Online hose calibration for pressure control in mechanical ventilation

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Abstract—Respiratory modules are used to assist patients who are unable to breathe sufficiently on their own. The aim of this paper is to develop a control method that achieves exact tracking of a time-varying target pressure, invariant to patient-hose-leak parameters. This is achieved by an online hose calibration that enables compensation for the pressure drop over the hose. Stability of the closed-loop system is analyzed and the performance improvement compared to stateof-practice feedforward and linear feedback control strategies is demonstrated by a simulation case study.

I. INTRODUCTION

Mechanical ventilators are commonly used in Intensive Care Units (ICUs) to assist patients who cannot breathe on their own or need support to breathe sufficiently. The main goals of mechanical ventilation are to ensure oxygenation and carbon dioxide elimination [1].

Blower-driven pressure controlled ventilation of sedated patients is an important aspect in mechanical ventilation. Such pressure controlled ventilation is addressed in this paper, with a single-hose setup, as depicted in Fig. 1. Note that, the proposed control strategy can directly be applied to spontaneously breathing patients and a dual-hose setup. The control goal of pressure controlled ventilation is to track a time-varying airway pressure set-point, see Fig. 2, where the airway pressure is the pressure in front of the patient's mouth, which can be measured using the sensor tube in Fig. 1. The blower is increasing the airway pressure during inspiration, to achieve the Inspiratory Positive Airway Pressure (IPAP), filling the patients lungs with air. After some time, it decreases the pressure to the Positive End-Expiratory Pressure (PEEP), such that the lungs are emptied. An example of a breathing cycle is displayed in Fig. 2. A substantial amount of research has been conducted to obtain the optimal ventilator settings, e.g., [2], [3], and [4], which focuses on the design of the pressure set-point.

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Fig. 1. Schematic representation of the blower-hose-patient system of the considered positive pressure ventilation system.



Fig. 2. Airway pressure and patient flow during one breathing cycle of pressure controlled ventilation (p_{aw} : airway pressure, Q_{pat} : flow into the patient's lungs, see also Fig. 3).

Accurate tracking of the pressure target may be considered less relevant from a clinical point of view. Nonetheless, high tracking performance is important for achieving sufficient support to the patient, especially in case of large flows, as a result of large lungs and unintentional leaks (e.g., in noninvasive ventilation). Secondly, accurate pressure tracking results in better patient-ventilator synchrony; in [5] and [6], it is discussed that better tracking prevents false triggers, improving patient-ventilator synchrony. Thirdly, for more complex ventilation modes, allowing patient effort, exact tracking is essential to deliver the required level of assistance more accurately.

The tracking performance achieved by linear feedback control is typically sub-optimal in terms of overshoot and settling time, as shown in Fig. 2. The main cause for such sub-optimal performance are the large plant variation for which the linear feedback controller should be designed. The controller should ensure robust performance for a broad spectrum of patients, from infants to adults, varying disposable hose-filter systems, unknown leakage and possibly unknown patient activity.

Different control strategies have been investigated to im-

prove the performance of controllers for mechanical ventilation. In [7], an overview of modeling and control techniques for mechanical ventilation is presented. Variable-gain control is proposed in [5] and [6], which aims to achieve pressure tracking while reducing the overshoot in patient flow, preventing false triggering. In [8], an adaptive feedback control approach is applied which is estimating the patient model and using this to adaptively tune a controller which achieves a desired closed-loop transfer function. In [8], the hose resistance is neglected; however, for large air flows, induced by large lungs and/or leakage, the hose-induced pressure drop cannot be neglected. This pressure drop is especially big in a single-hose system with an intended leak, which already causes a significant flow and thus pressure drop along the hose. Furthermore, funnel-based control [9] is applied to mechanical ventilation, however, the obtained gain in tracking performance is not very significant. In [10] a model-based control approach is used and in [11] a model predictive control approach is applied, these methods require accurate patient parameters which are typically not available in practice. Furthermore, iterative learning control [12] is applied to mechanical ventilation, which is limited to repeated sequences of the set-point and initial conditions.

Although the mentioned literature improves the tracking performance of ventilation, it does not achieve exact tracking of the airway pressure invariant to patient-hose-leak characteristics and independent of the set-point. To achieve this, a control strategy is developed that compensates for the pressure drop over the hose. Using an estimated hose resistance and the output flow to compensate for the pressure drop over the hose. Manual calibration of the hose-filter system to obtain the hose resistance is an undesired option, because of the already increasing demand of health care and the lack of trained personnel, see [13] and [14]. Further, the hose resistance might change during ventilation, due to clogging of the filter. Therefore, we propose an online Recursive Least Squares (RLS) estimator [15] to estimate the hose resistance automatically during ventilation.

The first contribution of this paper is the design of a control strategy which ensures exact tracking of the airway pressure independent of the patient, hose, leakage, patient effort, and set-point. The key advantages of the proposed approach include

- allows for a fast and accurate response, even for large lungs and big leaks;
- prevents overshoot in the patient flow and therewith prevents false triggering;
- is not using direct feedback on the patient airway pressure, which improves robustness.

The second contribution is a stability theorem of the resulting closed-loop system, ensuring exponential convergence of the estimation and tracking errors to zero. As a third contribution, a significant improvement in tracking performance in comparison to state-of-practice control strategies is shown through a simulation case study.

The outline of this paper is as follows. In section II, a mathematical model of the patient-hose system is presented.



Fig. 3. Schematic representation of the blower-hose-patient system, with the corresponding resistances and lung compliance.

In Section III, the control problem and high-level control approach are described. In Section IV, the developed control strategy is described and a stability theorem is presented. A model-based simulation study is presented in Section V, to show the time-domain performance of the proposed control strategy in comparison to state-of-practice control strategies. Finally, the conclusions and recommendations are presented in Section VI.

II. PATIENT-HOSE MODEL

In this section, a model for the patient-hose system is presented. Consider the schematic representation of the respiratory system depicted in Fig. 3. The system is operated by the blower, which pressurizes ambient air in order to ventilate the patient. A hose is used to connect the respiratory module to the patient. The flow Q_{out} , which leaves the blower, runs through the hose towards the patient. The patient exhales partly back through the blower, and partly through a leak in the hose near the patients mouth, see Fig. 3. The leak, with leak resistance R_{leak} , is used to refresh the air in the hose, such that the patient does not inhale previously exhaled, low-oxygen, air.

Using conservation of flow, the output flow Q_{out} , patient flow Q_{pat} and leakage flow Q_{leak} are related by

$$Q_{pat} = Q_{out} - Q_{leak}.$$
 (1)

The pressure at the outlet of the mechanical ventilator is the output pressure p_{out} . Due to the hose resistance R_{lin} , the output pressure p_{out} is not equal to the so-called airway pressure p_{aw} at the patient's mouth. The airway pressure p_{aw} is the performance variable that is controlled and measured using a pressure sensor on the module, see Fig. 3. The hose resistance is approximated using a linear resistance model, which is reasonably accurate for typical flows in ventilation.

Note that all pressures are defined relative to the ambient pressure, i.e., $p_{amb} = 0$, and the lung pressure p_{lung} cannot be measured in general. The lung is modeled using a linear one-compartmental lung model as described in [16], with lung compliance C_{lung} and resistance R_{lung} . Assuming linear resistances R_{lung} , R_{leak} and R_{lin} , the pressure drop across these resistances is related to the flow as follows:

$$Q_{out} = \frac{p_{out} - p_{aw}}{R_{lin}}$$

$$Q_{leak} = \frac{p_{aw}}{R_{leak}}$$

$$Q_{pat} = \frac{p_{aw} - p_{lung}}{R_{lung}}.$$
(2)



Fig. 4. Control scheme of closed-loop linear feedback control with unit feedforward.

Moreover, the lung dynamics are governed by

$$p_{lung}(t) = \frac{1}{C_{lung}} \int Q_{pat} dt, \qquad (3)$$

hence

$$\dot{p}_{lung}(t) = \frac{1}{C_{lung}} Q_{pat}.$$
(4)

Combining (2) and (4), the lung dynamics are described by:

$$\dot{p}_{lung} = \frac{p_{aw} - p_{lung}}{C_{lung} R_{lung}}.$$
(5)

The following relation for the airway pressure is obtained by (1) and (2):

$$p_{aw} = \frac{R_{lin}R_{leak}p_{lung} + R_{leak}R_{lung}p_{out}}{\bar{R}},$$
 (6)

with $R := R_{lin}R_{leak} + R_{lin}R_{lung} + R_{leak}R_{lung}$. By substituting (6) into (5), a differential equation for the lung dynamics is obtained

$$\dot{p}_{lung} = \frac{-(R_{lin} + R_{leak})}{C_{lung}\bar{R}} p_{lung} + \frac{R_{leak}}{C_{lung}\bar{R}} p_{out}.$$
 (7)

Given (7), (6) and (2), the patient-hose system dynamics can be written as a linear state-space system with input p_{out} and outputs p_{aw} and Q_{pat} , and state p_{lung} :

$$\dot{p}_{lung} = \mathbf{A}_h p_{lung} + \mathbf{B}_h p_{out}$$

$$\begin{bmatrix} p_{aw} \\ Q_{pat} \end{bmatrix} = \mathbf{C}_h p_{lung} + \mathbf{D}_h p_{out},$$
(8)

with

$$\mathbf{A}_{h} = -\frac{R_{lin} + R_{leak}}{C_{lung}\bar{R}}, \ \mathbf{B}_{h} = \frac{R_{leak}}{C_{lung}\bar{R}},$$
$$\mathbf{C}_{h} = \begin{bmatrix} \frac{R_{lin}R_{leak}}{\bar{R}} & -\frac{R_{lin}+R_{leak}}{\bar{R}} \end{bmatrix}^{T},$$
$$\mathbf{D}_{h} = \begin{bmatrix} \frac{R_{leak}R_{lung}}{\bar{R}} & \frac{R_{leak}}{\bar{R}} \end{bmatrix}^{T}.$$
(9)

Since all resistances and the compliance are strictly positive constants, A_h is negative and hence the patient-hose system is asymptotically stable.

III. CONTROL PROBLEM FORMULATION AND APPROACH

In the previous section, a mathematical formulation of the patient-hose model is presented. In this section, the control problem formulation is presented and the state-of-practice control approach is discussed in this context. Next, a highlevel description of the control approach proposed in this paper is given.

In state-of-practice blower-driven respiratory systems, typically linear integral feedback controllers are used. Implementing a linear feedback controller results in the closedloop system, where the airway pressure p_{aw} is the variable to be controlled (i.e., to track the target pressure p_{target}), as depicted in Fig. 4. The control goal is to minimize the tracking error (or ideally let it converge to zero asymptotically) defined as:

$$e := p_{target} - p_{aw}. \tag{10}$$

To ensure that the blower output pressure (p_{out}) is as desired, an accurate lookup table is used as well as a feedback controller using feedback of the blower error $(p_{control} - p_{out})$. This results in a transfer function from blower input $p_{control}$ to blower output pressure p_{out} which is one in the frequency domain of interest. Therefore, we assume unit-gain blower characteristics $(p_{out} = p_{control})$. Consequently, the unit feedforward (see Fig. 4) in combination with the blower characteristic ensures that p_{out} is exactly tracking p_{target} . However, the feedback controller has to compensate for the pressure drop $\Delta p = p_{out} - p_{aw}$ along the hose. Note that it is very complex to predict the pressure drop along the hose, due to several factors:

- the type of lung attached (i.e., the patient) is in principle unknown. Although the pressure target is a priori known, the amount of flow entering a lung depends on the lung resistance R_{lung} and lung compliance C_{lung} and is therefore unknown (therewith, also the flow through the hose, and thus the pressure drop Δp are unknown);
- the characteristic of the hose system attached is also unknown, hence the pressure drop along the hose is unknown;
- during (non-invasive) ventilation, there can be leakage around the mask, which cannot be predicted, and therefore also results in an a priori unknown pressure drop;
- additionally, patients can have spontaneous breathing activity (resulting in a flow and hence, a pressure drop along the hose), which also cannot be predicted a priori.

Therefore, exact feedforward control cannot be used to compensate for the pressure drop effects.

We propose a control strategy that uses an estimated hose resistance \hat{R}_{lin} and the output flow Q_{out} , which is measured near the blower, to compensate for the the pressure drop Δp over the hose, see Fig. 5. Because the hose-filter resistance R_{lin} is unknown, an off-line calibration could be conducted by hospital personnel, to estimate the hose resistance R_{lin} prior to ventilation. This requires extra time of the hospital staff, which is undesired because of the already existing lack of time for hospital staff, as emphasized in Section I. Furthermore, the resistance might change over time.



Fig. 5. Schematic representation of the proposed closed-loop system with a recursive least squares estimator for the hose resistance estimation.

Therefore, an adaptive control approach is developed, which is using an online Recursive Least Squares (RLS) estimator [15] to estimate (learn) the hose resistance automatically during ventilation, see Fig. 5. Practically, this approach is considerably more robust than the state-of-practice feedback method, which is using p_{aw} directly in the feedback loop. The proposed strategy is only using p_{aw} for updating the estimator. In practice, the sensor tube might get detached, e.g., when it gets stuck behind something. In such a scenario, the proposed controller can keep running without updating the resistance, whereas the feedback controller is useless and potentially dangerous. In the following section, the design of this adaptive control approach is elaborated and stability conditions for the resulting closed-loop dynamics are presented.

IV. DEVELOPED CONTROL APPROACH

In this section, the proposed adaptive control approach, as sketched in Section III, is described in detail. In Section IV-A, the closed-loop dynamics with the new control strategy, with a constant estimate \hat{R}_{lin} of the hose resistance R_{lin} , are presented. In Section IV-B, the RLS estimator, used to estimate the hose resistance, is given. Finally, in Section IV-C, stability conditions for the resulting closed-loop dynamics are presented.

A. Closed-loop dynamics for given hose-resistance estimate

Since feedback using the hose resistance estimate \hat{R}_{lin} is included in the control approach, as depicted in Fig. 5, a state-space description of the closed-loop controlled system (without estimator) is derived. Using $p_{out} = p_{control} = \Delta \hat{p} + p_{target}$ and (7), we have that

$$\dot{p}_{lung} = \mathbf{A}_h p_{lung} + \mathbf{B}_h \left(p_{target} + \Delta \hat{p} \right). \tag{11}$$

The estimated pressure drop $\Delta \hat{p}$ is given by

$$\Delta \hat{p} = \hat{R}_{lin} Q_{out}$$

= $\hat{R}_{lin} (Q_{pat} + Q_{leak})$
= $\hat{R}_{lin} \left(C_{lung} \dot{p}_{lung} + \frac{p_{aw}}{R_{leak}} \right).$ (12)

Note that $p_{control} = \Delta \hat{p} + p_{target}$ together with (11) essentially form the proposed feedback law that aims at compensating for the pressure drop over the hose-filter system. Substituting the airway pressure, given in (5), into (12) gives

$$\Delta \hat{p} = \hat{R}_{lin} \left(C_{lung} \left(1 + \frac{R_{lung}}{R_{leak}} \right) \dot{p}_{lung} + \frac{p_{lung}}{R_{leak}} \right).$$
(13)

Subsequent substitution of (13) in (11) gives

$$\dot{p}_{lung} = \frac{-R_{leak} - e_{LS}}{C_{lung}R_{eLS}} p_{lung} + \frac{R_{leak}}{C_{lung}R_{eLS}} p_{target}, \tag{14}$$

with $R_{eLS} := e_{LS} (R_{leak} + R_{lung}) + R_{leak} R_{lung}$, and the estimation error $e_{LS} := R_{lin} - \hat{R}_{lin}$.

The variables p_{aw} , Q_{pat} and Q_{out} are considered as outputs and the resulting closed-loop system model is as follows:

$$\dot{p}_{lung} = \mathbf{A}_{l} p_{lung} + \mathbf{B}_{l} p_{target}$$

$$\begin{bmatrix} p_{aw} \\ Q_{pat} \\ Q_{out} \end{bmatrix} = \mathbf{C}_{l} p_{lung} + \mathbf{D}_{l} p_{target}$$
(15)

with

$$\mathbf{A}_{l} = \frac{-R_{leak} - e_{LS}}{C_{lung}R_{eLS}}, \ \mathbf{B}_{l} = \frac{R_{leak}}{C_{lung}R_{eLS}},$$
$$\mathbf{C}_{l} = \begin{bmatrix} 1 - \frac{(R_{leak} + e_{LS})R_{lung}}{R_{eLS}} & \frac{-R_{leak} - e_{LS}}{R_{eLS}} & \frac{-R_{leak}}{R_{eLS}} \end{bmatrix}^{T}, \quad (16)$$
$$\mathbf{D}_{l} = \begin{bmatrix} \frac{R_{leak}R_{lung}}{R_{eLS}} & \frac{R_{leak}}{R_{eLS}} & \frac{R_{leak} + R_{lung}}{R_{eLS}} \end{bmatrix}^{T}.$$

B. Recursive least squares estimation of the hose resistance

In the previous section, the equations describing the proposed controlled plant model are presented for a constant hose resistance estimate \hat{R}_{lin} . Since the hose resistance is an unknown parameter, we use an RLS estimator that estimates the value of R_{lin} automatically during ventilation; hence no additional calibration steps are required in the hospital. Because data far in the past is considered to be less important than more recent data, an RLS algorithm with exponential forgetting factor β is used [15]. A schematic representation of the system with resistance estimator is depicted in Fig. 5.

The RLS estimator with forgetting factor is given by:

$$\dot{R}_{lin} = P \frac{\Delta p - \dot{R}_{lin} Q_{out}}{m^2} Q_{out}, \qquad (17)$$

$$\dot{P} = \beta P - P^2 \frac{Q_{out}^2}{m^2}, \qquad (18)$$

in which $Q_{out}(p_{lung}(t), e_{LS}(t), p_{target}(t))$ is written as Q_{out} for readability, P(t) is called the covariance and $m^2 > 0$ a constant normalization parameter. Since $\Delta p = R_{lin}Q_{out}$ and $e_{LS}(t) = R_{lin} - \hat{R}_{lin}(t)$, the least squares error dynamics are written as

$$\dot{e}_{LS} = -P \frac{Q_{out}^2}{m^2} e_{LS},$$
(19)

since R_{lin} is a constant. The resulting closed-loop dynamics with estimator and adaptive controller are given by (15), (16), (18) and (19).

C. Stability conditions

The closed-loop system dynamics with the adaptive controller are given by (15), (16), (18), and (19). In this section, stability conditions for this closed-loop controlled system are presented. Using some mild assumptions on the estimator design and pressure target, Theorem 1 is presented below. This theorem provides sufficient conditions for exponential convergence to zero of the tracking error e(t) and of the estimation error $e_{LS}(t)$, for time varying pressure targets $p_{target}(t)$.

First, it is assumed that the RLS estimator in (18) and (19) is designed and initialized, such that Assumption 1 holds.

Assumption 1. The RLS estimator in (18) and (19) is designed and initialized such that these following properties hold:

- P(0) is chosen to be positive, i.e., P(0) > 0.
- $\hat{R}_{lin}(0)$ is chosen such that the following inequalities hold (with $\varepsilon > 0$ a small constant):

$$\begin{aligned} R_{lin}(0) < R_{lin} + R_{leak}, \\ \hat{R}_{lin}(0) \leq R_{lin} + \frac{R_{leak}R_{lung}}{R_{leak} + R_{lung}} - \varepsilon. \end{aligned}$$

• β is chosen to be positive, i.e., $\beta > 0$.

We are free to design the RLS estimator, i.e., β , P(0), and $\hat{R}_{lin}(0)$ can be chosen freely. Therefore, we can always ensure that Assumption 1 holds. Furthermore, choosing $\hat{R}_{lin}(0) = 0$ always ensures the satisfaction of the inequalities in Assumption 1, since all resistances are positive.

Furthermore, Assumption 2 states that the target pressure profile is always positive and bounded.

Assumption 2. $p_{target}(t)$ is bounded and positive by design; in particular, $\varepsilon_1 < p_{target}(t) < \infty$, $\forall t \ge 0$, with $\varepsilon_1 > 0$ a small positive constant.

This is a valid assumption since a positive and bounded target pressure, i.e., input, is desired during positive pressure ventilation see Fig. 2, with PEEP > 0.

Theorem 1 ensures exponential convergence of the least squares error $e_{LS}(t)$ and the tracking error e(t) to zero for time-varying target pressures. This Theorem can be proved using the assumptions, the closed-loop dynamics, and estimator dynamics presented in Section IV. The proof of Theorem 1 is omitted for the sake of brevity.

Theorem 1. Consider the system dynamics (15), (16), (18), and (19) and suppose that Assumptions 1 and 2 hold. Then, solutions of the dynamical system (15), (16), (18), and (19) have the following properties:

- P(t), $P^{-1}(t)$, $p_{lung}(t)$ and $Q_{out}(t)$ are bounded $\forall t \ge 0$,
- $e_{LS}(t) = R_{lin} \hat{R}_{lin}(t)$ and $e(t) = p_{target}(t) p_{aw}(t)$ exponentially converge to zero.

Theorem 1 ensures exponential convergence of the tracking error e(t) to zero for a time-varying target pressure, under mild conditions on the initial estimate for the hose resistance and the target pressure profile $p_{target}(t)$. In control systems, perfect tracking is typically possible when inverseplant feedforward is applied and no further disturbances are present. Since the estimated resistance \hat{R}_{lin} describes the relationship that is described by the hose resistance R_{lin} , inverse feedforward is essentially applied through feedback.

Remark 1. The relation between the hose-induced pressure drop Δp and the measured flow through the hose Q_{out} is independent of the patient and leak parameters. The patient and leak parameters only influence the measured blower output. Therefore, we achieve exact tracking of the target pressure independent of patient and leak parameters.

V. COMPARATIVE SIMULATION CASE STUDY

In this section, the improvement in tracking performance of the adaptive control approach over state-of-practice control strategies is shown through simulations. The following two state-of-practice control strategies are considered:

- Feedforward control,
- Linear feedback control.

Fig. 4 shows a schematic representation of the closed-loop controlled system with linear feedback and unit feedforward control. The feedforward controller is a unit feedforward; in other words, the desired airway pressure is applied as

 TABLE I

 ESTIMATION PARAMETERS OF THE ADAPTIVE CONTROLLER AND THE PATIENT AND HOSE PARAMETERS, AS USED IN THE SIMULATIONS.

Parameter	Value	Unit
β	0.7	-
P(0)	$5 imes 10^{-8}$	-
$\hat{R}_{lin}(0)$	0	mbar s/L
m	1	mL/s
R _{leak}	24	mbar s/L
R _{lung}	5	mbar s/L
$R_{lin}(0)$	4.4	mbar s/L
C_{lung}	20	mL/mbar

 $p_{target} = p_{control} = p_{out}$ and no feedback based on measurements is used. The linear integral feedback controller is used to ensure convergence of the tracking error to zero for constant target pressures. Because in respiratory systems the plant variation are large, the linear feedback controller has to be tuned for robustness instead of performance resulting in an integral controller with transfer function $C(s) = \frac{10}{s}$, with $s \in \mathbb{C}$. For the system with feedback control, also unit feedforward is used. The RLS estimator parameters and the patient-hose system parameters are presented in Table I. In the simulations, target pressures of 5 and 20 mbar are used for the PEEP and the IPAP, respectively. Furthermore, we introduce a step of a factor 1.5 in the hose resistance at t = 10 s, to show that the controller can handle a change in resistance, e.g., when someone sits on the hose.

The resulting airway pressure of the simulations is shown in Fig. 6. These results clearly show that the feedforward controlled system has a steady-state tracking error, which is caused by the pressure drop Δp over the hose. For the linear feedback controller we observe that the pressure is converging to the desired pressure but there is undesired overshoot. This overshoot results in non-optimal patient support, and clearly causes overshoot in the patient flow, resulting in false triggers during ventilation modes that allow for patienttriggered breaths, see [5]. The resulting airway pressure of the developed adaptive controller is also displayed in Fig. 6. It shows that during the first breathing cycle the proposed controller behaves almost the same as the feedforward controller. This is caused by the fact that the initial estimate of $\hat{R}_{lin}(0)$ is zero, see Table I, so we have pure feedforward, i.e., the adaptive controller is not compensating the pressure drop yet. In the third breathing cycle, we already obtain almost perfect tracking with no overshoot and oscillations. Thereafter, the controller has to adapt to the step in R_{lin} , introducing a small error. This error vanished after the fifth breathing cycle.

In Fig. 7, the significant improvement in tracking performance is visualized. The tracking error of the adaptive controller is converging to zero. The tracking errors of the feedforward and feedback controllers remain the same over successive breathing cycles, with a slight increase when the hose resistance is increased. Furthermore, this figure shows that the estimated resistance is converging to the actual value, as expected. It is also clearly seen that the controller can handle the step in hose resistance, since the tracking error is converging to zero again after the step in resistance.



Fig. 6. Simulation results of the feedforward, feedback, and adaptive control strategy. This figure shows the resulting airway pressure and patient flow.



Fig. 7. Tracking errors of the different controllers and convergence of \hat{R}_{lin} of the adaptive controller.

Pressure profiles for different lung characteristics (resistance and compliance, see legend) are displayed in Fig. 8. It can be concluded that the control approach works for a broad range of lungs.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, an adaptive control approach for mechanical ventilation has been developed to improve tracking performance for large variations of patient-hose parameters, unintended leakages, and unknown breathing efforts. Since no calibration of the hose-filter system is required, this approach does not require extra time to set up the machine. The proposed method estimates the linear hose resistance and uses the measured flow and estimated resistance to compensate for the pressure drop over the hose. It is shown that the estimated resistance converges exponentially to the actual value and therewith the tracking error converges exponentially to zero for time-varying pressure profiles. A



Fig. 8. Airway pressure p_{aw} for multiple types of lungs, with the adaptive controller. The lung characteristics are given in the legend where the units for *R* are mbar s/L and the units for *C* are mL/mbar.

stability analysis supports these claims. Furthermore, using a simulation study, it is shown that the proposed control approach improves tracking performance significantly over state-of-practice linear feedback control. Also, the proposed control method can handle a time-varying hose resistance.

In future work, the practical applicability of this method will be analyzed through an experimental study.

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