Control Applications in Artificial Ventilation

(Invited Paper)

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Abstract—This paper presents a review on the use of feedback control and automation in artificial ventilation. Based on the key features of patient-machine-interaction, the authors attempt to develop a hierarchical scheme of different categories of control loops and give application examples.

I. INTRODUCTION

The history of artificial ventilation is closely related to the origin of anesthesia. After the introduction of ether for use as an anesthetic drug in Boston, USA, in 1846, the need for artificial ventilation soon became evident. Soon after, the first medical devices allowing proper dosing of the agents, guaranteeing pressure control of the carrier gases and offering bags for manual mask ventilation became available. However, in those days surgical procedures were rather short, with one of the limiting factors being manual ventilation. In the fifties of the last century, the first devices for pneumatically operated bellows were introduced, which improved the possible duration of surgical procedures significantly.

The dawn of long-term artificial ventilation and thus the beginning of modern intensive care can also be dated to this time period [1]. Drivers of these developments were the huge polio epidemics where a large patient population was in need of temporary artificial ventilation within a short period of time. Large numbers of so called iron lungs were rapidly produced to save the lives of infected persons, see Fig. 1.

In a way, iron lungs simulate the physiological way of ventilation by applying a subathmospheric pressure to the stomach of the patient. However, they are bulky and access to the patient is rather limited. Thus, as soon as it became known that intubation is feasible for long-term intubation, subathmospheric pressure ventilation was replaced by the more simple positive pressure ventilation [2].

During the last 25 years, positive pressure ventilators and anesthesia machines have further developed from a pneumatic to a mechatronic state. Coloured displays, flat touch screens and monitoring has already been integrated into current device technology, see e.g. Fig. 2.

At the same time, additional sensors and expanded local computing power have been a basic platform for the increasing amount of control applications in modern devices. In the following, we shall introduce a few categories on how to classify the different levels of automatic control in artificial ventilation and give some examples, both on the industrial and on the research level. However, as a basis for this, we shall first summarize some basics of dynamic modelling of components involved.
II. MODELS FOR ARTIFICIAL VENTILATION

A. Breathing Mechanics

The most simple model of breathing mechanics is a first order lumped parameter model. Here, the pressure in the upper airways \( p_{aw} \) (which equals 0 during spontaneous ventilation) is determined by \( R_{rs} \), the pneumatic resistance to air flow, and \( C_{rs} \), the volume storage capacity of the respiratory system. In addition, the diaphragm may add a subatmospheric pressure \( p_{diaph} < 0 \) if active, see Fig. 3.

\[
\text{Fig. 3. Simple electrical analogue of breathing mechanics}
\]

Applying Kirchhoff's voltage law, \( p_{aw} \) is equal to

\[
p_{aw} = R_{rs} \dot{V}_{breath} + \frac{1}{C_{rs}} (V_{lung} - FRC) + p_{diaph}, \tag{1}
\]

where FRC (functional residual capacity) is the pressure-free reference volume inside the lung and

\[
V_{lung}(t) = FRC + \int_0^t \dot{V}_{breath}(t) dt. \tag{2}
\]

B. Components for Artificial Ventilation

Inside most breathing systems of ventilators used in anesthesia or intensive care, there typically are two actuators, one responsible for the inspiration and the second one being responsible for the expiration phase. In many cases, the inspiration actuator is a flow source (like a piston device or a supercritical gas dowing valve), while in the expiratory phase a positive end-expiratory pressure (PEEP) can be guaranteed by the application of a special pressure-controlled valve (called PEEP valve), see Fig. 4.

\[
\text{Fig. 4. Breathing system of a modern anesthesia workstation. Arrows indicate direction of gas transport.}
\]

Note that a \( \text{CO}_2 \) absorber is only necessary inside a closed anesthesia breathing system, but is not necessary inside an open breathing system used in an intensive care scenario. Assuming a piston pump system as the inspiratory actuator, the dynamics of \( p_{aw} \) can be divided into two subcomponents, namely "piston and drive" and the "lung mechanics" already introduced before (Fig. 5).

\[
\text{Fig. 5. Block diagram of inspiratory system dynamics including the two major subcomponents.}
\]

If the electrical time constant of the motor is modelled by a simple first order system and friction assumed to be linear (captured by \( K_R \)), the whole system may be described by a third order differential equation [4].

For the first subsystem, input variables are the applied motor voltage \( U_a \) and the load torque \( T_L \), which is fed back from the lung mechanics subsystem. The major output variable is the piston speed \( \dot{z} \), see Fig. 6.

\[
\text{Fig. 6. Dynamic model of the subsystem "piston and drive".}
\]

Here \( \psi \) is the field flux linkage and \( J_{eff} \) is the resulting moment of inertia. The overall torque balance is given by

\[
J_{eff} \cdot \dot{\omega} = T_L + \frac{K_a}{1 + T_a} \cdot U_a - \frac{\psi^2}{1 + T_a} \cdot \omega - K_R \cdot \omega. \tag{3}
\]

For the second subsystem, the block diagram given in Fig. 7 with input variable \( \dot{z} \) and output variables \( p_{aw} \) and load torque \( T_L \) is appropriate.

\[
\text{Fig. 7. Dynamic model of the subsystem "lung mechanics" as introduced in Fig. 3.}
\]

Here, \( A_{piston} \) is the piston area and \( K_M \) symbolizes the transfer ratio from \( p_{aw} \) to the load torque \( T_L \). In Laplace domain, the transfer function of this subsystem is given by

\[
T_L = K_M \cdot A_{piston}^2 \cdot \left( R_{rs} + \frac{1}{C_{rs} \cdot s} \right) \cdot \dot{z}. \tag{4}
\]
III. CATEGORIES OF CONTROL LOOPS

Regarding the amount of interaction between patient and medical device, it seems useful to define three major categories [5]: (I) device-internal control loops, (II) patient oriented control loops and (III) physiological compensatory control loops.

Typically, device-internal control loops feature sensor signals that can be measured inside the device and have no backward interaction from the patient (decoupling), see Fig. 8.

![Fig. 8. No backward interaction between patient and medical device in class I control loops.](image)

In patient orientiert control loops, all necessary signals may still be obtained inside the medical device, but these control loops feature a backward interaction between patient and device.

![Fig. 9. Backward interaction exists in patient orientiert control loops, typically as a disturbance.](image)

Finally, physiological compensatory control loops distinguish themselves by the fact that the patient is part of the control loop and that the controlled variables are rather physiological than physical parameters (Fig. 10).

![Fig. 10. Patient fully integrated into the control loop in physiological compensatory control loops.](image)

However, in many of class III applications, the corresponding physiological variables are rather difficult to measure. Under some lucky circumstances, like expiratory anesthesia gas or CO₂ concentrations), these signals may be measured inside the medical device. In many other cases, however, it is necessary to include external measurement devices or even develop new sensors. Another important criterion to differentiate the level of difficulty is quantifiability of the therapeutic goal. In some applications, the optimal conditions are difficult to quantify due to lack of explicit knowledge and pathophysiological understanding and the medical goal therefore is rather fuzzy (like "minimize lung tissue shear forces"). Therefore, it seems appropriate to introduce two subcategories, namely (IIIa) "measurable signals, quantifiable therapeutic goal" and (IIIb) "not (yet) measurable signals, mainly qualitative therapeutic goal". In the following, we shall introduce a few examples to further illustrate these concepts.

A. Device-internal control loops

An example for a class I control loop is the fresh gas control unit of an anesthesia device or an ICU ventilator. Here, the medical user defines the desired gas concentration and the internal control loop guarantees that this gas concentration is delivered to the patient (Fig. 11). There is no backward interaction.

![Fig. 11. Electronic dosing of fresh gas contains adjustable fractions of air and oxygen(O₂) or - in anesthesia devices - of O₂ and nitrogen oxide (N₂O).](image)

B. Patient oriented control loops

In type II control loops, the patient may interact with the medical device, e.g. as a disturbance. An example is inspiratory pressure control using flow sources.

In general, during pressure controlled ventilation (PCV) the desired trajectory of \( p_{aw} \) is transferred to the controller as a reference input. If this trajectory is chosen to be rectangular, then the corresponding \( V_{breath} \) is an exponential, see Fig. 12.

![Fig. 12. Pressure controlled breathing pattern for inspiration and expiration.](image)
The expert system SmartCare<sup>T:M</sup>/PS is an intelligent auto-adjusting PCV ventilation mode. The expert knowledge is implemented in if-then-else rules [8]. First versions of the expert system were introduced by Brochard and coworkers in the 90’s [9], [10] and it was integrated into the Draeger Evita XL Workstation [11], see Fig. 14.

The current implementation of the therapy plan measures three sensory signals from the patient every 10 seconds: spontaneous respiration rate RR<sub>spont</sub>, tidal volume V<sub>T</sub> and endtidal CO<sub>2</sub> concentration. Each parameter is valued by the rule base and the pressure support level (level of the machine ventilatory support) is adjusted every 2.5 minutes.

![Electrical analogue of PCV using a flow source.](image)

![Systemarchitektur des therapeutischen Expertensystems Smart Care<sup>T:M</sup>/PS.](image)

The three measurement values span a three dimensional vector space which is categorized in the target area of normal ventilation and other less desirable ventilatory states, see Fig. 15. The main strategy is first to direct the patient into the normal zone (respiratory comfort zone) and keep him there stable. If, for example, the spontaneous respiration is not sufficient (‘hypoventilation’, V<sub>T</sub> is OK, but etCO<sub>2</sub> is too high and RR<sub>spont</sub> too low) the machine support of the ventilation is increased. The according if-then-rule is:

\[
\text{IF} \quad 0 < \text{RR}_{\text{spont}}(t) < \text{RR}_{\text{spont, LOW}} \quad \text{AND} \quad (V_T, LOW < V_T(t) < \text{inf}) \quad \text{AND} \quad \text{etCO}_2, HIGH < \text{etCO}_2(t) < \text{inf} \\
\text{THEN} \\
\text{STATUS} : \text{Hypoventilation} \\
\text{ACTION} : P_{\text{ASB}}(t + \Delta T) = P_{\text{ASB}}(t) + x \text{ mbar}
\]

(7)

Other states feature similar rules, which also include history or specific care situations. The rule base can be visualized in graphical form, see Fig. 15.

As soon as the patient is within the respiratory comfort zone for a longer time, the actual weaning procedure starts. The pressure support is reduced every 15, 30 or 60 minutes by a preset value. The reaction is subsequently supervised and if the comfort zone is left, the patient is brought back into the comfort zone before the weaning is resumed.

SmartCare<sup>T:M</sup>/PS is one of the few commercially available medical expert systems and has been successfully

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### Mechanical Lung Parameters as a Function of Age

<table>
<thead>
<tr>
<th>Age</th>
<th>R&lt;sub&gt;rs&lt;/sub&gt; [mbar/l/s]</th>
<th>C&lt;sub&gt;rs&lt;/sub&gt; [ml/mbar]</th>
<th>T&lt;sub&gt;rs&lt;/sub&gt; [s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>newborns</td>
<td>30 - 50</td>
<td>3 - 5</td>
<td>0.1 ... 0.25</td>
</tr>
<tr>
<td>infants</td>
<td>20 - 30</td>
<td>10 - 15</td>
<td>0.2 ... 0.45</td>
</tr>
<tr>
<td>small children</td>
<td>10 - 20</td>
<td>20 - 40</td>
<td>0.2 ... 0.4</td>
</tr>
<tr>
<td>adults</td>
<td>2 - 4</td>
<td>70 - 100</td>
<td>0.14 ... 0.4</td>
</tr>
</tbody>
</table>

By contrast, the piston position z is given by

\[
C_{\text{pos}}(s) = \frac{z(s)}{U_a(s)} = \frac{b_0}{s^3 + a_2 s^2 + a_1 s + a_0}.
\]  

(6)

which makes volume controlled ventilation (VCV) with flow sources a much easier task.

### C. Physiological compensatory control loops

As has been mentioned already, in type III control loops the controlled variables are not physical, but physiological signals. Especially in more complex therapeutic scenarios, like therapy plans or medical flow charts, some of these physiological compensatory control tasks may best be represented by expert systems rather than classical controllers. These expert systems may be either implemented based on classical if-then-else rules or in a Fuzzy Logic framework.

1) **Smart Care<sup>T:M</sup>/PS - automated weaning from artificial ventilation**: The timely weaning from artificial ventilation is one of the key issues in successful ventilatory therapy. While a delayed weaning from the ventilator is related to unnecessary costs and possible risk for ventilator induced long term lung damage, unsuccessful premature weaning attempts result in great stress for the patient. During the last few years, several projects for automated weaning procedures have been described [6], [7].
evaluated in a large multi-center study [12]. Regarding the introduced categories, it is a type IIIa control application.

2) Automated artificial ventilation in patients with acute lung failure: While automated weaning marks the end-point of intensive ventilator therapy, the treatment of acute lung failure (acute respiratory distress syndrome, ARDS) is still a major challenge in intensive care therapy with poor prognosis in outcome. On one hand, gas exchange lung areas are reduced, such that an increase in oxygen supply is necessary. On the other hand, the reduction of $C_{rs}$ leads to a dramatic pressure rise when trying to maintain sufficient ventilation. Although artificial ventilation is definitely necessary to survive the crisis, the assumed long term effect of the ventilation damages the lung tissue additionally (so called ventilator induced lung injury, VILI). In order to optimize therapy, several complex treatment strategies have been introduced in the last years. The most popular ones are the ‘open lung’ concept after Lachmann [13] and the ARDSnet protocol [14], [15]. These treatment strategies can be categorized as category IIIb control systems, because of the difficult quantifiable therapy goal (ventilation with as small as possible shear force in the lung) and the additionally needed sensor technology.

In the open lung concept collapsed lung tissue is recruited by application of static pressure and thus the dangerous dynamic shear forces inside the delicate lung tissue can be minimized. First automation concepts have been developed [16], where the linguistic therapy guidelines have been translated into a fuzzy expert system which was implemented on a control-PC. The control concept consists of a state machine with the states (1) identification of the opening pressure, (2) identification of the closing pressure, (3) reopening of the lung and (4) steady state ventilation above the closing pressure. Transition between the states and feedback adjustment of the actuation values is governed by the fuzzy rule set [16]. Figure 16 shows a successful automatic recruitment manoeuvre, figure 17 shows the integrated ventilation, sensor and control platform.

**IV. CONCLUSIONS AND OUTLOOK**

Based on different examples from anesthesia and intensive care, an attempt for general categorization of automation and control technologies in medical devices has been made. The allocation to different categories has been aligned with the intensity of interaction between physiological system and machine.

Device-internal automatic control loops of category I are typically well-posed problems and can be solved analytically. Since process behavior is only dependent on machine internal parameters, robust automation systems can be developed with relatively moderate effort. This kind of automation systems can be found in many state-of-the-art ventilators on the market. Category II systems of patient oriented automation systems are characterized by an interdependency between the technical and the physiological system. These control systems can already be found in some high end devices. Physiological com-
Pneumonatory control systems of category III were separated in two sub-categories. They may be differentiated wether quantifiable sensor and/or setpoint information is available. The physiological quantities are often difficult to measure or even sensors may not be available at all. The situation becomes more difficult, if the therapeutic goal is indistinct: how does one actually measure fabric damage or pain? In addition to research of suitable control strategies, proper sensor technologies have to be developed as well.

Automation technology plays an increasingly important role in life supporting therapeutic devices. This is closely connected to the rapid advancement in computing an sensor technologies, but must also be supported by appropriate procedures and algorithms. The implementation of simple therapeutic functions which -until now- were exclusively reserved to physicians, are a challenge also from the legal point of view. Driving force of the evolution is the increasing pressure on efficiency but also the growing complexity of intensive care treatment. In order to concentrate on important issues many users welcome the relief from just time consuming and repetitive tasks. At the same time automation enables the implementation of complex treatment schemes which could hardly be implemented clinically just with manual workforce.

To the latter group belong clinical guidelines which gain importance in todays evidence based medicine. These therapy guidelines often contain expert knowledge formulated as flow-charts or rule systems. These are especially suited for technical support and may be implemented using classical binary or fuzzy inference mechanisms. From todays point of view the computerization of these clinical guidelines will be one of the major trends in the future.

Such machine standardized therapy guidelines could well be used for evaluation, optimization and validation of the whole treatment process. Compilation, formalizing and computerization of such a process, (or therapy plan), requires modern knowledge engineering technologies like a common thesaurus (e.g. UMLS) and modelling notations (e.g. UML). These are superposed to the basic therapy regulation mechanisms where the patient is integrated completely in the automatic control loop. If it is possible to extend this variety with further implementations of other therapy guidelines remains to be seen.

From the theoretical-conceptual view a uniform modelling language is desirable, which can be used by researchers and developers as well as by the end users. One possible development for such a universal approach could be the fusion of UML and Modelica like computing languages [18].

REFERENCES


