Linear controller proposal applied to the virtual servomechanism from an open source mechanical ventilator system

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***Abstract*— Nowadays a new infectious disease has been spreading world-wide (Covid-19), this disease mainly affects the respiratory system and requires the use of mechanical ventilators; unfortunately, the worldwide availability of such artificial ventilators is scarce. Therefore, some international efforts have been developed to get simpler and cheaper mechanical ventilators, although the main challenge is the air flow control, because of the dynamic complexity that links the servomechanism and the bio-hydraulic system. In this context, as a first stage in the development of robust control algorithms with the described intention, this paper presents the design and analysis of a feedback vector linear controller implemented in a virtual servomechanism from an open source mechanical ventilator. The numerical validation of this feedback vector controller is analyzed through two gains tuning scenarios, the results show a positive implementation taking in consideration the strong nonlinearity the system has. The novelty of the work resides in the accuracy of the model being quite simple. The proposed model changes the idea we have of controllers being over complicated and difficult to manage, inviting more students to experiment with such controllers more confidently.**

Keywords — servomechanism; linear control; states space

I. Introduction

COVID–19 is no news around the world, Mexico started quarantine since March 17th and has remained this way until the present day. Around 318,000 cases have been confirmed, where approximately 199,000 patients recovered and 36,906 died. Statistically, 11.60% of the patients died and 62.67% recovered [1].

Since the COVID-19 started, the worldwide medical infrastructure has been strengthened to have the capability of treating the whole population if infected. The state of the art ICU ventilators' price (Intensive Care Unit) oscillates between $20,000 and $50,000 USD being approximately between 2,415 and 6,039 Mexican minimum wages, expenses that cannot be supported by emergence economies and poor countries [2] [3]; therefore, different companies and universities have decided to create several open-source ventilators. [4] [5] [6].

In this context, the main objective of this educational effort is to tune an algorithm to control a virtual ventilator behavior using numerical solvers such as MATLAB Simulink, in order to learn how this kind of servomechanism reacts by the implementation of a feedback vector linear controller; this was achieved by considering the numerical values of the concerned servomechanism open source design parameters [4] without any modification from [2,3] or [5 – 16].

Our hypothesis is that using the eigenvalues from the open-loop system we will be able to define a new set of eigenvalues to design a state feedback controller that can turn our initial slow system into a faster and more stable one.

Mechanical ventilators have been widely studied in the last decade. One of the most significant works related to the subject was developed by F.T. Tehrani and J.H. Roum. Their paper published by the IEEE *Closed-loop control of artificial respiration* shows the main characteristics of ventilators and developed their own using open-loop or closed-loop controllers according to the necessary characteristics of the ventilator [7].

Another article published by the IEEE is the one developed by Anup Das, Prathyush P. Menon, Jonathan G. Hardman and Declan G. Bates called *Optimization of Mechanical Ventilator Settings for Pulmonary Disease States,* where it was shown how the authors generate in silico experiments to examine current practice and uncover optimal combinations of ventilator settings for individual patient and disease states. They achieved this by combining validated computational models of pulmonary pathophysiology with global optimization algorithms [8].

Declan G. Bates and Jonathan G. Hardman made another study with John G. Laffey and Marc Chikhani. They realized that a lot of countries were being affected by COVID-19, and that patients will require mechanical ventilation for around six days. They studied how viable it is to support more than one patient with a single mechanical ventilator [3].

On the other hand, there is another study during the COVID-19 pandemic made by Martín A., Rodrigo B., Luciano A., Pedro A., Arturo A and Cristina S. about the mechanical risks of ventilator sharing, like the uneven distribution of tidal volume between the two patients [9].

Another group of researchers studied the management of CO_2 absorbent while using the anesthesia machine, with an empty absorbent reservoir, as a mechanical ventilator. They found out that using a fresh gas flow 20% higher than the adjusted minute-volume, the inspired gas was CO_2-free [10].

H. Al-Otaibi, N. Bedforth, R. Mahajan and J. Hardman made a study to evaluate the accuracy in predicting arterial blood gases values following mechanical ventilator adjustment [11].

Adler F. and Leonardo B. investigated the performance of an Iterative Learning Control (ILC) algorithm applied on the accuracy of tracking pressure profiles associated with a commonly used ventilator mode. Thus, they discovered that an ILC by itself is not suitable to replace a conventional feedback controller, but an ILC with feedback control can significantly improve performance [12].

Hasan G. and Fikret A. explain key factors to consider for the design and implementation of training mechanical ventilator set. Clinicians have to determine the best treatment for patients due to the fact that ventilators generally work as open-loop controlled [13].

A servomechanism is a system made up of mechanical and electronic parts, it can also be made up of pneumatic, hydraulic and precisely controlled parts. Edward J. Davison realized that there are severe limitations affecting the system's performance, these limitations prompted him to study intelligent servomechanism controllers. These controllers contain a switching device which applies a sequence of LTI (Learning Tools Interoperability) controllers to the system [14].

Ruben G. and Alberto S. decided to use a simple non-linear proportional-derivative controller to improve the settling time of a servomechanism. This algorithm improves the settling time regarding a linear proportional-derivative controller. [15].

CONACYT and CIDESI have also presented the Mexican mechanical ventilator called Ehécatl 4T and Gätsi, devices that have been technologically modified to accredit the medical certification required [16].

The next section describes the theoretical foundations of the linear control proposed in this study, with a brief description of the states space dynamic systems modeling paradigm and the feedback vector linear control strategy, following the dynamic model and the corresponding feedback vector tuning are shown. The third section illustrates the simulation results and their analysis shown in the fourth one; finally, conclusions about the simulation performance are on the last section.

II. Theoretical Foundations

State space system representation lays the foundations for modern control theory as it solves many of the limitations of the classic control theory in which transfer functions were implemented.

A state space model describes the behavior of a dynamic system as a set of first order ordinary differential equations (ODE), even if the dynamic model is described by a higher order ODE. The response of a system is described by a set of first order differential equations, in terms of the state variables {x1,x2,x3,…,xn} and the inputs {u1,u2,u3,…,um}. This first order differential equations can be written in the general form, but also in a matrix form as:

$$\dot{x} = \frac{d}{dt}\begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}\begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1m} \\ b_{21} & b_{22} & \dots & b_{2m} \\ \dots & \dots & \dots & \dots \\ b_{n1} & b_{n2} & \dots & b_{nm} \end{bmatrix}\begin{bmatrix} u_1 \\ u_2 \\ \dots \\ u_m \end{bmatrix} \quad (1)$$

the column matrix *X* consisting in the state variables and it is called the state vector. The transition matrix n x n is identified as *A*, as well as the input matrix n x m is called *B*. Finally, the vector of input signals is defined as *u*.

The state differential equation relates the rate of the change of the state of the system to the input signals. Also, the output of the linear system can be related to the state variables and the input signals by the output equation

$$y=C\cdot x+D\cdot u, \quad (2)$$

where *C* is the output matrix and *D* is the direct matrix and it is commonly zero, because the inputs do not typically affect the output directly.

The internal variables of the state space model are called state variables and they fully determine the future behavior of a system when the present state of a system is provided. In other words, the state variables are the specific variables that can fully describe the future behavior of a system. The number of state variables of the state-space model is the same as the highest order of the ODE describing the system and equal to the number of initial conditions needed to solve the model [17 - 18].

Assuming that all components of the state vector can be measured, since the state at time *t* contains all the information necessary to predict the future behavior of the system, the most general time invariant control law is a function of the state and the reference input:

$$u = \alpha(x, r) \tag{3}$$

If the state feedback control law is assumed linear, the feedback can be written as a linear combination of all state variables, including the reference:

$$x = (A - BK)x + Bkxr, \quad x(0) = xo \tag{4}$$

The poles of the closed-loop system are the roots of the characteristic equation:

$$\det(sI - A + BK) = 0 \tag{5}$$

The state feedback control law consists of selecting earnings such that the roots of the characteristic equation of the closed-loop system. Assuming, that the designer has selected the desired poles of the closed loop system being: p1, p2, ..., pn. The desired poles (of the closed loop system) can be either real or complex. If they are complex, they must be in complex conjugate pairs. This is due to the use of real kij earnings. Once we define the desire poles, we can form the desired closed-loop characteristic polynomial where the objective is to select a K feedback matrix such that [19]

$$\det(sI - A + BK) = sn + \alpha\, sn-1 + ... + \alpha\, s + \alpha \tag{6}$$

III. Model and Control Validation

This article specifically focuses on a controller for the mechatronic unit of the mechanical ventilator. The definition of the system was accomplished with the use of State-space representation as the equation (7) depicts. The equations (7) through (9) show the process followed to calculate the open-loop eigenvalues. The constants were substituted with the following values:

$$K_e = 3 \qquad k_\theta = 0.01\left[\frac{N}{m}\right] \qquad J_\theta = 25\left[\frac{N-s^2}{m}\right]$$

$$K_{m_1} = 100\left[\frac{V-s}{rad}\right] \qquad B_\theta = 2\left[\frac{N-s}{m}\right] \qquad L = 0.82[\Omega - s]$$

$$K_{m_2} = 2.5\left[\frac{A}{N-m}\right] \qquad R = 5[\Omega]$$

Where:

$K_e = gear\ relationship$

$K_{m_1} = voltage - speed\ relationship$

$K_{m_2} = current - torque\ relationship$

$J_\theta = polar\ moment\ of\ inertia$

$k_\theta = rotational\ stiffness$

$B_\theta = viscous\ damping$

$R = motor's\ electric\ resistor$

$L = motor's\ electric\ inductane$

Then we proceeded to calculate the determinant of the identity matrix multiplied by lambda minus the original matrix ($\lambda I - A$) using the calculated values shown above.

$$\frac{d}{dt}\begin{bmatrix}\alpha(t)\\ \omega(t)\\ T(t)\end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{k_e} & 0 \\ -\frac{k_\theta k_e}{J_\theta} & -\frac{B_\theta}{J_\theta} & \frac{1}{J_\theta} \\ 0 & -\frac{K_{m_2}}{LK_{m_1}} & -\frac{R}{L}\end{bmatrix}\begin{bmatrix}\alpha(t)\\ \omega(t)\\ T(t)\end{bmatrix} + \begin{bmatrix}0\\0\\ \frac{1}{LK_{m_1}}\end{bmatrix} v(t) \tag{7}$$

Equation (8) establishes the determinant of the original matrix shown in Equation (7) being subtracted from the identity matrix multiplied by λ. This new matrix is re-written with the numerical values substituted.

$$\det(\lambda I - A) = det\begin{bmatrix} \lambda & -\frac{1}{3} & 0 \\ 0.0012 & \lambda + 0.08 & -0.04 \\ 0 & \frac{2.5}{82} & \lambda + \frac{5}{0.85}\end{bmatrix} \tag{8}$$

$$= \lambda^3 + \lambda^2(5.96235) + \lambda(0.472208) + 0.002353 \tag{9}$$

We obtained the roots of Equation (9) and thus calculated the eigenvalues for the open loop system, which are the following:

$$\lambda_1 = -5.88214$$
$$\lambda_2 = -0.074867$$
$$\lambda_3 = -0.005343$$

The first graph obtained from Simulink, Figure 3.1 shows the estimated error of the open-loop system, while the second graph, Figure 3.2, the behavior of the system's response. Further analysis of the results is presented in section *Analysis Results*.

$$\lambda^3 + 5962.35\,\lambda^2 + 472206\lambda + 2.35294E6 \quad (13)$$

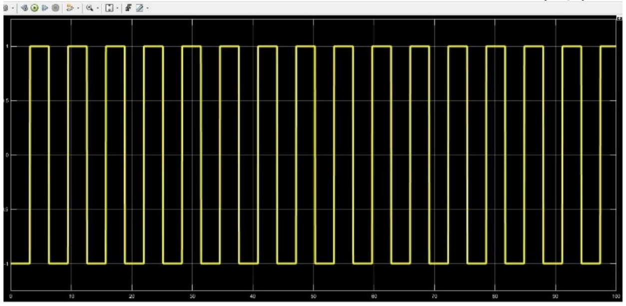

Fig. 3.1. Open-loop error graph

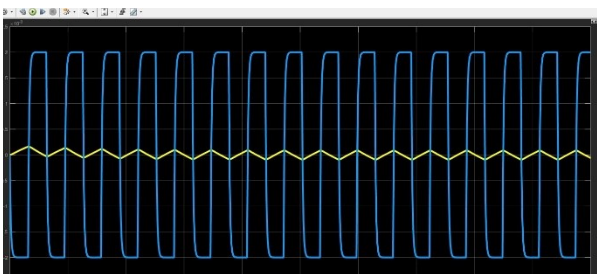

Fig. 3.2. Open-loop behavior graph

Based on the calculated eigenvalues, we established the closed-loop system should be 1,000 times more stable. The proposed eigenvalues in this stage were as follows:

$$\alpha_1 = -5882.14$$
$$\alpha_2 = -74.867$$
$$\alpha_3 = -5.343$$

These values were used to design the controller and calculate the system's gains. The equations (10) through (17) show the process followed to obtain these. Equation (10) shows I-A+BKc. We equalize this to the determinant of Equation (8) with the difference that the gains are involved in the operation as the last row of Equation (10) shows. This was equalized to Equation (11) which contains the new eigenvalues, shown above, for the closed-loop controller. Once we expanded these equations, we proceeded to equalize different equations depending on the lambda exponent they were multiplied by; Equation (14).

After equalizing and clearing Equations (15) through (17), we obtained the gains values.

$$\lambda I - A + BK_c = det\begin{bmatrix} \lambda & -\frac{1}{3} & 0 \\ 0.0012 & \lambda + 0.08 & -0.04 \\ \frac{k_\alpha}{82} & \frac{2.5 + k_\omega}{82} & \lambda + \frac{5}{0.85} + \frac{k_T}{82} \end{bmatrix} \quad (10)$$

$$= \lambda^3 + 5962.35\,\lambda^2 + 472206\lambda + 2.35294E6 \quad (11)$$

$$\lambda^3 + \lambda^2(6.17756 + 0.01219K_T) + \lambda(0.48942 + 0.00097K_T + 0.00048K_\omega) + 90478.7 - 6K_T + 0.00016K_\alpha = \quad (12)$$

$$\begin{gathered} 1 = 1 \\ 6.17756 + 0.01219K_T = 5962.35 \\ 0.48942 + 0.00097K\_T + 0.00048K\_\omega = 472206 \\ 90478.7 - 6K_T + 0.00016K_\alpha = 2.35294E6 \end{gathered} \quad (14)$$

$$K_T = \frac{5962.35\text{-}6.17756}{0.01219} = 488611 \quad (15)$$

$$K_\omega = \frac{472206 - 0.48942 - 0.00097(488611)}{0.00048} = 9.82845E8 \quad (16)$$

$$K_\theta = \frac{2.35294E6 - 90478.7 + 6(488611)}{0.00016} = 3.24633E10 \quad (17)$$

The states feedback vector is the following:

$$\bar{K} = [3.24633E10 \quad 29.82845E8 \quad 488611]$$

A simulation of the applied control and the Simulink graphs were obtained. The results are shown in figures 3.3 and 3.4; and analyzed in *Analysis Results*

After analyzing these graphs and due to the excessive gains obtained, a secondary set of eigenvalues was created, designed to be ten times bigger.

$$\alpha_1 = -60$$
$$\alpha_2 = -74.86$$
$$\alpha_3 = -50.34$$

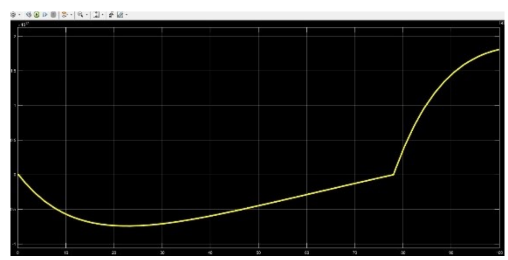

Fig. 3.3. Closed-loop error graph

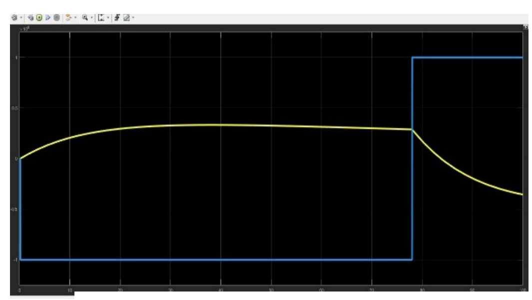

Fig. 3.4. Closed-loop behavior graph

This set of eigenvalues was selected, looking for a better state feedback vector (in comparison with the first one calculated). Equations (18) through (27) show the mathematical process followed to calculate the new control. These operations are parallel to the ones shown in Equations (10) through (17).

Equation (18) establishes the matrix involving the gains that need to be determined. Equation (19) is the equation obtained using the new set of eigenvalues. After equalizing Equations (18) and (19) we proceeded to break down the factors to obtain new expressions; shown in points (21) through (24). And then cleared the values, Equations (25) through (27) to obtain the new gains.

$$\lambda I - A + BK_c = det\begin{bmatrix} \lambda & -\frac{1}{3} & 0 \\ 0.0012 & \lambda + 0.08 & -0.04 \\ \frac{k_\alpha}{82} & \frac{2.5 + k_\omega}{82} & \lambda + \frac{5}{0.85} + \frac{k_T}{82} \end{bmatrix} \quad (18)$$

$$= \lambda^3 + 185.2\,\lambda^2 + 11280.5\lambda + 226107 \quad (19)$$

$$\det(\lambda I - A + BK) = \lambda\left((\lambda + 0.08)\left(\lambda + \frac{5}{0.85} + \frac{k_T}{82}\right) - (-0.04)\left(\frac{2.5 + k_\omega}{82}\right)\right) + \frac{1}{3}\left((0.0012)\left(\lambda + \frac{5}{0.85} + \frac{k_T}{82}\right) - (-004)\left(\frac{k_\alpha}{82}\right)\right) = \lambda^3 + \lambda^2(6.17756 + 0.01219K_T) \quad (20)$$

$$1 = 1 \quad (21)$$

$$6.17756 + 0.01219K_T = 185.2 \quad (22)$$

$$0.48942 + 0.00097K_T + 0.00048K_\omega = 11280.5 \quad (23)$$

$$90478.7 - 6K_T + 0.00016K_\alpha = 226107 \quad (24)$$

$$K_T = \frac{185.2\text{-}6.17756}{0.01219} = 14686 \quad (25)$$

$$K_\omega = \frac{11280.5 - 0.48942 - 0.00097(14686)}{0.00048} = 2.34703E7 \quad (26)$$

$$K_\theta = \frac{226107 - 90478.7 + 6(14686)}{0.00016} = 1.3984E9 \quad (27)$$

The new states feedback vector is the following:

$$\overline{K} = [1.3984E9 \quad 2.34703E7 \quad 14686]$$

Using these values, we simulated the applied control and the Simulink graphs obtained are shown in the figures 3.5 and 3.6 and analyzed in *Analysis Results*.

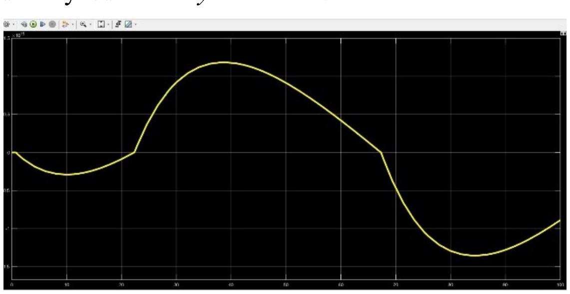

Fig. 3.5. New closed-loop error graph

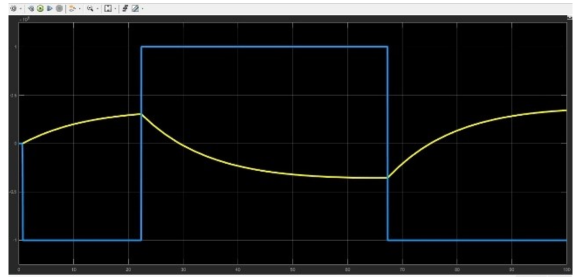

Fig. 3.6. New closed-loop behavior graph

IV. Analysis Results

On the open-loop system, the eigenvalues are real and negative, which means we are dealing with an overdamped system. Even though such systems are considered stable and can get rid of their energy, this process is quite slow. Figure 4.1 represents this energy relief process and figure 4.2 depicts how the system is behaving.

Once the first controller was applied, the controller´s gains turned out highly unreasonable and its error graph (figure 4.3) proved the controller not to be as optimum as possible. Therefore, a new system was designed. This controller showed smaller gains; even though they are still quite high. Its error graph (figure 4.5) shows that the original system is quite slow. Therefore, the system must use a great amount of energy to behave in the desired way.

A controller´s gains represent how aggressive it is; in other words, how much power the control ought to have over the open-loop system to change its response. In this case, as we have already stated, the system requires a very drastic change in its behavior, justifying the gains.

V. Conclusions

This article has a huge impact on our present and maybe future situation. Covid-19 has brought a lot of new problems to our lives but has also opened our eyes to serious conflicts that were not under our radar, like the poor availability of health machinery and technology in Mexico. There is still a lot of work to do, and we may even have to adapt our lives to this new virus. However, thanks to this pandemic, we have put in practice our knowledge acquired to create and invent, in as many ways we can, to provide support to anyone who may need it. Our proposed model can change the way we see a controller and the idea of them being over complicated and difficult to manage, opening a door for more students to experiment with different controllers more confidently.

As we have learned, open-loop eigenvalues establish the behavior of a system in its natural state. By obtaining these eigenvalues, we noticed they were real and negative, meaning that the system dissipates energy. So, we knew we were dealing with a stable, overdamped system. When the controller was made, we used eigenvalues 1000 times more stable, these generated high gains, which means that the controller needed too much energy to stabilize the system. We then decided to use eigenvalues in a new controller only 10 times bigger. The gains were elevated but in a more reasonable measure. Analyzing the error graph and the one of its general response, we conclude that the error obtained was huge, because the system is being forced to modify its behavior to a faster and more stable system that can provide a better response. Finally, we were able to obtain a state feedback controller, accomplishing the established objectives.

By developing this project, we accomplished to complete all our objectives; after analyzing our Model simulation results, we can also conclude that there are several options when building a controller, as there are many different methods. However, the one proposed in this project has the advantage of being easily modifiable. This means that if after experimenting with the theoretical values one is not content with the outcome, recalculating such values is easy, fast, and inexpensive. We compared our model and results to other control strategies exposed by Robert L Chatburn in his paper *Computer Control of Mechanical Ventilation*, where he focuses on the different types of control to manipulate more complex systems. In this paper he concludes that the control depends mostly on the power of the learning machine. So, even though our control may not be the most complex one, it is more than acceptable for the algorithm we analyzed. This is because the algorithm handled is simple and linear.

Acknowledgement

Authors thanks MIT, SSC group, CIDESI and all those people that has supported the virtual servomechanism CAD design and open loop simulations, where the input data for this work were obtained by considering the open source mechanical ventilator information [4] without any modification documented or considered on [2, 3] or [5 - 16].

Clarification Notes

It is important to clarify that the all information used in this work does not include any modification from the open source design available for the mechanical ventilator [4], neither on hardware not on software, because this work scope just has the educational intention to verify how this kind of servomechanism reacts when using a state space feedback vector linear control; therefore, any author rights from [2, 3] or [5 – 16] were not affected.

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