

Improved Prediction of Minute Volume Flow Rates

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ABSTRACT

The ability to predict respiratory minute volumes while wearing respirators can be important to the design, specification, testing, and use of respirators. Starting with minute volume data and equations previously appearing in the paper by Caretti and Coyne (2006), a power transformation was made to improve the linearity of the fit. The resulting transformed data improved the agreement between measured and predicted values of minute volumes. The equation is:

$$V_E = (0.00366 W - 0.392 R_{in} + 0.173 m - 7.586)^{1.382}$$

where V_E is minute volume in L/min, W is specific work rate in Watts/m², R_{in} is inhalation resistance in cm H₂O•sec/L, and m is body mass in kg.

Using this equation, values of minute volumes may be predicted for 95% of the population of data points by multiplying by 1.5. Peak flows can also be calculated based upon these minute volumes.

Keywords: minute volumes, peak flows, prediction equations, respirator masks

INTRODUCTION

Minute volume is used to describe the rate of air movement in the respiratory system. Current studies use minute volumes to specify flow rates provided by respirator masks. The assumed or measured minute volume rates given by the investigators determine the rate of air supply that a breathing system should provide for the person wearing the device. Coyne (2001) discussed the need for accurate models of variables, such as flow rate, in respiratory function to improve respirator mask design. Accurate models can also help circumvent the need for multiple rounds of experimentation with each new respirator model.

Although respiratory flow rate models are currently available, current respirators may not satisfy the air flow needs of all individuals (Coyne et al. 2006). Knowledge of the general population's minute volume can allow better specification of the volume flow rates that need to be provided for all types of respirators, including powered breathing devices (PAPRs) with blowers, maximum resistance of filters of air-purifying respirators (APRs), or tank capacities of self-contained breathing apparatus (SCBAs). If the flow rate of a loose fitting PAPR is under specified, the person can over breathe the system and be exposed to ambient contaminants. If flow rate for a tight fitting respirator is under specified, the person will not be able to function well at the desired work rate and probably be forced to terminate work sooner than would otherwise be the case (Johnson, 2006). If the tank capacity of an SCBA is too small, the wearer will run out of breathable air too soon.

There are many different respirator masks with various uses and purposes. Miners, firefighters, and the military all require respirator masks to be used at high work rates. Under specification of flow

rates might prove quite hazardous to these individuals. Better models of average and peak inhalation could help ensure the safety of the people in these occupations.

Caretti and Coyne (2006) presented minute ventilation values as the combined set of data for inhalation and exhalation minute volumes from various sources. Inhalation and exhalation volumes are not equal in individuals but are relatively close (Caretti and Coyne, 2006). Minute ventilation, like oxygen uptake, varies with the level of activity and by individual, which complicates identifying trends in the data (Johnson et al., 2005). Investigators have presented data for minute volumes related to resistance, body mass, and work rate (Johnson, 2007). Different authors (Johnson et al., 1999; Coyne, 2001; Berndtsson, 2004; Kaufman and Hastings, 2005; Caretti et al., 2006) have characterized volume flow rates of people at various work rates, and some of these have provided peak flow values.

MODELING THE GENERAL POPULATION

Being able to model volume flow values based on work rate, resistance, and body mass would help to design respirator masks that would meet the requirements of an allotted percentage of the target population. Caretti and Coyne (2006) combined the minute ventilation data sets from various sources (Johnson et al., 1999; Coyne, 2001; Berndtsson, 2004; Kaufman and Hastings, 2005; Caretti et al., 2006). The fact that these groups tested distinct populations with various respiratory resistances and body masses enables this compiled data set to lead to a better model of the population at large.

The research used in the combined study from Johnson et al. (1999) pertained to people wearing full facepiece air purifying respirators with variable resistances and examined how performance was affected by work rate. Work rate was held at 80-85% of the maximum of the individuals, using a treadmill, until subjects decided to stop. A Fleish No. 3 pneumotach, a mass spectrometer, and custom software were used to obtain measurements of tidal volume, minute ventilation, and oxygen consumption (Johnson, 2007).

Coyne (2001) did research with half masks and full-facepiece air purifying respirator masks. Once again, the desired work rate was obtained using a treadmill. In this study, maximum flow rates were observed as exercise intensity changed to examine how masks were affecting performance.

Berndtsson (2004) discussed how breathing is affected by variable exercise on a bicycle ergometer. In this study, inspired minute ventilation was observed instead of oxygen consumption. The observed maximum ventilation points were taken as the peak inhalation values.

Kaufman and Hastings (2005) collected data during United States Marine Corps fitness testing. M40 respirators were worn in the study. Minute ventilation data were observed during the testing, and peak respiration was noted.

Caretti et al. (2006) also considered the effects of M40 respirators. Variable resistances were used and performances at certain work rates were measured while subjects exercised on a treadmill. Minute volume and ventilation data were recorded using a mass spectrophotometer and pneumotachograph.

Caretti and Coyne (2006) took the combined data of these groups and calculated any missing information in these studies. For example, Berndtsson's and Kaufman and Hasting's studies did not provide precise work rates as a percentages of the maximum, so work rates were estimated using procedures from the 2000 edition of the American College of Sports Medicine (ACSM, 2000). Caretti and Coyne (2006) then established a prediction equation for volume flow rates based on work rate (W), inhalation resistance (R_{in}), and body mass (m) to be representative of the general population:

$$V_E = (0.011 W) - (1.18 R_{in}) + (0.52 m) - 22.81 \quad (1)$$

where units for V_E are L/min, for W are Watts/m², for R_{in} are cm H₂O·sec/L, and m is in kg.

When work rate was not provided by the data source, it was calculated through the following equation (Caretti and Coyne, 2006):

$$W = 349 \text{ VO}_2 / \text{SA} \quad (2)$$

where VO_2 is the oxygen consumption in L/min and SA is body surface area in m^2 ; surface area was calculated through the Dubois body surface area equation (Caretti and Coyne, 2006; Johnson, 2007):

$$\text{SA} = 0.202 \text{ h}^{0.725} \text{ m}^{0.425} \quad (3)$$

where h is height (m) and m is body mass (kg).

Predicted values using equation (1) did not appear to be linearly related to the measured values, but instead demonstrated a nonlinear relationship (Figure 1). This paper discusses the transformation of that equation to obtain a more linear relationship between the measured and predicted ventilation values to create statistically significant variance data. The quality of the fit to the measured data varies with the model structure. The resulting model can assist in modeling average ventilation of the population and average ventilation rates that would be sufficient for a specified percentage of the population.

LINEARIZATION OF PREDICTED AND MEASURED RELATIONSHIP OF VENTILATION

The transformation that is discussed in this report maintains the original model equation used by Caretti and Coyne (2006). Figure 1 shows the original data presented by Caretti and Coyne with various best fit equations compared by R^2 values. Various transformations were attempted using the forms:

$$y = ax + b \quad (4a)$$

$$y = a e^{bx} \quad (4b)$$

$$y = a \ln x + b \quad (4c)$$

$$y = a x^b \quad (4d)$$

The values of parameters a and b were obtained using the least squares criterion. The predicted data points were then linearized using the prediction equations developed in the previous step. Both the log equation and the power equation appeared to linearize the data, but the power equation gave a slightly better fit (Figure 1). The best fit transformation was chosen for which the observed data points and the predicted data points best matched the line of identity ($V_{E \text{ obs}} = V_{E \text{ pred}}$). The R^2 values for the graph of $V_{E \text{ obs}}$ vs. $V_{E \text{ pred}}$ were used as the judgment criteria.

Comparisons of various fitting equations showed that the original data followed more of a power law relationship with the measured points than a linear relationship. This power law equation was used as the best fit of the data. The equation was inverted to create a new prediction equation, thus linearizing the predicted data to measured data relationship. Our transformation consisted of division by 3.0067 and raising the result to a power of 1.382:

$$V_E = (0.00366 W - 0.392 R_{in} + 0.173 m - 7.586)^{1.382} \quad (5)$$

The transformed minute ventilation data are seen in Figure 2, after the linear fit of the data was forced through zero. From these linear best fits of that data it is seen that after transformation the equation is quite close to $V_{E \text{ obs}} = V_{E \text{ pred}}$ and the R^2 value is closer to 1.0 than the original linear fit of the data (Figure 1A). This means that the transformed predicted equation is a more accurate model of the measured data. All of the R^2 values were statistically significant with very small p values, and the differences in the explained variation, ΔR^2 , between the models was physically significant.

It would be of interest to determine minute volumes that encompass certain percentages of the population. Those data could then be used to design and test respirators. For instance, a certain respirator could be designed to meet the minute volume demands of 90% of the population, and it could be tested against that standard. A linear fit allows this because it means that the predicted equation directly relates to the measured values.

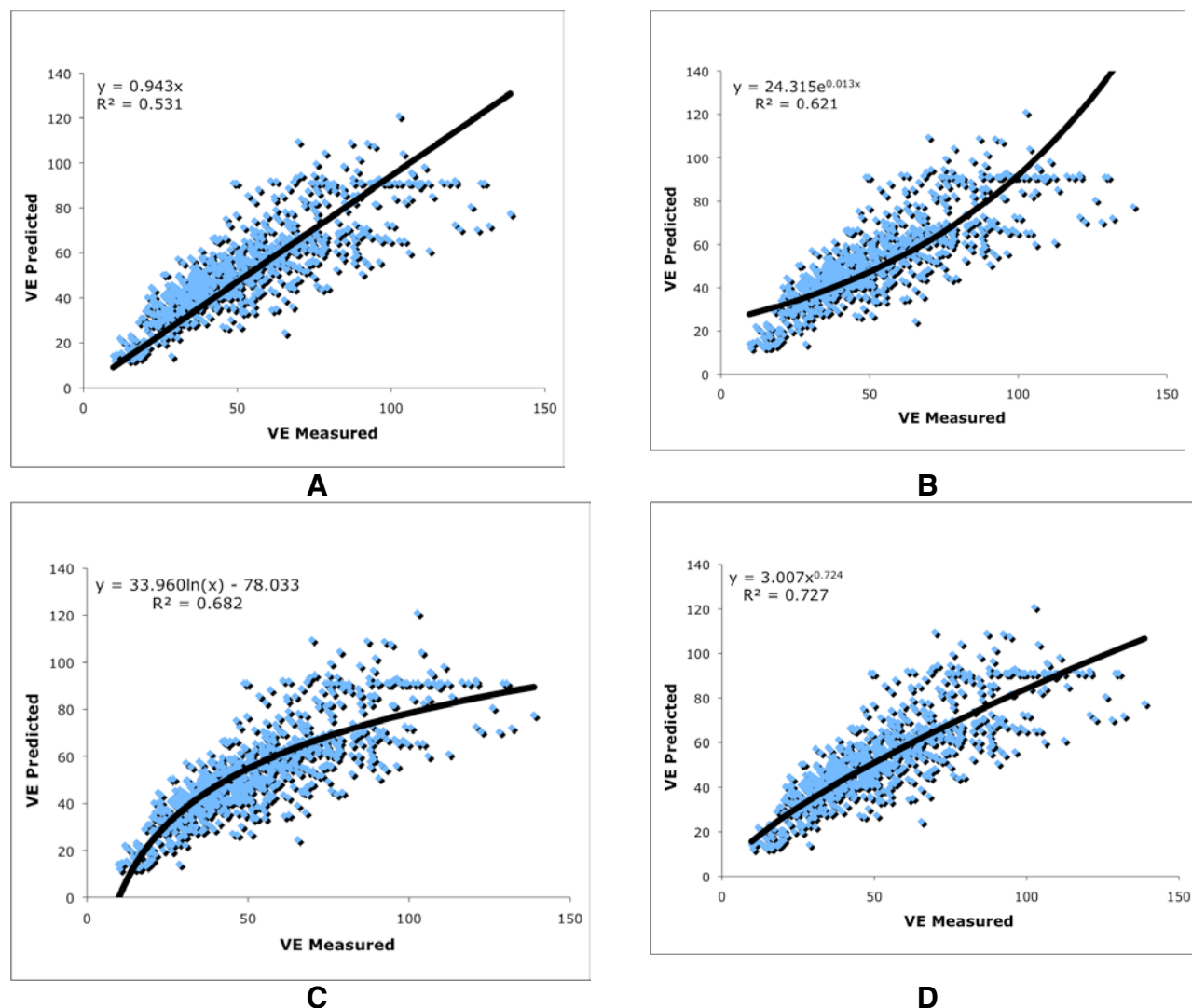


Figure 1. Comparison of the shapes of the functions between predicted and measured ventilation. A. Shows the original linear fit of the data that appeared in Caretti and Coyne (2006). B. Shows the exponential fit. C. shows the logarithmic fit. D. Shows the power equation fitting the data.

The transformed equation was used to determine variances. General equations of 0.7, 1.3, 1.45 and 1.5 times the transformed (linearized) value of minute volume were chosen to examine for population variance. These multiplier values were chosen by trial and error to include various portions of the population of data points. Figure 3 shows how these equations predict data that are above certain percentages of the total. The values obtained from these equations were subtracted from the actual predicted values to see how many data points were below the values represented by the bounding equations. The percentages below the bounding equations were found by dividing by the total number of points (805). From this it was found that multiplying the prediction equation by 0.7 includes 12% of the data. Using the same method, it was found that multiplying by 1.3 includes 82% of the data points. Multiplying by 1.45 includes 91% of the data points, and multiplying by 1.5 includes 95% of the data points. Multiplying the linearized equation by 1.5 would be the most appropriate for modeling breathing apparatus to include a large percentage of the population without over specifying for outliers.

The equation that includes 95% of the data points:

$$V_E = 1.5 (0.00366 W - 0.392 R_{in} + 0.173 m - 7.586)^{1.382} \quad (6)$$

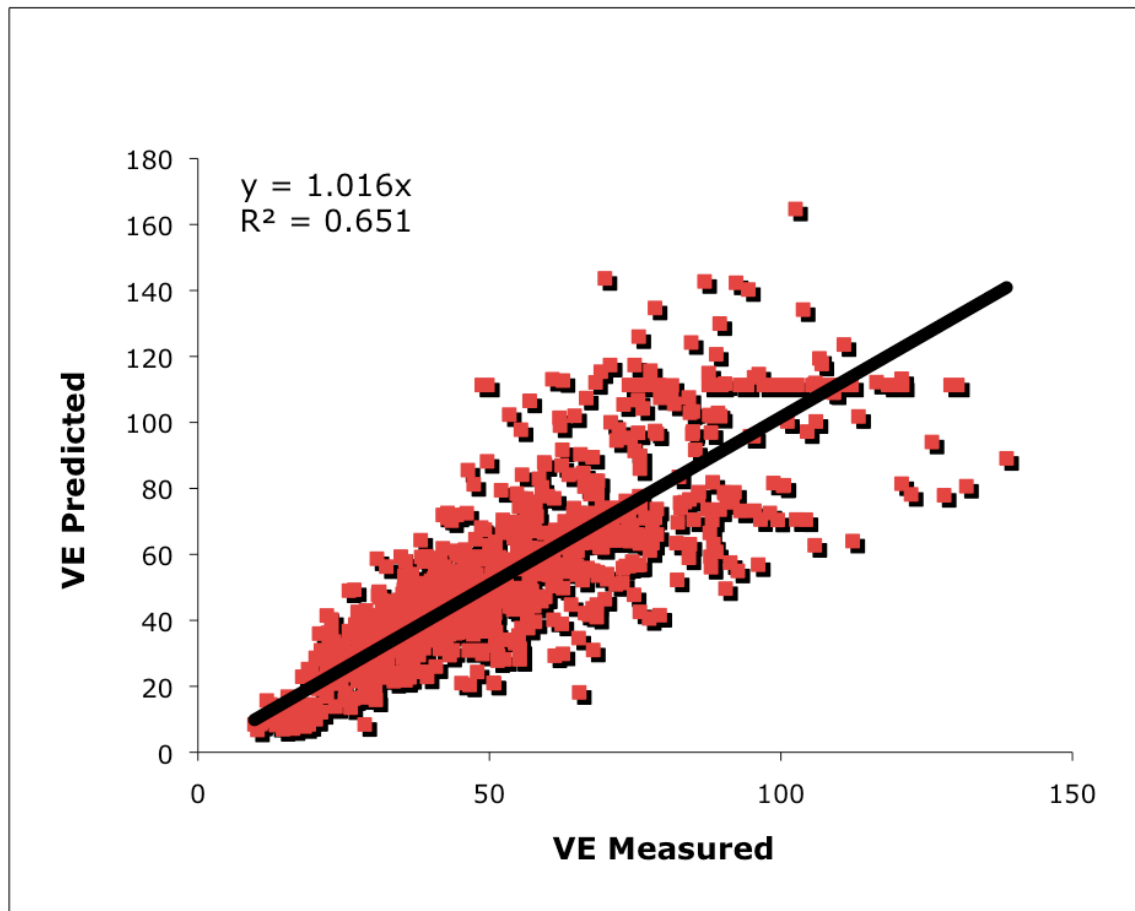


Figure 2. Display of the linearized data using the new power equation. The data closely match the line of identity $y = x$, or $V_{E \text{ obs}} = V_{E \text{ pred}}$.

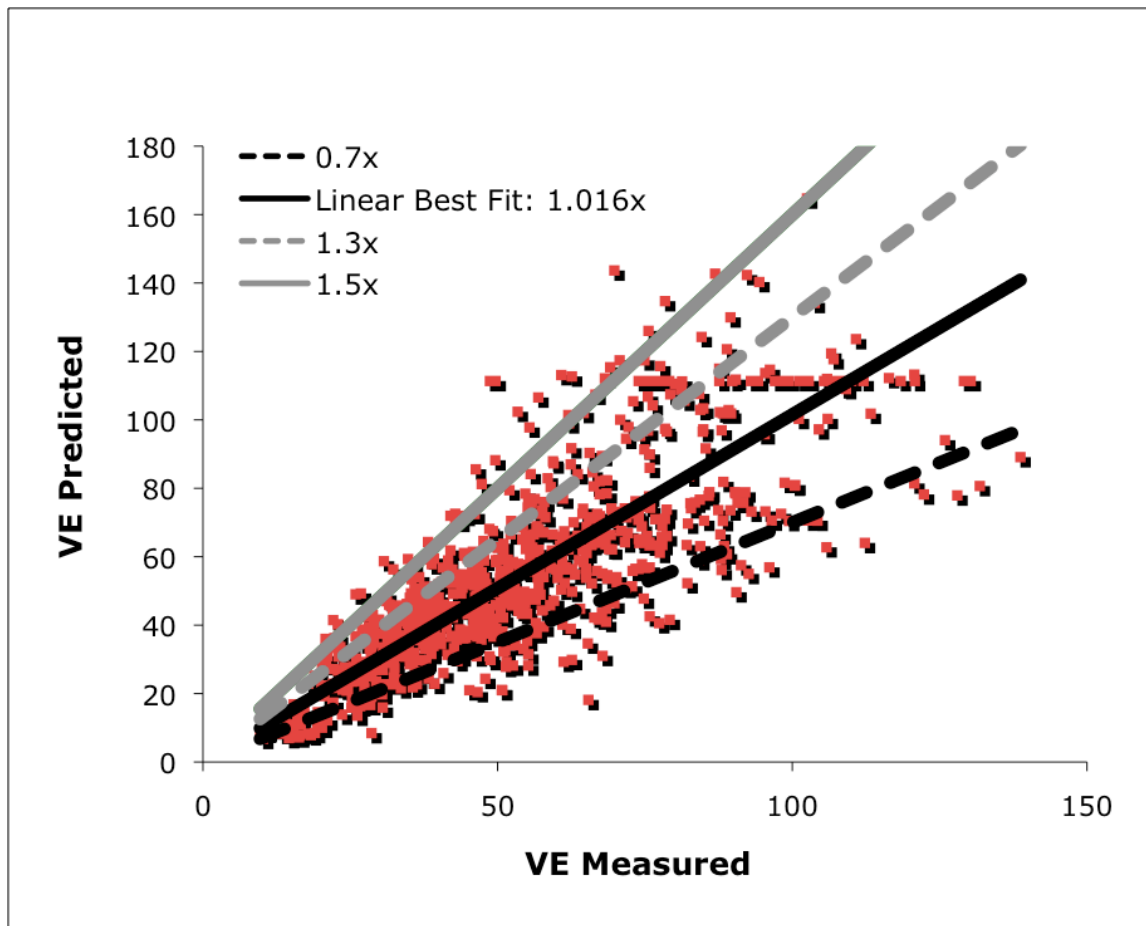


Figure 3. Equations bounding different percentages of the population of points. The lines are identified by their values to multiply the transformation power equation.

DISCUSSION

The coefficient of determination, R^2 , is commonly used as a measure of accuracy. Statistically speaking, it is only valid for linear models, but it is also generally useful for nonlinear models. R^2 denotes the fraction of the data distribution that can be explained by the regression equation (Henry, 2001). R^2 can be a bad means of determining how well a best fit line corresponds to the data if the fitting equation is over specified through the use of multiple variables (Annis, 2007). Over specification is commonly associated with the use of high-order polynomial fitting equations (Annis, 2007). Researchers end up using polynomial fitting incorrectly to obtain high R^2 values if key variables have been overlooked in the modeling, or if there is high variability in the data (Henry, 2001). In this research the use of R^2 is a valid method of statistical analysis because polynomial fitting was avoided and the data showed a consistently linear trend (Annis, 2007). If the trend was not consistent and the nonsystematic variation dominated the relation, then the R^2 value would not be a reliable indicator of the accuracy of the fit. In cases of large amounts of nonsystematic random variations, and with fits using unjustified multiple variable polynomial fitting, the fit will not hold true beyond its immediate range (Annis 2007). The fit may not even provide a rational representation within the range of measured data.

Some groups have argued that respirator masks should be specified to satisfy peak flow values (Coyne et al., 2006; Johnson, 2006). Even if this cannot be done, being able to model ventilation values would still be helpful because peak flow and ventilation are closely related. Carretti and Coyne (2006) considered the maximum ventilation values independently of the rest of the data and created the following predictive equation:

$$\text{PIF} = 0.06 W + 2.57 V_E + 72.32 \quad (7)$$

The units for PIF are L/min. Johnson et al. (2005) found the relationship to be:

$$\text{PIF} = 2.746 V_E + 18.90 \quad (8)$$

PIF has units of Equation (8) can be corrected for respirator inhalation resistance by first adjusting V_E for resistance (in cm H₂O•sec/L) by means of (Johnson et al., 1999; Johnson, 2009):

$$V_{E,R} = (1 - 4.12 R_{in}) V_E \quad (9)$$

These relationships allow for ventilation to be used to predict peak flow if that is desired. All data inputs to any model are subject to error; therefore, a value estimated from a model is not precise. Relative sensitivity is a modeling tool used to assess the relative importance of inputs. Relative sensitivity is the percentage change in the criterion variable, for example V_E in equation (5), that results from a one-percent change in any model input, e.g. W , R_{in} , or m in equation (5). The relative sensitivities for W , R_{in} , or m in equation (5) are:

$$S_W = 0.00486 W / V_E^{0.7236} \quad (10a)$$

$$S_{R_{in}} = -0.5206 R_{in} / V_E^{0.7236} \quad (10b)$$

$$S_m = 0.2297 m / V_E^{0.7236} \quad (10c)$$

An input with a large relative sensitivity is overly sensitive to error in the input value. An input that has a low relative sensitivity may still cause inaccurate estimates of V_E if the input contains considerable error.

The data showed that if the predictive equation is multiplied by a factor of 1.5 it encompassed 95% of the data points. This can be used to design devices to accommodate 95% of the population's ventilation rates. This will allow for the specification of masks to be used at various work rates and still allow most of the population to maintain regular breathing rates based on the expected resistance of the mask and the required work rate of the individual using the mask.

CONCLUSIONS

Shown in this paper is a superior fit of minute ventilation data for respirator design, testing, and use. Curves containing over 95% of the data can be used as equations for modeling flow rates for the overwhelming majority of the population.

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