

Daniel Voss*, Steffen Leonhardt, and Marian Walter

Data-Driven Approach for Left Ventricular Volume Estimation using Intracardiac Admittance

<https://doi.org/10.1515/cdbme-2025-0156>

Abstract: Accurate estimation of left ventricular volume (LVV) is essential for managing cardiovascular diseases such as heart failure and myocardial infarction. A promising approach for continuous LVV estimation is using intracardiac admittance measurements. The prevalent methods in literature are based on analytical models, for which several simplifying assumptions had to be made. It is not clear if the models are the optimal choice to describe the relationship between the admittance measurement and the LVV. This study explores intracardiac admittance measurements as a promising alternative for continuous LVV estimation. We utilized symbolic regression to derive mathematical models describing the relationship between intracardiac admittance measurements and LVV without predefined structures and compare their performance with classical models from literature. Through simulations based on a cylindrical left ventricle model, we rediscovered the model of Baan and identified further interpretable models that outperform the approaches by Baan and Wei on our dataset. Our findings support that symbolic regression can uncover meaningful patterns in biomedical data, paving the way for more efficient diagnostic tools in cardiovascular health monitoring.

Keywords: bioimpedance, admittance, symbolic regression.

1 Introduction

Cardiovascular diseases are a major cause of mortality worldwide, with around 20 million deaths reported in 2022 [1]. For many of these patients, the health outcome depends on individualized care and close monitoring of their vital parameters. Among the important vital parameters, the left ventricular volume (LVV) has a high prognostic value and close monitoring of the LVV has the potential to improve patient outcomes [2].

The improved information about the patient state may allow physicians to make better-informed decisions. Further potential is the continuous monitoring of patients on mechanical circulatory support [3]. Continuous monitoring may enable au-

tomatic changes in the support provided by the mechanical assist device, thereby improving patient care and reducing staff workload [4].

Established techniques for LVV monitoring, such as echocardiography and magnetic resonance imaging, while effective, often require significant manual intervention and are therefore not suitable for continuous monitoring [5].

Intracardiac admittance measurements represent a promising approach for continuous LVV estimation. This approach involves the use of a multi-electrode catheter positioned within the left ventricle (LV) to measure electrical admittance changes associated with varying blood volumes during the cardiac cycle. The two most well established methods were developed by Baan et al. [6] and Wei et al. [7]. The method of Baan et al. uses multiple conductance measurements and postulates a linear relationship between this combined measured signal and the LVV. The method of Wei et al. uses a single conductance measurement and assumes a non-linear relationship between this measurement and the LVV. In this method the phase information of the admittance measurement is used for the calibration of the model parameters, therefore this method is also called the admittance method while the method of Baan et al. is also referred to as the conductance method.

Both methods are based on simple analytical models and were developed through insight of the authors and manual specification of the problem structure. However, the actual relationship between the measurement and the LVV is more complex and is only partially captured through these approaches.

We analyzed the influence of the LVV and the conductivity of blood on the measurements and evaluated possible models describing this relationship. The intracardiac admittance measurements were simulated for a simplified ventricle model similar to those used by Baan and Wei. The LVV and the blood conductivity were varied to cover the range of physiological and pathological values for different patients. Using this dataset, we used symbolic regression to identify mathematical functions that best fit the data without assuming a predefined model form. In this way, we have identified interpretable models that fit the dataset and performed a preliminary comparison with the classical models from literature.

*Corresponding author: Daniel Voss, Chair for Medical Information Technology, RWTH Aachen University, Aachen, Germany, e-mail: d.voss@hia.rwth-aachen.de

Steffen Leonhardt, Marian Walter, Chair for Medical Information Technology, RWTH Aachen University, Aachen, Germany

2 Methods

2.1 Dataset

We generated a synthetic dataset through a series of simulations to analyze the admittance at different operating points. To have a high correspondence to the analytical modeling approaches of Baan and Wei we used a similar geometry for our model. The model is based on the cylindrical LV model from our previous works [8, 9] and has shown a high qualitative agreement to clinical data.

The model approximates the LV by three compartments: blood in the ventricle, myocardium, and surrounding tissue. The LV is a cylinder with a fixed length of 90 mm and a variable diameter depending on the LVV. The myocardium has a uniform fixed thickness of 12 mm and is surrounded by the background tissue model as lung tissue.

A 10-electrode catheter is positioned in the center of the LV. In agreement with Baan and Wei, the lowest electrode, electrode 1, is placed just above the apex; the top electrode, electrode 10, is placed just outside the ventricle. This setup uses the four-point probe method, with 2 electrodes for current injection and 2 electrodes for voltage measurement. The complete model is shown in Fig. 1.

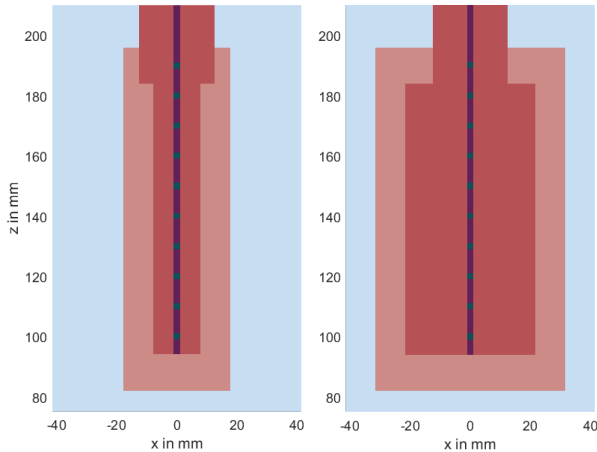


Fig. 1: The simulation model for a LVV of 25 mL (left) and 190 mL (right). The catheter in the center is surrounded by blood, myocardium, and background tissue.

The model parameters can be chosen freely, of primary interest are the variations of the LVV and the conductivity of blood σ_{bl} . Thus, only these two parameters are varied, while all other parameters are kept fixed at their physiological values.

The LVV has a high inter- and intra-patient variability; to cover the physiological and pathological range [10], we vary the LVV from 20 mL up to 190 mL.

The conductivity of blood is known to be influenced by many factors, such as temperature [11], haematocrit [12], as well as anticoagulants [13], which are often required during treatment of patients on mechanical circulatory support. Since there is no clear literature reference, we chose the wide range of 0.5 S/m to 0.8 S/m. All other electrical properties are chosen as described in [9].

The parameters LVV and σ_{bl} are varied in the chosen intervals. As sampling method, we used Latin Hypercube Sampling to generate near-random operating points [14].

The admittance measurements are simulated by a finite element method simulation using the Matlab toolbox EIDORS [15]. The electrical fields for a measurement were simulated to determine the admittance. Therefore, a fixed current was applied between the injection electrodes, here always electrodes 1 and 10, and the complex potential difference $U_{i,j}$ of two measurement electrodes i and j was determined. Through this the transfer admittance $Y_{i,j}$ can be calculated

$$Y_{i,j} = \frac{I_{1,10}}{U_{i,j}} \quad . \quad (1)$$

2.2 Reference Models

To evaluate the performance of newly found models we compare them with the state-of-the-art models. These are the models of Baan [6] and Wei [7], which are briefly described in the following. We have excluded their calibration procedure and instead fitted them directly on the dataset using a least squares approach.

Both methods use four-point probe measurements with current injection in the outermost electrodes (1, 10) and use only the conductance (real part of the admittance) to calculate the LVV. In the method of Baan et al. the conductance signal G_{Baan} is a sum of multiple measurements. The method of Wei et al. uses only a single measurement G_{Wei} with the measurement at the electrodes adjacent to the injection electrodes. For the 10-electrode catheter these measurements are given by

$$G_{\text{Baan}} = \sum_{i=2}^8 \Re(Y_{i,i+1}) + \frac{1}{3} \Re(Y_{2,3}) \quad , \quad (2)$$

$$G_{\text{Wei}} = \Re(Y_{2,9}) \quad . \quad (3)$$

The Baan et al. method establishes the relationship between the LVV_{Baan} and the conductance G_{Baan} . Rearranged for G_{Baan} and merging the constants to the new parameters θ_i yields

$$G_{\text{Baan}} = \theta_1 \sigma_{bl} \text{LVV} + \theta_0 \quad . \quad (4)$$

The Wei et al. method establishes the relationship between the LVV_{Wei} and the conductance G_{Wei} . Rearranging for G_{Wei} and renaming the constants to the new parameters θ_i yields

$$G_{Wei} = \frac{1}{\theta_1 + \frac{\theta_2}{\sigma_{bl}LVV}} + \theta_0 \quad (5)$$

2.3 Symbolic Regression

We have used symbolic regression (SR) to discover mathematical models that best describe the dataset without specifying a predefined model structure. SR does not rely on a predefined model structure, but instead employs techniques from genetic programming and evolutionary algorithms to explore the space of potential equations of different model structures. The models are formulated as expression trees, with operators, inputs, or constants as the nodes. Operator nodes can have one or two children (unary or binary operators), while constant and inputs are leaf nodes (no children). We determined two sets of equations for functions f with

$$G = f(LVV, \sigma_{bl}) \quad (6)$$

where the output G is either G_{Baan} or G_{Wei} .

Model training was done in the Julia programming language using the SymbolicRegression.jl package [16]. We trained 30 populations with a total of about 800 models for 50 000 iterations. During each iteration, the models were modified heuristically by mutations, cross-overs, simplifications, and parameter fitting.

The complexity of a model can be described by the size of the expression tree, which is the number of nodes (operators, inputs, or constants). For the classical models of Baan, eq. (4), and Wei, eq. (5), the complexity is 7 and 10 respectively. For the SR approach we limit the complexity to 20 nodes, so that the algorithm can explore equations with 1 node up to 20 nodes. We also restrict the depth of the expression tree to 8 levels to avoid excessive nesting of functions.

In SR the generated models can include arbitrary mathematical operations to generate explainable models the only allowed operators are the binary operators: addition, subtraction, multiplication, division, and exponential as well as the unary inverse operator. We excluded other unary operators (such as sin and tan) because we do not have periodicity in the dataset.

We divided the data into training and test sets. For the training we randomly selected 80 % of the data and used the remaining 20 % as the test set. Since the dataset is quite large, we further performed the training only on random batches of 128 data points to improve the performance of the SR fitting procedure. As the performance metric we chose the L2 norm since our dataset is free of measurement errors and outliers.

3 Results

In this study, we used SR to derive mathematical models that can accurately describe the relationship between intracardiac admittance measurements, focusing specifically on the conductance signals G_{Baan} and G_{Wei} and LVV.

The performance of the SR-derived models for the output G_{Baan} is shown in Fig. 2. Here we have plotted the normalized training loss against the model complexity, measured by the number of nodes in the expression tree. All models found via

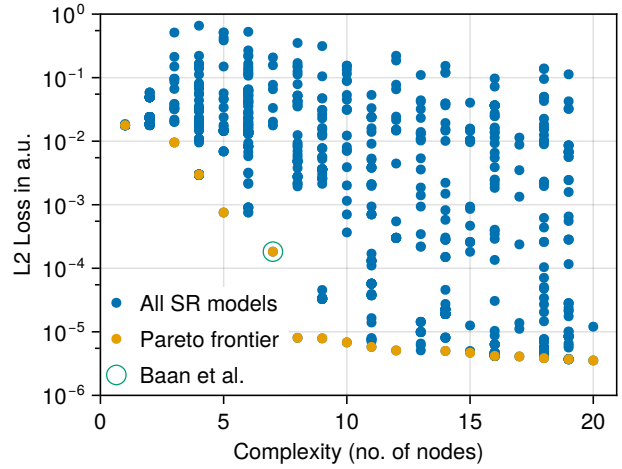


Fig. 2: Loss over Complexity for output G_{Baan} .

SR with a loss below 1 are shown in blue. The model with complexity 1 is simply a constant. For higher complexities, models with better fit become possible. However, some models perform even worse due to the heuristic approach which also generates poorly performing models. The best-fitting models are made possible at the highest complexities, but they overfit the dataset. The Pareto frontier highlights models with optimal trade-offs between accuracy (small loss) and simplicity (low complexity); it is shown in yellow.

Notably, Baan's classical model, shown as a green circle, has been rediscovered and is Pareto optimal. Thus, it is part of the Pareto frontier, indicating that there is no better model at the same or lower complexity. However, SR identified several models with substantially smaller loss with only one additional node. These models also perform well on the test dataset, suggesting potential improvements over Baan's approach when allowing for more complex equations.

For the output G_{Wei} , Fig. 3 presents a similar analysis where SR-generated models are compared with Wei's classical model. The overall performance is similar, with many models fitting the data well. In contrast to Baan's case, Wei's model does not lie on the Pareto frontier; instead, it is surpassed by

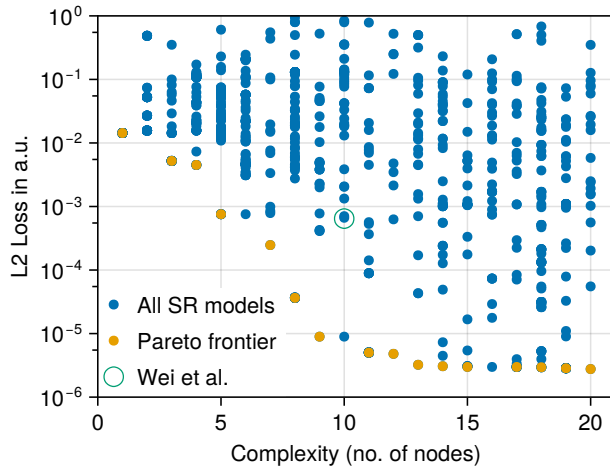


Fig. 3: Loss over Complexity for output G_{Wei} .

simpler models achieving lower losses. We have confirmed a similar performance of these models on the test dataset, thus showing that this is not due to overfitting.

4 Discussion and Conclusion

In this study, we explored SR for deriving mathematical models for estimating LVV using intracardiac admittance measurements. While model generation via SR is an automated machine learning approach, the generated models are explicit mathematical expressions, making them easy to interpret and compare to analytical models. Our findings show that SR can effectively generate models that match or surpass the performance of established methods by Baan and Wei on our dataset. For measurements akin to Baan, we have rediscovered Baan’s model and have shown that it is Pareto optimal. Baan’s model has been clinically proven; the agreement with our findings, thus, supports our use of a synthetic dataset for the initial model discovery. For measurements akin to Wei, several SR-derived models have been found with a lower complexity and higher accuracy on our dataset than Wei’s model. These models are promising, but require further analysis and validation with a clinical dataset.

This study found promising candidate models for improving the accuracy of LVV estimation and demonstrates the potential of SR as a powerful data-driven modeling approach in biomedical research.

Author Statement

We gratefully acknowledge funding from the Deutsche Forschungsgemeinschaft (DFG), grant no. 452009371, LE 817/44-1. Authors state no conflict of interest.

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