Applied Computer Science, vol. 16, no. 2, pp. 53–67
doi:10.23743/acs-2020-12

Submitted: 2020-05-06
Revised: 2020-05-19
Accepted: 2020-06-15

Mean Arterial Pressure, Squirrel Search Algorithm,
Model Reference Adaptive Controller

Rawaa HAAMED[*], Ekhlas HAMEED[**]

CONTROLLING THE MEAN ARTERIAL PRESSURE BY MODIFIED MODEL REFERENCE ADAPTIVE CONTROLLER BASED ON TWO OPTIMIZATION ALGORITHMS

Abstract

This paper Presents Modified Model Reference Adaptive Controller (MRAC) to regulate the hight blood pressure. It is based on slate model that represent the mathematical equation that clarifies relationship between blood pressure and vasoactive drug injection. In this work Squirrel Search Algorithm (SSA) and Grey Wolf Optimizer (GWO) algorithms are considered to optimize the controller parameters. the results showed that the suggested controller has good performance and stabilize the mean arterial pressure with small settling time (below than 400s) and small overshoot (below than 1 mmHg) with low amount of error.

1. INTRODUCTION

The rise of blood pressure is one of the diseases that most people suffer from, Blood pressure (BP) is articulated with 2 dimensions, systolic pressure is maximum pressure and diastolic pressure is minimum pressures in arterial system. The systolic BP of living person exists between the range of 110–140 millimetres mercury (mmHg) whereas diastolic pressure exists between 70–90 mmHg mean arterial pressure (MAP) is define as the average of the pressure in the systemic arteries that based on the diastolic pressures and systolic (Singh & Urooj, 2019).

[*] Mustansiriyah University, Computer Engineering Department, Palestine Street, 14022, Baghdad, Iraq, engrawaa1990@gmail.com
[**] Mustansiriyah University, Computer Engineering Department, Palestine Street, 14022, Baghdad, Iraq, ekkaram2020@gmail.com

Controlling the MAP is consider as a relevant problem in many applications such as hypertension control in the cardiac post-surgery healing process, in which the MAP has to be reduced as well as during the surgery anaesthesia. The procedure of the MAP lowering is usually implemented by injecting the patient body by vasodilator drug like Sodium Nitroprusside (SNP) (de Moura Oliveira, Durães & Pires, 2014). SNP is a vasodilator drug, which causes the widening in the walls of arterioles to be reduced, thereby lowering blood pressure it is Quickly acting and solid strong enough to resulting serious hypotension and or cyanide toxicity in case of an Excessive dose (Malagutti, Dehghani & Kennedy, 2013). The procedure of the lowering MAP can be done manually but is subject to human error and can take a long time in clinical environments where staff levels can be a problem and/or timely intervention (Malagutti, 2014). So, an Automatic Drug Infusion System is Helpful Efficient the control of drug infusion in a proper way, the Patient injection system is an integrated system contains of injection materials as per the medical standards, which will be sensing the blood pressure level and Determine the amount of drug required to injecting the human body with the help of automatic pump (Basha, Vivekanandan & Parthasarathy, 2018). In recent years, several researchers developed adaptive control system to regulate the rising of blood pressure like fractional order adaptive regulator which is suggested by Samir Ladaci et al. (Ladaci, 2012). The simulation results show the efficiency of this regulation controlling the MAP in presence of disturbances for different patients' sensitivities. Anderson Luiz etal. (Cavalcanti & Maitelli, 2015) use an adaptive predictive controller and a proportional integral controller with Fuzzy system consideration of two patients simulated, the results showed that the Suggested idea has Good results and stabilize the blood pressure with very small value of settling time and overshoot. Humberto A. Silva1 et al. (Silva, Leão & Seabra, 2018) use the Multi-Model Adaptive Control (MMAC) to regulate the MAP, they developed a procedure to control the blood pressure in the presence of significant time delays and parameters uncertainty. Simple adaptive PI controller suggested by Samuel Justino da Silva1 et al. (da Silva1, et al., 2019) for mean arterial pressure regulation, the controller was evaluated with desktop and Hill simulation through the known MAP parameter set of patients, with successful regulation of MAP in all cases considered.

In this paper, Modified Model Reference Adaptive controller (MRAC) is used to regulate the Mean Arterial Pressure, based on the Squirrel Search Algorithm (SSA) and Grey Wolf Optimizer (GWO) algorithm to tune its parameters. The suggested controller gives better performance and accuracy and more effective in handling the environmental changes and unknown parameter variations. To achieve these goals, since the 1980s, different mathematical models that clarifies relationship between blood pressure and vasoactive drug injection have been investigated, one of them is the Slate model which considered here.

The remaining article is consisting of section 2 discussed the mathematical model of MAP. Section 3 describes the MRAC controller with the suggested modification, while section 4 illustrates the SSA and GWO algorithms. Section 5 contain the results of simulation and comparison between SSA and GWO algorithms. Section 6 is the final conclusion section.

2. MEAN ARTERIAL PRESSURE MODELIZATION

To identify the proper infusion, we need to ascertain the mathematical model and the modelling of blood pressure and this model general denoted as SNP (sodium Nitroprusside) model, the modelling is a complex task in bio medically involves multiple inter connected system's Slate et. al. (1980) (Slate & Sheppard, 1983; Saxena & Hote, 2012) did are search and developed an SNP model with the dynamic infusion for hypertension stabilization based on the related analysis of the patient's data. The concluded model as described below based on the behavioural properties the human system (Basha & Vivekanandan, 2019).

$$\frac{\Delta pd(s)}{I(s)} = \frac{K\, e^{-Ti\, s}\left(1+\alpha e^{-Tc\, s}\right)}{1+\mathrm{T}s} \tag{1}$$

where $I(s)$ is infusion rate, Tc is the time consuming by the drug to transported via the patient's body, the time Ti is the initial transport lag from injection sit, α is the drug fraction recirculation, the constant K is the drug sensitivity, T is the time required for Dispersal and biological transition of the drug (Urooj & Singh, 2019; Jones & Tham, 2005).

3. MODEL REFERENCE ADAPTIVE CONTROLLER (MRAC)

The adaptive controller is control scheme that used widely to design the advanced control systems for accurate performance and very influential to handle the environmental changes and the unknown parameter variations. The adaptive controller include two loops, the internal loop (adjustment of parameter loop) and the external loop (feedback loop).The MRAC is usually used to design an adaptive controller which works based on adjusting the control parameters such that the actual output of the plant follow the output of the desired reference model that has the same input reference signal (Jain & Nigam, 2013). This paper deals with designing of adaptive controller with MRAC scheme using SSA and GWO algorithms for optimizing control parameters. Fig. 1 present the patient's model and MRAC controller diagram. The control signal up represents the rate of infusing drug which is a linear combination of the error feedback $K_d\ e_d$,reference model output $K_m\ Y_m$ and reference model input $K_e\ U_e$. The law of the adaptive controller involves the values of the reference model output " Y_m", tracking error

“ e_d”, and the reference model input “ U_e” with a suitable adaptive gain (K_e, K_m and K_d). The adaptive control equation is given by (Enbiya, Mahieddine & Hossain, 2011):

$$up(t) = K_e\, U_e\,(t) + K_m\, Y_m\,(t) + \, K_d\, e_d\,(t) \tag{2}$$

The suggested modification is tuning the gains (K_e, K_m and K_d) online using Adaline neural network See Fig. 2.

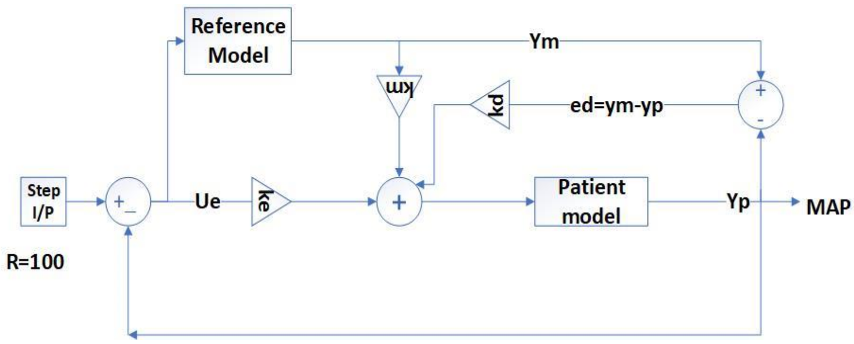

Fig. 1. The block diagram for the patient’s model with MRAC

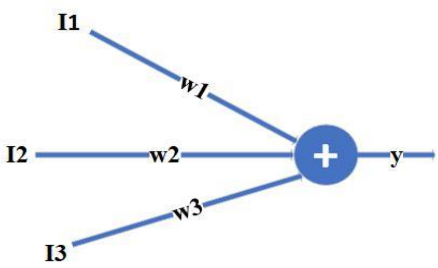

Fig. 2. The ADALINE Network Architecture

The neuron weights W_1, W_2 and W_3 will act as the gains (K_e, K_m, and K_d) of the MRAC controller. With the help of some learning algorithm the weights of the neural network are modified to attain the desired goal. The inputs I_1, I_2 and I_3 will act as U_e, Y_m and e_d respectively. These input signals are multiplied with their corresponding weights and act as the input to the single neuron the transfer function of the output neuron is linear function. The least mean square error algorithm adjusts the weights has been given by (Saeed Al-Khayyt, 2017):

$$K_e(t+1) = K_e(t) + \eta_e\; e\; U_e \tag{3}$$

$$K_m(t+1) = K_m(t) + \eta_m\; e\; Y_m \tag{4}$$

$$K_d(t+1) = K_d(t) + \eta_d\; e\; e_d \tag{5}$$

where η_e, η_m and η_d is the learning value, e is the error between the output system and the desired output. note that the value of the basis is considered zero.

The various steps in tuning a MRAC controller using Adaline neural network are as follows:

Step1: Choose random values for the weights.

Step2: Calculate the error which is the difference between the reference input and the output and multiplied with an optimized gain K_{og} to obtain a better closed loop response.

Step3: The gains of MRAC controller are decided by least mean square error algorithm.

The output of the single neuron act as the control signal which regulate the amount infusion rate of SNP. The learning values (η_e, η_m and η_d) and the optimized gain K_{og} are optimized using two algorithms SSA and GWO algorithms.

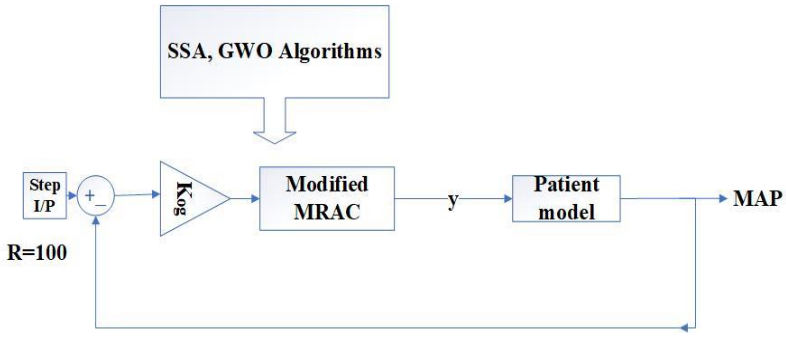

Fig. 3. The suggested controller with patient's model

4. OPTIMIZATION ALGORITHMS

4.1. The Squirrel Search Algorithm

This algorithm (SSA) Suggested et al. in 2019 by Mohit Jain. it was a novel nature-inspired algorithm for optimization, (SSA) algorithm consist of four the search processes of flying squirrels: (i) there are n flying squirrels and n trees and only one squirrel on one tree, (ii) each flying squirrel is tries to find the food so each one searching for food individually, (iv) there are only three types of trees such as normal tree, oak tree and hickory tree (which is the favour tree) in forest only three oak trees and one hickory tree in the forest (Hu, et al., 2019). The following steps explained the operation of this algorithm (Khan & Ling, 2020):

Step 1: Initialization Let that the number of the population is N, the upper and lower bounds of the search space are Fsu and Fsl, and start the loop iteration, N individuals are randomly produced according to equation:

$$fsi = Fsl + rand(1, D) - (Fsu - Fsl) \qquad (6)$$

Step2: Evaluate the fitness value for each individual based on the least-square error (LSE) criterion. ranking the fitness values of the individuals in ascending order, the squirrels are classified into three types: (i) Fh squirrels located at hickory trees (the best food resource for the squirrels), (ii) Fa squirrels located at acorn trees (takes second place food resource for the squirrels), (iv) Fn squirrels located at normal trees (no food).

Step3: Update the Position (winter strategy). All squirrels try to move to the hickory trees or acorn trees, the positions of each squirrel updated according to the updating equation:

$if \ \ p > pdp$

$$fsi(t+1) = fsi(t) + dg\ Gc\ (fth - fsti) \qquad (7)$$

$Random\ location \qquad\qquad otherwise$

$if \ \ p > pdp$

$$fsi(t+1) = fsi(t) + dg\ Gc\ (fta - fsti) \qquad (8)$$

$Random\ location \qquad\qquad otherwise$

where: pdp is the predator appearance probability, Gc is the constant with the value, dg is the gliding distance which can be calculated by this equation.

$$d = \frac{hg}{tan(\Phi)\ sf} \qquad (9)$$

where: hg the constant, sf the constant, $tan(\Phi)$ is the angle of gliding which can be calculated as shown below:

$$tan(\Phi) = \frac{D}{L} \qquad (10)$$

$$D = \frac{1}{2p\ v\ s\ CD} \qquad (11)$$

$$L = \frac{1}{2p\ v\ s\ CL} \qquad (12)$$

where p, v, s, CL and CD are all the constants.

Step4: Seasonal Transition whether the season changes is judged according to these equation:

$$S_c^t = \sqrt{\sum_{k=1}^{D} (F_{ai,k}^t - F_{h,k}^t)} \; i = 1,2,\dots,Nfs \tag{13}$$

At the beginning of each iteration, the whole population is in Winter, so all the individuals are updated in the way introduced step (3) When the season turns to summer, the individuals updated location, by these equations:

$$FS_{inew}^{t+1} = Fsl + Le\text{'}\, vy(n)\,(Fsu - Fsl) \tag{14}$$

$$Le\text{'}\, vy(n) = 0.01\, \frac{r_a\, \sigma}{|r_b|^{1/\beta}} \tag{15}$$

$$\sigma = \left(\frac{\Gamma(1+\beta)\, sin\frac{\beta\pi}{2}}{\Gamma\left(\frac{1+\beta}{2}\right)\beta\, 2^{\frac{\beta-1}{2}}}\right)^{\frac{1}{\beta}} \tag{16}$$

where: $\Gamma(x) = (x1)!$

Figure 4 illustrates the procedure of SSA algorithm.

4.2. Grey Wolf Optimizer

Mirjalili proposes the GWO algorithm in 2014. It is suggested in order to find prey According to the Gray wolf social hierarchy Hunting practices are the solution to the problem of optimisation. The social hierarchy is represented by splitting the quest agent population into four groups of wolves, i.e., alpha, beta, delta, and omega, based on their fitness. In order to mimic the hunting actions of grey wolves, the quest technique is modelled using three stages that encircle and attack the prey (Precup, et al., 2017).

The GWO comprises the steps established by the revision of the measures (Mirjalili, Mirjalili & Lewis, 2014):

Step1: The initial random grey wolf population, represented by *N* agents' positions in the *D* dimensional search space, is generated. The iteration index is initialized to *t* = 0 and the maximum number of iterations is set to *T*.

Step 2: The performance of each member of the population of agents is evaluated by simulations conducted on the Model Reference Adaptive Control based on the least-square error (LSE) criterion.

Step 3: x^{α}, x^{β}, x^{δ}, which represented alpha, beta, delta positions are identified according to the first three best solutions.

Step 4: The agents are moved to their new positions according to the Equation below.

$$X_{new} = \frac{(x_1 + x_2 + x_3)}{3} \tag{17}$$

x_1, x_2, x_3 calculated from equations below.

$$x_1 = x^{\alpha} - A_1 D_{alpha} \tag{18}$$

$$x_2 = x^{\beta} - A_2 D_{\mathrm{beta}} \tag{19}$$

$$x_3 = x^{\delta} - A_3 D_{\mathrm{delta}} \tag{20}$$

$$A_1, A_2, A_3 = 2a\, r_1 - a \tag{21}$$

r_1 is random value having different value for $A_1,\ A_2, A_3, a$ is variable value.

$$a = 2 - t \left(\frac{2}{T}\right) \tag{22}$$

$D_{alpha}, D_{\mathrm{beta}}, D_{\mathrm{delta}}$ are computed from equations below.

$$D_{alpha} = abs(c_1\ x^{\alpha} - X_{current}) \tag{23}$$

$$D_{beta} = abs\left(c_2\ x^{\beta} - X_{current}\right) \tag{24}$$

$$D_{delta} = abs\left(c_3\ x^{\delta} - X_{current}\right) \tag{25}$$

$$c_1, c_2, c_3 = 2r_2 \tag{26}$$

$r_2$is random value having different value for c_1, c_2, c_3.

Step 4: If all iteration will be finished, stop the search and display the value (alpha position is best solution). Otherwise, repeat step (2) to step (4) before iterations have been finalized.

Figure 5 illustrates the procedure of the GWO.

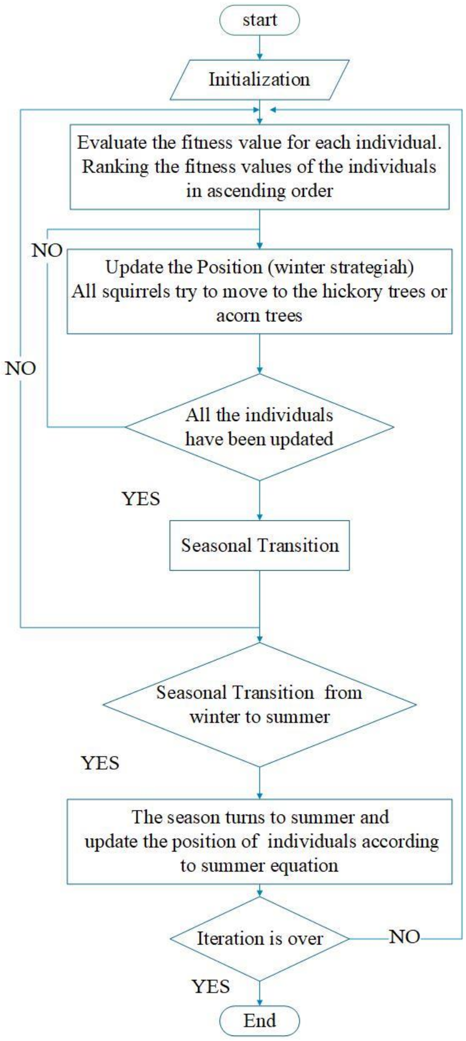

Fig. 4. SSA Procedure

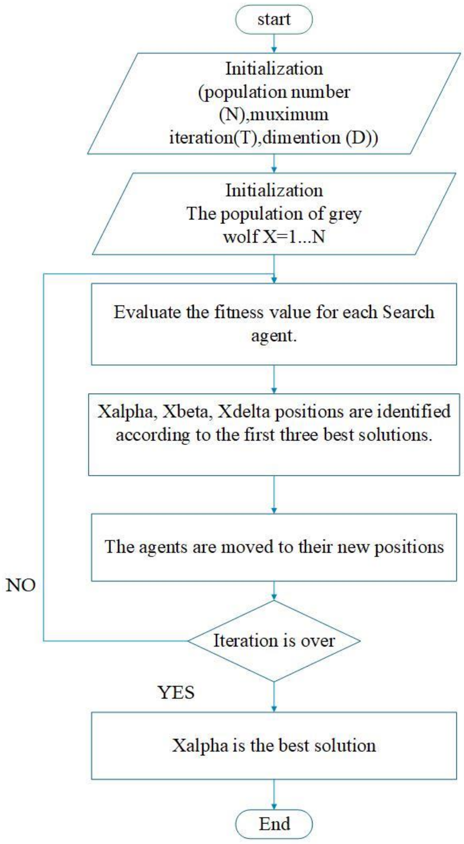

Fig. 5. GWO Procedure

5. SIMULATION AND RESULTS

The simulation results of the suggested controller based on the SSA, GWO algorithms for controlling MAP regulation model have been presented in this section. The control simulated with patient model using MATLAB program. The initial value of the patient MAP is chosen as 140 (mmHg), The control objective is to reduce the MAP to 100 (mmHg) for three cases (sensitive patient, normal patient, insensitive patient) without disturbance, the parameters of MAP model illustrated in Table (1).

The parameters SSA and GWO are considered in this Table (2) Shown. The simulation response of MAP model after regulated it by the suggested controller (Model Reference Adaptive Controller) which tuned by the SSA and GWO algorithms as illustrated in Table (3,4*)* is shown in Figure (6) and Figure (7) respectively. Figure (8) and Figure (9) show the controller signal (SNP Injection).

It is obvious It from Figure (6) and Figure (7) that the controller satisfies the design requirement by making the MAP system follows the desired level with small steady state error (e_{ss}), settling time (t_s), drop time (t_d) and undershoot (M_p) as shown in Table (5).

Table (5) illustrates that the performance of the Modified Model Reference Adaptive Controller optimized with SSA algorithm is nearly similar to the performance of controller when optimized with GWO algorithm.

From the results it can be noted that the controller has less settling time, drop time when optimized with SSA algorithm.

Tab. 1. Model parameters (Nirmala, Muthu & Abirami, 2013)

Model variables	SEN (underneath normal)	NOR (normal)	INS (above normal)
α	0	0.4	0.4
Ti	20	30	60
K	–9	–0.7143	–0.1786
T	30	40	60
Tc	30	45	75

Tab. 2. The SSA and GWO algorithms parameters

SSA parameter	value	GWO parameter	value
Search agent no (S)	20	Search agent no (N)	20
Max iteration (T)	10	Max iteration (T)	15
Dimension (D)	3	Dimension (D)	3
Upper limit (Fsl)	0	–	–
Lower limit (Fsu)	0.5	–	–
predator appearance (Pdb)	0.25	–	–

Tab. 3. Optimal controller parameters (η_e, η_m, η_d)

	η_e	η_m	η_d
SSA Algorithm	0.0019	0.00186	0.00227
GWO Algorithm	0.00218	0.0004	0.0024

Tab. 4. Optimal controller parameter (K_{og})

Optimized Gain (K_{og})		
Case	**SSA Algorithm**	**GWO Algorithm**
Sensitive	–0.0017	–0.0014
Normal	–0.0082	–0.0075
Insensitive	–0.0247	–0.0226

Tab. 5. The evaluation parameters of simulation results for three cases

SSA Algorithm					
Case	**M_p (mmHg)**	**t_s (sec)**	**t_d (sec)**	**e_{ss} (mmHg)**	**SNP (ml/h)**
Sensitive	0.1403	197.9941	119.6477	$1.543 \cdot 10^{-6}$	4.444
Normal	0.03229	249.8644	134.9153	$3.602 \cdot 10^{-5}$	40.02
Insensitive	0.0313	377.4166	205.0418	0.00074	160.5
GWO Algorithm					
Sensitive	0.0026	266.1911	133.4159	$7.492 \cdot 10^{-5}$	4.444
Normal	0.0376	277.2142	158.1251	$3.838 \cdot 10^{-5}$	40.02
Insensitive	0.0528	377.1661	205.3626	0.000689	160.23

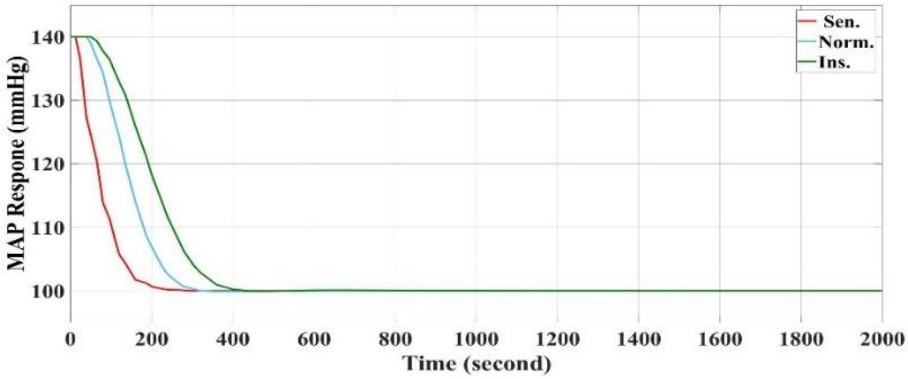

Fig. 6. The response of MAP according to the MRAC optimized with SSA

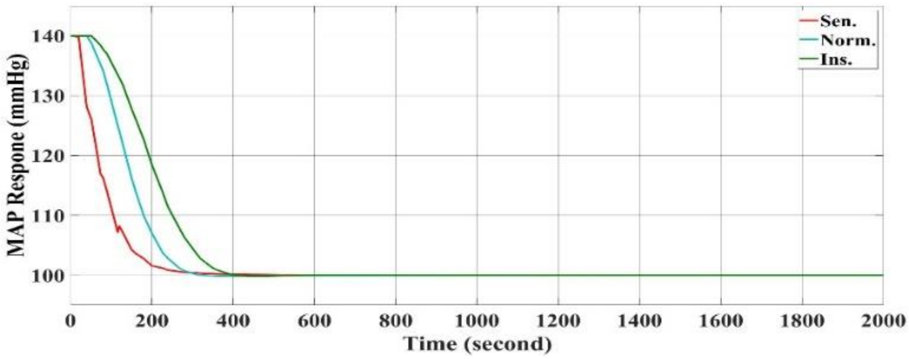

Fig. 7. The response of MAP according to the MRAC optimized with GWO

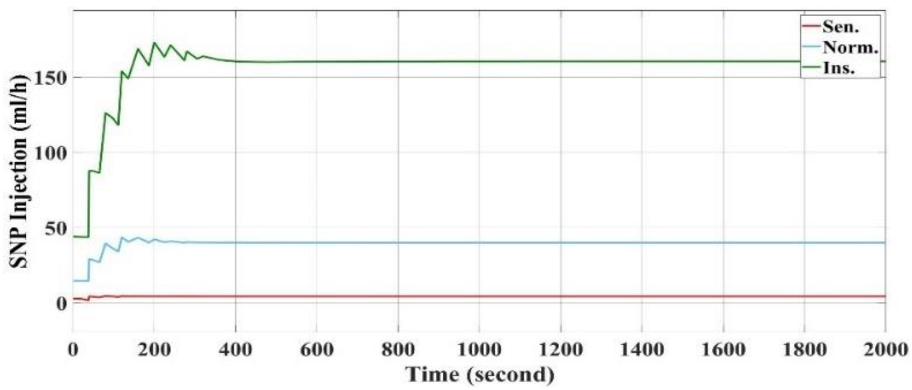

Fig. 8. SNP Injection according to the MRAC Optimized with SSA

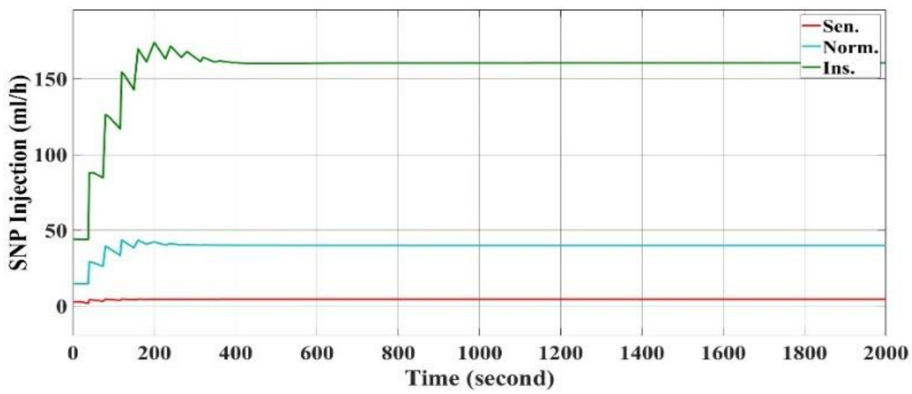

Fig. 9. SNP Injection according to the MRAC Optimized with GWO

6. CONCLUSION

The paper has presented an adaptive single-drug control scheme for MAP control. The suggested controllers designed and evaluated by simulation results for different variations in patients (normal, sensitive, and insensitive). The single drug which is used is the Nitroprusside. The results of the simulation have shown that MRAC is more efficient in regulating the MAP by calculated the infusion rates of the SNP. In order to improve the characteristics of the controller, SSA, GWO algorithms have been applied. For future work we suggest use same controller in multi input multi output system rather than single input single output system to regulate the mean arterial pressure and cardiac output using two drugs: dopamine and Nitroprusside.

REFERENCES

Basha, A.A., & Vivekanandan, S. (2019). Enhanced Optimal Insulin Regulation in Post-Operative Diabetic Patients: An Adaptive Cascade Control Compensation-Based Approach With Diabetic and Hypertension. *IEEE Access*, *7*, 90973–90981. https://doi.org/10.1109/ACCESS.2019.2927248

Basha, A.A., Vivekanandan, S., & Parthasarathy, P. (2018). Evolution of blood pressure control identification in lieu of post-surgery diabetic patients: a review. *Health Inf Sci Syst*, *6*, 17. https://doi.org/10.1007/s13755-018-0055-z

Cavalcanti, A.L., & Maitelli, A.L. (2015). Design of an Intelligent Adaptive Drug Delivery System for Arterial Pressure Control. *WSEAS Transactions on Systems and Control*, *10*, 704–712.

da Silva, S.J., Scardovelli, T.A., & da Silva Boschi, S.R.M. *et al.* (2019). Simple adaptive PI controller development and evaluation for mean arterial pressure regulation. *Res. Biomed. Eng.*, *35*, 157–165. https://doi.org/10.1007/s42600-019-00017-y

de Moura Oliveira, P.B., Durães, J., & Pires, E.J.S. (2014). Mean Arterial Pressure PID Control Using a PSO-BOIDS Algorithm. In: Á. Herrero, et al. (Eds.), *International Joint Conference SOCO'13-CISIS'13-ICEUTE'13. Advances in Intelligent Systems and Computing* (vol. 239). Springer, Cham

Enbiya, S., Mahieddine, F., & Hossain, A. (2011). Model reference adaptive scheme for multi-drug infusion for blood pressure control. *J Integr Bioinform*, *8*(3), 173. https://doi.org/10.2390/biecoll-jib-2011-173

Hu, H., Zhang, L., Bai, Y., Wang, P., & Tan, X. (2019). A Hybrid Algorithm Based on Squirrel Search Algorithm and Invasive Weed Optimization for Optimization. *IEEE Access*, *7*, 105652–105668. https://doi.org/10.1109/ACCESS.2019.2932198

Jain, P., & Nigam, M.J. (2013). Design of a Model Reference Adaptive Controller Using Modified MIT Rule for a Second Order System. *Adv. Electron. Electr. Eng*., *3*(4), 477–484.

Jones, R.W., & Tham, M.T. (2005). An undergraduate CACSD project: The control of mean arterial blood pressure during surgery. *Int. J. Eng. Educ.*, *21*(6) PART I, 1043–1049.

Khan, T.A., & Ling, S.H. (2020). An improved gravitational search algorithm for solving an electromagnetic design problem. *J Comput Electron*, *19*, 773–779. https://doi.org/10.1007/s10825-020-01476-8

Ladaci, S. (2012). Postoperative Blood Pressure Control Using a Fractional order Adaptive Regulator. In *13th International conference on Sciences and Techniques of Automatic control & computer engineering* (pp. 254–265). Monastir, Tunisia.

Malagutti, N. (2014). Particle filter-based robust adaptive control for closed-loop administration of sodium nitroprusside. *J Comput Surg*, *1*, 8. https://doi.org/10.1186/2194-3990-1-8

Malagutti, N., Dehghani, A., & Kennedy, R.A. (2013). Robust control design for automatic regulation of blood pressure. *IET Control Theory Appl.*, *7*(3), 387–396. http://dx.doi.org/10.1049/iet-cta.2012.0254

Mirjalili, S., Mirjalili, S.M., & Lewis, A. (2014). Grey Wolf Optimizer. *Adv. Eng. Softw.*, *69*, 46–61.

Nirmala, S.A., Muthu, R., & Abirami, B.V. (2013). Drug infusion control for mean arterial pressure regulation of critical care patients. In *2013 IEEE International Conference of IEEE Region 10 (TENCON 2013)* (pp. 1-4). Xi'an. https://doi.org/10.1109/TENCON.2013.6718882.

Precup, R.-E., David, R.-C., Szedlak-Stinean, A.-I., Petriu, E.M., & Dragan, F. (2017). An Easily Understandable Grey Wolf Optimizer and Its Application to Fuzzy Controller Tuning. *Algorithms*, *10*, 68.

Saeed Al-Khayyt, S. (2017). Tuning PID Controller by Neural Network for Robot Manipulator Trajectory Tracking. *Al-Khwarizmi Engineering Journal*, *9*(1), 19-28.

Saxena, S., & Hote, Y.V. (2012). A simulation study on optimal IMC based PI/PID controller for mean arterial blood pressure. *Biomed. Eng. Lett.*, *2*, 240–248. https://doi.org/10.1007/s13534-012-0077-4

Silva, H.A., Leão, C.P., & Seabra, E.A. (2018). Parametric Sensitivity Analysis of a Multiple Model Adaptive Predictive Control for Regulation of Mean Arterial Blood Pressure. In *Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2018)* (vol. 1, 510–516). http://dx.doi.org/10.5220/0006909805100516

Singh, B., & Urooj, S. (2019). Blood pressure control by deterministic learning based fuzzy logic control. *Int. J. Eng. Adv. Technol.*, *8*(3), 6–10.

Slate, J.B., & Sheppard, L.C. (1983). Model-Based Adaptive Blood Pressure Controller. *IFAC Proc. Vol.*, *2*(4), 1437–1442.

Urooj, S., & Singh, B. (2019). Fractional-order PID control for postoperative mean arterial blood pressure control scheme. *Procedia Comput. Sci.*, *152*, 380–389. https://doi.org/10.1016/j.procs.2019.05.002