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Physiological Control of Left Ventricular Assist Devices Based on Gradient of Flow [(1)]

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***Abstract*— The new generation of left ventricular assist devices (LVADs) is based on rotary pumps used to augment the blood flow from the failing heart of a patient. A controller is necessary for these devices to properly control the blood flow, to detect failure modes, and to avoid adverse effects of the pump operation. In particular, it is essential that the pump accommodate changes to preload and afterload of the patient's circulatory system. The pump must increase blood flow in response to additional venous return, and maintain pressure in response to changes in systemic vascular resistance (SVR) of the patient. However, the limited availability of observable variables makes it difficult to explicitly close the feedback loop to generate the control. In this paper, we describe a feedback mechanism which uses the gradients of mean pump flow and minimum (diastolic) pump flow to control the pump speed. The objective of this controller is to optimize flow while avoiding suction. The optimum speed is obtained by minimizing in real time the gradient of blood flow with respect to speed. Simulations were carried out on a state-space model of the cardiovascular system combined with a rotary pump to demonstrate the responsiveness and robustness of this algorithm. The results show that the gradient methods can continuously track the optimal flow point in response to step perturbations of preload and SVR. Our results also show that a feedback controller based on the gradient method applied on a diastolic pump flow demonstrates better performance than when applied on mean pump flow.**

I. Introduction

The Left Ventricular Assist Device (LVAD) is a blood pump used to support a failing left ventricle in a patient with heart disease. Turbodynamic "rotary" pumps which comprise the new generation of LVADs have demonstrated clear advantages over the previous generation such as small size and high efficiency [1-5]. The rotary part of this type of pump is an impeller, which is typically driven by a brushless DC motor, to generate a pressure difference. In a typical bypass application, where the inlet and outlet of the pump connect the apex of the left ventricle and the aorta respectively, the pump helps unload the failing left ventricle as an active pressure source interacting with the natural circulatory system.

One of the challenges that remain a major issue in the usefulness of rotary pumps is how to control the rotation speed. If the rotational speed is too low, the blood will regurgitate from the aorta to the left ventricle through the pump (backflow). If the rotational speed is too high, the pump will attempt to draw more blood than available. The latter may cause collapse of the flow tract to the pump (a phenomenon called suction). More generally, the physiological status of the patient may demonstrate a wide range of Systemic Vascular Resistance (SVR) due, for example, to differing levels of physical activity and emotional changes [4], [5]. Whether the controller can accommodate different physiological conditions is a crucial factor for recipient patients to leave the hospital and return to a normal lifestyle.

Since the LVAD is used to help unload the failing heart, the basic control objective is to mimic the natural heart function [1], [2]. The normal cardiac output is dominated by the Frank-Starling's law which dictates that the heart increases or decreases its output based on the amount of blood returning from the body and the hemodynamic load presented by the circulation. In the present study we perturb the physical state by variation of SVR.

For a normal heart, the Cardiac Output (CO) is determined by two factors: stroke volume and heart rate. Stroke volume increase is the result of a complex physiological process, dependant upon: *preload*, the amount of the venous blood returning to the heart; *contractility* of the heart, an index of its strength of contraction; and *afterload*, referring to the SVR. As the left ventricle ejects the same amount of blood to the systemic circulation, high SVR leads to a high arterial pressure in the systemic circulation. In contrast, low SVR leads to a low pressure.

The principal goal of the blood pump controller is to respond to the body's demand for cardiac output. Since (at this time) it is not realistic to place sensors in the human body for long term applications, the availability of information about the circulation is limited.

A control approach using the heart rate as an input has been reported [6]. Although this provides an advantage over fixed-rate operation, it does not necessarily avoid the risk of suction. An investigation using oxygen saturation of

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the blood for control purpose has also been reported [7]. However this approach requires implanted transducers, and furthermore cannot respond to sudden changes of the load.

The use of pump flow as a source for estimating change of physiological status, in this case as indicated by a change in SVR, has not been exploited. This paper will present some preliminary work on two controllers which use the extracted gradient information of the pump flow to indicate blood demand and adaptively adjust the pump speed based on this gradient. Combined with an extremum tracking algorithm, one of the controllers is based on optimization of the mean flow. The other one is based on optimization of minimum flow.

This paper is organized as follows. First, a simple combined model of the cardiovascular system and rotary pump is derived. Then the Extremum Seeking Algorithm (ESA) is applied to the mean pump flow, and a simple gradient method is applied to the minimum pump flow of this model. Finally, the implications of the simulation results are discussed.

II. THE PUMP AND CARDIOVASCULAR MODEL

A. Pump model

The pump is an electro-mechanical device driven by a motor that rotates the impeller to cause the blood to flow from the inlet of the pump to the outlet. Electrical power is converted to mechanical power during this process. The following pump model was developed in [1].

$$H = P_O - P_i = b_0 Q + b_1 \frac{dQ}{dt} + b_2 \omega^2 \qquad (1)$$

The above equation describes the relationship between the pump rotational speed ω, the pump flow Q and pressure difference $P_0 - P_i$ generated by the pump. It is a semi-empirical model with parameters b_0, b_1 and b_2 estimated from experiments. The pump speed ω is to be determined by the control algorithm.

B. Cardiovascular system model

How the normal heart and the circulation system are controlled to provide the necessary cardiac output is a complex process of electrical and biochemical interactions. The process includes feedback interaction of local neural and hormone control. However, for the purpose of this study, a time varying nonlinear circuit model of a combined cardiovascular system and pump [8] was developed and used to test the feedback controller. Briefly, in this model which is shown in Figure 1, pressure is represented by voltage and flow by current. The left ventricle is modeled as a time-varying compliance $E(t)$. The mitral valve and aortic valve are modeled as pressure-dependent diodes (or switches) D_M and D_A plus small resistors R_M and R_A. Suction is modeled as a nonlinear resistor R_k and the SVR is modeled as a linear resistor R_s. Other components in the model are constant capacitors and inductors.

C. Combined model

The platform for the implementation of gradients method is the combination of the cardiovascular system model and the pump model, shown in Fig. 1. Descriptions of parameters in the combined model are given in Table I.

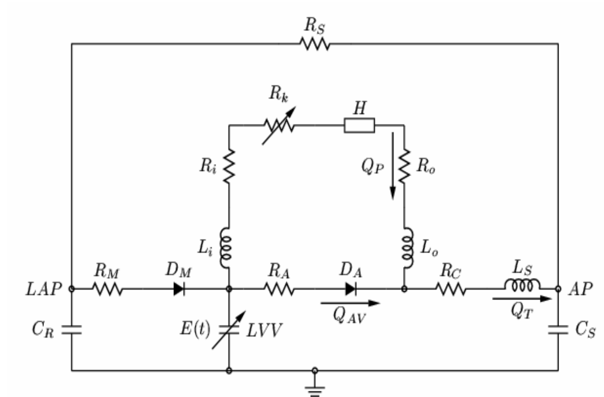

Fig. 1. The combined model of cardiovascular system and pump (Heart + LVAD)

Table I. Parameters in the combined model

D_M	Mitral Valve Value (0 or 1)
R_M	Mitral Valve Resistance
D_A	Aortic Valve Value (0 or 1)
R_A	Aortic Valve Resistance
R_C	Characteristic Resistance
C_S	System Compliance
L_S	Inertance of Blood in Aorta
R_S	System Resistance
C_R	Pulmonary Compliance
$E(t)$	Elastance of Left Ventricle
R_i	Pump Inlet Cannula Resistance
L_i	Pump Inlet Cannula inductance
R_O	Pump Outlet Cannula Resistance
L_O	Pump Outlet Cannula inductance
R_K	Suction Resistance

A pressure dependent nonlinear resistor R_k is inserted between the left ventricle and the inlet of the pump [1] to simulate the physics of the collapsible inflow tract [9]. It is defined as

$$R_K = \begin{cases} 0 & if \quad P_{LV} > P_{th} \\ -3.5P_{LV} + 3.5P_{th} & otherwise \end{cases} \qquad (2)$$

Where P_{LV} is the left ventricular pressure and P_{th} is a threshold pressure for the suction simulation.

The following assumptions are made in the derivation of the above model: (1) the circulation regulatory system is working appropriately even though the left ventricle is failing; (2) the left ventricle still has residual contractility; (3) the pump flow is measurable or can be estimated. Based on these assumptions, gradient information of pump flow is extracted as an indication of blood demand by the body and used to update pump speed in the closed loop.

III. ESA Using Mean Pump Flow

In many applications, the problem is to choose an operating point for a plant to keep the plant output at the extreme value (gradient = 0). However, it is not definitely known where the extremum will occur. What makes the problem more complicated is that the extremum itself may move with changes in plant parameters. The LVAD application is one example of this kind of problems, where the pump flow achieves a maximum at a certain pump speed. The problem is therefore to control the pump speed so that the pump flow is maintained at a maximum.

In the Extremum Seeking Algorithm (ESA) discussed in [10], the control variable is modulated by a sinusoid with low frequency and small amplitude. The modulation will cause a corresponding output variation. The gradient of the output with respect to the control variable is extracted by the ESA. This gradient estimation is in turn used to drive the control variable towards the corresponding point for the extremum output.

When the pump speed is high enough, the cardiac output is provided by pump flow only. Thus it is reasonable to apply the ESA on the mean value of pump flow. The block diagram for the application on Heart + LVAD system is shown in Fig. 2. Heart + LVAD is the plant with pump speed ω as the plant input and pump flow Q_P as the plant output. The pump speed updating rule used in the model in Fig. 2 is:

$$\omega(k+1) = \omega(k) + c\sum_{i=k-T}^{k} \left.\frac{dQ_{Pmean}}{d\omega}\right|_i \qquad (3)$$

where c is a constant. The parameters of the ESA algorithm are:

1. Sinusoid frequency $f = 0.5$ Hz
2. Sinusoid amplitude $a = 0.01$
3. High pass filter cut off frequency $f_h = 0.3$ Hz
4. Low pass filter cut off frequency $f_l = 0.3$ Hz
5. Updating gain $c = 0.2$
6. Summation period $T = 2$ seconds (400 points)

The perturbations are sinusoids with period greater than 1 cardiac cycle to ensure that the perturbations will not interfere with the plant. The high pass filter lets the sinusoid with frequency 0.5 Hz pass, and the low pass filter lets the dc component pass. The cardiac cycle is set to 1 second in the simulations.

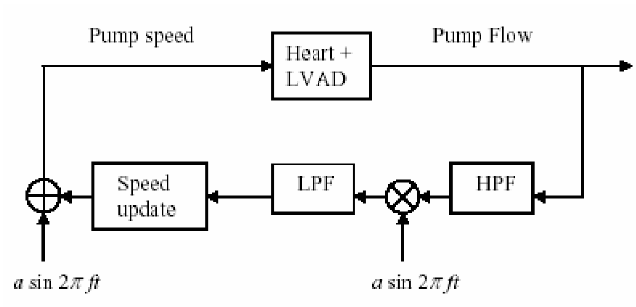

Fig. 2. ESA on mean pump flow

A. Simulation without noise

The simulation results are shown in Fig. 3 and Fig. 4. The output was allowed to reach steady state and ESA was turned on at 15 seconds. A low pass 5th order Butterworth filter was applied to all outputs with cut off frequency of 0.3 Hz.

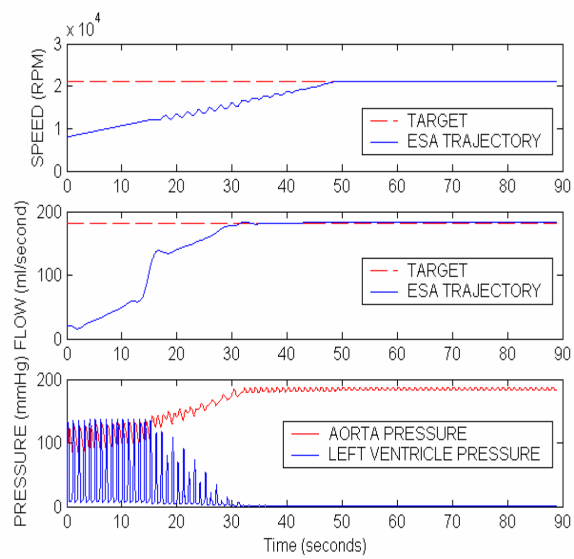

Fig. 3. ESA on mean pump flow without noise (fixed target)

In Fig. 4, for $t > 50$, we used a value for systemic resistance given by the expression:

$$R_S = 0.98 + 0.5 * \sin[2\pi * d * (t - 50)/40] \qquad (4)$$

where $R_S = 0.98$ represents a normal value of SVR, t is time, and d is a parameter that determines how quickly the maximum flow is changing. In this simulation we used d=4.

The target for reference (indicated by dashed lines in the figures) is the maximum of mean pump flow while the speed is increasing linearly from 7,600 to 19,100 RPM. The presence of suction was defined by the left ventricular pressure falling to zero, these results show that the ESA achieves optimal flow but produces significant suction. The ESA however tracked the moving target.

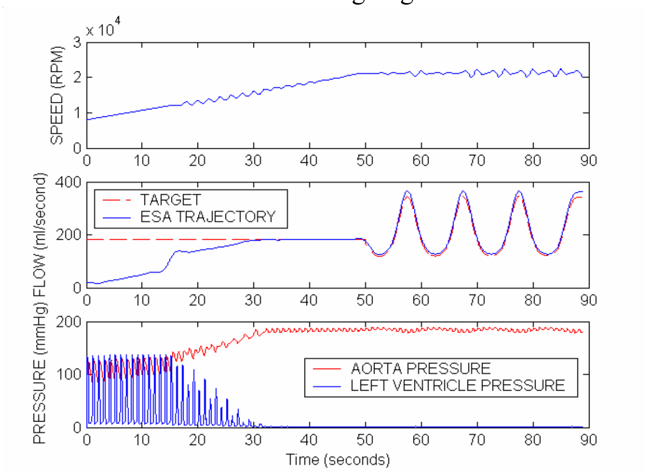

Fig. 4. ESA on mean pump flow without noise (moving target)

B. Simulation with noise

Uniformly-distributed noise was added to the pump flow, which is the input for the ESA. The results are shown in Fig. 5 and Fig. 6.

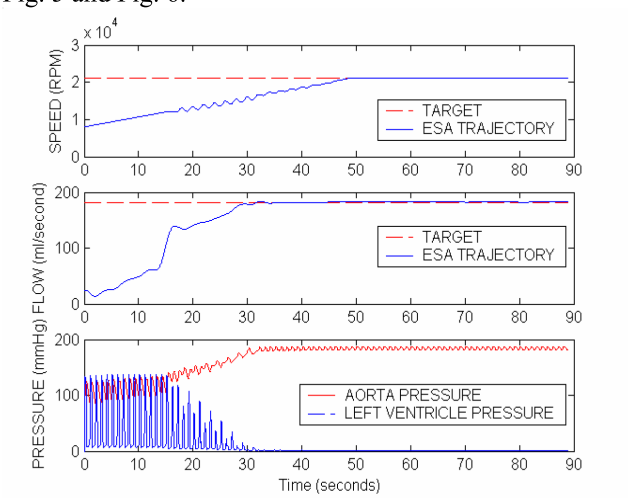

Fig. 5. ESA on mean pump flow with noise (fixed target, SNR=26 dB)

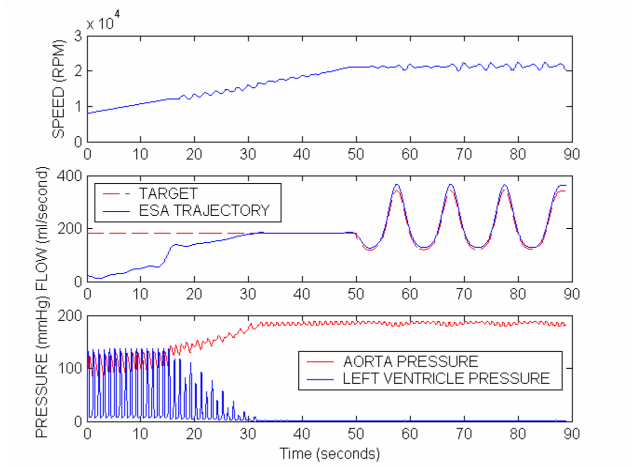

Fig. 6. ESA on mean pump flow with noise (moving target, SNR=26 dB)

The ESA can approximately achieve the target even with changing SVR and presence of moderate uniformly-distributed noise. Unfortunately, the target speed itself is in suction region.

IV. A Simple Gradient Method Using Minimum Pump Flow

Fig. 7 shows that minimum pump flow reaches a maximum just as the flow enters the suction region. The envelop of minimum pump flow is unimodal (i.e. has one maximum) for a specific range of speed (< 16,000 RPM).

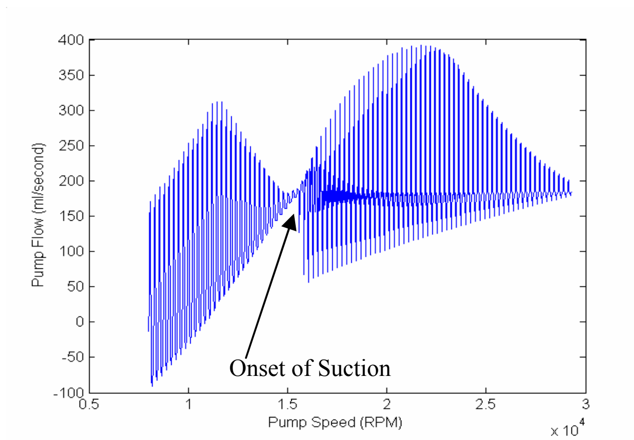

Fig. 7. Instantaneous pump flow vs. pump speed (Suction begins at the maximum of minimum flow; right hand side of this point is the suction region)

Mathematically, this point satisfies: $\frac{dQ_{\min}}{d\omega} = 0$. Using the chain rule of differentiation, we have $\frac{dQ_{\min}}{d\omega} = \frac{dQ_{\min}}{dt} \Big/ \frac{d\omega}{dt} = 0$. Thus, instead of calculating

$\frac{dQ_{\min}}{d\omega}$, we calculate $\frac{dQ_{\min}}{dt}$ as long as $\frac{d\omega}{dt}$ does not go to infinity. Thus the point that makes $\frac{dQ_{\min}}{dt} = 0$ also makes $\frac{dQ_{\min}}{d\omega} = 0$. In other words, to find the maximum of minimum pump flow vs. speed, we can vary pump speed with time and find the maximum of the minimum pump flow vs. time. The maximum of minimum pump flow is the tracking target for the proposed controller.

The procedure for finding the minimum flow is as follows:

(1) Calculate the minimum value of flow samples within a moving window (width=2.5 seconds)

(2) Calculate the mean value of these minima (width=2.5 seconds).

Then the gradient of minimum flow is calculated and is used to update the pump speed towards the point corresponding to the maximum of minimum pump flow.
The speed update rule is as follows:

$$\omega(k+1) = \omega(k) + c \left. \frac{dQ_{P\min}}{dt} \right|_{t=k} \qquad (5)$$

where c is a constant gain.

Fig. 8 shows the block diagram for the gradient method on minimum pump flow.

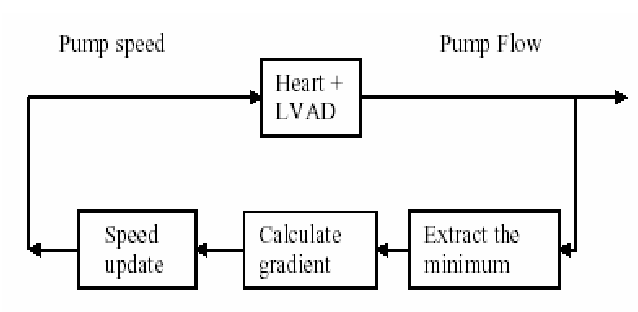

Fig. 8. Gradient method on minimum pump flow

A. Simulation without noise

Typical results are shown in Figs. 9 and 10. The target speed is plotted as a reference. The target speed is the speed at which the minimum pump flow achieves its maximum as a function of pump speed. The corresponding mean flow is the target flow.

The plots in Fig. 9 show the behavior of the method when the value of R_S changes suddenly at t = 60 sec from 0.98 to 1.48 and then goes back to 0.98 at t = 75 sec. Fig. 10 shows the moving target for t > 50 and R_s as given by expression (4) with d=0.5. This value of d is used because there is only one minimum in the cardiac cycle. The reference targets in the plots of Fig. 10 (dashed lines) are for values of SVR = 0.98 and SVR = 1.48 respectively.

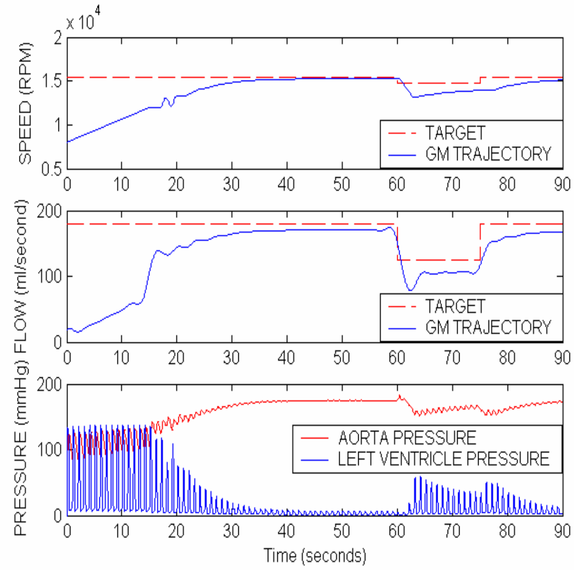

Fig. 9. Gradient method with sudden changes in the target

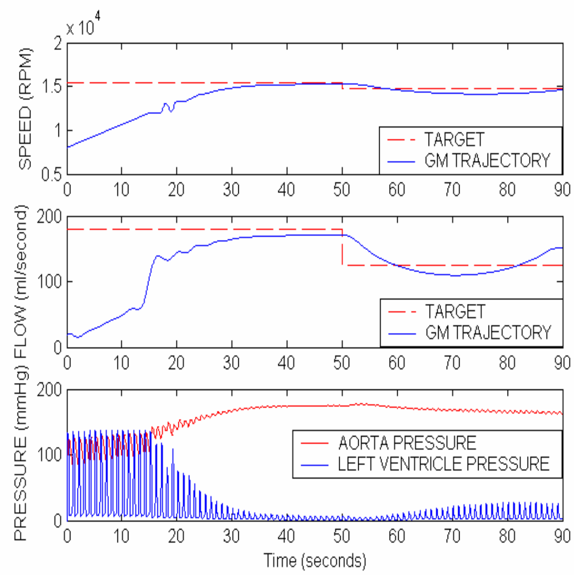

Fig. 10. Gradient method with a moving target given by expression (4) with d=*0.5*

B. Simulation with noise

With the same value of c, white noise (uniformly-distributed random numbers) was added to the pump flow. The value of R_S was changed as in the previous plots. The results show that presence of moderate uniformly-distributed noise does not degrade the performance considerably.

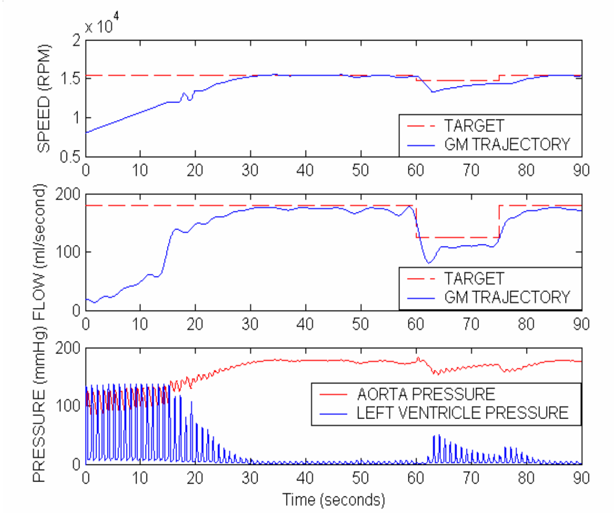

Fig. 11. Gradient method with noise (SNR=26 dB) and sudden changes in the target.

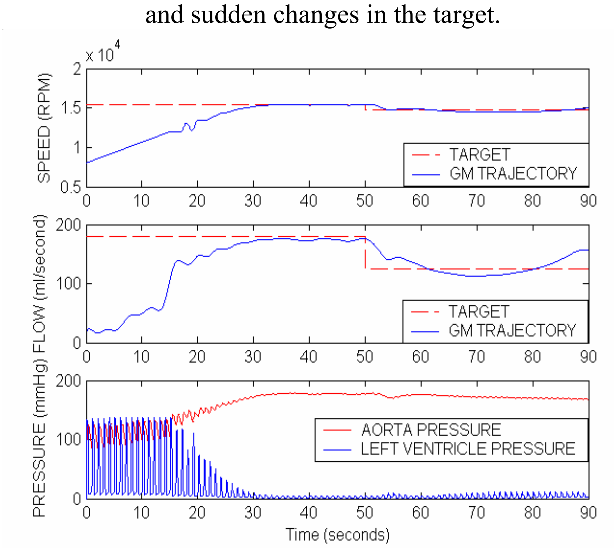

Fig. 12. Gradient method with noise (SNR=26 dB) and a moving target given by expression (4) with $d=0.5$

V. Conclusions

In this paper, we examined two gradient approaches to determine an optimum speed for the LVAD pump. One is based on applying the ESA method on mean pump flow; and the other is a gradient method applied on the minimum pump flow. Both can find the maximum target flow and track a moving maximum. Both are resistant to uniformly-distributed noise. For the ESA on mean pump flow, the target is in the suction region. Thus it is not the desired operating point. Some stopping criteria are necessary to keep the LVAD recipients from entering into suction. A fixed gradient threshold was also tried. It worked for a fixed SVR but failed when SVR was changing. Other disadvantages for this method include long time observation for calculating mean values and filters lags. It may not be responsive enough for avoiding suction and hence may not be a good candidate for LVAD controller. For the case of gradient method on minimum pump flow, the maximum occurred earlier than that of mean pump flow. The target operating point is therefore safer than that of the method above. Instead of calculating $\frac{dQ_{\min}}{d\omega}$, the algorithm calculates $\frac{dQ_{\min}}{dt}$. This method can respond to change of SVR in 1 or 2 cardiac cycles. However, its convergence is sensitive to the constant gain. Adaptive gain for different SVR may improve the performance of this method. It is one of the topics for ongoing investigation.

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