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Original Article

A new immune-LQI controller to regulate dialysate conductivity

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Abstract

Dialysate conductivity regulation is the most important factor behind a successful dialysis. In this study, a new Immune-LQI controller was designed to regulate the dialysate conductivity. Linear Quadratic Integrator (LQI), Immune Control (IC), Fuzzy Logic (FL) and Genetic Algorithm (GA) were used. The new controller combines LQI and IC methods, and the IC gains were adjusted using FL and GA. For the purpose of comparison, a number of controllers (Proportional Integral Derivative (PID), LQI, and LQI-PID) were designed. The results showed that Immune-LQI controller was the best as it gave a 10% improvement in rise time, 66% in overshoot, and 42.7% in settling time, when compared with LQI.

Keywords: linear quadratic integrator controller, immune controller, fuzzy logic controller, conductivity model

1. Introduction

The morbidity and mortality rates of patients on renal dialysis therapy are influenced by a number of factors such as age, underlying diseases and the quality of hemodialysis (Uwe-Rainer *et al.*, 2001). Dialysis aims to remove waste products, such as toxins (e.g., urea) and excess solution that accumulate in the body due to inadequate kidney function. It maintains the safe levels of certain electrolytes such as potassium, sodium and bicarbonate (Ahmad, 2013a).

Two essential components are required for blood purification by dialysis: a semipermeable membrane and a plasma-water-like solution called dialysis solution or dialysate. Dialysate is a chemical solution that is prepared carefully and accurately (Ledebo, 2002). The preparation of the dialysate is of high importance for the success of blood purification. To prepare the dialysate, two concentrated components (acid and bicarbonate) are added simultaneously to treated water by using pumps. The addition of concentrate components is critical because if the permissible values are exceeded, the electrolyte transfer will be reversed to go from the dialysate to the blood. The dialysate quality is checked by monitoring its conductivity, which represents the concentrations of electrolytes in the dialysate (measured in mS/cm). The conductivity is usually kept constant during the dialysis session by continuously monitoring and controlling it (Ahmad, 2013b).

The immune system is a naturally occurring event response system. It is our primary defense against pathogens and it can adapt to changing situations. The efficiency of a biological immune system depends on in its ability to remember (it remembers past encounters, which leads to a fast response the second time around), classify, and neutralize the effects of foreign objects. When the body is attacked by a foreign antigen, the immune system can produce a corresponding antibody to resist the antigen through a series of biological reactions (Janis, 1997). The Artificial Immune System (AIS) is an adaptive system that is inspired by theoretical immunology and by observed immune functions. Principles and models of AIS are used to solve complex problems in new fields of computer science, control, and communication (Satyasai, 2009).

1.1 Literature review

To overcame a system's nonlinearities and the

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uncertainties in parameters, an optimal design for nonlinear model predictive control based on modified multitracker optimization algorithm was suggested. The new proposed algorithm was applied to a robotic manipulator to track different linear and nonlinear trajectories (Elsisi, 2020c).

Fuzzy Logic Controller (FLC) is very active and robust, especially when dealing with too complicated processes. Fuzzy gain scheduling controllers optimized by genetic algorithm were designed to enhance the quality and reliability of Automatic Generation Control (AGC) of interconnected electrical power systems. (Arya & Kumar, 2016). To improve AGC performance in power systems, artificial intelligence algorithms were widely used to:

1. Improve the performance of traditional PID or PI controllers. For example, to overcame unexpected load disturbances (Arya, Kumar, & Sinha, 2012; Sharma, Dhundhara, Arya, & Prakash, 2021), generation rate constraints, wide variations in nominal loading conditions and in system parameters (Arya & Kumar, 2017; Elsisi, 2020b), changed operating conditions and nonlinearities (Arya, 2020), deviations in the generator speed in wind energy conversion system, and uncertainties in plant parameters (Elsisi, 2020a).

2. Improve the performance of optimal controllers in state space (Arya, Kumar, & Gupta 2017; Dahiya, Mukhijia, Saxena, & Arya, 2017).

3. Improve the performance of adaptive model predictive control (Elsisi, 2019).

The AIS is widely used as a control technique that has strong robustness and self-adaptability in complex disturbed and indeterminate environments. Immune control is an attractive method to improve traditional PID controller. Two self-tuning PID controllers based on fuzzy and immune sciences were designed to control the level of a liquid in three tanks. Simulation results showed that the system's response with the immune PID controller was quicker and with a smaller overshoot than with the conventional PID controller and fuzzy PID (Sharad & Gagandeep, 2011). A PID controller based on immune mechanism was designed to control a robot dexterous hand. GA and fuzzy inference were used to optimize the parameters of the immune PID controller. The simulation results showed that the designed IC was ideal (Xin-hua, Xiao-hu, Xiao-hu, Sheng-peng, & Zhong-ben, 2014). A PID controller was tuned to control DC servo motor speed using AIS algorithm. A comparison with the Ziegler-Nichols tuning method showed that the AIS algorithm had better ability to find the global optimum solution (Muna & Saad, 2016). Three structures of an immune-PID control system were proposed to regulate the heart rate. The controller parameters were optimized using differential evolution algorithm. In the first structure, the PID controller was connected serially with the IC, while in the second one the PID was connected in parallel with the IC. In the third structure, the control signal was considered to be the product of the control signal of PID and that of IC. Comparison between the three structures showed that the performance of the third one was the best (Tariq, Ekhlas, & Eman, 2019). A control system based on IC was used to maintain the thermal comfort while reducing energy consumption. The experimental results showed that the IC was able to regulate the inside air temperature to be more stable than the two-position controller (Jiawei, Fabrice, Abderrafiaa, Vincent, & Marcelo, 2013). A tuning process of PID controller was implemented using an AIS with Social Learning mechanisms (AIS-SL). The solution accuracy and convergence speed of the AIS-SL algorithm was better than those of other algorithms (Mingan, Shuo, Chunhui, Zhonghua, & Yu, 2017).

The concept of conductivity measurement, which has been called the "effective ionic dialysance" method, has been reported since early 1990s. In 1993, two papers were published nearly at the same time, showing that instantaneous ionic dialysance can be measured, without the need for any blood or dialysate sampling and at no extra cost. The measurement was simply done by using two conductivity probes placed at the dialyzer inlet and outlet, or a single probe alternately activated at the outlet (Petitclerc, Goux, Reynier, & Bene, 1993; Polaschegg, 1993). This allows repeated measurements of ionic dialysance, which can be used to obtain the mean value over the dialytic session as a whole (Ahmad, 2013b).

Online conductivity monitoring is a valid, practical, and useful tool, with which one studies the pattern of sodium balance in patients on hemodialysis (Lambie, Taal, Fluck, & McIntyre, 2005). A small number of reaserch papers were found in the literature concerning the control of conductivity. An FLC was used to adjust the parameters of a hemodialysis machine so that the patient's hemodynamic condition remained stable during hemodialysis treatment. This was achieved depending on heart rate, arterial blood pressure, and relative blood volume. The results showed that using FLC can reduce treatment time as well as stabilize the patient's condition (Vahid, Manouchehr, Mohammed, & Fatema, 2019). To regulate conductivity by controlling pumping rates of the two concentrate components (acid and sodium bicarbonate), three controllers (PID, Linear Qauadratic Gaussian (LQG), and Model Predictive Control (MPC)) were designed (Måns, 2016). The results showed that LQG was the most suitable.

1.2 Research gap and motivation

There is a lack of investigations regarding the control of dialysate conductivity. In the above-mentioned research conducted by Måns Fällman (Måns, 2016), an LQG controller, a type of LQI, was designed. The researcher concluded that LQG was the best option compared to other tested controllers. The dialysate was prepared at two separate stages. The first relates to acid pumping and the second relates to sodium bicarbonate. This separation is different to what happens in reality, as the two concentrate components are pumped together at the same time and, hence, the conductivity is based on both.

Most reasearchers who combined artificial intelligence algorithms with conventional control techniques confirmed that these algorithems improve the performance of conventional controllers. This motivated us to use AIS, FL, and GA algorithms in this reaserch to improve the performance of the LQI controller, with use of the new improved controller to prepare the dialysate in one stage.

1.3 Contribution and paper organization

Keeping the importance of regulating dialysate conductivity in mind, due to its crucial role in dialysis, a new controller that combined the optimality of LQI, the accuracy and conversion speed of AIS, and the good adaptivity accomplished by fuzzy logic and genetic algorithm is introduced in this research. The notable novelties of the proposed controller are as follows:

a) Improved performance indices and regulating the conductivity faster and with minimal settling time compared with other control methods used in prior literature.

b) Regulating the conductivity affected by simultaneous pumping of bicarbonate and acid, which is consistent with what happens in the dialysis device in reality, in contrast to previous studies that worked on pumping the two components sequentially.

This paper is organized as follows. Section 2 introduces the mathematical model of the dialysis system with regard to conductivity, gives brief description of the LQI control method, the feedback control structure in the mechanism of immunity, and the proposed optimization technique of immune-LQI controller using FL and GA. Simulation results are presented and discussed in Section 3. The concluding remarks on controller performance are presented in the last section.

2. Materials and Methods

2.1 Conductivity model

In this research, a mathematical model that describes the mechanism of preparing the dialysate in state space was adopted. This mathematical model has been evaluated, and its ability to accurately describe the process of dialysate preparation was verified by Måns Fällman (Måns, 2016). It considers the preparation mechanism as a collection line (Figure 1). The process starts by adding treated (degasification, filtration, etc.) water (called RO-water), then a mixture of charges that are similar to those found in blood (called A-Concentrate) is added. The resulting mixture is pumped into the first chamber. Bicarbonate (called B-Concentrate) is then added and the resulting mixture is pumped into the second chamber. Finally, the conductivity is measured at the output of the second chamber. Each chamber is divided into two sections in order to reduce the effect of disturbances resulting from the pumping action.

The well-known model of a linear system in state space is expressed as follows:

$$\dot{X} = AX + BU,\ Y = CX + DU \tag{1}$$

where X is the system state vector, Y is the output vector, U is the input vector and A, B, C, D are state matrices.

The conductivity model used in our research contains four state variables that represent the conductivity in each of the previously defined four chambers. The output of the model is the final conductivity, i.e. X_4 , and the input vector U has two components: the pumping rates of A (Pu_a) and B (Pu_b):

$$U = \begin{bmatrix} Pu_a \\ Pu_b \end{bmatrix} \tag{2}$$

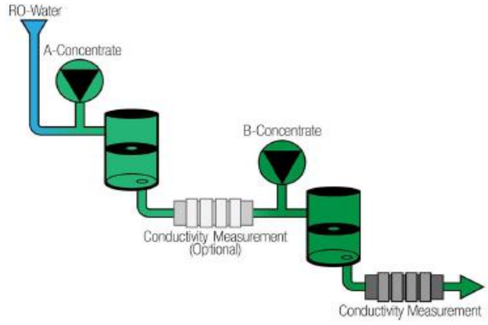

Figure 1. A schematic diagram of dialysate preparation (Måns, 2016)

The state matrices are (Måns, 2016):

$$A = \begin{bmatrix} -\frac{Q}{V1} & 0 & 0 & 0 \\ \frac{Q}{V2} & -\frac{Q}{V2} & 0 & 0 \\ 0 & \frac{Q}{V3} & -\frac{Q}{V3} & 0 \\ 0 & 0 & \frac{Q}{V4} & -\frac{Q}{V4} \end{bmatrix}, B = \begin{bmatrix} \frac{Q}{V1}KA & 0 \\ 0 & 0 \\ 0 & \frac{Q}{V3}KB \\ 0 & 0 \end{bmatrix}, \tag{3}$$

$$C = \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix}, D = \begin{bmatrix} 0 & 0 \end{bmatrix}$$

The symbols used in the model are described in (Table 1).

Table 1. The parameters of the conductivity model

Symbol	Description	Unit
K_A	Acid conductivity	ms/cm
K_B	Bicarbonate conductivity	ms/cm
Q	The main flow of distilled and sterilized water	L/Sec
V_1	The largest volume of the first container	L
V_2	The smallest size of the first container	L
V_3	The largest volume of the second container	L
V_4	The smallest size of the second container	L
Pu_a	Acid pump flow	mL/min
Pu_b	Flow of bicarbonate pump	mL/min

2.2 LQI controller

The linear quadratic regulator (LQR) is an optimal control technique for linear systems. As described in the state space, it depends on reducing the cost function J(u) shown in Equation 4. The solution to the optimization problem, i.e., obtaining the minimum value of the cost function, gives the control law: $U = -KX$, where U is the control signal (controller output), K is the feedback control matrix and X is the system state vector. LQR method is used when the reference input is zero (r = 0), whereas the LQI method is usually used when the reference input is nonzero ($r \neq 0$).

$$j(u) = \int_0^\infty ([X^T(t)QX(t) + U^T(t)RU(t)]\,d(t) \tag{4}$$

The LQI cost function has the form of Equation 5, where Q is the state weighting matrix, R is the control signal weighting matrix, and N is the state and control cross-weighting matrix. When using the LQI technique, the integral of the error ∫e (where e = r-y) is added to the state vector and the control law becomes $U = -KZ$, where $Z = [X \ \int e]^T$. A block diagram of the LQI method is shown in (Figure 2).

$$j(u) = \int_0^\infty [Z^T(t)QZ(t) + U^T(t)RU(t) + 2Z^T(t)NU(t)]dt \quad (5)$$

In our model, the state vector consists of four variables, while the error is the difference between the reference conductivity (r = 14 mS/cm) and the output of the system (y) represents the instantaneous conductivity during preparation of the dialysate. The conductivity should remain in the range 12-16 mS/cm and it is usually maintained at 14 mS/cm in order to obtain a good dialysis process.

The resulting feedback gain matrix K, when solving the LQI problem for our system, is shown in Equation 6. Therefore, the control signal resulting from LQI controller will be as shown in Equation 7.

$$K = \begin{bmatrix} k_{11} & k_{12} & k_{13} & k_{14} & k_{15} \\ k_{21} & k_{22} & k_{23} & k_{24} & k_{25} \end{bmatrix} \quad (6)$$

$$U_{LQI} = \begin{bmatrix} U_a \\ U_b \end{bmatrix} = \begin{bmatrix} k_{11}z_1 + k_{12}z_2 + k_{13}z_3 + k_{14}z_4 + k_{15}z_5 \\ k_{21}z_1 + k_{22}z_2 + k_{23}z_3 + k_{24}z_4 + k_{25}z_5 \end{bmatrix} \quad (7)$$

2.3 Immune controller

Lymphocytes are the basic immune cells. They are produced in the bone marrow and come in two types: T-cells and B-cells. B-cells remain in the bone marrow to mature and specialize, and are responsible for producing antibodies. T-cells travel to the thymus to mature. They are either suppressor T-cells (Ts) or helper T-cells (T_H). When the cell gets a signal from an antigen, it transfers the information to T_H and T_S. Next, B-cells produce corresponding antibodies to get rid of the antigen with stimulation by T_H and T_S (Xin-hua *et al.*, 2014).

There is a kind of feedback control in the mechanism of immunity. Ts inhibits the production of T_H. B-cells are stimulated by T_H and suppressed by Ts. B-cells produce antibodies to resist antigens, which leads to a reduction in the amount of antigen by negative feedback. This process goes on until reaching the state of no antigens. This mechanism is illustrated in (Figure 3).

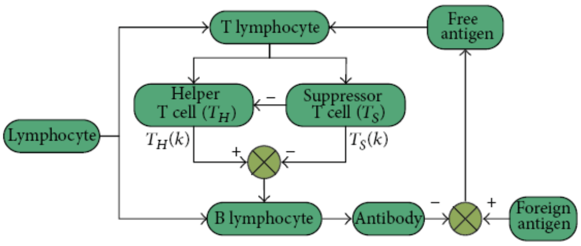

Figure 3. The immunity feedback control mechanism (Xin-hua *et al.*, 2014)

According to the immunity feedback control mechanism, all B-cells that are obtained by the received stimulations are (Xin-hua *et al.*, 2014):

$$B(k) = T_H(k) - T_S(k)$$
$$T_H(k) = k_1\varepsilon(k)$$
$$T_S(k) = k_2 f(B(k), \Delta B(k))\varepsilon(k)$$
$$B(k) = k_1(1 - \mu f(B(k), B(k))\varepsilon(k))$$

where:

$T_H(k)$ is the k^{th} generation output of T_H cell that receives activation from the cell that is damaged by the antigen,
$T_S(k)$ is the k^{th} generation inhibit action on B-cell by T_S cell,
$\varepsilon(k)$ is the k^{th} generation antigen amount,
$k1$ is an enhancement gain factor of T_H cell,
$k2$ is an inhibitory factor of T_S cell,
μ is $k2/k1$,
$f(*)$ is a nonlinear function that describes the immunity interaction between B-cell antibody and the antigen corresponding to the amount of B-cell.

The immune controller is described by Equation 8.

$$u(t) = k(1 - \mu f)e(t) \quad (8)$$

where $k(1-\mu f)$ represents the immune controller gain (Xin-hua *et al.*, 2014).

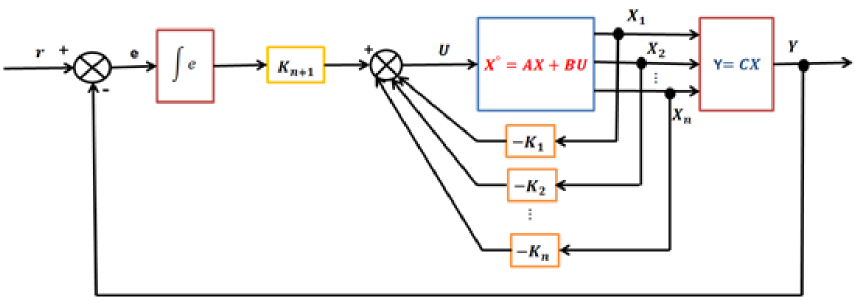

Figure 2. A block diagram of the LQI method

2.4 Optimization of parameters using FL and GA

A block diagram of the closed loop Immune-LQI controlled system is shown in Figure 4. The immune controller is used to improve the output response of the LQI controller, as the output of LQI is multiplied by the immune controller gain. The immune controller gain K_m is given by Equation 9, where k and μ are immune parameters. k improves the time response, μ improves the stability of the control system (Xin-hua *et al.*, 2014) and f is a nonlinear function that depends on the control signal of LQI and its derivative, $f(u, u')$.

$$K_m = k(1-\mu f) \tag{9}$$

Our dialysis conductivity system has two inputs, therefore, it requires two immune gains, as shown in Equations 10.

$$\begin{aligned} km_1 &= k_1(1-\mu_1 f_1) \\ km_2 &= k_2(1-\mu_2 f_2) \end{aligned} \tag{10}$$

There are no analytical methods to obtain the gains of the IC, but it has to be tuned to obtain the optimal values. To achieve this, GA was used to adjust the parameters (k_1, k_2, μ_1, and μ_2) and FL was used to get the functions (f_1 and f_2).

The GA cost function has the form of Equation 11:

$$J(e) = \int_0^{\infty} [w_1 e^2(t) + w_2 u^2 + w_3 t_r + w_4 Mp\%]\, d(t) \tag{11}$$

where $w_1, w_2, w_3, \text{and } w_4$ are the weights of the cost function, e is the error signal, u is the control signal, t_r is the rise time, and Mp% is the percentage overshoot.

Two fuzzy systems were designed to obtain f_1 and f_2. The fuzzy system used in (Xin-hua *et al.*, 2014) was considered. The input variables (u and its derivative u') and the output f were divided into standard Gaussian normally distributed fuzzy values. The rule matrix is presented in Table 2.

3. Results and Discussion

The plant, PID, LQI, and Immune controllers were modeled and simulated using Matlab /Simulation Tool. The two responses of the closed loop when using the LQI and Immune-LQI controllers are shown in Figure 5, and the control signals U_A (Acid pumping rate) and U_B (Bicarbonate pumping rate) from both controllers are shown in Figure 6.

Table 2. The rule matrix of the fuzzy system (Xin-hua *et al.*, 2014)

	U'			
U	NB	NS	PS	PB
NB	PB	PM	PS	ZO
NS	PM	PS	ZO	NS
PS	PS	ZO	NS	NM
PB	ZO	NS	NM	NB

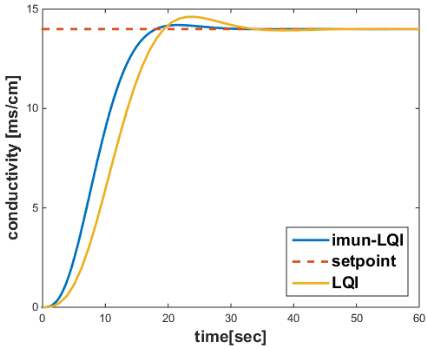

Figure 5. The closed loop responses using LQI and Immune-LQI controllers

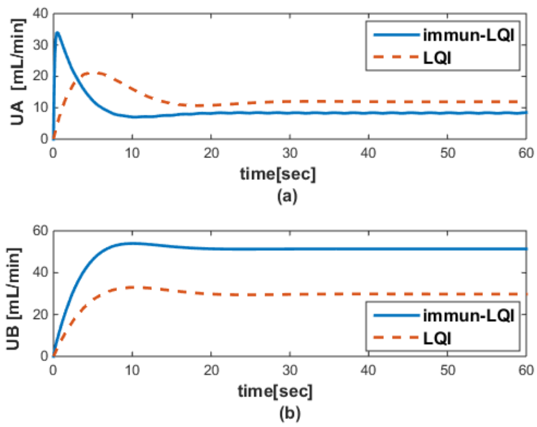

Figure 6. The pumping rates using LQI and Immune-LQI controllers (a) Acid pumping rate (U_A), (b) Bicarbonate pumping rate (U_B)

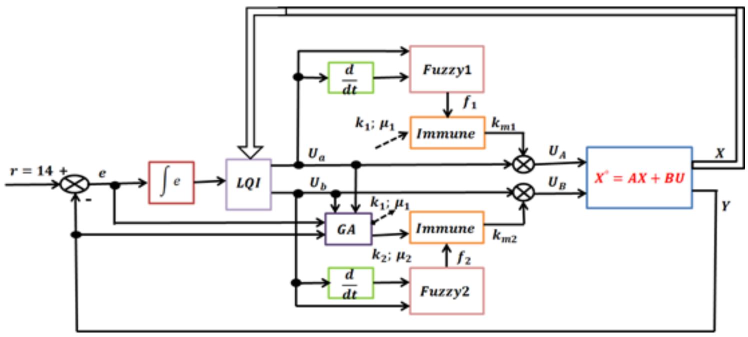

Figure 4. A block diagram of the closed loop Immune-LQI controlled system

The closed loop response specifications (Rise time, Overshoot%, and Settling time) obtained with all the designed controllers are shown in Table 3.

3.1 PID controller

The control signal provided by the standard PID is given by Equation 12.

$$U_{PID}(t) = k_p(e(t) + \frac{1}{T_i}\int e(t)dt + T_d\frac{de(t)}{dt} \tag{12}$$

where, k_p, T_i, and T_d are the controller parameters that represent the proportional gain, integration time, and differential time respectively.

In this research, a PID controller was designed using Matlab PID controller tuning tool. The simulated system response in the closed loop is fairly good but with a large overshoot (Table 3), and the conductivity remains within the permissible limits. However, the resulting control signals are very bad, U_A has stabilized at very small value (approximately 0 mL/min), and the two signals U_A and U_B have extremely large initial values (about 30000 mL/min).

The PID controller presented in (Måns, 2016) was successful in giving a control signal within the permissible limits, but it had two inadequacies. First, two separate subsystems were used, as the conductivity resulting from component A was separated from that resulting from component B. Second, there was assumption that r = 0 in the proportional and differential terms. This forced the two terms to follow the output y instead of the error e. This, in turn, made the dynamics of the controller depend only on the error in one term namely the integral term.

3.2 LQI controller

The LQI controller was designed using the cost function in Equation 5, where all weights were identity matrices. The closed loop response resulting from the LQI controller (Figure 5) was slow and had relatively large overshoot (Table 3), whereas the control signals were good (Figure 6).

3.3 LQI-PID controller

The previously designed PID and LQI controllers were combined together. The control signal was considered to be the product of the control signal of PID and that of LQI. The closed loop response was very good and improved relative to the case of using LQI alone (Table 3). However, the resulting control signals are poor, as U_A has stabilized at a large value (approximately 140 mL/min, bearing in mind that the maximum permissible limit is 60 mL/min), while the U_B has stabilized at a negative value.

3.4 Immune-LQI controller

The two control signals $U_A\,and\,U_B$ of Immune-LQI controller are obtained by multiplying LQI controller output $U_A\,and\,U_B$ from Equation 7 by the Immune gains $Km1\,and\,Km2$ from Equation 10, as shown in Figure 4.

Table 3. The closed loop response specifications of all the designed controllers

Settling time (seconds)	Overshoot %	Rise time (seconds)	Controller
PID	6.13	6.79	19.55
LQI	4.39	11.16	29.10
LQI-PID	0.56	7.52	11.99
Immune-LQI	1.46	9.99	16.67

The functions f_1 and f_2 were computed online using FL, and the parameters k_1, k_2, $\mu_1\,and\,\mu_2$ and were obtained using the GA depending on the cost function shown in Equation 11. Weights were obtained using a trial-and-error method. The upper limits of parameters $k_1\,and\,k_2$ are both 15, and for parameters $\mu_1 and\,\mu_2$ both upper limits are 1. The minimum values for all parameters are set at -1.

The Immune-LQI controller improved both the response (Figure 5) and the control signals (Figure 6). The conductivity regulation was better when using Immune-LQI controller than that when LQI was used (Figure 5). The response was faster and with less overshoot (Table 3). Acid and bicarbonate pumping rates were higher when using Immune-LQI controller than when LQI was used, but they were within the permissible ranges (Figure 6).

Immune-LQI controller has provided better response specifications when compared with the LQI controller (Table 3). The improvements were by 10% in rise time, 66% in overshoot, and 42.7% in settling time.

4. Conclusions

In this work a new immune-LQI controller was designed to regulate dialysate conductivity. Three intelligent techniques (AIS, FL, and GA) were used to improve the LQI method. The following conclusions can be drawn from the presented work:

1) The new immune-LQI controller succeeded in regulating global conductivity of dialysate and the response was fast and accurate.

2) The new immune-LQI controller was superior to PID, LQI, and LQI-PID as it provided faster rise time, with reduced overshoot and settling time.

3) Although the LQI controller is an optimal controller, it did not give the desired optimum response. Therefore, the resulting control signals had to be modified by using an IC.

4) GA succeeded in giving the optimal values of the parameters k_1, k_2, $\mu_1\,and\,\mu_2$.

5) IC helped in online tuning of the LQI parameters using the time varying function f(u,u') that was obtained by FL.

In future work the proposed method can be improved to be suitable to work with uncertainty and time-varying or nonlinear models of dialysate conductivity.

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