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Neural Network Approach for E-Motor Development

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***Abstract*— In this study, the development of electric motor design optimization methods and algorithms for electric vehicles, which have become widespread as a result of energy policies, is discussed. The rapidly increasing need for micro transportation within the scope of small cities has increased the interest in short-range transportation vehicles such as electric bicycles and electric scooters. Therefore, an electric scooter model is considered and the desired motor requirements are determined by analyzing its dynamic model. Then, IPM topologies are investigated and the appropriate topology is decided. IPM design parameters are dealt with in the ANSYS RMXprt environment, and all design combinations by selecting the appropriate test matrix in Taguchi's experiment design method are modeled in ANSYS RMXprt and logged in the appropriate file format together with the obtained results. The motor design models of all experiments are saved as the .png format in the aspect format to be determined. Then, the labeled pictures with the obtained results in the experimental design are trained in MATLAB on a neural network model with appropriate input and output. Thereafter, the trained neural network derives the appropriate motor geometry in terms of the design requirements. The derived motor geometry is converted into a 2D technical drawing format with the help of a package program (Img2CAD) and uploaded to the ANSYS Maxwell environment. To assess the motor performance are performed in ANSYS Maxwell. The proposed methodology shows that the results of parameter estimation and geometry generation in solution space with the trained neural network give sufficient performance.**

Keywords— Electric Vehicle, Electric Machine, IPM Motor, Design of Experiment, Artificial Neural Networks

I. INTRODUCTION

It is undeniable that electric vehicles are a part of our lives. The main reason for this factor is defined as global warming and carbon dioxide emissions, which have actually become the whole world [1].

Fossil fuels are used worldwide for transportation, production (including energy generation), and the transportation core industry. Clean energy is needed in order to protect and own the environment. This need also has a positive effect on clean energy and energy-saving. These requirements have increased the importance of Electric vehicles, which are increasingly in demand in the automotive market [2].

Electric-based vehicles are generally divided into two. 1- Electric vehicles only (EV), 2- Plugin Hybrid Electric vehicles (PHEV). Electric motors are used for both types of vehicles. BEV (Battery Electric Vehicles) and FCEV (Fuel Cell Electric Vehicles) are used in electric vehicles. In Plug-in Hybrid Electric vehicles, fuel is used to power the electric motor, while petroleum-based fuel is used for the internal combustion engine [3].

EVs use traction motors that can provide torque to the wheels. We can define the motors used by electric vehicles as AC motors and DC motors.

The required characteristics of the engine used for an electric vehicle are as follows:

- High efficiency
- High instantaneous power
- Fast torque response
- High power density
- Low storage
- High acceleration
- Robustness

TABLE I. COMMONLY USED ELECTRIC MOTOR TYPES [4]

Technical Properties	DC	Async.	Wound Rotor Sync.	PM Sync.	PM Sync.	Switched Reluctance
Field Orientation	Radial	Radial	Radial	Radial	Axial	Radial
Torque	+	-		++	++	+
Efficiency	-	-	(+/-)	++	++	+
Max. Speed	-	(+/-)		(+/-)	(+/-)	+
Cooling Performance	-	-	(+/-)	+	-	+
Field Weakening	+	+	+	(+/-)	(+/-)	(+/-)
Reliability		+		+	+	+
Economic Potential	+	++		-	(+/-)	+

Table I shows the most used electric motor types. In terms of the technical properties are compared in Table I [4]. Considering the evaluation results in Table I, the Permanent Magnet Synchronous Motor type is discussed in the research topic in this study.

With the efficiency increases (6%) obtained by the design optimization of electric motors, the range increase in vehicles with similar battery capacity and low range can reach 25% [5]. This means that designs for the design of electric motors are controlled by both design and new optimization techniques.

Genetic Algorithm, Particle Swarm Optimization, Ant Colony Algorithm, Taguchi's Experimental Design, and Neural Network Based Parameter Estimation can be summarized as some optimization techniques applied in design optimization of electric motors [6-10].

The term Deep Learning or Deep Neural Network refers to multi-layer Artificial Neural Networks (ANNs). In recent years, it has been recognized as one of the most powerful tools and has become very popular in the literature because it can handle large amounts of data [11].

II. METHOD

1) Specify Parameters

If we consider cost, performance, and quality among design optimization methods, *Taguchi's* parameter design method offers a simple and systematic approach. The two main tools used in robust design [12–14] are:

- Measuring quality by taking into account signal-to-noise ratio, variation
- Orthogonal arrays contain more than one design feature at the same time

In order to determine the priority of the parameters, the analysis of the parameters that will affect the result is done with the Taguchi experimental design (DoE)method. Within the framework of the result obtained, the optimization process is discussed by considering the relevant parameters.

a) Artificial Neural Network, ANN

ANN is defined as a model consisting of tens of millions of nervous systems in communication with each other, inspired by the human brain. Among them are private members who allow services to be forwarded to facilities close to it [15-17].

In fact, a complex and highly interactive system that consists of a set of data processing elements and responds with its own dynamics depending on external data input is called Artificial Neural Network [17].

The information transfer process with neural networks is represented by the trillions of neurons that make up the networks. This communication occurs by exchanging electrical impulses between cells, called action potentials. Figure 1 shows the mathematical model of simplified ANN.

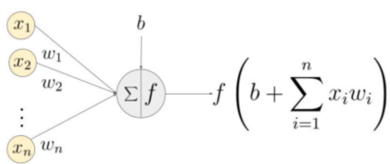

Fig. 1. Simplified a Neural Network

A multi-layer feedforward sine network, which is used for very complex or very time-consuming problems, is actually an improved version of the single-layer network.

Any network consists of three most important parts, the first is the neuron input layer, the second is one or more hidden neuron layers, and the third is the output neuron layer. What powers a network is actually the hidden layer that allows extra features to be derived from the input data.

2) Ansys RMXprt and Ansys Maxwell

Optimum design and post-production performance control are key processes in the manufacture of any motor. The right material selection and the right design increase the performance of the electric motor.

When it comes to the design of different electric motors, ANSYS RMxprt software is a strong candidate for accurate and cost-effective design.

ANSYS RMxprt is a template-based electrical machine design tool that enables fast analytical calculations of machine performance and the creation of 2D and 3D geometry for detailed finite element calculations. In addition to these, RMxprt is also very capable software in simulation and analysis operations. [18].

The manufacture of these motors includes many processes such as design, material selection, production, testing, performance control, etc. Electromagnetic computing is an essential part of the design process that defines various parameters of the magnetic core such as voltages, currents, flux, inductances in teeth, core, yoke, coil, etc. [19-21]. Figure 2 shows a 3D motor model for finite element computation.

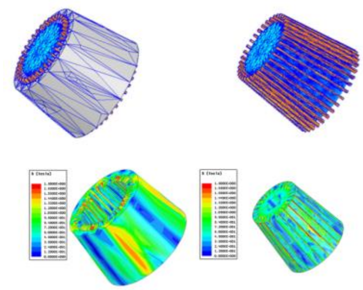

Fig.2. Maxwell 3D Geometry [23]

In addition, using finite element computation, the motor performance results and analysis are obtained as different graphic charts which are shown in Figure 3.

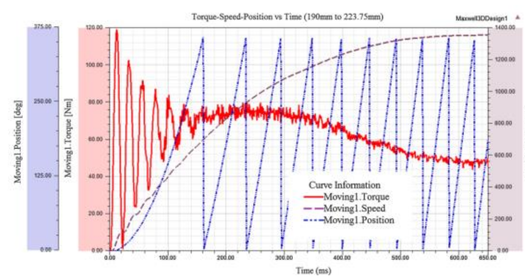

Fig. 3. Torque-Speed-Degree Curves of Electric Motor [21]

3) Interior Permanent Magnet

By improving the powertrains of conventional Internal Combustion Engines (ICE) or replacing them with electric powertrains, it is possible to reduce the use of fossil fuels, thereby reducing exhaust emissions and increasing efficiency [22-23].

Electric traction motors, which are among the key and indispensable technologies, have always been demanded in the market thanks to their high power density, high efficiency, and wide speed range [24-25].

AC machines dominate the DC machines market thanks to advanced power electronics and innovative controls. There are AC asynchronous and synchronous machines in the commercial electric vehicles sold [26-27].

The reason for having deep product knowledge and technology is actually due to the development of Asynchronous machines for decades [25].

The asynchronous electric machine is low in cost and relatively easy to control. Thus, the cooling requirement is high due to rotor copper losses. Therefore, its efficiency is lower than permanent magnet synchronous machines (PMSM) [28].

The most glorious and spectacular advancement of internal permanent magnet electric machines has appeared in the last two decades. During this time, high-efficiency electric traction drives for internal permanent magnet synchronous machines (IPSMM), the latest generation of electric vehicles (EV), and hybrid electric vehicles (HEV) have become quite popular in the automotive market. Therefore, IPM topologies are dealt with in this study.

Within this scope, the proposed methodology for design parameter generation of IPM is given in Figure 4. Here the process steps of generation the motor geometry for an IPM are presented in Figure 4.

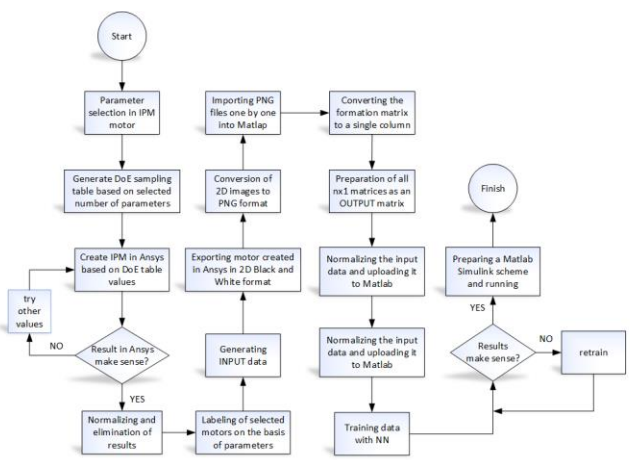

Fig.4. Flowchart of proposed methodology

III. Analysis and Findings

The reason why Internal Permanent Magnet Motors (IPM) is used effectively and widely in Automotive and Servo drives is due to the positive characteristics of IPMs such as high power density, high torque density, high efficiency, high power factor, and operation over a wide speed range. Knowing the critical parameters is vital for a Permanent Magnet Motor design and performance predictions[29-30]. Figure 5 shows the motor geometry structure of IPM.

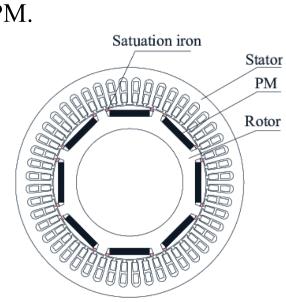

Fig. 5. IPM Structure

In this paper, the determined parameters for IPM and the parameter values are given in Table II.

TABLE II. Design Parameters and Levels for IPM

Parameters	Level 1	Level 2	Level 3
S.Outer Diameter (mm)	108	120	144
S.Inner Diameter (mm)	67.5	75	90
HS0 (mm)	0.45	0.5	0.6
HS1 (mm)	0.9	1	1.2
HS2 (mm)	7.4	8.2	9.8
BS0 (mm)	2.25	2.5	3
BS1 (mm)	5	5.6	6.7
BS2 (mm)	6.8	7.6	9.1
R.Outer Diameter (mm)	67	74	89
R.Inner Diameter (mm)	23	26	31
D1 (mm)	65	72	86
O1 (mm)	2.7	3	3.6
O2 (mm)	2.7	3	3.6
B1 (mm)	3.6	4	4.8
RIB (mm)	2.7	3	3.6
HRIB (mm)	2.7	3	3.6
Magnet Thickness (mm)	4.5	5	6
Magnet Width (mm)	36	40	48

Considering Table II in terms of the parameter numbers and levels, Taguchi's DoE table offers L36 experimental series which is determined for 18 parameters and 3 Levels.

Therefore, L36 are re-arranged for design constraints and linear dependency of parameters as shown in Figure 6.

IPM No	S.Out Diam	S.Inn Diam	HS0	HS1	HS2	BS0	BS1	BS2	R.Out Diam	R.Inn Diam	D1	O1	O2	B1	RİB	HRİB	Mag Thick	Mag Widt
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1->2	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2
3	1	1	1	1	1	1	3	3	3->1	3	3->1	3->2	3->1	3->2	3	3->1	3->2	3->1
4	1	1->2	1	1	1	2	1	1	1->2	1	2	2	2	2	3	3	3->2	3->2
5	1->2	1->3	1	1	1	2	2	2	2->3	2	3	3->1	3->1	3	1	1	1	1
6	1	1	1	1	1	2	3	3	3->1	3	1	1	1	1	2	2	2	2->1
7	1	1	2	2	2	1	1	1	2->1	3	1	2	3->1	3->2	1	2	2	3->1
8	1	1->2	2	2	2	1	2	2	3->2	1	2	3->1	1	1	2	3	3->2	1
9	1	1	2	2	2	1	3	3	1	2	3->1	1	2->1	2	3	1	1	2->1
10	1	2	1	2	2	1	1	1	3->2	2->1	1	3->1	2	3	2->3	1	3->2	2->1
11	1	2	1	2	2	1	2	2	1->2	3->1	2	1	3->1	1	3->2	2	1	3->2
12	1->2	2->3	1	2	2	1	3	3	2->3	1	3	2->1	1	2	1	3	2	1
13	1->2	2->3	2	1	2	2	1	2	3	1	3	2	1	3->2	3	2	1	2
14	1->2	2->3	2->1	1	2->1	2	2	3	1->3	2->1	1	3	2->1	1	1	3	2	3
15	1	2	2	1	2	2	3	1	2	3	2	1	3	2	2	1	3	1
16	1	2	2	2	1	2	1	2	3->2	2	1	1	3	2->1	3	3	2	1
17	1	2	2	2	1	2	2	3	1->2	3->1	2	2	1	3	1	1	3	2
18	1->2	2->3	2	2	1	2	3	1	2->3	1	3	3	2	1	2	2	1	3
19	2	1->3	2	2	1->3	1	1	2	1->3	3->1	3	3	1	2	2	1	2	3
20	2	1->2	2	2	1	1	2	3	2	1	1->2	1	2->1	3->1	3	2	3->1	1
21	2	1->3	2	2	1	1	3	1	3	2	2	2	3	1	1	3	1	2
22	2	1->2	2	1	2	2	1	2	2	3	3->2	1	2	1	1	3	3	2->1
23	2	1->3	2	1	2	2	2	3	3	1	1->3	2	3	2	2	1	1	3
24	2	1->2	2	1	2	2	3	1	1->2	2	2	3	1	3	3	2	2	1
25	2	1->2	1	2	2	2	1	3	2	1	2	3	3	1	3	1	2	2
26	2	1->3	1	2	2	2	2	1	3	2	3	1	1	2	1	2	3	3
27	2	1	1	2	2	2	3	2	1	3	1	2	2	3->2	2	3->1	1	1
28	2	2->3	2	1	1	1	1	3	2->3	2	2	1	1	3	2	3	1	3
29	2	2->3	2	1	1	1	2	1	3	3	3	2	2	1	3	1	2	1
30	2	2	2	1	1	1	3	2	1->2	1	1->2	3	3	2	1->3	2	3	2
31	2->3	2->3	1	2	1	2	1	3	3	3	2	3	2	2	1	2	1	1
32	2	2->3	1	2	1	2	2	1	1->3	1	3	1	3	3	2	3	2	2
33	2	2	1	2	1	2	3	2	2	2	1	2->1	1	1	3	1	3->2	3->1
34	2	2->3	1	1	2	1	1	3	1->3	2	3	2	3	1	2	2	3	1
35	2	2	1	1	2	1	2	1	2	3->1	1->2	3	1	2	3	3	1	2
36	2	2->3	1	1	2	1	3	2	3	1	2->3	1	2	3	1	1	2	3

Fig. 6. Taguchi's L36 IPM motor design parameters series

Maxwell design image is created for each of the IPM RMXprt motors created depending on the DoE table. The geometry images for the determined IPM model on L36 are given in Figure 7.

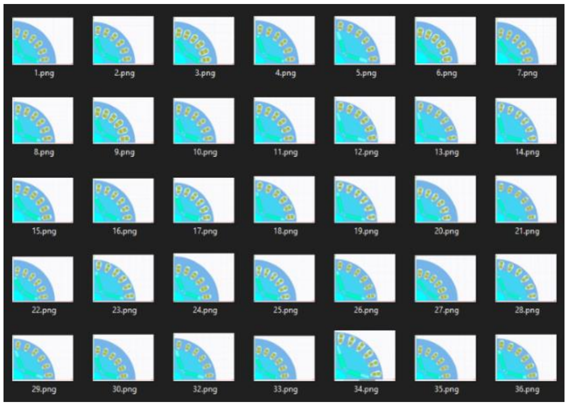

Fig. 7. Geometry images of IPM motor model

By using the AutoCAD program, dxf files obtained from ANSYS Maxwell are converted to PDF as shown in Figure 8.

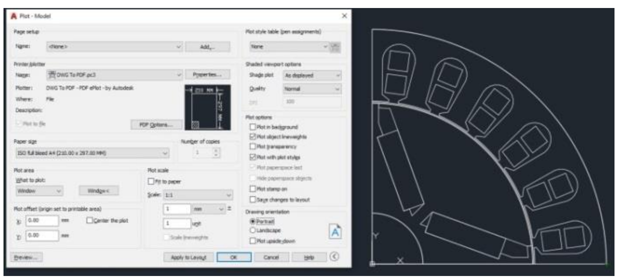

Fig. 8. Converting DXF to PDF

The same process is done for all motors on the L36 experiment series as shown in Figure 9.

Fig. 9. IPM images ready to be imported

For each motor combination, the obtained motor performance results from ANSYS are logged as a matrix. Then the obtained motor performance result data are imported to the Matlab environment as shown in Table III.

TABLE III. IPM ANALYSIS RESULTS FOR L36

Results/ IPM Exp.	1	2	3	…	34	35	36
S.Too.Flx.Dns	0.98	0.72	1.66		0.91	0.34	0.34
S.Yk.Flx.Dns	1.47	1.83	1.62		1.33	2.35	2.35
R.T.Too.Flx.Dns	0.50	0.32	0.48		0.50	0.2	0.20
R.Yk.Flx.Dns	0.57	0.41	0.53		0.52	0.31	0.31
Mag.Flx.Dns	0.89	0.76	0.86		0.89	0.57	0.57
AirGapFlx.Dns	0.49	0.33	0.49		0.48	0.17	0.17
Avg.Inp.Current	3.01	3.07	3.06		2.94	4.68	4.68
Rt.M.Sqr.Arm.Curr	3.19	3.97	4.10	⋱	3.07	8.44	8.44
Arm.Therm.Loa.	116.3	129.1	121.15		86.69	433.1	433.1
Spec.Electric Load	18.9	21.2	24.3		16.40	37.51	37.51
Arm.Curr.Dns	6.14	6.08	4.98		5.28	11.54	11.54
Irn.Cor.Los.	22.7	19.6	27.5		24.58	17.27	17.27
Arm.Cop.Los.	81.3	105.8	89.8		70.53	462.6	462.6
Output Power	558.	549.9	557.26		552.2	549.7	549.7
Efficiency (%)	84.2	81.4	82.6		85.3	53.3	53.38
Rated Torque	1.48	1.45	1.47		1.46	1.45	1.45

The imported input and output data from images and IPM analysis results are arranged for ANN training data as shown in Figure 10.

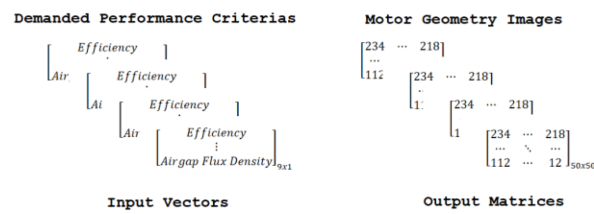

Fig. 10. Related Input Vectors and Output Matrics for ANN training

The obtained input and output data are trained by nftool (Neural Network Fitting) module in Matlab as shown in Figure 11. Here ANN has two-layer as hidden and output. In the hidden layer, 320 neurons activations function are used. In the ouput layer 2500 neuron and pureline activation function are used. ANN is trained by Scaled conjugate algorithm to get the desired performance.

The predictive success and overall success rate on the training, validation, and test data of our network indicates the total success of our artificial neural network is 94.925% .

Simulink makes it possible to obtain an motor image as shown in Figure 11, due to the demanded value into the system and the trained network.

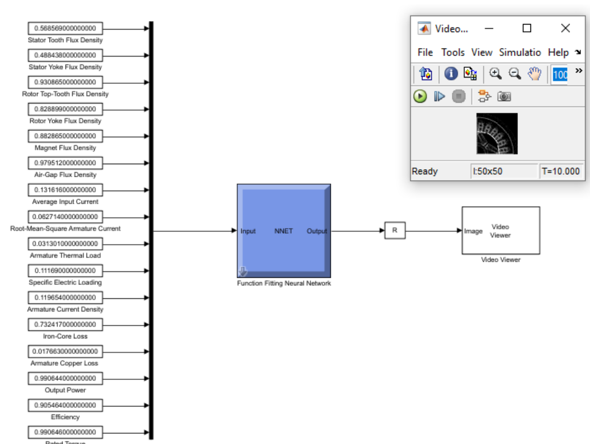

Fig. 11. Derived motor geometries from ANN

IV. Conclusion

In this study, a neural network approach for electric motor design is used to derive the motor geometry-image corresponding to the desired motor design parameters from the output of the neural network. To derive the motor geometry-images, a neural network was trained by generating a data set from the motor geometries and analysis results obtained using the ANSYS RMXprt and ANSYS Maxwell. The motor geometry-image corresponding to the desired motor performance values is tried to be obtained from the output of the trained ANN.

The meaning of the result of 94.925% represents the desired convergence rate of the proposed approach.

The image generation of the Electric Motor geometry has been observed to be successful considering the outcome of the proposed approach.

Therefore, the proposed methodology provides a better initial start for motor optimization studies against the uncertainty for geometric design problems. Furthermore, this study is planned to use a computation for the electromagnetic analysis for electric motors instead of finite element computation due to the superior features such as fast response.

References

[1] U. Demir and M.C. Akuner, "Calculation of Performance Characteristic ofln-Wheel Asynchronous Motor for Electric Vehicle", Gaziosmanpa a Bilimsel Arasrma Dergisi, vol. 6, no. Ozel Say1 (ISMSIT2017), pp. 10-20, Dec. 2017

[2] U. Demir and M.C. Akuner, "Design and analysis ofradiaxial induction motor", Demir, U., Akliner, M.C. Design and analysis of radiaxial induction motor. Electrical Engineering, vol.l 00, 2361-2371 (20 I 8). https://doi.org/10.1007/s00202-018-0708-6

[3] M. Ehsani, Y. Gao, and A. Emadi "Modern Electric, Hybrid Electric, and Fuel Cell Vehicles - Fundamentals, Theory, and Design". CRC Press 2nd ed., Boca Raton, FL: Taylor and Francis Group, LLC, 2010. https://doi.org/10.1201/9781420054002

[4] Demir, Uğur and Kocabıçak, Zeliha Kamış. "Performance assessments of the material for the traction motor cores of an electric racing kart" Materials Testing, vol. 63, no. 6, 2021, pp. 519-528. https://doi.org/10.1515/mt-2020-0085

[5] X. Sun, Z. Shi, G. Lei, Y. Guo and J. Zhu, "Multi-Objective Design Optimization of an IPMSM Based on Multilevel Strategy," in IEEE Transactions on Industrial Electronics, vol. 68, no. 1, pp. 139-148, Jan. 2021, doi: I 0.1109/TIE.2020.2965463.

[6] U. Demir ve M. Akuner, "Elektrikli bir aray iyin tekerlek iyi asenkron motorun tasanm ve optimizasyonu", Gazi Oniversitesi Mtihendislik Mimarlik Faktiltesi Dergisi, c. 33, say1. 4, ss. 1517-1530, Ara. 2018, doi: I 0.17341/gazimmfd.4l 6448

[7] U. Demir and M.C. Akuner, "Using Taguchi method defining critical rotor pole data of LSPMSM considering the power factor and efficiency", Tehnicki vjesnik, vol.24, br. 2, str. 347-353, 2017. https://doi.org/10.17559/TV- 20140714225453

[8] Yong-Hwan Oh, Tae-Kyung Chung, Min-Kyu Kim and Hyun-Kyo Jung, "Optimal design of electric machine using genetic algorithms coupled with direct method," in IEEE Transactions on Magnetics, vol. 35, no. 3, pp. 1742-1745, May 1999, doi: IO.I 109/20.767366.

[9] Demir, U. Improvement of the power to weight ratio for an induction traction motor using design of experiment on neural network. Electr Eng 103, 2267–2284 (2021). https://doi.org/10.1007/s00202-020-01204-2

[10] Demir, U. IM to IPM design transformation using neural network and DoE approach considering the efficiency and range extension of an electric vehicle. Electr Eng (2021). https://doi.org/10.1007/s00202-021-01378-3

[11] S. Albawi, T. A. Mohammed and S. AI-Zawi, "Understanding of a convolutional neural network," 2017 International Conference on Engineering and Technology (ICET), Antalya, Turkey, 2017, pp. 1-6, doi: 10.1109/ICEngTechnol.2017.8308186.

[12] S.H. Park, Robust Design and Analysis for Quality Engineering, Chapman & Hall, London, 1996.

[13] R. Unal, E.B. Dean, Taguchi approach to design optimization for quality and cost: an overview, in: Proceedings of the International Society of Parametric Analyst 13th Annual, May 21–24, 1991.

[14] M.S. Phadke, Quality Engineering Using Robust Design, PrenticeHall, Englewood Cliffs, NJ, 1989.

[15] Cha, D., Zhang, H., & Blumenstein, M. (2011). Prediction of maximum wave-induced liquefaction in porous seabed using multi-artificial neural network model. Ocean Engineering, 38(7), 878–887.

[16] Kocabicak, Z. K. and Demir, U.. "Design and optimization of an electromechanical actuator for the latch of a foldable vehicle seat" Materials Testing, vol. 62, no. 7, 2020, pp. 749-755. https://doi.org/10.3139/120.111539

[17] Caudil, M. (1987). Neural networks primer part 1. AI Expert, 2(12), 46–52.

[18] Olga V.Tikhoniva and Anatoliy T.Plasturn,2018 IEEE 978-1-5386-4320-2,

[19] Y. Yang and A. Emadi, "Hybrid and plug-in hybrid vehicles," in Wiley Encyclopedia of Electrical and Electronics Engineering, John Wiley & Sons, 2013, pp. 1-22.

[20] A. Fenercioğlu and Y. Avşar , "Design and analysis of EI core structured transverse flux linear reluctance actuator", Turkish Journal of Electrical Engineering and Computer Science, vol. 23, no. 4, pp. 945-955, Aug. 2015, doi:10.3906/elk-1304-145

[21] M. Eker, M. Akar, C. Emeksiz, and Z. Doğan, "Rotor design for line start AF-PMSM," IET Electric Power Applications, vol. 13, no. 9, pp. 1273–1279, Sep. 2019.

[22] Demir, U., Aküner, M.C. Design and analysis of radiaxial induction motor. Electr Eng 100, 2361–2371 (2018). https://doi.org/10.1007/s00202-018-0708-6

[23] Y. Yang and A. Emadi, "Integrated Electro-Mechanical Transmission Systems in Hybrid Electric Vehicles," in IEEE Vehicle Power and Propulsion Conference, Chicago, IL, USA, 2011.

[24] S. Rogers, "EV everywhere grand challenge, Electric drive status and challenges," U. S. Department of Energy, Energy Efficiency & Renewable Energy, 2012.

[25] Z.Q. Zhu and D. Howe, "Electrical machines and drives for electric, hybrid, and fuel cell vehicles," Proceedings of the IEEE, vol. 95, no. 4, pp. 746-765, April 2007.

[26] J. de Santiago, H. Bernhoff, B. Ekergård, S. Eriksson, S. Ferhatovic, R. Waters, and M. Leijon, "Electrical motor drivelines in commercial all-electric vehicles: a review," IEEE Transactions on Vehicular Technology, vol. 61, no. 2, pp. 475-484, Feb. 2012.

[27] A. Bazzi, "Electric machines and energy storage technologies in EVs and HEVs for over a century," in IEEE International Electric Machines & Drives Conference (IEMDC), Chicago, IL, 2013.

[28] B. Bilgin and A. Sathyan, "Fundamentals of Electric Machines," in Advanced Electric Drive Vehicles, Boca Raton, FL, CRC Press, 2014, pp. 107-186.

[29] Lovelace, E. C., T. M. Jahns, and J. H. Lang, "A saturating lumped-parameter model for an interior PM synchronous machine," IEEE Trans. on Industry Applications, Vol. 38, No. 3,645–650, May–Jun. 2002.

[30] Rezaie, J., M. Gholami, R. Firouzi, T. Alizadeh, and K. Salashoor, "Interior permanent magnet synchronous motor (IPMSM) adaptive genetic parameter estimation," Proceedings of the WCECS, Oct. 2007.