Volume 3, Issue 11, November 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

A Hierarchical Self- Organizing fuzzy logic Control to Control Anesthesia using Weiner Models

Joeeta Anurag Tomer*
Applied Mathematics, R.C.E.T, Bhilai. India

Dr.R.P Dubey
Dr.C.V.Raman University, Bilaspur India

Dr.Ashok Sonkar
Senior Anesthetist, Raipur India

Abstract*— *In the use of multivariable Self- organizing fuzzy logic control (SOFLC) with absolute output to control anaesthesia in operation theatre, different set points need different scale factors or rule bases. In the standard SOFLC structure, the Performance Index table (P.I) is fixed which makes the system inefficient in terms of performance. In this paper a new SOFLC structure with dynamic Performance Index table is proposed. Simulation results shows that the new proposed SOFLC structure is superior to the traditional structure in terms of performance with regards to selection of scaling factors. The mathematical model used is the Wiener Model and simulation of the Wiener Model for the Neuro Muscular Blockade (NMB) has also been discussed.

Keywords*— *Self-organizing fuzzy logic control (SOFLC),Neuro Muscular Blockade (NMB), Bispectral Index (BIS),Performance Index Table (P.I),Wiener Model, Relative Gain Array (RGA).

I. INTRODUCTION

Over the years, SOFLC has been used as a control methodology [1-2].But when using fuzzy logic to control anaesthesia, the choice of relevant scale factors prior to fuzzification and subsequent to defuzzification is a problem [3].When rule bases are established with absolute outputs for a specific set of set points, then the controller using this set of rule bases and scaling factors only can control anaesthesia system to a designated set point. The set points can be changed only by changing the rule bases and resetting the suitable scaling factors. But since human body is a highly nonlinear system, it is very difficult to modify rule bases and scaling factors. This problem is solved by using a dynamic Performance Index table. If the changing magnitudes of anaesthetics are chosen as the outputs of the control, then the control can find the fitting amount of drug by itself. But the SOFLC is in itself incapable of controlling the anaesthesia system [2].As a result, the enhanced SOFLC with Relative Gain Array (RGA) and third order filter is used.

II. The Multi variable Self-Organizing Fuzzy Logic structure.

Self-organizing Fuzzy Logic control is a two level hierarchical controller. The basic level is a simple fuzzy logic control, while the second level is a self-organizing level that supervises the basic level by monitoring its performance, subsequently generating and modifying the control rules. By incorporating a self learning layer to the fuzzy logic controller, self learning can be performed real time in clinical situations[5],[6],[7].Since it is unsafe to start control with a blank rule base, because the output value may move to a region of the fuzzy rule base where no control rule is available. But a self organizing hierarchical controller starts with a previous rule base to ensure safety and calculates the rule possibilities from the previous rule base and modifies recently generated control rules. The recently generated rule base carries more weight and is thus more relevant. This helps eliminate steady state error and improves the controller performance.

SOFLC is an extension of a simple fuzzy logic controller which incorporates
(1) The previous rule-base generator.
(2) Performance index
(3) Rule-base modification algorithm
(4) The control rule-base performance measure.

III. Mathematical modelling of a patient under anaesthesia-

Anaesthesia comprises of the triad of muscle relaxation, unconsciousness and analgesia. Here analgesia is a post operative condition, so muscle relaxation, unconsciousness is considered as the inputs for the controller. Muscle relaxation is obtained by using atracurium and unconsciousness is obtained by using isoflurane.The output is measured using Neuro Muscular Blockade (NMB) and BiSpectral Index (BIS).In this paper ,the Wiener Model has been considered. A Single Input Single Output (SISO) model has been considered for NMB and Multiple Input and Single Output (MISO) model for the BIS.As a result of the declining structure of the Wiener Models it is impossible to track the linear dynamics independently of the static nonlinearity [8].So independent parameterizations of the two blocks are used to reach a unique system parametrization.This is done by choosing a linear dynamic block. The differential static gain is then estimated by the parameters that are to be adapted in the nonlinear block. Hence partitioning of the partition vector Θ is given by Θ $=[\theta_l^T \quad \theta_n^T]^T$ ....(1)

Where θ_l parameters to be identified in the linear are block and θ_n are parameters to be identified in the nonlinear block.

The Neuro Muscular Blockade-

Minimally parameterized model-

The SISO Wiener model describing the effect of the muscle relaxant atracurium in the NMB [9] is presented in Fig.1

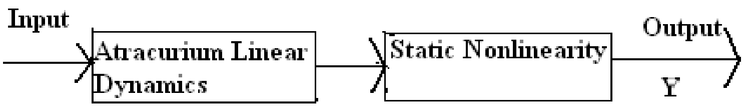

Fig.1 Block Diagram of SISO Wiener Model

In the frequency domain, the linear dynamics can be represented by

$$\hat{Y}_a^{\,c}(s,\theta_l)= \frac{k_1k_2k_3\alpha^3}{(s+k_1\alpha)(s+k_2\alpha)(s+k_3\alpha)}\, U_\alpha(s) \quad \ldots\ldots\ldots\ldots\ldots \quad (2)$$

Where $\hat{Y}_a^{\,c}(s,\theta_l)$ is the Laplace transform of the time output $\hat{Y}_a^{\,c}(t,\ \theta_l)$ and $U_\alpha(s)$ is the Laplace transform of the time input signal $U_\alpha(t)$.The parameter θ_l= α is defined as the variability of the patients dynamics. The value of the constants $k_i\{i = 1,2,3\}$ are chosen as 1,4,10 respectively [9].

The proposed model structure in (2) was sampled using Zero- Order hold method as in 1/3 min^{-1}, which corresponds to the fact that data acquisition takes place every 20
seconds in an operation theatre.

Thus the discrete time model is given by

$$\hat{Y}_a(t,\theta_l) = \frac{B(q^{-1},\theta_l)}{A((q^{-1},\theta_l))}\, U_a(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where $\hat{\boldsymbol{Y}}_{\boldsymbol{a}}(\boldsymbol{t},\boldsymbol{\theta}_{\boldsymbol{l}})$ is output of linear dynamic block , $\boldsymbol{U}_{\boldsymbol{a}}(\boldsymbol{t})$ is input signal,$\boldsymbol{q}^{-1}$ is backward shift operator. From the Hill Equation [11] ,we have

$$\hat{\boldsymbol{Y}}(\boldsymbol{\theta}_n, \hat{\boldsymbol{y}}_a(\boldsymbol{t},\ \boldsymbol{\theta}_l)) = \frac{100\, C^{\gamma}50}{C^{\gamma}50 + (\hat{y}_a(t,\theta_1))^{\gamma}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The Bispectral Index-

Minimally parameterized model-

The Wiener Model describing the combined effect of the hypnotic drug Isoflurane and the opiod remifentanil [10] is shown in Fig.2

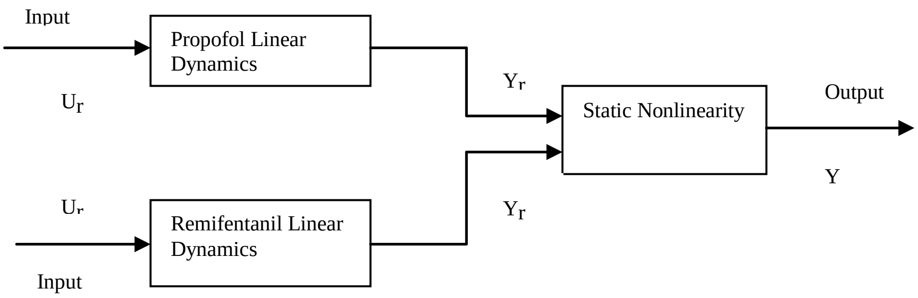

Fig.2 Block Diagram of BIS MISO Wiener Model

Isoflurane linear dynamics is given by

$$\hat{Y}_a^{\,c}(s,\theta_l)= \frac{d_1\, dk_2 d_3\chi^3}{(s+d_1\chi)(s+d_2\chi)(s+d_3\chi)}\, U_\alpha(s) \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

Where $\hat{Y}_a^{\,c}(s,\theta_l)$ is the Laplace Transform of $\hat{Y}_a^{\,c}(t,\theta_l)$,$U_p(t)$,χ is the pole location to be determined. The constants $d_i\{i = 1,2,3\}$ were chosen as Remifentanil Linear dynamics [10], which can be similarly modelled as

$$\hat{Y}_r^{\,c}(s,\theta_l)= \frac{l_1l_2l_3\alpha^3}{(s+l_1\eta)(s+l_2\eta)(s+l_3\eta)}\, U_r(s) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where $\hat{Y}_r^{\,c}(s,\theta_l)$ is the Laplace Transform of $\hat{Y}_r^{\,c}(t,\theta_l)$.$U_r(s)$ is the Laplace Transform of $U_r(t)$, $\eta$is the pole location to be determined. The constants $l_i\{i = 1,2,3\}$ were chosen as [10].So

$$\theta_l = [\chi \quad \eta]^T \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

Simulation results for The Wiener Model-

The NMB data has a record of 50 patients and was controlled using closed loop [11].The muscle relaxant was administered intravenously so as to keep the NMB around 10% of the induction stage. For the NMB, k =20000,β = 0.1 and 1 as diagonal elements(to facilitate the convergence of α and γ in Θ), and $\overline{\theta^{(0)}} = [0.5 \quad 2.0]^T$ For the BIS,k = 200000, β = 0.01,0.01,0.5 and 0.3 as diagonal elements and $\overline{\theta^{(0)}} = [0.4 \quad 0.8 \quad 1.5 \quad 1.0]^T$.

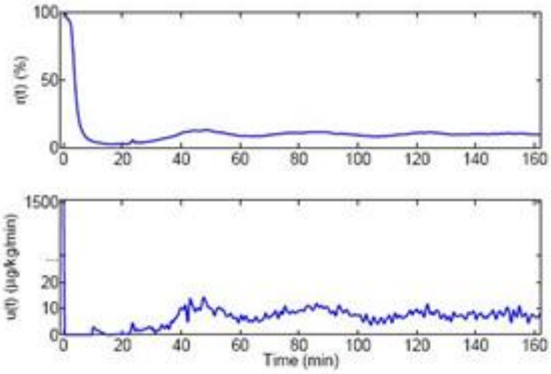

Fig.3 Measured NMB response (Upper Plot) and muscle relaxant Atracurium (Lower Plot).

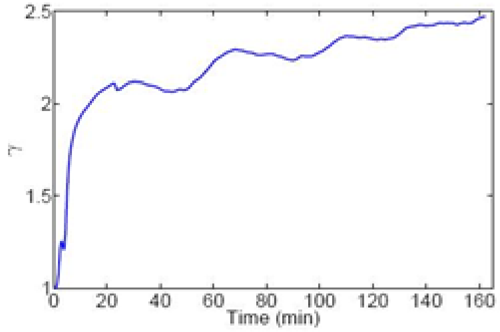

Fig.4 Time evolution of the parameter of the non linear block of the NMB Wiener model.

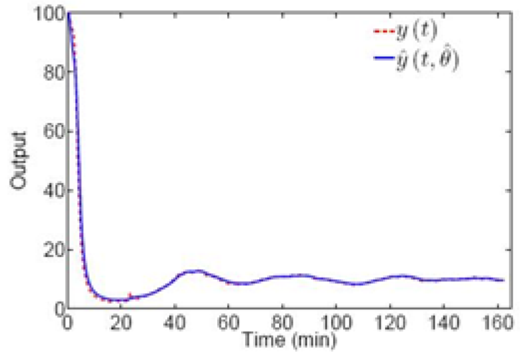

Fig.5 Time evolution of clinical and identified NMB level.

Design Methodology of the multi-drug SOFLC-

Self- organizing fuzzy logic control works on the principle of continuous performance evaluation and rule modification as proposed in [11].The error and change in error are taken as the inputs and the output will be the change in control action. The basic structure of a SOFLC is as shown

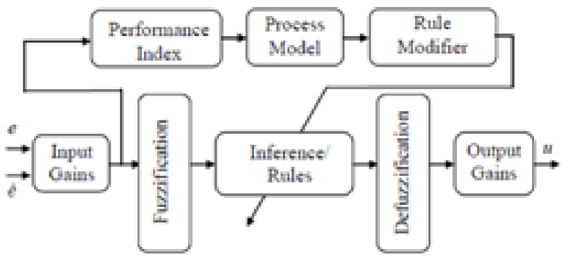

Fig.6 Basic structure of SOFLC

Here e and $\dot{e}$ denote error and change in error respectively, and U is controller output. The inputs and outputs are adjusted according to trial and error. The performance index or PI is usually in the form of rules which point t towards the correction required to control the output and thus automatically the fuzzy rule-base. As such to necessitate the correction required, some previous knowledge of power plant is required. The adjustment is as follows-

$$F(i,j)_{n-d} = F(i,j)_{n-d} + PI(i,j)_{n-d} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

Where F is fuzzy rule base
i,j are indices corresponding to current error and change of error
PI is performance Index
n is current sample
d is delay
A third order polynomial filter with an intake of 20 samples was used to improve the performance of the SOFLC.Polynomial filters use least-square fitting method, whose general form is given by

$$P(x) = \sum_{i=1}^{m} c_k \, \emptyset_k(x) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

Where $\emptyset_k(x)$ is the k^{th} order polynomial function and $c_1, c_2, \ldots\ldots\ldots\ldots c_m$ can be obtained by solving the equation

$$\frac{\partial E}{\partial c_j} = \sum_{k=1}^{m} 2\left[\sum_{i=1}^{m} C_i \emptyset_i\big(x(k)\big) - y(k)\right] \emptyset_j\big(x(k)\big) = 0 \quad \ldots\ldots\ldots\ldots \quad (10)$$

$$E = \sum_{k=1}^{m}\left[\sum_{i=1}^{m} C_i \emptyset_i\big(x(k)\big) - y(k)\right]^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (11)$$

Aset of n samples is used to calculate y(k) where k= 1,2…………t.The smoothed value is given by $\hat{y}(t) = \sum_{i=1}^{m} c_i \, \emptyset_i\big(x(t)\big)$ from previous values. The difference between smoothed value $\hat{y}(t)$ and its previous derivative $\hat{y}(t-1)$ are used in the control mechanism.

Most of the drugs have direct effect on their sites of action, however there maybe some other vital parameters. In case of multi-variable control such kind of interaction can give rise to two undesirable situations –
Controller tuning may become very difficult.
The main loops may cross couple which in turn may lead to large output fluctuations.
As a means of measuring control interaction and subsequently reducing its effect Relative Gain Array [12] was proposed. The RGA for a system of n inputs and n output can be defined as follows:

$$\begin{bmatrix} \lambda_{11} & \lambda_{12} & . & . & \lambda_{1n} \\ \lambda_{21} & & & & \lambda_{2n} \\ . & & & & . \\ . & & & & . \\ \lambda_{n1} & \lambda_{n2} & . & . & \lambda_{nn} \end{bmatrix}$$

Where $\lambda_{ij} = \dfrac{\text{Open loop gain between } y_i \text{ and } u_j}{\text{Closed loop gain between } y_i \text{ and } u_j}$

For example for a two input/two output system λ_{11} can be defined as follows-

$$\lambda_{11} = \frac{1}{1 - \frac{k_{12}}{k_{11}} \frac{k_{21}}{k_{22}}}$$

where $k_{11} = \frac{\Delta_{y1}}{\Delta_{u1}}$ with respect to u_2

$k_{12} = \frac{\Delta_{y1}}{\Delta_{u2}}$ with respect to u_2

$k_{21} = \frac{\Delta_{y2}}{\Delta_{u1}}$ with respect to u_2

$k_{22} = \frac{\Delta_{y2}}{\Delta_{u2}}$ with respect to u_2

In spite of the fact that RGA is a powerful tool of measuring and controlling loop interactions, it does have noticeable weaknesses. This method does not provide perfect decoupling as it assumes a linearised model at some operating point.

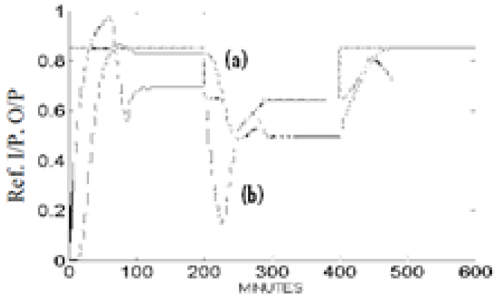

Fig.7 (a) Input Signal I/P (b) Output signal O/P using standard SOFLC algorithm.

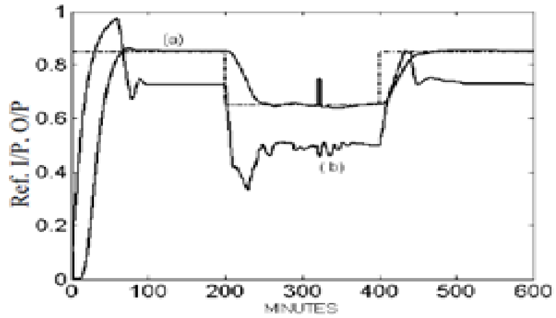

Fig.8 Closed loop simulation using the new RGA-SOFLC with added noise.(a) Output Signal (b)Input Signal.

Conclusion

The performance index table (P.I) fails to control the output as such the fuzzy controller infers the wrong output. However the new method of using polynomial filters removes this hurdle. As such this scheme is superior to the standard SOFLC algorithm with regards to the performance in both the transient and steady state phases and also in terms of robustness against disturbances and the choice of the scaling factors which play a vital role in fuzzy logic based control.

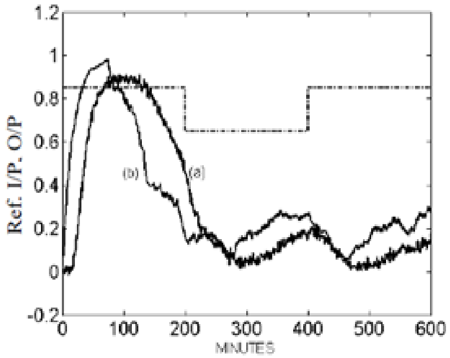

Fig.9 Closed control simulation with added noise to the output. (a) Output Signal (b)Input Signal.

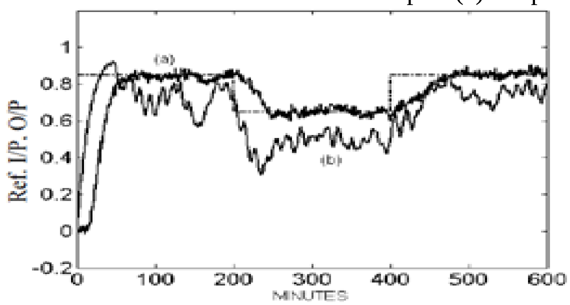

Fig.10 Simulation result of the new SOFLC using third order filter. (a) Output Signal (b)Input Signal.

References

[1] J.S. Shieh, M.F. Abbod, C.Y. Hsu, S.J. Huang, Y Han and S.Z. Fan,"Monitoring and control of anesthesia using multi variable self-organising fuzzy logic structure," *Fuzzy Systems in Bioinformatics*,Yaochu Jin and Lipo Wang (Eds.),Bioengineering and Computational Intellignce Springer's Book Series on Studies in Computational Intelligence, 2008.

[2] E.D Krishna,Y.C.Chou,J.S.Shieh,M.F.Abbod,C.Y.Hsu," The Simulation of Controlling of anaesthesia Using Multi-Variable Self-Organizing Fuzzy Logic Structure",*CACS International Conference* 2008.

[3] D.A.Linkens,"Adaptive and Intelligent Control in Anesthesia,"*IEEE Control Systems*,Mag. 1992,pp.6-11.

[4] T.J.Procyk,E.H.Mamdani," A linguistic self-organizing process controller",*Automatica* 1979,15(2),pp.15–30.

[5] D.A.Linkens,S.B.Hasnain,"Self-organizing fuzzy logic control and application to muscle relaxant anaesthesia", *IEEE Proceedings* 1991,*Part D* ,pp.274–284.

[6] J.J.Ross,D.G.Linkens and N.D.Edwards," Self-learning fuzzy logic control of neuromuscular block. *British Journal of Anaesthesia* 1997- *78*,pp.412–415.

[7] D.G.Mason,J.J.Ross,N.D.Edwards,D.A.Linkens,C.S.Reilly,"Self-learning fuzzy control of atracurium-induced neuromuscular block during surgery", *Medical & Biological Engineering & Computing* 1997,*35*,pp. 498–503.

[8] M.M.dasilva Prediction error identification of minimally parameterized Wiener models in anesthesia,*18th IFAC World Congress Milano*,2011.

[9] M.M.Silva,T.Wigren,T.Mendonca,"Nonlinear identification of a minimal Neuromuscular Blockade model in Anesthesia", *IEEE Trans. Contr. Sys. Tech.* 2012; 20(1),pp. 181-188.

[10] M.M.Silva,T.Wigren,T.Mendonca, "Identification of the BIS and SE in anaesthesia using a new minimally parameterized nonlinear MIMO model",.*Int. J. Adaptive, Control, Signal Processing* 2010.

[11] H.Derendorf,B.Meibohm,"Modeling of Pharmacokinetic/Pharmacodynamic (PK/PD) relationships concepts and perspectives. *Pharmaceutical Research* 1999, 16(2),pp. 176–185

[12] J.W.Johansen., P.S.Sebel," Development and clinical application of electroencephalographic bispectrum monitoring",*Anesthesiology* 2000,,pp.1336–1344.

[13] T.Mendonça J.Lemos, H.Magalhães, P.Rocha,and S.Esteves,"Drug delivery for neuromuscular blockade with supervised multimodel adaptive control", *IEEE Transactions on Control Systems Technology* 2009; 17(6),pp.1237 –1244.

[14] T.Mendonça,H.Magalhães,P.Lago,and S.Esteves,"Hipocrates: a robust system for the control of neuromuscular blockade", *Journal of Clinical Monitoring and Computing* 2004;18(1),pp.265–273.

[15] T.Söderström,P. Stoica,"*System Identification*, Prentice-Hall, Hemel Hempstead, UK.

[16] J.Sigl, N.Chamoun ,"An introduction to bispectral analysis for the electroencephalogram",*Journal of Clinical Monitoring and Computing* 1989;10(1),pp. 392–404.

[17] M.M. Silva, T.Mendonça and T.Wigren," Online nonlinear identification of the effect of drugs in anaesthesia using a minimal parameterization and BIS measurements", In *Proc. American Control Conference (ACC'10)* 2010a ,pp.4379–4384, Baltimore, USA.

[18] M.M.Silva, T.Wigren, T.Mendonça ,"Nonlinear identification of the human response to anaesthesia by the use of BIS measurements",*Technical Report* 2010-008, Available: Dept. Information Technology, Uppsala University, Uppsala, Sweden, (2010b).

[18] M.M.Silva,T.Wigren and T.Mendonça," Nonlinear identification of a minimal neuromuscular blockade *model in anesthesia", IEEE Transactions on Control Systems Technology, 2011.*

[19] B.Weatherley,S. Williams,E.Neill,"Pharmacokinetics, pharmacodynamics and dose-response relationships of atracurium administered",. *Br. J. Anaesth* 1983, 55,pp.39–45.

[20] T.Wigren Recursive prediction error identification method using the nonlinear Wiener model", *Automatica* 1993,29(4),pp.1011–1025,

[21] M.Mahfouf,O. King,M.Denai,J.J.Ross,L.U.Quing,"A Hierarchical Self- Organizing Fuzzy Logic-Based-On-Line Advisor for Management of Cardiac Septic Patients",.*18th IFAC World Congress,Milan,Italy*,2010;18(1).

[21] M.M.Silva," Prediction error identification of minimally parameterized wiener models in anesthesia",*18th IFAC World Congress Italy* 2011.

[22] R.P.Dellinger,"Cardiovascular Management of Septic Shock", *Crit Care Med* 2003; **31(3)**,pp.946-955.

[23] E.J.Bridges,S. Dukes," Cardiovascular Aspects of Septic Shock: path physiology, monitoring, and treatment", *Crit. Care Nurse* 2005; **25(2)**,pp. 14-42.

[24] J.E.Parrillo," The Cardiovascular Pathophysiology of Sepsis", *Annual Rev Med.* 1989; **40**:pp.469–485.

[25] M.P.W.Grocott and M.G.Mythen," Fluid Administration in Septic Shock", *Sepsis* 2001; 2,pp.111-124.

[26] D.G.Mason ,"Comprehensive Circulatory Management of Seriously Ill patients with a Closed-loop System", *PhD Thesis for Dept of Electrical and Electronic Engineering*, University of Melbourne 1989..

[27] S.L.Xie,R.K.Reed,B.D Bowen and J.L. Bert," A Model of Human Microvascular Exchange", *Microvascular Research* 1995., **49(2)**, pp.141-62.

