Noninvasive Method of Assessing Power of Breathing (POB) for Patients Receiving Pressure Support Ventilation

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Introduction

A primary goal of mechanical ventilatory support is reduction of excessive work of breathing (WOB) per minute or POB. POB, the rate at which work of breathing is done, is a better assessment of respiratory muscle workloads than work of breathing because POB reflects the spontaneous inspiratory effort over time, not for an individual breath. Pressure support ventilation (PSV) is commonly used to assist spontaneous inhalation to maintain POB in a tolerable range (respiratory muscle load tolerance concept).

Although appealing for directly assessing respiratory muscle workloads, measurement of POB on a routine basis is impractical due to the need to insert a balloon catheter to measure intraesophageal pressure (Pes). Other factors limiting the practicality of this approach are added equipment costs, and training to use these devices. We hypothesize that by using an artificial neural network (ANN) [5] with appropriate physiologic predictor variables, real-time POB data can be predicted accurately and noninvasively, without inserting a Pes catheter.

Methods

IRB informed consent was obtained on 63 intubated adults (30 males, 33 females, weight: 80 ± 21 kg, age: 60 ± 15) diagnosed with acute respiratory distress syndrome (ARDS) and attached to ventilators. The intermittent mandatory ventilation (IMV) rate was maintained at approximately 2 breaths/minute and no changes in FIO_2, positive end expiratory pressure (PEEP), and IMV tidal volume (V_T) were made during the study. Typically, the ranges for these settings were 0.30 – 0.50, 5 – 15 cm H_2O, and 8 – 10 ml / kg, respectively.

A NG tube with a built-in balloon (SmartCath, nasogastric balloon catheter, Viasys) was substituted for the standard NG tube to measure esophageal pressure. An occlusion test was performed to verify correct placement. A combined pressure / flow / carbon dioxide sensor was positioned between the endotracheal tube (ETT) and Y-piece of the ventilator breathing circuit. The signals from the sensor (Figure 1) were directed to a computerized monitoring system (NICO, Respironics – Novametrix and NeuroDimension) to measure:

- airway pressure,
- breathing frequency (f),
- flow rate, tidal volume (V_T),
- spontaneous minute ventilation (Spon. Min.Vent.), and
- partial pressure of end-tidal carbon dioxide ($PetCO_2$) .

Work of breathing per breath (including physiologic elastic and resistive work and imposed resistive work of the ETT and ventilator) was measured using software (developed by NeuroDimension) by integrating the changes in Pes and V_T during assisted inhalation and applied to a Campbell Diagram. Chest wall compliance was set at 0.1 L / cm H_2O. POB was determined by measuring work of breathing over one minute.

Respiratory system compliance (C_{RS}) and total resistance (R_{TOT} : respiratory system resistance + ETT imposed resistance) were measured during the IMV breaths using a constant flow waveform. C_{RS} was measured by dividing V_T by the change in (pressure – PEEP) using least square analysis. R_{TOT} was measured by dividing the initial transient spike in airway pressure (pressure generated associated with 50 ml of tidal volume) at the onset of mechanical inflation by inspiratory flow rate. Respiratory system elastance was calculated as the reciprocal of C_{RS}.

Respiratory muscle pressure (Pmus) was calculated based on the following general equation:

Pmus = Elastic Pressure + Resistive Pressure

Where:

Elastic Pressure = Respiratory system elastance X Tidal volume

Resistive Pressure = R_{TOT} X Inspiratory flow rate

An estimated value for intrinsic positive end expiratory pressure (PEEPi) was determined from a flow–volume loop. Gas volume trapped in the lungs at end-exhalation is derived by projecting the calculated slope of the exhalation portion of the loop to the volume axis on the graph. This volume is then divided by C_{RS} to estimate PEEPi.

Inspiratory trigger pressure depth (PT Depth) was calculated as the difference from baseline PEEP to the lowest value of airway pressure at the onset of inhalation. Inspiratory trigger pressure slope (PT Slope) was calculated as a line drawn through the point on the PEEP baseline to the lowest point of airway pressure at the onset of inhalation.

In random order, PSV was applied in 5 cm H_2O increments ranging from 5 to 15 cm H_2O for all subjects. PSV was applied at 20 and 25 cm H_2O only in those subjects where the V_T did not exceed 12 ml / kg body weight. This was done for safety reasons. These latter subjects had more severe forms of ARDS than the others. After 15 minutes at each level of PSV, measurements were obtained.

Data were analyzed using a nonlinear multi-layer perceptron (MLP) ANN with a single hidden layer of eight processing elements to develop a model for predicting POB (Figure 2). This approach is somewhat analogous to using conventional multiple linear regression analysis (multiple predictors combined to predict a dependent variable). An advantage of the MLP ANN approach is that prediction is not restricted to linear constraints as in multiple linear regression analysis. By employing more mathematical terms, as in a nonlinear multiple prediction model, more variance in the dependent variable may be explained.

Results

All measured patient parameters were considered as potential physiologic predictor variables of POB. Only those that predicted or explained a significant amount of additional variance in POB ($p < 0.05$) were retained and used to formulate a model. Five variables were found to be significant predictors of POB: Spon. Min. Vent., Pmus, PT Depth, PT Slope, and PEEPi .

Table 1. Predictor variables at incremental levels of PSV (data are mean ± SD)

PSV ($cm\ H_2O$)	POB (Joule / min)	Spon.Min.Vent (L / min)	Pmus ($cm\ H_2O$)	PT Depth ($cm\ H_2O$)	PT Slope ($cm\ H_2O$ / sec)	PEEPi ($cm\ H_2O$)
5	6.3 ± 3.3	7.3 ± 2.1	86 ± 41	2.5 ± 0.9	10.7 ± 4.5	2.8 ± 2.7
10	4.9 ± 3.0	7.8 ± 2.1	62 ± 29	2.1 ± 0.9	7.9 ± 3.5	3.1 ± 3.0
15	4.7 ± 3.7	8.0 ± 2.5	64 ± 35	1.9 ± 1.0	8.1 ± 5.2	4.4 ± 6.0
20	6.2 ± 5.8	9.4 ± 3.3	87 ± 35	1.9 ± 1.0	10.2 ± 6.9	5.1 ± 4.0
25	5.1 ± 4.1	8.5 ± 2.9	74 ± 49	1.9 ± 0.9	10.7 ± 7.1	5.6 ± 2.6

The correlation coefficient (r) for directly measured POB and predicted POB was: $r = 0.91$ ($p < 0.05$). Coefficient of Determination or predictor coefficient (r^2) for predicting POB was: $r^2 = 0.83$, $p < 0.05$ (Figure 3).

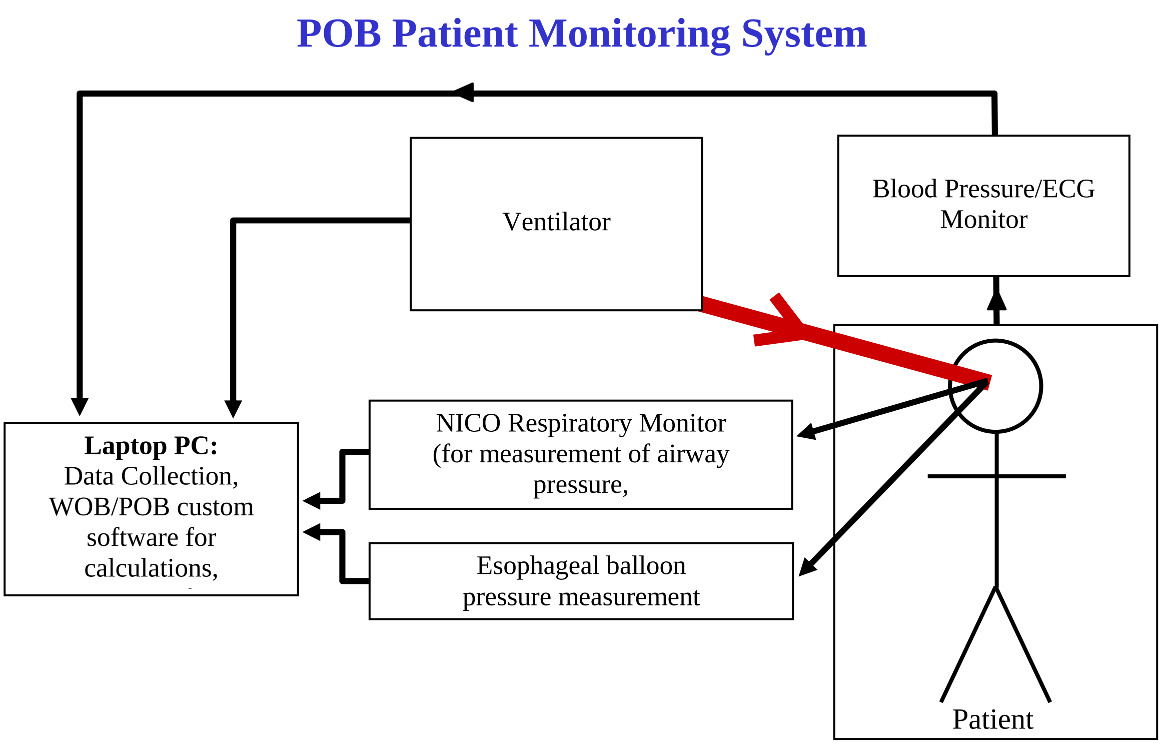
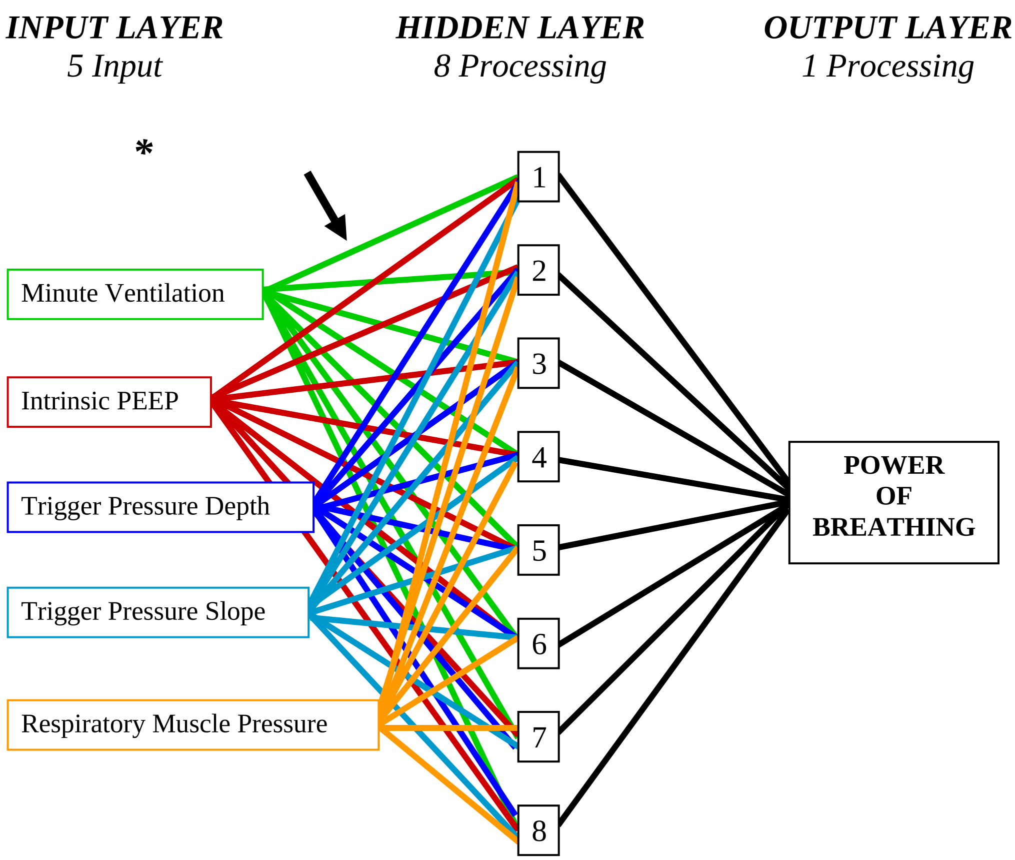


Figure 1. Schematic representation depicting a patient with ARDS attached to a life-support ventilator and connected to related monitoring equipment is shown. All data are directed to a computer which supports the multi-layer perceptron Artificial Neural Network (see Methods and Figure 2).

Multi-layer Perceptron Artificial Neural Network (ANN) architecture used in the model



* Various synaptic connection strengths are referred to as “weights.” The synaptic weights contain the “intelligence” of the system. There are 48 synapses / weights in the above system.

Figure 2. The multi-layer perceptron Artificial Neural Network, a popular type of feedforward network, used for predicting power of breathing is shown. Three layers are modeled. (1) An *input layer* consists of a specific set of input elements / neurons, i.e, the five physiologic predictor variables. (2) A *hidden layer* consists of eight processing elements, each of which is connected to each input element via a synapse and having a specific mathematical weight. (3) An *output layer* consists of one processing element, which is used for summing all the weighted inputs of the hidden layer and thus, predicting power of breathing.

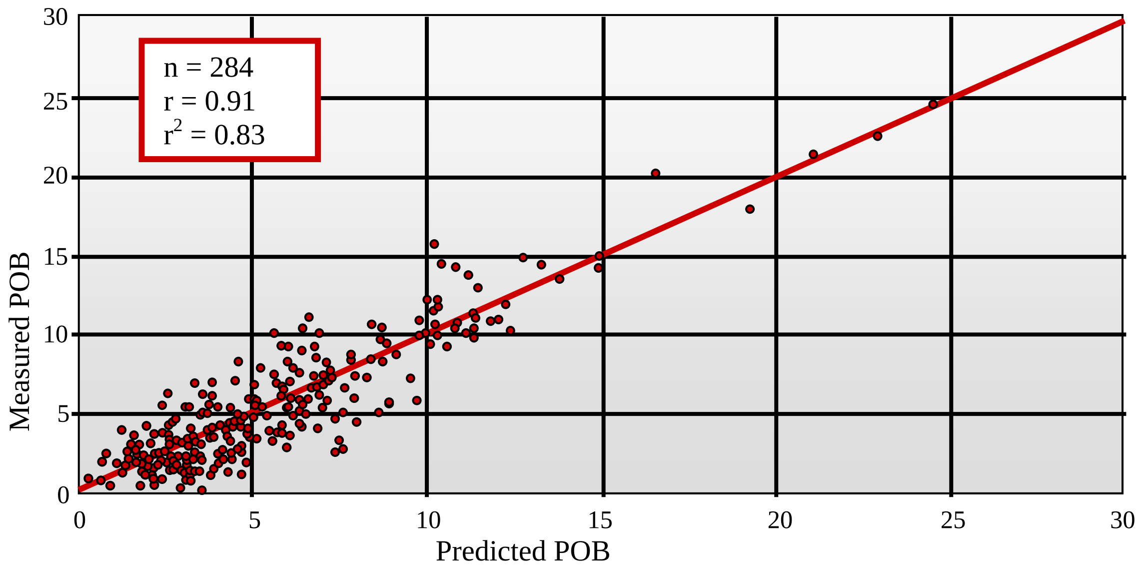


Figure 3. Relationship between directly measured power of breathing (POB) (Y-axis) and predicted POB (X-axis) using the nonlinear multi-layer perceptron Artificial Neural Network model is shown. The line drawn on the figure is the line of identity, not the regression line. A highly significant correlation ($r = 0.91$, $p < 0.002$) between the two was found. The model was a very good predictor of POB as evidenced by the high value for the Coefficient of Determination, $r^2 = 0.83$.

Conclusions

Because our model predicts or explains 83 % of the variance in POB, it provides an accurate means of determining POB noninvasively, and on a real-time basis. This approach does not require direct esophageal pressure measurement for determination of POB. Measurement of POB for patients receiving PSV is greatly simplified with this approach. Real time, noninvasive POB data may be combined with breathing pattern data (f, V_T, minute ventilation, and $PetCO_2$) in a complementary strategy for assessing respiratory muscle workloads of patients with ARDS receiving PSV.

At times when breathing pattern data do not correlate with respiratory muscle workloads, [8] knowledge of workload data (i. e., POB) provides better insight into patient assessment and management. It is important to know when patients are experiencing fatiguing workloads or when workloads are negligible over long periods predisposing to disuse muscle atrophy. Either factor may prolong ventilatory support. POB data are important because when the workload is maintained in a tolerable range using PSV, and combined with breathing pattern data, patients wean approximately 50% faster from ventilatory support.

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