Received: Added at production | Revised: Added at production | Accepted: Added at production

DOI: xxx/xxxx

REGULAR PAPER

Control strategies for ventilation networks in small-scale mines using an experimental benchmark

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Summary

In view of the frequent ventilation network changes during production in underground mining, decreasing sensors and actuators without altering production control and safety is one of the chief engineering challenges. This work is focused on modeling identification and control strategies for underground ventilation networks in small-scale mines using an experimental benchmark. Guidelines to obtain a discrete state space model are provided, considering the conservation laws in the network to define the structure of the linear model. The main purpose of the paper is to analyze the use of classic controllers on the mine ventilation system when there are limitations on the number of sensors and actuators available to design a feedback control system. A comparison of three classic control strategies is presented considering the a constraint on the available number of sensors. Experimental and simulation results are presented.

KEYWORDS:
Control applications, ventilation networks, modeling, experimental benchmark

1 | INTRODUCTION

The mining industry is an important economic activity for many countries around the world. A high accident rate is reported each year in the underground mining sector. To address this problem, several academic and industrial research papers have been focused on improving safety conditions in the underground mining operation using auxiliary fan control [3]. Modeling air flow dynamics in ventilation systems in mines is vital, not only to describe the system variables but also to design control systems regulating the air flow along the network.

The steady-state description of ventilation networks is usually performed using the Hardy-Cross method: the air flow in mine ventilation circuits is determined algebraically by combining graph theory and classical Kirchhoff's laws [2]. A non-linear dynamic lumped parameter model for mine ventilation systems is described in [14], where a multi-variable control strategy is proposed for the linearized model. Hu, *et al.* [7] propose a model based on Kirchhoff's algebraic equations and the differential equation describing the air flow dynamics in the branch, to design a non-linear feedback controller for a mine ventilation system with the assumption of full equipment (actuators and sensors throughout the entire network). This method is extended, controlling fluid networks forced periodically and including adaptive methods [9, 10, 21]. A similar model is proposed by [22], including external perturbation in the model and designing an H_1 optimal controller. Sui *et al.* [16] introduce a control law based on feedback linearization and genetic algorithms to obtain optimal branch resistance values for complex networks. In a different context, a 0-D approximation of the 1-D pressure transport (advection and sink) as a time-delay system is proposed in [19, 20] and shown to be efficient as a reference model for feedback control of the large advective flows appearing in the mining ventilation problem, this class of approximation focused on the control of pure transport phenomena. On the other hand, scale models have been implemented to investigate the behavior of air flow in underground mining. In [6] presents the results of the Pittsburgh-based, 1:30 scale physical model, the Longwall Instrumented Aerodynamic Model (LIAM), equipped with sensors, actuators and a data acquisition system to verify air flow and dynamics for varying roof caving characteristics, In the same way, experimental models have been used to study the dynamic behavior of ventilation networks regulated by means of the control strategies presented in [5, 1].

Most of the existing control strategies focus on analyzing the ventilation network system in the multiple-input multiple-output (MIMO) processes, considering sensors and actuators in every branch of the network [18]. Controllability and observability analysis present an interesting problem when large-scale systems are considered. In [12, 11], the observability and controllability problems are studied in network-based models when the number of branches in the system increases.

This paper is focused on the application of classic control strategies for the control and regulation of ventilation networks in underground mines considering the conditions in small-scale facilities. The lack of sensors and actuators is a limitation to install automatic feedback control systems in this class of mines, therefore an estimate of the flow variables in the mine branches would reduce the number of necessary sensors at the time of control system implementation; the reduction of sensors has been requested by engineers and mine owners to optimize the company's resources.

The main concern in a ventilation network is to provide fresh air in a sufficient quantity in the working areas, normally modeled as a single branch of the network. Classic modeling, identification and control strategies are applied to an experimental set-up to test their effects on the entire mine, observer based controllers are also considered to overcome the limitations of the number of sensors in the network. Experimental data and simulations are given to evaluate the proposed results. Whereas directed mainly to underground mining operations, our results can also be applied to the ventilation of spaces such as intelligent buildings, nuclear waste repositories, commercial accommodation or vehicular networks. Other types of fluid networks such as gas and water distribution networks and irrigation networks can also be analyzed with a similar perspective.

The paper is organized as follows: Section 2 describes the characteristics of the experimental benchmark; Section 3 illustrates the mining ventilation control problem and a linear model is defined by considering the conservation laws in the network and identification of a discrete system in open loop is provided; Section 4 illustrates the design and application of the controllers with experimental results obtained from a small-scale benchmark to validate theoretical results. This section ends with a discussion about the implemented controllers.

2 | BENCHMARK AND PHYSICAL COMPONENTS

When extraction work starts in underground mining, as shown in Figure 1, a ventilation network is necessary to ensure the air flow through the branches meets safety standards for workers. One way to represent the ventilation network at scale is based on tunnels built with sanitary pipes and low-cost fans. A small-scale benchmark to perform different tests on the control of ventilation networks on underground mines is built at GIPSA-Lab [15], considering the conditions in a typical small mine, a scale 1:500 has been used in order to configure the cross-section of the tunnels. The air distribution network shown in Figure 2 which simulates the small mine, is built with PVC pipes with a diameter of 80 *mm*. A centrifugal fan powered at 12 Volts, with a nominal delivery of volumetric air flow rate of $35m^3/h$ actuates the system. An H-bridge is used to vary the fan velocity by means of a Pulse Width Modulated (PWM) signal. The network has a set of different sensors to measure the volumetric air flow in each branch, an orifice plate device, a mass air flow sensor and a hot-wire sensor are used to measure the volumetric air flow $Q_1(t)$, $Q_2(t)$ and $Q_3(t)$, respectively. The configuration is shown in Figure 2. An Arduino Mega 2560 board has been selected to be used as a data acquisition system and control unit.

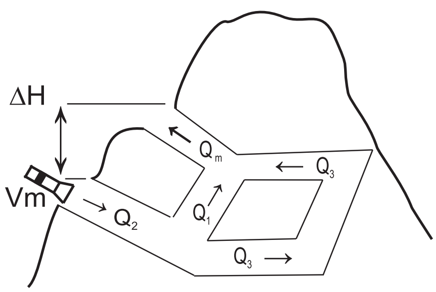

FIGURE 1 Typical configuration of small underground mining ventilation network.

2.1 | The ventilation mine network

The main purpose of an underground ventilation system is to provide air flows in sufficient quantity and quality to dilute contaminants to safe concentrations in all parts of a mine where

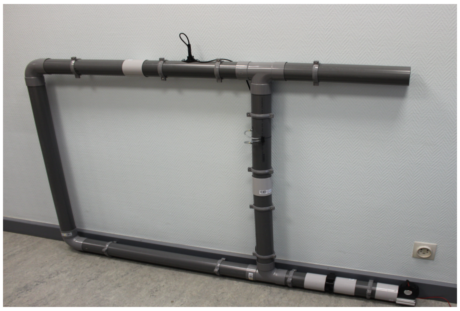

FIGURE 2 Experimental benchmark for underground mining ventilation network.

employees are required to work and travel [17]. The ventilation system supplies fresh air through one or more downcast shafts connected to the surface. Air flows along intake airways to the working areas or places where most pollutants are emitted into the air. The return air returns to the surface via one or more up-cast shafts.

The primary means of producing and controlling the air flow are the fans. These are usually, but not necessarily, located on surface, either exhausting air through the system or connected to downcast shafts, forcing air into and through the system.

For any given total air flow requirement, the energy cost of ventilation is proportional to the resistance offered to the passage of air. This resistance depends on the size and number of mine branches and the manner in which they are interconnected by nodes.

The air flow direction depends on the fan location and needs associated with the transportation of the mined material. An ascentional ventilation system implies that the air flow moves upwards through inclined workings, taking advantage of the natural ventilating effects of adding heat to the air. Descentional ventilation may be employed on more compact mining systems such as long-wall faces. As the air flow is in counter direction of the natural ventilation, it can cause control problems related with the buoyancy effects of gases [13].

2.2 | Network branches

A single branch can be represented as a dynamic component of the network, influenced by the inertance of the fluid and a resistance term due to the friction in the pipe. The following assumption is considered in this work.

Assumption 1. The air is incompressible and the temperature throughout the network is constant [5].

The fundamental dynamic equation for a branch is:

$$L_f \frac{dQ(t)}{dt} = H(t) - RQ(t)|Q(t)|, \tag{1}$$

Where $Q(t)$ is the volumetric air flow in the network branch, the aerodynamic resistance is represented by $R = \rho f \Pi l / 8S^3$, ρ is the fluid density, f is the friction factor, Π is the pipe perimeter, l is the pipe length and S is the cross-section area. The inertance term is $L_f = \rho l / S$ and the total pressure drop along the branch is $H(t) = P_{in}(t) - P_{out}(t)$.

If the variation in air flow with respect to time is zero, the pressure drop in a branch is given by:

$$H(t) = RQ(t)|Q(t)| = RQ(t)^2 \tag{2}$$

3 | LINEAR MODEL OF THE VENTILATION NETWORK

An accurate model of the ventilation network is necessary to design and test feedback control strategies. The parameters of a mine are typically unknown but can be derived from measurements and experimental data. To simplify the modeling task, a system parameter identification based on the air flow rate measurements in the network branches is employed. The linear state representation is obtained by means a line search method. Even if the parameters of the model are unknown, the *structure* of the model can be defined by the Kirchhoff's laws in the network, *i.e.* the zero and non-zero parameters in the model matrices.

3.1 | Model structure

Let us consider a ventilation network system with N number of branches. The volumetric air flow in every branch is considered as a state variable. The Kirchhoff's law for the flows in the network can be represented as follows:

$$\sum_{i=1}^{N_{in}} Q_{in}(t) = \sum_{j=1}^{N_{out}} Q_{out}(t) \tag{3}$$

where $\sum Q_{in}(t)$ is the sum of air flows going into the node and $\sum Q_{out}(t)$ is the sum of air flows going out from the node. N_{in} and N_{out} are the number of branches connected to the node. According to the Kirchhoff's law for the flows, the state matrix structure can be set as follows:

$$A_{ij} = \begin{cases} \theta_{ij} & \text{if branch } \boldsymbol{i} \text{ and branch } \boldsymbol{j} \text{ are both connected to the same node} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where $i = 1,\ 2, \cdots N$, $j = 1,\ 2, \cdots N$, and θ represents a non-zero value, used to initialize the parameter identification. In a similar way, the input matrix is defined as follows:

$$B_{ik} = \begin{cases} b_{ik} & \text{if the fan } \boldsymbol{k} \text{ is connected to the branch } \boldsymbol{i}, \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

whith a network with k number of fans are used as actuators. Finally, the output matrix is built as follows:

$$C_{ii} = \begin{cases} 1 & \text{if a sensor is connected to the branch } \boldsymbol{i}, \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

3.2 | Application on the experimental benchmark

A system identification method has been employed based on the response of the ventilation network shown in Figure 3. A linear state space model is proposed to describe the air flow dynamics in every branch of the network. Considering the Pulse Width Modulation (PWM) duty cycle as the input of the system, $u(t)$, the air flows in the branches $Q_i(t)$, with $i = 1,\ 2$ and 3 as the state variables. An initial state space representation of the network model is given by the system provided by the matrices $A,\ B,\ C$ to use a line search method and find a discrete state space representation:

$$\begin{aligned} x(k+1) &= A_d x(k) + B_d u(k) \\ y(k) &= C_d(k) \end{aligned} \tag{7}$$

The matrix A_d, B_d and C_d are found by using an identification method, the SSEST (Iterative method that uses prediction error minimization algorithm) is selected to represent the discrete space-state as follows:

$$A_d = \begin{bmatrix} 0.9200 & 0.0560 & 0.0233 \\ -0.0727 & 0.9168 & 0.0772 \\ 0.1560 & 0.3869 & 0.4842 \end{bmatrix} \tag{8}$$

$$B_d = \begin{bmatrix} 0 \\ 0 \\ 0.0923 \end{bmatrix} \qquad C_d = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$$

A_d, B_d and C_d define the discrete model with sampling period of 100 ms. The obtained model is stable, namely all the eigenvalues of the matrix A_d are contained in the unit circle. A comparison between identification system and experiment benchmark responses is shown in Figure 3.

For the experiment, a step input was used, the duty cycle of the PWM to power on the fan was changed periodically with values of $DC \in [65\%,\ 80\%,\ 95\%]$.

The estimated model has a fit of $[91.5155\%,\ 74.2634\%,\ 73.1160\%]$ for each state variable respectively, with a mean-square error of 1.6752. The computed model is simulated with the input signal used in the experiments. The obtained results are shown in Figure 3, where the solid line indicates the experimental data obtained from the sensors in the ventilation network. The simulation results of the obtained state-space representation are shown by means of a dashed line.

The dynamics of the ventilation network can be represented using a nonlinear model, considering the quadratic relation

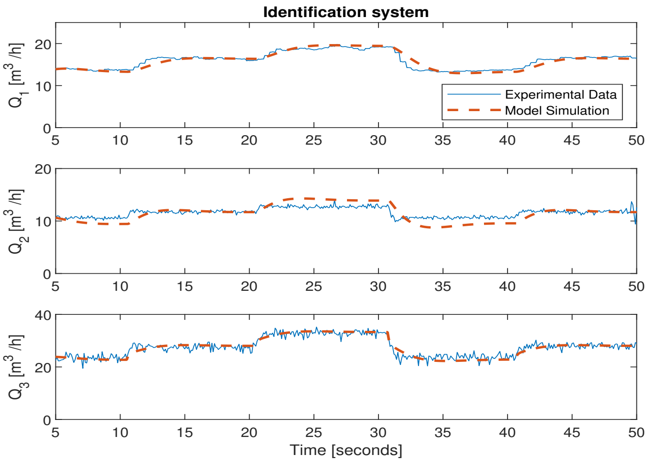

FIGURE 3 Signals obtained for the system identification of volumetric air flows on the benchmark

between the air flow and the pressure drops. However, the linear discrete model (8) is a satisfactory approximation when a operating point is selected.

4 | CLASSICAL CONTROLLERS

Ventilation systems in the underground mining industry are regulated by government to ensure safe conditions for workers. From a control point of view, the aim is to guarantee fresh air quantity and quality in the working area, according to the regulations.

This section provides an analysis of different classical control strategies applied to a ventilation benchmark. The main purpose is to evaluate such control systems with regards to their possible application in the industrial context. Three control strategies are presented in this section with design considerations projected to be applicable in small underground coal mining.

4.1 | Proportional Integral Control (PI)

The control aim is to regulate the volumetric air flow $Q_1(t)$ in the branch where the hot wire sensor is connected. Based on the model, a PI controller is designed to obtain a response with a settling time without overshoots in the closed loop behavior.

$Q_{ref}f(z)$ is defined as the set-up reference, the error is given by $e(z) = Q_{ref}(z) - Q_1(z)$ and the control signal is computed as follows

$$u(z) = K_p e(z) + K_i \int e(z) dz \tag{9}$$

The closed loop system must comply with government safety regulations. The Colombian regulations outlined in Decree 1886 of the year 2015 can be taken as a benchmark here which establish that for each person entering the mine, air flow must be increased by $360m^3/h$ [4]. By considering the selected scale 1:500 in the construction of the experimental benchmark, the equivalent volumetric air flow per person should be $0.72m^3/h$. For a working area in which seven workers enter, for example, the control system must regulate air flow by increasing volumetric air flow by $5m^3/h$ the volumetric air flow in the benchmark. Considering the given specifications, the PI controller constants are: $K_p = 1.92$ and $K_i = 1.246$.

4.2 | State Feedback Control (SFC)

In the mining extraction processes it is important to guarantee the air flow in all working areas, therefore, the ideal situation is to have sensors in all the branches of the ventilation network in order to implement a state feedback control, as shown in Figure 4. The purpose is to compute an state-feedback control law in the following form:

$$u(t) = Setpoint - FQ_{meas}(t), \tag{10}$$

where $Q_{meas}(t)$ is the set of state variables, namely, $[Q_1(t),\ Q_2(t),\ Q_3(t)]^T$, and F is the vector of controller gains with appropriate dimensions. The state feedback controller is designed as such that the volumetric air flow $Q_1(t)$ is regulated to desired values depending on the number of workers in the area.

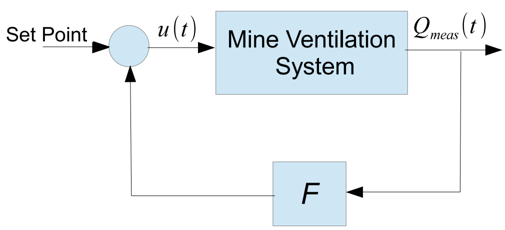

FIGURE 4 Diagram of the static state feedback controller.

4.3 | Linear-Quadratic-Integral control (LQI)

Considering a limited number of sensors in the ventilation network, an observer-based controller is shown in Figure 5. The reduced set of air flow variables $Q_c(t)$ are considered as the state variables. Moreover, we consider the measurement of the set of variables $Q_{meas}(t)$, such that the pair (A, C) is observable. Then, with the estimated states $\hat{Q}_c$, a LQI (Linear-Quadratic-Integral) control is implemented.

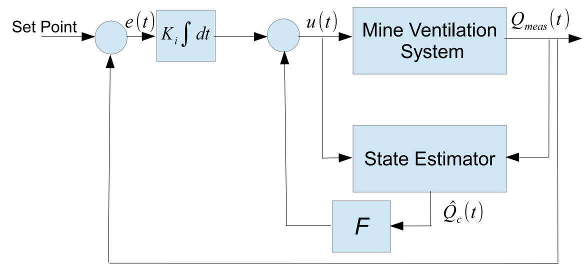

FIGURE 5 Diagram of the LQI observer-based controller.

The purpose is to compute an optimal state-feedback control law of the form:

$$u(t) = F\hat{Q}_c(t) + K_i \int e(t)dt \tag{11}$$

where $e(t) = Q_{ref} - Q_{meas}(t)$, with a constant set-point Q_{ref}. A constraint of the system is defined by the air flow through the working area, [8]. It can not exceed the maximum and minimum permissible bound, namely:

$$Q_{i_{min}} \leq Q_i \leq Q_{i_{max}}, \tag{12}$$

on the other hand, the control signal must also be restricted, that is, the pressure drop generated by the fans must be limited, avoiding mechanical or electrical efforts in the fans, then:

$$U_{i_{min}} \leq U_i \leq U_{i_{max}}. \tag{13}$$

The objective for the optimization in the ventilation network is to reduce energy consumption and to regulate the air flow in the working area. Therefore the cost function can be defined as:

$$J(t) = \int_{t_0}^{t_f} \{V_i(t)^2 + Q_1(t)^2\} d(t) \tag{14}$$

4.4 | Discussion of Controllers response

Three kinds of classical controllers are carried out to analyze the closed-loop behavior of the ventilation system.

The PI(D) Controller is the most common controller in the industrial environment because it is easy to design and implement. In the ventilation system for an underground mining context, the main limitation is that only the air flow in a branch of the network can be controlled on an operating set-point, without considering the information from the rest of the variables in the system. However, in small scale mining, it can be considered as a solution since only a particular working area is exploited at once, allowing us to reduce the number of sensors in the ventilation system.

The closed-loop response of the system with a PI controller is shown in Figure 6(Above). Initially, the operating point is set

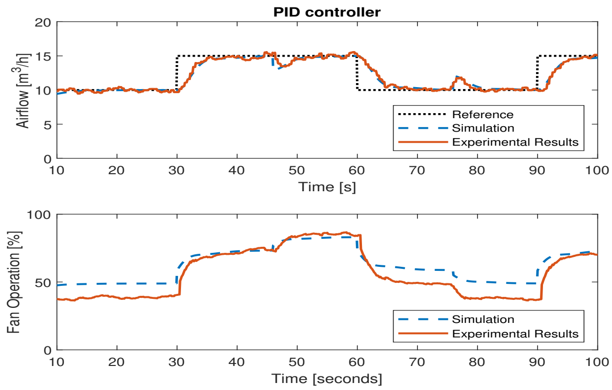

FIGURE 6 Closed-loop response: PI controller

to 10 m^3/h, after 30 seconds the set up is changed to 15 m^3/h. The behavior of the control system in the event of a disturbance can be seen in $t = 45$ seconds, the disturbance is cancelled in the instant $t = 75$ seconds. The integral control action seems to satisfactorily eliminate the steady state error. Figure 6(below) shows the fan control action on the experimental benchmark (solid line), and the corresponding simulated control signal (dashed line).

The full state feedback control (SFC) is designed and tested. The control action depends on state variables, in this configuration all the state variables are measured and used as feedback signals. The output $Q_1(t)$ present errors in steady state as shown in Figure 7, in addition the system seems to be sensitive to external disturbances, introduced at instant $t = 30s$ and $t = 50s$, obtaining a 20% error in the steady state response.

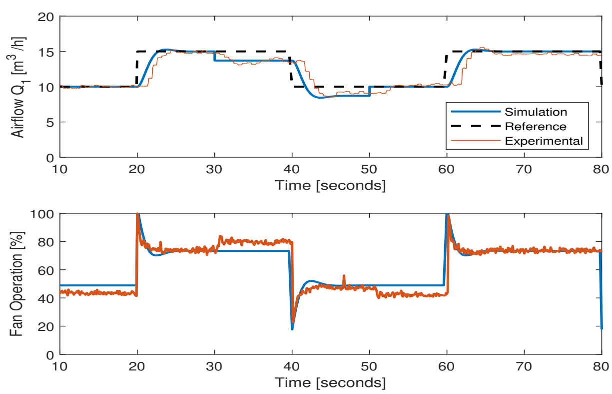

FIGURE 7 Closed-loop response: state feedback controller.

Finally, in the underground mining ventilation, there is a large number of branches are available and it is difficult to measure every variable in the network. An observer-based LQI controller is designed and implemented to overcome the limitation of sensors in the ventilation system. The observer is able to estimate the air flows $Q_2(t)$ and $Q_3(t)$ by means of the available measurement of $Q_1(t)$.

The closed-loop response of the system is shown in Figure 8. The system is set to an operation point with $Q_1(t) = 10m^3/h$ and changed periodically to $Q_1(t) = 15m^3/h$ every 20 seconds. An external disturbance is introduced into the system at instant $t = 50s$ in order to visualize the disturbance rejection provided by the integral term. The Red line shows the response of the simulated system and blue line corresponds to the experimental results of the benchmark controlled by means of the observer-based controller.

It can be noted that the estimation of the volumetric air flows $Q_2(t)$ and $Q_3(t)$ is satisfactory; $\hat{Q}_2(t)$ and $\hat{Q}_3(t)$ have a steady state error of 5% and 2%, respectively, with respect of the simulated process, allowing to us to reduce the number of sensors in the network by 63% in order to apply an appropriate control strategy.

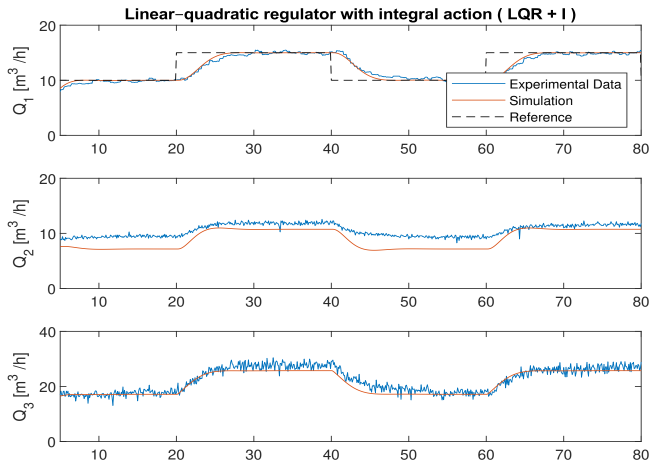

FIGURE 8 Estimated states of the ventilation network using a LQI observed based controller.

5 | CONCLUSION AND FUTURE WORK

The problem of controlling ventilation systems of underground small-scale mines is considered in this paper. A ventilation benchmark has been built to evaluate experimentally different control strategies related with the regulation of volumetric air flow in specific branches of a mine. The main purpose is to provide solutions for industrial systems where several flows are connected and there are limitations on the available number of sensors and actuators. Considering the small-scale model, the analysis has been shown that is possible to obtain satisfactory results controlling the volumetric airflow with a limited number of sensors, required in an automation application for mining ventilation. The guidelines to obtain a linear discrete state-space model has been provided considering the conservation laws of the network and the zero-nonzero parameters in the model matrices. If the system is observable, an observer based LQI controller can be implemented where the values of volumetric air flow in the branches of all the network have been estimated based on the measurement of only one sensor, the steady state error of the estimated variables has been calculated in the range of 3% to 5%.

Our work is focused on mine ventilation networks but the results can be extended in a straightforward way to interconnected systems distributing a different incompressible fluid. Further works on this topic include the design and validation of control strategies considering the proposed model as well as the the transport phenomena when dangerous gases, such as CO_2 or NO_x, are present in ventilation networks. Further work is also being carried out on the application of control strategies in mining environments using industrial equipment such as programmable logic controllers and sensors.

ACKNOWLEDGMENTS

We acknowledge the support of COLCIENCIAS, Universidad Pedagógica y Tecnológica de Colombia, and GipsaLab (France) in the research project "CONTROL STRATEGIES IN SMALL UNDERGROUND COAL MINING VENTILATION NETWORKS", and extend our thanks to the ECOS-NORD Program for supporting the exchange of researchers between France and Colombia through the mobility project 66979.

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How to cite this article: Rodriguez-Diaz O.O, Novella-Rodriguez D., Witrant E., and Franco-Mejia E. (2020), *Q.J.R. Meteorol. Soc., 2020;00:1–6.*