Virtual Patients for Managing Mechanical Ventilation in the ICU

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***Abstract*— Mechanical ventilation (MV) is a primary therapy in the intensive care unit (ICU). Sub-optimal ventilator settings can cause lung damage, but optimal selection is confounded by significant inter- and intra- patient variability in response to MV. Titrating PEEP (positive end expiratory pressure) to minimum elastance is a proven approach. However, in clinical practice finding this value is difficult. A predictive elastance model, or virtual patient, would directly assess a current PEEP level should be changed based on whether a nearby PEEP had lower elastance, as well as enable safe PEEP titration. A predictive, virtual patient model for MV in the ICU is presented.**

I. INTRODUCTION

Mechanical ventilation (MV) is used in the intensive care unit (ICU) to support breathing and gas exchange for patients with respiratory failure or ARDS [1]. However, poorly applied MV can cause ventilator induced lung injury or VILI [2]. Setting PEEP to minimum elastance is a proven approach [3], but there is no set method optimally or safely find this PEEP value. Thus, while simple in theory, optimising respiratory treatment and concomitantly minimising lung damage is difficult in practice, as there is no direct means of finding the best pressure and volume settings prior to trying them on the patient and risking VILI. A predictive, patient-specific model or virtual patient is required.

II. METHODS

A single compartment model of respiratory mechanics is the basis for the model [4]:

$$P(t)=(E(V(t),P(t)))V(t)+R(Q(t))Q(t)+PEEP \quad (1)$$

Where P(t) is the airway pressure (cmH_2O), V(t) is the volume (L), Q(t) is the flow of air (L/s). E and R are pulmonary elastance (cmH_2O/L) and pulmonary resistance (cmH_2O*s/L) R, respectively.

Basis functions allow the model to be defined over the MV pressure, volume and flow range yielding a new model:

$$P(t) = \left(E_1 e^{-b(V(t))} + E_2 \frac{P(t)}{60}\right) V(t) + (R_1 + R_2|Q(t)|)Q(t) + PEEP \quad (2)$$

Where constants E_1, E_2, R_1 and R_2 can be identified from the clinical data from the ventilator. Fitting to clinical data and testing prediction in recruitment maneuvers is used for validation, including estimated volume recruited, found by iterating:

$$V_{frc}^{n} = \frac{(PEEP_{n+1} - PEEP_n)}{E_1 e^{-bV_{frc}^{n}} + E_2 PEEP_{n+1}/60} \quad (3)$$

Pressure-flow data from 3 MV patients at the Christchurch Hospital ICU in the August 2016 CURE pilot trial [5].

III. RESULTS

Table I summarises peak inspiratory pressure predictions.

TABLE I. SUMMARISED PIP ERROR FOR PREDICTION RESULTS (MEDIAN [IQR] AND PERCENTAGE). DIRECTION OF PREDICTION IS INDICATED

Set	*1 Step Prediction*		*2 Step Prediction*	
	Error (cmH_2O)	*Median Error (%)*	*Error (cmH_2O)*	*Median Error (%)*
1 ∧	*-0.1 [-0.7 – 1.3]*	*3.1%*	*-0.7 [-1.8 – 2.2]*	*4.0%*
2 ∨	*-1.3 [-2.0 - -0.5]*	*4.2%*	*- 2.1 [-3.9 –-0.9]*	*6.7%*
3 ∧	*0.7 [-0.4 – 3.0]*	*3.9%*	*2.2 [-0.3 – 6.2]*	*6.9%*
4 ∨	*-1.0 [-3.1– -0.1]*	*4.8%*	*-1.2 [-5.0 – 0.0]*	*10.1%*

IV. DISCUSSION & CONCLUSION

The results show very accurate prediction of peak pressures, a surrogate for the risk of VILI in volume controlled patients. Similar results are found for wider ranges of data. Thus, basis functions can be used to create an accurate, predictive virtual patient model for MV. This model can be further used to assess the risk of any change in MV settings, or even in the mode of MV, before they are made. This latter outcome thus enables the use of models to guide, personalize, and optimise MV care in these patients, where the potential reductions in length of ventilation are directly related to patient outcome and cost to the healthcare system.

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REFERENCES

[1] A. Slutsky, "Mechanical Ventilation. American College of Chest Physicians' Consensus Conference," *Chest*, vol. 104(6), pp. 1833-1859, 1993.

[2] P. P. Terragni, G. L. Rosboch, A. Lisi, A. G. Viale, and V. M. Ranieri, "How respiratory system mechanics may help in minimising ventilator-induced lung injury in ARDS patients," *Eur Respir J*, vol. 22, pp. 15S - 21S, 2003.

[3] M. B. P. Amato *et al.*, "Driving Pressure and Survival in the Acute Respiratory Distress Syndrome," *New England Journal of Medicine*, vol. 372, no. 8, pp. 747-755, 2015.

[4] S. E. Morton *et al.*, "A virtual patient model for mechanical ventilation," *Comput Methods Programs Biomed*, vol. 165, pp. 77-87, Oct 2018.

[5] A. Szlavecz *et al.*, "The Clinical Utilisation of Respiratory Elastance Software (CURE Soft): a bedside software for real-time respiratory mechanics monitoring and mechanical ventilation management," *BioMedical Engineering OnLine*, vol. 13, no. 1, p. 140, 2014.

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