Original Research Article

Torque estimation of electric vehicle motor using adaptive-network based fuzzy inference systems

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ARTICLE INFO

ABSTRACT

This paper presents to estimating studies of the torque data of the Electric Vehicle (EV) motor using Adaptive-Network Based Fuzzy Inference Systems (ANFIS). The real-time data set of the Outer-Rotor Permanent Magnet Brushless DC (ORPMBLDC) motor which was designed and manufactured for using in ultra-light EV, was used in these estimation process. The current, the power and the motor speed parameters are defined as input variables, and the torque parameter defined as output variable. Five distinct ANFIS models were designed for torque estimation process and the performances of each model were compared. The most effective model for testing data set among the ANFIS models was anfis: 2 with 98 nodes and 36 fuzzy rules, and the worst model was anfis: 5 with 286 nodes and 125 fuzzy rules. Performance results of all designed models were presented in tables and graphs.

Keywords: Electric vehicle motor, Adaptive-Network Based Fuzzy Inference Systems (ANFIS), Outer-Rotor Permanent Magnet Brushless DC (ORPMBLDC), torque estimation

1. Introduction

The global population and the number of cars in traffic are growing day by day. Fossil fuels used in Internal Combustion Engine (ICE) vehicles are in a state of exhaustion over time, and the gases emitted from these vehicles damage the ecosystem. On the other hand, Electric Vehicles (EVs) do not emit any greenhouse gases and are a good alternative to eliminating reliance on sources dependent on fossil fuels [1].

The widespread usage of EVs is related to the technical/ economic benefits of these vehicles will offer compared to ICE vehicles. These benefits may include less pollution, reduced consumption, reduced costs of management, lack of circulation constraints and reduced noise level. The main challenges of EV spread include insufficient number of charging stations, long standby time for charging [2] and battery range [3].

EV technology consist of battery, electric motor, motor driver circuit and transmission gears [4, 5]. Features like wide spread range, high power density, high efficiency and maintenance-free are expected from electric motors, which have an significant role in this technology [4].

In this study, real-time data such as current, power and motor speed of the Outer-Rotor Permanent Magnet Brushless DC (ORPMBLDC) motor, which was designed to be used in EV of Kahramanmaraş Sütçü İmam University named Kurtuluş, were modeled with

Table 1. Some literature on estimation studies using ANFIS models

Model	Implementation Area	Evaluation Metrics	Reference
ANFIS	Estimating the effect on emissions and motor performance of the various proportions of methanol mixtures	RMSE, R	[6]
ANFIS	Estimating the piles' bearing capacity	RMSE, R, MAPE, BIAS, SI	[7]
ANFIS	Estimating the yields of biogas produced by combining waste.	RMSE, R, R^2, MAE, SEP, AAD	[8]
ANFIS	Estimating the crop yield	MSE, MAE, SSE	[9]
ANFIS	Estimating the wind speed	MAPE , R^2	[10]
ANFIS	Estimating the producing of biogas from spent mushroom compost	RMSE, R, R^2	[11]
ANFIS	Estimating the groundwater level	RMSE, R^2, EV	[12]
ANFIS	Inflation prediction	RMSE	[13]
ANFIS	Shear capability prediction of channel shear connectors	MSE, R^2	[14]
ANFIS	Estimating the content of sweet natural gas water	R^2	[15]
ANFIS	Density estimating for bitumen-tetradecane mixtures	RMSE	[16]
ANFIS	Heat capacity estimation of non-newtonian ionanofluid systems	RMSE, R^2, MSE, MRE, STD	[17]
ANFIS	Estimating the global solar radiation	RMSE, R^2, MAE	[18]
ANFIS	Estimating the enthalpies of petroleum fractions and pure hydrocarbons for vaporization	RMSE, R^2	[19]
ANFIS	Estimating the charging status of the battery	MSE	[20]
ANFIS	Thermal conductivity enhancement estimation of nanofluids depending on metal and metal oxide	RMSE, MSE, R^2, AARD, STD	[21]
ANFIS	Estimating and optimizing the parameters affecting biodiesel production yield and cost	RMSE, R, MAE	[22]
ANFIS	Predicting the compressive strength of cement-based mortar materials	RMSE, R^2, MAPE, VAF	[23]
ANFIS	Prediction of ground vibrations arising from the blasting of quarries	RMSE, R^2, VAF	[24]
ANFIS	Predicting the solar chimney power plants performance	RMSE, R^2, MAE	[25]
ANFIS	Elastic modulus prediction of normal and high-strength concrete	RMSE, MAPE	[26]
ANFIS	Estimation of solar radiation	RMSE, R^2, MBE	[27]
ANFIS	Estimating the demand of biochemical oxygen of the Surma River	MSE, R, MAE, EFF	[28]
ANFIS	Wear a prediction of a multi-joint mechanism	NRMSE	[29]
ANFIS	Wuhan City air quality prediction	MSE, R^2, MAE, MAPE	[30]
ANFIS	State estimation for load uncertainty and false data in electric power systems	RMSE, MAE, MRE	[31]
ANFIS	Prediction of the concentration of CO pollutants in the air in Tabriz city	RMSE, R^2, MAE, DC	[32]

Abbreviations:
AAD: Average Absolute Deviation, AARD: Average Absolute Relative Deviation, DC: Determination Coefficient, EFF: Model Efficiency, EV: Error Variation, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error, MBE: Mean Bias Error, MRE: Mean Relative Error, MSE: Mean Square Error, NS: Nash-Sutcliffe coefficient, R: Correlation coefficient, R^2: Coefficient of determination, RMSE: Root Mean Square Error, NRMSE: Normalized Root Mean Square Error, P: Probability, SEP: Standard Error of Prediction, SSE: Sum Squared Error, STD: Standard Deviation, VAF: Variance Account For

ANFIS models and the torque data were estimated. Five distinct ANFIS models which are called anfis:1, anfis:2, anfis:3, anfis:4 and anfis:5 were created and the successes of each model were observed. The estimation error values of the models were calculated with statistical metrics such as coefficient of determination (R^2), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). Some literature on estimation studies using ANFIS models are given in Table 1.

Figure 1. Implementation works of ORPMBLDC motor on ultra-light EV

Table 3. Statistical parameters of ORPMBLDC motor used in each ANFIS models

variable	category	statistical						
		min	average	max	std	median	variance	total data
current	input	1,290	12,125	23,350	7,624	11,445	57,925	300
power	input	48,620	1252,572	2092,060	720,514	1398,770	517410,203	300
speed	input	805,390	920,118	1027,150	80,455	951,090	6451,413	300
torque	output	0,420	12,482	22,550	7,823	12,770	60,999	300

2. ORPMBLDC Motor for EV

BLDC motors are commonly used in the industry, particularly in the automotive sector. These motors have a simple structure, high speed range [33], high efficiency, simplistic control, compactness, quite low noise pollution [34], large initial torque with lower physical specifications, simplistic maintenance [35] and reduced weight thanks to absence of bruhes [36].

There are two types of BLDC motors: Permanent Magnet Brushless DC (PMBLDC) and Permanent Magnet Synchronous Motor (PMSM). These motors have distinct characters in terms of output wave back emf. Thus, the output wave back emfs are trapezoidal wave and sinusoidal wave for PMBLDC and PMSM, respectively [33].

2.1. Experimental works

In this study, the data of the ORPMBLDC motor, which was designed and prototyped to be used in ultra-light EV (driver and vehicle body ~ 200kg), was used. Technical features of ORPMBLDC motor are given in Table 2. Implementation works of ORPMBLDC motor on ultra-light EV are given in Fig. 1. Statistical parameters of ORPMBLDC motor used in each ANFIS models Table 3.

3. ANFIS Structure

A combination of Artificial Neural Network (ANN) and Fuzzy Inference Systems (FIS) is considered to be the structure of the ANFIS model. In this model, a mapping between the inputs and outputs known as the "Takagi-Sugeno inference model" is produced according to "IF-THEN rules" [30]. It is a rule based system which has membership functions for input and output variables, fuzzy rules, and output characteristics and outcomes of the system [9].

Table 2. ORPMBLDC motor parameters (experimental)

Parameters	Experimental values	Unit
slot / pole	36 / 40	-
power	2000	W
speed	815,16	rpm
torque	21,4	Nm
efficiency	88,76%	-
voltage	96	V
stator material	M330 – 50 A AISI / SAE	-
rotor material	4340 Alloy Steel	-
magnet type	N40UH	-
Weight (stator and rotor)	~ 10,4	kg

ANFIS model incorporates the Back Propagation (BP) and the Least-Square Model (LSM) as learning models, extracting structural properties such as the number of fuzzy rules, membership function coefficients, and the linear and nonlinear parameters numbers [7]. The general structure of ANFIS model is given in Fig. 2.
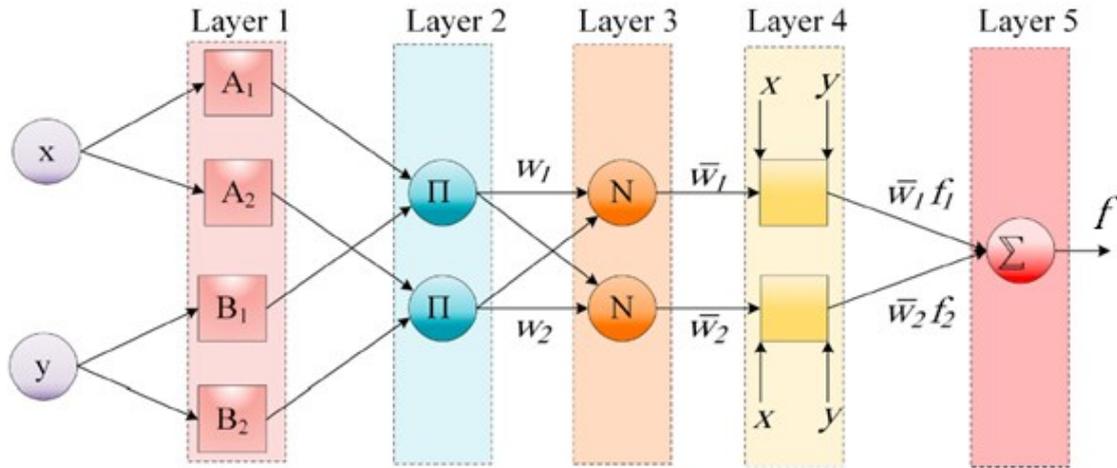
Figure 2. The general structure of ANFIS model [30]

Table 4. Layer parameters of ANFIS model

parameter	definition	description	equ.
Rule i	IF x is A_i y is B_i THEN $f_i = p_i x + q_i y + r_i$ $i = 1,2,...,n$	Rule i	(1)
O_i^1	$O_i^1 = \mu_{Ai}(x)$, $O_i^1 = \mu_{Bi}(y)$	first layer	(2)
O_i^2	$O_i^2 = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y)$	second layer	(3)
O_i^3	$O_i^3 = \sum w_i = \dfrac{w_i}{\sum_{i=1}^n w_i}$	third layer	(4)
O_i^4	$O_i^4 = \sum w_i f_i = \sum w_i(p_i x + q_i y + r_i)$	fourth layer	(5)
O_i^5	$O_i^5 = \sum_{i=1}^n \overline{w_1}, \quad f_i i = 1,2,...,n$	fifth layer	(6)

ANFIS model has a five-layered feed forward network [12]. These layers are known as the layer of fuzzify, layer of product, layer of normalized, layer of defuzzifier, and layer of total output [14].

The first layer (Layer 1) is define as system fuzzification [7]. It obtains all input parameters and uses them to introduce to ANFIS [11]. The second layer (Layer 2) is the output of first layer. Calculation of firing strength is performed in this layer. Furthermore, each node multiplies input signals and gives out the product [7]. The third layer (Layer 3) normalizes the activity degree for whole rules [11]. The ratio is calculated for each weight and the total weight in this layer [14]. The fourth layer (Layer 4), each node outputs the crisp value of the corresponding fuzzy rule and, in addition, the output is computed between the output of the third layer and the linear combination of input variables by virtue of the product. The fifth layer (layer 5) contains just one node and, by summing all the outputs relevant to the fourth layer, provides the total crisp output value [7]. The layer parameters of ANFIS model are given in Table 4.

where n is rules number, p_i, q_i, r_i are the determined parameters on training process defined by Equ. (1). μ is Gaussian membership function, A_i and B_i linguistic labels defined by Equ. (2). w_i is the ith the second layer's output defined by Equ. (3). f denotes the function defined by Equ. (5) [14, 30].

3.1. Design of ANFIS models

In this study, the ANFIS models were developed using ANFIS toolbox on MATLAB software. The torque data was determined as an output variable, and, it is aimed to estimate to torque data by using input variables such as current, power and speed data. Input and output variables of designed ANFIS models are shown in Fig. 3.
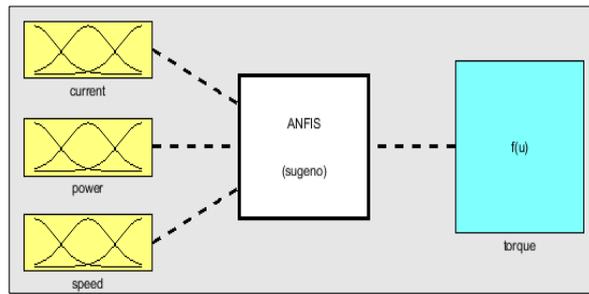
Five distinct ANFIS models which are named

Figure 3. Input and output variables of designed ANFIS Models

Table 5. Specifications of designed ANFIS models

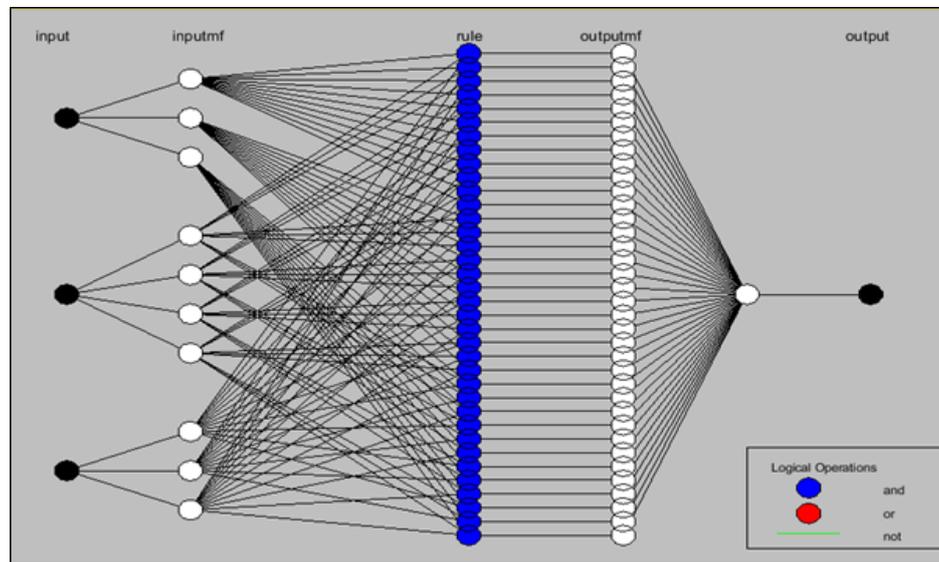| info	anfis:1	anfis:2	anfis:3	anfis:4	anfis:5
Number of nodes	78	98	150	158	286
Number of linear parameters	27	36	60	64	125
Number of nonlinear parameters	27	30	36	36	45
Total number of parameters	54	66	96	100	170
Number of training data pairs	210	210	210	210	210
Number of fuzzy rules	27	36	60	64	125

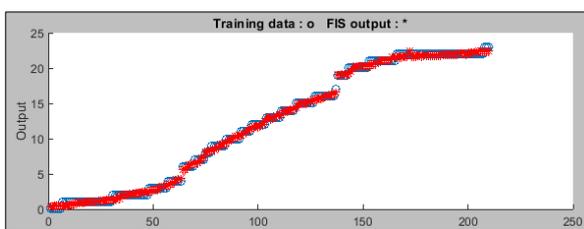**Figure 4.** The designed ANFIS model structure (anfis:2 model)

Figure 5. Actual and estimated data (training, anfis:2 model)
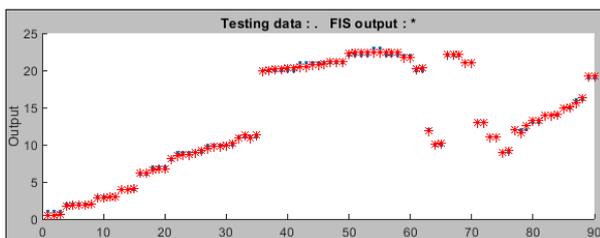

Figure 6. Actual and estimated data (testing, anfis:2 model)

anfis:1, anfis:2, anfis:3, anfis:4 and anfis:5 have been designed to obtain the more accurately estimations. Features of each designed ANFIS model are shown in Table 5.

The structure of anfis:2 model with 98 nodes and 36 fuzzy rules, in which current, power and speed are used as input variables and torque as output variables is given in Fig. 4.

The actual and estimated data of anfis:2 model for training and testing performances are given in Fig. 5 and Fig. 6, respectively.

A total of 36 rules were created in the anfis:2 model. 30/36 of these created rules are shown in Fig. 7.

3.2. Evaluation process

Four distinct statistical evaluation methods were used to evaluate the each ANFIS model success. The estimation errors of these ANFIS models were calculated with R^2, MAPE, MSE, RMSE metrics. Evaluation metrics are given in Table 6.
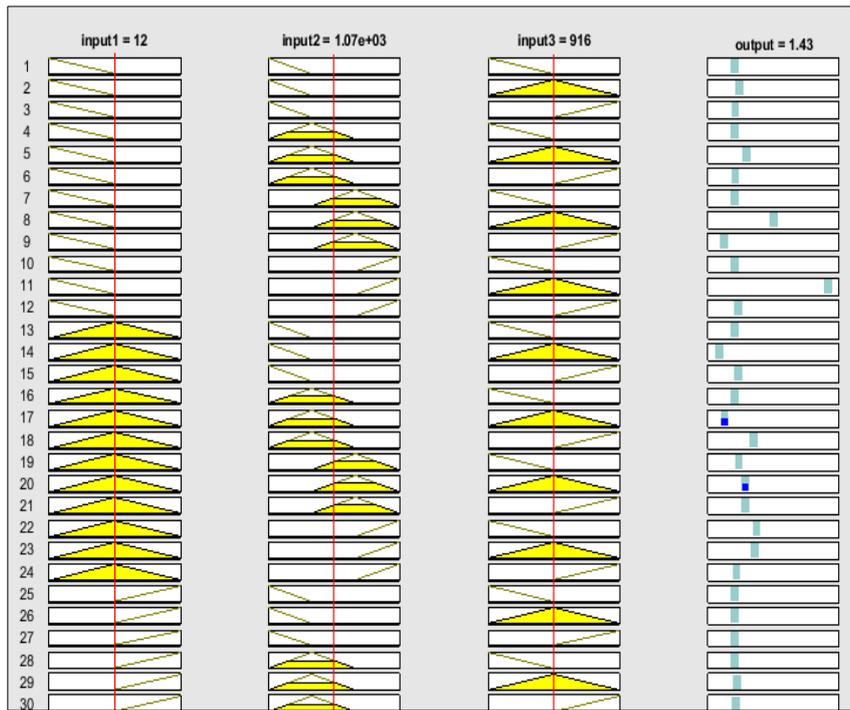
Figure 7. 30/36 of ANFIS rules (anfis:2 model)

Table 6. Evaluation metrics

parameter	definition	description	equ.
R^2	$R^2 = 1 - \left(\dfrac{\sum_{i=1}^{n}(P^* - P)^2}{\sum_{i=1}^{n} P^{*2}_i}\right)$	coefficient of determination	(7)
MAPE	$MAPE = \dfrac{1}{n} \sum_{i=1}^{n}\left\|\dfrac{P^* - P}{P^*}\right\| 100$	mean absolute percentage error	(8)
MSE	$MSE = \dfrac{1}{n} \sum_{i=1}^{n}(P^* - P)^2$	mean square error	(9)
RMSE	$RMSE = \sqrt{\dfrac{1}{n} \sum_{i=1}^{n}(P^* - P)^2}$	root mean square error	(10)

Table 7. Estimation error results of designed ANFIS models

models	data set (training)				data set (testing)			
	R^2	MAPE	MSE	RMSE	R^2	MAPE	MSE	RMSE
anfis: 1	0,99980	2,024	0,017	0,309	0,99981	1,190	0,010	0,272
anfis: 2	0,99978	2,324	0,018	0,307	0,99977	**1,112**	0,012	0,273
anfis: 3	0,99972	2,466	0,022	0,300	0,99967	1,256	0,017	0,274
anfis: 4	0,99978	2,498	0,019	0,305	0,99978	1,247	0,012	0,267
anfis: 5	0,99958	3,486	0,032	0,281	0,99950	1,865	0,026	0,276

where P^* is the actual value and P is the estimated value defined by equ. (7-10) [7, 11, 30]. anfis:2 model's scattering diagram of measured and estimated torque values of training process and testing process are given Fig. 8. and Fig. 9, respectively.

Comparison of the torque estimation of designed anfis:1, anfis:2, anfis:3, anfis:4 and anfis:5 models is given in Fig. 10.

The data used in this study, 210 data were classified as training data and 90 data as testing data, and a total of 300 data were used. According to MAPE error results for testing data sets, the anfis:2 model has achieved the best value with 1,112, and, the anfis:5 model has reached to worst value with 1,865. Estimation error results of designed ANFIS models for both data sets are given in Table 7.
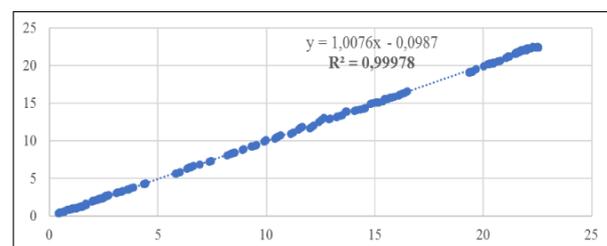

Figure 8. Scattering diagram of measured and estimated torque values of training process (anfis:2 model)
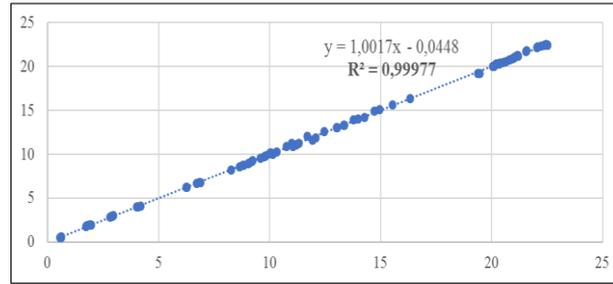
Figure 9. Scattering diagram of measured and estimated torque values of testing process (anfis:2 model)

Figure 10. Comparison of the torque estimation of designed ANFIS models

4. Conclusion

In this study, the torque estimating studies of the EV motor were carried using ANFIS models. Used real-time data were obtained from ORPMBLDC motor, which was designed to be used in EV of Kahramanmaraş Sütçü İmam University, named Kurtuluş. According to the whole process of this study;

• Five distinct ANFIS models named anfis:1, anfis:2, anfis:3, anfis:4 and anfis:5 have been designed for reaching accurately estimations (given in Table 5).

• In all models, while the current, the power and the motor speed were determined as inputs variables, the torque were determined as an output variable (shown in Fig. 3).

• A total of 300 experimental data were used, including 210 data were determined for the training process and the remaining 90 data for the testing process.

• Four distinctive statistical metrics, R^2, MAPE, MSE and RMSE, were used to observe the estimation performances.

• When the MAPE of testing results of five distinct ANFIS models were examined, it has seen that the anfis: 1, anfis: 2, anfis: 3, anfis: 4 and anfis: 5 models were 1,190, 1,112, 1,256, 1,247 and 1,865, respectively (given in Table 7).

• It has seen that the best effective model was anfis: 2 with 98 nodes and 36 fuzzy rules, and, the worst model was anfis: 5 with 286 nodes and 125 fuzzy rules.

• For obtaining more accurately estimations studies with lower error values, the metaheuristic-based hybrid ANFIS models such as ANFIS-Particle Swarm Optimization (PSO), may also be studied for future estimation studies.

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