Sophie Morton*, Paul Docherty, Jennifer Dickson, and J. Geoffrey Chase

# An analysis of the impact of the inclusion of expiration data on the fitting of a predictive pulmonary elastance model

**Abstract:** Mechanical ventilation is a primary therapy for patients with respiratory failure. However, incorrect ventilator settings can cause lung damage. Optimising ventilation while minimising risk is complex in practice. A common lung protective strategy is to titrate positive end-expiratory pressure (PEEP) to the point of minimum elastance. This process can result in additional available lung volume due to alveolar recruitment but comes with the risk of subjecting the lungs to excessive pressure and lung damage. Predictive elastance models can mitigate this risk by estimating airway pressure at a higher PEEP level. Due to the increased risk of barotrauma during inspiration, many models exclude expiration data. However, this section of the breath can include useful information about lung mechanics. This research investigates the impact that including expiration data into the fitting of a validated predictive elastance model will have on its ability to predict peak inspiratory pressure. Results showed that expiration data did not improve the efficacy of the model in this case with an increase in error (median (%)) of predicting peak inspiratory pressure through an increase in PEEP of 8 $cmH_2O$ from 6% to 16%.

**Keywords:** Pulmonary elastance, mechanical ventilation, system identification, prediction

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## 1 Introduction

Mechanical ventilation (MV) is a life support therapy for intensive care unit (ICU patients with respiratory failure [1]. However, incorrect settings can result in further lung damage due to excessive pressure or volume [2]. Maximising ventilation and perfusion while minimising risk is complex in practice, due to the heterogeneous nature of many lung diseases [3]. Model based methods to monitor lung behaviour can help to guide clinical decisions [4], [5].

Many clinical lung protective strategies exist [6]. One titrates positive end expiratory pressure (PEEP) to minimum elastance through staircase recruitment manoeuvres (RM). Increasing PEEP has the added benefit of recruiting alveoli that have collapsed due to injury or disease, increasing the functional volume of the lungs.

However, excessive pressures in RMs can lead to barotrauma. A robust method of predicting the pressure lungs will be subjected to as a result of increasing PEEP will allow clinicians to more accurately manage this process, improving patient outcomes.

As peak inspiratory pressure (PIP) is achieved during inspiration, most research concentrates on modelling lung behaviour during inspiration. This research investigates the impact that including expiration data into the fitting of a validated predictive elastance model will have on its ability to predict PIP [7].

## 2 Method

### 2.1 Patients and Data

Pressure-flow data from four MV patients in the Christchurch Hospital ICU who underwent MV therapy for respiratory failure in August 2016 during the CURE pilot trial (ANZTR Number: ACTRN-12613001006730) [8]. All patients were invasively ventilated with an endotracheal tube and fully sedated to prevent ventilator asynchrony. Trial admission criteria excluded patients with spinal injury, head trauma, neurological problems, or pulmonary disease admission (asthma, COPD). Each patient was also diagnosed with ARDS by a $PaO_2/FiO_2$ ratio PF < 300 mmHg [9].

***Corresponding author: Sophie Morton:** Department of Mechanical Engineering, University of Canterbury, Kirkwood Avenue, Christchurch, New Zealand, e-mail: sophie.morton@pg.canterbury.ac.nz
**Paul Docherty, Jennifer Dickson, J. Geoffrey Chase:** Department of Mechanical Engineering, University of Canterbury, Christchurch, New Zealand

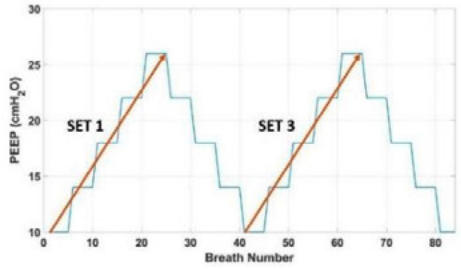


**Figure 1.** Demarcation of recruitment manoeuvre arms.

Pressure and flow data were extracted at 50Hz from a Puritan Bennett 840 ventilator (Covidien, Boulder, CO, USA). Flow data was integrated to determine volume above fractional residual volume ($V_{frc}$). RMs were comprised of two staircase increases and decreases in PEEP as part of typical MV treatment. [10], [11]. To capture changes in lung mechanics, each data set was split into four sections, two increasing PEEP and two decreasing PEEP arms (Figure 1). Patient demographic data and clinical data is shown in Table 1.

**Table 1.** Patient demographic information.

| Patient # | Length of MV (days) | # RM arms studied | Clinical Diagnostic |
|---|---|---|---|
| 1 | 22.6 | 2 | Peritonitis |
| 2 | 24.2 | 2 | Legionella pneumonia |
| 3 | 23.0 | 2 | Staphylococcus Aureus pneumonia |
| 4 | 1.90 | 2 | Streptococcus pneumonia |

### 2.1.1 Split of Breath Data into Inspiration and Expiration

To assess the impact of expiration data on model fit, each breath was split into inspiration and expiration. The initial 200ms was discarded as it contains too much ventilator induced dynamics and noise to identify stable, accurate parameter values. Expiration was defined as the point at which the ventilator flow first became negative after PIP. This point often occurs 1/3 of the way through a breath cycle based on the set inspiration : expiration ratio.

Three cases were analysed in this study. The first used only inspiration data to fit the model. The second used the entirety of the breath. The third case attempted to normalise the effect of expiration on the fit by halving all input measurements during expiration ($P(t)$, $Q(t)$, $V(t)$) so that inspiratory and expiratory data points each had equal weight.

## 2.2 Model

The model used in this analysis was based on a single compartment model of lung elastance and pressure [4], [12], [13]. Elastance and resistance are defined by four basis functions. The first two cover the recruitment and distension components of elastance. The exponential decay and linearly increasing slope used to define these components, respectively, were based on observed physiological behaviour. Elastance was thus modelled by both a pressure (distension) and volume (recruitment) dependent terms. Resistance was based on the two parts of the Rohrer equation [14]. The shapes of these functions are depicted in Figure 2. Equation 1 outlines the final fitting model.

$$\dot{\boldsymbol{P}}(\boldsymbol{t}) = (\boldsymbol{E_{rec}}(\boldsymbol{V}(\boldsymbol{t})) + \boldsymbol{E_{dist}}(\boldsymbol{P}(\boldsymbol{t})))\boldsymbol{V}(\boldsymbol{t}) + (\boldsymbol{R_1} + \boldsymbol{R_2}|\boldsymbol{Q}(\boldsymbol{t})|)\boldsymbol{Q}(\boldsymbol{t}) + \boldsymbol{PEEP}$$

$$\therefore \dot{\boldsymbol{P}}(\boldsymbol{t}) = \left(\boldsymbol{E_1}\boldsymbol{e}^{-\boldsymbol{b}(\boldsymbol{V}(\boldsymbol{t}))} + \boldsymbol{E_2}\frac{\boldsymbol{P}(\boldsymbol{t})}{\boldsymbol{60}}\right)\boldsymbol{V}(\boldsymbol{t}) + (\boldsymbol{R_1} + \boldsymbol{R_2}|\boldsymbol{Q}(\boldsymbol{t})|)\boldsymbol{Q}(\boldsymbol{t}) + \boldsymbol{PEEP} \quad (1)$$

Here $P(t)$ is the airway pressure ($cmH_2O$), $V(t)$ is the volume (L), $Q(t)$ is the flow of air (L/s). $E_{rec}$ is the recruitment component of elastance ($cmH_2O/L$), and $E_{dist}$ is the distension component ($cmH_2O/L$). $b$ is the rate of decay of recruitment as lung volume increases. $R_1$ and $R_2$ are the two components of pulmonary resistance ($cmH_2O*s/L$).

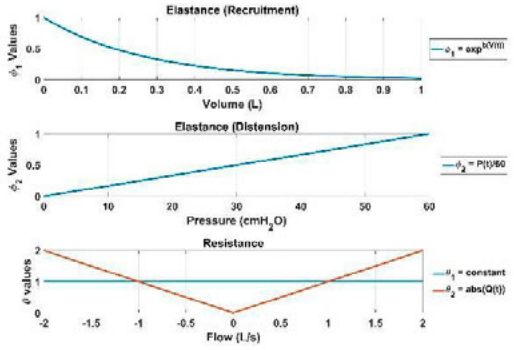


**Figure 2.** Depiction of basis function shapes used in the predictive elastance model.

### 2.2.1 Model Identification

Breath data was used to identify model parameters. An iterative linear identification was undertaken. Initially,

Equation 2 was identified to provide estimates of $E_2$, $R_1$ and $R_2$. Then Equations 3 and 4 are iterated to estimate $E_1$ and $b$, then $E_2$, $R1$ and $R_2$, respectively.

$$\begin{bmatrix} \boldsymbol{V(t)} & \boldsymbol{V(t)\odot P(t)} & \boldsymbol{Q(t)} & \boldsymbol{|Q(t)|Q(t)} \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} \boldsymbol{E_{1*}} \\ \boldsymbol{E_2} \\ \boldsymbol{R_1} \\ \boldsymbol{R_2} \end{bmatrix} = \begin{bmatrix} \boldsymbol{P(t) - PEEP} \\ \vdots \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} \boldsymbol{1} & \boldsymbol{-V(t)} \\ \vdots & \vdots \end{bmatrix} \begin{bmatrix} \boldsymbol{\ln(E_1)} \\ \boldsymbol{b} \end{bmatrix} = \begin{bmatrix} \dfrac{\boldsymbol{\ln\left(P(t) - PEEP - E_2 \frac{P(t)}{60} V(t) - (R_1 + R_2|Q(t)|)Q(t)\right)}}{\boldsymbol{V(t)}} \\ \vdots \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} \boldsymbol{V(t)\odot P(t)} & \boldsymbol{Q(t)} & \boldsymbol{|Q(t)|Q(t)} \\ \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} \boldsymbol{E_2} \\ \boldsymbol{R_1} \\ \boldsymbol{R_2} \end{bmatrix} = \begin{bmatrix} \boldsymbol{P(t) - PEEP - E_1 e^{-bV(t)} V(t)} \\ \vdots \end{bmatrix} \quad (4)$$

Forward simulation of pressure using volume and flow inputs at increased PEEP was used to assess the ability of the model to predict lung behaviour. Prediction of behaviour across PEEP levels required an estimation of the change in lung volume ($V_{frc}$) as a result of recruitment and derecruitment. It was assumed that $V_{frc}$ would increase with an increase in PEEP. Equation 5 was iterated until convergence to determine the change in $V_{frc}$ across a PEEP level ($|\Delta V_{frc}^n < 0.01\%$).

$$\boldsymbol{V_{frc}^n = \frac{(PEEP_{n+1} - PEEP_n)}{E_1 e^{-bV_{frc}^n} + E_2 PEEP_{n+1}/60}} \quad (5)$$

These identification methods are applied over inspiration, the entire breath, and a weighted breath. PIP error is compared to assess the effect.

# 3 Results

The model was fit and predicted over 768 breaths across 9 PEEP levels and 4 patients. The PIP error for model fit is shown in Table 2. Each of the three cases studied have very low PIP error, indicating that the model fits behaviour across inspiration and expiration well.

**Table 2.** PIP Error (median [IQR]) for model fit.

| | Median [IQR] PIP Error ($cmH_2O$) | Median PIP Error (%) |
|---|---|---|
| **Case 1 (Inspiration Only)** | 0.0 [-0.1 - 0.1] | 0% |
| **Case 2 (Inspiration + Expiration)** | 1.1 [0.6 - 1.3] | 3% |
| **Case 3 (Inspiration + .5*Expiration)** | 0.7 [0.3 - 0.9] | 2% |

Prediction error for an increase in PEEP of 1 4$cmH_2O$ step and 2 4$cmH_2O$ steps are shown in Table 3 and Table 4. The model is more effective at predicting PIP when it is fit solely using inspiration mechanics. However, normalising the length of expiration to inspiration so each point is treated equally results in over-prediction of pressure. This outcome is preferable in a clinical setting as it presents the more conservative prediction case in decision making.

**Table 3.** PIP Error (median [IQR]) for 1 step prediction.

| | Median [IQR] PIP Error ($cmH_2O$) | Median PIP Error (%) |
|---|---|---|
| **Case 1 (Inspiration Only)** | -0.5 [-0.7 - 0.5] | 2% |
| **Case 2 (Inspiration + Expiration)** | 1.3 [0.1 - 4.6] | 5% |
| **Case 3 (Inspiration + .5*Expiration)** | 3.9 [1.9 - 5.5] | 10% |

**Table 4.** PIP Error (median [IQR]) for 2 step prediction.

| | Median [IQR] PIP Error ($cmH_2O$) | Median PIP Error (%) |
|---|---|---|
| **Case 1 (Inspiration Only)** | -1.4 [-2.5 - 1.1] | 6% |
| **Case 2 (Inspiration + Expiration)** | 6.4 [1.1 - 8.9] | 15% |
| **Case 3 (Inspiration + .5*Expiration)** | 7.0 [3.6 - 8.7] | 16% |

Figure 3 is an indication of the prediction results across one PEEP step increase from 22 – 26 $cmH_2O$.

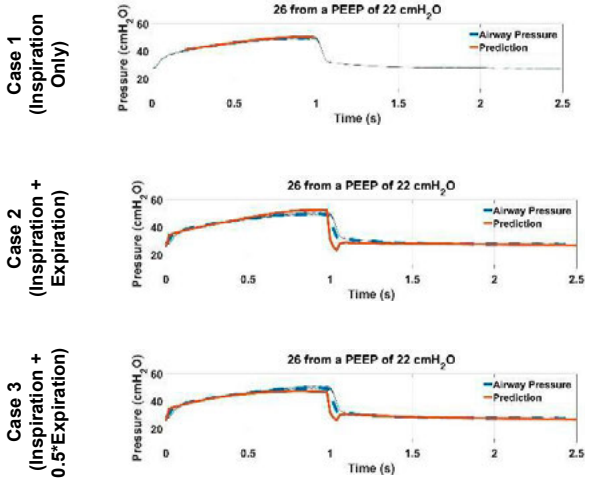


**Figure 3.** Typical prediction results for each case. Airway data is denoted by the blue dashed lines, and model prediction by a solid orange line. Light grey lines show the range of breath data at a given PEEP level.

# 4 Discussion

The model fit extremely well to the data with a median PIP % error less than 4% in all three cases. Median PIP % error was 10% or less for predicting lung mechanics in a 4 $cmH_2O$ increase in PEEP in all cases. However, it was greater than 10% for Case 2 and Case 3 for 2 step predictions 4$cmH_2O$ ahead.

The analysis in this study used data from a limited number of patients. In addition to this, three of the patients were diagnosed with bacterial pneumonia, which can lead to reduced alveolar recruitability [15]. While pneumonia often presents heterogeneously, future work would need to be carried out on a more diverse data set to further verify the results.

It was anticipated that normalising the expiration data to allow each data point to allow inspiration and expiration to be weighted equally in analysis would improve model fit. This proved to be correct with an improvement in model fit error. However, as shown in Tables 3 - 4, the inclusion of expiration had a detrimental effect on prediction. However, asymmetric opening and closing pressures suggest that expiration-specific basis function parameters could improve model fit.

In typical model-based analysis it would be beneficial to use all available data to enable identification of the underlying mechanics. However, in this case the quality of the inspiratory data was sufficient to provide a model that can give a prediction of PIP that was better than the prediction available when data from expiration was incorporated.

### Author Statement

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