Proceedings of the
44th IEEE Conference on Decision and Control, and
the European Control Conference 2005
Seville, Spain, December 12-15, 2005

Robust Feedback Design for Proportional Assist Ventilation-System Dynamics and Problem Definition

Mehdi M. Jafari, Senior Member, IEEE, and Francisco J. Lopez, Member, IEEE
Tyco Healthcare Puritan Bennett, Carlsbad, California

Abstract— **Robust control analysis and design of feedback controllers for life support medical ventilators are discussed in the context of Proportional Assist Ventilation. Controllers for critical care ventilators are required to have robust performance in the presence of time-varying global dynamic uncertainty. Proportional Assist Ventilation (PAV) is intended to detect, estimate, and track patient's spontaneous breathing effort and provide timely ventilatory support with specified air and O_2 gas mix. The main design consideration for a PAV controller is the non-deterministic, time-variant, and patient-dependent nature of the reference tracking trajectory. The controller's reference is determined quasi-real time based on estimated lung model parameters, predicted spontaneous breathing effort, and percent support set by clinician. In this paper, we discuss system dynamics, define the control design problem, and briefly comment on well posedness, internal stability, and controller synthesis.**

I. INTRODUCTION

THE act of breathing consists of rhythmic activation of inspiratory and expiratory muscles performed by a motor (effector) subsystem controlled by neural mechanisms that use a host of sensory (afferent) networks. Problems with one or more of the subsystems dealing with muscular actuation, gas exchange, sensory measurement, control, or communication could result in the need for mechanical ventilation. A ventilated patient system consists of the patient's respiratory subsystem controlled by highly complex neural centers and physiologic feedback mechanisms, the ventilator's dynamics and delivery algorithms, and the clinician-selected (operator) settings and protocols. Coordination and synchrony between the patient and ventilator significantly influence patient comfort, treatment effectiveness, and homeostasis. Younes [1] developed Proportional Assist Ventilation (PAV) as a form of synchronized partial ventilatory support in which the ventilator controls the airway pressure in proportion to the patient's spontaneous inspiratory effort. For practical purposes, the magnitude of the negative pressure generated by the inspiratory muscles (P_{mus}) is used as an index of breathing effort. The PAV controller is intended to track the patient's breathing pattern and deliver the desired ventilation support as determined by the patient's demand and clinician-selected settings. Airway pressure (P_{aw}) measured at the ventilator-patient interface may be calculated on an ongoing basis using patient parameters and P_{mus} according to the equation of motion [2],

$$P_{aw}(t) = E_p \int Q_p dt + Q_p R_p - P_{mus}(t) \tag{1}$$

Q_p is the instantaneous flow inhaled by the patient, and E_p and R_p are patient's respiratory elastance and resistance, respectively. Inspiratory muscle pressure is negative with a magnitude of P_{mus}.

Under PAV, the clinician sets a percentage support level k (0.0-1.0) to proportionally divide the total work of breathing between the patient and ventilator.

$$P_{mus}(t) = (1.0 - k)[E_p \int Q_p dt + Q_p R_p] \tag{2}$$

$$P_{aw}(t) = k[E_p \int Q_p dt + Q_p R_p] \tag{3}$$

Figure 1 shows a conceptual representation of PAV operation.

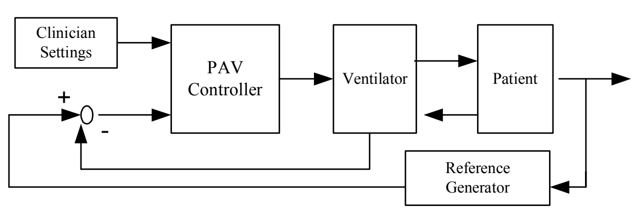

Fig.1 PAV conceptual framework demonstrating patient-generated tracking reference.

In Section II, the general dynamics of a PAV system is presented and sample transfer functions for ventilator components are provided. System well posedness, internal stability, and controller synthesis are briefly addressed in Section III.

II. PAV SYSTEM

In conventional Pressure Support ventilation, PSV, inspiratory and expiratory flow rates delivered to and exhaled by the patient (load) are regulated to track prescribed airway pressure trajectories determined by the

Manuscript submitted March 4, 2005. Parts of this paper was presented at the American Control Conference, held June 8-10, 2005 in Portland, Oregon, at a special tutorial session on "Modeling and Control of Systems for Critical Care Ventilation".

Mehdi M. Jafari is with the Control Systems Engineering Group, Tyco Healthcare Puritan Bennett R&D, 5931 Priestly Dr., Suite 100, Carlsbad, CA 92008 USA (e-mail: Mehdi.Jafari@ tycohealthcare.com).

Francisco. J. Lopez is a project manager with Tyco Healthcare Puritan Bennett R&D (e-mail: Francisco.Lopez@ tycohealthcare.com).

clinician-selected settings for steady state target and rise time [2]. In contrast, under PAV, the reference trajectory is not pre-determined and is predicted quasi-real time from patient effort (3). A PAV system consists of a ventilator with Proportional Assist pressure support functionality and capabilities to either input respiratory parameters by the operator or estimate them online. Fig. 2 is a schematic representation of major components of a PAV patient-ventilator system. The inspiratory module mainly consists of gas source, regulators, and the valving components. The expiratory module includes the exhalation valve and heated filter. Accessories include gas delivery/exhaust circuits, and elements such as filters, humidifiers and water traps. Examples of patient interface include endotracheal tubes (invasive ventilation) and masks (noninvasive ventilation). During inhalation, the PAV controller commands actuators in the inspiratory module to regulate gas delivery (flow and oxygen mix) through patient circuit and interface such that proximal airway pressure tracks the patient-based reference trajectory. Desired airway trajectory is computed every command cycle using estimated patient respiratory parameters, instantaneous inspiratory lung flow, patient-generated muscle pressure, and clinician-set support level. During expiration, flow through the exhalation valve is controlled to maintain a desired positive end expiratory pressure (PEEP) level.

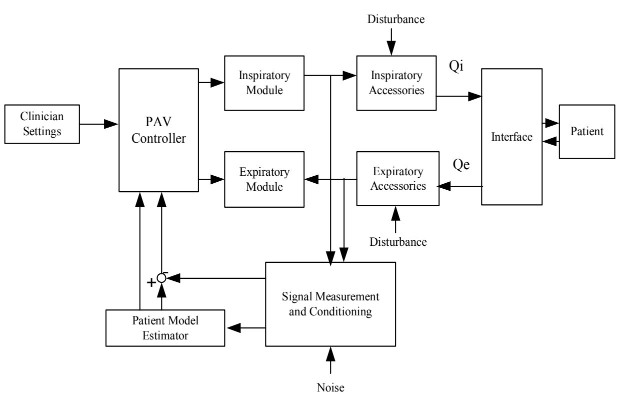

Fig. 2 PAV patient-ventilator modular block diagram.

Spontaneous respiratory frequency, intensity (muscle pressure and subsequent tidal volume), and duty cycle (inspiration and expiration timing) are controlled and coordinated by a complex network of neuromuscular and sensory mechanisms. In addition, inputs from a number of other sources (e.g., behavioral, postural, swallowing, temperature control) influence patient's breathing [3]. Under PAV, spirometric output is controlled by the patient and serves as a measure of the patient's respiratory motor output. Respiratory output is indicated by P_{mus} and determines the spontaneous tidal volume (V_T). The relationship between P_{mus} and V_T is complex but is primarily influenced by respiratory mechanics and temporal characteristics of neural inspiration and expiration. During spontaneous breathing, V_T is a function of P_{mus} waveform characteristics. All other conditions kept constant, V_T increases with peak inspiratory P_{mus}, neural inspiratory duration, convexity of rising phase of inspiratory P_{mus} waveform, and phasic expiratory muscle activation [3]. On the other hand, V_T decreases in the presence of high inspiratory or expiratory resistance, flow limitation, and high respiratory elastance (i.e., low compliance) [3]. There is substantial variation in the breathing pattern and V_T demand and control in healthy as well as diseased populations. To maintain the overall physiologic homeostasis, respiratory motor output is adjusted in response to variations in metabolic rate, chemical stimuli (e.g., pH), temperature, mechanical load, sleep state, and other behavioral inputs [3]. Therefore, spontaneous breathing patterns are highly variable and possess complex, and in many cases unpredictable, interdependencies. Moreover, when a patient is breathing spontaneously on a ventilator, the tidal volume produced by a given P_{mus} will also depend on the ventilator's event detection accuracy and temporal synchrony between the patient's actual inception of inspiration (triggering) and neural expiration (cycling) and the ventilator's breath phase transitions.

Regarding respiratory mechanics, reducing the patient's respiratory system's dynamic model to single elastance and single resistance components is a great conceptual simplification. However, this simplified lumped-parameter single compartment modeling approach is computationally feasible and is used for PAV pressure reference calculations. Discussions of respiratory output sensory-motor and physiologic dynamics, adequacy and effectiveness of respiratory mechanics modeling and estimation methodologies, and ventilator-patient interactions and synchrony are beyond the scope of this paper.

In this paper, we present a simplified PAV system limited to the inspiration phase depicted in Fig. 3. K(s) represents the reference generator that receives estimated patient lung flow and outputs desired airway pressure; C(s) is the PAV controller; V(s) incorporates ventilator's inspiratory dynamics (inspiratory module and accessories); P(s) is a patient model including respiratory parameter estimation; and F(s) represents signal conditioning dynamics. It is assumed that respiratory resistance and elastance are either provided by the clinician or estimated internally based on pressure and flow measurements. Lung flow, Q_p, is either measured at the patient interface or estimated based on ventilator measurements and pneumatic path characteristics.

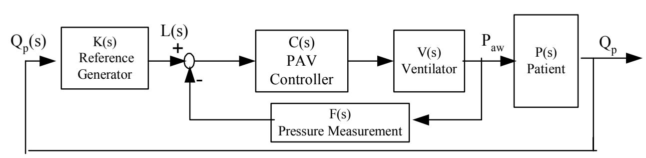

Fig. 3 Simplified PAV system for inspiration phase.

A. Patient Model and Pressure Reference Trajectory

Fig. 4 shows a simplified lumped-parameter analog model for patient circuit and single-compartment respiratory system. Patient circuit is represented by resistance (R_t) and compliance (C_t). Respiratory dynamics are captured by total respiratory resistance (R_p), total respiratory compliance

(C_p=1/E_p), and generated muscle pressure (P_{mus}). Using this model, airway pressure (P_{aw}) is a function of ventilator output flow (Q_v) and patient muscle pressure (P_{mus}):

$$P_{aw}(s) = T_1(s)Q_v(s) - T_2(s)P_{mus}(s) \tag{4}$$

$$T_1(s) = \frac{(s + \frac{1}{R_p C_p})}{s(s + \frac{C_p + C_t}{R_p C_p C_t})C_t} \tag{5}$$

$$T_2(s) = \frac{\frac{1}{R_p C_t}}{s + \frac{C_p + C_t}{R_p C_p C_t}} \tag{6}$$

The desired inspiratory patient flow, Q_p, to be provided by the ventilator, may be derived from (2):

$$Q_p(s) = (\frac{C_p}{1-k})(\frac{s}{1+\tau_p s})P_{mus}(s) \tag{7}$$

τ_p =R_pC_p.

The desired P_{aw} tracking reference, L(s), by definition is given by

$$T_3(s) = \frac{L(s)}{P_m(s)} = \frac{k}{1-k} \tag{8}$$

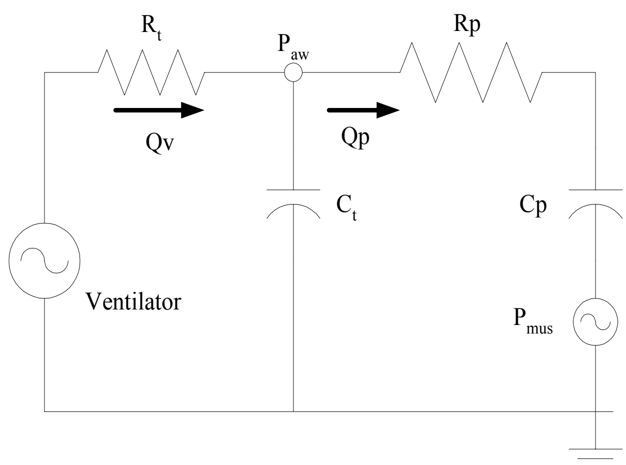

Fig. 4 Simplified analog model for patient circuit and lung.

Constructing an accurate and predictive model of the patient muscle pressure generator is challenging. Inspiratory muscle pressure, P_{mus}, is a time-variant excitation function with inter- and intra-subject variations. In normal subjects, it is believed that P_{mus} is in general dependent on breath rate, inspiration time, and characteristic metrics of inspiratory pressure waveform. However, in patients, other factors related to demanded and expendable muscle energy may critically influence muscle pressure generation. According to [3], for a given peak inspiratory pressure, the maximum sustainable muscle pressure may be affected by factors impairing muscle blood flow (blood pressure, vasomotor tone, muscle tension in the off-phase), the oxygen content of perfusing blood (P_{O2}, hemoglobin concentration), blood substrate concentration (glucose, free fatty acids), and the ability to extract sources of energy from the blood. Thus, respiratory motor output may vary significantly in response to variations in metabolic rate, chemical stimuli, temperature, mechanical load, sleep state, and behavioral inputs. Moreover, there is a breath-by-breath variability in respiratory output that could lead to tidal volumes varying by a factor of four or more. The mechanism of this variability is not yet known [3]. In this paper, a periodic function that seems to approximate actual clinically- observed inspiratory muscle pressures [4] will be used for demonstration purposes. Muscle pressure, P_{mus}, represents the magnitude of P_{musi} defined below:

$$P_{musi} = -P_{\max}(1 - \frac{t}{t_v})\sin(\frac{\pi t}{t_v}) \tag{9}$$

P_{max} is maximum inspiratory pressure, t_v is ventilator detected inspiration duration, and t is elapsed breath time varying between 0 and the total sum of inspiration and expiration periods.

P_{max} is assumed constant for fixed steady state conditions of physiologic and interactive parameters affecting muscle pressure generation. Under real conditions, P_{max}, and t_v will demonstrate time-variance in response to variations in metabolic rate, chemical stimuli, temperature, mechanical load, sleep state, behavioral inputs, and patient-ventilator interactions. In addition, R_p, and C_p vary inter- and intra-subject based on many factors including size and disease condition. During inspiration, the magnitude of R_p, and C_p change dynamically as the lung is inflated.

Taking the Laplace transform of (9) and substituting into (8), the desired airway pressure tracking reference is given by

$$L(s) = (\frac{\pi k}{1-k})\frac{\frac{P_{\max}}{t_v}(s - \frac{\pi}{t_v})^2}{[s^2 + (\frac{\pi}{t_v})^2]^2} \tag{10}$$

B. Breath Delivery System

The major mechanical components of a ventilator breath delivery system consist of air and oxygen gas supply, air and oxygen flow delivery valves, exhalation valve, and pneumatic circuitry. Breathing algorithms reside on a microprocessor that computes and issues valve commands based on signal measurements. In this paper, we discuss inspiratory ventilation and assume that the exhalation valve is closed during inspiration phase. We will not discuss the dynamics of the ventilator air blower and assume compressed air and oxygen are piped to the ventilator and supply the inspiratory valves through pressure regulators. For simplicity, gas delivery by only one valve is considered and gas mixing dynamics involved in maintaining specific levels of oxygen concentration will not be addressed. The transfer functions presented below were empirically derived for components of a commercial ventilator [5].

The regulator transfer function relating output pressure (input to delivery valve), $P_u(s)$, and flow, $Q_v(s)$ is given by

(11) with a, b, c, d, and e as modeling constants.

$$T_R(s) = \frac{P_u(s)}{Q_v(s)} = \frac{a(s^2 + bs + c)}{s^2 + ds + e} \tag{11}$$

$T_R(s)$ relates the drop in the regulated pressure to the change in flow through the regulator.

Flow through the air or oxygen valve, $Q_v(t)$, is assumed turbulent and computed by (12), where A is the valve orifice area, P_u the valve input pressure, P_d the pressure downstream from the valve, and C a constant [5].

$$Q_v(t) = CAP_u(\frac{P_d}{P_u})^{0.714}\sqrt{1-(\frac{P_d}{P_u})^{0.286}} \tag{12}$$

Orifice area A is a nonlinear function of valve poppet displacement (D). Poppet displacement is a function of valve input current, I, and is given by

$$T_v(s) = \frac{D(s)}{I(s)} = \frac{f}{s^2 + gs + h} \tag{13}$$

where f, g, and h are modeling constants. Combining (12) and (13), it is seen that flow through the valve, Q_v, can be controlled by current input to the valve.

Ventilator flow (12) may be linearized around an operating point to derive a linear transfer function. Linearization sensitivities will be dependent on the operating point and their consequent variations and effects should be included in the model as uncertainty. The linearized flow relationship is given by

$$Q_v(t) = q_1A + q_2P_u + q_3P_d \tag{14}$$

where q_1, q_2, and q_3 are sensitivity gains for area, valve input pressure, and valve downstream pressure, respectively. They are evaluated at the operating point and given as follows:

$$q_1 = \frac{\partial Q_v}{\partial A} \tag{15}$$

$$q_2 = \frac{\partial Q_v}{\partial P_u} \tag{16}$$

$$q_3 = \frac{\partial Q_v}{\partial P_d} \tag{17}$$

From Fig. 4, we can approximate P_d as

$$P_d = P_{aw} + R_tQ_v \tag{18}$$

A spline function was found to relate empirical data pairs for orifice area and poppet displacement. For variations about the operating point, we assume a linear relationship between A and D with q_4 as an operating point-dependent constant.

$$A = q_4D \tag{19}$$

Flow and pressure transducers for the example ventilator possessed sufficiently high bandwidth (>1 KHz) and therefore, for P_{aw} measurement dynamics we only include a two-pole Butterworth antialiasing filter given by

$$F(s) = \frac{f_1}{s^2 + f_2s + f_3} \tag{20}$$

where f_1, f_2, and f_3 are constants.

Referring to Fig. 3, the PAV controller output I(s) is given by

$$I(s) = [R(s) - P_{aw}(s)F(s)]C(s) \tag{21}$$

Finally, combining (4), (11), (13), (14), (18), (19), (20), and (21), the overall transfer function relating the control variable P_{aw} to patient input P_{mus} is derived as

$$G(s) = \frac{P_{aw}(s)}{P_{mus}(s)} = \frac{q_1q_4T_v(s)T_3(s)C(s) - T_2(s) + q_2T_R(s)T_2(s) + q_3R_tT_2(s)}{1 - q_2T_R(s) - q_3R_t + q_1q_4T_1(s)T_v(s)F(s)C(s) - q_3T_1(s)} \tag{22}$$

Substituting for the component transfer functions and rearranging, we have

$$G(s) = \frac{P_{aw}(s)}{P_{mus}(s)} = \frac{q_1q_4fC_t(\frac{k}{1-k})s(s+\frac{C_p+C_t}{R_pC_pC_t})T_4(s)C(s) - (\frac{C_t}{R_pC_p})T_5(s)}{C_ts(s+\frac{C_p+C_t}{R_pC_pC_t})T_5(s) + (s+\frac{1}{R_pC_p})[ff_1q_1q_4(s^2+ds+e)C(s) - q_3]} \tag{23}$$

$$T_4(s) = s^4 + (f_2 + d)s^3 + (f_3 + df_2 + e)s^2 + (df_3 + ef_2)s + ef_3 \tag{24}$$

$$\begin{aligned} T_5(s) = {} & (1 - q_3R_t - aq_2)s^6 + [(1 - q_3R_t)(f_2 + g + d) \\ & - aq_2(f_2 + g + b)]s^5 + [(1 - q_3R_t)(f_3 + gf_2 + h + dh_2 \\ & + dg + e) - aq_2(f_3 + gf_2 + h + bf_2 + bg + c)]s^4 + [(1 - q_3R_t) \\ & (gf_3 + hf_2 + df_3 + dgf_2 + dh + ef_2 + eg) - aq_2(qf_3 + hf_2 + bf_3 + \\ & bgf_2 + bh + cf_2 + cg)]s^3 + [(1 - q_3R_t)(hf_3 + dgf_3 + dhf_2 + ef_3 \\ & + egf_2 + eh) - aq_2(hf_3 + bgf_3 + bhf_2 + cf_3 + cgf_2 + ch)]s^2 + \\ & [(1 - q_3R_t)(dhf_3 + egf_3 + ehf_2) - aq_2(bhf_3 + cgf_3 + chf_2)]s + \\ & [(1 - q_3R_t)ehf_3 - aq_2chf_3] \end{aligned} \tag{25}$$

C. Parameter Estimation and Variation Range

Total respiratory resistance R_p and compliance C_p are estimated using lumped-parameter models [6]. There are a number of computational algorithms for assessment and estimation of respiratory parameters during mechanical ventilation at a given frequency, tidal volume, or mean airway pressure [7, 8, 9]. As a part of the PAV controller, R_p and C_p are estimated quasi-real time or input by the operator. Therefore, parameter estimation errors should be included as model uncertainty.

Respiratory resistance and compliance vary widely among healthy and diseased populations. Table 1 summarizes respiratory parameter ranges recommended by the American National Standards Institute (ANSI) for ventilator testing.

During invasive ventilation, endotracheal or tracheostomy tubes are utilized for breath delivery. Tube resistance is flow-dependent and is calculated by Rohrer's equation using K_1 and K_2 as modeling constants.

$$R_{tube} = K_1 + K_2Q \tag{26}$$

K_1 and K_2 depend on tube type and internal diameter (ID). Table 2 is an indicator of tube resistance variation range.

Patient circuit resistance and compliance, R_t and C_t, vary

TABLE I
ANSI Recommended Respiratory Parameter Range

Patient Type	Resistance ($cmH_2O/L/s$)	Compliance (ml/cmH_2O)
Adult	5-20	20-50
Pediatric	20-200	3-20
Neonatal	200-1000	1-3

based on size and material characteristics. Table 3 shows example ranges for R_t and C_t for three circuit types. There are additional sources of circuit impedance such as humidifier chambers, filters, and water traps. These devices, particularly humidifiers, constitute a challenge for quantifying circuit compliance uncertainty. For example, even if a humidifier's compliance is known for given levels of water volume, the actual water level during ventilation is not usually measured.

TABLE II
Tube Resistance Model Parameter Range

Tube Type (ID in mm)	K_1 (cmH_2O/LPM)	K_2 (cmH_2O/LPM^2)
Endotracheal (4.5-10.0)	0.1145-0.0078	0.0116-0.0004
Tracheostomy (4.5-10.0)	0.04854-0.00448	0.0081-0.0004

LPM= Liters Per Minute.

TABLE III
Example Inspiratory R_t and C_t Range

Circuit Type	Resistance K_1	K_2	Compliance (ml/cmH_2O)
Adult	0.0246	0.00050	2.88
Pediatric	0.0164	0.00054	1.42
Neonatal	0.0366	0.00410	0.58

D. Muscle Pressure Feedback Loop

In the derivations above, P_{mus} was taken as an independent input to the system. However, the patient's respiratory control system continuously interacts with the clinician-selected settings and ventilator dynamics and would make adjustments to the patient input, P_{mus}. Fig. 5 shows a conceptual block diagram of the overall closed-loop system including the patient's sensory-motor respiratory control dynamics, H(s), and physiologic inputs for respiratory control, J(s). As discussed earlier, the ventilator's closed-loop pressure tracking dynamics (inner loop in Fig. 5) are incorporated in G(s). $P_{AL}(s)$ represents patient's airway-lung dynamics model. H(s) and J(s) are not completely known or predictable and therefore, are not well-defined.

To derive some insight into the minimal performance requirements for a PAV ventilator, we assume stable steady state homeostatic patient conditions with P_{mus} incorporating the breath-by-breath component of the respiratory output

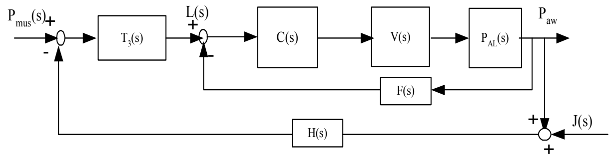

Fig. 5 Conceptual closed-loop block diagram including patient airway-lung model, $P_{AL}(s)$, physiologic control dynamics, H(s), and physiologic inputs, J(s).

variability. In this way, adjustments to P_{mus} will be only due to the patient's reaction to ventilator dynamics, namely, J(s) is not being considered. Furthermore, we assume that the "delivered" muscle pressure (P_{mus} pressure that would have resulted in delivered P_{aw}) is a scaled and delayed version of the actual muscle pressure sensed through a simple single-pole dynamic,

$$P_{mus,\,deliver}(s) = \frac{We^{-s\tau}}{s+z} P_{mus}(s) \tag{27}$$

where W is a scaling factor incorporating the magnitude ratio of actual to "delivered" muscle pressure, τ is the delay time constant, and z is the single pole. The error input to G(s) is given by

$$P_{mus,\,error}(s) = P_{mus}(s) - P_{mus,\,deliver}(s) \tag{28}$$

Thus, the system transfer function (23) may be updated as

$$G_c(s) = \frac{P_{aw}(s)}{P_{mus}(s)} = \left(1 - \frac{We^{-s\tau}}{s+z}\right) G(s) \tag{29}$$

Based on this assumption, H(s) may be inversely derived to be given by

$$H(s) = \frac{We^{-s\tau}}{(s+z-We^{-s\tau})G(s)} \tag{30}$$

Limits for magnitudes and uncertainties related to τ and W need to be discussed for robust stability analysis. In general, magnitudes of τ and W reflect the performance characteristics of the PAV controller in terms of responsiveness and tracking accuracy. These characteristics directly impact the man-machine synchrony and patient comfort which are among the most important performance requirements for every breath delivery system.

III. SYSTEM WELL POSEDNESS, STABILITY, AND SYNTHESIS

A feedback loop is considered to be well posed if and only if all possible transfer functions between all the inputs and all the outputs exist and are proper. In other words, a feedback system is well posed if well defined inputs produce well defined outputs [10]. The PAV controller, C(s), may be represented as

$$C(s) = K \frac{\sum_{i=0}^{m} A_i s^i}{\sum_{j=0}^{n} B_j s^j} \tag{31}$$

where K, A_i, and B_j are constants, and m and n are the degrees of the numerator and denominator polynomials, respectively. Next, we replace the exponential term in $G_c(s)$ by its Pade approximation. Inspection of G(s) and approximated $G_c(s)$ for properness will lead us to impose the following condition on C(s) to obtain a well posed feedback system.

$$n \geq m - 2 \tag{32}$$

Thus, for the example ventilator presented here, the total number of zeros of C(s) should not exceed the total number of poles by more than 2.

In general, if the respiratory physiologic controller H(s) is identified experimentally, then, the feedback system in Fig. 5 is well posed if the inverse of [1+G(s)H(s)] is proper.

The nominal transfer functions derived above do not include the global dynamic uncertainty inherent to the system. The nominal feedback loop in Fig. 5 is internally stable if and only if $[1+G(s)H(s)]^{-1}$ is stable and there are no right-hand plane pole-zero cancellations between the plant (ventilator including PAV controller), G(s), and the physiologic muscle pressure controller, H(s). Dynamics of the physiologic controller, H(s), is not well-defined. However, it is possible to determine reasonably practical transfer function(s) such that major application-relevant dynamics are captured. Using a sufficiently-adequate approximation to H(s), internal stability of the system may be investigated to derive requirements for the ventilator hardware and PAV controller's goals and objectives.

General system design specifications are derived from clinical needs, marketing requirements, safety and hazard considerations, hardware limitations, and cost (components, development, time-to-market). Specifically, major requirements for PAV controller design are derived from criteria for stability, disturbance rejection, and tracking performance characteristics. An important consideration for deciding on a PAV control structure for robust tracking is existence of uncertainties in both plant parameters as well as desired tracking trajectory. We recommend a PAV structure incorporating an internal-model-based controller for tracking and an overall system stabilizer. Alternative synthesis methods, such as dynamic inversion and adaptive control, do not address uncertainties in both plant model and trajectory. Dynamic inversion requires precise initial state, reference trajectory, and plant model. Adaptive control can handle uncertainties but requires a prescribed trajectory. Internal-model-based tracking is able to deal with uncertainties in plant parameters as well as desired trajectory. Isidori et al [11] maintain that for reference trajectories belonging to a set generated by a fixed dynamical system, an internal-model-based control system would be able to secure robust asymptotic tracking fidelity in the presence of parameter uncertainties.

IV. Summary

The patient-ventilator system dynamics were presented in the context of Proportional Assist Ventilation (PAV). Ventilator hardware dynamics extracted from models developed for a commercial ventilator were used to derive generalized transfer functions needed for assessment and realization of a stable PAV controller with robust performance requirements for tracking accuracy and responsiveness. A structure comprising of an internal-model-based controller for tracking and an overall stabilizer is proposed. Future work needs to address physiologic modeling of patient effort, robust system analysis and synthesis for a ventilator-patient plant with global dynamic uncertainty and investigate issues concerning stability, ventilator performance, PAV controller design, patient safety, hardware limitations, and economic feasibility.

Acknowledgment

The authors would like to thank Tani Barbour for reading the manuscript and providing excellent recommendations., Rhomere Jimenez, Jeff Aviano, and Edward McCoy are acknowledged for their assistance with component models.

References

[1] M. Younes. (1992, January). Proportional Assist Ventilation, a new approach to ventilatory support. *American Review of Respiratory Disease*. 145 (1), pp. 114-120.

[2] R. D. Branson, D. R. Hess, and R. L. Chatburn., *Respiratory Care Equipment.* Philadelphia: J. B. Lippincott Company, 1995.

[3] M. Younes, D. Georgopoulos, "Control of breathing relevant to mechanical ventilation", in *Physiological Basis of Ventilatory Support*, J.J Marini and A.S. Slutsky , Ed. New York: Marcel Dekker, 1998, pp. 1-73.

[4] P. S. Crooke, J. D. Head, J. J. Marini, and J. R. Hotchkiss.(1998). Patient-ventilator interaction: A general model for nonpassive mechanical ventilation. *IMA Journal of Mathematics Applied in Medicine and Biology*. 15, pp. 321-337.

[5] K Behbehani, N. T. Watanabe. A new application of digital computer simulation in the design of a microprocessor-based respirator. *Summer Simulation Conference*, Reno, Nevada, July 28-30, 1986. pp. 415-420.

[6] R. L. Chatburn, F. P. Primiano, Jr., "Mathematical models of respiratory mechanics", in *Fundamentals of Rrespiratory Care Research*, R. L. Chatburn and K. C. Craig, Ed. Norwalk, Conn.: Appleton & Lange, 1998, pp. 59-100.

[7] J. H. T. Bates, A. M. Lauzon. (1992). A nonstatistical approach to estimating confidence intervals about model parameters: Application to respiratory mechanics. *IEEE Trans. Biomed. Eng*. 39, pp. 94-100.

[8] D. W. Kaczka, G. M. Barnas, B. Suki, and K. R. Lutchen. (1995). Assessment of time-domain analyses for estimation of low-frequency respiratory mechanical properties and impedance spectra. *Ann. Biomed. Eng.* 23, pp. 135-151.

[9] R. Peslin,J. Felico de Silva, F. Chabot, and C. Duvivier. (1992). Respiratory mechanics studied by multiple linear regression in unsedated ventilated patients. *Eur. Respir. J.* 5, pp. 871-878.

[10] R. S. Sanchez-Pena, and M. Sznaier, *Robust Systems, Theory and Applications*. New York: John Wiley & Sons, 1998.

[11] A. Isidori, L. Marconi, and A. Serrani. *Robust Autonomous Guidance, An Internal Model Approach.* London: Springer, 2003.