J Electr Eng Technol.2016; 11(2): 470-479
http://dx.doi.org/10.5370/JEET.2016.11.2.470

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

The Energy Saving for Separately Excited DC Motor Drive via Model Based Method

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Abstract – The model based method for energy saving of the separately excited DC motor drive system is proposed in the paper. The accurate power loss model is necessary for this method. Therefore, the adaptive tabu search algorithm is applied to identify the parameters in the power loss model. The field current values for minimum power losses at any load torques and speeds are calculated by the proposed method. The rule based controller is used to control the field current and speed of the motor. The experimental results confirm that the model based method can successfully provide the energy saving for separately excited DC motor drive. The maximum value of the energy saving is 48.61% compared with the conventional drive method.

Keywords: Adaptive tabu search, Energy saving, Model based method, Rule based controller, Separately excited DC motor

1. Introduction

Nowadays, the separately excited DC motor is widely used in industries. This motor is suitable for the electric vehicle and conveyer [1] because it can provide the high torque to drive the load. Moreover, this motor is easy to control the speed for automatic control system. Presently, the energy saving in electrical system is a considered issue for industrial sectors, particularly in the electric motor drive. Therefore, the energy saving of the separately excited DC motor is proposed in the paper. In the previous works [2-7], the conventional approach based on mathematics is applied to calculate the field current for energy saving. Unfortunately, the equation used in that approach is complicated and it is difficult to solve this problem. Therefore, the new method called the model based method (MBM) is used to calculate the field current for energy saving easily at any load torques and speed commands. The accurate power loss model is very important for the MBM method. Hence, the artificial intelligence technique called adaptive tabu search (ATS) is applied to identify the parameters in the power loss model. The ATS method is developed by Puangdownreong et al. in 2002 [8]. In order to perform its effectiveness, the ATS has been tested against several well-known benchmark functions, that is, Bohachevsky, Rastrigin, Shekel's foxholds, Shubert and Schwefel functions [9-13]. Moreover, the convergence property of the ATS has been proved to assure that it can reach the optimal solution within finite search time [9-14]. Thus, the ATS algorithm can provide the global solutions for system identification. A single – phase bridge rectifier connected with two buck converters is a studied system in the paper as shown in Fig. 1. The expert controller called the rule based controller [15] is also presented for the field and speed controls. This controller is easy to implement and sufficient to control the field current and speed of the motor. In addition, the results of the electric energy consuming of the motor using the conventional drive method are compared with the MBM drive method. The results from the implementation in laboratory can confirm that the MBM method can provide the minimum losses at any load torques and speed commands. The maximum percent of the energy saving using the MBM drive method is equal to 48.61% compared with the conventional drive method. However, the MBM method cannot provide to save the energy in case of the high load torque.

The reviews of power losses of the separately excited DC motor and the identification of the power loss model

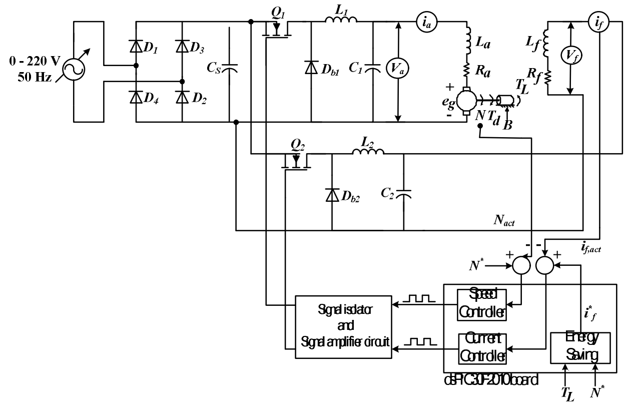

Fig. 1. The block diagram of a separately excited DC motor drive for energy saving

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Received: August 6, 2014; Accepted: September 9, 2015

are presented in Section 2. The energy saving algorithm using the MBM method and the design of rule based controllers are fully described in Section 3 and 4, respectively. The experimental results of the energy saving using the MBM drive method compared with the conventional drive method and discussion are shown in Section 5. Finally, Section 6 concludes the overall advantages using the MBM method to save the energy in separately excited DC motor drive system.

2. Power Losses of Separately Excited DC Motor and Power Losses Identification

2.1 Power losses of separately excited DC motor

The power losses can be classified into five types. These losses are both electrical and mechanical losses. The details of the losses are described in this section.

2.1.1 Copper losses

The copper losses are divided in two cases. These losses consist of the armature and field copper losses that can be calculated by (1).

$$\begin{aligned} P_a &= i_a^2 R_a \\ P_f &= i_f^2 R_f \end{aligned} \tag{1}$$

2.1.2 Friction and windage losses

These losses occur from the friction of the bearings in the motor and the friction between the moving parts of the motor and the air in the motor case [16]. These losses are given in (2).

$$P_m = K_m N^3 \tag{2}$$

2.1.3 Core loss

The core loss occurs in the iron core of the motor. The core loss consists of the hysteresis loss [2, 16] and the eddy current loss [17] defined by (3).

$$P_i = K_h \omega i_f^2 + K_e \omega^2 i_f^2 \tag{3}$$

2.1.4 Brush loss

This loss that occur the voltage drop across the brushes in the motor can be calculated by (4).

$$P_{BD} = U_e i_a \tag{4}$$

2.1.5 Stray loss

The stray loss depended on the armature current and the motor speed can be calculated by (5).

$$P_s = K_{st} i_a^2 N^2 \tag{5}$$

The friction and windage losses and eddy current loss are neglected because the motor using in the paper is small horsepower (0.5-hp). Therefore, the total power losses can be defined by (6).

$$\begin{aligned} P_{loss} &= i_a^2 R_a + i_f^2 R_f + 2 i_a \\ &\quad + 3600 K_{st} i_a^2 \omega^2 / 4\pi^2 + K_h i_f^2 \omega \end{aligned} \tag{6}$$

2.2 Power Losses Identification

In the paper, the total power losses can be calculated by (6). The accurate parameters in (6) are necessary to achieve the precise total power losses value. Thus, the method to identify the power loss parameters is presented in this section. The armature current (i_a), field current (i_f), and motor speed (ω) values in (6) can be measured by sensors, while armature resistance (R_a) and field resistance (R_f) are also measured by an ohmmeter. In the paper, R_a and R_f are equal to $16\ \Omega$ and $735\ \Omega$, respectively. Moreover, the coefficients of the stray losses (K_{st}) and hysteresis losses (K_h) in (6) are difficult to measure or calculate. In previous researches [3], the equation to calculate the K_{st} and K_h values are not appeared. Therefore, the identification of two parameters are necessary. In the paper, the artificial intelligence technique called adaptive tabu search method (ATS) is applied to identify these parameters (K_{st} and K_h). The ATS method is confirmed by [8] to achieve the global solution. The back tracking and adaptive search radius are the main mechanisms of the ATS method to escape the local solution to global solution. The block diagram to identify the power loss parameters in the paper is illustrated in Fig. 2.

In Fig. 2, the equation (7) is used as the objective function to calculate the cost value (W). This equation is the root mean square error between the power loss values from experiment ($P_{loss(experiment)}$) and computation

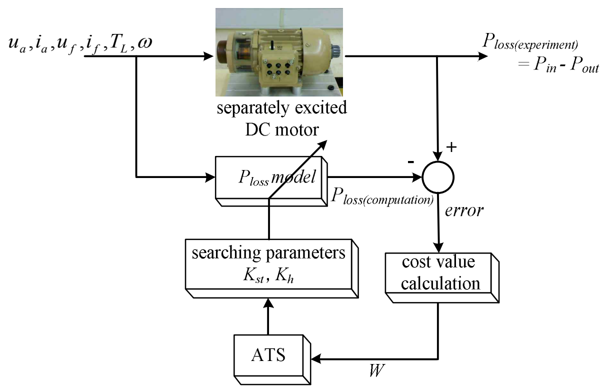

Fig. 2. The block diagram to identify the parameters of power loss equation using ATS algorithm

Table 1. The motor testing results

speed		u_a (V)	i_a (A)	u_f (V)	i_f (A)	T_L (N·m)	P_{in} (W)	P_{out} (W)	P_{loss} (W)
% rated speed	rad/s								
80	197.71	182.80	2.20	220.00	0.30	1.54	468.16	304.28	163.88
90	222.43	201.20	2.20	220.00	0.30	1.54	508.64	342.53	166.11
100	247.87	220.00	2.20	220.00	0.30	1.55	550.00	383.71	166.29
110	270.28	220.00	2.20	186.50	0.22	1.39	524.10	374.34	149.76
120	297.40	220.00	2.20	143.30	0.19	1.23	511.23	365.81	145.42

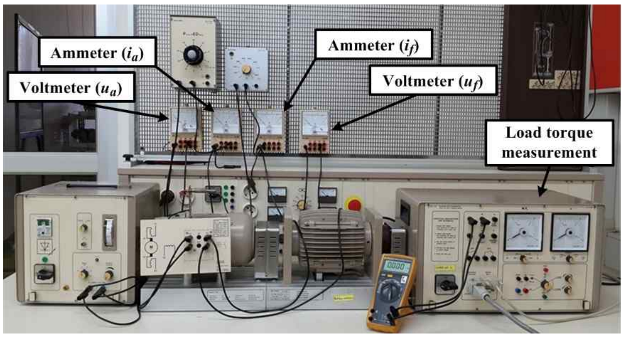

Fig. 3. The experimental rig for testing

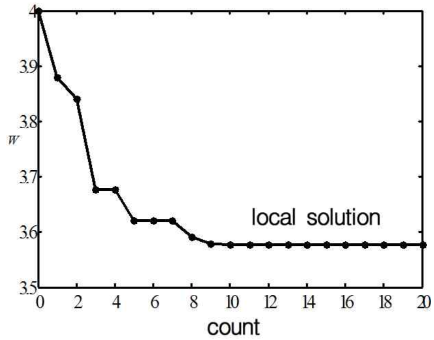

Fig. 4. The *W* convergence

($P_{loss(computation)}$) as given in (8). The n value in (7) is the total data number. The experimental rig to measure the ($P_{loss(experiment)}$) is depicted in Fig. 3. In addition, the results from motor testing at 80%, 90%, 100%, 110% and 120% of rated speed are shown in Table 1. The data of 80%, 100% and 120% of rated speed are used to identify the power loss parameters (K_{st} and K_h), while the data of 90% and 110% of rated speed are used for validation.

$$W = \sqrt{\frac{\sum error^2}{n}} \tag{7}$$

$$error = | P_{loss(experiment)} - P_{loss(computation)} | \tag{8}$$

From Fig. 2, the ATS is applied to search the K_{st} and K_h parameters. The new K_{st} and K_h values from ATS searching is used to calculate the power losses ($P_{loss(computation)}$). The new $P_{loss(computation)}$ value calculated by using the new K_{st} and K_h parameters is subtracted with $P_{loss(experiment)}$ again. The ATS process is used to tune the K_{st} and K_h values until the minimum W value can be obtained. The convergence of W value is shown in Fig. 4. In this paper, the initial solutions for ATS searching are determined by random. However, the authors define the suitable search space that can provide the initial solution as better as possible. As a result, the W value is equal to 4 at the beginning. If the search space is not appropriate, the initial W value will be higher than 4. As for this case, the count for ATS searching equal to 20 is not enough to achieve the best solution. The more details of the ATS searching process can be found in [8]. The results from the power loss parameters identification with ATS algorithm are shown in Table 2. In Table 2, the K_h value from the 1st experimental is different from the others because of the random process of the initial solution in ATS searching. In the paper, the ATS searching process was conducted 5 trials with random initial solutions. Therefore, the average values of K_h and K_{st} are suitable for using in the paper. The average values of K_{st} and K_h are equal to 8.68×10^{-7} W·s²/A² and 4.77×10^{-8} W·s/A²·rad, respectively. It can be seen from the results that the K_{st} and K_h values are very small because the motor using in the paper is a small size. In addition, the parameters validation is necessary to guarantee the identification results. The validation results show that the K_{st} and K_h values are appropriate to use at any operating points. Therefore, the equation to calculate the total power losses of the motor using in the paper is shown in (9). In the paper, the voltage drop across the brushes (U_e) is set to 2 V [1].

Table 2. The ATS searching results and the validation results of the power loss equation

The ATS searching results			
Testing	K_{st} (W·s²/A²)	K_h (W · s / A² · rad)	W
1st	8.68×10^{-7}	2.89×10^{-8}	3.5764
2nd	8.68×10^{-7}	5.10×10^{-8}	3.5764
3rd	8.68×10^{-7}	5.34×10^{-8}	3.5764
4th	8.68×10^{-7}	4.28×10^{-8}	3.5764
5th	8.68×10^{-7}	6.23×10^{-8}	3.5764
Averaged value	$\mathbf{8.68\times10^{-7}}$	$\mathbf{4.77\times10^{-8}}$	**3.5764**
The validation results of the power loss equation			
% of rated speed	$P_{loss(experiment)}$ (W)	$P_{loss(computation)}$ (W)	***% error***
90	166.11	166.93	0.49
110	149.76	143.77	4

$$P_{loss} = 16i_a^2 + 735i_f^2 + 2i_a + (7.92\times10^{-5})i_a^2\omega^2 + (4.77\times10^{-8})i_f^2\omega \tag{9}$$

3. Energy Saving using Model Based Method

3.1 The conventional method

The conventional method to control the speed of the separately excited DC motor is divided into two cases. In the first case, the armature voltage control can be adjusted, while the field voltage is set to be constant at rated value. For this case, the speed command is less than the rated speed. In the second case, the speed command is more than the rated speed. The armature voltage is fixed to rated and the field voltage is adjusted to increase the motor speed. The input power (P_{in}) calculation of the motor for conventional control approach can be calculated by (10).

$$P_{in} = u_a i_a + u_f i_f \tag{10}$$

3.2 The model based method

In the paper, the new method to minimize the power losses for separately excited DC motor is presented. This method is called the model based method (MBM). The MBM is applied to calculate the field current for energy saving at any operating points. The total power loss values calculated by (9) from section 2.2 at load torque (T_L) equal to 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4 and 1.5 N·m are shown in Fig. 5. From this figure, the motor speed and field current are varied from 500-3000 rpm and 0.1-0.3 A, respectively. The armature currents in Fig. 5 are calculated by the basic equation as shown in (11) using K = 2.49 N·m /A^2.

$$i_a = T_L / K i_f \tag{11}$$

$$i_f = a_0 + a_1 N \tag{12}$$

From Fig. 5, it can be seen that the minimum power loss value is depended on the field current at any load torques and speeds. Therefore, the field current for the minimum loss can be calculated. The optimal field current values for loss minimization at any load torques and speeds from Fig. 5 are shown in Fig. 6. The curve in Fig. 6 is called $i_f - N$ curve for loss minimization. In case of T_L = 0.6 N·m and speed command N =1500 rpm, the field current (i_f) for minimum power loss is equal to 0.197 A. The $i_f - N$ curve in Fig. 6 can be approximated by linear regression as depicted in Fig. 7. The equation (12) is used to approximate the i_f value for loss minimization. The a_0 and a_1 coefficients at any load torques are shown

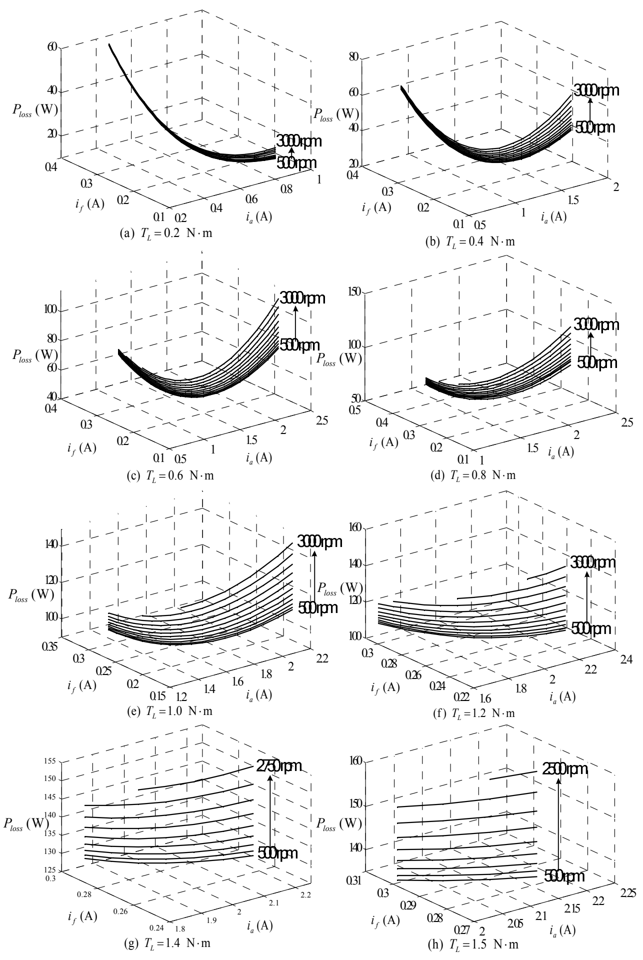

Fig. 5. The minimum power loss at any speeds and load torques

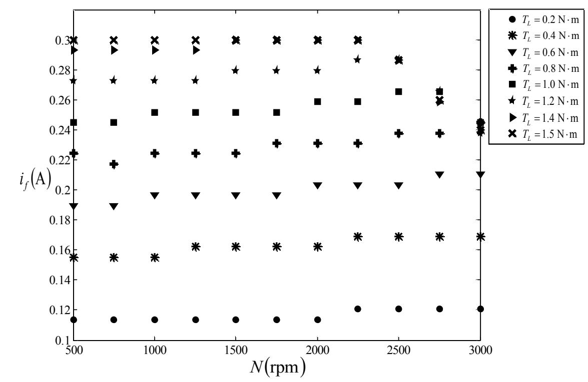

Fig. 6. The $i_f - N$ curves for loss minimization.

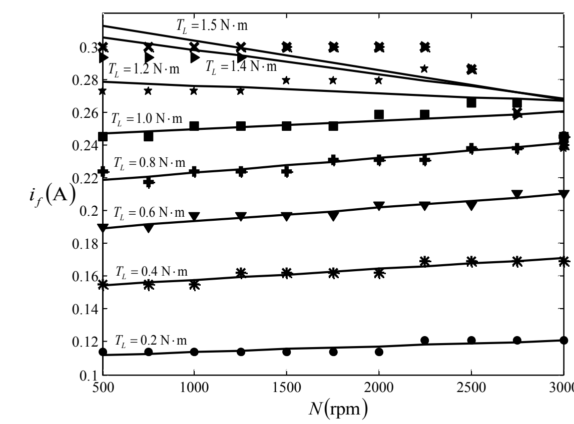

Fig. 7. The linear approximation of $i_f - N$ curve using linear regression method.

in Table 3.

In Fig. 7, there are eight $i_f - N$ curves for T_L = 0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4 and 1.5 N·m. The $i_f - N$ curves for other load torques can be determined by using the linear interpolation method. The a_0 and a_1 coefficients from linear interpolation method can be calculated by the equations in Table 4. For example, if T_L = 0.3 N·m, the equations to calculate the a_0 and a_1 coefficients can use the equations in $0.2 < T_L < 0.4$ interval. The $i_f - N$ curves for any load torques using the linear interpolate are shown in Fig. 8. In the paper, the equation (12) with the coefficients in Table 4 is used to calculate the field current for loss minimization at any load torques and speeds.

Table 3. The a_0 and a_1 coefficients from linear regression method

T_L (N·m)	a_0	a_1
0.2	0.1112	3.5140×10^{-6}
0.4	0.1513	6.5210×10^{-6}
0.6	0.1852	8.2760×10^{-6}
0.8	0.2140	9.0280×10^{-6}
1.0	0.2444	5.2664×10^{-6}
1.2	0.2810	4.7651×10^{-6}
1.4	0.3130	1.4920×10^{-5}
1.5	0.3220	1.8230×10^{-5}

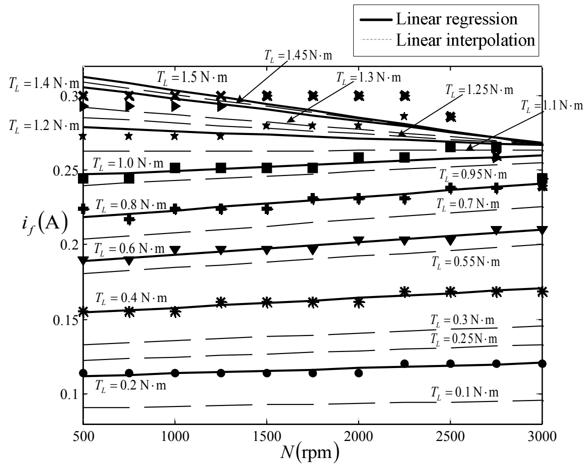

Fig. 8. The i_f–N curves using linear interpolation method.

4. Rule Based Controller

The expert controller called the rule based controller is applied for speed and field current controls in the paper. The inference engine and knowledge based are the important parts of this controller. The rules of the controller are generated from the engineer experiences.

Table 4. The a_0 and a_1 coefficients from linear interpolation method

T_L (N·m)	a_0	a_1
$T_L < 0.2$	$0.1102-\left[\dfrac{((0.2-T_L)\times(0.1513-0.1102))}{(0.4-0.2)}\right]$	$3.514\times10^{-6}-\left[\dfrac{((0.2-T_L)\times(6.521\times10^{-6}-3.514\times10^{-6}))}{(0.4-0.2)}\right]$
$0.2 < T_L < 0.4$	$\left[\dfrac{((T_L-0.2)\times(0.1513-0.1102))}{(0.4-0.2)}\right]+0.1102$	$\left[\dfrac{((T_L-0.2)\times(6.521\times10^{-6}-3.514\times10^{-6}))}{(0.4-0.2)}\right]+3.514\times10^{-6}$
$0.4 < T_L < 0.6$	$\left[\dfrac{((T_L-0.4)\times(0.1852-0.1513))}{(0.6-0.4)}\right]+0.1513$	$\left[\dfrac{((T_L-0.4)\times(8.276\times10^{-6}-6.521\times10^{-6}))}{(0.6-0.4)}\right]+6.521\times10^{-6}$
$0.6 < T_L < 0.8$	$\left[\dfrac{((T_L-0.6)\times(0.214-0.1852))}{(0.8-0.6)}\right]+0.1852$	$\left[\dfrac{((T_L-0.6)\times(9.028\times10^{-6}-8.276\times10^{-6}))}{(0.8-0.6)}\right]+8.276\times10^{-6}$
$0.8 < T_L < 1.0$	$\left[\dfrac{((T_L-0.8)\times(0.2444-0.214))}{(1.0-0.8)}\right]+0.214$	$\left[\dfrac{((T_L-0.8)\times(5.266\times10^{-6}-9.028\times10^{-6}))}{(1.0-0.8)}\right]+9.028\times10^{-6}$
$1.0 < T_L < 1.2$	$\left[\dfrac{((T_L-1.0)\times(0.281-0.2444))}{(1.2-1.0)}\right]+0.2444$	$\left[\dfrac{((T_L-1.0)\times(-4.765\times10^{-6}-5.266\times10^{-6}))}{(1.2-1.0)}\right]+5.266\times10^{-6}$
$1.2 < T_L < 1.4$	$\left[\dfrac{((T_L-1.2)\times(0.313-0.281))}{(1.4-1.2)}\right]+0.281$	$\left[\dfrac{((T_L-1.2)\times(-1.492\times10^{-5}+4.765\times10^{-6}))}{(1.4-1.2)}\right]-4.765\times10^{-6}$
$1.4 < T_L < 1.5$	$\left[\dfrac{((T_L-1.4)\times(0.322-0.313))}{(1.5-1.4)}\right]+0.313$	$\left[\dfrac{((T_L-1.4)\times(-1.823\times10^{-5}+1.492\times10^{-5}))}{(1.5-1.4)}\right]-1.492\times10^{-5}$

4.1 Field current control

The MBM method described in Section 3 is used to calculate the field current for loss minimization. The buck converter in the field side of Fig. 1 is used to adjust the field current to the command value. The duty cycle of Q_2 is adjusted by the rule based controller. There are ten rules for field current control.

Rule 1:
if <*err_ f* is positive and more than 15 mA>
then <increase duty cycle 2.5%>
Rule 2:
if <*err_ f* is positive and more than 12 mA>
then <increase duty cycle 1.5%>
Rule 3:
if <*err_ f* is positive and more than 10 mA>
then <increase duty cycle 1.0%>
Rule 4:
if <*err_ f* is positive and more than 7 mA>
then <increase duty cycle 0.5%>
Rule 5:
if <*err_ f* is positive and more than 5 mA>
then <increase duty cycle 0.1%>
Rule 6:
if <*err_ f* is negative and more than 15 mA>
then <decrease duty cycle 2.5%>
Rule 7:
if <*err_ f* is negative and more than 12 mA>
then <decrease duty cycle 1.5%>
Rule 8:
if <*err_ f* is negative and more than 10 mA>
then <decrease duty cycle 1.0%>
Rule 9:
if <*err_ f* is negative and more than 7 mA>
then <decrease duty cycle 0.5%>
Rule10:
if <*err_ f* is negative and more than 5 mA>
then <decrease duty cycle 0.1%>

The *err_ f* in the rules is the error between the field current value for loss minimization calculated by MBM method ($i_{f,minimize}$) and the actual field current ($i_{f,act}$) as defined by (13). For example in *Rule 1*, the $i_{f,minimize}$ is more than the $i_{f,act}$ (more than 15 mA), the *err_ f* is the positive value. In this case, the $i_{f,act}$ should be increased by increasing the duty cycle of Q_2 2.5%.

$$err\_f = i_{f,minimize} - i_{f,act} \tag{13}$$

4.2 Motor speed control

The rule based controller is also used to control the motor speed to the desired value. The buck converter connected in the armature side in Fig. 1 is applied to adjust the armature voltage to control the motor speed. The duty cycle of Q_1 is adjusted by the eight rules of the rule based controller.

Rule 1:
if <*err_ s* is positive and more than 200 rpm>
then <increase duty cycle 1.5%>
Rule 2:
if < *err_ s* is positive and more than 100 rpm >
then <increase duty cycle 1.0%>
Rule 3:
if <*err_ s* is positive and more than 50 rpm>
then <increase duty cycle 0.5%>
Rule 4:
if <*err_ s* is positive and more than 10 rpm>
then <increase duty cycle 0.1%>
Rule 5:
if <*err_ s* is negative and more than 200 rpm>
then <decrease duty cycle 1.5%>
Rule 6:
if <*err_ s* is negative and more than 100 rpm>
then <decrease duty cycle 1.0%>
Rule 7:
if <*err_ s* is negative and more than 50 rpm>
then <decrease duty cycle 0.5%>
Rule 8:
if <*err_ s* is negative and more than 10 rpm>
then <decrease duty cycle 0.1%>

The *err_ s* is the error between the speed command (N^*) and the actual speed (N_{act}) as shown in (14). For example in *Rule 5* case, the N_{act} is more than the N^* (more than 200 rpm), the *err_ s* is the negative value. In this case, the duty cycle of Q_1 is decreased 1.5% to reduce the armature voltage.

$$err\_s = N^* - N_{act} \tag{14}$$

In the paper, the dsPIC30F2010 microcontroller is used to implement the rule based controllers for current and speed control loops. Moreover, the dsPIC30F2010 is used to calculate the $i_{f,minimize}$ using the MBM method for energy saving. The overall procedures for energy saving and controls are explained in Fig. 9. From this figure, the speed command (N^*) and load torque (T_L) are set by user ($\leq$ rated of the motor). After setting N^* and T_L values, the dsPIC30F2010 calculates the $i_{f,minimize}$ for energy saving using MBM method. The actual field current ($i_{f,act}$) from current sensor is used to calculate the *err_ f*. The *err_ f* value is the input of the rule based controller to adjust the duty cycle of Q_2. After the duty cycle adjustment to adapt the field current to command value ($i_{f,minimize}$), the speed control is action. The actual speed (N_{act}) from speed sensor is detected to calculate the *err_ s*. This error is used to check in eight rules for rule based controller. The controller adjusts the duty cycle Q_1 to change the armature voltage

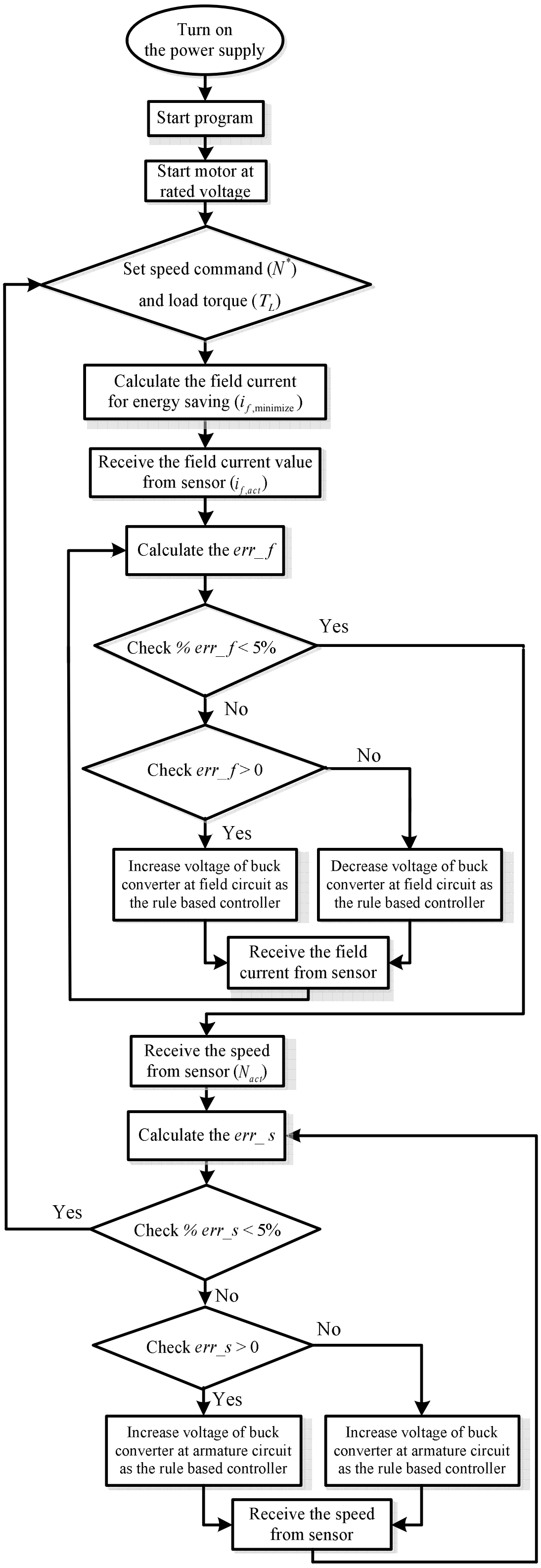

Fig. 9. The block diagram of motor drive with the rule based controller

for speed control. For this situation, the motor speed is equal to speed command and the field current is equal to $i_{f,minimize}$ for energy saving. In case of the speed command or variation of load torque, the dsPIC30F2010 calculates the new $i_{f,minimize}$ value again and the rule based controller starts to control the field current and motor speed to track the command value.

5. Experimental Results and Discussion

The experimental setup of the separately excited DC motor drive system is shown in Fig. 10. It can be seen in Fig. 10 that the single phase bridge rectifier connected with two buck converters are the power converters of the system.

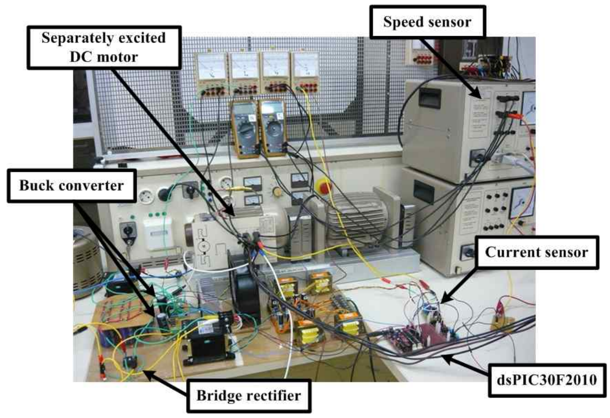

Fig. 10. A driving system for separately excited DC motor

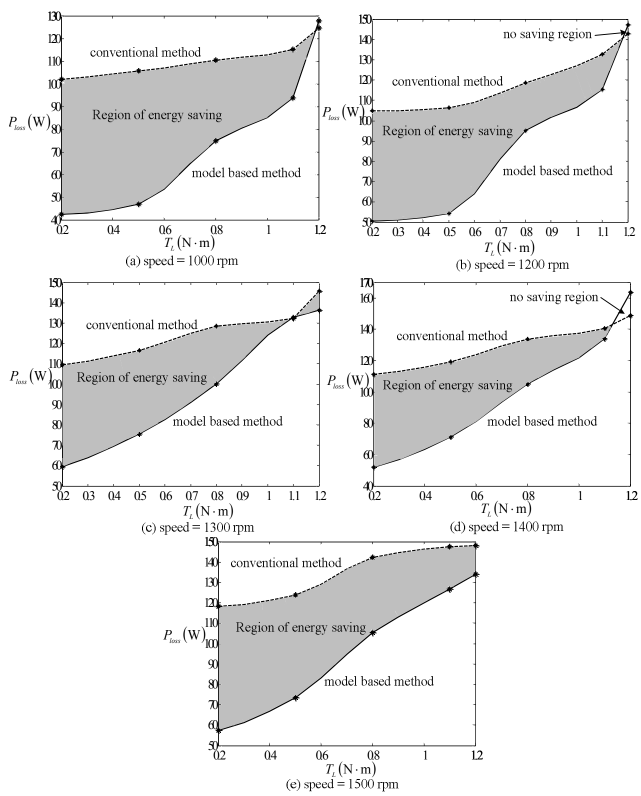

Fig. 11. The energy saving of the motor using difference technique to control the motor speed

Table 5. The comparison results of energy saving

T_L (N·m)	N^* (rpm)	Conventional method						Model based method						% loss minimization
		N_{act} (rpm)	i_f (A)	u_f (V)	i_a (A)	u_a (V)	$P_{in,CON}$ (W)	N_{act} (rpm)	i_f (A)	u_f (V)	i_a (A)	u_a (V)	$P_{in,MBM}$ (W)	
0.2	1000	1043	0.30	200	0.75	85	123.75	1012	0.12	80	0.90	60	63.60	48.61
	1200	1205	0.30	200	0.70	100	130.00	1219	0.12	80	0.95	70	76.10	41.46
	1300	1318	0.30	200	0.70	111	137.00	1341	0.11	70	1.00	80	87.70	35.99
	1400	1395	0.30	200	0.70	115	140.50	1408	0.12	80	0.90	80	81.60	41.92
	1500	1565	0.30	200	0.70	130	151.00	1495	0.11	70	0.90	90	88.70	41.26
0.5	1000	1020	0.30	200	1.10	90	159.00	988	0.18	120	1.10	70	98.60	37.99
	1200	1218	0.30	200	1.10	100	170.00	1211	0.18	120	1.20	80	117.60	30.82
	1300	1335	0.30	200	1.10	115	186.50	1321	0.19	130	1.20	100	144.70	22.41
	1400	1389	0.30	200	1.10	120	192.00	1401	0.17	115	1.25	100	144.55	24.71
	1500	1513	0.30	200	1.10	130	203.00	1527	0.18	120	1.20	110	153.60	24.33
0.8	1000	1010	0.30	200	1.50	90	195.00	1002	0.22	140	1.60	80	158.80	18.56
	1200	1181	0.30	200	1.50	105	217.50	1184	0.23	150	1.60	100	194.50	10.57
	1300	1332	0.30	200	1.50	120	240.00	1317	0.23	150	1.60	110	210.50	12.29
	1400	1447	0.30	200	1.50	130	255.00	1447	0.23	150	1.60	120	226.50	11.18
	1500	1502	0.30	200	1.60	130	268.00	1510	0.22	145	1.60	125	231.90	13.47
1.1	1000	1006	0.30	200	1.90	90	231.00	1001	0.25	170	1.85	90	209.00	9.52
	1200	1183	0.30	200	1.90	110	269.00	1169	0.27	185	2.00	100	249.95	7.08
	1300	1268	0.30	200	1.90	115	278.50	1337	0.26	180	2.00	120	286.80	no saving
	1400	1446	0.30	200	1.90	130	307.00	1342	0.27	180	2.00	120	288.60	5.99
	1500	1526	0.30	200	1.95	135	323.25	1460	0.25	180	2.00	125	295.00	8.74
1.2	1000	990	0.30	200	2.10	90	249.00	995	0.28	180	2.25	90	252.90	no saving
	1200	1180	0.30	200	2.10	110	291.00	1177	0.28	190	2.20	110	295.20	no saving
	1300	1324	0.30	200	2.10	120	312.00	1238	0.27	185	2.20	110	291.95	6.43
	1400	1380	0.30	200	2.10	125	322.50	1360	0.27	180	2.20	130	334.60	no saving
	1500	1471	0.30	200	2.10	130	333.00	1457	0.28	190	2.20	120	317.20	4.74

The dsPIC30F2010 microcontroller board is used to calculate the command value of field current for energy saving based on MBM method. Moreover, it acts as the current and speed controllers using rule based control technique. The rating of the separately excited DC motor using in the paper is 0.5-hp, 220 V, 2360-rpm, 2.2 A. The conventional method and MBM described in Section 3 are applied to drive the motor. The experimental results using MBM method compared with the conventional method are depicted in Table 5. The load torque (T_L) values for testing are in the range 0.2-1.2 N·m. The speed commands (N^*) for testing at any load torques are 1000, 1200, 1300, 1400 and 1500 rpm. In Table 5, the input powers using the conventional method are compared with the MBM method. In case of $T_L = 0.2$ N·m and N^* =1000 rpm, the MBM method can save the energy to 48.61%. However, the MBM method cannot save the energy in high load torque cases. From Table 5, the percent of energy saving becomes lower for higher load torque. The MBM drive method can provide the small input power compared with the conventional drive. The small input powers in each situation indicate that the power losses of the motor are small. The power losses for MBM and conventional methods at any load torques and speeds are shown in Fig. 11. From this figure, it can be seen that the region of energy saving is a large area at slight load torque. At high load torque, the region of energy saving becomes small area. The experimental results confirm that the proposed MBM drive method can provide the good result in terms of energy saving for a separately excited DC motor drive system.

6. Conclusion

This paper presents the new method to drive the separately excited DC motor called the MBM method. The MBM method provides the good results in case of energy saving compared with the conventional drive method. The parameters of the power loss model are identified by using the adaptive tabu search (ATS) algorithm. This accurate power loss model is used in the MBM method to calculate the field current value for energy saving. The rule based controller is applied to control the field current and speed of the motor to track the command values. The experimental results show that the MBM drive method can provide the minimum losses at any load torques and speed commands. The maximum percent of the energy saving is equal to 48.61%. However, in case of the high load torque values, the MBM drive method cannot provide to save the energy.

Acknowledgements

This work was supported by Suranaree University of Technology (SUT).

Nomenclature and Units

i_a , i_f are the armature and field currents.
u_a , u_f are the armature and field voltages.
U_e is the voltage drop across the brushes.
R_a , R_f are the armature and field resistances.
K_m is the coefficient of the friction and windage losses.
K_h is the coefficient of the hysteresis loss.
K_e is the coefficient of the eddy current loss.
K_{st} is the coefficient of the stray loss.
P_a , P_f are the armature and field copper losses.
P_m is the friction and windage losses.
P_{ai} is the core loss.
P_{BD} is the brush loss.
P_s is the stray loss.
P_{loss} is the total power loss.
P_{in} is the input power.
P_{out} is the output power.
N is the motor speed (rpm).
ω is the angular motor speed (rad/s).
T_L is the torque load.
W is the cost value.
$P_{loss(experiment)}$ is the power loss from experiment.
$P_{loss(computation)}$ is the power loss from computation.
n is the total data numbers.
a_0, a_1 are the coefficients of the linear regression at any load torques.
$i_{f,minimize}$ is the field current value for the loss minimization.
$i_{f,act}$ is the actual field current.
N^* is the speed command.
$\mathbf{N_{act}}$ is the actual speed.
err_f is the error between $i_{f,minimize}$ and $i_{f,act}$.
err_s is the error between N^* and N_{act}.

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