A Global Optimization Technique For Modelling And Control Of Permanent Magnet Synchronous Motor Drive

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Abstract. In this paper, model order reduction and controller design of permanent magnet synchronous motor (PMSM) drive has been carried out with the help of a firefly-based hybrid metaheuristic algorithm in the complex delta domain. Two relatively new algorithms, namely, the firefly technique and an adaptive version of the flower pollination method are combined to develop an effective global optimization approach. Originally, the permanent magnet synchronous motor drive constituting speed and current controllers yields a higher-order system reduced to a lower-order model via an identification approach applied in signal processing techniques. The reduced-order model, cascaded with a PI controller is then matched with a reference model approximately to estimate the unknown controller parameters. The tuned controller parameters using the delta operator method almost resemble those obtained by the continuous-time system. Thus, a unified framework of controller design for the drive system is also established. Thus, the hybrid intelligent algorithm is employed for order reduction and controller parameter estimation of PMSM drives. A case study can also be considered for the speed control of switched reluctance and brushless motor drives are widely predominant in several domestic and industrial applications.

Keywords: Permanent magnet synchronous motor (PMSM) drive; controller synthesis; approximate model matching (AMM); firefly algorithm (FA); Adaptive flower pollination algorithm (AFPA).

1. Introduction

The most commonly used control applications namely, fuel injectors, control of fighter planes, automobile spark timer, etc. produce higher-order mathematical models. These models are often difficult to handle for which diminished order modelling is preferred, which aids in reducing the burden of computation and implementation issues associated with controller synthesis for higher-order systems. Although intelligent control techniques for speed control of permanent magnet synchronous motor drives are reported in the literature [1], the Proportional-Integral (PI) controller continues to attract industries due to its uncomplicated structure and robustness for a wide operating range. Some of the significant works carried out in the field of speed control of permanent magnet synchronous motor (PMSM) drives, available in the literature, are discussed below to create interest among researchers.

[2] developed an experimental approach for a fuzzy logic-based AC motor drive system. An adaptive internal model with the current feedback mechanism provided the solution. [3] presented a current controller to reduce torque ripples and provide robust current regulation in PMSM drives. A stability study was conducted based on the discrete-time Lyapunov function to obtain the adaptive gain limits. [4] surveyed multi-phase electric machines to suit variable speed applications. The control aspects and multi-phase inverters used in multi-phase machines are also investigated in detail. [5] developed a disturbance rejection control topology for the PMSM drive system. The proposed control law employed disturbance rejection for the speed loop and the q-axis current loop with an extended state observer's help. A comparative study was presented using both simulations and experiments to prove the efficacy of the proposed technique.

Moreover, [6] developed a new PI controller that preserved the transient performance due to variations in parameter and other external disturbances to control AC motor drives' speed. A minimum steady-state error was ensured with the aid of integral control action. The closed-loop stability of the system was also guaranteed with the help of convergence of the output-tracking error. The control strategy proposed was validated, applying both simulation work as well as experiments. [7] presented a fuzzy adaptive internal model control schemes for the PMSM speed regulation system. The speed loop was designed using a standard internal model control while in the two current loops, PI controllers were employed. The proposed methods were verified using MATLAB as well as TMS320F2808 DSP experimental results.

[8] developed a direct control approach in a sensor less interior PMSM based on the sliding mode method. Both the speed and the motor position were estimated online applying the concept of active flux. A torque/flux sliding mode controller was employed to overcome a huge ripple associated with the direct torque. [9] provided...
a nonlinear speed control algorithm for the PMSM servo system utilizing sliding mode control and disturbance compensation technique. First of all, a new sliding-mode control law was developed, which reduced the chattering problem in control input and maintained the controller's good tracking performance. An extended sliding-mode disturbance observer was also presented to assess the uncertainties concerning the lumped parameters directly, account for the significant disturbances, and yield a very high precision level in the servo mechanism. Both simulations supported with experiments confirmed the effectiveness of the proposed methodology. [10] applied a simplification of the vector control with the genetic algorithm to tune PI controllers for PMSM drives. The speed and torque responses in continuous and discrete-time domains performed fairly well. [11] formulated a neural network-based adaptive controller for the PMSM system. Initially, neural networks were employed to obtain the unknown and the nonlinear functions of the PMSM drive system. To avoid the backstepping component complication, a new adaptive dynamic surface control was further developed. [12] designed an adaptive PID controller for the PMSM drive system. The proportional part was utilized to compensate for the nonlinearities' effects. The integral control action was meant to adjust the gains automatically, and the derivative action guaranteed the system's stability. [13] developed a disturbance rejection scheme for output control of servomotors. An extended state observer based on the higher-order sliding-mode differentiator concept was constructed to assess the unmeasured velocity to realise the output feedback. [14] discussed the stability and robustness issues for disturbance-observer based motion control systems. A reaction torque observer was attempted, and its robustness was assessed. The suggested technique was cross-validated with the help of simulations as well as experimentation.

[15] proposed a neuro-fuzzy based fault-tolerant control for six-phase PMSM servo drive. The fault detection and the operating decision method was conceptualized initially for the six-phase motor. Then a torque controller was developed to track the reference command of the rotor position. [16] presented a new predictive-integral-resonant controller to attenuate periodic disturbances in PMSM drives, ensuring great speed and current performance. Their method increased the disturbances' suppression ability by incorporating the integral and resonant loop's internal model. [17] came up with a digital current controller for ac motor drives based on internal model principles with a disturbance rejection feature. The voltage disturbances were generally suppressed with the help of inner active resistance feedback. The conventional sampling was removed, and an oversampling-based error-free feedback scheme was employed to reduce sampling errors due to switching noise and parasitic oscillations. Thus, a new current controller structure was devised having the benefits of error-free sampling and active resistance feedback. A simplified version of the model predictive control (MPC) scheme was proposed by [18] for an open winding PMSM fed from two separate power sources. Torque and flux constraints in the traditional MPC topology were transformed into an equivalent flux vector to remove the fitness function's weighting factor. A rapid voltage selection approach was also adapted to minimize the burden of system calculation. Moreover, a switching states distribution scheme was also formulated to reduce the dual converter switching frequency. 3-phase PMSMs employed in robots, and machine tool drives were modelled by [19].

Further, a predictive control scheme was applied to overcome the standard control topology based on the vector cascade approach. [20] developed a new control philosophy in forming a predictive control scheme for a three-level inversion-fed open-end winding permanent magnet synchronous motor (OEW-PMSM) to minimize the torque and the stator flux ripples consuming less computation. The suggested technique utilized four voltage vectors instead of nineteen, in three-level traditional MPC. The decrease in the number of voltage vectors reduced the number of predictions and the computation time required for the predictions. A higher sampling rate was also achievable, thereby reducing the steady-state stator flux and torque ripples. A detailed survey regarding the speed control mechanism for the PMSM drive system can also be referred to from [21]. However, no work has yet been reported for modeling and controlling PMSM drives in the delta domain. Hence, a sincere attempt has been made to investigate heuristic-based modeling and control of PMSM drives.

The fact that most discrete systems arise from continuous-time systems sampling is well known. Such structures are modelled, analyzed, and controlled using a time-domain shift operator or z-transformation in the complex domain. However, these discrete-time systems do not take very high sampling frequency into account and do not stabilize due to the pole crowding near the point (1,0). This question can be addressed if discrete-time systems are formulated by the delta operator developed by [22]. The delta system simulation of discrete-time systems helps to achieve almost continuous at an extremely high sampling frequency [23]. It increases their numerical strength over the discrete-time systems by the shift operator. Delta operators are now widely used in the literature on analysing and design control systems [24].

In the classical control literature, the “Truxal” method [25] is an established technique in control system synthesis, based on the philosophy of exact model matching in which first the reference model is developed to meet the given time, and frequency domain performance specifications and then the controller parameters are computed such that the overall closed-loop controlled system to match both time and frequency responses of the reference model. The main drawback of exact model matching (EMM) [26] is that the controller so designed does
not guarantee its physical hardware implementation. To overcome the same, approximate model matching (AMM) [27] may be a viable alternative and applied to the delta domain's design control scheme. The firefly-based hybrid method proposed in [28] is now being employed to reduce the higher-order PMSM drive model and tune the controller parameters in the unified domain of analysis applying the AMM technique.

The remaining paper is structured as follows. In Section 2, order diminution and control of PMSM drives are dealt with constituting a unified domain approach. Section 3 deliberates on the methodology of work. Section 4 narrates the results, whereas Section 5 discusses the salient conclusions with future work directions.

2. Problem Statement
This paper's problem formulation has two vital aspects: the model order reduction and the controller design. [29] developed a new heuristic method to diminish higher-order models in the delta domain, taking into account matching dc gain, stability, and minimum-phase features. Preserving time and frequency domain parameters can also be considered an additional constraint to yield a reduced system's quality solution. Accordingly, the reduction scheme is discussed as follows.

Usually, the input-output relation of the parent higher-order system in the unified domain of analysis is described by

$$G_\delta(\gamma) = \frac{N_{k-1}}{D_k}(\gamma) = \frac{\sum_{i=0}^{k-1} b_i \gamma^i}{\sum_{i=0}^{k} a_i \gamma^i}$$

(1)

where $a_i$ and $b_i$ are the denominator and the numerator coefficients, respectively. The system represented in Equation (1) must be stable too for reduction. Moreover, it is taken into account that $G_\delta(\gamma)$ should be irreducible. This means that $N_{k-1}(\gamma)$ and $D_k(\gamma)$ will not have any factors in common. The main motto will be to determine a lower-order system having an order less than that of the original system, such that it retains all the essential characteristics of the parent system and provided below in Equation (2)

$$G_R(\gamma) = \frac{N_{r-1}}{D_r}(\gamma) = \frac{\sum_{i=0}^{r-1} d_i \gamma^i}{\sum_{i=0}^{r} c_i \gamma^i}$$

(2)

However, the major challenges in performing order reduction heuristically are as follows:

- matching dc gain
- ensuring stability
- retaining the minimum/non-minimum phase characteristics.
- Preserving both time and frequency domain features of the original higher-order model to its reduced counterparts.

These constraints have been appropriately addressed in deciding the cost function used to obtain the reduced system's model parameters. Thus, the integrated topology with the firefly algorithm to be discussed in details ahead in section 3 will be employed to find the coefficients of the numerator and denominator of the proposed second-order model by optimizing the objective (J) represented by in Equation (3)

$$J = \sum_{i=1}^{N} [y_\delta(\gamma) - y_{R\delta}(\gamma)]^2$$

subject to the constraints discussed above. The minimization of this cost function enables the determination of the diminished model parameters. $y_\delta(\gamma)$ represents the PRBS response of the parent model whereas $y_{R\delta}(\gamma)$ denote the PRBS response of the reduced system with unknown parameters. Both responses are obtained in the delta domain, having 'N' samples. The reduced-order model can be of any order less than the original system. However, for simplicity, a second-order reduced model is considered as follows in Equation (4)

$$G_{R\delta}(\gamma) = \frac{d_0 + d_1 \gamma}{c_0 + c_1 \gamma + c_2 \gamma^2}$$

(4)

It is seen from the Equation (4), the reduced system has a predefined structure. Even, in this model, the value of $C_2$ has assumed unity for further simplicity. The second-order model's remaining unknown parameters are then evaluated to minimise the fitness function J, as given in Equation (3) with a firefly-based hybrid optimization technique.

A technique for controller design that establishes an approximate matching with a desired reference transfer function is presented by applying some nature-inspired metaheuristic algorithms. The firefly-based hybrid algorithms developed in [29] are utilized to synthesize the controller parameters in the unified discrete-delta domain considering integral of square error (ISE) as the fitness tool utilizing the benefits of approximate model matching. The parent algorithms, as well as several standards and latest heuristic approaches, are used for comparison. A generalized step-by-step procedure for controller synthesis in the delta domain is thus provided below as shown in Equation (5)
Step 1: Choose a general form of the controller as $C(s) = \frac{\beta_0 + \beta_1 s + \cdots + \beta_r s^r}{\alpha_0 + \alpha_1 s + \cdots + \alpha_r s^r}$ (5)

Step 2: Choose a reference model transfer function that satisfies the desired specification.

Step 3: Evaluate the unity feedback output response and reference model response.

Step 4: Compute the error (ISE) between reference model output and the closed-loop response obtained by cascading the plant and the controller.

Step 5: Minimize the above error by using any metaheuristic technique. Thus, the coefficients of the controller i.e., $\beta_i$ and $\alpha_i$ are obtained by exploring in specified search bounds.

3. Proposed Methodology

The main goal of hybridizing various algorithms is to build improved performance structures that incorporate the parent technique's strengths. In [30], terminology was suggested by Talbi metaheuristic algorithms, which are hybrid. Two high-level or low-level algorithms can be hybridized either homogeneously or heterogeneously with a relay or co-evolutionary method. The hybrid algorithm proposed in this paper is of low-level and relay type, and heterogeneous. The integrated technique is low-level since both the parent algorithms retain their functionalities. The hybrid method is relay-type since one after the other they use the parent algorithms. Two separate algorithms are wired into all the hybrid propositions to produce the desired results. So, the hybrid solution is heterogeneous.

This amalgamation's main reason is to overcome the single optimization algorithm's limitations and get a better representation. Therefore, to achieve the appreciably good outcome within the specified time, it is also necessary to determine the proposed method's vigour and finally to effectively harmonize both diversification and intensification. These two principles strengthen the hybrid method to yield a better outcome than the individual algorithms.

A novel hybrid topology called the FA-AFPA algorithm was conceived by combining the firefly algorithm (FA) with the adaptive flower pollination algorithm (AFPA) to solve very few unconstrained problems of lower-dimensional optimization [31]. The switching probability of the flower pollination algorithm was made adaptive by the formula as shown in Equation (6)

$$p = p_2 - (p_2 - p_1) \times \frac{l}{L}$$

where $p_1$ and $p_2$ are the two fixed parameters of the algorithm considered as 0.4 and 0.9 as the standard choice as per literature. Further, the terms ‘L’ and ‘l’ represent the total and the present iterations, respectively [32].

![Flow diagram of proposed hybrid topology.](image)
Further, it was also utilized to identify Hammerstein and Wiener systems in the delta domain [33]. This approach has balanced diversification and intensification by using FA for exploration and AFPA for exploitation. This algorithm used both the advantages of FA and DFPA methods efficiently and avoided their inconvenience. In FA-AFPA, a set of random operators with the FA initialized the search process. For a certain number of iterations, the calculation continued with the FA to look for the overall best location in the search domain as a whole. As the initial starting point for AFPA, the best solution obtained via FA was taken. The search mechanism was then switched to AFPA to step up the convergence process to obtain the best possible solution. A flowchart for the hybrid architecture is thus provided in Figure 1.

Figure 1 shows that the Firefly Algorithm (FA) performs the task of exploration. Simultaneously, the Adaptive Flower Pollination Algorithm (AFPA) carries out the exploitation to determine the local best solution. Thus, the merit of each of these algorithms is utilized in the hybrid topology. However, this algorithm's success depends on the parameter choice and selection of termination criteria.

Model order reduction for PMSM drives has been carried out in the delta domain using the hybrid firefly technique whose PI controller is further designed applying approximate model matching. A reference model is chosen [34] to satisfy the desired transient and steady-state specifications shown with step responses. The controller parameters and the minimum fitness function are obtained in the delta domain, thus unifying the continuous and discrete-time domain approaches. Additionally, a PMSM motor drive has been considered [35] to perform order reduction and PI controller tuning of the reduced model. Standard algorithm parameters are assumed for tuning PI controller parameters.

4. Simulation results
The mathematical model of the PMSM drive is thus represented by as shown in in Equation (7)

\[ G(s) = \frac{7.94s + 13.23}{9.6 \times 10^{-7}s^3 + 3.99 \times 10^{-9}s^2 + 6.973s + 34.63} \]  

(7)

Our final objective of the investigation is to yield a suitable controller for this PMSM drive. Since the input-output relation developed from the data provided is higher-order, the first step will be to reduce it to a lower-order model for which a standard PI controller can be found suitable [36]. A PI controller is usually preferred over a standard PID controller because it can prevent large disturbances and noise that may arise during drive operation. The transfer function of the model given in Equation (7) in the discrete-delta domain for a sampling time \( \Delta = 0.001 \) secs are given by Equation (8)

\[ G_d(\gamma) = \frac{100\gamma^2 + 12000\gamma + 1995900}{\gamma^3 + 2040\gamma^2 + 1061200\gamma + 5224200} \]  

(8)

Suitable values of population size and maximum iterations, such as 20 and 100, are assumed to develop the reduced models in the unified analysis domain [37]. The standard parameters of all the algorithms are considered as available in the literature. Table 1 provides a list of reduced systems developed in the unified domain. The fitness function values are also provided in the same table. The best fitness value is further marked in bold.

**Table 1.** Reduced-order models and their fitness values of the PMSM drive in the unified domain.

| Algorithms | Reduced models in the delta domain | \( J_{\text{min}} \) (SSE) |
|------------|-----------------------------------|--------------------------|
| FA-AFPA    | \( \frac{990.4\gamma + 1033.4246}{\gamma^2 + 843\gamma + 2705.3} \) | **2.9755e-04** |
| FA [36]    | \( \frac{989.4\gamma + 2435.2118}{\gamma^2 + 843.8\gamma + 6374.9} \) | 3.5926e-04 |
| FPA [37]   | \( \frac{991.2487\gamma + 3819.9506}{\gamma^2 + 847.2199\gamma + 9999.8706} \) | 3.6617e-04 |
| GWO [38]   | \( \frac{990.5\gamma + 3685.918}{\gamma^2 + 849.5\gamma + 9649} \) | 3.0213e-04 |
| PSO [39]   | \( \frac{989.7\gamma + 3742.4158}{\gamma^2 + 845.4\gamma + 9796.9} \) | 3.9686e-04 |
| MVO [40]   | \( \frac{993\gamma + 3800.6708}{\gamma^2 + 851.5\gamma + 9949.4} \) | 3.4352e-04 |
The proposed hybrid algorithm outperforms the parent, standard, and some well-known heuristics available in the literature. As seen in Table 1, FA-AFPA produces the least fitness value than the other methods. Further, the reduced models' transient parameters are also calculated, whose results are provided in Table 2. The nearest values to the original model parameters are represented using bold letters.

### Table 2. Transient specifications of the reduced PMSM drive using the unified approach.

| Test system | Algorithms | Rise time (secs) | Settling time (secs) | % overshoot |
|-------------|------------|------------------|----------------------|-------------|
| Original system | | 0.0027 | 0.7803 | 204.4378 |
| FA-AFPA | | 0.0003 | 0.9135 | 203.0383 |
| FA [36] | | 0.0004 | 0.5205 | 200.162 |
| FPA [37] | | 0.0004 | 0.3336 | 196.9586 |
| GWO [38] | | 0.0004 | 0.3466 | 196.2211 |
| PSO [39] | | 0.0004 | 0.3397 | 197.2367 |
| MVO [40] | | 0.0004 | 0.3370 | 196.1040 |
| DA [41] | | 0.0004 | 0.5801 | 200.7878 |
| GOA [42] | | 0.0004 | 0.5897 | 200.5623 |
| SSA [43] | | 0.0004 | 0.3133 | 217.7805 |

Once again, the integrated approach performs better as compared to the other algorithms considered in this paper. Further, the performance indices widely employed in systems theory and control are assessed in Table 3 for the reduced order systems. The best result, i.e., the minimum value, corresponding to every index in the table, is marked in bold.

### Table 3. Error indices of the reduced PMSM drive in the unified domain of analysis.

| Algorithms | IAE   | ITAE      | ISE     | ITSE     | $H_\infty$ norm |
|------------|-------|-----------|---------|----------|-----------------|
| FADFPA     | 0.0055 | 3.4967e-04 | 2.9755e-04 | 2.0136e-05 | 0.0776 |
| FA [36]    | 0.0057 | 3.6923e-04 | 3.5926e-04 | 2.0179e-05 | 0.0889 |
| FPA [37]   | 0.0060 | 3.8201e-04 | 3.6617e-04 | 2.2131e-05 | 0.1144 |
| GWO [38]   | 0.0057 | 3.4991e-04 | 3.0213e-04 | 2.0887e-05 | 0.0861 |
| PSO [39]   | 0.0060 | 3.8543e-04 | 3.9686e-04 | 2.2047e-05 | 0.1111 |
| MVO [40]   | 0.0057 | 3.5837e-04 | 3.4352e-04 | 2.2212e-05 | 0.1176 |
| DA [41]    | 0.0058 | 3.6936e-04 | 3.2754e-04 | 2.0988e-05 | 0.0867 |
From the results represented in Table 3, it is found that the suggested approach supersedes many of the latest heuristic techniques. Even all the error indices have fewer values with the integrated method than the parent and other algorithms used for comparison, proving that the proposed technique is far more superior than the existing methods [38]. Finally, the PI speed controller is tuned using the complex delta domain approach. AMM technique is applied for the controller synthesis [39]. A heuristic tool is utilized to obtain the controller parameters with the help of the proposed metaheuristic algorithms [40]. Apart from the controller gains, the best fitness value determined using the heuristic scheme is also highlighted in bold [41].

Table 4. Controller tuning parameters and the fitness function values of the second-order PMSM model using the delta operator framework.

| Algorithms | $K_p$   | $K_i$   | $J_{\text{min}}$ (ISE) |
|------------|---------|---------|-----------------------|
| FADFPA     | 1.8678  | 3.7042e-05 | 7.3715e-05          |
| FA [36]    | 0.7172  | 3.3084e-04 | 7.5926e-05          |
| FPA [37]   | 0.61314 | 1.3541e-04 | 7.6091e-05          |
| GWO [38]   | 1.8012  | 1.3171e-04 | 7.388e-05           |
| PSO [39]   | 0.7799  | 1.0429e-04 | 7.5815e-05          |
| MVO [40]   | 0.9792  | 1.3541e-04 | 7.5635e-05          |
| DA [41]    | 0.1641  | 2.4361e-05 | 7.6606e-05          |
| GOA [42]   | 0.97922 | 1.2431e-05 | 7.5379e-05          |
| SSA [43]   | 1.8679  | 8.9412e-04 | 7.3781e-05          |

The results obtained in Table 4 indicate that the integrated method outperforms the parent, standard, and some of the latest reported heuristic techniques in terms of closeness towards reaching the optimum value [42]. Thus, the suggested technique could successfully develop the reduced-order model of the PMSM drive and produce the PI controllers using an approximate model matching technique with the least fitness functions compared to the parent as other standard methods [43].

5. Conclusion
The problem of order reduction and controller design in the discrete delta domain has been considered for PMSM drives in this paper. Constrained global optimization techniques are being employed to develop the reduced-order models of the PMSM drive. The method further uses the concepts of approximate model matching approach to obtain the parameters of the controller. A firefly-based hybrid technique namely the FADFPA, successfully minimized the scalar fitness function, ISE to obtain the controller parameters. The important feature of the proposed method is that only output feedback is used. This provides a low order of practically implemented plants. The control system responses match those of the desired model very closely. The present paper tackles efficiently only one salient application for order reduction and controller synthesis of the PMSM drive in the unified delta domain. Modelling and controlling other popular drives like the switched reluctance motor drive and the brushless dc motor drive can also be undertaken in the future.

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