Respiratory Airway Resistance Monitoring in Mechanically Ventilated Patients

Nor Salwa Damanhuri, Yeong Shiong Chiew, Paul D. Docherty, Patrick H Geoghegan, J. Geoffrey Chase
Centre for Bioengineering, Department of Mechanical Engineering,
University of Canterbury,
Christchurch, New Zealand
nor.damanhuri@pg.canterbury.ac.nz

***Abstract*—Physiological models of respiratory mechanics can be used to optimise mechanical ventilator settings to improve critically ill patient outcomes. Models are generally generated via either physical measurements or analogous behaviours that can model experimental outcomes. However, models derived solely from physical measurements are infrequently applied to clinical data.**

This investigation assesses the efficacy of a physically derived airway branching model (ABM) to capture clinical data. The ABM is derived via classical pressure-flow equations and branching based on known anatomy. It is compared to two well accepted lumped parameter models of the respiratory system: the linear lung model (LLM) and the Dynostatic Model (DSM).

The ABM significantly underestimates the total pressure drop from the trachea to the alveoli. While the LLM and DSM both recorded peak pressure drops of 17.8 cmH_2O and 10.2 cmH_2O, respectively, the maximum ABM modelled pressure drop was 0.66 cmH_2O. This result indicates that the anatomically accurate ABM model does not incorporate all of the airway resistances that are clinically observed in critically ill patients. In particular, it is hypothesised that the primary discrepancy is in the endotracheal tube. In contrast to the lumped parameter models, the ABM was capable of defining the pressure drop in the deep bronchial paths and thus may allow further investigation of alveoli recruitment and gas exchange at that level given realistic initial pressures at the upper airways.

Keywords-component; Mechanical Ventilator; Airway Branching Model; Linear Lung Model; Dynostatic Model; Airway resistance

I. INTRODUCTION

Modelling respiratory mechanics in conjunction with clinical data enables patient-specific understanding of lung mechanics. Respiratory system modelling has been carried out extensively, ranging from simple lumped parameter models to highly complex finite element models [1-5]. However, to date, very few models have been designed to achieve a specific therapeutic goal or outcome [6, 7].

Mechanically ventilated (MV) intensive care unit (ICU) patients have impaired respiratory function and are exposed to the risk of further lung injury if MV settings are not optimal [8, 9]. In particular, high pressure at the end of airway branches may benefit alveoli recruitment, but may also cause further damage by over-distension of the alveoli [10]. Development and application of respiratory system models has the potential to reduce negative outcomes from poorly conditioned respirator settings by using models to estimate and monitor these pressures, along with alveolar recruitment [11].

Airway branching models (ABM) [12, 13] with the airway dimensions and pathways of the airway system have been used to predict respiratory pressure-flow responses [14]. In ABMs, the airway resistance at each branching generation can be identified using Poiseulle flow and branching head-loss equations [5, 15]. These resistance values can then be used to define pressure drop as a function of flow rate measured at the airway. The bronchial tree model has been applied in estimating the shear stress of the airway walls of mechanically ventilated patients [16]. However, while anatomically accurate, these models are complicated and require *a-priori* knowledge of the lung dimensions, which can limit application in real-time clinical settings.

In contrast, lumped parameter models, such as the single compartment linear lung model (LLM), are less computationally intense. These simpler models have shown clinical potential in monitoring patients respiratory mechanics in real-time to guide clinical therapy [17, 18]. The trade-off being that these simple models are not capable of providing high resolution information compared to more complex models.

This work presents several model-based methods to monitor airway pressure drop due to airway resistance in mechanically ventilated patients. More specifically, the performance of an airway branching model (ABM) [12, 13], single compartment linear lung model (LLM) [19] and dynostatic model (DSM) [20] are compared in MV patients. Model-based estimation of airway pressure drop in real-time clinical setting, provides information on end alveoli pressure, which, in turn, could potentially define optimal MV settings to reduce lung injury improve treatment and thus reduce treatment cost [21].

II. METHODS

In this study, 3 airway models are used in estimating the pressure drop due to airway resistance in 6 MV patients diagnosed with acute respiratory distress syndrome (ARDS) in two different cohort [11, 22]. Each patient was ventilated at positive end-expiratory pressure (PEEP) of 5 cmH_2O. In particular, 3 patients (B1-3) have constant square wave input flow profiles [11] and the other 3 patients (S1-3) are ventilated using a decreasing input flow profile [22].

A. Airway Branching Model (ABM)

The analysis was performed using the airway branching model (ABM) based on measured airway dimensions [14]. In this model, the respiratory airways are branched into generations, with the trachea at generation 0, through 23 generations of bronchioles to the alveoli. Each airway branch has specific length, diameter and cross sectional area measured by Pedley *et al.* [14]. Fig. 1 shows the airway branching model structure schematically and Table 1 defines the physical dimensions at every branch generation.

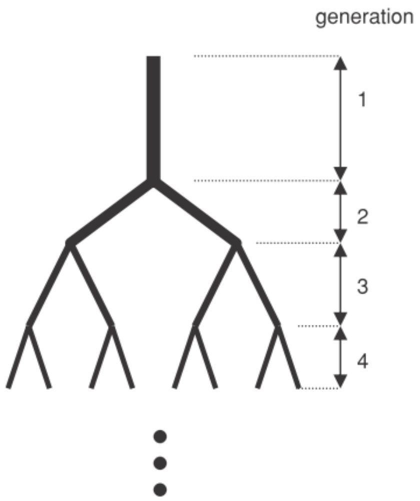

Figure 1. The airway tree structure in which airways are specified by generation number, beginning with trachea [23].

TABLE I. PHYSICAL MEASUREMENTS OF BRONCHIAL PATHS ABLE [14]

Branch Generations	Diameter (cm)	Length (cm)
0 (Tracheal)	1.80	12.0
1	1.22	4.80
2	0.83	1.90
3	0.56	0.80
4	0.45	1.30
5 -16	0.35 - 0.06	1.07 - 0.17
17 - 22	0.05	0.10
23	0.04	0.05

At each airway generation, the resistance (R_n) can be estimated using Poiseulle flow:

$$R_n = \frac{1}{2^n}\left(\frac{128\mu L}{\pi d^4}\right) \quad (1)$$

where μ, is the dynamic viscosity of air ($1.9\text{x}10^{-5}$ Pa·s /$1.9\text{x}\,10^{-7}$ cmH_2O·s), n represents the airway branch generation, L is the length of airway branch [m], and d is the diameter of airway branch [m].

Equation 1 is then extended to estimate the pressure drop (ΔP_n) due to the resistive component of the airway branch:

$$\Delta P_n = R_n Q_n \quad (2)$$

where Q_n is the flow rate of that airway branch. In this study, the flow in each new branch generation is assumed as:

$$Q_{n+1} = \frac{1}{2} Q_n \quad (3)$$

The total resistance of the airway branch can be calculated as:

$$R_T = \sum_{n=0}^{23} \frac{1}{2^n} R_n \quad (4)$$

Thus, the total pressure drop of the ABM model (ΔP_{R_ABM}) can be modelled:

$$\Delta P_{R\_ABM} = \sum_{n=0}^{23} R_n Q_n \quad (5)$$

It is important to note that the ABM does not include any pressure drop due to the endotracheal tube (ETT). These are added to the modelled value using Poiseulle flow assumptions.

B. Single Compartment Linear Lung Model (LLM)

The single compartment lung model is a lumped parameter model that uses airway pressure, P_{aw}, volume, V, flow, Q_{aw}, and offset pressure, P_0, to estimate respiratory Elastance, E_{rs}, and respiratory resistance, R_{rs}. The model is defined:

$$P_{aw} = E_{rs}V + R_{rs}Q_{aw} + P_0 \quad (6)$$

With $E_{rs}V$ is the alveoli pressure and $R_{rs}Q_{aw}$ is the resistive pressure. Using integral-based methods [19, 24], the respiratory Elastance (E_{rs}) and resistance (R_{rs}) can be estimated. In turn, the resistive pressure ($\Delta P_{R\_LLM} = R_{rs}Q_{aw}$) can be estimated.

C. The Dynostatic Model (DSM)

The dynostatic algorithm proposed by Karason *et al* [20] estimates dynostatic pressure, P_{dyn}. The algorithm assumes that the airway resistance during inspiration, R_{insp}, is the same as the expiration resistance, R_{exp}, during iso-lung volume. Thus:

$$R_{insp} = \frac{P_{insp} - P_{dyn}}{\dot{V}_{insp}} \quad (7)$$

$$R_{exp} = \frac{P_{exp} - P_{dyn}}{\dot{V}_{exp}} \quad (8)$$

And at isovolume, it is assumed that:

$$R_{insp} = R_{exp} \quad (9)$$

Combining Equations (7) and (8), the dynostatic pressure can be defined:

$$P_{dyn} = \frac{P_{insp} \times \dot{V}_{exp} - P_{exp} \times \dot{V}_{insp}}{\dot{V}_{exp} - \dot{V}_{insp}} \qquad (10)$$

where, $\dot{V}_{exp}$ is the expiration flow, $\dot{V}_{insp}$ is the inspiration flow, P_{insp} is the pressure during inspiration process, and P_{exp} is the pressure during the expiration process.

Equation (6) is then rearranged to estimate the resistive pressure during inspiration, defined as:

$$\Delta P_{R\_Dyn} = \dot{V}_{insp} R_{insp} = P_{insp} - P_{dyn} \qquad (11)$$

D. Analyses

The resistive pressure or pressure drop from the airway to alveoli is determined for each patient using all 3 models. Values are compared to assess the conformity of these (well accepted) models. Each model is simulated using measured P_{aw} and Q_{aw} and flow rate at the airway. ABM results are presented with and without the added ETT pressure drop to delineate the drop due to the ETT and that due to physical anatomy.

III. Results and Discussion

The estimated resistance and pressure drop in the ABM for each branch generation is presented in Fig. 2. Fig. 3 shows the comparative pressure drop for a given flow rate for each of the models tested. Note that the pressure scale of the ABM is significantly smaller than the other models indicating a much smaller pressure drops through the bronchial path in general for this model. Table 2 shows the median [Interquartile range, IQR] and maximum (Max) resistive pressure for Patients 1-6. Fig. 4 shows the airway pressure drop for Patient S1 in different flow profile for each of models tested.

In the ABM, it can be observed in Fig. 2 that at the 5^{th} generation branch, the airway resistance is higher compared to other generations, which are around 0.8 $cmH_2O{\cdot}s/l$. Initially, the resistance starts to drop from generation 0, which is the trachea up to generation 4. The resistance starts to rise at generation 5 as the length of the bronchial tube is higher at this generation compared to the previous branches [14]. The resistance is the lowest at the 23rd generation, which is at the end of the bronchial path and contains the alveoli. Fig. 2 also

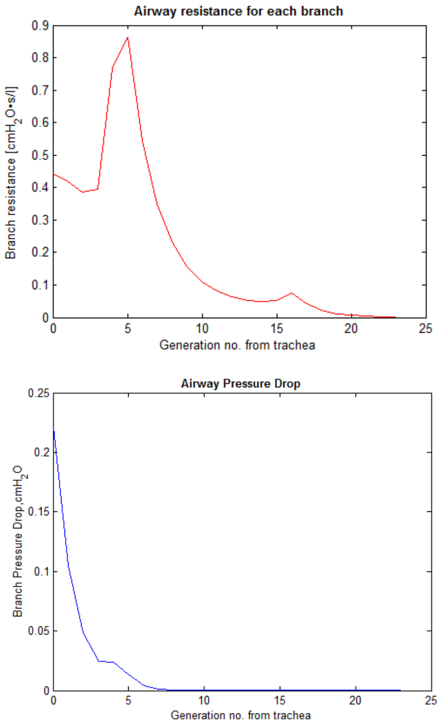

Figure 2. Airway resistance and pressure drop for each branch/generation of the ABM model.

shows that the pressure drop is highest for the ABM at the 0^{th} generation, the trachea, at approximately 0.23 cmH_2O. The total resistance for the ABM model is 5.13 $cmH_2O{\cdot}s$ /l and the total pressure drop is 0.443 cmH_2O. However, this model does not define the pressure drop in the endotracheal tube (ETT), which has been estimated to have a significant resistance [15]. With the ETT, these values are 30.4 $cmH_2O{\cdot}s/l$ and 3.14 cmH_2O respectively. Including this value to the clinical data will result in increase of the total pressure drop to 3-4 cmH_2O as show in Table 2 and Fig. 3 and 4.

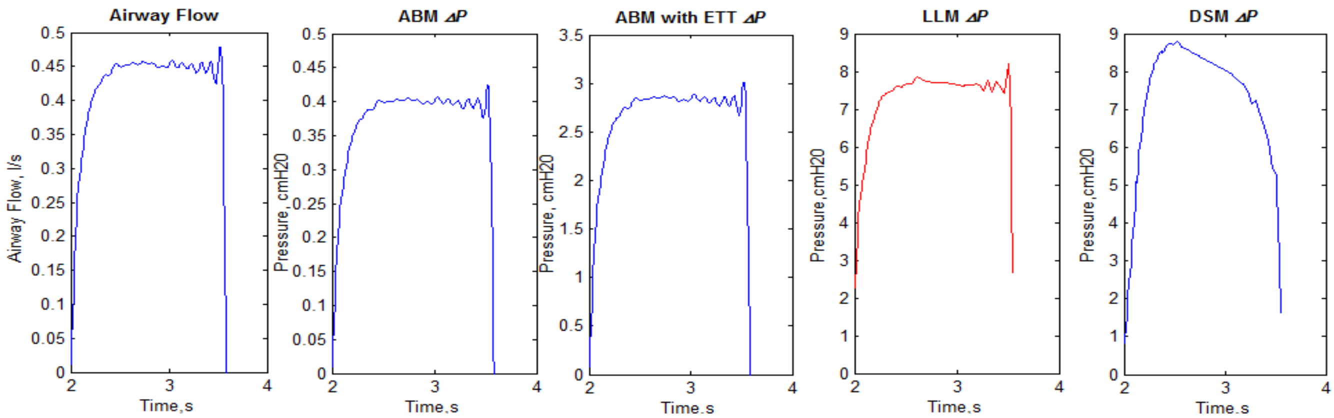

Figure 3. Patient B2 airway pressure drop. From left: Airway flow, Q_{in}. ABM estimated pressure drop. ABM estimated pressure drop including the effect of ETT. LLM estimated pressure drop. DSM estimated pressure drop.

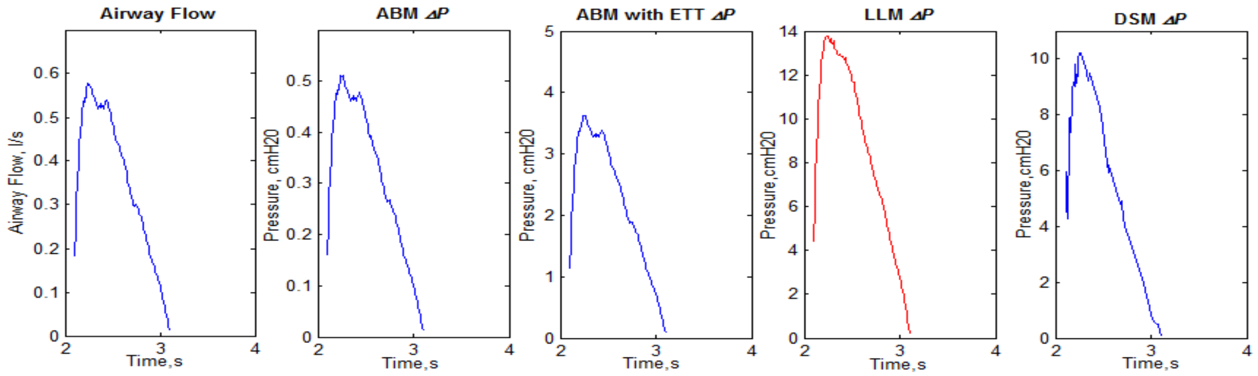

Figure 4. Patient S1 airway pressure drop. From left: Airway flow, Q_{in}. ABM estimated pressure drop. ABM estimated pressure drop including the effect of ETT. LLM estimated pressure drop. DSM estimated pressure drop.

TABLE II. MEDIAN [IQR] AND MAXIMUM AIRWAY RESISTIVE PRESSURE, ΔP_R (cmH_2O)

Patient	ABM		ABM with ETT		LLM		DSM	
	Median [IQR]	*Max*	*Median [IQR]*	*Max*	*Median [IQR]*	*Max*	*Median [IQR]*	*Max*
B1[a]	0.49 [0.47 -0.49]	0.51	2.1 [2.2 – 2.2]	2.3	8.7 [5.4 - 9.3]	9.6	4.7 [2.0 - 5.8]	6.3
B2[a]	0.40 [0.39 –0.40]	0.43	2.7 [2.8 – 2.9]	3.0	6.5 [4.8 - 7.6]	8.2	5.4 [3.0 - 7.9]	8.8
B3[a]	0.49 [0.47 – 0.50]	0.51	2.1 [2.2 – 2.2]	2.3	9.1 [7.7 - 9.4]	9.7	3.2 [2.3- 3.6]	4.1
S1[b]	0.34 [0.20 -0.46]	0.51	2.4 [1.4 – 3.3]	3.6	9.0 [5.3 – 12.6]	13.8	6.2 [4.5 – 8.9]	10.2
S2[b]	0.41 [0.27 – 0.53]	0.66	2.4 [1.9 – 3.0]	3.5	11.3 [7.3 – 14.2]	17.8	3.1 [1.7 – 4.4]	6.8
S3[b]	0.34 [0.27 – 0.43]	0.50	2.1 [2.2 – 2.2]	2.3	9.3 [7.4 – 11.9]	13.6	2.9 [1.0- 3.5]	5.4

a. Patients ventilated using square-wave flow profile [22].
b. Patients ventilated using decreasing flow profile [11].

In Fig. 3, it is observed that the pressure drop in LLM and DSM are significantly different from the ABM. The maximum total pressure drop for LLM and DSM models ranges from 8.2 to 8.8 cmH_2O. In contrast, the maximum pressure drop is 0.43 cmH_2O in ABM (without ETT). Comparing Fig. 3 and 4, it was observed that the trend of pressure drop is flow dependant. Patient S1 from different cohort is ventilated at much higher flow rate (0.6 l/s) and different flow profile, resulting in higher pressure drop due to airway resistance.

The pressure drop due to airway resistance, ΔP_R, identified from clinical data in the LLM and DSM models were significantly higher than the ABM model with or without ETT, as expected. The median [IQR] of resistive pressure in LLM model is 9.1 [5.3 – 12.6] and 4.0 [1.7 – 7.9] in DSM model. These resistive pressures are within physiological ranges [25], indicating that the models were capable of estimating the resistance component.

The ABM model allows pressure drops at every branch generation to be estimated, which provides valuable physiological information, as alveoli begin to appear at branch 17. In contrast, the LLM and DSM are only capable of defining a lumped bronchial resistance parameter, which means a specific alveolar pressure cannot be explicitly estimated except for an overall average value. However, the pressure drop in higher generations is very small and would be very difficult to identify from clinical data. Thus, the present study allows insight into the pressure flow mechanics of alveoli recruitment that is not possible with lumped parameter models. Further investigation is required to ascertain whether the ABM outcomes can be scaled using lumped parameter models for ETT to provide patient-specific indications of high bronchial branch fluid dynamics and recruitment characteristics.

In this study, aside from differences in pressure drop magnitude, there is also a trend difference between the models. In particular, the ABM and LLM have similar trends, where the maximum pressure drop occurs at the end of inspiration. However, the maximum pressure drop was observed in an earlier stage of the dynostatic model pressure drop estimation. This difference may be due to the expiration cycle flow profile. Moller et al [26, 27] found that airway resistance between inspiration and expiration cycle were different and flow dependant. Thus, the assumption used in the dynostatic model, where resistance during inspiration and expiration are assumed equal, warrants further investigation.

IV. LIMITATIONS

The main limitation of this study is the use of a population constant for the airway dimension in airway branching model. A population constant only allows a general overview of pressure drop in each branch generation. However, it was also found in this comparison that the major pressure drop occurs from the endotracheal tube and only relatively minimal pressure drops occur after branch generation 5 which is less than 10% compared to the pressure drop in ETT tube.

Furthermore, airway dimensions may vary in both inter- and intra- patient sense, which will also result in different pressure values.

V. Conclusions

This work presents several models of pressure drop estimation in the respiratory system. Having the pressure drop due to the resistive component is important as it is a pathway to estimate the end alveoli pressure that could be used in clinical guidance to avoid ventilator induced lung injury for MV patients.

References

[1] D. W. Carley and D. C. Shannon, "A minimal mathematical model of human periodic breathing," *J Appl Physiol,* vol. 65, pp. 1400-9, Sep 1988.

[2] F. S. Grodins, J. Buell, and A. J. Bart, "Mathematical analysis and digital simulation of the respiratory control system," *J Appl Physiol,* vol. 22, pp. 260-76, Feb 1967.

[3] T. J. Trueb, N. S. Cherniack, A. F. D'Souza, and A. P. Fishman, "A mathematical model of the controlled plant of the respiratory system," *Biophys J,* vol. 11, pp. 810-34, Oct 1971.

[4] C. Schranz, C. Knobel, J. Kretschmer, Z. Zhao, and K. Moller, "Hierarchical parameter identification in models of respiratory mechanics," *IEEE Trans Biomed Eng,* vol. 58, pp. 3234-41, Nov 2011.

[5] K. S. Burrowes, P. J. Hunter, and M. H. Tawhai, "Anatomically based finite element models of the human pulmonary arterial and venous trees including supernumerary vessels," *J Appl Physiol,* vol. 99, pp. 731-8, Aug 2005.

[6] A. Ben-Tal, "Simplified models for gas exchange in the human lungs," *J Theor Biol,* vol. 238, pp. 474-95, Jan 21 2006.

[7] A. Sundaresan and J. G. Chase, "Positive end expiratory pressure in patients with acute respiratory distress syndrome – The past, present and future," *Biomedical Signal Processing and Control,* vol. 7, pp. 93-103, 2012.

[8] D. Dreyfuss and G. Saumon, "Ventilator-induced lung injury: lessons from experimental studies," *Am J Respir Crit Care Med,* vol. 157, pp. 294-323, Jan 1998.

[9] A. S. Slutsky, "Lung injury caused by mechanical ventilation," *Chest,* vol. 116, pp. 9S-15S, Jul 1999.

[10] K. Schirrmann, M. Mertens, U. Kertzscher, W. M. Kuebler, and K. Affeld, "Theoretical modeling of the interaction between alveoli during inflation and deflation in normal and diseased lungs," *J Biomech,* vol. 43, pp. 1202-7, Apr 19 2010.

[11] A. Sundaresan, J. G. Chase, G. M. Shaw, Y. S. Chiew, and T. Desaive, "Model-based optimal PEEP in mechanically ventilated ARDS patients in the intensive care unit," *Biomed Eng Online,* vol. 10, p. 64, 2011.

[12] E. R. Weibel, "Principles and methods for the morphometric study of the lung and other organs," *Lab Invest,* vol. 12, pp. 131-55, Feb 1963.

[13] K. Horsfield, G. Dart, D. E. Olson, G. F. Filley, and G. Cumming, "Models of the human bronchial tree," *J Appl Physiol,* vol. 31, pp. 207-17, Aug 1971.

[14] T. J. Pedley, R. C. Schroter, and M. F. Sudlow, "The prediction of pressure drop and variation of resistance within the human bronchial airways," *Respir Physiol,* vol. 9, pp. 387-405, Jun 1970.

[15] I. M. Katz, Martin, A.R., Feng, C.H., Majoral, C., Caillibotte, G., Marx, T., Bazin, J.E., Daviet,, "Airway pressure distribution during xenon anesthesia: The insufflation phase at constant flow (volume controlled mode)," *Applied Cardiopulmonary Pathophysiology,* vol. 16, pp. 5-16, 2012.

[16] G. Nucci, B. Suki, and K. Lutchen, "Modeling airflow-related shear stress during heterogeneous constriction and mechanical ventilation," *J Appl Physiol,* vol. 95, pp. 348-56, Jul 2003.

[17] G. Avanzolini and P. Barbini, "A versatile identification method applied to analysis of respiratory mechanics," *IEEE Trans Biomed Eng,* vol. 31, pp. 520-6, Jul 1984.

[18] U. Lucangelo, F. Bernabe, and L. Blanch, "Lung mechanics at the bedside: make it simple," *Curr Opin Crit Care,* vol. 13, pp. 64-72, Feb 2007.

[19] Y. S. Chiew, J. G. Chase, G. M. Shaw, A. Sundaresan, and T. Desaive, "Model-based PEEP optimisation in mechanical ventilation," *Biomed Eng Online,* vol. 10, p. 111, 2011.

[20] S. Karason, S. Sondergaard, S. Lundin, J. Wiklund, and O. Stenqvist, "A new method for non-invasive, manoeuvre-free determination of "static" pressure-volume curves during dynamic/therapeutic mechanical ventilation," *Acta Anaesthesiol Scand,* vol. 44, pp. 578-85, May 2000.

[21] J. F. Dasta, T. P. McLaughlin, S. H. Mody, and C. T. Piech, "Daily cost of an intensive care unit day: the contribution of mechanical ventilation," *Crit Care Med,* vol. 33, pp. 1266-71, Jun 2005.

[22] A. D. Bersten, "Measurement of overinflation by multiple linear regression analysis in patients with acute lung injury," *Eur Respir J,* vol. 12, pp. 526-32, Sep 1998.

[23] J. H. T. Bates, *Lung mechanics an inverse modelling approach* vol. 1. United States of America: Cambridge University Press, 2009.

[24] C. E. Hann, J. G. Chase, J. Lin, T. Lotz, C. V. Doran, and G. M. Shaw, "Integral-based parameter identification for long-term dynamic verification of a glucose-insulin system model," *Comput Methods Programs Biomed,* vol. 77, pp. 259-70, Mar 2005.

[25] A. M. Wilson, D. M. Gray, and J. G. Thomas, "Increases in endotracheal tube resistance are unpredictable relative to duration of intubation," *Chest,* vol. 136, pp. 1006-13, Oct 2009.

[26] K. Möller, Z. Zhao, C. A. Stahl, and J. Guttmann, "On the analysis of dynamic lung mechanics separately in ins- and expiration," in *MEDICON 2010, IFMBE Proceedings*, Chalkidiki, Greece, 2010, pp. 164-7.

[27] K. Möller, Z. Zhao, C. Stahl, and J. Guttmann, "Seperate analysis of respiratory system mechanics in inspiration and expiration," in *55. GMDS-Jahrestagung*, Mannheim, Germany, 2010, pp. 566-7.