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Adaptive controller for a low-cost mechanical ventilator

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Resumen

La ventilación mecánica requiere un control preciso de variables como la presión y el flujo en las vías respiratorias para garantizar un soporte seguro y eficaz. Este trabajo propone un controlador adaptativo para regular la presión en un ventilador mecánico de bajo costo (VMAR+), considerando la variabilidad del paciente, las incertidumbres del modelo, las no linealidades del actuador y los retardos de comunicación. La estrategia combina control en cascada, acción feedforward y predictor de Smith. La resistencia y la distensibilidad pulmonares se estiman en línea mediante mínimos cuadrados recursivos, permitiendo actualizar continuamente el modelo y los parámetros del controlador. El sistema se valida experimentalmente en un pulmón artificial bajo distintas condiciones respiratorias, incluyendo cambios de distensibilidad. Los resultados muestran un control estable y una respuesta adecuada pese a las limitaciones del hardware, destacando el potencial del esquema propuesto para aplicaciones de ventilación mecánica en diferentes escenarios clínicos reales de uso hospitalario.

Palabras clave: Ventilación mecánica, Control adaptativo, Modelado pulmonar, Sistemas biomédicos, PID, Control en cascada

Abstract

Mechanical ventilation is a key tool in treating patients with respiratory failure, where precise control of variables such as airway pressure and flow is essential for safe and effective support. This paper proposes an adaptive cascade control strategy for airway pressure regulation in a low-cost mechanical ventilator (VMAR+), addressing challenges such as patient variability, model uncertainties, actuator nonlinearities, and communication delays. The control scheme combines cascade control with feedforward action and a Smith predictor to compensate for dominant time delays. Lung resistance and compliance are estimated online using a Recursive Least Squares algorithm, enabling continuous updates of the model and controller parameters. The approach is validated experimentally on an artificial lung under varying respiratory conditions, including changes in compliance. Despite hardware limitations, the system achieves stable and responsive pressure control, highlighting the potential of the adaptive control strategy proposed for real-world ventilator applications.

Keywords: Mechanical ventilation, Adaptive control, Lung modelling, Biomedical systems, PID, Cascade control

1. Introduction

Mechanical ventilation is a life-support technique used to assist or fully replace spontaneous breathing in patients with respiratory failure. Its primary objective is to ensure adequate gas exchange by regulating airway pressure, flow, and delivered volume when the physiological respiratory effort is insufficient or absent (Benumof, 2012). Depending on the clinical condition, ventilation can be applied in invasive or non-invasive modes. It can operate under different control strategies, typically classified as pressure-controlled or volume-controlled ventilation.

Physiologically, breathing is driven by pressure gradients between the atmosphere and the alveolar space. During spontaneous respiration, the diaphragm generates the pressure variations required to overcome airway resistance and lung elasticity, enabling inspiration and expiration. These mechanical

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properties are commonly characterised by lung compliance and airway resistance, which strongly influence the patient-specific respiratory dynamics (Bates, 2009). Mechanical ventilators reproduce or support the respiratory cycle through positive-pressure ventilation, generating a pressure above atmospheric pressure at the airway inlet. During inspiration, this pressure gradient drives airflow into the lungs, while expiration is generally passive through an expiratory valve. The overall system performance strongly depends on the interaction between the ventilator and the patient's respiratory mechanics, which are nonlinear, uncertain, and subject to continuous variations (Henderson and Sheel, 2012). Since these parameters may vary significantly over time and between patients, the ventilator–patient interaction can be interpreted as a dynamical system with uncertainty and time-varying behaviour, making accurate modelling and control particularly challenging.

Several modelling approaches have been proposed to describe lung mechanics. Among them, lumped-parameter models based on resistance and compliance elements are widely used. They provide a simple effective representation of the airway pressure–flow–volume relationship suitable for control-oriented applications (Lindup et al., 2024). Nevertheless, patient variability still represent major challenges for controller design.

In clinical practice, the respiratory cycle is defined by variables such as airway pressure, tidal volume, respiratory rate, and the inspiratory-to-expiratory ratio. Among them, airway pressure is particularly relevant because excessive pressure can lead to lung injury. For this reason, modern ventilators are typically designed to operate within strict pressure limits while maintaining adequate gas exchange (Chiumello et al., 2020). Accurate tracking of the target pressure is essential to ensure adequate patient support.

To enhance the performance of mechanical ventilators, several control strategies have been developed in the literature. A review of modelling and control techniques for mechanical ventilation is provided in Borrello (2005). Traditional mechanical ventilation systems primarily rely on linear time-invariant feedback controllers, such as PIDs. However, fixed-gain control strategies often suffer from overshoot, oscillatory responses, and degraded tracking performance when respiratory parameters vary (Sheltag and Kadhim, 2024). Consequently, research has focused on adaptive and model-based control techniques that adjust the control action online based on the patient's condition. In Borrello (2001), an adaptive feedback control strategy is used in which the patient model is estimated and subsequently used to adaptively tune a controller to achieve a desired closed-loop transfer function. The limitations of this work are that the validation of the proposed approach is performed using a respiratory simulator, in practice it is complex to obtain an accurate patient model.

The authors in Ionescu and De Keyser (2009) proposed a model-free adaptive control approach for mechanical ventilation that uses frequency-domain information extracted from measured signals, rather than an explicit lung model. Their contribution demonstrated that adaptive controller tuning can improve robustness against inter-patient variability and time-varying respiratory dynamics. Reinders et al. (2020) developed an adaptive control framework for pressure support ventilation that accounts for unknown and time-varying patient respiratory dynamics. More recently, machine learning approaches have also been explored to enhance monitoring, parameter estimation, and control performance in mechanical ventilation systems (Suo et al., 2021; Yang and Wan, 2022).

In this context, this paper presents an adaptive control framework for the low-cost VMAR+ mechanical ventilator. In contrast to many studies in the literature, which typically validate using simulation, commercial ventilators or sophisticated laboratory setups, the VMAR+ system relies on affordable, non-commercial hardware. It adds additional control challenges, mainly due to limited sensing capabilities, actuator nonlinearities, modelling uncertainties, and transmission delays in the system. Therefore, obtaining stable and accurate pressure regulation under these conditions highlights the practical relevance and contribution of the proposed approach.

To address these challenges, a simplified respiratory system model is combined with an experimentally validated valve model to support the design of a cascade pressure control architecture. The proposal control strategy is based on cascade control. While in the inner loop, a PI controller controls the valve opening; in the outer loop, a proportional controller is set. An online estimation of lung parameters using a Recursive Least Squares (RLS) algorithm with an adaptive tuning mechanism enables controller parameters to adapt to changes in respiratory dynamics from one breathing cycle to the next. To further enhance system response, feedforward compensation, together with a Smith predictor, is included to mitigate the effects of transport delays and improve transient behaviour. The performance of the proposed control structure has been evaluated using an artificial lung. The test results have shown accurate pressure tracking and robust behaviour under varying conditions, despite the limitations of the system.

The paper is organised as follows. Section 2 describes the experimental setup used in this work. Section 3 presents the development of the valve and lung models employed for system modelling and control design. Section 4 details the proposed control strategy, while Section 5 discusses the experimental results obtained from the real tests. Finally, Section 6 summarises the main conclusions of the study.

2. Experimental Setup

In this section, the design of the VMAR+ is presented. Figure 1 shows a schematic representation of the VMAR+.

The ventilator features two main air flow lines. The first one is responsible for lung inflation and starts from the inlet port connected to the air supply source, characterized by its input pressure (IP), and ends at the port through which air is delivered to the lungs (ILP).

The second line is dedicated to exhausting the air accumulated in the lungs and starts from the lung output port (OLP), terminating at the ventilator output port (OP). The input pressure is manually regulated by means of a pressure regulator (PR), which ensures a stable pressure level even in the presence of variations in the supply pressure. The regulated pressure is then fed to the proportional electric valve (IEV), which allows continuous modulation of the airflow delivered to the lungs. The opening of this valve is controlled by the programmable logic controller (PLC) during the inspiratory phase, while it remains closed during expiration. A flow sensor is installed after the valve to measure the delivered airflow. At the interface ports between the ventilator and the lungs, two pressure sensors are installed to measure airway pressure. Although physically distinct, these sensors are treated as a single measurement by the control system, which computes their average value within the PLC. An output electric valve (OEV) is used to regulate the airflow exiting the lungs. This valve is normally closed during inspiration and fully open during expiration to allow lung deflation as quickly as possible.

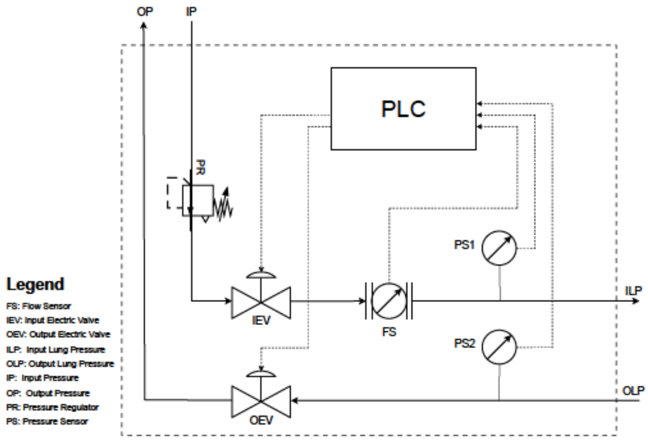

Figure 1: Scheme of the VMAR+. Continuous lines indicate air flow paths, while dashed lines represent electrical connections.

3. Patient-Ventilator Model

In the context of mechanical ventilation, a reliable model of a patient's lungs is essential, as it provides the basis for the design and analysis of the control system. In this work, a complete control framework is developed, which requires not only the patient's lung model but also the actuator model dynamics (IEV), culminating in the cascade control architecture.

3.1. Valve model

To determine the valve model, a sequence of step changes has been applied to the valve. Since there is a dead zone and a saturation zone within the range in which the valve could operate, it was decided to start from an opening value of 30% and increase by 2% until reaching a value of 60%, in order to focus only on the zone where actual changes in flow are seen as the valve opening varies. It is important to emphasise that the pressure entering the valve must remain constant; otherwise, for the same opening, the airflow may be greater or lesser depending on the input pressure. For this experiment and all those to come, a pressure of 600 *mbar* was used.

The valve dynamics can be approximated by a first-order system, as represented in the following equation:

$$\frac{\dot{V}(s)}{O_{\%}(s)} = \frac{k_v}{\tau_v\, s + 1} e^{-L_v s} \tag{1}$$

where $\dot{V}(s)$ is the flow rate, $O_{\%}(s)$ is the valve opening, expressed in percentage and has a range between 0-100%.

Figure 2 shows the validation test of the model, focusing on the opening range $40 - 54\%$, where $\tau_v = 0.06$s, $k_v = 3\text{L}\cdot(\text{min}\cdot\%)^{-1}$ and L_v=0.18s.

For valve control, a PI controller is designed and tuned using the Lambda method (Panagopoulos et al., 1997). The parameters of the controller are $K_{p,v} = 0.078$, $T_{i,v} = 0.06$s.

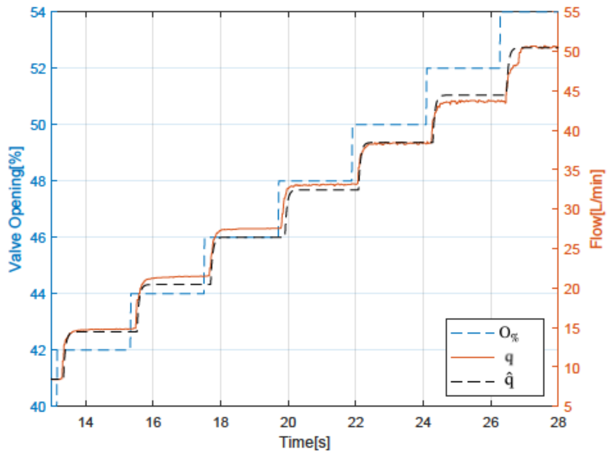

Figure 2: Flow rate comparison between measured flow and estimated.

3.2. Lung model

In modern literature, numerous lung models exist, each with varying degrees of complexity (Bates, 2009). However, in order to develop a control system, a simple linear model is chosen for this work (Lindup et al., 2024):

$$P_{aw}(t) = PEEP + \frac{V(t)}{C} + R\dot{V}(t) \tag{2}$$

where PEEP represents the baseline pressure, C is the lung compliance, R is the airway resistance, $V(t)$ is the lung volume, and $\dot{V}(t)$ is the airflow.

Defining $\Delta P(t) = P_{aw}(t) - PEEP$, the equation becomes:

$$\Delta P(t) = \frac{V(t)}{C} + R\dot{V}(t) \tag{3}$$

Taking Laplace transforms and using $V(s) = \dot{V}(s)/s$, the following trasnfer function is obtained:

$$\frac{\Delta P(s)}{\dot{V}(s)} = K \cdot \frac{1+\beta s}{s} \qquad K = \frac{1}{C} \qquad \beta = RC \tag{4}$$

The model described by Equation 2 applies only to sedated patients with no inspiratory effort, meaning the ventilation is set to control mode. Nevertheless, for the porpouse of this work, this model is enough, as for estimation and control strategy, artificial lungs will be considered, where it is not possible to replicate the inspiratory effort of a conscious patient. In the real system, it is important to note that an additional time delay of $L0.26$s is introduced by the measurement dynamics.

Parameters R and C are not explicitly defined as they are subject to variability and their value will be estimated online by the proposed RLS adaptive method. The control strategy is detailed in the following section.

4. Control Design

The control strategy adopted in this work is based on airway pressure regulation, as pressure can be directly measured from ventilator sensors, whereas volume is typically estimated from flow integration. To ensure patient safety, overshoot relative to the pressure setpoint must be avoided, resulting in a desired first-order dynamic response of the lung system when operating in closed loop. The controller is designed to meet the timing constraints imposed by clinical parameters such as the respiratory rate and the inspiratory-to-expiratory ($I : E$) ratio (Borrello, 2001), ensuring that the target pressure is reached within the prescribed inspiration time.

The overall architecture (see Figure 3) is based on a cascade control structure.

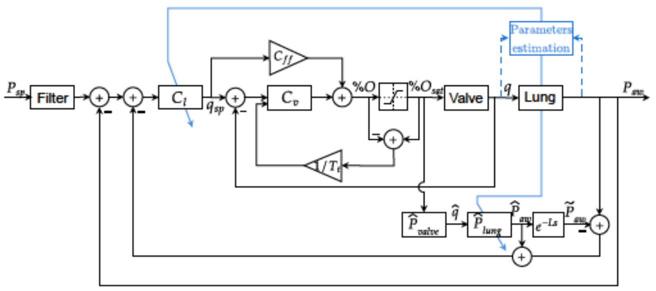

Figure 3: Complete adaptive cascade control architecture for the VMAR+ mechanical ventilator platform.

The inner loop controller was defined in the previous section. Moreover, the delay associated with the inner loop is mitigated with the reference feedforward action, which anticipates valve opening and compensates it. It is set as $C_{ff} = 1/k_v$. A back-calculation anti-windup scheme is included with T_t=$T_{i,v}$. For the outer controller design, the inner-loop dynamics are not considered, since their response is significantly faster than the desired dynamics of the outer loop. However, the outer loop is still affected by an additional delay due to communication and measurement. Since this delay is dominant over the respiratory system's closed-loop time constant, it can degrade the system response if it is not properly compensated. For this reason, a Smith predictor is included.

Using the valve opening command $O_{\%}$, the airflow $\hat{q}$ is estimated through the valve model $\hat{P}_{valve}$ using Equation 1. This estimated flow is used to predict the airway pressure $\hat{P}_{aw}$ through the lung model in Equation 4. The predicted pressure is fed back to the controller K_p. To align the estimated and measured airway pressures, the system delay L is applied to the predicted signal, yielding the delayed pressure response $\tilde{P}_{aw}$. The difference between the two signals is then computed.

A reference filter with a time constant of 0.3 s is also included to smooth the response to the reference setpoint.

The design of the outer loop controller is carried out in two stages. First, the lung model parameters are estimated from mechanical ventilator sensor data using the RLS algorithm (Åström, 1995). The estimation is performed at each respiratory cycle, using only inspiratory phase data. At the end of each cycle, the RLS algorithm updates the new values of R and C for the next respiration cycle, adapting the Smith predictor lung model and the outer controller. This adaptive strategy enables the control system to account for changes in lung conditions and to assess the effectiveness of the combined modelling and adaptive control approach.

As discussed in the previous section, the lung model is defined in Equation 4. The outer loop controller is selected as a proportional controller, $C_l = K_{p,l}$. Therefore, the closed-loop transfer function can be derived as follows:

$$F(s) = \frac{1+\beta s}{1+(\frac{1}{K_p \cdot K}+\beta)s} = \frac{1+\beta s}{1+\tau_{bc}\, s} \tag{5}$$

where $\tau_{bc} = \frac{1}{K_p \cdot K} + \beta$ is the time constant of the closed-loop system. The zero coming from the lung model is kept but, as β is normally a small value due to the compliance C, the closed-loop system is mainly regulated by the pole, which is typically dominant respect to the zero. Assuming this and, as the dynamics response of a first-order system takes five times the value of the time constant of its pole to reach the steady state, the following condition can be written:

$$5 \cdot \tau_{bc} < T_I \tag{6}$$

where T_I is the inspiration time set by clinicians. By developing the condition, the tuning rule for the pressure controller K_p is obtained:

$$\frac{1}{K_p \cdot K} + \beta < \frac{T_I}{5} \quad \longrightarrow \quad K_p > \frac{1}{K \cdot (\frac{T_I}{5} - \beta)} \tag{7}$$

With Equation 7, it is possible to calculate K_p at each respiratory cycle, which, as can be seen, is a term dependent both on the inspiration time and on the parameters of the lung model that make up β. However, some operating conditions may lead to negative values of K_p or to closed-loop poles too close to the origin, potentially causing instability. To avoid these situations, a lower stability bound was introduced for the controller tuning. Defining n as the ratio between the pole and zero time constants, the following condition was imposed:

$$n = \frac{\tau_{bc}}{\beta} \geq N_{min} \tag{8}$$

where N_{min} represents the minimum acceptable ratio to guarantee stable operation. From this condition, the following limit for the proportional gain is obtained:

$$\frac{\frac{1}{K_p \cdot K} + \beta}{\beta} \geq N_{min} \quad \longrightarrow \quad K_{p,stab} \leq \frac{1}{K \cdot \beta \cdot (N_{min} - 1)} \tag{9}$$

A larger value of N_{min} increases system stability but also slows down the pressure response. Therefore, a compromise value of $N_{min} = 1.6$ was selected based on a parametric sweep over β and τ_{bc}, ensuring stable performance across a wide range of lung mechanics and operating conditions. The objective of this additional constraint is not to satisfy the nominal control specifications, but to ensure stable and sufficiently fast operation under unfavourable parameter estimations or demanding inspiration times.

5. Results

This section presents the results related to the adaptive pressure control during the inspiratory phase. The test carried out aims to verify whether the implemented control strategy satisfies the imposed control objectives and whether the parameter estimates provided by the RLS algorithm converge towards the actual lung parameter values.

Figure 4: Fluke ACCU LUNG. Precision lung used for the adaptive pressure control test.

Table 1: Simulation parameters

Parameter	Value
Respiratory rate	6.7 $\frac{resp}{min}$
I:E ratio	1 : 2
Number of respiratory cycles	16
Pressure setpoint	30 $mbar$
PEEP pressure	5 $mbar$
Initial resistance estimation (R_0)	12 $\frac{mbar \cdot s}{L}$
Actual resistance set (R)	5 $\frac{mbar \cdot s}{L}$
Initial compliance estimation (C_0)	50 $\frac{mL}{mbar}$
Actual compliance (C)	20 and 50 $\frac{mL}{mbar}$

The artificial lung used for these tests is shown in Figure 4, where the lung resistance (R) and compliance (C) values can be adjusted. It is important to note that the abrupt changes in these parameters were intentionally introduced to evaluate the robustness and effectiveness of the control strategy. In a real lung, however, these parameters typically vary gradually over time.

The simulation parameters are shown in Table 1. These parameters are in line with standard clinical practice in mechanical ventilation. A respiratory rate in the range of 6–10 breaths per minute, together with an inspiratory to expiratory ratio of 1:2, is commonly adopted in controlled ventilation (Tobin, 2006). PEEP was set to 5 mbar as a basic physiological reference value to help prevent alveolar collapse. The inspiratory pressure limit of 30 mbar was selected following usual lung protective ventilation criteria aimed at reducing the risk of lung injury (Hess, 2001).

Figure 5 shows the test results of pressure and airflow dynamics. In the first and upper panel, the evolution of the pressure control can be observed. P_{sp} is the pressure reference given during the inspiratory phase; P_{aw} is the actual pressure measured by the mechanical ventilator, and $\hat{P}_{aw}$ is the airway pressure estimated by the lung model with the parameters estimated after the inspiration phase and application of the RLS algorithm, with actual airflow as input. The goal is to verify that the new estimation fits the pressure measured during the inspiratory time.

In the test, a change in lung compliance occurs at the vertical red dotted line. Before this point, the RLS algorithm gradually updates the estimated parameters. It converges to a compliance value of around 15 mL/mbar, close to the true value used in the model. During the first respiratory cycles, the airway pressure P_{aw} progressively improves its tracking and reaches the reference signal after approximately the third cycle. In contrast, the airway resistance estimated converged at the seventh cycle.

After the compliance change, the system dynamics change accordingly, and the estimator readjusts within a few respiratory cycles. The airway pressure P_{aw} again converges to the reference trajectory after approximately three cycles. At the same time, the estimated compliance is estimated near 46 mL/mbar, which matches the new compliance value introduced in the model.

Notably, a sudden variation can be observed in the airway resistance, decreasing from approximately 10 $\frac{mbar \cdot s}{L}$ to 2.5 $\frac{mbar \cdot s}{L}$, even though the resistance value set in the lung model remained unchanged throughout the entire test. This behaviour is related to the spring-based mechanism used to adjust artificial lung compliance, which can introduce an additional resistive effect. Further evidence supporting this interpretation can be found in the PEEP behaviour observed during the experiment. Although the PEEP pressure was set to 5 $mbar$, the measured pressure at the end of the respiratory cycle is approximately zero during the first half of the test. At the same time, it returns to a value close to 5 $mbar$ during the second half, when the spring mechanism is no longer present.

Regarding control performance, the pressure controller remains stable throughout the experiment and adapts properly to the compliance change. No overshoot is observed, and the airway pressure P_{aw} reaches the reference pressure P_{sp} within the prescribed inspiratory time in both operating conditions. Although some estimation errors are present, they do not significantly affect the closed-loop pressure tracking.

6. Conclusions

This work presented the development of an adaptive pressure control strategy for a low-cost mechanical ventilator. A simplified patient–ventilator model was combined with an adaptive control architecture that uses online lung parameter estimation using the RLS algorithm.

The experimental results demonstrated that the proposed strategy can regulate airway pressure to the desired specifications while adapting to variations in lung dynamics. The implemented cascade control structure is enhanced with feedforward compensation and a Smith predictor.The study also highlighted several practical aspects affecting system performance. In particular, the limitations of the proportional valve, characterised by a reduced effective operating range and saturation

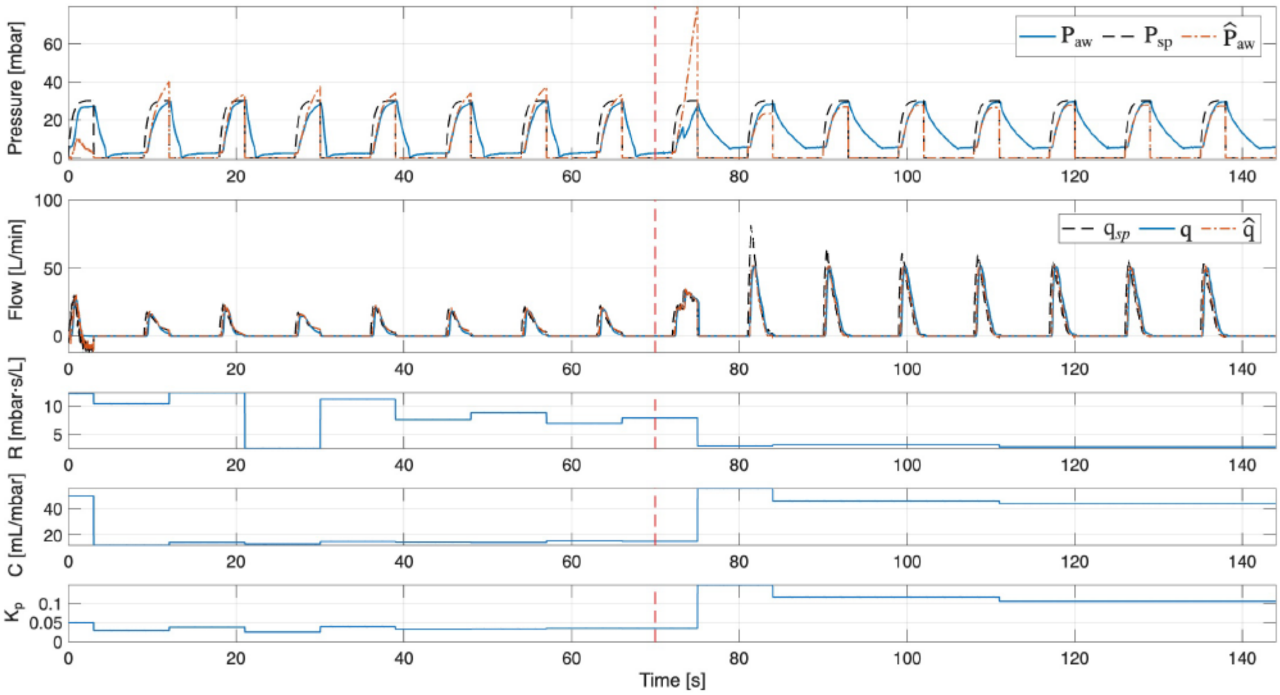

Figure 5: Airway pressure control (upper panel), actual and estimated airflow (middle panels), and adaptive parameter evolution (lower panels) with compliance switching.

effects, constrained the achievable control performance. Furthermore, communication delays introduced by the real-time interaction between MATLAB and the ventilator PLC affected the system responsiveness, although satisfactory results were still achieved.

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