Adaptive fuzzy logic-controlled surface mount permanent magnet synchronous motor drive

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Permanent magnet synchronous machines (PMSMs) are becoming popular in industries due to their fast transient response, high power density and high efficiency. This paper presents rotor field-oriented control of a surface mount permanent magnet synchronous motor drive with a fuzzy logic-based speed controller. A model reference adaptive fuzzy logic controller is utilised in the place of a conventional speed proportional plus integral (PI) controller. Simulation and experimental results are provided to show the applicability of artificial intelligence-based speed control of PMSMs. Results are presented for both conventional PI-based control and proposed adaptive fuzzy logic control and compared. The novelty of the paper lies in the experimental implementation of the adaptive fuzzy logic controller in vector-controlled PMSM drive.

Keywords: fuzzy logic; model reference learning controller; permanent magnet

1. Introduction

Permanent magnet synchronous machines (PMSMs) are becoming serious competitors to induction machines due to the lowering cost of the permanent magnet materials, high efficiency, no reactive power demand from the grid side and fast dynamic response. PMSMs are used in many industries applications ranging from small servo drive for machine tools to large electric/hybrid electric vehicles and ship propulsion applications (Bose, 2006; Dai, Song, & Cui, 2007; Vas, 1998; Yanliang, Jiaqun, & Wenbin, 2001). More recently an energy-optimised control algorithm is proposed for interior PMSMs (Nasirudin & Abera, 2009). A model-based efficiency optimisation algorithm is proposed for vector-controlled interior PMSM drive. However, owing to the general nature of the proposed algorithm, it is equally applicable to a surface mount PMSM.

Conventionally proportional plus integral (PI) controllers are employed in control loops due to their simplicity and wide acceptability. However, there are some known problems that exist in PI controllers such as noise, drift, poor bandwidth and tedious tuning characteristics. PI controllers are known to be parameter sensitive, and this adaptive mechanism needs to be incorporated in the controller structure to cope with the nonlinearity and parameter sensitivity. Several adaptation mechanisms are proposed in the literature such as model reference adaptive control, sliding mode control, variable structure controller, self-tuning PI controller, predictive controller, etc. However, the major problems with these controllers are their strong dependence on the plant mathematical models. However, it is difficult to precisely represent any practical system by its mathematical models as the electromechanical systems are prone to temperature and other environmental condition changes.

Thus a robust controller is required which is insensitive to these variables. One of the most powerful tools that can convert linguistic control rules based on an expert knowledge is fuzzy logic control. Its design philosophy is different from all previous methods by accommodating expert users’ knowledge in the controller design (Su & Stepanenko, 1994; Tang, Li, & Kung, 1996; Yan, Ryan, & Power, 1995). Fuzzy logic can be considered as a mathematical theory combining multi-valued logic, probability theory and artificial intelligence to simulate the human approach in the solution of various problems by using an approximate reasoning to relate different data sets and to make decisions. It has been reported that fuzzy controllers are more robust to plant parameter changes than classical PI or proportional plus integral plus derivative controllers and have better noise-rejection capabilities. Fuzzy controller performance is dependent on the membership functions, their distribution and the rule base that influences the fuzzy sets in the systems. No formal method has been proposed so far to choose these parameters and tune fuzzy controllers; hence, it is basically a trial and error procedure unless expert knowledge is known and dependable. Moreover, a simple fuzzy logic controller fails to offer best results if the operating conditions change in a wide range and available expert knowledge is not adequate and reliable. Thus, the adaptation

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mechanism is incorporated for situations where there are chances of large variation in parameters and operating conditions of the system under control. The adaptation of a fuzzy logic controller can be achieved by fuzzy reasoning which is simple and straightforward compared with the tedious mathematical approach of classical adaptive controllers. Fuzzy logic-based speed control of ac machines is proposed by many authors (Heber, Xu, & Tang, 1997; Ibrahim & Levi, 2002; Masiala & Knight, 2006; Mrad & Deeb, 2002; Nasiruddin, Radwan, & Azizur, 2002; Tang & Xu, 1994; Zhen & Xu, 2000) as an alternative to the PI controller. A decentralised adaptive fuzzy controller for a permanent magnet synchronous motor based on type-2 fuzzy logic systems and adaptive control theory is presented in Barkat, Tlemçani, and Nouri (2011). The type-2 fuzzy logic systems are utilised to model unknown functions, while adaptive law is designed to compensate for inter-connection effects and reconstruction errors, using a sliding mode term. Stability based on Lyapunov’s criteria is proved with simulation results. A fractional-order proportion-plus-differential (FOPD) controller for the control of PMSM is reported in Zhang and Pi (2012). Robustness is enhanced by acting on an acted function (AF) instead of tracking errors directly. A tuning method is illustrated for the gains of an FOPD controller and a fuzzy logic inference algorithm is also presented to obtain the parameters of an AF. Satisfactory tracking performance is achieved with parameter variation and load disturbance. Generally, the fuzzy logic controller offers superior transient response, while the PI controller offers better steady-state response. A combination of FLC and PI, called hybrid fuzzy–PI speed control, is presented in Sant, Rajagopal, and Sheth (2011). The proposed solution is less computationally intensive with faster response. The performance of the vector-controlled permanent magnet synchronous motor drive with hybrid fuzzy–PI is reported. However, the limitation of the proposed scheme lies with the robustness and stability of this approach. An adaptive fuzzy control scheme is presented for PMSMs in Chaoui and Sicard (2012). The discussed adaptive control technique consists of a Lyapunov stability-based fuzzy speed controller. A robust control technique is used for parameter variations. No explicit current loop regulation is needed in this approach and hence a simpler structure is obtained. However, no experimental proof is given in this paper.

Several artificial intelligence techniques have been developed of a single-input single-output pure-feedback nonlinear system considering known state variables (Zhang, Wen, & Zhu, 2010; Zou & Hou, 2008) and a multi-input multi-output (MIMO) system (Wang, Ge, & Hong, 2011; Zhou, Shi, Lu, & Xu, 2011). Recently an adaptive fuzzy back-stepping control technique was developed for an uncertain MIMO pure-feedback nonlinear system where the state variable is unknown (Tong, Li, Feng, & Li, 2011; Tong, Li, & Li, 2009). The fuzzy logic approach is employed to approximate the unknown nonlinear functions and further a fuzzy state observer is utilised to estimate the unknown state variables. This gives rise to a new class of adaptive fuzzy back-stepping output feedback control technique that guarantees a semi-globally uniformly ultimately bounded (SUUB) system (Tong, Li, & Shi, 2012). In this control approach, the observer errors and tracking errors converge to origin if a proper design parameter is chosen. A similar approach is employed for a strict-feedback system with unknown state variables and unknown dead zones in Tong and Li (2012). A fuzzy logic control system is employed for approximating the nonlinear function and a state observer is used to estimate the unknown states. Then using the adaptive back-stepping recursive control technique provides a new adaptive control system that guarantees the SUUB system. Generally speaking, the adaptive fuzzy control approach provides a systematic methodology to eliminate the tracking error and solve the regulation control problem for nonlinear systems.

A fuzzy model reference learning controller (FMRLC)-based speed control of a three-phase surface mount PMSM drive is proposed in this paper. The PMSM drive system is controlled in sensorless mode and a field-oriented control scheme used in speed mode of operation in a base speed region. An adaptation mechanism is executed by fuzzy logic based on the error and change of error measured between the motor speed and the output of a reference model. The control performance of the learning fuzzy controller is evaluated by experimentation for various operating conditions. In contrast to Kadjoudj, Golea, and Benbouzid (2007) where only simulation results are provided, this paper presents experimental implementation of the proposed concept. The organisation of the paper is such that at first the modelling of PMSM is reviewed, followed by the discussion on the vector control and FMRLC structures. The simulation and experimental results are provided in the subsequent sections followed by the conclusion and references.

2. Modelling of a three-phase PMSM

The PMSM considered here has a surface-mounted structure and, like the name suggests, the permanent magnets are mounted on the surface of the rotor. The difference between the quadrature and direct axis inductances in this machine is small and the machine can be usually considered as having a uniform air gap (i.e., \( L_d = L_q = L_s \)). In such a PMSM, torque is produced solely due to the existence of flux developed by the permanent magnets attached to the rotor.

Modelling of synchronous machines in \( d - q \) domain can be performed by analogy with corresponding three-phase induction machine modelling. One important observation is that all synchronous machines, regardless of the type and the number of phases, have to be modelled in the rotating frame firmly fixed to the rotor. This is so since, in general, \( d - q \) axis inductances of synchronous machines are mutually different. In such a case only selection of the rotating frame fixed to the rotor (i.e. synchronous rotating
frame) leads to elimination of the phase domain inductance dependence on the rotor angular position.

In general, one defines the following $d-q$ axis inductances for a synchronous machine without rotor windings (White & Woodson, 1959):

\[ L_d = L_{ls} + L_{md}, \]
\[ L_q = L_{ls} + L_{mq}. \]

Transformation of the phase variable model of a three-phase PMSM to the $d-q$ reference frame is achieved using the decoupling transformation matrices and the rotational transformation matrices with the common reference frame fixed to the rotor.

The voltage equilibrium equations can be obtained by applying transformation matrices and are given as:

\[ \begin{align*}
    v_{ds} &= R_{s}i_{ds} - \omega \psi_{qs} + p\psi_{ds}, \\
    v_{qs} &= R_{s}i_{qs} + \omega \psi_{ds} + p\psi_{qs}.
\end{align*} \]

Flux linkage equations of a PMSM take the following form:

\[ \begin{align*}
    \psi_{ds} &= (L_{ls} + L_{md})i_{ds} + \psi_{ms} = L_{d}s_{ds} + \psi_{ms}, \\
    \psi_{qs} &= (L_{ls} + L_{mq})i_{qs} = L_{q}s_{qs}.
\end{align*} \]

Torque equation of a PMSM is

\[ \begin{align*}
    T_e &= P(\psi_{ds}i_{qs} - \psi_{qs}i_{ds}), \\
    T_e &= P(\psi_{ms}i_{qs} + (L_{ed} - L_{eq})i_{ds}i_{qs}) = P\psi_{ms}i_{qs}.
\end{align*} \]

The torque equation resembles the equation of dc machine, and thus, the torque can be controlled directly by controlling the $q$-axis stator current.

3. Vector control of a PMSM

The equations given in Section 2 are already in the rotor flux-oriented reference frame for a PMSM, since the $d$-axis coincides with the direction of the permanent magnet flux. Inductances along $d-q$ axes are assumed to be equal, and the base speed region is only considered. Assuming that current control is performed in the rotating reference frame, the vector controller takes the form given in Figure 1. For speed control in the base speed region in a PMSM, a number of control strategies exist such as zero $d$-axis current, maximum torque per unit current, maximum efficiency, unity power factor, constant mutual flux linkage, etc. (Kazmierkowski, Krishnan, & Blaabjerg, 2002). This paper utilises the zero $d$-axis control strategy for simulation purposes; however, in experimental investigation it is held constant. The zero $d$-axis control technique is widely used in industries. It offers a similar characteristic as that of an armature-controlled dc motor where the torque is proportional to the current magnitude.

The closed-loop control has two loops; the inner is current control while the outer is speed control. The speed control loop utilises an adaptive fuzzy logic controller, while the current control is accomplished by a conventional PI controller. The input to the fuzzy controller is the speed error and the output is the reference $q$-axis current, which is further processed in the PI current controller to yield $\beta$-axis voltage reference. The $\alpha$-axis voltage is obtained from another PI current controller which processes the $d$-axis current. The reference voltages thus generated are then transformed into a rotating reference frame using a vector rotator block. The reference $d-q$ axis voltage is then fed to the appropriate modulation block to produce the necessary switching signals for the voltage source inverter. In the present study, the space vector pulse width modulation technique is used to control the voltage source inverter.

4. Fuzzy logic model reference learning controller structure

The fuzzy logic control is an expert system paradigm where human-like intelligence may be adopted and
applied to some complex systems. This fuzzy logic artificial intelligence setting adjusts controller parameters or membership functions based on specified performance characteristics. The prerequisite of a conventional control is a highly accurate mathematical model of the plant or process to be controlled. In case of a motor drive system, a number of components are involved such as motor, sensors, actuators, etc. Their individual models are well established; however, as an integrated system, the overall model becomes very complex and thus the conventional controllers which are model dependent do not offer precise control (Passino & Yurkovich, 1998). Thus, one has to resort to intelligence-based control and one such method is fuzzy logic-based control. It has been shown that fuzzy logic-based control offers any nonlinear control action with proper choice of the system parameters. Thus, fuzzy logic controller is parameter dependent which may vary with the operating conditions. The remedy for this is the use of a fuzzy logic model reference learning controller.

The FMRLC consists of mainly four components: the plant, the fuzzy controller, the reference model and the learning mechanism (or adaptation mechanism) as shown in Figure 2. The learning mechanism observes the current values for $r(kT)$ and $y(kT)$ at $T$ (sampling period) and by using these values it adjusts the fuzzy controller accordingly to achieve the desired performance. These performance objectives (closed-loop specifications) are characterised via the reference model. Basically, the lower part of Figure 2 operates to make $y(kT)$ follow $r(kT)$ by influencing $u(kT)$, while the upper part of Figure 2 (adaptation control loop) operates to make $y_m(kT)$ follow $y_m(kT)$ by manipulating the fuzzy controller parameters.

4.1. Fuzzy controller

The plant has an input $u(kT)$ and output $y(kT)$. The inputs to the fuzzy controller are the error $e(kT) = r(kT) - y(kT)$ and change in error $c(kT) = [e(kT) - e(kT - T)]/T$. The scaling gains are $g_e$, $g_c$ and $g_u$ for the error $e(kT)$, change in error $c(kT)$ and controller output $u(kT)$, respectively (Passino & Yurkovich, 1998).

4.2. Rule base

The rules for the fuzzy controller have the following form.

If $\tilde{e}$ is $\tilde{E}^j$ and $\tilde{c}$ is $\tilde{C}^i$ then $\tilde{u}$ is $\tilde{U}^m$ where $\tilde{e}$ and $\tilde{c}$ denote the linguistic variables associated with controller inputs $e(kT)$ and $c(kT)$, respectively, $\tilde{u}$ denotes the linguistic variable associated with the controller output $u$, $\tilde{E}$ and $\tilde{C}$ denote the $j$th ($l$th) linguistic value associated with $\tilde{e}$ ($\tilde{c}$), respectively, and $\tilde{U}$ denotes the consequent linguistic value associated with $\tilde{u}$. For example, one fuzzy control rule could be: if error is positive-large and change-in-error is negative-small, then plant input is positive-large (Passino & Yurkovich, 1998).

In this paper, in the speed controller, the speed error “$e$” and the rate of change of error “$\Delta e$” are taken as the input crisp variables. The output crisp is taken as the $q$-axis reference current. The membership functions and the corresponding rules used for simulation are illustrated in Figures 3 and 4, respectively. The simulation is done using simple nine rules and the triangular membership functions and the direct fuzzy controller is used instead of the adaptive one. The adaptive fuzzy logic controller is used for experimental purposes.

A Mamdani type of fuzzy logic controller is used for speed control. On the basis of the values “$e$” and “$\Delta e$,” fuzzy...
numbers are calculated in the fuzzification block using the membership function of Figure 3. Simple membership functions for the three linguistic variables “N”-negative, “Z”-Zero and “P”-Positive are used. Symbol “G” means great and symbol “S” represents small. The resulting block consists of the logic table such as “if...then,” listed in Table 1.

Although the FMRLC may provide promising simulation and experimental results, it is important to note that the FMRLC provides no guarantee of stability or convergence (Passino & Yurkovich, 1998). For example, the closed-loop system may become unstable for a large adaptation gain or different reference models.

5. Simulation results

For simulation purposes, the PMSM model is normalised with respect to their nominal values. Per-phase equivalent circuit parameters of the 50 Hz three-phase surface mount PMSM, used in the paper, are \( R_s = 0.032988 \) p.u., \( L_d = L_q = 0.86431 \) p.u., \( J = 0.00529 \) p.u. The complete vector-controlled drive is run using all PI and then using
Table 1. Fuzzy logic controller rules of inference.

| \( \Delta i_{qs}^* \) (output reference q-axis current) | \( e \) (speed error) | N | Z | P |
|---------------------------------------------------|-------------------------|---|---|---|
| \( \Delta e \) (change in speed error)            | N                       | GN | SN | SP |
|                                                  | Z                       | GN | Z  | GP |
|                                                  | P                       | SN | SP | GP |

current PI and the speed model reference learning fuzzy controller. The rules and the surface plot of the fuzzy logic controller are depicted in Figures 4 and 5, respectively. These figures clearly show the contribution of input to the output.

Figure 4. Rules plot of fuzzy controller obtained from Matlab.

Figure 5. Surface plot of fuzzy logic controller obtained from Matlab.

Figure 6. Simulation results of vector-controlled PMSM under no-load condition.
The simulation conditions are such that stator $d$-axis current reference is kept zero for the whole simulation period. The output of the speed fuzzy speed controller and the PI speed controllers are limited to 2.5 times the rated value. The outputs of the current controllers are also limited to 2.5 times the rated value. Ideal conditions are assumed and hence the inverter model is not incorporated in the simulation. The simulation step size is kept as 1 ms and the solver is a simple ordinary differential equation of order 1 (ODE1) (Euler).

Command of 0.8 p.u. is applied at $t = 0$ s in a square wave step manner until $t = 30$ s when it is dropped to zero value. Once again speed command of 0.8 p.u. is applied at $t = 70$ s. Operation takes place under no-load conditions. The resulting waveforms are depicted in Figure 6.

It is observed from Figure 6 that reference and actual $q$-axis current follows very well for both PI and fuzzy logic controllers. The speed plot shows fast acceleration behaviour of the PMSM following well the commanded speed. Acceleration takes place with the maximum allowed value of the motor torque. The dynamics of the machines look similar for both PI and fuzzy-based systems. However, it is expected that if higher rules and a more precise fuzzy controller are used, then it will give better response compared with the PI controller. Nevertheless the complexity will increase and the computation time may increase.

Disturbance rejection properties of the drive are investigated next. The motor at first is started under no-load condition and once it reaches steady-state speed, rated load torque is applied. The resulting simulation waveforms are depicted in Figure 7. Application of the load torque causes an inevitable dip in speed. But the drop in speed is very small and almost unnoticeable in the simulation waveform. Motor torque quickly follows the torque reference and enables rapid compensation of the speed dip. However, under load condition, the dynamic response of the fuzzy logic controller is faster compared with the PI controller as evident from the $q$-axis current plot of Figure 7.

Figure 7. Simulation results of vector-controlled PMSM under load condition.

Figure 8. Block diagram of the experimental set-up.
6. Experimental set-up

The experimental set-up consists of a 4 kW three-phase surface mount permanent magnet synchronous motor drive system (Appendix 1). The load to the PMSM is a dc machine acting as a generator and mechanically coupled to it (Appendix 2). The drive system is controlled using a floating point Digital Signal Processor (DSP, ADSP 21065L) and Field Programmable Gate Arrays (FPGA, Flex 6016). The motor is being fed using a DSP-based three-phase inverter. The control algorithm used in the set-up is a field-oriented sensored control scheme. The whole drive system is controlled using a PC. The control code is written in the PC, and it is then passed on to the DSP and FPGA boards through an optical fibre communication cable through the USB port of the PC. The calculations are realised in one cycle. The use of DSP and FPGA makes it possible to realise a very sophisticated and advanced control system. The use of FPGA makes it possible to perform parts of the control system using hardware, which unloads the processor from parts of the realised task. FPGA in the experimental set-up realises the following functions:

- Timing of switching on of each transistor for one switching period of the inverter.
- Providing dead time between the turning on of the two power switches of the same leg in the inverter.
- Control of breaking resistor.
- Service of A/D converters.
- Shut down of the inverter in the case of emergency signals.
- Data exchange between the DSP and the drive system.

The set-up can be controlled locally using configurable analogue and digital inputs and outputs. The set-up can also be controlled remotely using Sharc Drive or Tkombajn suitable PC programming tool. This software allows access to parameters, diagnostic messages, trip, settings and full application programming. The block diagram of the whole drive system is illustrated in Figure 8. Speed sensors are used to compare the actual and estimated speeds obtained using observers.

![Figure 9. Twenty five rules of FMRLC for PMSM drive.](image)

![Figure 10. Reversing transients from −0.4 to 0.4 p.u. speed: (a) speed response, (b) q-axis stator current and (c) d-axis current.](image)
7. Experimental results

Experiments are conducted to implement the indirect rotor field-oriented control of surface mount PMSM using the FMRLC in the speed feedback loop. The adaptation mechanism is based on a gradient algorithm method. The adaptation mechanism adjusts the characteristic of the fuzzy controller in response to the error between the outputs of the reference model and the actual model. The fuzzy rules and the membership functions used for the experimental approach are illustrated in Figure 9. For experimental purposes, 25 rules are utilised to reduce the computational burden on the processor. The rest of the details of the fuzzy controller are presented in Section 4. The experimental results are recorded using Tkombajn software and the data are transferred to the Matlab software for further processing to obtain the resulting waveforms. The resulting experimental waveforms are illustrated in Figures 10–12 for various transients.

At first, no-load condition is tested followed by operation under loaded condition. The motor is accelerated to

![Figure 11](image1.png)  
**Figure 11.** Reversing transients from 0.8 to 0 p.u. and then to 0.8 p.u. speed: (a) speed response, (b) $q$-axis stator current and (c) $d$-axis current.

![Figure 12](image2.png)  
**Figure 12.** Loading transient from 0.5 to $-0.5$ p.u. speed: (a) speed response, (b) $q$-axis stator current and (c) $d$-axis current.
−0.4 p.u. speed before reversing it to 0.4 p.u. speed and the operation takes place under no-load condition. The motor quickly follows the commanded speed without any overshoot or any oscillatory transient. Very fast dynamics are observed as evident from Figure 10. The small value of the $d$-axis current is also forced in the reverse direction in contrast to the simulation where it is kept zero. The $q$-axis current remains constant during the whole transition. This is done in order to compensate for the no-load losses, which are not present in simulation condition. Other no-load test results are provided in Figure 11, where the motor runs at a high speed of 0.8 p.u., is brought to halt and once again accelerated to 0.8 p.u. speed. The speed response shows a very good dynamic response of the motor drives. A satisfactory braking characteristic of the motor is also evident from Figure 11. The $q$-axis and $d$-axis currents show a typical vector-controlled drive response. The $q$-axis current shows the nature of the electromagnetic torque produced by the PMSM. The load rejection behaviour of the drive is also tested, and the resulting plot is given in Figure 12. The machine is accelerated, loaded and then reversed under loaded condition. The reversal part of the transient is shown in Figure 12. Once again a good dynamic behaviour is noted. The $q$-axis current is almost a rated value due to a rated load and the same value of current is observed with reverse polarity due to a changed direction. The $d$-axis current remains more or less constant. A small increase in $d$-axis current is due to increased losses during load condition. Thus successful implementation of an FLMRC-based speed control system is demonstrated.

8. Conclusion

The paper deals with vector control of a three-phase surface mount PMSM, utilising an indirect rotor flux-oriented controller and model reference adaptive fuzzy logic speed controller. Operation in the speed mode is studied, utilising the current control in the synchronous reference frame. The attainable performance is examined by simulation as well as experimentation. Very fast dynamic behaviour is achieved by utilising a model reference fuzzy logic controller in the speed loop. A number of transients including acceleration, deceleration, reversing and load rejection are examined. It is shown that by using an FLMRC very quick and precise control can be achieved.

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Appendix 1

| Parameters      | Ratings        |
|-----------------|----------------|
| Nominal power   | 4000 (Watt)    |
| Nominal voltage | 400 V, 50 Hz, Star |
| Nominal current | 7.5 A         |
| Nominal efficiency | 93%          |
| Mass            | 50 kg         |
| Nominal speed   | 1500 rpm      |
| Nominal torque  | 25.4 (Nm)     |

Appendix 2

| Parameters      | Ratings        |
|-----------------|----------------|
| Nominal power   | 6600 (Watt)    |
| Nominal voltage | 440 V         |
| Nominal current | 16.5 A        |
| Mass            | 139 kg        |
| Nominal speed   | 1500 rpm      |
| Nominal torque  | 42 (Nm)       |

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