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Optimization of Field-Oriented Control for PMSM Motor

Ng Soon King[1], Chua Hong Siang[2], Ting Sie King[3]

[1,2,3] Faculty of Engineering, Computing and Science, Swinburne University of Technology, Sarawak, Malaysia

ABSTRACT: This research focuses on designing and simulating a sensorless control technique for optimising field-oriented control to achieve an optimization control applicable to water pressure regulation management. In the irrigation system, water pressure changes are determined by the number of activated emitters operating at different times. Unstable water pressure may reduce irrigation efficiency, leaving brown areas of the landscape not receiving adequate watering. Thus, the Field-oriented control technique is introduced in the paper to regulate the water pressure in the water pump controller using a permanent magnet synchronous motor (PMSM). The PSO-SFC field-oriented control technique for the PMSM was studied to improve motor efficiency and precision motor control over the torque and speed. The cascade-free state feedback controller (SFC) can achieve better dynamics and disturbance compensation in the controller. The SFC's tuning process has been achieved by using a linear-quadratic optimization method and PSO (particle swarm optimization) in the cascaded process. The process improves the coefficient of gain K produced by linear-quadratic optimization and PSO to obtain promising Q and R matrices in the adaptive system with improved output response in the simulation.

KEYWORDS: Field-oriented control; water pressure; permanent magnet synchronous motor; state feedback controller; particle swarm optimization

I. INTRODUCTION

The paper focuses on robust design using the sensorless Field oriented control (FOC) technique as an essential motor control approach for the brushless motor to achieve manageable control of required water pressure in the irrigation water supply system. Precision irrigation is vital to conserving water in a vast agricultural land for large commercial crop production (Dhanaraju et al., 2022). Precision irrigation provides higher water efficiency in both off-farm and on-farm operations. Precision irrigation must involve accurate and precise application of water to meet the desired output of individual plants. The water pressure of irrigation depends on the number of activated emitters at different times. Thus, it will lead to unstable pressure at different operations, and the amount of water supplied to the crops is hard to estimate. To ensure the uniform amount distribution of water to the crops, accurate and precise irrigation through sensing provides decision support and adaptive control over the dynamic issue. Field-oriented control can adaptively adjust to a particular speed needed to stabilize water pressure by controlling the real motor variable through torque and flux perspective. Its controls can be directly achieved through the current on the electromagnetic state of the motor (Gopal B T, 2017). The conventional field-oriented control can improve the motor performance efficiency by up to 95%, allowing lower power consumption and enhancing motor dynamics, heat dissipation and noise (Grofu, 2021). Due to its distinct performance, the technique can be applied to the permanent magnet synchronous motors (PMSMs) commonly used in electromechanical applications. The motor is used due to its significant advantages: excellent power density, high efficiency, and numerous torque to current ratios. In addition, since there are no copper losses, there will be no rotor current in PMSM (Zhao, 2014). The PMSM has received significant attention from most researchers in the controller application of research.

The paper presents an LQR state-feedback control technique optimized with PSO in the FOC controller. The type of cascade-free on the state-feedback controller is being investigated. Although the tuning process of the state-feedback controller is complex, it could be achieved by linear-quadratic optimization or pole-placement technique. A standard coefficient of SFC with an expected value of plant parameters is used. However, if constant coefficients are used in non-constant plant parameters, it will lead to unsatisfactory system behaviour (Szczepański et al., 2020). A poor application of controller coefficients would usually cause unstable system consequences. To avoid such circumstances, the coefficient of the controller has to be adjusted based on the operation situation. Thus, an optimization control method introduced for stabilizing the system proportionally depends on the system parameters (Ghoreishi & Nekoui, 2012)

Linear Quadratic Regulator (LQR) is a method that minimizes a quadratic cost function to design a controller for linear systems. It contains two main matrices, Q and R, where Q represent the state weighting matrix while R is the weighting matrix. Selecting these matrices can be done in several ways, such as trial-and-error, iterative, and pole placement. However, the trial-and-error method is unsuitable for high-dimensional works since it consumes much time, and the pole-placement technique requires a given pole for the weighting matrices. Thus, the performance and constraint cannot be guaranteed [6]. Yet, this issue can be addressed by the particle swarm optimization (PSO) approach to selecting the correct state and control weighting matrix. The swarm intelligence-based technique is intensified by social interactions of flocking birds, a method that achieves the globally best optimal solution within a promising iteration (Song et al., 2014). Searching promising Q and R matrices by PSO for the gain coefficient of the state feedback controller can significantly achieve favourable speed control of the PMSM.

This paper uses PSO as the optimization method for adjusting the weighting matrices of the LQR state-feedback controller. The speed response of the PMSM motor drive is based on the coefficient of the SFC computed from the Q and R matrices optimally obtained by PSO. Using PSO as the adjustment mechanism can help achieve desirable control performance on the transient and steady-state characteristics.

II. STATE FEEDBACK CONTROLLER FOR PMSM DRIVE

Typically, designing a state feedback controller for a PMSM drive consists of two main stages. One is creating a state-feedback controller, and the next step is introducing a coefficient adjustment method. To design the SFC for PMSM drive, a mathematical model is required. Thus, the linear models shown in the state space representation are expressed as.

$$\frac{dx_i(t)}{dt} = A_i x_i(t) + B_i u_i(t) + F_i r_i(t)$$

$$A = \begin{bmatrix} -\frac{R_s}{L_s} & 0 & 0 & 0 \\ 0 & -\frac{R_s}{L_s} & 0 & 0 \\ 0 & \frac{K_t}{J_m} & -\frac{B_m}{J_m} & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad B_i = \begin{bmatrix} \frac{K_p}{L_s} & 0 \\ 0 & \frac{K_p}{L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$F_i = \begin{bmatrix} 0 \\ 0 \\ 0 \\ -1 \end{bmatrix} \quad x_i(t) = \begin{bmatrix} i_d(t) \\ i_q(t) \\ \omega(t) \\ x_\omega(t) \end{bmatrix} \quad u_i(t) = \begin{bmatrix} u_{id}(t) \\ u_{iq}(t) \end{bmatrix}$$

where: R_s & L_s indicates the resistance and inductance of PMSM, respectively, J_m represents the moment of inertia while K_t is the torque constant and B_m is viscous friction. $i_d(t)$& $i_q(t)$ represent the current space vector components, $\omega(t)$ is the velocity of PMSM shaft and K_p is the gain of the voltage source inverter, and $\omega_{ref}(t)$is the reference angular velocity.

The state feedback controller (SFC) control law is defined as in the equation below:

$$u_i(n) = Kx_i(n) = \begin{bmatrix} k_{x1} & k_{x2} & k_{x3} & k_{\omega 1} \\ k_{x4} & k_{x5} & k_{x6} & k_{\omega 2} \end{bmatrix}$$

where: n represent the discrete sample time index, $k_{x1} - k_{x6}$ & $k_{\omega 1}, k_{\omega 2}$ is the SFC gain coefficient. According to [5], the initial value for Q and R matrices gained through trial-and-error is shown below.

$$Q = diag([7.2e-3 \quad 7.2e-3 \quad 7.2e-3 \quad 4.0]$$

$$R = diag([1.0 \quad 1.0])$$

These matrices are used for linear-quadratic optimization (LQR) to minimize discrete performance index as shown in the following equation:

$$I_{LQR} = \sum_{n=0}^{\infty} [x_i^T(n) Q x_i(n) + u_{li}^T(n) R u_{li}(n)]$$

where Q and R are the weighting matrices. If Q and R parameters are appropriately selected and, the derived Riccati equations can be represented as follows:

$$A^T P + PA + Q - PBR^{-1}B^T P = 0$$

The matrix P can be obtained from the equation above. If P is definite as positive, it is considering as stable system. Then, substituting the P into $K = R^{-1}B^T P$ would eventually identify the feedback gain matrix of the K value.

III. PARTICLE SWARM OPTIMIZATION

A. *Particle Swarm Optimization (PSO) Method*

Particle Swarm Optimization (PSO) is used in the control to randomly initialise each particle's position and velocity when it is first produced (Paponpen & Konghirun, 2015). Each particle produced contains its position and velocity representing a candidate solution to the problem being solved. The evaluation of fitness value can be obtained through an objective function conditionally assessing each particle's position. In each iteration, pbest and gbest are defined and memorized as the best personal position and best global position of i^{th} particles according to the fitness function. All the particles were memorized and replaced with the best position once a promising particle was found during each iteration. These PSO equations can be presented as shown below (Kennedy & Eberhart, 1995):

$$v_i(new) = w.v(old)$$
$$+c_1.rand_1.(pbest - x_i)$$
$$+c_2.rand_2.(gbest - x_i)$$

where, w represents the inertia weight factor in the form of constant, variable, or random. This coefficient guarantees the particles can provide the best response that is not halted and can continue with their previous trajectories. The c_1 and c_2 are the learning coefficients where $c_1 + c_2 = 4$ are usually selected in interval. The rand1 & rand2 represent the random numbers with uniform distribution. The pbest represents the best position from the i-th particle, while gbest is the global best of the total population. To ensure the stability and good performance of the PSO, two scalar factors ϕ_1 *and* ϕ_2 are set where $\phi_1 + \phi_2 > 4$, and the constriction coefficients are defined by:

$$w = \frac{2}{(\phi_1 + \phi_2) - 2 + \sqrt{(\phi_1 + \phi_2)^2 - 4(\phi_1 + \phi_2)}}$$
$$c1 = \phi_1 w$$
$$c_2 = \phi_2 w$$

According to (Neto & Bottura, 1999), the selection of $\phi_1 = \phi_2 = 2.05$ will produce $w = 0.729$ & $c_1 = c_2 = 1.496$

B. *Fitness Function*

The fitness function of PSO is vital and directly influences the decision on the trajectories of the particles. It is a process used to evaluate the best solution to the optimization problem. The searching of Q and R matrices needs to be tuned and defined in promising terms. The LQR system requires the closed-loop controller to execute as fast as possible and stable using the lowest control effort (Ghoreishi et al., 2011). This can be presented in the equation below:

Stability index. This index is related to the real parts of closed-loop poles and is defined as follows:

$$SI = -\frac{1}{maxRe\{\lambda_i\}}$$

A smaller stability index can be obtained by good Q and R weighted matrices.

Settling-time index. This index is the minimum time response to reach an absolute error of 0.05, as indicated below:

$$ST = \frac{In(0.05)}{w * f}$$

where w is the inertia weight factor and f is the natural frequency.

Maximum control effort Index to the system can be defined as

$$u_{max} = \max(u_i(t))$$

where

$$u_i(t) = \begin{bmatrix} u_{id}(t) \\ u_{iq}(t) \end{bmatrix}$$

Based on these indexes, to find the Q and R matrices and avoid complication, the objective function can be defined as below:

$$J_{total} = a_1 SI + a_2 ST + a_3 u_{max}$$

where, a_1, a_2 *and* a_3 are based on system design.

IV. METHODOLOGY

A. Adaptive State feedback controller design

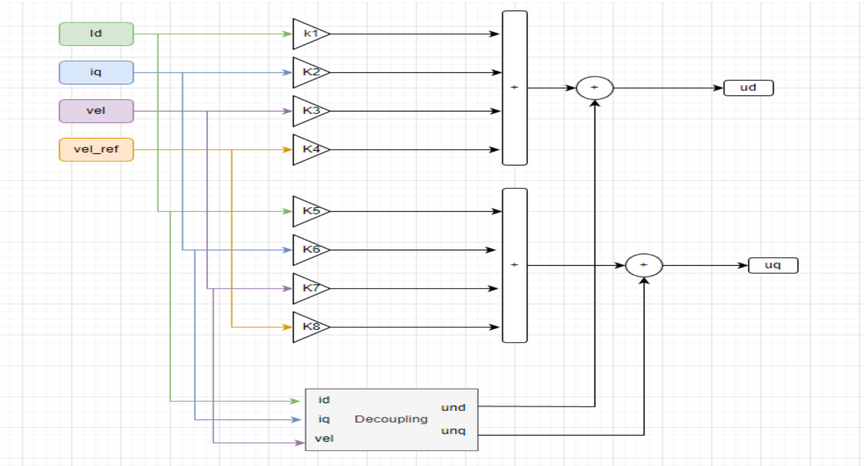


Figure 1. State feedback controller design

Figure 1 shows the state feedback controller designed by MATLAB Simulink. The SFC is used to produce u_d *and* u_q that are linear components of the control voltages. As mentioned, the controller gain coefficient is obtained through LQR, computed from the MATLAB script below.

```
A = [-Rs/Ls 0 0 0; 0 -Rs/Ls 0 0; 0 Kt/Jm -Bm/Jm 0; 0 0 1 0];
B = [Kp/Ls 0; 0 Kp/Ls; 0 0; 0 0];

    Q = diag([7e-3 7e-3 7e-3 4]);
    R = diag([1 1]);
    K = lqr( A, B, Q, R )
```

Figure 2. MATLAB LQR design

Based on the calculations above, the controller coefficient is obtained by LQR, where Q and R parameters are initially selected through a trial-and-error method [5].

```
K =

    0.0738   -0.0000   -0.0000    0.0000
    0.0000    0.0776    0.1770    2.0000
```

Then it is converted into K^T where

$$K^T = \begin{bmatrix} 0.0738 & 0 \\ 0 & 0.0776 \\ 0 & 0.1770 \\ 0 & 2.000 \end{bmatrix}^T$$

```
A=transpose(K)
k00=[A(1,1)]
k01=[A(2,1)]
k02=[A(3,1)]
k03=[A(4,1)]
k10=[A(1,2)]
k11=[A(2,2)]
k12=[A(3,2)]
k13=[A(4,2)]


urd=-1*(k00*id+k01*iq+k02*vel+k03*vel_ref)
urq=-1*(k10*id+k11*iq+k12*vel+k13*vel_ref)
```

where id & iq are space vector current components in the d-q coordinate system. The parameters vel & vel_ref are the angular velocity and reference signal respectively where K is the gain matrix of the SFC.

The implementation of the SFC controller drive is applying the multiple-input multiple-output (MIMO) control system technique. In the adaptation of SFC control technique, PSO computation for each coefficient is actually required. Since the surface of the PMSM motor are used and there is a negligibly slight difference between d-axis and q-axis inductance of PMSM stator, thus its reluctance torque will not be occurred, and only the q-axis current will generate electromagnetic torque. Therefore, the d-axis current can be a zero value to maximize the efficiency of PMSM. To allow PMSM drive system to have unchanged behavior under moment of inertia variations, only the q-axis coefficients of SFC are used in the generation of electromagnetic torque.

B. Particle Swarn Optimization design for LQR

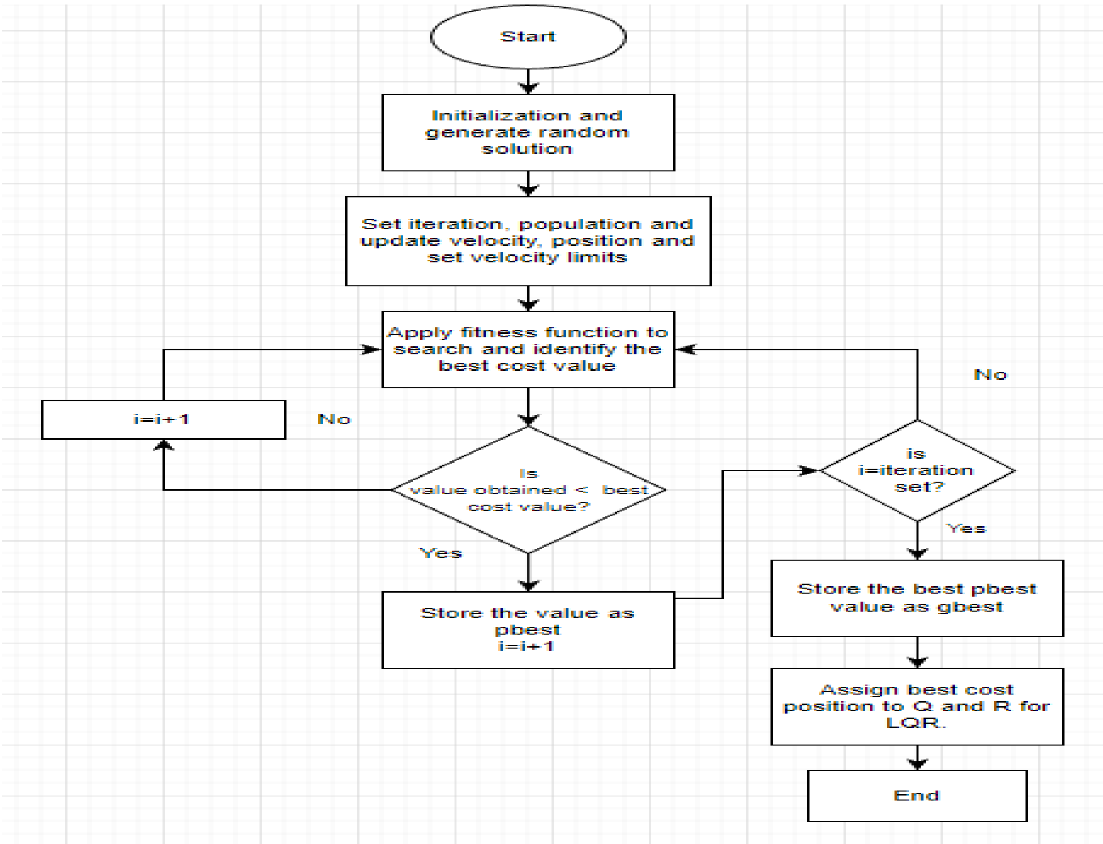


Figure 2. PSO for Q and R matrices

Figure 3 shows the particle swarm optimization for Q and R flowcharts. The PSO algorithm begins with initializing a population size. A random solution is generated based on the number of unknown variables, controlled at the lower and upper bound of decision variables where the velocity is initially set to zero. When the pbest is found during the iteration, an update will occur to the array particle. After computing all the pbest values at the end iteration, the best values located within the pbest will be stored as gbest. The velocity will be controlled by the search algorithm's lower and upper bound limits. In each iteration search, the fitness function always updates and evaluates every position. Once each position is evaluated, the fitness function will decide whether it is better than previous values. If better values are found, it will update the values to the pbest.

C. Experimental Procedure

The particle swarm optimization algorithms are created using MATLAB script to obtain the best cost. Once the best cost is obtained, the algorithm will take the best position array as Q and R matrices. Table 1 below shows the parameters set for PSO and PMSM drives. PMSM parameters are required in the fitness function to evaluate the best cost for LQR.

Table 1. PSO and PMSM parameters

	Fast Response	Slow Response
PSO	Number of particles = 50 Number of variables =6, $q_1\ to\ q_3 = [0.01\ 100]$ $q_4 = [0.01\ 500]$ $q_5 = q_6 = [0.004\ 0.1]$ $\phi_1 = \phi_2 = 2.05$ $\alpha_1 = 10$ $\alpha_2 = 5$ $\alpha_3 = 0.01$	Number of particles = 50 Number of variables =6, $q_1\ to\ q_3 = [0.01\ 10]$ $q_4 = [0.01\ 100]$ $q_5 = q_6 = [0.004\ 0.1]$ $\phi_1 = \phi_2 = 2.05$ $\alpha_1 = 10$ $\alpha_2 = 5$ $\alpha_3 = 0.01$
PMSM	$\mathrm{L_s} = 0.0127$ $k_p = 100$ $k_t = 0.2544$ $R_s = 1.0505$ $B_m = 0.0014$ $J_m = 0.0177$	$\mathrm{L_s} = 0.0127$ $k_p = 100$ $k_t = 0.2544$ $R_s = 1.0505$ $B_m = 0.0014$ $J_m = 0.0177$

By passing Q and R values to LQR. The gain coefficient is obtained and later to be executed in the FOC to achieve the speed control of the PMSM. The speed of the PMSM is then compared with the reference speed and conventional MRAS. Figure 4 shown below, represents the overall Simulink model.

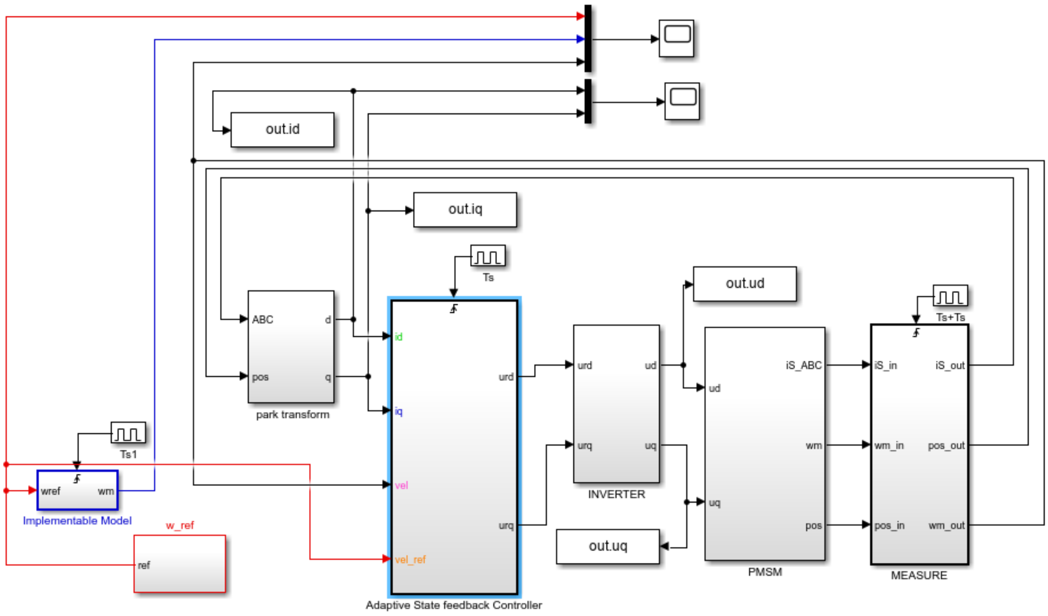


Figure 3. Overall PMSM speed control simulation model

Based on Figure 4, the ref speed is used in the state feedback controller. The gain coefficient is obtained from LQR calculations from the MATLAB scripts separately. The urq and urd value is calculated based on id, iq, vel_{ref} & vel as mentioned as above. The inverter or SVM is used to convert the u_{rq} and u_{rd} to u_d and u_q parameters needed for PMSM. The PMSM will produce an output of current in terms of i_{abc}, the speed and position then executed in the Park transform block. The Park transforms block, then transforms these components into the orthogonal rotating references frame in the form of (dq) and returns to the controller.

V. RESULTS AND DISCUSSION

Figure 5 and Figure 6 demonstrate the best cost of Q and R obtained by PSO iterations. The result shows that the objective function's value decreases rapidly at the initial iteration and gradually decreases until it reaches steady values. The value of the best cost position obtained is the best Q and R weightage matrixes for the LQR. If the Q and R matrices value is fixed, applying it to the system with different or non-constant parameters is unsuitable. Therefore, the Q and R can be obtained using the PSO depending on the system parameters and suitable for other systems' adaptation. The fitness function is the one that decides the best cost value depending on the upper and lower boundary set. In the fast response case, the best cost value is 0.2518, while in the slow response, the best cost value is around 0.3410. We can observe that increasing the range of the lower and upper boundary of the PSO parameters provides a lower best cost. Lower best cost gives shorter rise time and settling time of the system. The best cost obtained provides the best position for the controller coefficient.

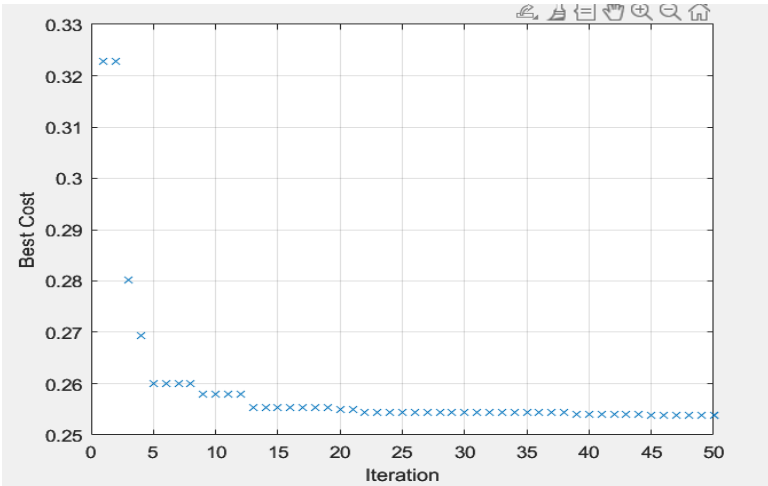


Figure 4. Best cost of Q and R for fast response

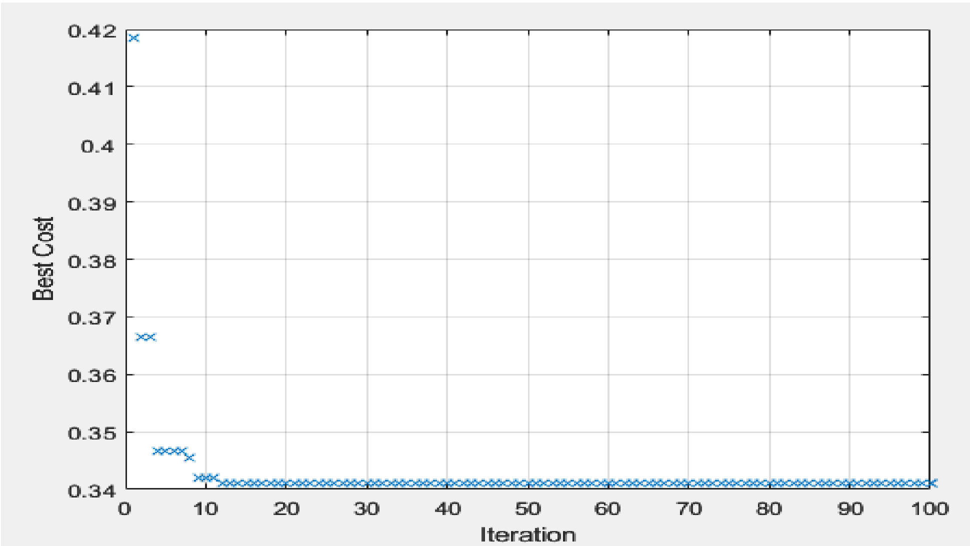


Figure 5. Best cost of Q and R for slow response

A. LQR for state feedback controller to obtain a gain coefficient

```
Q = diag([BestSol.Position(1) BestSol.Position(2) BestSol.Position(3) BestSol.Position(4)]);
R = diag([BestSol.Position(5) BestSol.Position(6)]);
```

Figure 7. Q and R value set from the best position

Table 2. Values of Q and R matrices and coefficient of ASFC for fast response

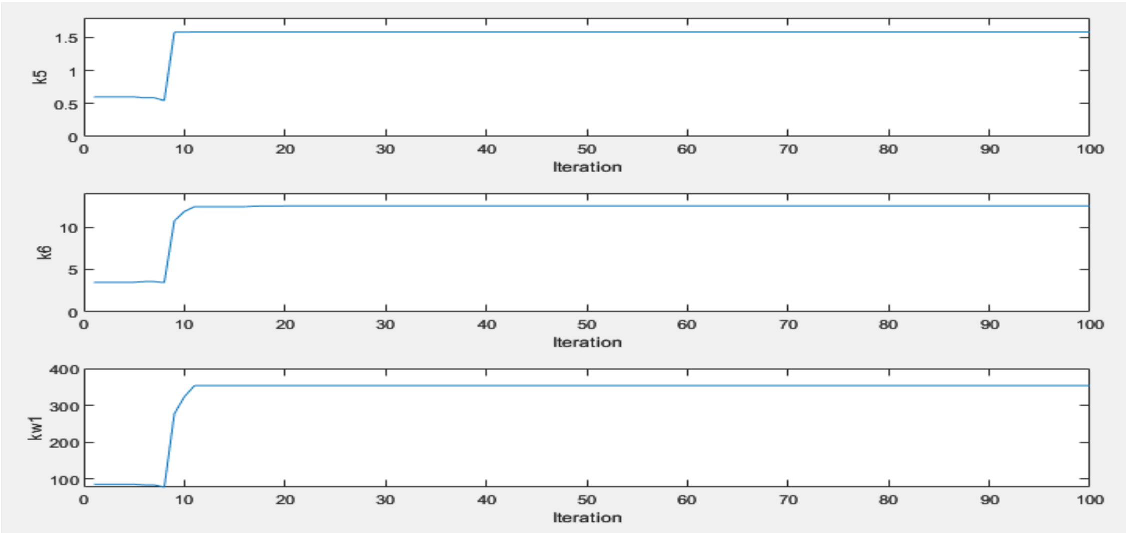
q_1	q_2	q_3	q_4	q_5	q_6
100.00	0.0100	0.3102	500	0.0040	0.0040
k_1	k_2,k_3	$k_{\omega1}$,k_4	k_5	k_6	$k_{\omega2}$
158.103	0	0	1.585	12.483	353.534

Table 3. Values of Q and R matrices and coefficient of ASFC for slow response

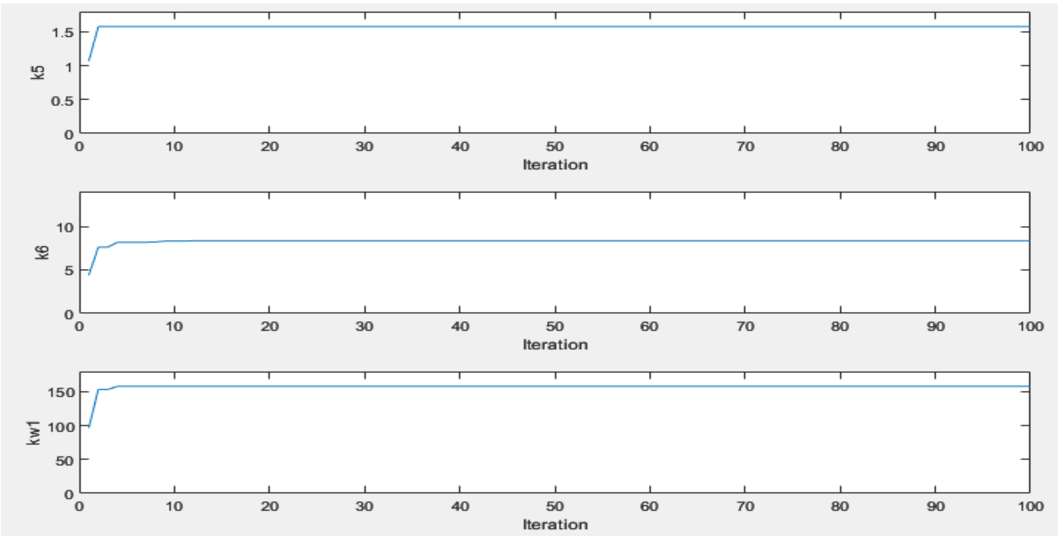
q_1	q_2	q_3	q_4	q_5	q_6
9.019	0.0100	0.1390	100	9.0193	0.0100
k_1	k_2,k_3	$k_{\omega1}$,k_4	k_5	k_6	$k_{\omega2}$
9.486	0	0	1.580	8.345	158.114

Table 2 and 3 show the Q and R matrices and the gain coefficient $k_{\omega1}$ & $k_{\omega2}$. Based on the results above, increasing the gain can provide a higher speed response to the system.

$Q = \begin{matrix} 100.0000 & 0 & 0 & 0 \\ 0 & 0.0100 & 0 & 0 \\ 0 & 0 & 0.3102 & 0 \\ 0 & 0 & 0 & 500.0000 \end{matrix}$	$R = \begin{matrix} 0.0040 & 0 \\ 0 & 0.0040 \end{matrix}$
$k\_t = \begin{matrix} 158.1034 & 0 \\ 0 & 1.5850 \\ 0 & 12.4833 \\ 0 & 353.5534 \end{matrix}$	SimParam.K_SFC=K_SFC_2;



(a) Figure 6. MATLAB simulation



(b)

Figure 7. k5, k6 and kw1 against iteration number (a) faster response, (b) slower response

Figure 9 above shows the value of k_5, k_6 *and* $k_{\omega1}$ against the iterations. Figure 8 with Figure 9(a) demonstrated that the best cost value of Q and R increased the gain coefficient of those parameters. Those gain coefficients would be considered promising after being computed in the PSO algorithms and suitable for the system. This gain coefficient is used to control the speed to an optimization state. For example, if a lower value is set, the gain coefficient obtained from the LQR is lower, so the system has a lower speed. On the other hand, setting a higher value at the upper boundary of PSO can increase the system's speed response.

B. Simulation Results

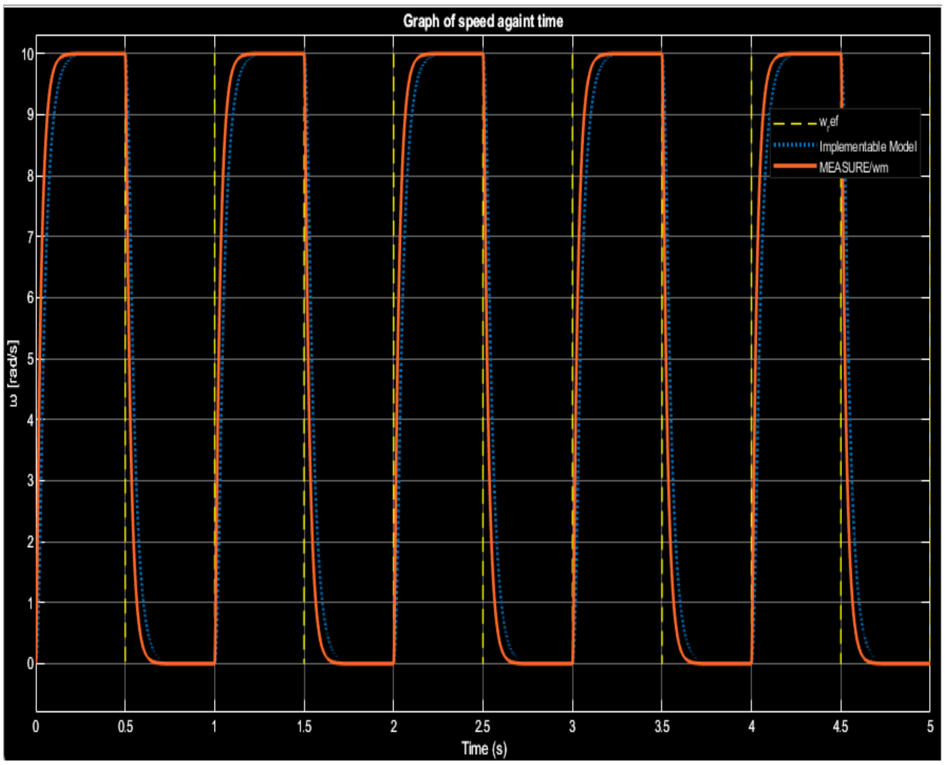
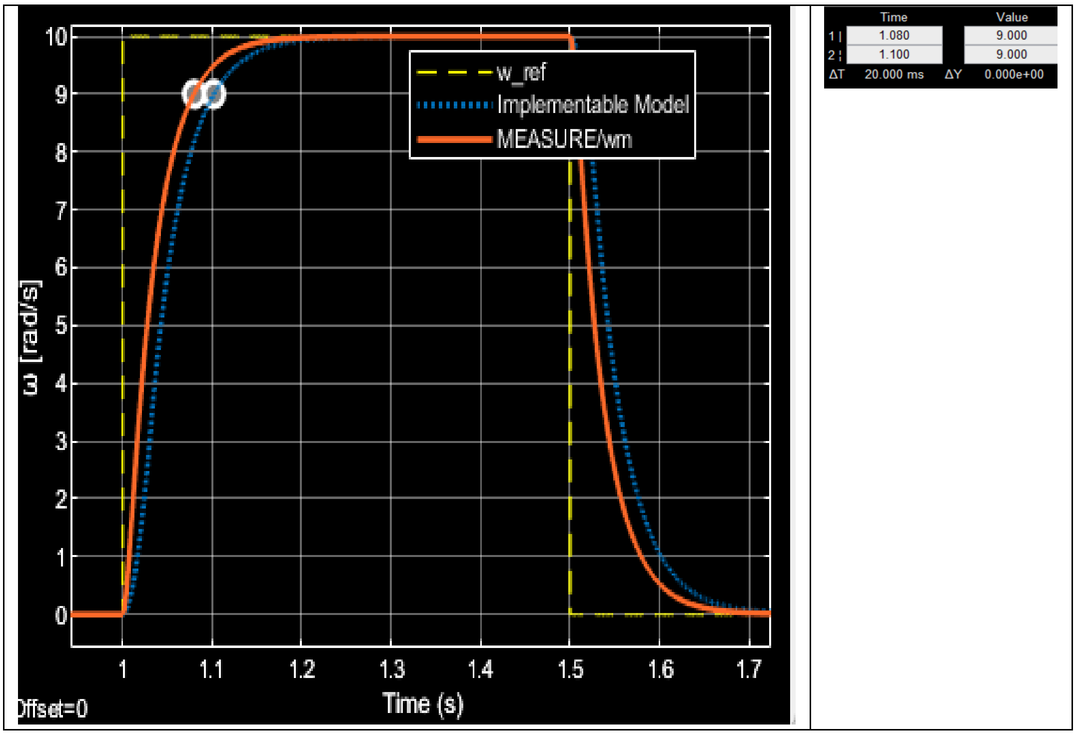
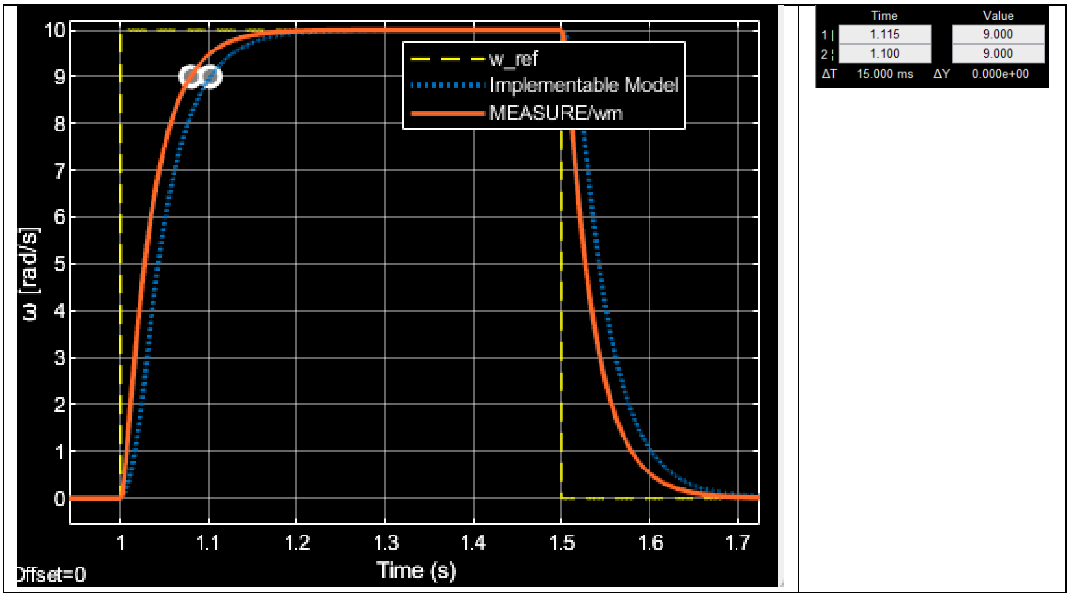


Figure 8. Simulation results for 5 seconds

As shown in Figure 10, the reference signal is a square wave with a period equal to 1s with an angular velocity of 10 rad/s. The step size is from 0 rad/s to 10rad/s at every 1s. Every test lasts until the stop time is set. Only the first five periods are presented in the figure, and results are zoomed to 1s to compare the system's rise time and settling time in Figure 11. The graph's red line indicates the system's response for the Adaptive State Feedback Controller (ASFC). Yellow lines indicate the reference signal, and the blue line indicates the conventional MRAS.



(a)



(b)Figure 9. Comparison of the angular velocity rise time

Figure 11 demonstrates the angular velocity rise time of ASFC comparable to others. Rise time is calculated based on 10% to 90% of the system, and 90% corresponds to around 9rad/s. Figure 11(a) demonstrates that a faster speed response with a rise time obtained from SFC of 1.080s is comparable to the conventional model of 1.1s. The difference between both rises is around 0.02s. Figure 11(b), it demonstrates a lower rise time, which indicates that it has a lower speed response. It is 0.35s slower compared to Figure 11(a). The system is considered stable where fast and slow response result have relatively similar characteristics as the conventional MRAS model. The settling time is also considered in both the SFC and the model. The tolerance band is the maximum allowable range in which the output can be settled. The tolerance band is usually set to 5% of the system. Thus, an amplitude of 9.5 is selected in this case. It can be concluded that the PMSM speed control can be set based on user requirements, where the system can be chosen to have a lower or faster speed response depending on the condition.

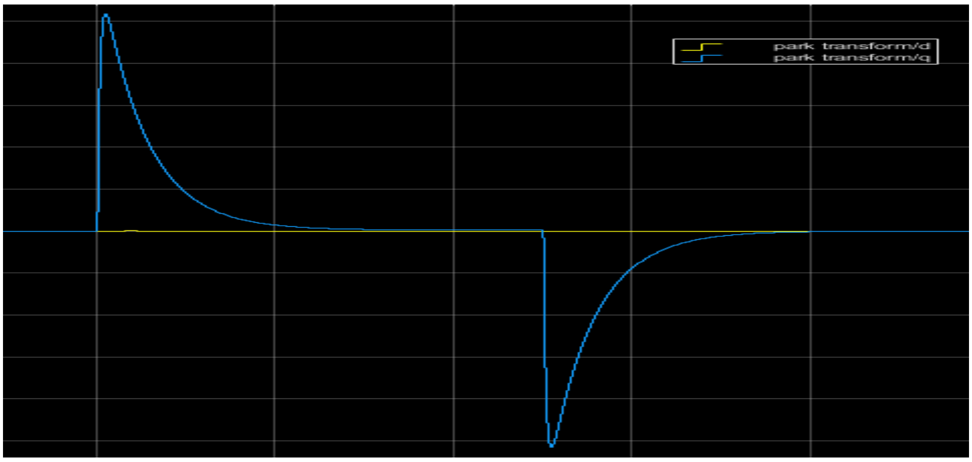


Figure 12. id and iq graph

Figure 12 shows the graph of the d and q current control signals. It shows that both parameters given to the system have stable current, which will not damage the equipment. The outstanding characteristic of the proposed LQR comes from the PSO, which yields the optimal weighting matrix with specific iterations and simple computed procedures. The simulation results show the method's feasibility and verify that the proposed optimizer LQR state-feedback controller based on PSO can be employed to drive the PMSM motor. It achieves the desired control performance in terms of transient and steady-state response characteristics and robustness in terms of its parameter tuning capability.

VI. CONCLUSION

The simulation works aim to optimize the speed control to the PMSM motor applicable to water pressure regulation. The PSO-SFC field-oriented control technique was developed for the PMSM simulation study to improve motor efficiency and precision motor control over the torque and speed. The Linear Quadratic Optimization method is used to overcome difficulties in tuning the SFC coefficient of gain for the linear operation of the speed controller. The Q and R matrices are the critical parameters of LQR for the gain coefficient tuning. The PSO technique is introduced for Q and R matrices, tuning the gain coefficient by searching for the best cost value through the fitness function. The upper and lower boundary range of the PSO parameters is directly proportional to the best cost value, which corresponds to the Q and R weightage matrixes of LQR that affect the rise time and settling time response. These parameters can be chosen based on the condition to regulate the speed response of the application system accordingly. For instance, if higher water pressure is detected, the system can generate appropriate Q and R values to regulate with a lower speed response and vice versa. It allows regulation of the gain coefficient to the system to prevent unsatisfactory operational behavior.

The phase-locked loop can be introduced to the system for future work to track the rotor position through back emf. Prototyping tests and type of more efficient algorithms can be investigated in the research work to improve the design of the Field oriented control of the PMSM motor.

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