

Tárgy **Fwd: ICCC 2025 submission 54 / notification**
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From:ICCC 2025 <iccc2025@easychair.org>
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Dear authors,

regarding your submission to ICCC 2025 entitled

NeuralODE-based Parameter Identification of the Three Chamber Model of the Circulatory System.

Thank you for your paper submission to conference IEEE 12th International Joint Conference on Cybernetics and Computational Cybernetics, Cyber-Medical Systems (ICCC 2025) to be organized on April 9-11, 2025 on Seychelles.

ICCC 2025 will be an in-person conference.

All accepted papers are going forward in the process as follows:

- Final paper submission site is IEEE PDF eXpress. Please follow the instructions on <https://conf.uni-obuda.hu/iccc2025/paper.html>, and submit your final paper until February 12. It will be open soon.
- At least one author of each paper must register online until February 12 on the conference website, <https://conf.uni-obuda.hu/iccc2025/registration.html>
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Congratulations! Your paper has been accepted after review process.

Result of review: accepted

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Reviewer's comments:

Review 1:

Interesting paper. The study aims to develop a Physics Informed Neural Network, i.e. NeuralODEbased parameter identification method for the Three Chamber cardiovascular model, which can potentially be used to define a novel perfusion marker. The adaptation of the NeuralODE method for parameter identification of the TCM was developed and optimized through the application of parameter constraints and the optimization of hyperparameters. The robustness of the developed method regarding the initial values of the parameters was evaluated. The applicability of the developed identification method was demonstrated on measurement data collected in animal experiments. The identified parameter values were validated using stroke volume measurements. The developed

NeuralODE-based Parameter Identification of the Three Chamber Model of the Circulatory System

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Abstract—In cases of Acute Circulatory Failure, fluid therapy is a commonly used intervention to stabilize heart function. However, the effectiveness of fluid therapy is not directly predictable, and the therapy can also be harmful. Physiological models can be used to predict fluid responsiveness - describing the effectiveness of fluid therapy for the patient - but require solving complex parameter identification problems. The current study aims to develop a Physics Informed Neural Network, specifically a NeuralODE-based parameter identification method for the Three Chamber cardiovascular model, which has the potential to be used to define a novel perfusion marker. The method is developed and validated on a clinical data set collected in model animal experiments.

Index Terms—Physics Informed Neural Network (PINN), NeuralODE, model-based medical therapy, cardiovascular diagnostics, physiological system modelling, parameter identification, intensive care, personalized fluid therapy

I. INTRODUCTION

In cases of Acute Circulatory Failure (ACF), fluid therapy is a commonly used intervention to stabilize heart function [1]. However, the effectiveness of fluid therapy is not directly predictable, and the therapy can also be harmful. Physiological models can be used to predict fluid responsiveness - describing the effectiveness of fluid therapy for the patient - but require solving complex parameter identification problems [2]–[5].

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In particular, it has been demonstrated that Stressed Blood Volume (SBV), defined as the blood volume generated by the pressure in the circulatory system, may serve as a potential index of fluid responsiveness. The estimation of SBV can be achieved by utilizing the Three Chamber cardiovascular system model (TCM) [6], thereby circumventing the necessity for the currently used highly invasive measurement techniques. Thus, assessing SBV can be employed in clinical practice as an indicator of fluid responsiveness [7].

In previous studies [8], [9], a NeuralODE-based parameter identification method was successfully applied for a similar physiological problem of the cardiovascular system [10]. The current study aims to develop a NeuralODE-based parameter identification method for the TCM using a clinical data set collected in model animal experiments.

II. METHODS AND DATA

A. Experimental Data Set

The experimental data set used in this study was collected from experiments carried out at the Central Hospital of the University of Liege (Ref. Num. 14-1726) with 8 pure Piétrain pigs. Mechanically ventilated subjects underwent different hemodynamic interventions and several respiratory recruitment manoeuvres during the measurements, as shown in Figure 1. Further details of data collection can be found in [9].

B. Three Chamber Model

The Three Chamber Model (TCM) is a lumped parameter model of the cardiovascular system, illustrated in Figure 2 [6]. The model comprises three elastic chambers, representing

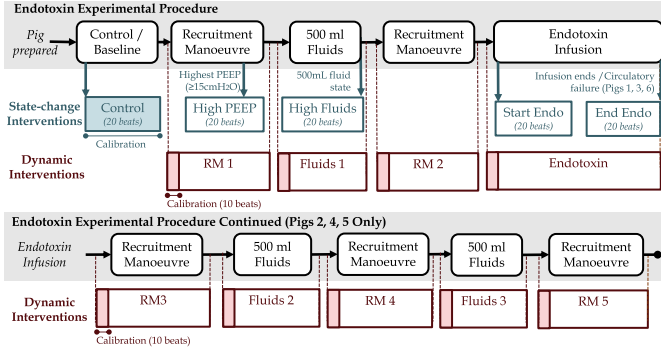


Fig. 1. The schedule of interventions performed on the examined pigs [11].

the left ventricle (lv), the aorta (ao) and one vena cava (vc). The first chamber is characterized as an active chamber, while the remaining two are classified as passive chambers. The following equations describe the two passive chambers:

$$P_{ao} = E_{ao}V_{S,ao}(t), \quad (1)$$

$$P_{vc} = E_{vc}V_{S,vc}(t), \quad (2)$$

where P is pressure, E is elastance, and V_S is the volume of blood in the chamber, each at the anatomical location indicated by the indexes. The left ventricle is the active chamber, represented by the following equation [12]:

$$P_{lv} = E_{lv}e(t)V_{S,lv}(t), \quad (3)$$

where E_{lv} is the maximum elastance, and $e(t)$ is the normalized pressure-volume ratio, which is a T-periodic function - T being the duration of a heartbeat - ranging from nearly 0 (during filling) to 1 (at end-systole) [6]. The product of $e(t)$ and E_{lv} represents the time-varying elastance of the left ventricle, which makes it an active chamber.

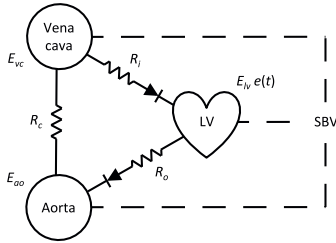


Fig. 2. The schematic representation of the TCM [6].

The chambers are connected through valves. Each connection has a resistance element, R_o and R_c represent the resistance of the aortic valve and systemic circulation, while R_i incorporates all resistances from the tricuspid valve to the mitral valve, including the entire pulmonary circulation. By defining the *valve()* function, returning 0 if the argument is not positive, and the argument otherwise and using Ohm's law to model the flow, the TCM model equations are:

$$\begin{bmatrix} Q_i \\ Q_o \\ Q_c \end{bmatrix} = \begin{bmatrix} \text{valve} \left(\frac{P_{vc} - P_{lv}}{R_i} \right) \\ \text{valve} \left(\frac{P_{lv} - P_{ao}}{R_o} \right) \\ \frac{P_{ao} - P_{vc}}{R_c} \end{bmatrix}. \quad (4)$$

The continuity equations give the volumes' change:

$$\dot{V}_{S,lv} = Q_i(t) - Q_o(t), \quad (5)$$

$$\dot{V}_{S,ao} = Q_o(t) - Q_c(t), \quad (6)$$

$$\dot{V}_{S,vc} = Q_c(t) - Q_i(t). \quad (7)$$

The summation of the three continuity equations yields

$$\dot{V}_{S,lv} + \dot{V}_{S,ao} + \dot{V}_{S,vc} = 0. \quad (8)$$

By integrating Equation 8, the sum of chamber volumes is constant, it is the SBV parameter:

$$V_{S,lv} + V_{S,ao} + V_{S,vc} = \text{SBV}. \quad (9)$$

As mentioned, SBV has a central role in this research as it has the potential to be used in clinical practice to indicate fluid responsiveness [7].

C. Benchmark Data Set for Robustness Assessment

To assess the robustness of the developed parameter identification method, a dataset is created by simulating the TCM model using known constant parameter values. The selected simulation parameters corresponding to a common physiological circulatory system state are given in Table I. The obtained synthetic dataset contains blood pressure data for all chambers, blood flow data for the Aorta chamber and volume data for the Left ventricle chamber.

TABLE I
THE PARAMETER VALUES USED TO CREATE THE SYNTHETIC DATASET.

	E_h	E_a	E_v	R_i	R_o	R_c	V_{s3}
Parameter values	1.4	1.2	0.2	0.05	0.04	2.0	250.0

D. Metrics and Loss Function for Identification

The NeuralODE-based process of identifying the parameters of the TCM aims to determine the parameter set that will yield the simulation output most closely aligned with the measurements. A cost function is defined as quantifying the difference between the simulation output and the measurement. During the identification process, the parameters are modified to minimize the cost function. Using the results published by A. Pironet et al., [13], a feature vector is defined to measure the similarity between the simulation and measurement data as it focuses on the physiologically relevant features of the given physiological signals. The feature vector is defined as:

$$[SV, \bar{V}_{lv}, PP_{vc}, \bar{P}_{vc}, PP_{ao}, \bar{P}_{ao}, dP_{ao}/dt_{max}] \quad (10)$$

where the elements of the feature vector are the following:

- SV : Stroke volume; the blood volume that the left ventricle pumps per beat,
- $\bar{V}_{lv}$: Mean left ventricular volume over one cardiac cycle,
- PP_{vc} : Venous pulse pressure; the range of vena cava pressure during one cardiac cycle,
- $\bar{P}_{vc}$: Mean vena cava pressure over one cardiac cycle,
- PP_{ao} : Aortic pulse pressure; the range of aortic pressure during one cardiac cycle,
- $\bar{P}_{ao}$: Mean aortic pressure over one cardiac cycle,
- dP_{ao}/dt_{max} : Maximum derivative of aortic pressure over one cardiac cycle.

A. Pironet et al. in [13] define the feature vector-based loss function by dividing the actual difference by the standard deviation of the given feature as weights:

$$Loss_x = \frac{feature_{measurement,x} - feature_{model,x}}{\sigma_x} \quad (11)$$

where x is one of the feature vector elements.

1) *Implementing parameter constraints*: In the NeuralODE-based identification process the model parameters are modified in multiple epochs (training steps) after the model initialization. In one epoch, the gradient of the defined loss function with respect to the parameter vector is calculated, and then the parameters are updated using the gradients. For the gradient calculation, the ForwardDiff.jl Julia library is used [14], that implements the gradient calculation when an ODE initial value problem is included in the loss function. After calculating the gradients, the ADAM optimizer is used to update model parameters [15].

Initially, the loss function was defined as the square sum of the error vector of the feature:

$$Loss = \sum_{i=1}^7 \left(\frac{feature_{measurement,i} - feature_{model,i}}{\sigma_i} \right)^2. \quad (12)$$

However, the parameter identification process was unsuccessful due to the assignment of values to the parameters after a few iterations, resulting in an unstable ODE solution. The issue was caused by an inappropriate flow resistance value, which was either close to zero or even negative. This phenomenon not only results in unstable ODE solutions but is also inconsistent with the physiological principles governing the cardiovascular system. To avoid such situations, multiple alternative methods were analyzed:

- It is possible to modify the loss function by introducing a constraint. E.g. an **exponential function** may be incorporated into the **loss function**, which increases significantly when the parameters fall below 0.001.
- An **activation function** may be incorporated into the output of the gradient-based method, ensuring that only positive parameters are produced.
- The crucial parameters can be re-parametrized using a **log transform**, thus enabling their values to fall below zero while maintaining the solubility of the ODE.

a) *Exponential term in loss function*: The loss function can be extended with a penalty term, that ensures that the parameters do not fall below a pre-defined value. An exponential term has been chosen that rises rapidly so that the parameters do not become negative. The loss function is expressed in Equation 13:

$$Loss = \sum_{i=1}^7 \left[\left(\frac{metrics_{measurement,i} - metrics_{model,i}}{\sigma_i} \right)^2 + e^{-\lambda(x_i - 0.001)} \right] \quad (13)$$

where x is the parameter vector, and λ is the coefficient of the exponential, which sets the slope of the penalty term.

b) *Activation function*: Assuming that the parameters take physiologically correct values once all of them converge, another solution is to use an activation function that constrains the parameters to remain positive. The optimisation using an activation function is described in Equation 14:

$$x_{i+1} = f(\text{Optimizer}(x_i)), \quad (14)$$

where f is the activation function, and Optimizer can be any gradient-based optimisation method, such as ADAM. In this work, the ReLU (Rectified Linear Unit) [16] activation function is shifted so that the parameters do not take values below 0.01:

$$f(x) = \max(x, 0.01). \quad (15)$$

c) *Log transform*: The third alternative method for avoiding the instability of the solved ODE during the parameter optimisation process is based on a log transform. For an original parameter x_i , it is possible to introduce a new parameter $\hat{x}_i$ so that $x_i = e^{\hat{x}_i}$. The newly introduced $\hat{x}_i$ parameter can be optimized, and the original parameter values can be calculated using the definition of the new parameter whenever needed in the ODE calculation. This way, the new parameter may take negative values, and the original parameters will still not decrease below zero based on the properties of the exponential function. In the present work, the first six parameters – $E_h, E_a, E_v, R_i, R_o, R_c$ – are prone to take negative values, so these are replaced with the new parameters using the log transform.

2) *Assessment of the identification's robustness*: To assess the robustness of the implemented NeuralODE-based method regarding the identification of the SBV parameter, a benchmark test was designed using a synthetic data set created by using different initial parameter configurations. The initial values of the parameters are either the reference value or the reference value shifted by a certain ratio (0.1, 0.2, 0.4, 0.5 or 0.6). Since the model has 7 parameters, the combinatorial space of variation is very large, and therefore, only 2 parameters were shifted at a time, either negatively or positively relative to the reference value. This method results in 2100 combinations where two parameters are shifted compared to the reference values; 70 combinations where one parameter is shifted; and one combination where all parameters have the reference values.

III. RESULTS AND DISCUSSION

A. Comparison of alternative loss functions implementing parameter constraints

Figures 3 and 4 show results obtained using an exponential penalty term. Initially, a lower learning rate was applied so that the parameters do not overshoot during the gradient-based method and do not become negative. Using an **exponential term** to augment the loss function (see Figure 3), the parameters do not take negative values. However, the high slope of the exponential term results in instability of the parameters during the learning process, as can be seen in Figure 4. The high gradient results in large parameter changes that may result in the algorithm finding a local minimum instead of the global optimum. This phenomenon is not experienced in settings with low learning rates. However, to speed up the training process, a higher learning rate is required, which results in instability.

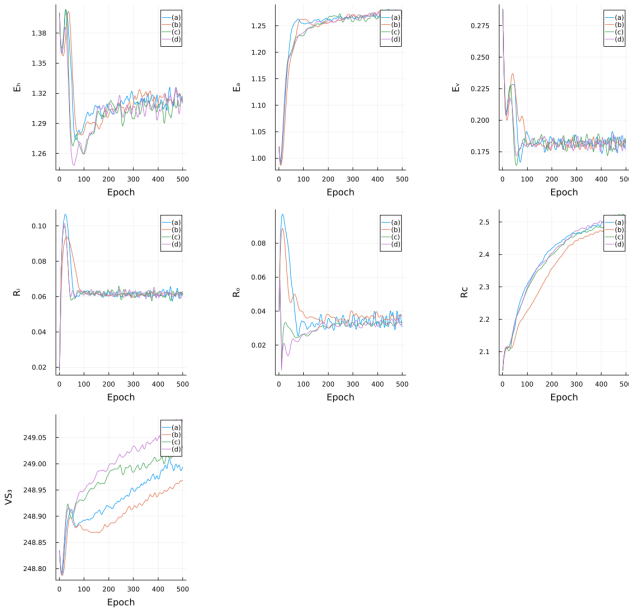


Fig. 3. The seven model parameters as functions of the number of training epochs. During the model training, the learning rate was 0.01, which gives more stability but results in slower progress. The different colours show results obtained with different exponential coefficients: (a) $\lambda = 10$; (b) $\lambda = 100$; (c) $\lambda = 500$ and (d) $\lambda = 1000$.

The results of the identification using the ReLU activation function are illustrated in Figure 5 with different learning rates. The results using the logarithmic transform are presented in Figure 6.

The **activation function** method avoids negative parameter values and unstable ODE solutions, however, it interferes with the training process and may slow down the process of finding the global minimum. As the activation function does not change all of the parameters – only those with low or negative values –, the ratio of the parameters can change, which can result in higher losses. High loss function values cause extreme parameter changes that may lead to local minima or extended time of learning required.

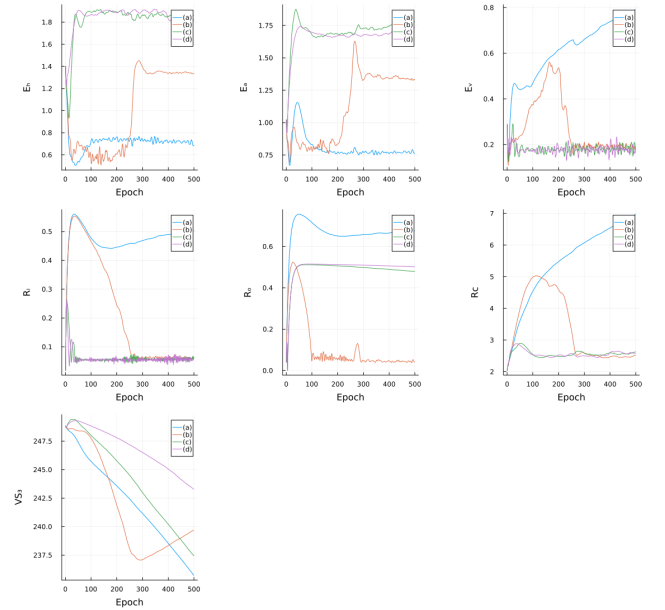


Fig. 4. The seven model parameters as functions of the number of training epochs. During the model training, the learning rate was 0.1, which gives less stability but results in faster progress. The different colours show results obtained with different exponential coefficients: (a) $\lambda = 10$; (b) $\lambda = 100$; (c) $\lambda = 500$ and (d) $\lambda = 1000$.

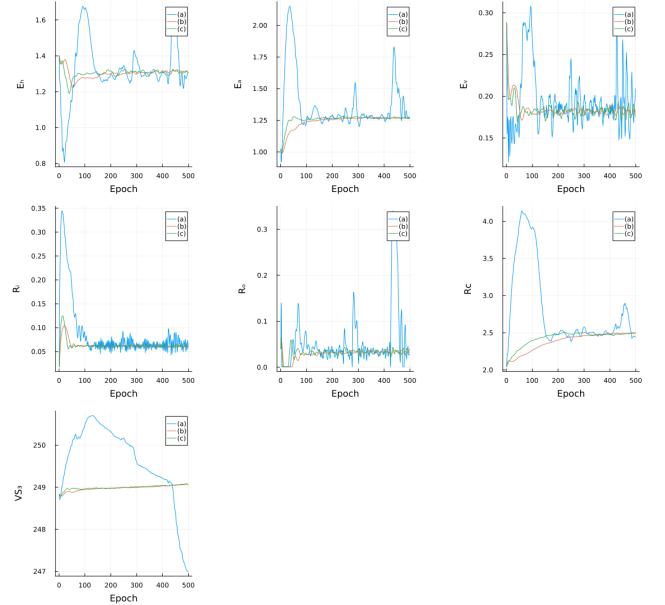


Fig. 5. The seven model parameters as functions of the number of training epochs. During the training, a ReLU activation function was used to ensure positive parameter values. The different colours show results obtained with different learning rates: (a) learning rate= 0.1; (b) learning rate= 0.01 and (c) learning rate= 0.02.

Applying the **log transform** to six of the seven parameters solves the problem of unwanted negative parameter values. The method does not involve the modification of the loss function and has the advantage of not interfering with the gradient-based optimisation process as the activation function-

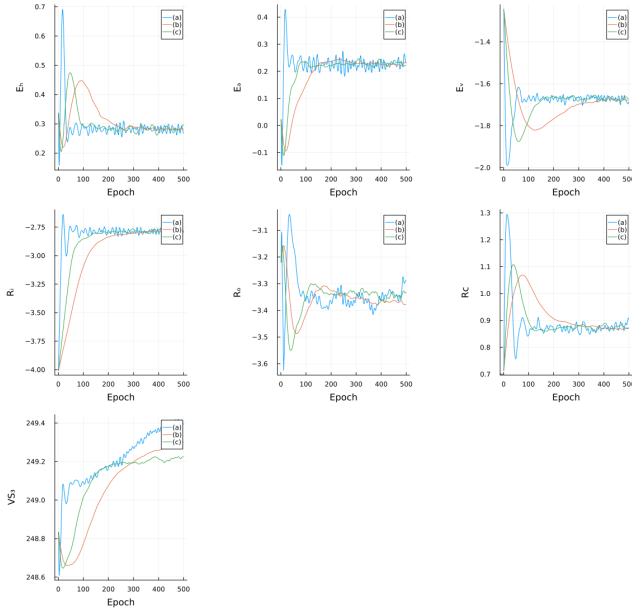


Fig. 6. The seven model parameters as functions of the number of training epochs. During the training, new parameters were introduced using the log transform to ensure positive parameter values. The different colours show results obtained with different learning rates: (a) learning rate= 0.1; (b) learning rate= 0.01 and (c) learning rate= 0.02.

based solution does. Due to its advantageous properties, this method was selected for this study.

B. Robustness Analysis

Tables II, III, and IV summarize the results of the benchmark test for each parameter. The results are grouped for each parameter according to the initial value in each simulation. The tables show the mean, standard deviation and coefficient of variation of the identified parameter values for each initial value of each parameter. The coefficient of variation is the normalized deviation, calculated as the ratio of the standard deviation and the mean. This represents the results better since the different parameters have different scales, which makes the standard deviations hard to interpret.

Based on the results, some observations can be made about the method:

- 1) The optimal values of the parameters do not precisely match the simulation values with the applied cost function. Analyzing the results when the parameters were initialized from the reference values (offset = 0%), it was observed that the identified parameters did not precisely take on the initial values.
- 2) The method demonstrated robustness with regard to the initial values of the parameters. The standard deviations and coefficients of variation indicated that the method was reliable, with the parameters converging even in instances where high initial value errors were present.

Figure 7 contains the identification results of the benchmark test for the SBV parameter. The x-axis shows the initial value of the SBV parameter for each configuration, while the y-axis

TABLE II
THE MEANS OF THE BENCHMARK TEST RESULTS FOR EACH PARAMETER.

offset	E_h	E_a	E_v	R_i	R_o	R_c	SBV
0%	1.377	1.201	0.210	0.055	0.040	2.097	247.434
10%	1.386	1.207	0.210	0.054	0.040	2.105	245.881
20%	1.381	1.206	0.211	0.055	0.040	2.107	245.826
40%	1.385	1.199	0.210	0.055	0.040	2.096	245.593
50%	1.384	1.207	0.210	0.055	0.039	2.094	245.445
60%	1.380	1.194	0.210	0.055	0.039	2.096	246.308
Reference	1.4	1.2	0.2	0.05	0.04	2.0	250.0

TABLE III
THE STANDARD DEVIATIONS OF THE BENCHMARK TEST RESULTS FOR EACH PARAMETER.

offset	E_h	E_a	E_v	R_i	R_o	R_c	SBV
0%	0.0164	0.0274	0.0034	0.0013	0.0015	0.0309	0.7336
10%	0.0175	0.0228	0.0037	0.0012	0.0018	0.0355	1.2142
20%	0.0211	0.0219	0.0038	0.0011	0.0012	0.03	1.4752
40%	0.0181	0.0209	0.0034	0.001	0.0025	0.0303	1.9834
50%	0.0156	0.0216	0.0033	0.001	0.0032	0.0306	2.1167
60%	0.0136	0.0199	0.0031	0.0015	0.0029	0.0279	12.365

TABLE IV
THE COEFFICIENTS OF VARIATION OF THE BENCHMARK TEST RESULTS FOR EACH PARAMETER.

offset	E_h [%]	E_a [%]	E_v [%]	R_i [%]	R_o [%]	R_c [%]	SBV [%]
0%	1.188	2.282	1.609	2.281	3.729	1.472	0.296
10%	1.262	1.89	1.749	2.182	4.605	1.684	0.494
20%	1.529	1.819	1.823	1.966	2.931	1.422	0.6
40%	1.303	1.741	1.601	1.849	6.207	1.447	0.808
50%	1.124	1.786	1.575	1.767	8.155	1.461	0.862
60%	0.988	1.666	1.487	2.751	7.417	1.333	5.02

shows the result of the identification of the SBV. The red line represents the reference value for SBV, which was used to create the synthetic dataset. The plot assures the statements summarizing the benchmark test results. The optimum of the identified parameters is not at the reference value. Figure 7 shows that the SBV parameter is more robust for higher than for lower initial values. Figure 8 shows additional information about the benchmark test. On the left of the Figure, the loss function values at the end of the identifications are shown. Based on the Figure, the initial parameter value does not cause any difference in the final loss value. This means, that the other six parameters compensate for the difference in the final SBV value. On the right of Figure 8, the iterations used for each identification are presented. An early stopping method was used which detects convergence and stops the identification process. The plot shows that starting the parameter farther from the optimal value results in higher training epoch numbers.

Table V summarizes the results of the benchmark test for the SBV parameter. The mean and standard deviation of the identified SBV values are shown as well as the mean and standard deviation of the error between the metrics of the identified model and the metrics of the synthetic dataset - the metrics are the elements of the output vector described

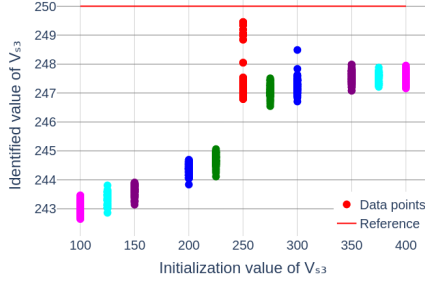


Fig. 7. The initial and identified values of SBV in the benchmark test.

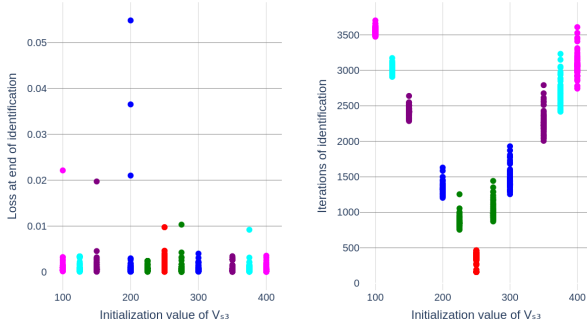


Fig. 8. The final losses and number of iterations during learning as functions of initial parameter values of SBV in the benchmark test.

in Section II-D, and the mean squared error is used.

TABLE V
THE BENCHMARK RESULTS FOR SBV PARAMETER.

offset	Identified values [*]		Error's	
	mean	std	mean	std
0%	247.434	0.73357	0.00113481	0.0014412
10%	245.881	1.21422	0.00091328	0.00111032
20%	245.826	1.47519	0.00146624	0.0056749
40%	245.593	1.98344	0.00111674	0.00181506
50%	245.445	2.11669	0.00101705	0.0011429
60%	246.308	12.3652	0.00207306	0.0140853

IV. CONCLUSIONS

The adaptation of the NeuralODE method for parameter identification of the TCM was developed and optimized through the application of parameter constraints and the optimisation of hyperparameters. The robustness of the developed method regarding the initial values of the parameters was evaluated. The applicability of the developed identification method was demonstrated on measurement data collected in animal experiments. The identified parameter values were validated using stroke volume measurements. The developed methods presented in the paper are major contributions toward an Artificial Intelligence-based semi-automated fluid responsiveness assessment method that is applicable in Intensive Care Units.

REFERENCES

- [1] A. Messina, F. Collino, and M. Cecconi, "Fluid administration for acute circulatory dysfunction using basic monitoring," *Ann Transl Med*, vol. 8, no. 12, p. 788, Jun. 2020.
- [2] A. Pironet, P. C. Dauby, J. G. Chase, S. Kamoi, N. Janssen, P. Morimont, B. Lambermont, and T. Desaive, "Model-based stressed blood volume is an index of fluid responsiveness," *IFAC-PapersOnLine*, vol. 48, no. 20, pp. 291–296, 2015, 9th IFAC Symposium on Biological and Medical Systems BMS 2015.
- [3] L. Murphy, S. Davidson, J. L. Knopp, J. G. Chase, T. Zhou, and T. Desaive, "State analysis of total stressed blood volume and arterial elastance during induced sepsis," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2019, pp. 2951–2954.
- [4] L. Murphy, J. G. Chase, S. M. Davidson, R. Smith, and T. Desaive, "Minimally invasive model based stressed blood volume as an index of fluid responsiveness," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 16 257–16 262, 2020, 21st IFAC World Congress.
- [5] L. Murphy, S. Davidson, J. G. Chase, J. L. Knopp, T. Zhou, and T. Desaive, "Patient-specific monitoring and trend analysis of model-based markers of fluid responsiveness in sepsis: A proof-of-concept animal study," *Annals of biomedical engineering*, vol. 48, no. 2, pp. 682–694, 2020.
- [6] A. Pironet, P. Dauby, J. Chase, S. Kamoi, N. Janssen, P. Morimont, B. Lambermont, and T. Desaive, "Model-based stressed blood volume is an index of fluid responsiveness," *IFAC-PapersOnLine*, vol. 48, pp. 291–296, 12 2015.
- [7] L. Murphy, J. G. Chase, S. M. Davidson, R. Smith, and T. Desaive, "Minimally invasive model based stressed blood volume as an index of fluid responsiveness," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 16 257–16 262, 2020, 21st IFAC World Congress. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2405896320309253>
- [8] Á. Antal, B. Szabó, Á. Szlávecz, K. Kovács, J. G. Chase, and B. Benyó, "Applying neural ode-based cardiovascular model identification for experimental data analysis," in *2024 IEEE 18th International Symposium on Applied Computational Intelligence and Informatics (SACI)*. IEEE, 2024, pp. 000 437–000 442.
- [9] B. Szabó, A. Antal, Á. Szlávecz, B. Paláncz, K. Kovács, L. Murphy, J. Cushway, N. Davey, C. Zhou, J. G. Chase, and B. Benyó, "Cardiovascular model identification using neural ode (accepted)," *IFAC-PapersOnLine*, 2024, 12th IFAC Symposium on Biological and Medical Systems BMS 2024.
- [10] G. Zhang, J.-O. Hahn, and R. Mukkamala, "Tube-load model parameter estimation for monitoring arterial hemodynamics," *Frontiers in physiology*, vol. 2, p. 72, 2011.
- [11] R. G. R. Smith, "Model-based hemodynamic management of critically ill patients." Ph.D. dissertation, University of Canterbury, 2022.
- [12] H. Suga, K. Sagawa, and A. Shoukas, "Load independence of the instantaneous pressure-volume ratio of the canine left ventricle and effects of epinephrine and heart rate on the ratio," *Circulation Research*, vol. 32, no. 3, pp. 314–322, Mar. 1973.
- [13] A. Pironet, P. D. Docherty, P. C. Dauby, J. G. Chase, and T. Desaive, "Practical identifiability analysis of a minimal cardiovascular system model," *Computer Methods and Programs in Biomedicine*, vol. 171, pp. 53–65, 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0169260715304570>
- [14] J. Revels, M. Lubin, and T. Papamarkou, "Forward-mode automatic differentiation in Julia," *arXiv:1607.07892 [cs.MS]*, 2016. [Online]. Available: <https://arxiv.org/abs/1607.07892>
- [15] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv:1412.6980 [cs.LG]*, 2017. [Online]. Available: <https://arxiv.org/abs/1412.6980>
- [16] A. F. Agarap, "Deep learning using rectified linear units (relu)," *arXiv:1803.08375 [cs.NE]*, 2019. [Online]. Available: <https://arxiv.org/abs/1803.08375>