Felix Röhren*, Ines Groß-Weege, Steffen Leonhardt, and Marian Walter

Evaluation of Hysteresis Models for Estimating the Characteristics of High Pressure Solenoid Valves for Mechanical Ventilation

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Abstract: The flow control of inspiratory valves for mechanical ventilation is a crucial element of the overall functionality as it mainly governs precision and safety. However, control tuning can be challenging as the widely used magnetic actuation principle comes with a hysteresis shaped characteristic. As a result, the production of ventilators is highly dependent on specific valves and therefore vulnerable if supply chains are interrupted as during the pandemic. An approach which is capable of providing a reliable control for a variety of standard solenoid valves would be beneficial. Therefore, this work examines different models of hysteresis and their precision when being applied to actual measurement data of high pressure solenoid valves as a foundation for a following model-based control approach which can be either feedback or feedforward. Regarding the precision, the Prandtl-Ishlinskii (PI) model outperformed alternative approaches (MAE below 2.5 L/ min) for the chosen parameters which is why the model is described for fitting both the forward and inverse case.

Keywords: Mechanical ventilation, Hysteresis, Model-based control, System identification

1 INTRODUCTION

The COVID-19 pandemic came with a significant shortage of ventilators and the re-production rate was limited by insufficient supply chains [1]. Following common topologies [2] proportional high pressure solenoid valves (HPSV) based on magnetic actuation are widely used for the dosage of inspiratory flow to the patient. Its control is therefore crucial for precision and safety but also challenging as the system behaviour is strongly non-linear. A model-based approach for control tuning including a toolchain for system identification would be beneficial to enable incorporation of a variety of arbitrary valves. Instead of focusing on the separate electrical, mechanical or pneumatic domains to establish a circuit diagram of the valve [3], it is desired to examine the overall behaviour. Due to the magnetic actuation principle, the behaviour is hysteresis-shaped [4] which enforces usage of corresponding models.
The aim of this work is therefore to review and parameterize different hysteresis models for measured flow data and evaluate them with respect to feasibility and precision. Furthermore, the corresponding inverse model is to be implemented in order to enable feedforward control.

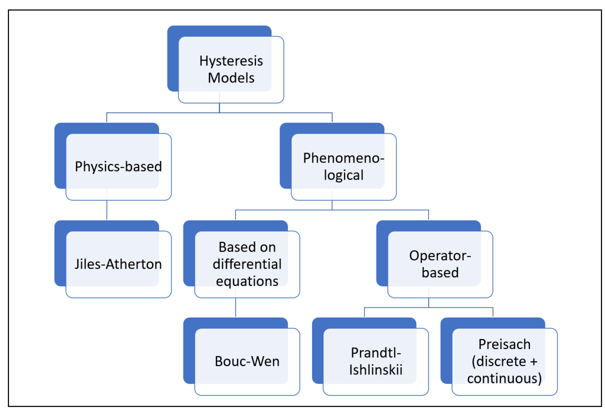

Fig. 1: Overview of considered hysteresis models.

Hysteresis describes a phenomenon in which an output is determined by the current and past state of the system due to memory properties. It occurs in particular in magnetic, ferromagnetic and ferroelectric materials. Hysteresis models can be divided mainly into two groups: Phenomenological models and physics-based models. Phenomenological models are based on mathematical equations that aim to represent the effect as accurately as possible. Due to their generality, they can be applied to a wide variety of fields. Physically-based models, on the other hand, are based on the description of physical principles [5]. An example of this is the Jiles-Atherton model, which maps the magnetic flux density B to the magnetic field strength H [6].
For modelling the system without reference to the physical properties, phenomenological models are preferred. They are either based on differential equations as the Bouc-Wen model

***Corresponding author: Felix Röhren,** All authors are with the Chair of Medical Information Technology (MedIT), RWTH Aachen University, 52074 Aachen, Germany, e-mail: roehren@hia.rwth-aachen.de

or based on operators as the Preisach and Prandtl-Ishlinskii (PI) model [7]. The Bouc-Wen model is mainly applied to piezoelectric actuators and characterizes nonlinear hysteresis by means of a differential equation which specifies the dependence of the mechanical excitation F on the hysteretic variable h [5]. Operator-based models include the discrete and continuous Preisach model, which are based on elementary hysteron operators and the PI model built on so-called linear play operators. [8]

2 METHODS

2.1 Implementation

Four different hysteresis models were implemented in MATLAB®/ Simulink® to model the non-linear behavior of the valve: The models of Bouc-Wen (Simulink®), Prandtl-Ishlinskii as well as Preisach both in its continuous and discrete form (all MATLAB®). In the following, the mathematical structure of the PI model as a representative of operator-based models is presented [9]. Its play operators are described using the equation

$$y_i(k) = max\{x(k) - r_i, min\{x(k) + r_i, y_i(k-1)\}\}, \quad (1)$$

where k represents the sampling number and x and y the input and output of the operator. $\mathbf{r} = [r_1, \ldots, r_n]^T$ describes the threshold vector with its elements being equidistantly distributed across the maximum input range and can be calculated by

$$r_i = \frac{i}{n+1} max\{|x(k)|\} \quad i = 1, \ldots, n, \quad (2)$$

where the number of the operators is given by the variable n. The initial condition of the operator is expressed by

$$y_i(0) = max\{x(0) - r_i, min\{x(0) + r_i, y_{i0}\}\} \quad (3)$$

The output can then be calculated as follows:

$$y(k) = \sum_{i=1}^{n} \omega_i y_i(k) = \boldsymbol{\omega}^T \mathbf{H}_r[x(k), \mathbf{y}_0] \quad (4)$$

Here, $\mathbf{H}_r$ denotes the linear play operator, whose initial condition is given by $\mathbf{y}_0$. The play operator is multiplied by the weight vector $\boldsymbol{\omega} = [\omega_1, \ldots, \omega_n]^T$.

Furthermore, for the prediction of a required input signal for a desired flow of the valve the inverse Prandtl-Ishlinskii model is of interest and denoted by:

$$x_i'(k) = max\{y(k) - r_i', min\{y(k) + r_i', x_i'(k-1)\}\} \quad (5)$$

This then results into the following formula for the inverse output:

$$x(k) = \sum_{i=1}^{n} \omega_i' x_i'(k) = H^{-1}(y(k)) = \boldsymbol{\omega}'^T \mathbf{H}_r'[y(k), \mathbf{x}_0] \quad (6)$$

Here $\mathbf{H}_r'$ is the inverse PI operator and $\mathbf{x}_0$ the initial state. Again $\boldsymbol{\omega}' = [\omega_1', \ldots, \omega_n']^T$ and $\mathbf{r}' = [r_1', \ldots, r_n']^T$ are the corresponding weighting and threshold vectors. The parameters can be retrieved as follows:

$$\begin{cases} \omega_1' = \frac{1}{\omega_1} & \\ \omega_i' = \frac{-\omega_i}{\left(\omega_1 + \sum_{j=2}^{i} \omega_j\right)\left(\omega_1 + \sum_{j=2}^{i-1} \omega_j\right)} & i = 2, \ldots, n \\ r_i' = \sum_{j=1}^{i} \omega_j (r_i - r_j) & i = 1, \ldots, n \\ x_i'(0) = \sum_{j=1}^{i-1} \omega_j y_i(0) + \sum_{j=i}^{n} \omega_j y_j(0) & i = 1, \ldots, n \end{cases} \quad (7)$$

2.2 Measurement

The hardware setup for flow measurement was arranged as follows: A proportional solenoid control valve type 2873 (Bürkert Fluid Control Systems, Ingelfingen, Germany) was supplied by a pressure of 3 bar and driven by an amplified 24 V pulse width modulated (PWM) signal resulting in an operational flow range of 0 to $200\,\mathrm{L/min}$. A single flow sensor (SFM3300, Sensirion, Stäfa, Switzerland) was attached to obtain the data against atmospheric pressure. The sensor was read out via the native I^{2}C bus using a STM32 Nucleo 767 ZI (STMicroelectronics, Geneva, Switzerland) which was also used to drive the actor's input. Logging was realized by data exchange over the ethernet port using the Transmission Control Protocol (TCP) between the STM32 and a laboratory computer.

A Simulink® model based on the *Simulink® Coder® Support Package for STMicroelectronics® Nucleo Boards* was used for code generation and running the STM32 whereas a second model on the PC was used for data storage incorporating the *Instrument Control Toolbox* for the ethernet port access.

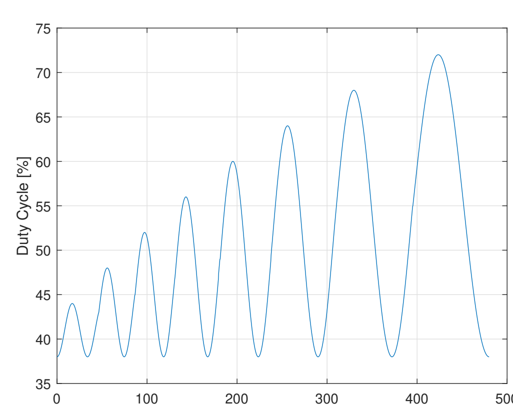

Fig. 2: Input signal for the quasi-static flow measurement.

The input signal was implemented in MATLAB® and embedded into the hardware model. Two requirements are essential for the input signal: Firstly, a quasi-static signal was needed and secondly, the amplitude must vary in the full operation range of the valve to trigger different sized hysteresis loops. The two requirements were achieved by selecting a sinusoidal signal with increasing amplitude size and maximum change of about 0.4 % duty cycle per second. The resulting input signal is shown in Fig. 2. The minimum value was set to 38 % duty cycle as the maximum value of the normal-closed state. The maximum input value of 72 % duty cycle was chosen to be just above full opened state such that the full operational range could be examined.

2.3 Model Fitting

The following steps were conducted to fit the recorded data to the hysteresis models: First, the data was downsampled and a lowpass Chebyshev Type I infinite impulse response (IIR) filter of order 8 was applied. The purpose of this was to remove redundant information and eliminate high-frequency noise. The recorded signal was then normalized to an interval of -1 and 1 as the hysteresis models expect symmetric input signals centered around the origin as input. The searched model parameters of the Bouc-Wen model were subsequently obtained using Simulink®'s Parameter Estimation Toolbox. For the PI model, the number of thresholds was set to 50 and the weight vector was obtained using the Least Squares Method. The tolerance for this optimization technique was chosen to be 1e-6 and the number of iterations was 200. For the inverse model, the number of thresholds was reduced to 25.

Regarding the discrete Preisach model, the level of discretization N_h was set to 50, resulting in a number of hysterons $N_q = N_h \cdot \frac{N_h+1}{2}$ of 1275. The number of iterations for the determination of the parameters was 20. The two parameters were approximated using MATLAB®'s Nonnegative Linear Least Squares and its Nonlinear Least Squares method. The parameterization process of the continuous Preisach model required the extraction of the first order reversal curves (FORCs) from the measured signal. From this information, the alpha beta mesh was created, based on which parameters of the continuous Preisach model were calculated.

3 RESULTS

Three metrics were examined for the evaluation of the different hysteresis models: The *Mean Absolute Error* (MAE), the *Root Mean Square Error* (RMSE) and the *Correlation* r. Table 1 lists the results after application of the described metrics for each implemented hysteresis model.

Hysteresis Model	MAE	RMSE	r
Bouc-Wen	5.79	7.47	0.9929
Prandtl-Ishlinskii	2.47	4.20	0.9977
Preisach (discrete)	3.06	4.47	0.9974
Preisach (continuous)	11.69	19.94	0.9695

Tab. 1: Evaluation of the considered hysteresis models using the metrics presented above.

With respect to the results, the Prandtl-Ishlinskii model turned out to be the most suitable for modelling the hysteresis properties of the valve on average (MAE = $2.47\,\mathrm{L/min}$), whereby the discrete Preisach model also results in a low MAE of around $3.06\,\mathrm{L/min}$.

The fitted hysteresis curve of the PI model $\hat{Q}$ is indicated in Fig. 3 in blue color next to the measured data Q_m in orange. The measured and estimated datasets closely follow each other in the ascending branch, however deviations occur during the descending branch which indicate the symmetry requirement of the model. Still, the global correlation of the data sets sums up to 99.77 %.

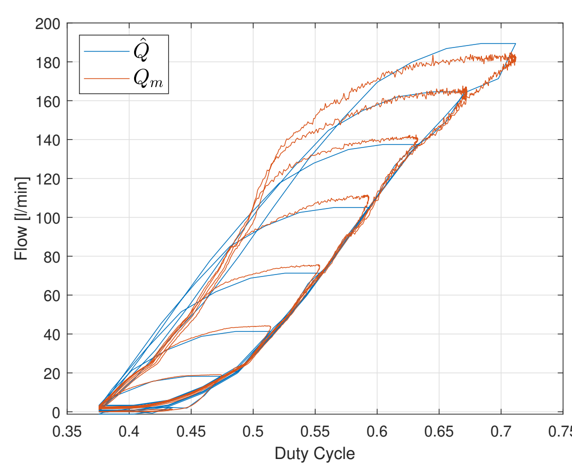

Fig. 3: Fitted hysteresis curve of the Prandtl-Ishlinskii model $\hat{Q}$, which maps the flow as a function of the duty cycle, compared to measured data Q_m.

Opposite to the forward PI model described above, its inverse model outputs the duty cycle to be set when the reference flow is entered. The resulting hysteresis curve of the inverse model can be seen in blue color in Fig. 4. The orange curve represents the hysteresis curve of the forward PI model given as input the duty cycle shown in Fig. 2. The simulated flow

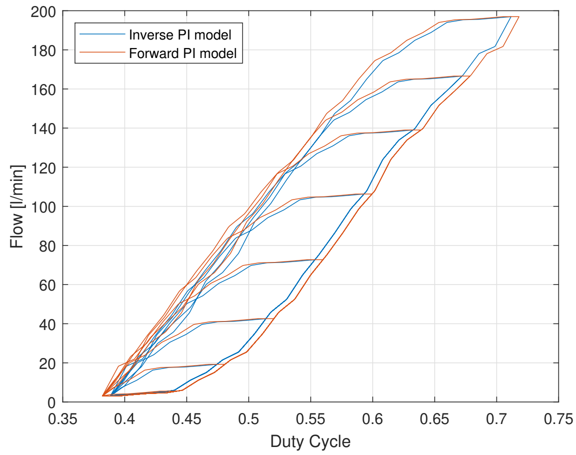

Fig. 4: Comparison of the forward and the inverse PI hysteresis model's curves, where the output of the forward model is used as input for the inverse model.

signal of this model was then used for the input of the inverse PI model. As can be seen, the curves are very similar during the nearly constant flow value ranges. However, the hysteresis curve of the inverse model is slightly narrower and has a roughly constant offset for the ascending and descending areas with regard to the reference curve. The MAE of the simulated duty cycle signal with respect to the reference duty cycle signal is 0.61, whereas the RMSE amounts to 0.62 % duty cycle. The correlation equals 99.81 %.

4 DISCUSSION and OUTLOOK

The parameterized hysteresis models for reflecting the nonlinear behavior of a HPSV showed promising results on a global scale. All evaluated models could prove a acceptable agreement with the measured data with a correlation of over 96 %. However, scaling a percentage to a flow of up to $200\,\mathrm{L/min}$ already comes with a significant absolute deviation which is why the high correlation needs to be viewed with with a sense of proportion, especially with respect to intensive care ventilation.

The comparison of the results is bound to the individually selected parameters of the models and should not be considered in general. However, in this specific cases the PI model performed best with an MAE of less than 2.5 L/min. Deviations occur locally, particularly in the higher flow ranges above $140\,\mathrm{L/min}$. In this region, the measured hysteresis curves exhibit a broader shape compared to the lower flow ranges. One main reason for the existing deviations is the symmetry requirement of the model.

In upcoming work, the estimation of the hysteresis models could be improved by a higher resolution of sine amplitudes regarding the input signal for identification or by the usage of asymmetric hysteresis models. Furthermore, time-varying effects such as the temperature dependence of the valve should be considered by adapting the models as these experiments were conducted in a saturated state.

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