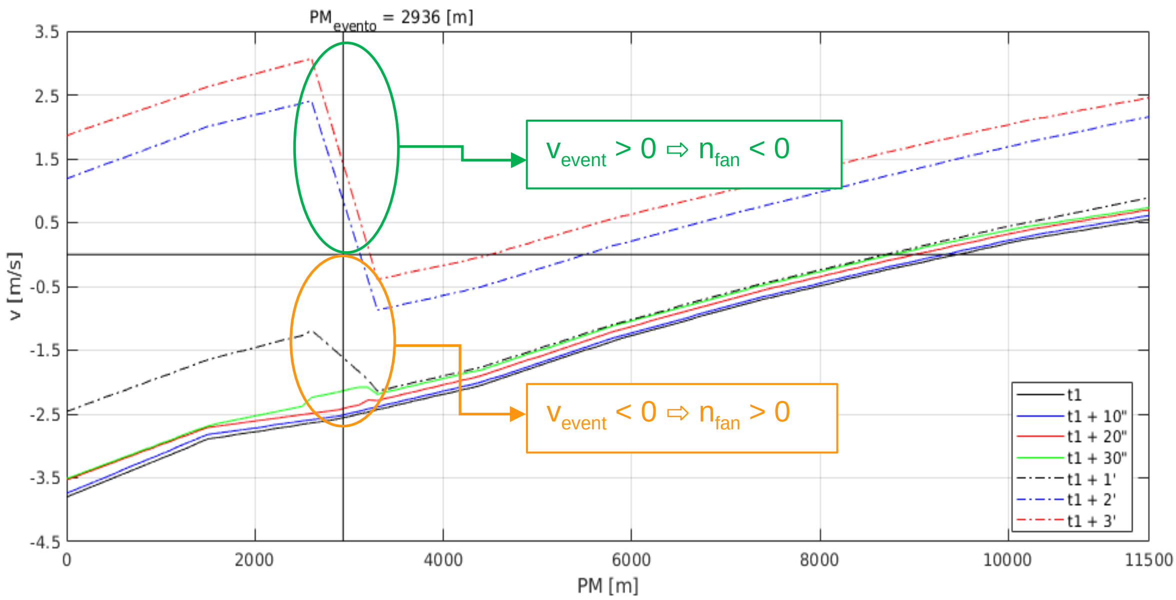


Figure 1: Evolution of the reconstructed TMB velocity profile during an event (starting at time t_1)

Although this characteristic is not always detrimental (in some cases, the delay helps stabilizing the zero-velocity point more quickly), in certain unfavorable combinations of Δp and $\mathrm{PM}_{\mathrm{event}}$, the extraction transient may even cause a sign reversal of the velocity at the event during the initial phase. Consequently, the initial corrective actions of the system may become counterproductive, delaying or hindering final stabilization. In practice, this manifests as early jet fan activations in the opposite direction of what is ultimately required for stable control (see again Figure 1). It is also important to note that velocity reversals near a fire or pollutant release can promote smoke destratification, which complicates rescue operations and increases risks for users.

2.2. Predictive Control Formulation

To overcome this limitation, a predictive term is introduced that estimates the future velocity using a correction matrix $\Delta \mathrm{v}_{\mathrm{corr}}(\Delta \mathrm{p}, \mathrm{PM}_{\mathrm{event}})$ multiplied by a blending function f_b, derived from a first-order Hermite polynomial (Figure 2). The blending function ensures gradual transition from predictive to standard PID behavior over a blending time constant τ_{b}:

$$v_{pred} = v_{event} + \Delta v_{corr}(\Delta p, PM_{\mathrm{event}}) \times f_b(t, \tau_b)$$

The correction matrix Δv_{corr} was pre-computed using the previously developed 1D CFD model of the TMB ventilation system described in [3].

The underlying idea originates from the observation that the extraction airflow rate – i.e., the alteration that extraction produces on the longitudinal velocity profile during the early phase of an event, as shown in Figure 1 – depends in general on both Δp and PM_{event}. As such, this effect can be pre-mapped, for example through field tests or CFD.

Values of Δv_{corr} were computed by simulating asymptotic scenarios for 31 values of $\Delta \mathrm{p}$ (from −750 to +750 Pa) and 17 evenly spaced event locations (5 m to 11 605 m), resulting in 527 scenarios. As shown in the plot of Figure 3, the general trend of the correction function confirms that extraction causes a measurable velocity rise or drop, depending primarily on the event location, while its variation with on Δp is minor.

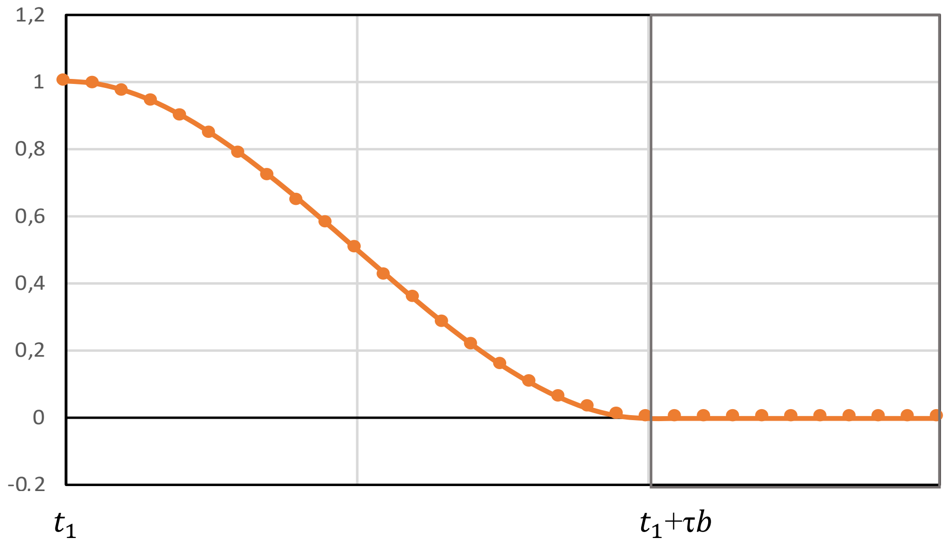


Figure 2: Predictive PID: smoothstep blending function $f_b(t, \tau_b)$.

The correction matrix Δv_{corr} was then used as a lookup table during subsequent calibration. Such format could also be conveniently implemented in the TMB control system.

The modified predictive PID law thus becomes:

$$n_{fan}(t) = K_P v_{pred}(t) + K_I \int_0^t v_{pred}(t)dt + K_D \frac{dv_{pred}(t)}{dt}$$

This approach endows the controller with short-term predictive capability while preserving the computational simplicity of the velocity reconstruction algorithm and of the operational PID structure.

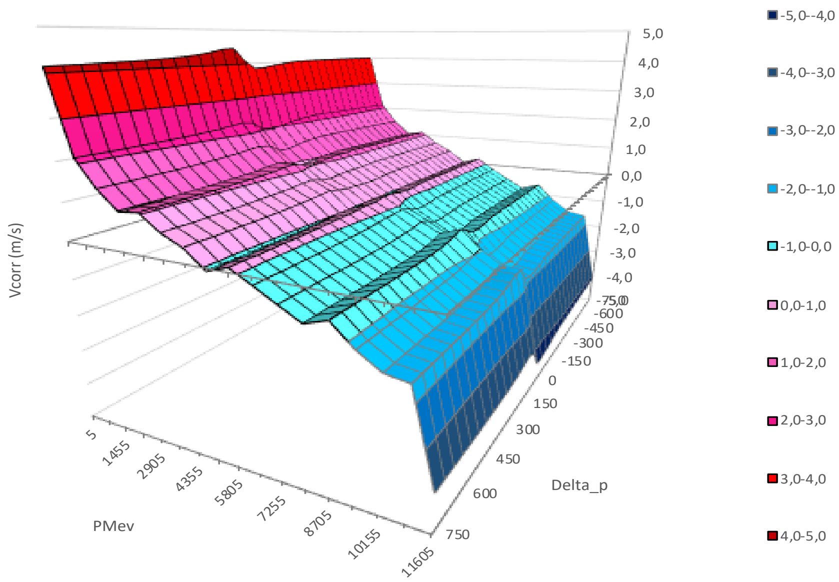


Figure 3: Predictive PID: correction matrix $\Delta v_{corr}(\Delta p, PM_{event})$.

2.3. Calibration

Compared to the current controller, the proposed modification introduces a new calibration parameter, τ_b, which extends the dimensionality of the parameter space from three (the PID gains (K_P, K_I, K_D) to four parameters: (K_P, K_I, K_D, τ_b). In this configuration, τ_b represents the temporal limit of the predictive correction, beyond which the standard control is fully restored. Meanwhile, the intensity of the correction gradually decreases according to the blending function f_b. Considering that the prescribed threshold for zero-velocity stabilization is 3 minutes, and that extraction stabilization typically occurs within 2–2.5 minutes, the range of τ_b was reasonably restricted between 90 and 150 seconds.

The calibration of the four parameters was carried out using a Design of Experiments (DOE) methodology. Three values of τ_b (90, 120, and 150 seconds) were tested, analyzing control performance over a matrix of (K_P, K_I) values, while K_D was kept constant and equal to the current coded value of the standard TMB controller, given that the derivative action is extremely sensitive to possible fluctuations of the measured field velocity, and that the current value already guarantees good stability.

A DOE campaign was executed to identify the optimal parameters (K_P, K_I, K_D, τ_b):

- $K_P \in$ [10, 20, 30, 40, 50]
- $K_I \in$ [0.07, 0.08, 0.09, 0.10, 0.11, 0.12]
- K_D = 1.38 (fixed)
- $\tau_b \in$ [90, 120, 150 s]

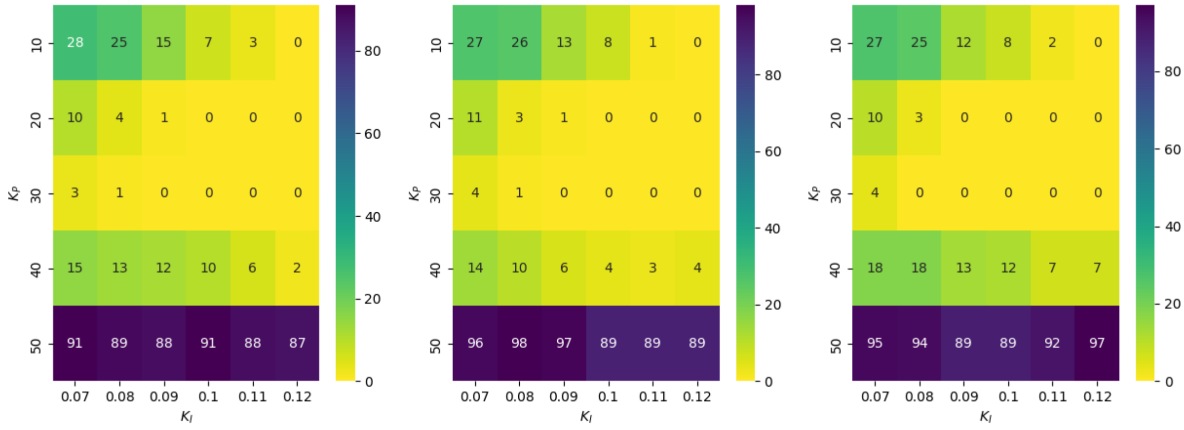
The ranges of (K_P, K_I) were chosen starting from the current values (10, 0.12) and increasing K_P to test higher responsiveness, while decreasing K_I to maintain stability. For each τ_b value, a total of 30 (K_P, K_I) combinations were simulated under 153 distinct conditions, representing all possible combinations of:

- 17 Δp-values: [−600, −450, −300, −250, −200, −150, −100, −50, 0, 50, 100, 150, 200, 250, 300, 450, 600 Pa],
- 9 $\mathrm{PM_{event}}$-values: [725, 1450, 2900, 4350, 5800, 7250, 8700, 10150, 10875 m].

In particular, the Δp range between −300 and +300 Pa was investigated with a finer resolution, since most of the non-conforming cases occurred in this interval. For Δp values greater than 600 Pa or less than −600 Pa, the system performance depends almost exclusively on the installed jet fan power. The $\mathrm{PM_{event}}$ spacing was set equal to the length of the tunnel segments served by each fresh air fan [2], adding one intermediate point near each portal, where velocity control is generally more difficult. This yielded a total of 13770 simulations, providing a statistically robust basis for assessing the control performance.

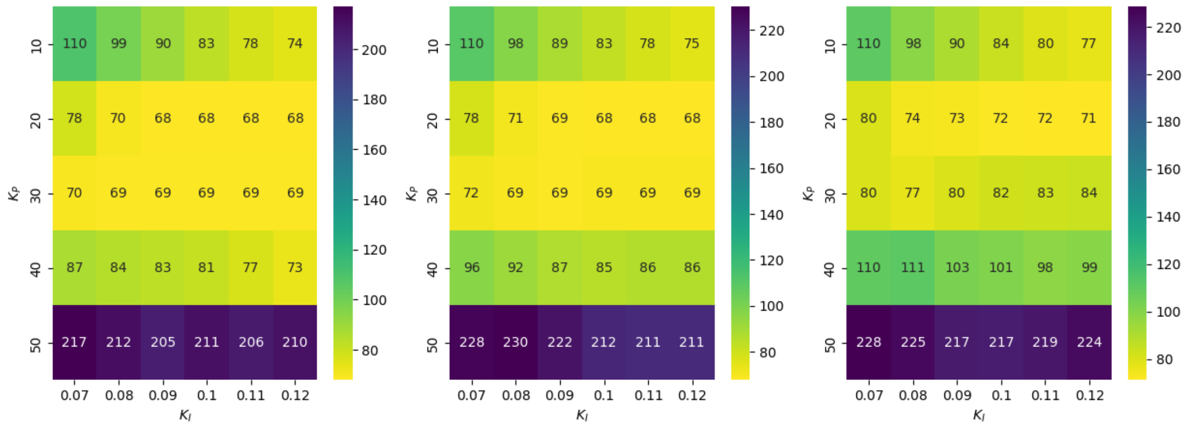
3. RESULTS AND DISCUSSION

Figure 4 shows three matrices (one for each τ_b value), indicating, for each (K_P, K_I) pair, the total number of cases in which velocity control proved non-compliant (i.e., cases where the event velocity did not fall within ±1 m/s in less than 3 minutes). For K_P = 20 and K_P = 30, more than one K_I-value produced fully compliant results. Values of K_P greater than 30, however, are characterized by excessive sensitivity and lead to numerous non-conformities, resulting from generally less stable control performance; therefore, such values were excluded from further consideration.



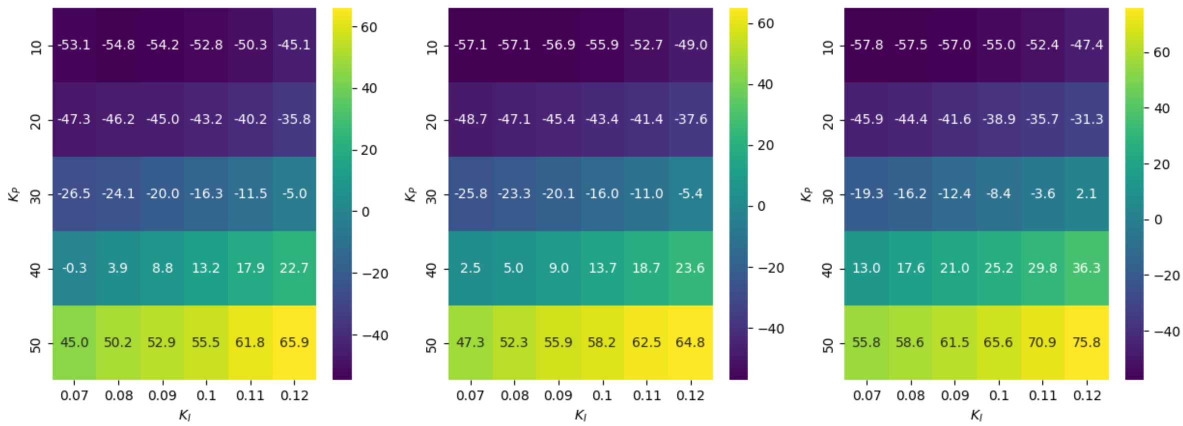
(a) (b) (c)

Figure 4: Cumulative number of non-conforming cases over the whole $(\Delta p, PM_{event})$ matrix used for calibration, and for (a) τ_b = 90 s, (b) τ_b = 120 s, (c) τ_b = 150 s.



(a) (b) (c)

Figure 5: Mean stabilization time over the whole $(\Delta p, PM_{event})$ matrix used for calibration, and for (a) τ_b = 90 s, (b) τ_b = 120 s, (c) τ_b = 150 s.



(a) (b) (c)

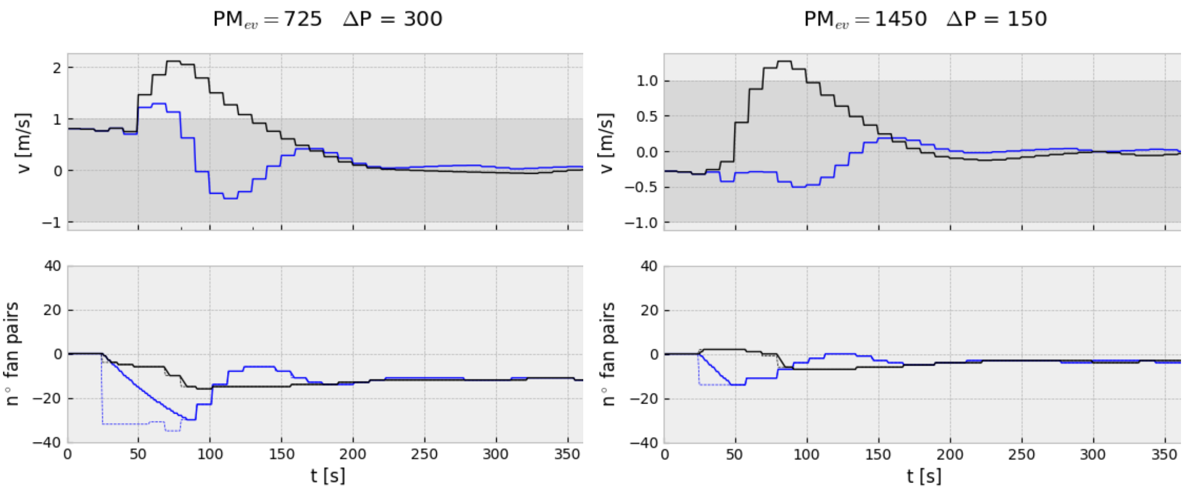
Figure 6: Cumulative velocity overshoot reduction over the whole $(\Delta p, PM_{event})$ matrix used for calibration, and for (a) τ_b = 90 s, (b) τ_b = 120 s, (c) τ_b = 150 s.

Two additional indicators were then analyzed to select the optimal configuration: the average time to reach the ±1 m/s threshold (Figure 5), and the cumulative reduction of velocity overshoot, that is, the maximum velocity values in the opposite direction of the jet fan thrust, compared with the current control logic (Figure 6). From the analysis of these indicators, it can be observed that:

- The value τ_b = 150 s results in slightly longer average time spans to reach the zero-velocity point, and these times are generally shorter for K_P = 20 and K_P = 30.
- For K_P = 30, the reduction of overshoot is smaller than in the cases with K_P = 20 and with the combination (K_P, K_I) = (10, 0.12) (representing the current parameter set).
- For K_P = 20, the greatest reduction of overshoot occurs for τ_b = 120 s and K_I = 0.1.
- The value τ_b = 120 s maximizes the reduction of velocity overshoots while at the same time limiting the average time to reach the zero-velocity point.
- The pair (K_P, K_I) = (20, 0.1) with τ_b = 120 s is overall the most favorable among those considered in the present analysis.
- The current pair (K_P, K_I) = (10, 0.12), if associated with the predictive logic, still ensures good performance.

Finally, Figure 7 presents two detailed comparisons between the current and the proposed control logic in terms of event velocity and algorithm output. In both cases, the parameter set (K_P, K_I, K_D, τ_b) = (20, 0.1, 120) was used for the predictive logic.

Figure 7a shows a case where the velocity at the start of the event is already within the prescribed threshold, but the extraction action causes an increase (overshoot) that the non-predictive PID counteracts only after a certain time. The predictive PID, on the other hand, by already accounting for the effect of extraction, mitigates this phenomenon and quickly reaches the desired stability conditions. Figure 7b instead shows a case where the extraction action associated with the non-predictive PID causes a sign change and a resulting overshoot. It can be noted that this phenomenon is almost eliminated by the predictive action of the proposed control logic.



(a) (b)

Figure 7: Comparison of the v_{event} and n_{fan} transients obtained with the current PID (black lines) and the predictive PID (blue lines) using the selected parameter combination (K_P, K_I, K_D, τ_b) = (20, 0.1, 120), for (a) $(\Delta p, \mathrm{PM}_{event})$ = (300, 725) and (b) $(\Delta p, \mathrm{PM}_{event})$ = (150, 1450). In the bottom graphs, dashed and solid lines indicate jet fan request (i.e. the controller output) and actual number of active jet fan pairs, respectively

4. SUMMARY AND CONCLUSION

A predictive extension of the TMB ventilation control algorithm, aimed at enhancing the overall performance and stability of the control system, was developed and calibrated. Such an extension consists in the introduction of a correction term added to the current measured velocity at the event location. This allows the system to estimate and feed into the PID controller the predicted velocity corresponding to the steady-state extraction regime. By doing so, the algorithm acquires predictive capabilities, which cannot be achieved through simple PID control. The correction term, interpolated from a precomputed matrix of values obtained via 1D CFD, is applied only during the initial phase of fire event management. Its influence is gradually reduced over time by a blending function, which governs the smooth transition from predictive to standard control.

An initial calibration of the predictive control parameters was conducted using a Design of Experiments (DOE) approach combined with 1D CFD analyses. A comprehensive matrix of scenarios was simulated to cover the entire operational range of the tunnel. The analysis theoretically confirmed the validity of the proposed approach, highlighting significant improvements in terms of control speed and stability. Specifically, the predictive modification allows for an increase in the proportional gain coefficient, resulting in a more responsive and precise control action.

While computationally lightweight, the method effectively introduces a model-informed feedforward correction. CFD-derived correlations embedded in the lookup matrix serve as a surrogate model of system dynamics, reducing the need for real-time estimation. The predictive controller thus offers a low-cost, high-impact enhancement for hybrid tunnel ventilation systems, demonstrating that integrating predictive elements into established control schemes can markedly improve tunnel safety and response performance. Future work will focus on field validation and potential coupling with real-time digital twin platforms for further adaptive optimization.

REFERENCES

[1] P. Levoni, D. Angeli, E. Stalio, E. Agnani, G.S. Barozzi, M. Cipollone, "Fluid-dynamic characterisation of the Mont Blanc tunnel by multi-point airflow measurements," Tunnelling and Underground Space Technology 48 (2015) 110–122

[2] P. Levoni, D. Angeli, P. Cingi, G.S. Barozzi, M. Cipollone, "An integrated approach for the analysis and modeling of road tunnel ventilation. Part I: Continuous measurement of the longitudinal airflow profile," Transportation Engineering 3 (2021) 100039.

[3] P. Cingi, D. Angeli, M. Cavazzuti, P. Levoni, E. Stalio, M. Cipollone, "An integrated approach for the analysis and modeling of road tunnel ventilation. Part II: Numerical model and its calibration," Transportation Engineering 4 (2021) 100063.

[4] M. Casini, A. Giannitrapani, "Model Predictive Control for HVAC Systems: Applications to Tunnels and Large Enclosures," Energy and Buildings 222 (2020) 110062.

[5] C. Poussot-Vassal et al., "Advanced control of ventilation in confined transport infrastructures," Control Engineering Practice 86 (2019) 95–108.

[6] X. Zhao et al., "Predictive control of tunnel ventilation using CFD-assisted data-driven modeling," Automation in Construction 129 (2021) 103809.