Improvement of Left Ventricular Assist Device (LVAD) in Artificial Heart Using Particle Swarm Optimization

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ABSTRACT

In this approach, the Left ventricular assist pump for patients with left ventricular failure is used. The failure of the left ventricle is the most common heart disease during these days. In this article, a State feedback controller method is used to optimize the efficiency of a sampling pump current. Particle Swarm Algorithm, which is a set of rules to update the position and velocity, is applied to find the optimal State feedback controller parameters for the first time. In comparison to other optimization algorithms, including genetic algorithm, PSO has higher convergence speed. As it is shown in the simulation part in the same number of iterations, the PSO algorithm decreases the cost function, which leads to desired transient and stability response of the system more effectively. In addition, in this work we propose a new structure for the cost function which includes the dynamical equations of current sampling pump in combination with penalty sentences which decrease the speed and output fluctuations. In this article, the system model and the system controlling parameters are set in such a way that the proposed cost function can be optimized. The efficiency of the method is illustrated in simulation part.

KEYWORDS: *Current sample, Optimization, Overshoot, PSO, Settling time, Stability*

1. INTRODUCTION

The results indicate that cardiovascular disease is the main cause of death of men and women all over the world [1]. Heart failure is a progressive and chronic disease that its symptoms and effects lead to some limitations in the patients' normal life and affect their life quality over time [2]. In realistic view to the existing models of Mechanical Artificial Heart, some failures such as large size, short lifetime, different shapes of blood pressure pulse, battery problems, blood clotting and rejecting are found [3]. LVAD[1] is used because of following reasons: 1) no need to remove normal heart when LVAD is used, 2) Right Ventricle working properly (in the most cases) 3) no interference with the normal order of heart rate 4) simple control of physiological conditions 5) possibility of normal heart recovery after some rest

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[1] Left Ventricular Assist Device

6) simplicity, low cost and higher reliability of LVAD 7) normal heart performance as a support in the case of LVAD failure [4]. LVAD optimization is essential. It may lead to interference decrease and energy source consumption reduction and it also can increase the accuracy of this system [5]. So far, some efforts have been made to improve LVAD performance [6]. In 2005, conditions of a cardiovascular system combined with the pump was provided with a model. The purpose of this model was achieving more stability in design, more controllability of pump speed and providing a model to simulate this system [7]. In [8], modeling, parameters estimation and control of cardiovascular system also was carried by LVAD in which a PI controller with a cost function and three parameters of cardiac output, arterial pressure and left atrium pressure were used. In another article, optimal control in LVAD was provided and cost function with the membership function including 1- stroke volume 2- mean of left atrium pressure 3- medium pressure of aorta and 4- mean speed of the pump were studied. It aimed to minimize the changes of function and pump speed, using the blood circulation model [9]. Although this aim was effective in improving performance of the system, it couldn't meet control needs, given the limitation in system modeling. In 2011, a new model of LVAD based on the current sampling was introduced. Combining this model with previous controllers established very effective improvement in the control process [10]. But this method also had limitations such as non-linear changes of speed with current, pump speed fluctuations due to heart rate and so on, and there was a need to improve them.

According to what was said above, we will provide current-based modeling in the second part of this article. Dynamic equations are derived in Section 3. Particle aggregation optimization algorithm will be presented as an effective step in usual optimizing with minimum time consumption in Section 4 and In Section 5, using a PSO method for introduced model effectiveness of this method in reducing Settling and overshoot time will be examined.

2. MODELING SYSTEM

The structure of a Pump including a rotor and stator is shown in figure 1.
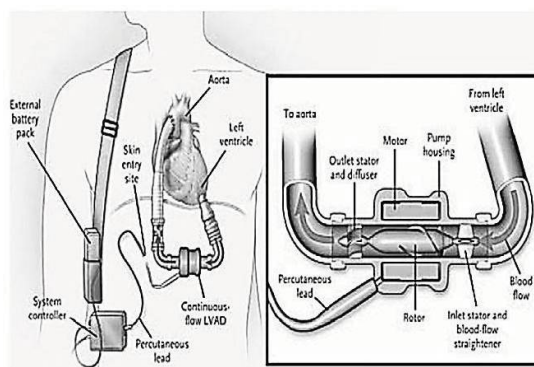

Fig. 1. Inside the pump

Combining cardiovascular system model and the functional model which can be extracted from the LVAD, leads to the mentioned combined model of figure 2.
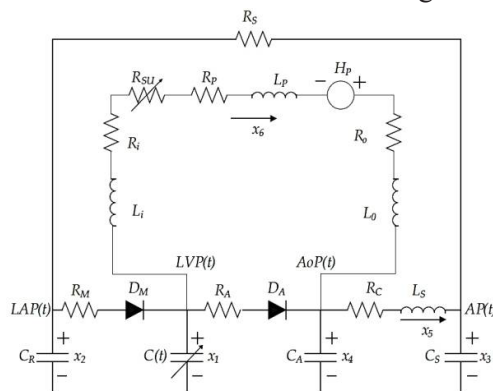

Fig. 2. Model of combined cardiovascular and LVAD

3. EXTRACTED DYNAMICAL EQUATIONS MODEL

For aortic and mitral valves which are modeled by D_M and D_A diodes in figure 2, there are several modes which are described in table 1.

Table 1. State of the valve within a heart cycle

Modes	Valves		Phases
	Mitral	Aortic	
1	Closed	Closed	Isovolumic Relaxation
2	Open	Closed	Filling
1	Closed	Closed	Isovolumic Contraction
3	Closed	Open	Ejection
-	Open	Open	Not feasible

Using system variables in table 2, the state space model of equation (1) is expressed.

Table 2. Variables blood circulation state of the left ventricle model

Variables	Name	Physiological meaning (units)
$X_1(t)$	LVP (t)	Left ventricular pressure (mmHg)
$X_2(t)$	LAP(t)	Left atrial pressure (mmHg)
$X_3(t)$	AP(t)	arterial pressure (mmHg)
$X_4(t)$	AoP(t)	aortic pressure (mmHg)
$X_5(t)$	$Q_T(t)$	Total flow (ml/s)

$$
\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \end{bmatrix} = \begin{bmatrix} \frac{-\dot{C}(t)}{C(t)} & 0 & 0 & 0 & 0 & \frac{-1}{C(t)} \\ 0 & \frac{-1}{R_S C_R} & \frac{1}{R_S C_R} & 0 & 0 & 0 \\ 0 & \frac{1}{R_S C_S} & \frac{-1}{R_S C_S} & 0 & \frac{1}{C_S} & 0 \\ 0 & 0 & 0 & 0 & \frac{-1}{C_A} & \frac{1}{C_A} \\ 0 & 0 & \frac{-1}{L_S} & \frac{1}{L_S} & \frac{-R_C}{L_S} & 0 \\ \frac{1}{L^*} & 0 & 0 & \frac{-1}{L^*} & 0 & \frac{-R^*}{L^*} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix} +
$$

$$
\begin{bmatrix} \frac{1}{C(t)} & \frac{-1}{C(t)} \\ \frac{-1}{C_R} & 0 \\ 0 & 0 \\ 0 & \frac{1}{C_A} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{R_M} r(x_2 - x_1) \\ \frac{1}{R_A} r(x_1 - x_4) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \frac{\gamma}{L^* x_6} \end{bmatrix} i(t) \quad (1)
$$

The numerical value of the parameters of the equation (1) is presented in table 3 [10].

Table 3. Parameters of the model

Parameters	Value	Physiological meaning
Resistances(mmHg.s/ml)		
R_S	1	Systemic Vascular Resistance
R_M	0.005	Mitral Valve Resistance
R_A	0.001	Aortic Valve Resistance
R_C	0.0398	Characteristic Resistance
R_i	0.0677	Inlet Cannula Resistance
R_P	0.1707	Pump Resistance
R_o	0.0677	Outflow Cannula Resistance
Compliances (ml/mmHg)		
C(t)	Time-varying	Left Ventricular Compliance
C_R	4.4	Left Atrial Compliance
C_S	1.33	Systemic Compliance
C_A	0.08	Aortic Compliance
Inertances (mmHg.s^2/ml)		
L_S	0.0005	Inertance of blood in Aorta
L_i	0.0127	Inlet Cannula Inertance
L_P	0.02177	Pump Inertance
L_o	0.0127	Outflow Cannula Inertance

In equation (1), $r(\xi)$ represents the ramp function which is defined in equation (2). The parameter γ depends on the conversion ratio pump, pump efficiency and supply voltage. The values of R^*, L^* are expressed according to equations (3) and (4). R_{su} is a non-linear and time-varying resistance in the form of an equation (5). Where α depends on scaling factor, and $\bar{x}_1$ represents the suction.

$$
r(\xi) = \begin{cases} \xi & \text{if } \xi \geq 0 \\ 0 & \text{if } \xi < 0 \end{cases} \quad (2)
$$

$$R^* = R_i + R_o + R_p + R_{su} \quad (3)$$

$$L^* = L_i + L_o + L_p \quad (4)$$

$$
R_{su} = \begin{cases} 0 & \text{if } LVP(t) > \bar{x}_1 \\ \alpha(LVP(t) - \bar{x}_1) & \text{if } LVP(t) \leq \bar{x}_1 \end{cases} \quad (5)
$$

4. PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization algorithm is a population-based optimization method which was proposed first by Kennedy and Eberhart [11]. Ease of implementation and speed of the PSO[1] are some advantages of this method in compare with other evolutionary methods such as genetic algorithm. In recent years different topologies for PSO algorithm is proposed. Some of these topologies which are used for information exchange between the particles are denoted by the star, ring and square topologies [12]. Figure 3 shows the relationship between particles in different topologies.
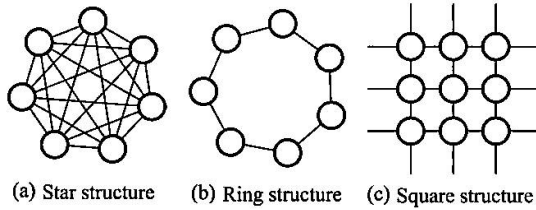

(a) Star structure   (b) Ring structure   (c) Square structure

Fig. 3. Topologies used in PSO algorithm

The D-dimensional search space the personal best position of particle i is denoted by $p_i = (p_{i1}, p_{i2}, ..., p_{iD})$ and the best position of the group is shown by $g = (g_1, g_2, ..., g_D)$. The particle velocity in the next iteration is defined by using Newtonian mechanics law in the form of an equation (6).

$$v_{id}(t+1) = \omega v_{id}(t) + c_1 rand_1 \left(p_{id}(t) - x_{id}(t) \right) + c_2 rand_2 (g_d(t) - x_{id}(t)) \tag{6}$$

After determination of the velocity vector of the equation (6), groups of particles move according to equation (7) from the current position to the new position.

$$x(t+1) = x(t) + v(t+1) \tag{7}$$

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[1] Partical Swarm Optimization

In equation (6), ω is particle inertia and c_1 and c_2 are acceleration coefficients. To create the random nature of the velocity, the coefficients c_1 and c_2 are multiplied with $rand_1$ and $rand_2$. Usually during PSO implementation, ω decreases linearly from one to zero. In general inertia coefficient ω is defined according to equation (8) [13]:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{iter_{max}}.iter \tag{8}$$

In equation (8) $iter_{max}$ is the maximum iteration number, iter is the current iteration number and ω_{max} and ω_{min} are maximum and minimum value of inertia coefficient respectively. The coefficients of cost function are determined considering to the importance of systems' speed response, Settling time and blood pressure control with minimum overshoot and undershoot. We also try to decrease the pressures of aortic and left atrium to reduce the damages. Our aim is optimizing the energy consumption and increasing efficiency in spite of changes of humans' biological system during, different activity modes such as resting, exercising and etc. It also should be mentioned that excessive suction speed during a short period will cause ventricle failure and damage the heart muscles.

According to the importance of the direct relationship between blood and stroke volume, we come to the conclusion that optimizing the stroke is very important because the increase in blood flow coronary artery is associated with pressure. It also leads to abnormal diastolic aortic pressure increase and results in damaging effects on organs such as eyes, brain and kidney. According to the stated objectives, the following cost function is suggested:

$$\begin{aligned}
\text{Cost} = &\; \alpha_1\,Ov_I + \alpha_2\,Ov_E + \alpha_3\,Ov_F + \\
&\alpha_4\,Un_I + \alpha_5\,Un_E + \alpha_6\,Un_F + \alpha_7\,St_I + \\
&\alpha_8\,St_E + \alpha_9\,St_F + \alpha_{10}\,SV + \alpha_{11}\,LAP + \\
&\alpha_{12}\,MAP + \alpha_{13}\,MPS
\end{aligned} \qquad (9)$$

In which the (Ov_I), (Ov_E), (Ov_F) are overshoot isovolumic, ejection, and filling, and (Un_I), (Un_E), (Un_F) are defined as undershoot isovolumic, ejection, filling, and (St_I), (St_E), (St_F) are denoted settling time isovolumic, ejection, filling, and (SV) is stroke volume, (LAP) is left atrial pressure, (MAP) is definitely the minimum aortic pressure, (MPS) is the mean pump speed. According to the cost function (9) and dynamic equations (1) to (5) we form a conditioned optimization which will be solved by PSO. The PSO algorithm is illustrated in figure 4 [14].
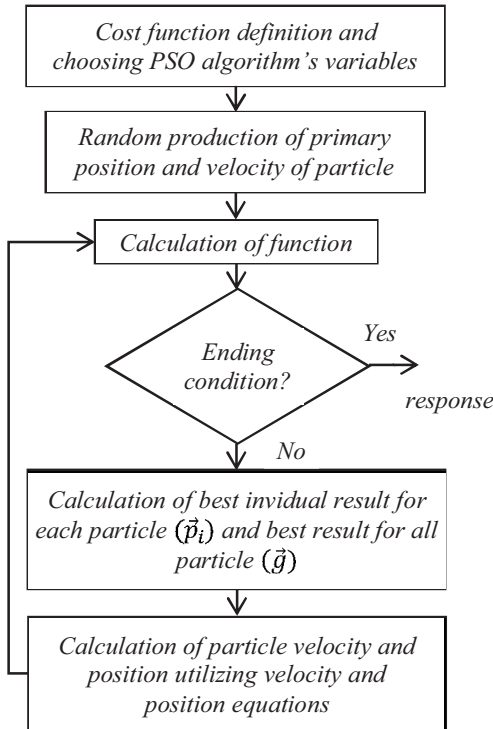

Fig. 4. Flowchart of the algorithm used

5. IMPLEMENTED PARTICLE SWARM ALGORITHM FOR COMPUTING THE OPTIMAL COST FUNCTION AND THE SIMULATION RESULTS

In this part, the system model described by (2) is used [10]. In implemented algorithm the initial number of generations is 20 and iterations number is 30, equation (5) shows the variations of generations' cost function at each iteration.
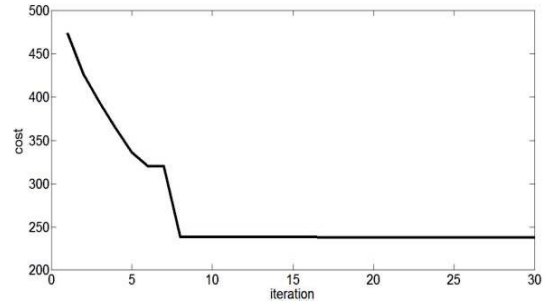

Fig.5. Cost function variation in each iteration

As it can be seen in figure 5, the amount of the cost function has reached to its minimum after 17 iterations and it has little changes up to 30th iteration. The calculated parameters which lead to best cost function value (238) has been defined and used to set the K value of the LQR feedback controller. The step response for the predefined K is shown in figure 6. As it is denoted in this figure for isovolumic situation the undershoot value is 0.085 which reaches to 0.036 and 0.02 using GA and PSO optimization methods respectively. It should be mentioned that we use the α_{10} to α_{13} values form [13]. In figure 4 the flowchart of the mentioned algorithm in equations (1) to (5) is defined.
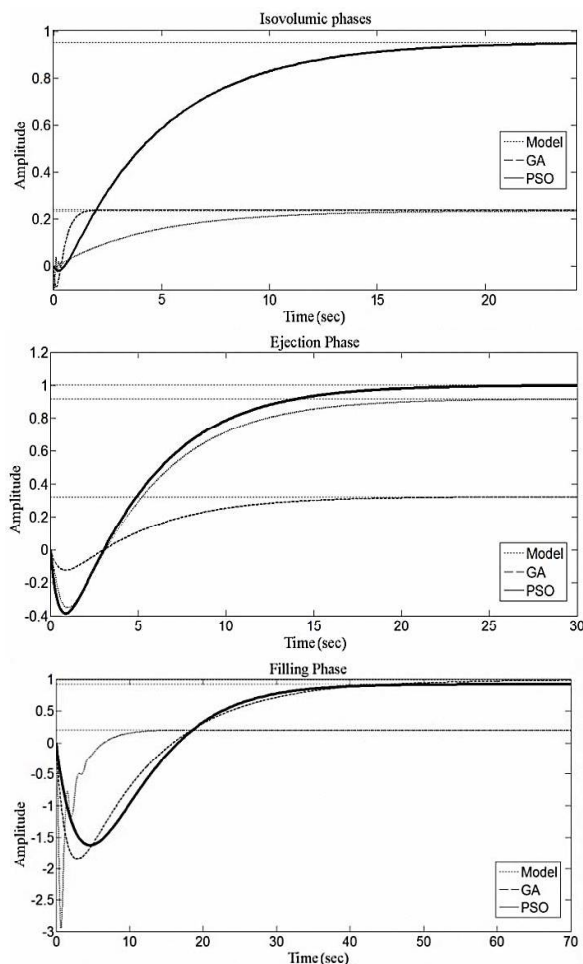
Fig.6. Step response optimization system for all modes

In figure (6), for mentioned model of equation (1), GA and PSO are compared with each other. The three modes may be due to mitral and aortic valves in table 1 is presented.

6. CONCLUSIONS

In this article, the designing optimal controller of PSO algorithm for artificial heart has been discussed and the results are compared with GA. The results show that Suggested feedback improves the GA undershoot from 0.01 to 0.2 units and settling time from 0.1 to 0.9 which results in reducing system cost function and increasing system accuracy.

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