Design Optimization of an SPM Motor Using the Fuzzy-based Taguchi Method With Finite Element Simulations

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Abstract —This paper describes a design optimization procedure based on the Taguchi method with fuzzy logics and finite element method (FEM). The proposed approach takes advantage of both the Taguchi method and a fuzzy rule based inference system, which forms a robust and practical methodology in tackling multi-objective optimization problems. The proposed methodology is applied to the optimization design of an surface-mounted permanent magnet (SPM) motor.

I. INTRODUCTION

The Taguchi method of experimental design was introduced to electromagnetic community and successfully optimized some electric machine applications [1]-[6]. Traditionally, the Taguchi method has been proven it useful for parameter design optimization of single objective problems [2], [3]. However, the majority of engineering problems encountered in real-world often require to deal with multi-objective optimization which, in general, conflict with each other. This paper presents an integrated approach using the Taguchi method and fuzzy logics for tackling multi-objective optimization problems. Results in the matrix experiments are computed using the FEM analysis. The proposed method will be verified by application to an SPM motor.

II. METHOD OF ANALYSIS

The procedure of Taguchi method starts with the problem initialization, including selecting the performance characteristics to be optimized, the control factors that can be adjusted in the optimization exercise and a proper orthogonal array (OA). Results of each experiment are conducted using FEM analysis.

To verify the robust design results, the signal-to-noise (S/N) ratio is used to transform the performance characteristics in optimization process. Normally, there are three categories of the performance characteristics in the analysis of S/N ratio, i.e., the lower-the-better, the higher-the-better, and the nominal-the-better. The lower-the-better and the higher-the-better of S/N ratios can be written respectively as

$$\eta_{ij} = -10\,log\left(\frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2\right);\ \eta_{ij} = -10\,log\left(\frac{1}{n}\sum_{k=1}^{n}\frac{1}{y_{ijk}^2}\right) \qquad (1)$$

where y_{ijk} is the experimental value of the i^{th} performance characteristics in the j^{th} experiment at the k^{th} trial, and n is the number of trials. Next, a linear normalization of the S/N ratio is performed in the range of zero and one. The normalized S/N ratio x_{ij} for the i^{th} performance characteristics in the j^{th} experiment of the lower-the-better and the higher-the-better can be written respectively as

$$x_{ij} = \frac{\eta_{ij} - min\,\eta_{ij}}{max\,\eta_{ij} - min\,\eta_{ij}};\ x_{ij} = \frac{max\,\eta_{ij} - \eta_{ij}}{max\,\eta_{ij} - min\,\eta_{ij}} \qquad (2)$$

where $min\,\eta_{ij}$ and $max\,\eta_{ij}$ are the smallest and largest values of η_{ij} for the i^{th} performance characteristics in the j^{th} experiment respectively. Then, the grey rational coefficient $\gamma_{ij}(k)$ is calculated from the normalized S/N ratios and can be expressed as

$$\gamma_{ij}(k) = \frac{\Delta_{min} + \xi\Delta_{max}}{\Delta_{ij}(k) + \xi\Delta_{max}} \qquad (3)$$

where $\Delta_{ij}(k) = \left\| x_{ii}(k) - x_{ij}(k) \right\|$ is the difference in absolute value between $x_{ii}(k)$ and $x_{ij}(k)$, ξ is the distinguishing coefficient, $\Delta_{\min} = \overset{\min}{\forall}\, j \in i\ \overset{\min}{\forall}\, k \left\| x_{ii}(k) - x_{ij}(k) \right\|$ is the smallest value of $\Delta_{ij}(k)$, and $\Delta_{\max} = \overset{\max}{\forall}\, j \in i\ \overset{\max}{\forall}\, k \left\| x_{ii}(k) - x_{ij}(k) \right\|$ is the largest value of $\Delta_{ij}(k)$. Finally, the fuzzy rule based inference system is used to convert the fuzzy value into a multiple performance characteristics index (MPCI), y_0. Fig. 1. shows the flow chart of the proposed method.

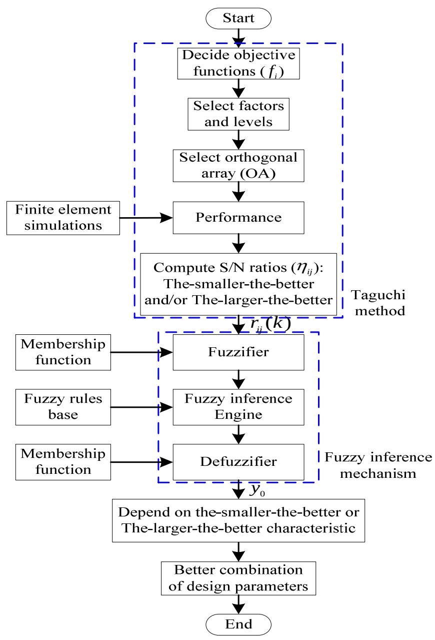

Fig. 1. Flow chart of the proposed optimization method.

III. NUMERICAL RESULTS

The proposed technique is applied to the optimization of an SPM motor as shown in Fig. 2(a). The objective functions are the minimization of the torque ripple (T_{rip}), the maximization of the torque to volume of permanent magnet ratio (T_{pm}), and the maximization of the efficiency (η).

In this experiment, eight design parameters have to be adjusted. As shown in Fig. 2(b), factor A is the magnetization of magnets (parallel or <u>radial</u>), factor B is the magnet arc angle in electrical degrees (levels <u>155</u>, 160 and 165), factor C is the thickness of magnet in mm (levels 4.2, 4.4 and <u>4.6</u>), factor D is the distance from motor center used as the center of a circle for magnet chamfered in mm (levels 0, <u>1</u> and 2), factor E is the slot opening in mm (levels 2.4, <u>2.7</u> and 3), factor F is the tooth width in mm (levels <u>5.5</u>, 6 and 6.5), factor G is the yoke width in mm (levels <u>12</u>, 12.5 and 13), and factor H is the air gap length in mm (levels 1, 1 and 1), The numbers with the underbar denote the initial design.

Following the procedure described in previous section, the experimental results are further transformed into the S/N ratios and grey rational coefficients based on grey rational analysis as shown in Table I. It is noted from Fig. 3 that the best combination of design parameters is determined to be ($A_1B_1C_1D_3E_2F_3G_3H_1$). The final results are found using 2D FEM analysis. Table II compares the data of the motor between initial, proposed method, and measurement.

IV. CONCLUSION

This paper has applied the Taguchi method with fuzzy logics and finite element method to the design optimization for torque ripple minimization and the torque to volume of permanent magnet ratio and efficiency maximization of an SPM motor. The technique would link the existing FEM packages to complete an iterative design loop.

ACKNOWLEDGMENT

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V. REFERENCES

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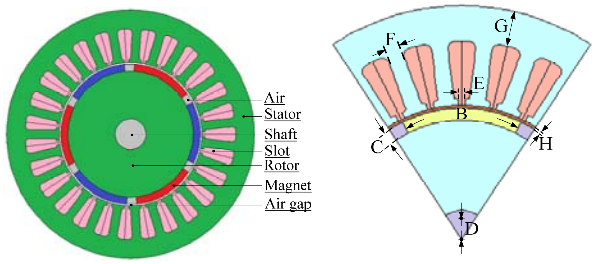

Fig. 2. Initial design of motor. (a) Cross-section, and (b) One pole pitch of the motor.

TABLE I
EXPERIMENTAL RESULTS FOR S/N RATIOS AND THEIR GRAY RATIONAL COEFFICIENTS

No.	S/N ratio			Grey rational coefficient			MPCI
	T_{rip}	$-T_{pm}$	η	T_{rip}	T_{pm}	η	MPCI
1	-21.54	-59.58	39.36	0.436	0.829	0.393	0.518
2	-20.09	-59.78	39.38	0.510	0.639	0.576	0.592
3	-19.49	-60	39.40	0.548	0.507	1.000	0.688
4	-23.34	-59.70	39.38	0.370	0.705	0.613	0.569
5	-22.35	-59.92	39.38	0.404	0.544	0.626	0.533
6	-20.91	-60.38	39.37	0.466	0.373	0.456	0.425
7	-17.90	-59.74	39.38	0.684	0.670	0.588	0.499
8	-19.14	-60.25	39.37	0.574	0.408	0.479	0.482
9	-20.42	-60.46	39.37	0.491	0.352	0.471	0.429
10	-24.25	-59.47	39.37	0.343	1.000	0.479	0.598
11	-24.39	-59.80	39.38	0.340	0.621	0.588	0.534
12	-24.65	-60.32	39.35	0.333	0.389	0.345	0.365
13	-22.16	-59.83	39.36	0.411	0.599	0.387	0.451
14	-22.27	-60.02	39.36	0.406	0.494	0.404	0.411
15	-21.45	-60.32	39.37	0.440	0.388	0.471	0.422
16	-15.88	-59.85	39.36	1.000	0.588	0.382	0.657
17	-20.50	-60.42	39.35	0.487	0.363	0.333	0.378
18	-18.21	-60.55	39.37	0.653	0.333	0.442	0.468

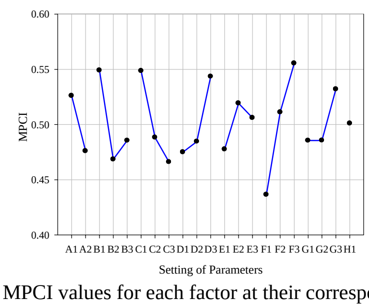

Fig. 3. The MPCI values for each factor at their corresponding levels.

TABLE II
COMPAEISON OF RESULTS

	Initial	Fuzzy	Test
T_{rip} (%)	17.1	8.68	--
$T_{pm}\times 10^{-6}$ (N.m/mm^2)	963.4	1075.38	1074.80
η (%)	92.84	93.31	93.23