Modeling Lung Functionality in Volume-Controlled Ventilation for Critical Care Patients

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***Abstract*—Mechanical ventilators are the instruments that assist breathing of the patients having respiratory diseases e.g., pneumonia and coronavirus disease 2019 (COVID-19). This paper presents a modified lung model under volume-controlled ventilation to describe the lung volume and air flow in terms of air pressure signal from the ventilator. A negative feedback is incorporated in the model to balance the lung volume that is influenced by a lung parameter called positive end expiration pressure. We partially solved the lung model equation which takes the form of a first-order differential equation and then unknown parameters associated with the model were computed using a nonlinear least-squares method. Experimental data required for parameter identification and validation of the lung model were obtained by running a volume-controlled ventilator connected to a reference device and an artificial lung. The proposed model considering negative feedback achieves a better accuracy than that without feedback as demonstrated by test results. The developed model can be used in intensive care units (ICU) to evaluate mechanical ventilation performance and lung functionality in real-time.**

Keywords— Lung Model, Critical Care, COVID-19, Mechanical Ventilation, Volume-Controlled Ventilation.

I. INTRODUCTION

Mechanical ventilator (MV) is live support machine that treats wide cases of patients who have lung malfunction, completely or partially, in intensive care units (ICU) [1]. The mechanical ventilation aims to maximize gas exchange to the patient's lung, and at the same time, minimize the possibility of ventilator-induced lung injury [2]. Mechanical ventilations are of two categories – (i) volume-controlled ventilation (VCV); (ii) pressure-controlled ventilation (PCV) [3, 4]. VCV that keeps the volume constant as much as possible during real-time ventilation process is commonly used in operation theatres and ICU. Different lung diseases that vary in severity can cause death and injury. The most common lung diseases e.g., acute respiratory distress syndrome (ARDS), chronic obstructive pulmonary disease, severe asthma and coronavirus disease 2019 (COVID-19) that require MV supports in case of higher severity level. However, incorrect settings of MVs may cause lung injury [5]. Therefore, in order to check the lung functionality and its response to MV, the lung characteristics (mechanics) are observed while connected to the ventilator.

The remaining positive pressure in the airways at the end of a respiratory cycle is called *Positive end-expiratory pressure* (PEEP) which is used to avert alveolar collapse and enhance oxygenation for the patients with MV. Some researchers recommended to keep optimal PEEP settings at maximum lung compliance during real-time mechanical ventilation [6]. Many complex engineering problems are solved using mathematical models to find the practical solutions [7]. In respiratory-system modeling, a fundamental model to represent the behavior of lung mechanics is the single-compartment model with the form of a differential equation of first-order [8, 9]. The models were developed to guide and optimize mechanical ventilation therapy. Modeling lung functionality in VCV can help to monitor lung pressure, volume, flow and compliance in real-time. MV performance and lung functionality can be assessed using the lung model [10].

This paper presents a modified lung model that is developed based on our previous work [11] in which a lung model was proposed considering a negative feedback to describe lung functionality during VCV in terms of pressure signal only. It can be noted that a higher PEEP in the model input generates a higher volume in the model output, and this affects lung functionality during VCV. Thus, a negative feedback was added to the model for keeping the lung volume constant. In the current research, we partially solved the lung model which takes the form of a first-order differential equation. Unknown parameters associated with the model were computed using a nonlinear least-squares method.

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The rest of this paper is arranged as follows. Section II provides the methodology of the proposed algorithm. Test results are given in section III and finally, section IV concludes the paper.

II. METHODOLOGY

A. General Lung Model

In general, RC mathematical model [8, 9] describes the lung functionality, where electrical resistance R represents the airflow resistance; electrical capacitance C represents the lung compliance that equivalents to 1/Elastance; current flow i_t equals to the airflow Q_t; voltage source V_{in} equivalents to the air pressure by the ventilator p_t; and voltage output V_{out} represents the lung volume V_t as shown in Fig. 1.

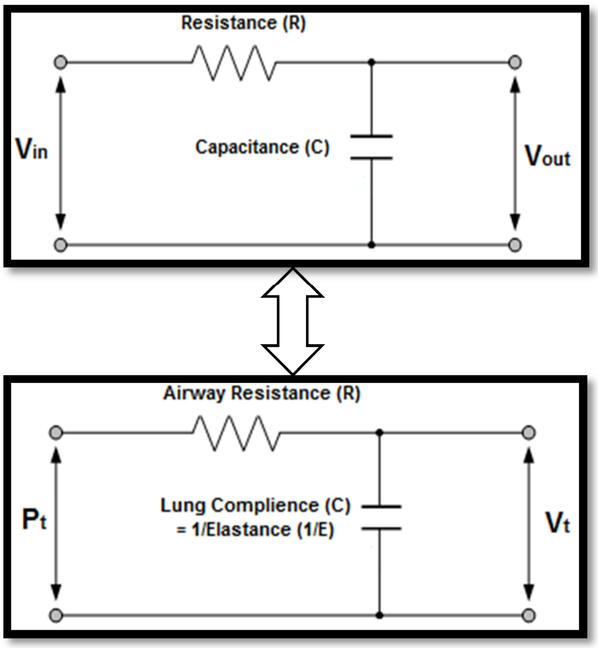

Fig. 1. Illustration of the RC model and lung model during mechanical ventilation.

B. Data Acquistion

The data acquisition scenario is illustrated as a block diagram in Fig. 2. In the figure, the experimental setup is comprised of a volume-controlled ventilator (ICU Electric Ventilator- Model SC-5) that is connected to an artificial lung through reference approved device (VT plus HF Gas Flow analyser [12]). The reference approved device measures pressure, volume and flow signals which are stored for parameter identification and validation of the lung model. Only pressure signals are passed to mathematical model to reconstruct volume and flow signals.

The experimental setup was made as follows:

- Operation mode was set at a respiration rate 16 *breaths per minute* (bpm) with *intermittent positive pressure ventilation* (IPPV);
- Ratio (I_t : E_t) = (1:2) where I_t is the inspiration time and E_t is the expiration time;
- PEEP was considered up to 5 cmH_2O;
- Artificial lung was attuned to a resistance R = 20 $cmH_2O/L/s$ and a compliance C = 20 ml/cmH_2O.

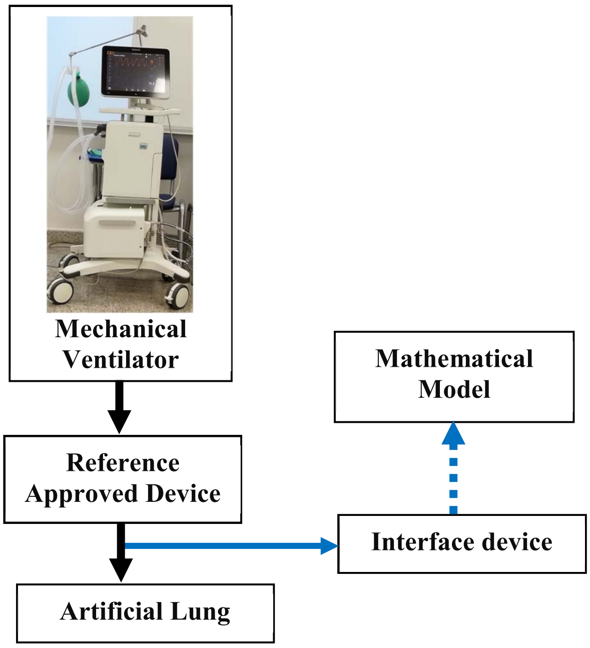

Fig. 2. Data acquisition scenario. (The source of the mechanical ventilator image [13])

C. Negative Feedback

It can be observed that a higher PEEP in the model input generates an additional volume in the model output, but the lung volume should be constant under VCV. Therefore, a negative feedback is added to adjust the lung volume as depicted in Fig. 3 and hence, the model becomes more accurate.

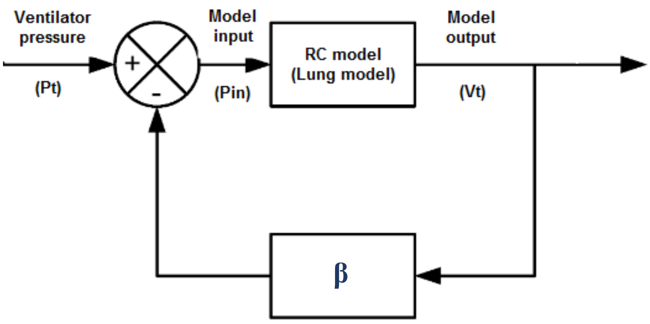

Fig. 3. The proposed model with a negative feedback.

From Fig. 3, one finds the input pressure p_{in} signal as follows:

$$p_{in} = p_t - \beta \tag{1}$$

Thus,

$$p_t = p_{in} + \beta \tag{2}$$

where p_t is the actual ventilator pressure, p_{in} is the corrected pressure for lung model input with feedback, and β is the feedback which equals $\frac{V_{min}}{\alpha}$, where V_{min} is the minimum lung volume and α is a parameter).

A general formula of first order lung model (RC model) [8, 9] can be presented by

$$p_t = RQ_t + EV_t + p_0 \tag{3}$$

where E denotes the lung elastance (1/compliance), V_t implies the lung volume, R refers to the airflow resistance, Q_t represents the airflow which equals dV_t/dt and p_0 indicates PEEP. Furthermore, the subscript t represents the time. Equation (3) with negative feedback can be expressed as follows:

$$p_{\text{in}} + \frac{V_{\min}}{\alpha} = R\frac{dV_t}{dt} + EV_t + p_0 \tag{4}$$

The equation can be arranged as:

$$R\frac{dV}{dt} + EV - p_{in} + p_0 - \frac{V_{min}}{\alpha} = 0 \tag{5}$$

D. Model Solution

Equation (5) can be reformulated as

$$\frac{dV}{dt} + \frac{E}{R}V = \frac{1}{R}\left[\frac{V_{min}}{\alpha} + p_{in} - p_0\right] \tag{6}$$

Taking $k = \frac{E}{R}$ and $w(t) = \frac{1}{R}\left[\frac{v_{min}}{\alpha} + p_{in}(t) - p_0\right]$ gives equation (7):

$$\frac{dV}{dt} + kV = w \tag{7}$$

To solve (7), the variable $u(t) = e^{\int k dt} = e^{kt}$ is introduced which is multiplied with the equation and this gives that

$$e^{kt}\frac{dV}{dt} + ke^{kt}V = e^{kt}w \tag{8}$$

which provides that

$$\frac{d}{dt}(Ve^{kt}) = e^{kt}w \tag{9}$$

Integrating (9) provides that

$$V(t)\, e^{kt} = V_0 + \int_0^t e^{k\tau}\, w\, d\tau$$

where integration is performed from 0 to t and $V_0 = V(0)$. Therefore, the final model equations can be written as

$$V(t) = e^{-kt}\left[V_0 + \int_0^t e^{k\tau}\, w(\tau)\, d\tau\right] \tag{10}$$

$$Q(t) = w(t) - kV(t) \tag{11}$$

E. Parameter Identification

Equation (11) can be written as

$$V = g(t, w, x) = e^{-kt}\left[V_0 + \int_0^t e^{k\tau}\, w(\tau)\, d\tau\right]$$

where $x = [R, k, \alpha, V_0, p_0]$ is the unknown parameters involved in (10), and the values of $[R, k, p_0]$ are available through PEEP p_0 (5 cmH2O), C (20 ml/cmH2O) and R (20 cmH2O/L/s), the remaining variables are $x = [\alpha, V_0]$.

The unknown parameters can be computed using a least-squares method [14]. In a least-squares problem, the vector x for given input-output pairs (t_i, p_i, V_i), where i = 1, …, m, is chosen to make the best fit in the least-squares sense to model a function $g(t, p, x)$. Components of the residual F are given by equation (12).

$$F_i(x) = g(t_i, p_i, x) - V_i \tag{12}$$

The aim is to compute the vector x such that the deviation between v_i and $g(t_i, p_i, x)$ are minimized for all i = 1, …, m. The least square problem (12) can be solved using MATLAB *lsqnonlin* function. Agreement of the model outputs with the corresponding experimental data is assessed by *average absolute percentage error* ∈ as follows:

$$\in = \frac{1}{m}\left[\sum_{i=1}^{m}\left(\left|\frac{g(t_i, p_i, x) - V_i}{V_i}\right|\right)\right] \times 100, \tag{13}$$

where $g(t_i, p_i, x)$ is the model value and V_i is the corresponding experimental value of i-th time.

III. Results and Discussion

The lung model was implemented in MATLAB and many tests were conducted. Some test results from the proposed model with the experimental data are presented in Figs. 4 – 5. In the tests, input signals from the experiments were taken as inputs for the models. The outputs – flow and volume as outputs are computed by the model. Next, it is checked whether the outputs match with the experimental data for validation purpose.

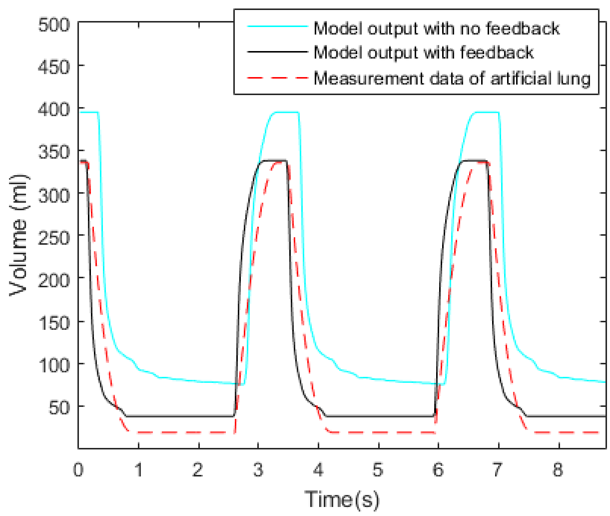

Fig. 4. Volume output signal at volume 400 ml.

Volume outputs are shown with and without the feedback β in Fig. 4. The volume output with the feedback obviously provides better results than that without feedback. Similarly, the flow signals are provided in Fig. 5, where one can see that the feedback increases the accuracy of the model.

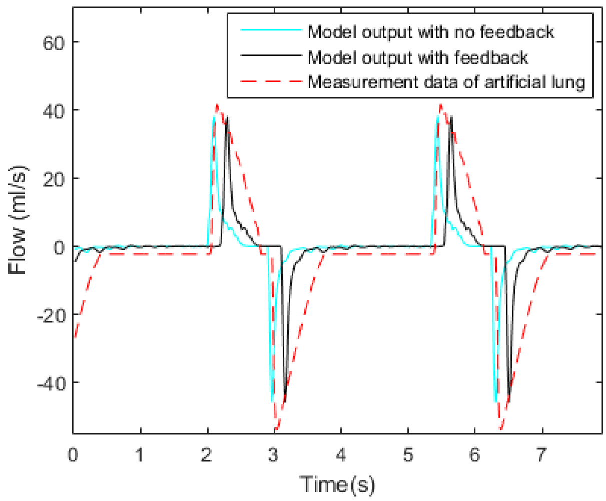

Fig. 5. Flow signal at volume 400 ml.

IV. CONCLUSION

This work focused on improvement of the existing lung model under volume-controlled ventilation to describe the lung volume and air flow in terms of only one signal - pressure signal from the ventilator. A negative feedback was added to the model for keeping the lung volume constant. We partially solved the lung model equation which takes the form of a first-order differential equation. Unknown parameters involved with the model were computed using a nonlinear least-squares method, while experimental data was obtained from a reference gas flow analyser connected to a VCV and an artificial lung. The test results demonstrate a superiority of the proposed model over the existing model in terms of accuracy. Hence, the compliance, volume and flow can be estimated by our model for MV in real-time with the input of a pressure signal only. Future work can be concentrated on enhancing model accuracy using optimization techniques.

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