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RESEARCH ARTICLE

Comparative Analysis of Single-Objective and Multi-Objective Genetic Algorithms for Blood Pressure Estimation using Cardiovascular Lumped-Parameter Model

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ABSTRACT - Monitoring blood pressure is vital in diagnosing and managing cardiovascular conditions. To support this, computational models that can accurately estimate both systolic (SBP) and diastolic blood pressure (DBP) are becoming increasingly important. However, many optimization methods tend to focus on one value at the expense of the other. This study explores the use of genetic algorithms to fine-tune parameters in a cardiovascular lumped-parameter model. Two approaches are examined: a single-objective genetic algorithm (SOGA) that prioritizes SBP, and a multi-objective genetic algorithm (MOGA) designed to optimize both SBP and DBP simultaneously. Using clinical data from healthy individuals, we assess how well each method replicates real-world measurements. The findings reveal that while SOGA delivers highly accurate SBP estimates, it does so by sacrificing DBP accuracy. MOGA, on the other hand, achieves a more balanced fit, offering reasonable accuracy for both pressure values. The choice between these optimization strategies should therefore be guided by the specific demands of the application. Continuous refinement of multi-objective formulations and validation on larger datasets will be essential to fully harness the potential of patient-specific lumped-parameter models in precision cardiovascular medicine.

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1. INTRODUCTION

Accurate blood pressure (BP) estimation is central to cardiovascular health monitoring and management. Systolic blood pressure (SBP) and diastolic blood pressure (DBP) are the common indicators for cardiovascular health management, and deviations in their values are linked to increased risks of cardiovascular diseases such as stroke and myocardial infarction [1]. Traditional non-invasive blood pressure measurement techniques, such as the cuff-based oscillometric method, offer intermittent and environment-sensitive readings, which can limit their utility in continuous monitoring or personalized simulation settings [2]. To overcome these limitations, computational cardiovascular modelling has been developed as a tool that enable a non-invasive strategy to estimate the haemodynamic behaviour of the circulatory system using patient-specific parameters [3]. Computational cardiovascular models utilize various mathematical techniques to achieve this goal, for examples, using electrochemical modelling [4, 5]. Fluid-structural interaction modelling [6], and lumped-parameter models [7, 8]. Among these models, lumped-parameter models have gained traction due to their computational efficiency and their ability to simulate key pressure and volume dynamics while utilizing zero-dimensional ordinary differential equations [9]. However, a central challenge in leveraging such models is the accurate estimation of model parameters to reproduce both patient-specific SBP and DBP.

Optimization is used for parameter estimation due to their robustness in handling non-linear and multi-dimensional search spaces [8]. Single-objective optimization is used to optimize a model by fulfilling a particular objective function. In contrast, multi-objective optimization provides a framework to simultaneously optimize multiple objective functions, which can offer a more holistic approach to cardiovascular parameter estimation [10]. In this study, a comparative analysis of different optimizations of the cardiovascular lumped-parameter is presented. Here, Genetic Algorithm (GA) will be used as the optimization technique. Then, single-objective Genetic Algorithm (SOGA) and multi-objective Genetic Algorithm (MOGA) will be compared in estimating parameters for a lumped cardiovascular model. Using clinical data from healthy subjects, both algorithms will be evaluated in estimating the model parameters to replicate both SBP and DBP. The findings aim to guide the selection of optimization strategies based on the trade-offs between precision and physiological realism in personalized cardiovascular simulations.

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2. METHODS AND MATERIAL

The methodology is divided into several subsections. First, the data used in this study will be described. Then, the cardiovascular lumped-parameter model used in this study will be explained. Lastly, the parameter estimation method using SOGA and MOGA will be detailed out.

2.1 Data Collection

Ten subjects between the age of 20 to 29 years old were selected for parameter estimation process. The data is obtained from a study conducted at the Guilin People's Hospital on non-invasive detection of cardiovascular diseases (CVD) [11]. All these subjects have no prior history of heart failure and hypertension. Each subject has heart rate (HR), SBP, and DBP within the range of a normal healthy individual. Table 1 discussed the detailed clinical data used for each subject.

Table 1. Detailed clinical data used for each subject

Subject	Heart rate (HR)	Systolic Blood Pressure (SBP)	Diastolic Blood Pressure (DBP)	Height	Weight
smo1	85	110	63	159	53
smo2	67	90	59	155	47
smo3	82	96	67	155	38
smo4	82	102	66	162	55
smo5	74	108	65	163	55
smo6	87	109	68	168	55
smo7	77	111	70	180	70
smo8	65	108	68	175	58
smo9	76	95	57	160	52
smo10	85	100	71	176	55

2.2 Cardiovascular Lumped-Parameter Model

The cardiovascular lumped-parameter model used in this is based on the model developed by Regazzoni et al. (2021) [12]. Figure 1 shows the lumped-parameter model in circuit diagram equivalent. The model is made of ordinary differential equations that relate the haemodynamic variables volume, V, pressure, P, and blood flow, Q with cardiovascular system parameters such as the blood vessel compliance, C, resistance, R, and inertial effect, L. The model also describes the human circulatory system, which consists of pulmonary and systemic systems.

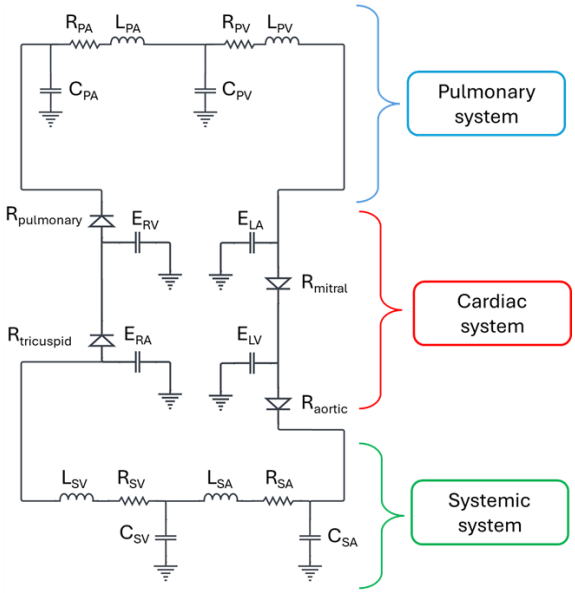


Figure 1. Cardiovascular lumped-parameter model

The system of equations of the model is as follows (Equations 1-12):

$$\frac{dV_{LA}}{dt} = Q_{PV} - Q_{mitral} \tag{1}$$

$$\frac{dV_{LV}}{dt} = Q_{mitral} - Q_{aortic} \tag{2}$$

$$\frac{dV_{RA}}{dt} = Q_{SV} - Q_{tricuspid} \tag{3}$$

$$\frac{dV_{RV}}{dt} = Q_{tricuspid} - Q_{pulmonary} \tag{4}$$

$$\frac{dP_{SA}}{dt} = \frac{1}{C_{SA}}(Q_{aortic} - Q_{SA}) \tag{5}$$

$$\frac{dP_{SV}}{dt} = \frac{1}{C_{SV}}(Q_{SA} - Q_{SV}) \tag{6}$$

$$\frac{dP_{PA}}{dt} = \frac{1}{C_{PA}}\left(Q_{pulmonary} - Q_{PA}\right) \tag{7}$$

$$\frac{dP_{PV}}{dt} = \frac{1}{C_{PV}}(Q_{PA} - Q_{PV}) \tag{8}$$

$$\frac{dQ_{SA}}{dt} = \frac{1}{L_{SA}}(P_{SA} - P_{SV} - Q_{SA}R_{SA}) \tag{9}$$

$$\frac{dQ_{SV}}{dt} = \frac{1}{L_{SV}}(P_{SV} - P_{RA} - Q_{SV}R_{SV}) \tag{10}$$

$$\frac{dQ_{PA}}{dt} = \frac{1}{L_{PA}}(P_{PA} - P_{PV} - Q_{PA}R_{PA}) \tag{11}$$

$$\frac{dQ_{PV}}{dt} = \frac{1}{L_{PV}}(P_{PV} - P_{LA} - Q_{PV}R_{PV}) \tag{12}$$

In this model, the subscripts are defined as follows: *SA* – systemic arterial; *SV* – systemic venous; *PA* – pulmonary arterial; *PV* – pulmonary venous; *LA* – left atrium; *LV* – left ventricular; *RA* – right atrium; *RV* – right ventricular; *mitral* – mitral valve; *tricuspid* – tricuspid valve; *aortic* – aortic valve; *pulmonary* – pulmonary valve. Furthermore, each of the heart chamber is assigned with a time-varying elastance, as follows (Equations 13-16):

$$P_{LV} = P_{ext} + E_{LV}\left(V_{LV} - V_{LV_o}\right) \tag{13}$$

$$P_{LA} = P_{ext} + E_{LA}\left(V_{LA} - V_{LA_o}\right) \tag{14}$$

$$P_{RV} = P_{ext} + E_{RV}\left(V_{RV} - V_{RV_o}\right) \tag{15}$$

$$P_{RA} = P_{ext} + E_{RA}\left(V_{RA} - V_{RA_o}\right) \tag{16}$$

where the term E represents the elastance of each chamber, which is further divided into active elastance, E_A and passive elastance, E_P. All the baseline value for the parameters to be optimized are listed in Table 2.

Table 2. Baseline value for the parameters to be optimized

Parameters	Baseline values	Unit
C_{SA}	1.2	mL/ mmHg
R_{SA}	0.64	mmHg s/mL
C_{SV}	60	mL/ mmHg
R_{SV}	0.32	mmHg s/mL
C_{PA}	10	mL/ mmHg
R_{PA}	0.032116	mmHg s/mL
C_{PV}	16	mL/ mmHg
R_{PV}	0.035684	mmHg s/mL
E_{PLA}	0.18	mmHg/mL
E_{ALA}	0.07	mmHg/mL
E_{PLV}	0.2	mmHg/mL
E_{ALV}	3.35	mmHg/mL
E_{PRA}	0.07	mmHg/mL
E_{ARA}	0.06	mmHg/mL
E_{PRV}	0.05	mmHg/mL
E_{ARV}	0.55	mmHg/mL

2.3 Genetic Algorithm for Parameter Estimation

In this work, Genetic Algorithm (GA) is chosen because it is widely used for non-linear models [13, 14]. The GA employed here is structured as follows:

a) The algorithm is first initialized with several populations with potential solution to the objective function. Each population represents the multiplier for each parameter of the lumped-parameter model. This multiplier is set to be within the range of 0 to 1.

b) The algorithm is then iterated through several evolutionary generations, with each generation undergoing random selection, crossover, and mutation.

c) Then, the lumped-parameter model is simulated using the parameter values from the population. The SBP and DBP are calculated from the model and compared with the patient-specific SBP and DBP. These are known as the objective functions.

d) Lastly, the population that minimizes the objective functions are selected for generating the offspring. The process is iterated until a convergence criterion is met, such as reaching a specific number of generations or surpassing a threshold fitness level.

For MOGA, the Pareto front is used. Since in Pareto front, there will be several best solutions for the optimization, a solution is randomly selected to represent the results for each patient. Figure 2 shows the flowchart for the optimization process.

3. RESULTS

This work compares the performance of the GA, i.e., SOGA and MOGA, in optimizing the SBP and DBP effectively using ten subjects. These GAs are utilized to determine the parameters of a lumped parameter cardiovascular model: resistance of systemic vein (R_{SV}), compliance of systemic arteries (C_{SA}), passive elastance of left ventricle (E_{PLV}), active elastance of left ventricle (E_{ALV}). The simulated SBP and DBP will later be compared with the real clinical data. The distribution of the four lumped parameters produced by those GAs is also compared. The description is as follows.

3.1 Comparison Between Simulated Systolic and Diastolic Blood Pressure with Clinical Systolic and Diastolic Blood Pressure

Figure 3 (a) compares the simulated and clinical SBP while Figure 3 (b) compares the simulated and clinical DBP using estimated parameters from SOGA and MOGA for each subject. This scatter plot compares clinical SBP (SBPclinical) and DBP values (DBPclinical) (x-axis) with their simulated counterparts (SBPsim and DBPsim) (y-axis) obtained from parameter estimation using SOGA (blue) and MOGA (orange). In terms of comparison for SBP (Figure 3 (a)), SOGA points are generally closer to the diagonal line, especially in the mid to high SBP range (100–113 mmHg), suggesting better agreement between simulated and clinical SBP. As in Table 3, SOGA demonstrates precision in matching systolic pressure, where the SBP error is almost zero (MAE ≈0.11 mmHg, RMSE ≈0.17 mmHg). On the other hand, MOGA shows more variability where some orange points significantly deviate from the diagonal (e.g., overestimations at clinical SBP ~94 and ~108 mmHg, and underestimations at ~110 mmHg).

In contrast, in terms of DBP (Figure 3 (b)), SOGA performs poorly compared to MOGA. SOGA shows more variability where some orange points significantly deviate from the diagonal (e.g., overestimations at clinical DBP ~63, ~66, and ~68 mmHg, and underestimations at ~59 and ~ ~71 mmHg). Severe overfitting to SBP caused DBP mismatches (DBP MAE ≈11.7 mmHg, RMSE ≈61 mmHg (Table 3). No severe outliers in MOGA. MOGA accepts a modest increase in SBP error (MAE ≈7.6 mmHg, RMSE ≈13.6 mmHg (Table 3)) and leads to improve diastolic accuracy (DBP MAE ≈3.3 mmHg, RMSE ≈12.1 mmHg (Table 3)), thereby striking a clinically relevant balance between the two objectives.

3.2 Parameters Estimation Using SOGA and MOGA

Figure 4 shows the distribution of the four lumped parameters i.e. R_{SV}, C_{SA}, E_{PLV} and E_{ALV} produced by SOGA and MOGA for ten subjects. These four parameters are important for maintaining blood flow and pressure in the circulatory system [15]. As in Figure 4 (b), the results are more consistent in MOGA, where the distribution of the R_{SV} is within the normal range of normal healthy DBP, ranging from 60 mmHg to 80 mmHg [16]. On the other hand, the R_{SV} values produced by SOGA are scattered until some of the subjects' DBP reach below the normal range (< 60 mmHg). MOGA also captured more consistent values for C_{SA}, especially for DBP (Figure 4 (d)). Several outliers for C_{SA} are seen produced by SOGA (in a circle in Figure 4 (d), where the values of DBP are below the normal range. Similar results have also been captured for both E_{PLV} and E_{ALV} for MOGA's simulated DBP. For SBP, both SOGA and MOGA produced the values within the normal healthy range, which is 80-120 mmHg [16]. However, SOGA produces more outliers for all parameter values (in a circle as in Figures 4 (a), (c), (e), and (g)). Based on these results, it is expected that MOGA to have better cardiovascular parameters. It shows lower variability or outliers compared to SOGA. MOGA accepts some SBP error but optimizes global model behavior, achieving good enough SBP fitting while also maintaining DBP accuracy and parameter realism.

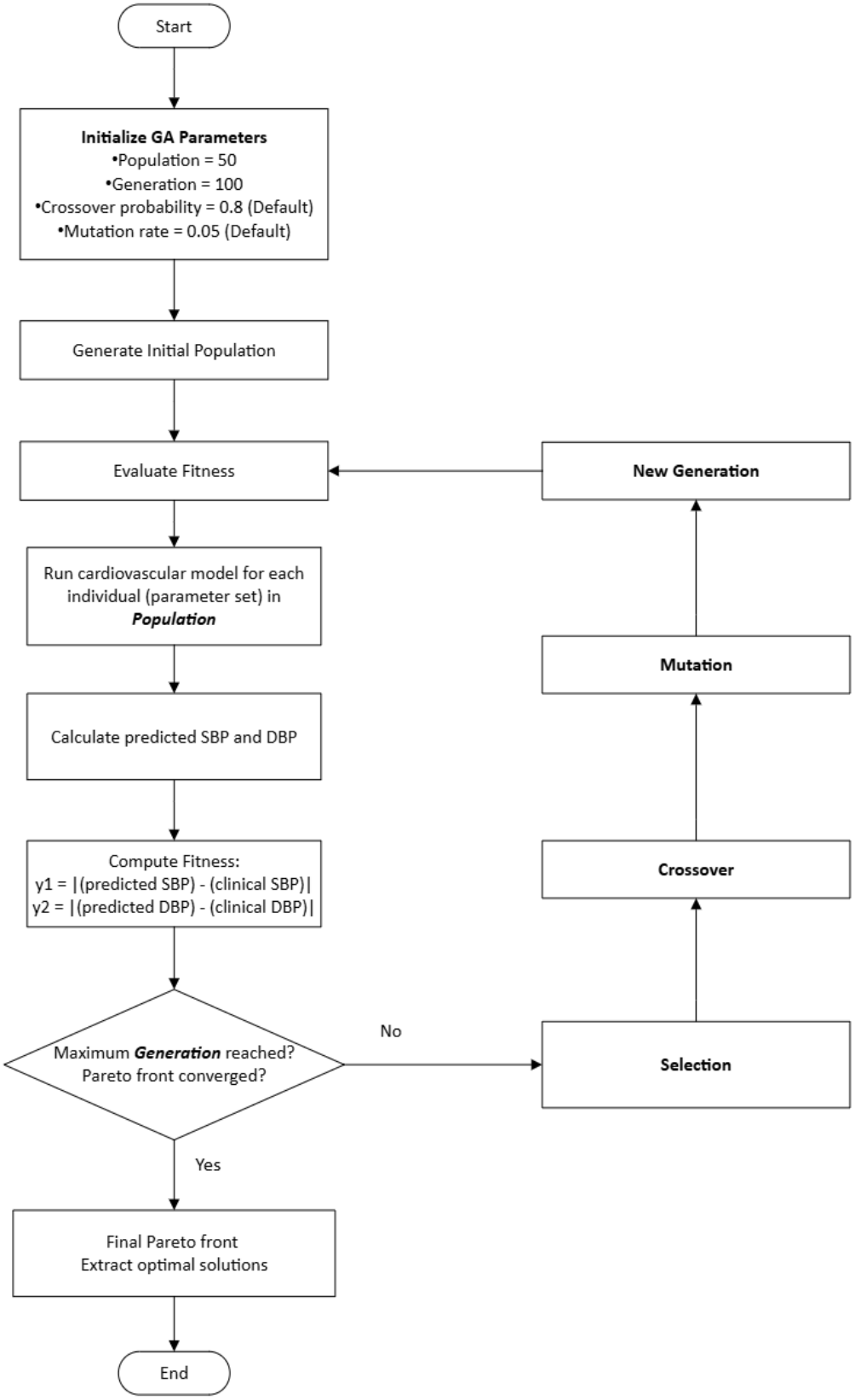
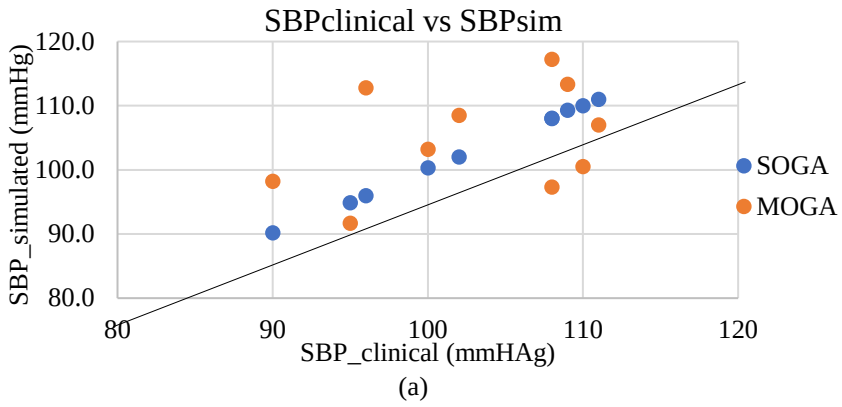
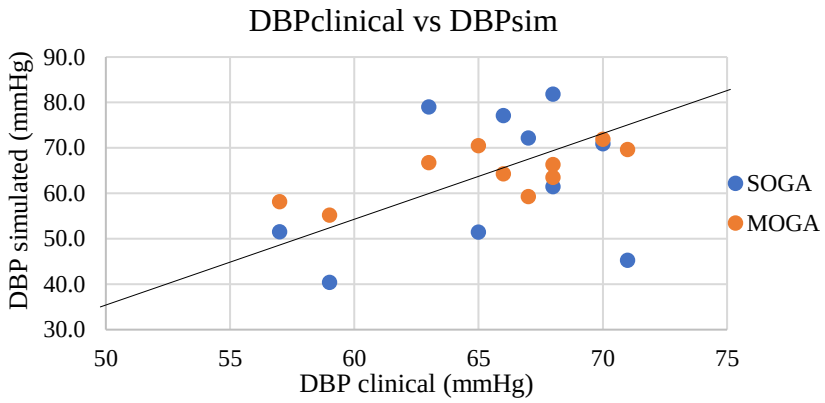


Figure 2. Flowchart for the optimization process



(a)



(b)

Figure 3. (a) clinical systolic blood pressure (SBPclinical) vs simulated systolic blood pressure (SBPsim) and (b) clinical diastolic blood pressure (DBPclinical) vs simulated diastolic blood pressure (DBPsim)

Table 3. Error metric between simulated systolic blood pressure (SBPsim) and simulated diastolic blood pressure (DBPsim) of SOGA and MOGA

Error Metric	delta SBP (SOGA)	delta DBP (SOGA)	delta SBP (MOGA)	delta DBP (MOGA)
Mean absolute error (MAE)	0.108	11.685	7.582	3.303
Root Mean Square Error (RMSE)	0.164864	60.9913082	13.63645	12.07142

4. DISCUSSION

The comparative analysis between the SOGA and the MOGA highlights a fundamental trade-off in patient-specific lumped-parameter modelling which is precision versus balance. SOGA excels at minimizing SBP error, but this narrow focus leads to DBP discrepancies (MAE ≈11.7 mmHg, RMSE ≈61 mmHg). Such extreme DBP errors suggest that SOGA overfits to the systolic target, producing parameter sets that satisfy one hemodynamic constraint while violating another. Although this may be acceptable in applications where only SBP is critical, it compromises physiological plausibility and undermines confidence in downstream simulated variables (e.g., stroke volume, cardiac output).

In contrast, MOGA shows balanced performance by accepting modest increases in SBP error to achieve substantial improvements in DBP accuracy (Figure 3). This dual-objective framework enforces simultaneous alignment with both systolic and diastolic pressures, yielding parameter estimates that more faithfully reproduce the overall pressure waveform (Figure 4). Clinically, MOGA's diastolic errors fall well within accepted measurement variability [16], making it a more robust choice for simulations intended to inform treatment planning or device design, where both phases of the cardiac cycle are consequential.

4.1 Limitation and Future Work

Both algorithms were tested on a limited sample (n=10), and the observed error distributions may shift with larger, more diverse cohorts. Future work should explore hybrid approaches such as weighted objective functions or adaptive penalty strategies that dynamically balance SBP and DBP priorities based on clinical context. In addition, extending the objective set to include metrics like pulse pressure or mean arterial pressure could refine model fidelity across the pulsatile cycle.

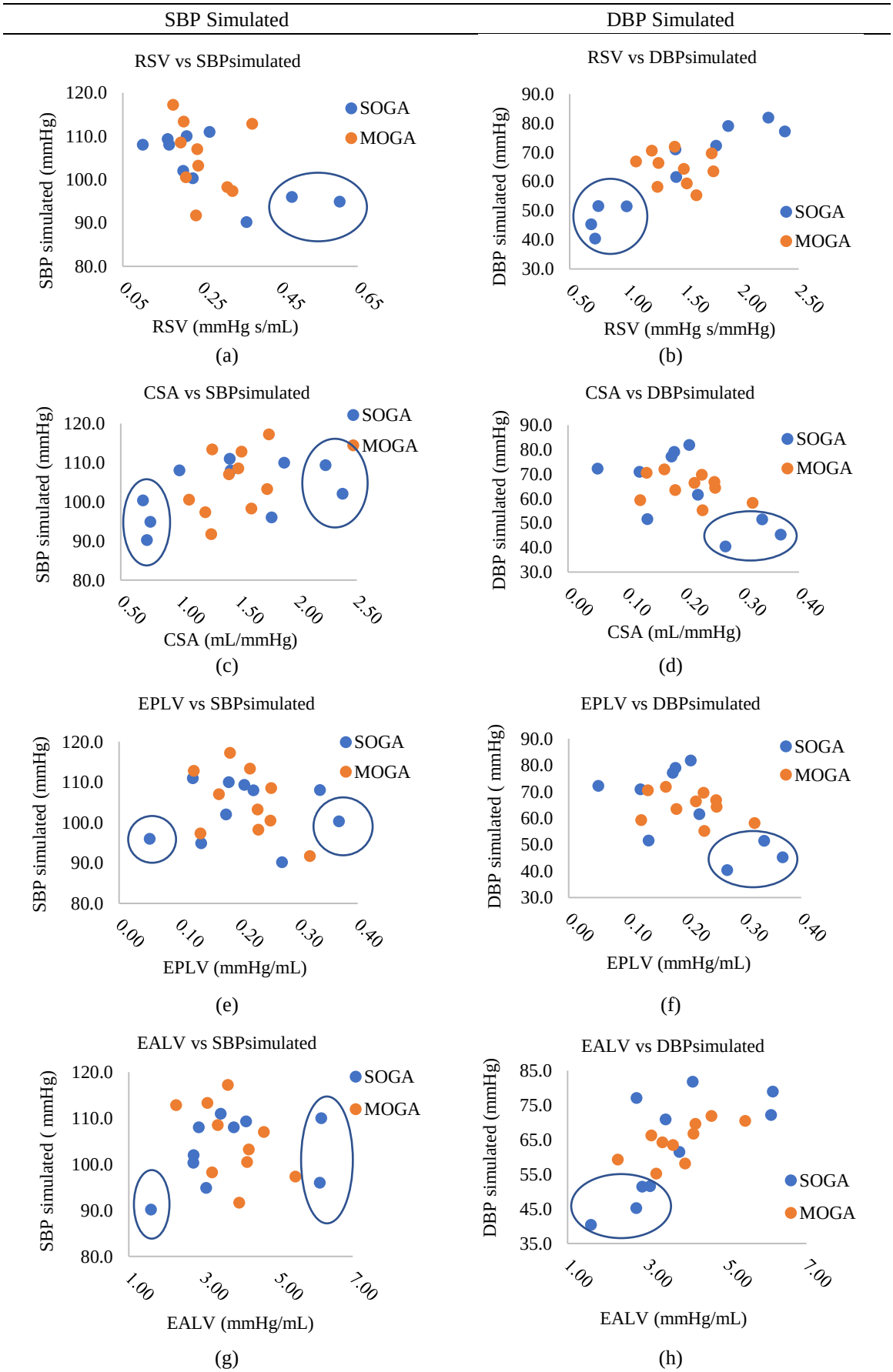


Figure 4. Parameters estimation using SOGA and MOGA for (a) R_{SV} during SBP; (b) R_{SV} during DBP; (c) C_{SA} during SBP; (d) C_{SA} during DBP, (e) E_{PLV} during SBP; (f) E_{PLV} during DBP; (g) E_{ALV} during SBP; and (h) E_{ALV} during DBP. R_{SV}: resistance of systemic vein, C_{SA}: compliance of systemic arteries, E_{PLV}: passive elastance of left ventricle, E_{ALV}: active elastance of left ventricle

5. CONCLUSION

In summary, while SOGA offers near-perfect systolic fitting at the expense of diastolic accuracy, MOGA provides a clinically meaningful compromise that better respects the integrated nature of cardiovascular hemodynamics. The choice between these optimization strategies should therefore be guided by the specific demands of the application: isolated systolic assessment versus holistic waveform replication. Continuous refinement of multi-objective formulations and validation on larger datasets will be essential to fully harness the potential of patient-specific lumped-parameter models in precision cardiovascular medicine

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CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHORS CONTRIBUTION

S. M. Muhammad Ali (Methodology; Data curation; Formal analysis; Writing - original draft; Resources)

W. El-Bouri (Writing - original draft; Writing - review & editing)

W. N. Wan Ab Naim (Writing – editing and proofreading)

M. J. Mohamed Mokhtarudin (Writing - review & editing; Project administration; Supervision)

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