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

Majid Neshat Yazdi¹, Reihaneh Kardehi Moghaddam²

¹Department of Electrical Engineering, Ahar Branch, Islamic Azad University, Ahar, Iran Email: M-neshat@iau-ahar.ac.ir

² Department of Electrical Engineering, Mashhad branch, Islamic Azad university, Mashhad,

Iran.

Email: R_k_moghaddam@mshdiau.ac.ir

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

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 3medium 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	Left ventricular pressure
	(t)	(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)

$$\begin{bmatrix} \dot{x}_{1} \\ \dot{x}_{2} \\ \dot{x}_{3} \\ \dot{x}_{4} \\ \dot{x}_{5} \\ \dot{x}_{6} \end{bmatrix} = \begin{bmatrix} \frac{-\dot{C}(t)}{C(t)} & 0 & 0 & 0 & 0 & \frac{-1}{C(t)} \\ 0 & \frac{-1}{R_{S}C_{R}} & \frac{1}{R_{S}C_{R}} & 0 & 0 & 0 \\ 0 & \frac{1}{R_{S}C_{S}} & \frac{-1}{R_{S}C_{S}} & 0 & \frac{1}{C_{S}} & 0 \\ 0 & 0 & 0 & 0 & \frac{-1}{L_{s}} & \frac{1}{L_{s}} & \frac{-R_{c}}{L_{s}} & 0 \\ \frac{1}{L^{*}} & 0 & 0 & \frac{-1}{L^{*}} & 0 & \frac{-R^{*}}{L^{*}} \end{bmatrix} \begin{bmatrix} x_{1} \\ x_{2} \\ x_{3} \\ x_{4} \\ x_{5} \\ x_{6} \end{bmatrix} + (1) \\ \begin{bmatrix} \frac{1}{C(t)} & \frac{-1}{C(t)} \\ \frac{-1}{C_{R}} & 0 \\ 0 & 0 \\ 0 & \frac{1}{R_{A}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{R_{M}} r(x_{2} - x_{1}) \\ \frac{1}{R_{A}} r(x_{1} - x_{4}) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \frac{1}{Y_{k}} x_{6} \end{bmatrix} i(t)$$

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-	Left Ventricular					
	varying	Compliance					
C _R	4.4	Left Atrial Compliance					
Cs	1.33	Systemic Compliance					
C_{A}	0.08	Aortic Compliance					
Inertances (mmHg.s ² /ml)							
Ls	0.0005	Inertance of blood in					
		Aorta					
\mathbf{L}_{i}	0.0127	Inlet Cannula Inertance					
Lp	0.02177	Pump Inertance					
Lo	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.

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

$$\mathbf{R}^* = \mathbf{R}_i + \mathbf{R}_o + \mathbf{R}_p + \mathbf{R}_{su} \tag{3}$$

$$L^* = L_i + L_o + L_p \tag{4}$$

$$R_{su} = \begin{cases} 0 & \text{if } \text{LVP}(t) > \overline{x}_1 \\ \alpha(\text{LVP}(t) - \overline{x}_1) & \text{if } \text{LVP}(t) \le \overline{x}_1 \end{cases}$$
(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 PSO¹ 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).

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

$$x(t+1) = x(t) + v(t+1)$$
(7)

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 rand₁ and rand₂. Usually during PSO implementation, ω decreases linearly from one to zero. In general inertia coefficient ω is defined according to equation (8) [13]:

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

In equation (8) itermax 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:

¹ Partical Swarm Optimization

$Cost = \alpha_1 Ov_I + \alpha_2 Ov_E + \alpha_3 Ov_F + $	
$\alpha_4 Un_I + \alpha_5 Un_E + \alpha_6 Un_F + \alpha_7 St_I +$	(0)
$\alpha_8St_E+\alpha_9St_F+\alpha_{10}SV+\alpha_{11}LAP+$	(9)
α_{12} MAP + α_{13} MPS	

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 isovolumic situation figure for 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.

REFERENCES

- A. Shamsi and A. Ebadi, "Risk Factors of Cardiovascular Diseases in Elderly People," *Iranian Journal of Critical Care Nursing*, vol. 3, no. 4, pp. 187-192, 2011.
- [2] F. Shojaei, "Quality of Life in Patients with Heart Failure," *Journal of Faculty of Nursing and Midwifery*, vol. 14, no. 2, pp. 5-13, 2008.
- [3] A. Pohlmann, et al., "Drive optimisation of a pulsatile Total Artificial Heart," *Archives Of Electrical Engineering*, vol. 60, no. 2, pp. 169-178, 2011.
- [4] Y. Wu, P. Allaire, G. Tao, and D. Olsen, "Modeling, Estimation and control of Human circulatory system with a Left Ventricular Assist Devices," *IEEE Transactions On Control Systems Technology*, vol. 15, no. 4, pp. 1-14, 2007.
- [5] M. Walter, S. Heinke, S. Schwandtner, and S. Leonhardt, "Control Strategies for Mechanical Heart Assist systems," *IEEE Multi-Conference* on Systems and Control, vol. 1, no. 5, pp. 57-62, 2012.
- [6] M. Walter, S. Heinke, S. Schwandtner, and S. Leonhardt, "Physiological Control of Left Ventricular Assist Devices Based on Gradient of Flow," *American Control Conference*, vol. 13, no. 4, pp. 3829-3834, 2005.
- [7] A. Ferreira, S. Member, and S. Chen, "A Nonlinear State-Space Model of a Combined Cardiovascular System and a Rotary Pump," *IEEE Conference on Decision and Control*, vol. 7, no. 4, pp. 897-902, 2005.
- [8] Y. Wu, P. Allaire, G. Tao, and D. Olsen, "Modeling, Estimation and Control of Cardiovascular Systems with A Left Ventricular Assist Device," *American Control Conference*, vol. 13, no. 6, pp. 3841-3846, 2005.
- [9] p. He, J. Bai, and D. D. Xia, "Optimum control of the Hemopump as a left-ventricular assist device," *Medical & Biological Engineering & Computing*, vol. 43, no. 1, pp. 136-141, 2005.
- [10] G. Faragallah, Y. Wang, E. Divo, and M. A. Simaan, "A New Current-Based Control Model of the Combined Cardiovascular and Rotary Left Ventricular Assist Device," *American Control Conference*, vol. 8, no. 11, pp. 4775-4780, 2011.
- [11] J. Kennedy and R. Eberhart, "Particle Swarm Optimization," *IEEE International Conference* on Neural Networks, vol. 5, no. 3, pp. 1942-1948, 1995.
- [12] J. Kennedy and R. Mendes, "Neighborhood topologies in fully-informed and best-of

neighborhood particle swarms," *IEEE International Workshop*, vol. 5, no. 3, pp. 45-50, 2003.

- [13] N. Jin and Y. Rahmat-Samii, "Advances in Particle Swarm Optimization for Antenna Designs: Real-Number, Binary, Single-Objective and Multiobjective Implementations," *IEEE Tran*, vol. 55, no. 3, pp. 556-567, 2007.
- [14] A. Sakhavati, G. Gharehpetian, and S. H. Hosseini, "Decentralized power system load-frequency control using a novel cost function based on particleswarm optimization," *Electronics and computers science*, vol. 2, no. 8, pp. 111-116, 2008.

www.SID.ir