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Optimizing Pulsatile Energy Consumption in Blood Pumps with PSO

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Abstract

Blood pump is a vital therapy for heart failure. Acting as the core device, it partially or fully supports the heart's pumping function, providing crucial support for patients with end-stage heart failure. Nevertheless, achieving efficient pulsatile output from blood pumps presents a significant challenge in terms of energy consumption. Pulsatile operation necessitates frequent acceleration and deceleration of the drive motor, a process that incurs substantial energy expenditure. High energy consumption directly shortens battery life and impedes device miniaturization and portability, constituting a key bottleneck hindering clinical application that urgently requires resolution. This study applies the Particle Swarm Optimization (PSO) algorithm for the global optimization design of pulsatile speed control curves for blood pumps. An energy consumption model quantified by average power and a blood pump-cardiovascular coupling model based on the hydraulic characteristics of the pump is constructed, incorporating the constraints that must be satisfied during pulsation. Combined with the PSO algorithm, key speed points of the speed curve are automatically iterated and optimized. This systematic approach aims to explore and identify the optimal speed control curve that minimizes energy consumption while complying with normal human physiological indicators. It helps to provide a novel optimization design methodology for speed control curves, facilitating the development of a new generation of low-power, highly intelligent portable pulsatile blood pumps, holding significant theoretical value and promising clinical application prospects.

Keywords

Blood Pump, Pulsatile Energy Consumption Optimization, Particle Swarm Optimization Algorithm

1. Introduction

Currently, over 64.3 million people worldwide suffer from heart failure [1]. As one of the leading causes of mortality globally, end-stage heart failure faces a critical shortage of donor hearts for transplantation, making ventricular assist devices (blood pump) a vital therapy for sustaining life [2]. Acting as the core device, the blood pump partially or fully assumes the heart's pumping function, providing crucial support for patients with end-stage heart failure [2]. Most blood pumps operate in continuous-flow mode; however, their non-physiological flow patterns can lead to complications such as gastrointestinal bleeding and the loss of arterial pulsatility [3] [4]. To address this, researchers are dedicated to developing pulsatile flow control strategies for blood pumps. By periodically modulating the impeller speed to mimic physiological pulsatile blood flow, the aim is to improve perfusion of end organs and enhance patient clinical outcomes [5].

Nevertheless, achieving efficient pulsatile output from blood pumps presents a significant challenge in terms of energy consumption. Pulsatile operation necessitates frequent acceleration and deceleration of the drive motor, a process that incurs substantial energy expenditure. High energy consumption directly shortens battery life and impedes device miniaturization and portability, constituting a key bottleneck hindering clinical application that urgently requires resolution.

Research focused on optimizing the energy consumption of blood pumps remains limited. Liu employed a variable current control method to optimize energy use during the pump startup phase [6]. Based on a sine wave, Zhao established a multi-objective optimization model to sing the NSGA-II algorithm targeting left ventricular stroke work, flow pulsatility, and hydraulic power. This optimized the sine wave, reducing the pump's hydraulic power while maintaining normal physiological indicators [7]. In other fields such as electric vehicles, rail transportation, and robotic arms, intelligent algorithms are commonly utilized to seek energy-optimal speed or trajectory profiles, achieving operational goals while minimizing energy consumption. In the electric vehicle industry, Huang *et al.* established an energy consumption model for the motor and combined it with a genetic algorithm for long-term speed planning in scenarios involving consecutive intersection crossings, demonstrating effective energy reduction through simulation [8]. In rail transport, Wang *et al.* designed an automatic train operation speed profile optimization procedure leveraging the global search capability of genetic algorithms. Combined with specific train parameters and routes, they verified that this approach meets requirements for speed protection, comfort, and energy saving [9]. Li *et al.* applied an improved Glowworm Swarm Optimization Algorithm (GSOANR) to optimize train speed curves, demonstrating through case studies that the improved algorithm yields better energy savings than the traditional version [10]. Regarding medical device applications, Mu *et al.* proposed an energy optimization method for the linear motor of a multi-leaf collimator based on speed planning. By establishing energy consumption and switching time models and optimizing them using the NSGA-II algorithm, they experimentally verified that this speed planning method reduces energy consumption while ensuring switching times [11]. In robot control, Han utilized a Particle Swarm Optimization (PSO) algorithm with a dynamic learning factor to solve for the optimal time-optimal trajectory of a robot [12].

Based on previous research, it is evident that studies on pulsatile speed control curves for blood pumps have primarily focused on enhancing blood pulsatility and achieving normal physiological perfusion [13]-[16], with limited attention given to the associated energy consumption. Within the scarce research concerning pulsation-induced energy consumption [7], although hydraulic power during pulsation was considered and optimized, this optimization was confined to fine-tuning parameters of a fixed-form speed curve (the sine wave). This approach heavily relies on empirical trial-and-error by researchers, making it difficult to adopt a global perspective and identify the globally optimal solution within the complex, multi-dimensional parameter space of speed curves—one that simultaneously satisfies human physiological perfusion requirements and minimizes total cycle energy consumption.

To address the aforementioned issues, this study proposes the application of the Particle Swarm Optimization (PSO) algorithm for the global optimization design of pulsatile speed control curves for blood pumps. As an efficient stochastic optimization technique based on swarm intelligence, the PSO algorithm possesses powerful global search capabilities particularly suited for solving such complex, nonlinear, multi-modal optimization problems. The rest of this paper is arranged as follows. First an energy consumption model and a blood pump-cardiovascular coupling model are constructed, incorporating the constraints that must be satisfied during pulsation. Then the PSO algorithm is applied to find the optimized speed curve that minimizes energy consumption while complying with normal human physiological indicators. The efficacy of this speed curve is evaluated and compared with other typical speed curves numerically. Finally, a brief discussion is given, and the conclusion is drawn.

2. Modeling the Coupled Blood Pump-Cardiovascular System

The blood pump-cardiovascular coupling model serves as the foundation for hemodynamic research on pulsatile blood pumps. In this study, such a model is established based on prior research.

2.1. Hydraulic Model of the Blood Pump

The expression for the hydraulic characteristic model of the blood pump is as follows:

$$H = \beta_0 q + \beta_1 \frac{\mathrm{d}q}{\mathrm{d}t} + \beta_2 \omega^2 \tag{1}$$

where H represents the pressure difference across the blood pump (unit: mmHg), q denotes the flow rate generated by the pump (unit: mL/s), and ω indicates the rotational speed of the pump (unit: r/min). The terms β_0 to β_2

are constant coefficients of the hydraulic characteristic model.

As reference [17] mentioned, the blood pump was operated in a sine wave, square wave and triangle wave mode, during which data on the pressure difference across the pump and the flow rate were recorded over time. The relevant constant coefficients in Equation (1) were determined through numerical fitting using the least squares method, thus establishing the hydraulic characteristic model of the blood pump. The resulting constant coefficients of the model are presented below [17]:

$$\beta_0 = -0.582, \beta_1 = -0.06, \beta_2 = 2.841 \times 10^{-6}$$

2.2. Blood Pump-Cardiovascular System Model

In this study, the left ventricular component of the model is developed based on reference [17] [18]. The schematic diagram of the lumped-parameter cardiovascular model with the blood pump is shown in **Figure 1**.

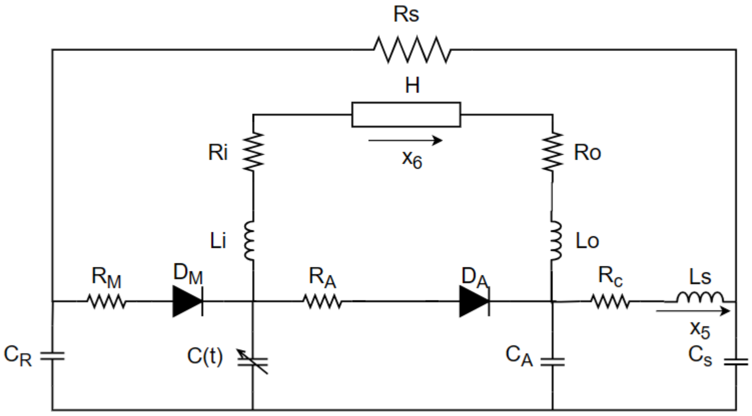

Figure 1. Blood pump-cardiovascular lumped parameter model.

The state equations of the blood pump-cardiovascular coupling model are derived in accordance with Kirchhoff's laws, and are expressed as: $\dot{x} = A(t)x + K(t)p(x) + c\omega^2$, where ω represents the rotational speed of the blood pump in rpm. The expressions for $A(t)$, $K(t)$, and $p(x)$ are:

$$A(t) = \begin{bmatrix} -\frac{\dot{C}(t)}{C(t)} & 0 & 0 & 0 & 0 & -\frac{1}{C(t)} \\ 0 & -\frac{1}{R_s C_R} & \frac{1}{R_s C_R} & 0 & 0 & 0 \\ 0 & -\frac{1}{R_s C_s} & \frac{1}{R_s C_s} & 0 & \frac{1}{C_s} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{C_A} & \frac{1}{C_A} \\ 0 & 0 & -\frac{1}{L_S} & \frac{1}{L_S} & -\frac{R_C}{L_S} & 0 \\ \frac{1}{L} & 0 & 0 & -\frac{1}{L} & 0 & -\frac{R}{L} \end{bmatrix}$$

$$K(t)=\begin{bmatrix} \dfrac{1}{C(t)} & -\dfrac{1}{C(t)} \\ -\dfrac{1}{C_R} & 0 \\ 0 & 0 \\ 0 & \dfrac{1}{C_A} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$p(x)=\begin{bmatrix} \dfrac{r(x_2-x_1)}{R_M} \\ \dfrac{r(x_1-x_4)}{R_A} \end{bmatrix}, r(\varepsilon)=\begin{cases} \varepsilon, \varepsilon>0 \\ 0, \varepsilon\le 0 \end{cases}$$

$$c=\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -\dfrac{\beta_2}{L} \end{bmatrix}$$

where $R=R_i+R_o+\beta_0$, $L=L_i+L_o+\beta_1$, the relevant parameters of the model are listed in Table 1 below:

Table 1. Parameters for the blood pump-cardiovascular model.

	Parameter	Value	Corresponding physiological significance
Resistance (mmHg*s/ml)	R_M	0.0050	Mitral Valve Resistance
	R_s	1.0000	Systemic Vascular Resistance
	R_A	0.0010	Aortic Valve Resistance
	R_C	0.0398	Characteristic Impedance
	R_i	0.0676	Blood Pump Inlet Resistance
	R_o	0.0676	Blood Pump Outlet Resistance
Capacitance (ml/mmHg)	C_R	4.4000	Left Atrial Compliance
	C_S	1.3300	Systemic Compliance
	C_A	0.0800	Aortic Compliance
	$C(t)$	Time-Varying Parameters	Left Ventricular Compliance
Valve	D_M	0 or 1	Mitral Valve
	D_A	0 or 1	Aortic Valve
Inductance (mmHg*s^2/ml)	L_S	0.0005	Aortic Vascular Inductance
	L_i	0.0127	Blood Pump Inlet Inductance
	L_i	0.0127	Blood Pump Outlet Inductance

3. Design of the Particle Swarm Optimization Algorithm

During pulsatile speed control, the blood pump undergoes frequent acceleration and deceleration. Conventional square-wave and triangular-wave drive profiles exhibit abrupt changes in acceleration, which can lead to additional energy losses. While sine wave ensures continuous acceleration, its fixed pattern is unlikely to achieve optimal energy efficiency. To effectively enhance the energy performance of the speed control process, this study employs a PSO algorithm to derive a pulsatile speed profile that minimizes energy consumption while maintaining physiologically normal performance indicators.

3.1. Theoretical Foundations of PSO

In PSO, each potential solution to the optimization problem is represented as a "particle" within a D-dimensional search space. The entire population, through communication and collaboration among individual particles, follows the current best-performing particles to explore and exploit the solution space, ultimately guiding the swarm toward the global optimum or a satisfactory solution.

Consider a swarm consisting of N particles collaboratively searching for the optimal solution in a D-dimensional search space. The state of the *i*-th particle at iteration t is defined by two vectors:

Position Vector $X_{id}(t)=(x_{i1},x_{i2},\cdots,x_{iD})$: This represents the particle's location in the search space and corresponds to a candidate solution for the optimization problem.

Velocity Vector $V_{id}(t)=(v_{i1},v_{i2},\cdots,v_{iD})$: This indicates the direction and step size of the particle's movement in the next iteration.

Additionally, each particle retains the best position it has personally encountered, referred to as the personal best position $P_{id,pbest}(t)=(p_{i1},p_{i2},\cdots,p_{iD})$. The best position discovered by any particle in the entire swarm is known as the global best position $P_{d,gbest}(t)=(p_{1,gbest},p_{2,gbest},\cdots,p_{D,gbest})$.

During each iteration, particles update their velocity and position by tracking these two best solutions according to the following equations:

Velocity update equation:

$$v_{id}(t+1)=\omega\cdot v_{id}(t)+c_1r_1\cdot\left(p_{id}-x_{id}(t)\right)+c_2r_2\cdot\left(g_d-x_{id}(t)\right) \tag{2}$$

Position update equation:

$$x_{id}(t+1)=x_{id}(t)+v_{id}(t+1) \tag{3}$$

where:

$d=1,2,\cdots,D$ denotes the dimension.

w is the inertia weight, which balances the global exploration and local exploitation capabilities of the algorithm. A larger w promotes global exploration, while a smaller w facilitates local refinement.

c_1 and c_2 are acceleration coefficients (learning factors), typically set as positive constants. Specifically, c_1 is the "cognitive" coefficient, reflecting the particle's reliance on its own experience, and c_2 is the "social" coefficient, indicating the particle's tendency to trust collective information.

r_1 and r_2 are random numbers uniformly distributed in [0, 1], introducing stochasticity into the search process and helping to maintain population diversity.

3.2. Definition of the Fitness Function

The objective of this study is to minimize energy consumption during the pulsatile speed control of the blood pump. Therefore, the optimization target is defined as the pump's energy consumption, quantified by its average shaft power over a specified operational duration from t_1 to t_2, with the unit in watts (W).

$$P = \frac{\int_{t_1}^{t_2} T_e * \omega \mathrm{d}t}{t_2 - t_1} \tag{4}$$

where T_e is the electromagnetic torque of the blood pump motor in N·m, ω is the rotational speed of the blood pump in rad/s. The electromagnetic torque can be derived from the rotor dynamics model of the blood pump as follows:

$$T_e - T_L - B * \omega = J * \alpha \tag{5}$$

where T_L is the load torque (N·m) during pulsation. B is the rotor damping coefficient (N·m·s/rad). In this study, its effect is neglected and its value is set to 0. α is the motor angular acceleration (rad/s). J is the rotor inertia (kg·m^2), and its value is 10^{-6} kg·m^2.

The load torque T_L was characterized via experimental fitting. The specific load torque model utilized in the present paper is:

$$T_L = a * \omega^2 + b * \omega + c \tag{6}$$

where $a = 1.825\mathrm{e}^{-5}$, $b = -0.002277$, $c = 0.3291$.

3.3. Selection of Optimization Variables

In prior research on blood pump speed modulation, the rotational speed—being the primary control variable—directly governs the acceleration magnitude via the shape of its profile. Consequently, defining the rotational speed as the optimization variable enables the pursuit of an optimal speed profile that balances energy efficiency with pulsatile performance.

The number of control points, which defines the search space dimension D, is a critical parameter. In this study, it is set to 5. Setting $D = 5$ was determined through a trade-off analysis. A lower number would overly constrain the profile shape, potentially failing to capture essential hemodynamic features. Conversely, a higher number would exponentially increase the computational cost of the Particle Swarm Optimization (PSO) without guaranteeing a commensurate improvement in physiological performance. Therefore, $D = 5$ was selected as it provides a flexible yet computationally tractable parameterization for constructing effective speed profiles.

3.4. Definition of Constraints

3.4.1. Physical Constraints

1) Rotational Speed Constraints

It is imperative to impose constraints on the rotational speed of the blood pump to ensure its normal operation and prevent adverse flow phenomena such as suction and regurgitation. Hemodynamic analysis identified that at 4000 rpm, regurgitation occurred, manifested as negative flow through the pump. At 10,000 rpm, suction was induced by suboptimal left ventricular pressure. Accordingly, the permissible operating speed for the blood pump is defined within the bounds of 4000 rpm and 10,000 rpm.

2) Acceleration Constraints

To minimize the energy consumption of the blood pump during operation, the acceleration was constrained within the range of −10,000 rpm/s to 10,000 rpm/s. This range is defined with reference to a 1 Hz sine wave, which has a baseline speed of 7000 rpm, a pulsatility amplitude of 2500 rpm, and a corresponding mean absolute acceleration of 10,000 rpm/s.

3.4.2. Physiological Constraints

The purpose of imposing hemodynamic constraints is to ensure that the pulsatile modulation, driven by the PSO-optimized speed profile, restores key physiological parameters to within healthy ranges. The recovery of physiological health is evaluated based on aortic pressure and aortic flow, which must be maintained within specified physiological ranges.

1) Aortic Pressure Constraints

Hemodynamic performance was assessed against established normal ranges. The mean aortic pressure is defined as 85 - 100 mmHg, while the aortic pulse pressure (the difference between systolic and diastolic pressure) falls within 20 - 60 mmHg.

2) Aortic Flow Constraints

According to widely accepted medical standards, the mean aortic flow rate in healthy individuals is 80 - 100 ml/s.

3.5. Algorithm Workflow

The Particle Swarm Optimization (PSO) algorithm is a metaheuristic that mimics the collective behavior of bird flocks or fish schools. It operates by having a population of particles explore the solution space through iterative updates based on both individual and collective best-known positions, thereby efficiently converging to an optimal solution for minimizing the energy consumption of pulsatile blood pumps.

The workflow for optimizing the pulsatile energy consumption of the blood pump based on the Particle Swarm Optimization algorithm is illustrated in Figure 2. The process begins with the initialization of the PSO parameters, including the number of optimization variables, inertia weight (w), learning factors (c_1 and c_2), and population size (m). Subsequently, the position and velocity of each particle are randomly initialized. The position values of the particles are then assigned to the Simulink model for simulation. Following this, the position and velocity of each particle are updated. The fitness value for each particle is calculated, leading to the update of the personal best fitness value and position for the current iteration, as well as the global best fitness value and position. If the termination criteria are met, the global best fitness value and position are output. Otherwise, the Simulink model is executed again to proceed with the next iteration.

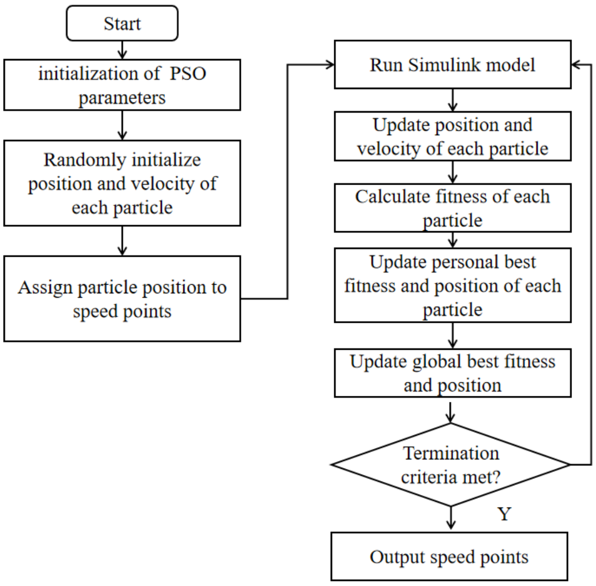

Figure 2. Workflow diagram of PSO.

4. Simulation and Analysis

The parameters for the PSO algorithm were configured as follows: search space dimension $D = 5$, inertia weight linearly decreasing from $w_{\max} = 0.9$ to $w_{\min} = 0.4$, cognitive and social learning factors decreasing from $c_{1\max} = c_{2\max} = 2.5$ to $c_{1\min} = c_{2\min} = 1.0$, population size of 500, and the max iteration is 100. The optimal particle position obtained from the optimization represents the interpolation points for the blood pump speed profile. A polynomial interpolation method was employed to construct the complete speed modulation curve over one cardiac cycle from these points. Using the aforementioned parameters, the PSO algorithm was independently executed 5 times, and the optimization results obtained are as Table 2:

Table 2. Optimization results

No.	Mean aortic pressure (mmHg)	Mean aortic flow rate (ml/s)	Aortic pulse pressure (mmHg)	Average power (W)
1	90.96	80.00	21.55	5.24
2	90.99	80.00	22.28	5.28
3	90.85	80.00	20.60	5.13
4	90.88	80.00	20.33	5.15
5	90.75	80.00	21.02	5.14

Based on a comprehensive evaluation of the energy consumption performance and physiological indicators corresponding to the five sets of results, the 5th set was selected for simulation comparison with sine wave, triangle wave, and constant wave profiles, as it achieved a relatively higher aortic pressure differential while maintaining lower energy consumption. The speed curves used in all simulations are presented in **Figure 3**.

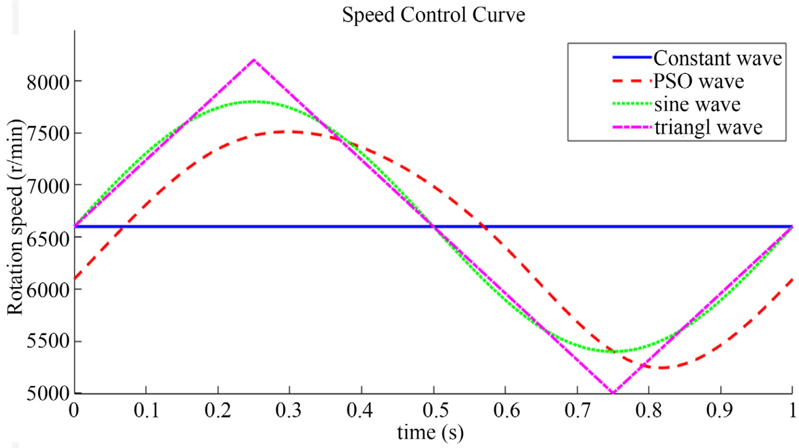

Figure 3. Curves Used in the Simulation. The constant wave speed is 6600 rpm. The PSO wave is generated by the optimization algorithm. The sine and triangle waves share a common central speed of 6600 rpm, with speed amplitudes of 1200 rpm and 1600 rpm, respectively.

With the simulation parameters set to Emax = 1, Emin = 0.05, and Tc = 1 s, the resulting hemodynamic characteristics and power profiles during pulsation for the different speed control curves are presented in **Figures 4-6**, respectively.

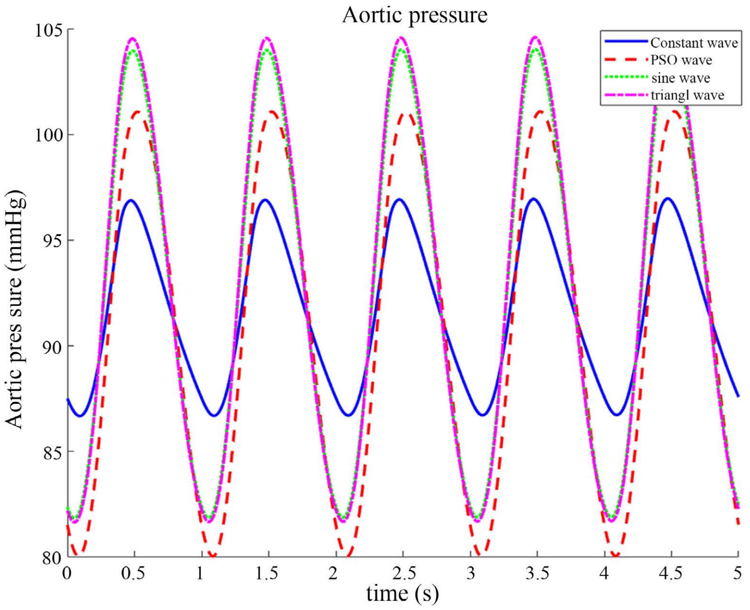

Figure 4. Simulation result of aortic pressure when the pump is driven by constant wave, PSO wave, sine wave and triangle wave.

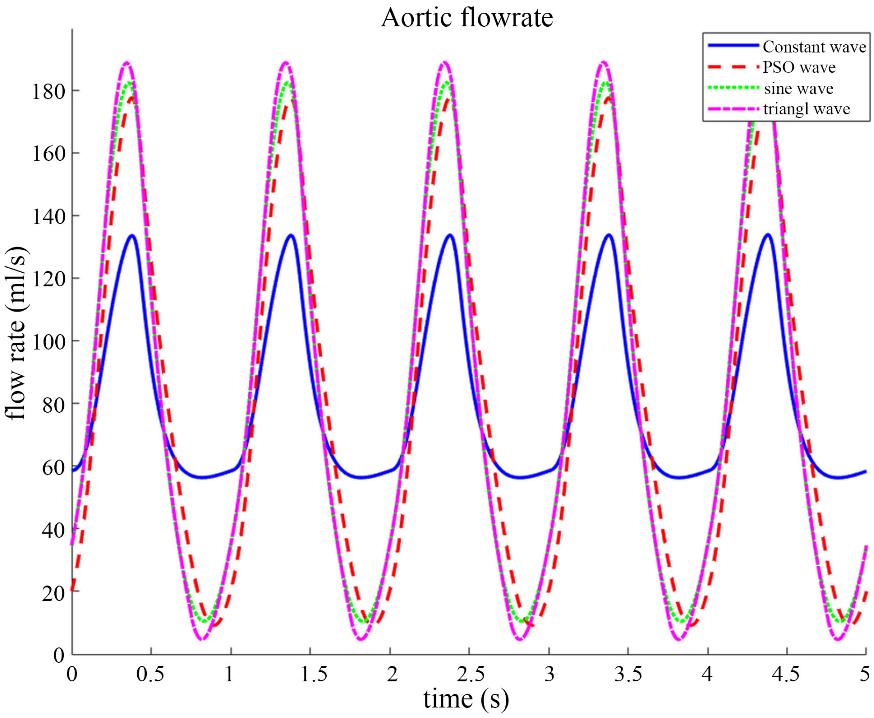

Figure 5. Simulation result of aortic flowrate when the pump is driven by constant wave, PSO wave, sine wave and triangle wave.

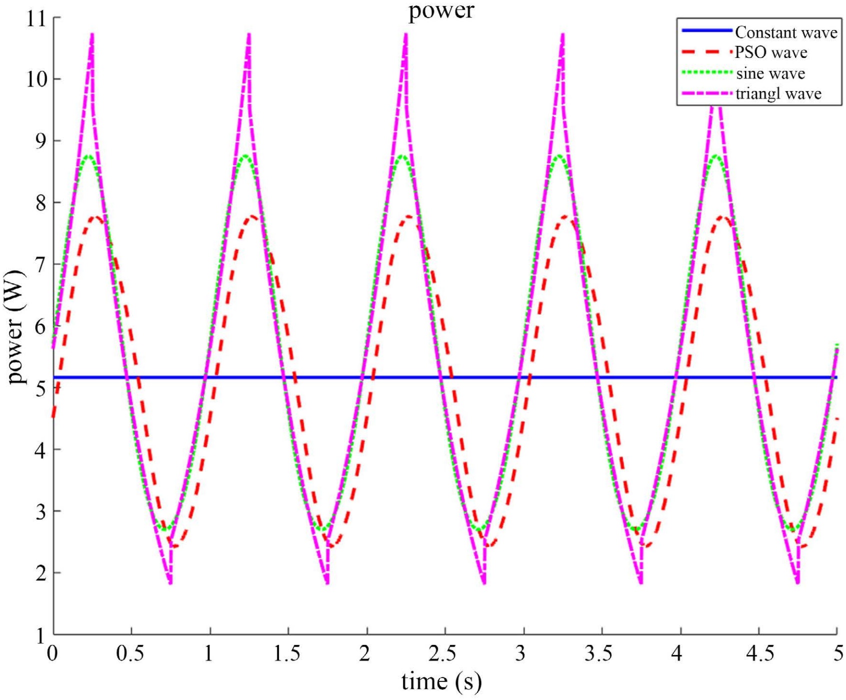

Figure 6. Simulation result of power when the pump is driven by constant wave, PSO wave, sine wave and triangle wave.

The performance of the various speed modulation curves with respect to physiological parameters and energy consumption is summarized in **Table 3**:

Table 3. Comparison of physiological indices and energy consumption under different waves.

	Mean aortic pressure (mmHg)	Mean aortic flow rate (ml/s)	Aortic pulse pressure (mmHg)	Average power (W)
PSO wave	90.75	80.00	21.02	5.14
Sine wave	92.65	81.71	22.16	5.44
Triangle wave	92.80	81.86	22.88	5.50
Constant wave	91.58	80.61	10.21	5.17

As evidenced by the results, the PSO wave demonstrates superior performance compared to conventional profiles. Specifically, relative to the Sine wave, it achieves comparable hemodynamic performance with only a 2% difference in mean aortic pressure and a 2% difference in mean flow rate, while reducing the average power consumption by 5.8%. In comparison to the Triangle wave, it exhibits a 2.2% difference in mean aortic pressure and a 2.3% difference in mean flow rate, along with a 6.5% reduction in average power. Moreover, the aortic pulse pressure reaches 21.02 mmHg, indicating significantly enhanced blood pulsatility compared to Constant wave. Therefore, the proposed PSO-based pulsatile speed control strategy not only fulfills essential physiological requirements but also effectively reduces energy consumption during pulsatile operation. This approach holds considerable theoretical significance and promising clinical application prospects for developing next-generation portable pulsatile blood pumps with low power consumption, compact size, and advanced intelligence.

5. Conclusions

This study proposes a speed profile optimization method to minimize pulsatile energy consumption in blood pumps. By integrating pump motor dynamics and hemodynamic principles, we developed an energy consumption model quantified by average power and a blood pump-cardiovascular coupling model based on the pump's hydraulic characteristics. The particle swarm optimization (PSO) algorithm was employed to automatically iterate and optimize key speed points in the rotational speed profile, with polynomial interpolation applied to ensure smooth speed transitions. This framework systematically identifies an energy-minimizing speed curve that satisfies physiological requirements. Simulation results demonstrate that the proposed method effectively reduces pulsatile energy consumption while maintaining normal perfusion levels, showing significant theoretical value and promising clinical potential for developing low-power, compact, and intelligent portable pulsatile blood pumps.

Finally, it should be acknowledged that this study employs a lumped-parameter cardiovascular model, which inherently simplifies the distributed nature of the actual circulatory system; nevertheless, this approach provides sufficient fidelity for evaluating the control strategies and hemodynamic responses of interest while maintaining computational tractability.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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