Jurnal
Teknologi

Full Paper

SENSORLESS POSITION CONTROL OF DC MOTOR USING MODEL PREDICTIVE CONTROLLER

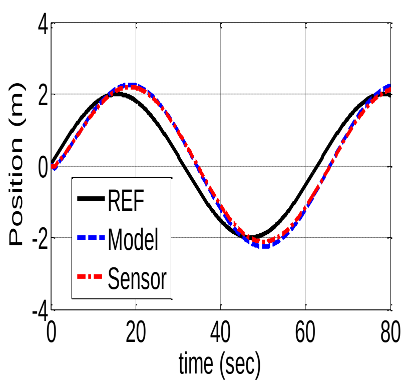
Amir A. Bature[a,b], Salinda Buyamin[b*], Mohamad N. Ahmad[b], Mustapha Muhammad[a], Auwalu M. Abdullahi[a,b]

[a]Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310, UTM Johor Bahru, Johor Malaysia
[b]Department of Electrical Engineering, Bayero University Kano, Nigeria

Article history
Received
15 April 2015
Received in revised form
29 September 2015
Accepted
12 November 2015

*Corresponding author
salinda@fke.utm.my

Graphical abstract



Abstract

Sensors like rotary encoders are widely used in measuring the speed and position of DC motor in applications. Due to expensiveness, calibration complexities of these type of encoders, sensorless methods for measurements were used alternatively. This paper presents sensorless position control of a wheeled DC motor using system identified model. This approach overcome some conventional sensorless techniques that uses some approximations. The model is developed using black box identification scheme, based on the identified model, a model predictive controller was designed to track a desired horizontal position of the wheel. Practical experiment shows the concept gives a very good estimation of the position and speed and can be used in control application.

Keywords: Model predictive controller, system identification, sensorless

1.0 INTRODUCTION

Direct current (DC) motors are widely used in almost every machine industries and vehicles [1], this leads to a numerous work done by researchers to model the DC motors [1-8], and also control of position and speed of the motor [3, 5, 6]. To mention a few, in [1], the DC motor is modelled using electromagnetic interferences signals of contact mechanisms between the brushes and the collector blades. Electro mechanic effects, like cogging and friction, and electromagnetic properties generated by eddy current and magnetic hysteresis where used in the modelling of the DC motor, as shown in [7]. Artificial Neural Network in modelling DC motor is presented in [2, 3]. In [4], Repulsive Particle Swarm Optimization (RPSO) is used in the modelling of the DC motor using Non-linear Auto-Regressive with exogenous input (NARMAX) approach.

In position control of DC motors, many approaches has been exploited by researchers, some use position sensor for the feedback control [3, 5, 9-15]. But these sensors have some disadvantages, they are expensive, very difficult to calibrate, they are prone to measurement noise and so on. To overcome these problems, some researcher use sensorless method of measuring and therefore control of DC motors [16-25]. Rotor position is estimated for feedback control using extended Kalman filter in [16, 22]. Back-EMF sensing methods, like Third Harmonic Voltage Integration (THVI), Terminal Current Sensing (TCS), Back-EMF Integration and PWM strategies, Terminal Voltage Sensing (TVS), sliding-mode observer, model reference adaptive System, adaptive observers, are fully explained in [19, 20, 23-25]. These sensorless techniques have the problems of zero crossings, failure of estimation at particular speeds due nonlinearity of current and speed of motors [19].

Different controllers have been designed in the past, to control position of DC motors. Model predictive controllers (MPCs) are one of the controllers used for controlling all class of motors [26-29]. Due to recent advances that increased the computational power of micro-controllers and DSP chips made MPC applicable in many advance systems [30].

In this work, sensorless control of wheeled DC motor will be presented. The main contribution is in using the identified model of the wheeled DC motor to estimate the horizontal position in meters and speed of the wheel in meters per second directly. This solves the problem of other sensorless that uses the measurements of flux or currents in the motor. It also remedies calibration issues. Black box system identification approach of modelling will be used to develop the wheeled DC motor model to directly estimate the position and velocity in desired unit. Also, using the identified model, MPC will be design to track a specified position. The rest of the paper is organized as follows, in section II, the model of the wheel driven DC motor is derived using system identification, the MPC design is explained in section III, the results of the experimental implementation and validation of the controllers are given in section IV, finally section V gives the conclusion of the work.

2.0 IDENTIFICATION OF DC MOTOR

Experimental setup and identification of the motor is given in this section.

2.1 Experimental Setup

The wheeled DC motor used in this experiment is shown in Figure 1. The DC motor used is MY1016Z2-250W, 24v operating voltage. It has no load speed of 434rpm and no load current of 1.8A. Its output is connected to a pneumatic wheel of radius 130mm via a gear as shown in the diagram. B106 rotary encoder [31] is used in the experiment, it has operating voltage 5v to 24v, pulse of 500P/R and maximum shaft speed of 6000rpm. It is designed to provide pulse feedback when the shaft is rotated. The shaft of the rotary encoder is connected to the DC motor and the pulses are recorded using STM32F4 discovery board which sends the pulses to MATLAB Simulink via computer where the horizontal position and speed of the wheel are computed and recorded.

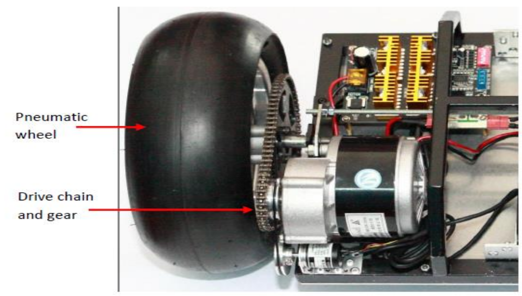


Figure 1 Wheeled DC motor setup

2.2 Identification of the DC motor

There are three different modelling approaches namely, white-box model which is based on mathematical modelling, black-box model, and grey-box model which are based on system identification [32].

a) White-box model: This type of model is based on first principles, for instance, a model for a physical process derived from the Newton equations or Euler Lagrange methods. All equations and parameters are obtained by theoretical modelling. Their parameters have direct interpretation in first principles.

b) Black box model: This is based on measurement of input and output data. The model structure and parameters are obtained from experimental modelling. To develop black box models, no or very little prior knowledge of plant is needed. The model parameters have no direct relationship to first principles.

c) Grey-box model: This model is based on both insight into the system and experimental data obtained. It is a compromise or combination between white and black box models. The model and structure of this type of model are known, only the values of the parameters are estimated [33, 34].

In this work, black box identification approach will be used in the modelling of the wheeled DC motor so that the output of the model will be the desired position in meters, and velocity in meters per second. The advantage of this approach is all the unmodelled uncertainties like gear ratios, gear frictions, and approximations of parameters, like motor inductance, that will be encountered when using white box approach, are overcome in this approach. The following steps are carried out in the identification.

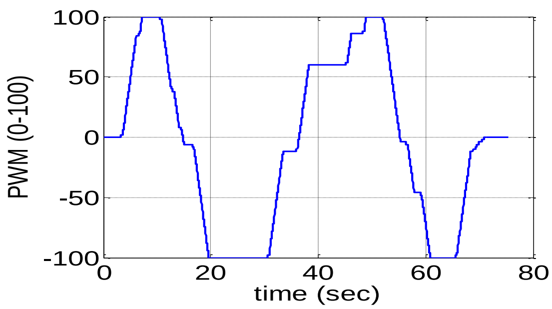
a) Selection model inputs and outputs: The input is the applied voltage to the DC motors using PWM signal. The outputs are the wheel horizontal position and speed in meters and meters per second respectively.

b) Selection of excitation signals: Random PWM signal shown in Figure 2 is used.

c) Model estimation algorithm: Weighted least square method is employ using MATLAB *ssest* command for the estimation. Before the estimation, a filter is used to smoothing the noisy speed measurement from the encoder.

d) Model validation: After identification, the model is validated as shown in Figure 3 and 4 for the position and speed respectively.

The effect of the filter incorporated in the identification is seen clearly in Figure 4. The identified model in state space is given in Eq. 1.



2 Random Input Signal

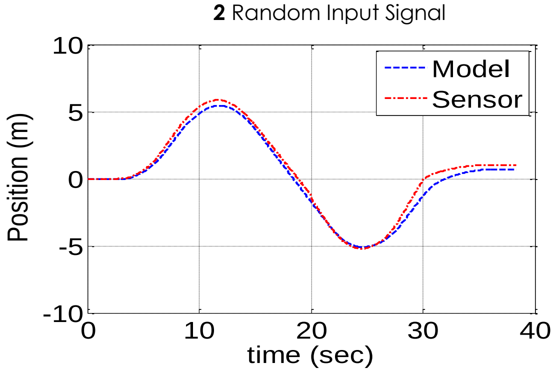


Figure 3 Position validation

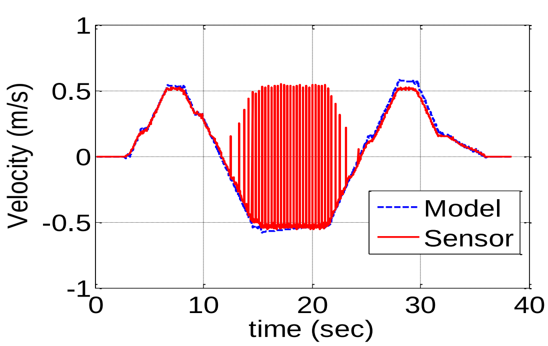


Figure 4 Speed validation

$$A = \begin{bmatrix} -1.333 & 7.031 & -0.42 & -3.491 \\ -2.939 & -1.179 & 14.85 & 0.9376 \\ -3.443 & -20.04 & -28.43 & 0.1822 \\ -2.551 & -5.397 & -70.18 & -11.46 \end{bmatrix},$$

$$B = \begin{bmatrix} -0.3208 \\ 0.3304 \\ -0.2069 \\ -1.852 \end{bmatrix}$$

$$C = \begin{bmatrix} 104 & -74.58 & 50.87 & -36.96 \\ 0.3189 & 1.599 & -0.8143 & 0.5318 \end{bmatrix} \quad (1)$$

3.0 MPC CONTROLLER DESIGN

MPC is based on the solution of an online optimal control problem where a receding horizon approach is used such that for any current state vector x(k) at time k, an optimal control problem is solved over some future interval taking into account current and future constraints [35]. The aim of controller is to set the predictive output of a system as close as possible to the desired set point. The model of the system is used to predict the future evolution of the system to optimize the control signal. Given a system in Eq. 2.

$$\dot{x} = A_m x(t) + B_m u(t), \quad y(t) = C_m x(t) \quad (2)$$

We define the auxiliary variables;

$$z(t) = \dot{x}(t), y(t) = Cx(t)$$

We choose a new state variable vector

$x(t) = [z(t)^T \; y(t)^T]$.

The new augmented state model is given in Eq. 3.

$$\begin{bmatrix} \dot{z}(t) \\ \dot{y}(t) \end{bmatrix} = \begin{bmatrix} A_m & 0^T{}_m \\ C_m & I_{0qxq} \end{bmatrix} \begin{bmatrix} z(t) \\ y(t) \end{bmatrix} + \begin{bmatrix} B_m \\ 0_{qxm} \end{bmatrix} \dot{u}(t)$$

$$y(t) = \begin{bmatrix} 0_m & I_{qxq} \end{bmatrix} \begin{bmatrix} z(t) \\ y(t) \end{bmatrix} \quad (3)$$

Where **I**qxq is identity matrix with dimension qxq, **0**qxq is zero matrix. The new model matrix is

$$A = \begin{bmatrix} A_m & 0^T{}_m \\ C_m & I_{0qxq} \end{bmatrix}, B = \begin{bmatrix} B_m \\ 0_{qxm} \end{bmatrix}, C = \begin{bmatrix} 0_m & I_{qxq} \end{bmatrix}$$

The cost function is given in Eq. 4.

$$J = \sum_{m=1}^{Np} x(k_i + m|k_i)^T Q x\,(k_i + m|k_i) + \Delta U^T R \Delta U \quad (4)$$

Where Q and R are positive definite weighing matrices, and ΔU is future control trajectory with length Nc. Np is the prediction horizon. Figure 5 shows the control block diagram. An embedded integrator is added to the design as shown in Eq. 3. The design parameters are given in Table 1.

Table 1 MPC parameters

Parameter	symbol	value
Prediction horizon	Np	30
Control horizon	Nc	4
Sampling time	t	0.02
State weighting matrix	Q	I_{4x4}
Output weghting matrix	R	0.1

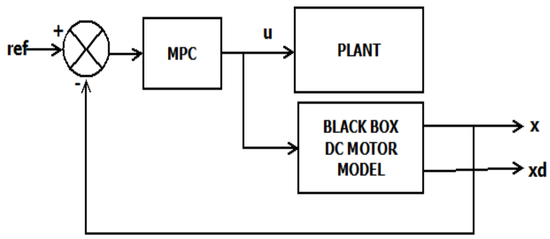


Figure 5 MPC Block diagram

4.0 RESULTS AND DISCUSSION

The experimental result of the position tracking controller is shown in this section. Figure 6 and 7 shows the position tracking of 2m step signal and 2m sine wave signal respectively, while Figure 8 shows the speed during the sine wave signal position tracking.

The black box identified model gives acceptable estimation of the position and speed of the wheeled DC motor.

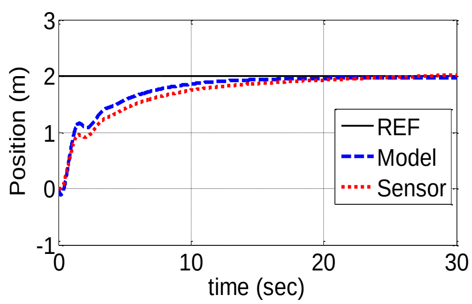
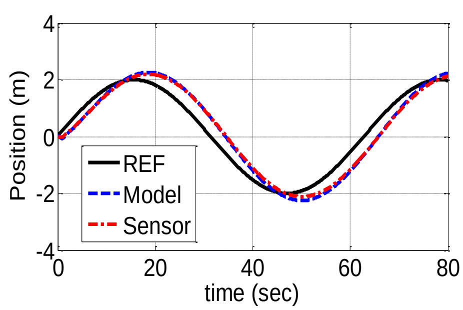


Figure 6 Step signal position tracking



gure 7 Sine wave signal position**Figure**

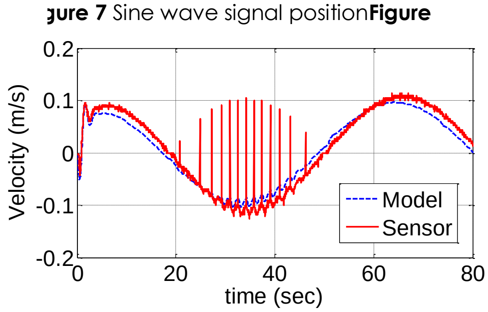


Figure 8 Speed during sine wave signal position tracking

5.0 CONCLUSION

Black box identification of wheeled DC motor for sensorless measurements and MPC position controller design using the model is presented in this paper. The controller was designed based on the identified model, and the model was used as an estimator of the wheel position for tracking purpose. The model accurately gives an acceptable estimation of both the position and speed. This sensor-less concept can be used in many applications and replace expensive sensors.

Acknowledgement

These authors are grateful to the Ministry of Higher Education (MOHE) and Universiti Teknologi Malaysia for the financial support through the GUP research fund, Vote Q.J130000.2523.05H40 and special thanks to Bayero University, Kano, Nigeria for their support.

References

[1] Kahoul, R., Y. Azzouz, B. Ravelo, and B. Mazari. 2013. New Behavioral Modeling of EMI for DC Motors Applied to EMC Characterization. *Industrial Electronics, IEEE Transactions on*. 60: 5482-5496.

[2] Yassin, I. M., M. N. Taib, M. Z. Abdul Aziz, N. A. Rahim, N. M. Tahir, and A. Johari. 2011 Identification of DC Motor Drive System Model Using Radial Basis Function (RBF) Neural Network. In *Industrial Electronics and Applications (ISIEA), 2011 IEEE Symposium on*. 13-18.

[3] Weerasooriya, S. and M. A. El-Sharkawi. 1991. Identification and Control of a DC Motor Using Back-Propagation Neural Networks. *Energy Conversion, IEEE Transactions on*. 6: 663-669.

[4] Supeni, E., I. M. Yassin, A. Ahmad, and F. Y. A. Rahman. 2009. NARMAX Identification of DC Motor Model Using Repulsive Particle Swarm Optimization. In *Signal Processing & Its Applications, 2009. CSPA 2009. 5th International Colloquium on*. 1-7.

[5] Ishak, N., S. K. Harun, H. Ismail, N. A. Razak, and R. Adnan. 2010. Model Identification and Real-Time Linear Position Control of Servomotor. In *Control and System Graduate Research Colloquium (ICSGRC). 2010 IEEE*. 71-74.

[6] Hidayat, S. Pramonohadi, Sarjiya, and Suharyanto. 2013. Modelling the Speed Control of Brushless DC Motor Base on Identification System. In *Instrumentation, Communications, Information Technology, and Biomedical Engineering (ICICI-BME), 2013 3rd International Conference on*. 237-241.

[7] Buechner, S., V. Schreiber, A. Amthor, C. Ament, and M. Eichhorn. 2013. Nonlinear Modeling and Identification of a Dc-Motor with Friction and Cogging. In *Industrial Electronics Society, IECON 2013 - 39th Annual Conference of the IEEE*. 3621-3627.

[8] Brock, S. 2002. Identification of The Parameters in Inverted Pendulum Model [DC Motor Control]. In *Advanced Motion Control, 2002. 7th International Workshop on*. 316-321.

[9] Kumar, D. and A. Kulkarni. 2014. Design of Non-Linear Sliding Surface for Robust Position Control of DC Motor. In *Engineering and Systems (SCES), 2014 Students Conference on*. 1-6.

[10] Xin, W., Z. Yaoming, S. Liguo, and D. Xiang. 2010. The Neural Network Inverse Control Method of Induction

Motor Based on Multiscalar Model. In *Measuring Technology and Mechatronics Automation (ICMTMA), 2010 International Conference on*. 3: 912-916.

[11] Thomas, N. and D. P. Poongodi. 2009. Position Control of DC Motor Using Genetic Algorithm Based PID Controller. In *Proceedings of the World Congress on Engineering.* vol. 2, ed. London, U.K.

[12] Ruderman, M., J. Krettek, F. Hofmann, and T. Bertram. 2008. Optimal State Space Control of DC Motor. In *The International Federation of Automatic Control*, ed. Seoul, Korea.

[13] Khan, S. and P. U. Kulkarni. 2012. Design and Implementation of Fuzzy Logic Controller for a DC Motor. *International Journal of Emerging Technology and Advanced Engineering.* 2: 372-375.

[14] I-Hai Lin, P., S. Hwang, and J. Chou. 1994. Comparison on Fuzzy Logic and PID Controls for a DC Motor Position Controller. In *Industry Applications Society Annual Meeting, 1994. Conference Record of the 1994 IEEE*. 3: 1930-1935.

[15] Ahmed, P. A., Y. Mohan, A. Chauhan, and P. Sharma. 2013. Comparative Study of Speed Control of D.C. Motor Using PI, IP, and Fuzzy Controller. *International Journal of Advanced Research in Computer and Communication Engineering.* 2: 2693-2697.

[16] Kettle, P., A. Murray, and F. Moynihan. 1998 Sensorless Control of a Brushless DC Motor Using an Extended Kalman Estimator in *PCIM*. 385-392.

[17] Hao, C. and Z. Yifeng. 2003 Rotor Position Sensorless Control of the Switched Reluctance Motor Drive for the Direct-drive Joint of the Robot. In *Electrical Machines and Systems, 2003. ICEMS 2003. Sixth International Conference on*. 2: 915-918.

[18] Bojoi, R., M. Pastorelli, J. Bottomley, P. Giangrande, and C. Gerada. 2013 Sensorless Control of PM Motor Drives 2014; A Technology Status Review. In *Electrical Machines Design Control and Diagnosis (WEMDCD), 2013 IEEE Workshop on*. 168-182.

[19] Acarnley, P. P. and J. F. Watson. 2006. Review of Position-Sensorless Operation of Brushless Permanent-Magnet Machines. *Industrial Electronics, IEEE Transactions on.* 53: 352-362.

[20] Fahimi, B., G. Suresh, and M. Ehsani. 2000 Review of Sensorless Control Methods in Switched Reluctance Motor Drives. In *Industry Applications Conference, 2000. Conference Record of the 2000 IEEE*. 3: 1850-1857.

[21] Gui-Jia, S. and J. W. McKeever. 2004. Low-cost Sensorless Control of Brushless DC Motors with Improved Speed Range. *Power Electronics, IEEE Transactions on.* 19: 296-302.

[22] Terzic, B. and M. Jadric. 2001. Design and Implementation of the Extended Kalman Filter for the Speed and Rotor Position Estimation of Brushless DC Motor. *Industrial Electronics, IEEE Transactions on.* 48: 1065-1073.

[23] Yue, Z., W. Chun, Z. Zhe, and Q. Wei. 2013. A Review on Position/Speed Sensorless Control for Permanent-Magnet Synchronous Machine-Based Wind Energy Conversion Systems. *Emerging and Selected Topics in Power Electronics, IEEE Journal of.* 1: 203-216.

[24] Raute, R., C. Caruana, C. S. Staines, J. Cilia, N. Teske, M. Sumner, and G. M. Asher. 2011 A Review of Sensorless Control in Induction Machines Using Hf Injection, Test Vectors and PWM Harmonics. In *Sensorless Control for Electrical Drives (SLED), 2011 Symposium on*. 47-55.

[25] Gamazo-Real, J. C., E. Vázquez-Sánchez, and J. Gómez-Gil. 2010. Position and Speed Control of Brushless DC Motors Using Sensorless Techniques and Application Trends. *Sensors.* 10: 6901-6947.

[26] Zicheng, L. and C. Shanmei. 2010. Torque Ripple Reduction in Brushless DC Motors Based on Model Predictive Control in *Electrical and Control Engineering (ICECE), 2010 International Conference on*. 4498-4501.

[27] Syaichu-Rohman, A. and R. Sirius. 2011 Model Predictive Control Implementation on a Programmable Logic Controller for DC Motor Speed Control. In *Electrical Engineering and Informatics (ICEEI), 2011 International Conference on*. 1-4.

[28] Peyrl, H., G. Papafotiou, and M. Morari. 2009 Model Predictive Torque Control of a Switched Reluctance Motor. In *Industrial Technology, 2009. ICIT 2009. IEEE International Conference on*. 1-6.

[29] Lu, G. and W. Liuping. 2013 Cascaded Model Predictive Position Control of Induction Motor with Constraints. In *Industrial Electronics Society, IECON 2013 - 39th Annual Conference of the IEEE*. 2656-2661.

[30] Mariethoz, S., A. Domahidi, and M. Morari. 2009 Sensorless Explicit Model Predictive Control of Permanent Magnet Synchronous Motors. In *Electric Machines and Drives Conference, 2009. IEMDC '09. IEEE International*. 1250-1257.

[31] Cytron. 2010. B016 Rotary Encoder. *Available: www.cytron.com.my/viewProduct.php?pcode=B.*

[32] Nelles, O. 2001. *Nonlinear System Identification: From Classical Approaches to Neural Networks and Fuzzy Models.* 1st ed. Springer-Verlag Berlin Heidelberg.

[33] Nelles, O. 2001. Nonlinear System Identification: From Classical Approaches to Neural Networks and Fuzzy Models.

[34] Ljiung, L. 1999. System Identification: Theory for the User.

[35] Wang, L. 2009. *Model Predictive Control System Design and Implementation Using MATLAB*. London, United Kingdom Springer-Verlag London Limited.