Sensorless estimation of inlet pressure in implantable rotary blood pump for heart failure patients

A.H. Alomari, A.V. Savkin, P.J. Ayre, E. Lim and N.H. Lovell

A dynamical model for mean inlet pressure estimation in an implantable rotary blood pump is proposed. Noninvasive measurements of pump motor power (P), pulse width modulation, and impeller rotational speed (ω) were used as inputs to the model. Linear regression analysis between estimated and measured inlet pressures obtained from *in vivo* greyhound data ($N = 3$) resulted in a highly significant correlation ($R^2 = 0.957$) and a mean absolute error (e) of 2.292 mmHg. Furthermore, the proposed model was stable which allowed accurate study and estimation of the transient response and the dynamics of the pump inlet pressure (P_{in}).

Introduction: The shortage of donor organs for heart transplantation has led to a variety of treatment options for heart failure patients. Implantable rotary blood pumps (IRBPs) are emerging not only as a bridge to the transplant option but also as a means of long-term support.

Noninvasive estimation of hemodynamic parameters of an IRBP plays a crucial role in designing an automatic, robust and responsive noninvasive control system that effectively copes with the body's physiological demands and perturbations. The implantation of additional sensors is not a preferred option as they result in thrombus formation and require regular calibration owing to measurement drifts. A stable dynamical model for noninvasive estimation of pulsatile flow and differential pressure in an IRBP was proposed and verified in [1]. The proposed model was also used to design a control algorithm for continuous and pulsatile flow [2]. A parameter-optimised model for the cardiovascular system assisted by an IRBP was verified in [3].

The problem of noninvasive estimation of inlet pressure (P_{in}) in an IRBP has not been frequently studied, possibly because of its highly variable nature especially during abnormal pumping states such as ventricular collapse where, for example, the inlet pressure (P_{in}) during the diastolic period in VentrAssist^{TM} (Ventracor Limited, Sydney, Australia) left ventricular assist device (LVAD) may be as low as -160 mmHg, and varies between ± 10 mmHg during normal pump operation. During diastole, inlet pressure (P_{in}) and left ventricular (LV) end diastolic pressure, i.e. preload to the LV, are closely related. In normal humans, the operation of the heart satisfies the Frank-Starling mechanism, i.e. the stroke volume depends on LV end diastolic volume. Therefore, one design requirement of IRBPs is to simulate the Frank-Starling law. On the other hand, in heart failure patients with an LV assisted by an IRBP, when the volume in the LV is low, inlet pressure (P_{in}) will automatically decrease and this may cause suction if the same target speed were to be maintained. To ensure patient safety, a control system that effectively detects and thus avoids such undesired pumping states is needed. This shows one example that makes the noninvasive estimation of inlet pressure of utmost importance for a pump control strategy. For instance, the proposed model could provide a definitive input for a controller to prevent highly negative pressures in the LV and thus autoregulate the pump impeller speed to avoid suction. Unlike [4], where invasive sensors were employed to measure inlet pressure and then used it as an input to a controller, a new dynamical autoregressive with exogenous inputs (ARX) model to noninvasively estimate average inlet pressure in an IRBP during the diastolic period is proposed. The resulting model is simple and stable which offers a tractable control design problem. Furthermore, the model was validated and verified using *in vivo* animal data obtained from acute implantation of a VentrAssist^{TM} LVAD in greyhound dogs under heart failure conditions.

Experimental data: VentrAssist^{TM} LVAD was acutely implanted in four healthy dogs. The inflow pump cannula was inserted into the apex of the LV while the outflow cannula was anastomosed to the ascending aorta. The dogs were instrumented with indwelling catheters (Dwellcath, Tuta Labs, Lane Cave, NSW, Australia) to measure the left ventricular (LVP), left atrial (LAP), aortic (AoP), pulmonary arterial (PAP), central venous (CVP), inlet (P_{in}) and outlet pressures (P_{out}). Aortic valve (Q_{ao}) and pump (Q_p) flows were measured by ultrasonic flow probes (Transonic Systems Inc., Ithaca, NY, USA). Q_p, P_{out}, and P_{in} were obtained near the outlet and inlet of the pump. Also, the instantaneous pump speed (ω), motor current (I), supply voltage (V) and pulse width modulation (PWM) were continuously monitored from the pump controller.

As an acute model of heart failure, and to reduce the cardiac contractility, the beta blocker (metoprolol) was administrated until the total cardiac output fell to approximately 50% of its baseline. Changes in blood volume were introduced by varying the rate of a cardiotomy suction machine. Responses to three different blood volume levels – low, medium, and high – were studied. For every volume level, each dog underwent several speed ramp tests in which impeller speed was increased from 1250 to 3000 rpm in a stepwise increment of 100 rpm, with each step lasting for 30 seconds. Blood samples were also taken regularly during the experiments for measurements of the hematocrit (HCT) values. Recorded data were sampled at 4 kHz, but in further analysis the data were downsampled to 50 Hz.

Dynamical modelling and system identification: We introduce a variable $f(k)$ as follows: $f(k) = g(P(k), \omega(k))$, where $g(P(k), \omega(k)) = a + bP(k) + cP^2(k) + dP^3(k) + e\omega(k) + g\omega^2(k)$ represents the right-hand side of a previously designed and verified static flow estimator (Q_{ss}) describing the pump in steady state as follows [5, 6]: $Q_{ss} = a + bP + cP^2 + dP^3 + e\omega + g\omega^2$. Here, k is the discrete time satisfying $t = kh$, $h > 0$ is the sampling interval equal to 0.02s, $P(k)$ is the input power ($P(k) = V(k)I(k)$ is the product of supply voltage ($V(k)$) and motor current ($I(k)$)), ω is the rotational speed, a, b, c, d, e, and g are functions of viscosity levels [5].

Now, a multi-input ARX model of the form is introduced as follows: $\hat{P}_{in}(k) + \sum_{i=1}^{n} b_i \hat{P}_{in}(k-i) = \sum_{j=1}^{4} \sum_{i=1}^{m_j} c_{ij} u_j(k-i+1) + e_1(k)$, where $\hat{P}_{in}(k)$ is the output of the system which represents the estimated mean pump inlet pressure during the diastolic period of the cardiac cycle, n is the model output order, m_j is the model inputs order, b_j and c_{ij} are the output and input parameter coefficients of the model, respectively, $e_1(k)$ represents the model error, and $u_j(k)$ are four exogenous inputs defined as follows: $u_1(k) = \bar{P}(k)$, $u_2(k) = \sqrt{\bar{\omega}(k)}$, $u_3 = \bar{f}(k)$, and $u_4 = \overline{PWM}(k)\bar{f}(k)$. Here, $\bar{P}(k)$ is the mean motor power, $\bar{\omega}(k)$ is the mean rotational speed, $\bar{f}(k)$ is the steady-state average flow, and $\overline{PWM}(k)$ is the mean pulse-width modulation signal during the diastolic period. Also, we assume that $m_1 = m_2 = \cdots = m_4 = m$.

The parameter coefficients b_i and c_{ij} of the model were identified using an off-line least squares method [7]. The measured data of P_{in}, P, ω, PWM, and f obtained from each animal were averaged during the diastolic period (T_{Dias}) of the heart, as shown in Fig. 1. Data were divided into two sets: one set was used for system identification while the other was used to validate the model. The first set of data consisted of one greyhound experiment corresponding to the three blood volume level changes (low, medium, high), while the other set contained data obtained from the other three experiments.

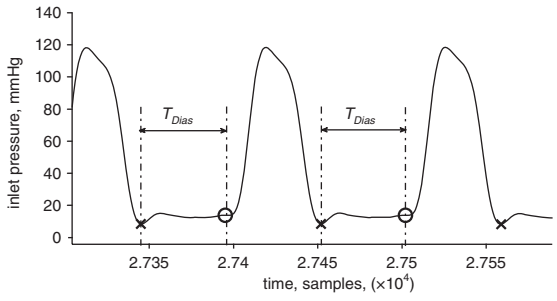

Fig. 1 *Extracted diastolic period (T_{Dias}) where 'x' and 'o' represent starting and end of period, respectively*

Values of parameter coefficients of the model were chosen so that the mean absolute error (e) between $\hat{P}_{in}(k)$ and $P_{in}(k)$ was minimised with highest correlation coefficient (R). n and m were chosen across a range of 1 to 10. The delay value was determined by estimating the impulse response of the system using cross-correlation analysis between the input and output signals. Values of e and R between $\hat{P}_{in}(k)$ and $P_{in}(k)$ were evaluated as follows: $e = (1/N)\sum_{i=1}^{N} (P_{in}(k) - \hat{P}_{in}(k))^2$, $R = (\sum_{i=1}^{N}(P_{in}(k) - \overline{P_{in}})(\hat{P}_{in}(k) - \overline{\hat{P}_{in}}))/(\sum_{i=1}^{N}(P_{in}(k) - \overline{P_{in}})^2) \sum_{i=1}^{N}(\hat{P}_{in}(K) - \overline{\hat{P}_{in}})^2)^{1/2}$. Here, N is the length of the data. $\overline{\hat{P}_{in}}$ and $\overline{P_{in}}$ are the mean values of the estimated and measured data, respectively.

Experimental results: System model orders of $n = 3$, $m = 3$, and delay value = 2 gave the minimal e and highest R values between $\hat{P}_{in}$ and P_{in}. The resulting system model is described by the following difference equation: $\hat{P}_{in}(k) = \sum_{j=1}^{4} \sum_{i=1}^{3} c_{ij} u_j(k-i+1) - \sum_{i=1}^{3} b_i \hat{P}_{in}(k-i) + e_1(k)$. Here c_{11}, c_{12}, c_{13}, c_{14}, c_{21}, c_{22}, c_{23}, c_{24}, c_{31}, c_{32}, c_{33}, and c_{34} are constants with values of -0.92600, -0.51517, 0.10960, -0.000665, 0.4683, 0.3625, 0.5384, -0.01216, 0.462, -0.2097, -0.4774, and 0.00987, respectively, $b_i = [-1.119 \quad 0.580 \quad -0.447]^T$, and u_j represents the four exogenous inputs previously defined.

The model was validated and verified using three *in vivo* greyhound experiments. The plot of estimated against measured mean inlet pressures while blood volume was changed from low, to medium, to high levels is shown in Fig. 2. Data were concatenated to facilitate the study of the transient response of the model. The model was able to accurately estimate and track changes in the measured mean inlet pressure with stable transient response at each volume change. Linear regression analysis between measured and estimated mean inlet pressure obtained from three dog experiments is illustrated in Fig. 3. A highly significant correlation coefficient ($R^2 = 0.957$, $P < 0.001$) between P_{in} and $\hat{P}_{in}$ with small mean absolute error value ($e = 2.292$ mmHg) was obtained. Furthermore, the mean slope of the linear regression line was very close to unity (1.169) with an offset value of 0.959.

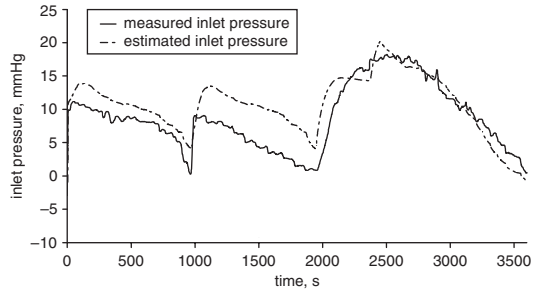

Fig. 2 *Estimated mean inlet pressure compared with measured pressure obtained in one animal. Blood volume was changed from low to medium at t = 990s, and from medium to high at t = 1980s*

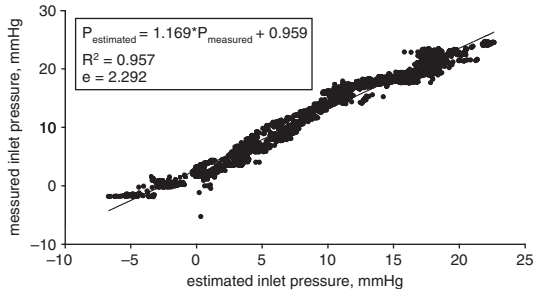

Fig. 3 *Linear regression plot of estimated against measured mean inlet pressure obtained from greyhound data (N = 3)*

Conclusion: A dynamical model for noninvasive estimation of mean inlet pressure during the diastolic period in an IRBP is proposed. Results show that the proposed model is able to track the variation in mean inlet pressure accurately during blood volume changes, with minimal error and stable transient response in the presence of model uncertainties. The model will play a crucial role in designing a robust and automatic controller to control and regulate inlet pressure within a predefined physiologically realistic limit.

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One or more of the Figures in this Letter are available in colour online.

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References

1 Alomari, A.H., Savkin, A.V., Karantonis, D.M., Lim, E., and Lovell, N.H.: 'Non-invasive estimation of pulsatile flow and differential pressure in an implantable rotary blood pump for heart failure patients', *Physiol. Meas.*, 2009, **30**, pp. 371–386

2 Lim, E., Alomari, A.H., Savkin, A.V., and Lovell, N.H.: 'Noninvasive deadbeat control of an implantable rotary blood pump: a simulation study'. Proc. 31st Annual Int. IEEE Engineering in Medicine and Biology Society Conf., Minneapolis, MN, USA, 2009, pp. 2855–2858

3 Lim, E., Dokos, S., Cloherty, S.L., Salamonsen, R.F., Mason, D.G., Reizes, J.A., and Lovell, N.H.: 'Parameter-optimized model of cardiovascular-rotary blood pump interactions', *IEEE Trans. Biomed. Eng.*, 2010, **57**, (2), pp. 254–266

4 Bullister, E., Reich, S., and Sluetz, J.: 'Physiologic control algorithms for rotary blood pumps using pressure sensor input', *Artif. Org.*, 2002, **26**, pp. 931–938

5 Malagutti, N., Karantonis, D.M., Cloherty, S.L., Ayre, P.J., Mason, D.G., Salamonsen, R.F., and Lovell, N.H.: 'Non-invasive average flow estimation for an implantable rotary blood pump: a new algorithm incorporating the role of blood viscosity', *Artif. Org.*, 2007, **31**, pp. 45–52

6 Ayre, P.J., Lovell, N.H., and Woodard, J.C.: 'Non-invasive flow estimation in an implantable rotary blood pump: a study considering non-pulsatile and pulsatile flow', *Physiol. Meas.*, 2003, **24**, pp. 179–198

7 Ljung, L.: 'System identification: theory for the user' (Prentice-Hall, Englewood Cliffs, NJ, 1999, 2nd edn.)