Optimal Design of Robot Joint Motor using Least Square Boosting based Meta-model Optimization Algorithm

Jong-Min Ahn[1], Min-Mo Koo[2], and Dong-Kuk Lim[1]

[1]Department of Electrical / Electronic and Computer Engineering, University of Ulsan, Daehak-ro 93, Nam-gu, Ulsan, 44610, Republic of Korea (South Korea), sapaajm@naver.com and ldk8745@ulsan.ac.kr
[2]Department of Purpose-Built Mobility Group, Korea Institute of Industrial Technology, 6 Cheomdan-gwagiro 208, Buk-gu Gwangju, 61012, Republic of Korea (South Korea), mmkoo@kitech.re.kr

In this paper, the least square boosting based meta-model optimization Algorithm (LSBMOA) is proposed for the optimal design of surface-mounted permanent magnet synchronous motor for robot joint. The LSBMOA uses machine learning to shorten the time to find multi-objective optimal solutions and improve the performance of meta-model. The conventional multi-objective optimization algorithms are stochastic algorithms that iterate on the algorithm by increasing the probability that an excellent solution will be chosen. Therefore, they take a lot of function calls and time to find the pareto front set. The proposed algorithm reduces the pareto front set derivation time by directly adding a solution to the objective function area to overcome the limitations of conventional algorithms through a meta-model. Furthermore, the grid subdivision and dynamic sampling process are added to improve the predictive performance of the algorithm. The LSBMOA is compared with conventional algorithms to evaluate the performance of the proposed algorithm using two test functions and to confirm its superiority. In order to apply the verified algorithm to the optimal design of a robot joint motor, design variables that affect torque, back-electromotive total harmonic distortion, and cogging torque, which are objective functions to be improved in the initially designed motor, are selected. From the extracted pareto front set, an optimal design is derived by selecting the most suitable solution based on the relative importance of the objective functions.

***Index Terms*— Machine learning, manipulators, pareto optimization, permanent magnet synchronous motors**

I. Introduction

Recently, the human productivity has become insufficient as the proportion of the elderly population has increased rapidly and the global economy enters an era of long-term low growth, and robots are emerging as a solution to this. The international federation robot classifies robots into industrial robots, professional service robots, personal service robots, and so on. Among them, industrial robots have the largest market size and are used in various industries [1]. The demand for industrial robots is steadily increasing. Because they can be widely used in 3D (difficult, dirty and dangerous) fields that people are reluctant to do, and productivity has been further improved by the advent of collaborative robots that work with humans.

Motors are one of the key components of robots, and as the applications of robots diversify and the tasks they perform become more complex, the number and size of motors used to achieve the appropriate movements are also becoming more varied. In particular, a high torque density design is required to satisfy limited in-space performance for motors used in collaborative robots with spatial limitations, and torque ripple and cogging torque that generate noise and vibration should be reduced to improve the robot's performance and precision [2].

Permanent magnet motors generate the rotor's magnetic flux through permanent magnets, and the rotor rotates due to the permanent magnet and the 3-phase alternating current flowing through the stator coils. This allows for high torque density and high efficiency. There are several types of permanent magnet motors, and among them, the surface permanent magnet synchronous motor (SPMSM) has magnets attached to the surface of the rotor. The SPMSM is widely used in industries that require instantaneous torque control due to its excellent responsiveness. Therefore, it is suitable for robot joint motors because it has has simple control and small leakage flux and has high power density. However, the SPMSM generates torque ripple due to the back-electromotive (B-EMF) harmonic, which generates noise and vibration of the motor and has a problem of lowering the precision of the motor. Therefore, the consideration of B-EMF total harmonic distortion (THD) and cogging torque that affect torque ripple is necessary when designing a motor. In addition, the finite element analysis (FEA) is essential for accurate characteristic analysis since these motor characteristics have nonlinearity [3]. However, the FEA has the disadvantage of taking a very long time because it performs iterative interpretations to find a solution. Therefore, this paper proposes a least square boosting based meta-model optimization Algorithm (LSBMOA) that can reduce the number of function calls in a multi-objective optimization (MOO) problem and derive a pareto front set as an objective function to improve torque density, reduce B-EMF THD and cogging torque through a meta-model using machine learning.

II. Proposed Algorithm

The initial values must be set to perform the proposed algorithm. For example, the range of the problem area, the number of initial samples and repetitions. The latin hypercube sampling (LHS) method is used to ensure that the samples do not have biased data when initial samples are generated. The LHS is sampled to have randomness while being evenly distributed throughout the problem area [4]. The initial pareto front set are constructed using a non-dominated sorting method for the generated samples. Furthermore, the dataset of least square boosting is constructed using initial samples and generates a meta-model for each objective function. The Fig. 1

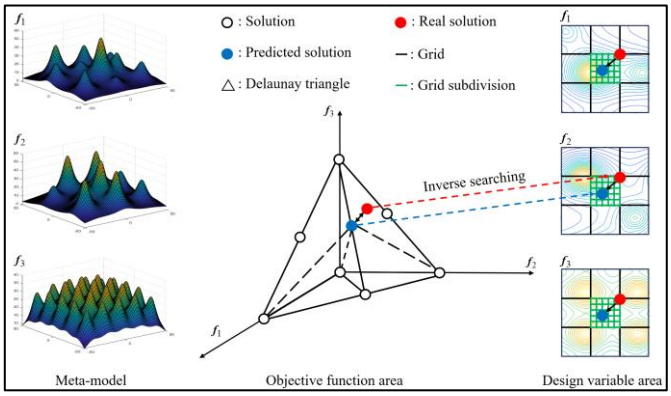


Fig. 1. Conceptual diagram of LSBMOA.

TABLE I
COMPARISON OF ALGORITHM RESULTS FOR TEST FUNCTIONS

Test function 1	*GD*	*SP*	*Function calls*
LSBMOA	0.0079	0.0162	649
NSGA-II	0.0918	0.0234	1440
MOPSO	0.0771	0.0228	1560
Test function 2	*GD*	*SP*	*Function calls*
LSBMOA	0.0041	0.0120	529
NSGA-II	0.0791	0.0214	1950
MOPSO	0.0793	0.0235	1890

is a conceptual diagram of LSBMOA and the initial pareto front set is divided into the form of triangle through Delaunay triangulation, as shown in the objective function area of Fig. 1. A new solution is added to the center of gravity of the largest triangle to be redivided for the uniform distribution. The added solution is a solution that is hoped to be generated, and in order to actually generate it, a design variable with a corresponding objective function value must be inverse searching. However, the real solutions are generated only on the grid points, as in the design variable area in Fig. 1, which may lead to differences from the predicted solutions. The grid subdivision is performed to address this issue. However, if the grid is segmented from the beginning, all grid points must be calculated, which significantly increases computational time. Therefore, the grid subdivision is performed only on areas near the optimal solution to improve the performance of the algorithm and reduce computation time. The dynamic sampling method performes additional sampling around the sample that had the greatest impact on changes to the meta-model, in order to improve its accuracy. Finally, the fill blank is used that adds solutions to the area with the fewest solutions, thereby enhancing the likelihood of identifying potential optimal points that might otherwise be overlooked within the design variable space.

III. ALGORITHM VERIFICATION

The MOO algorithms are evaluated based on solution accuracy, solution uniformity, and the number of function calls. *GD* is an indicator that represents the difference from the actual solution, while *SP* indicates how evenly the solutions are distributed. The closer these two indicators are to 0, the better the algorithm performs. Table I shows the algorithm results of test functions and LSBMOA shows superior performance compared to existing algorithms.

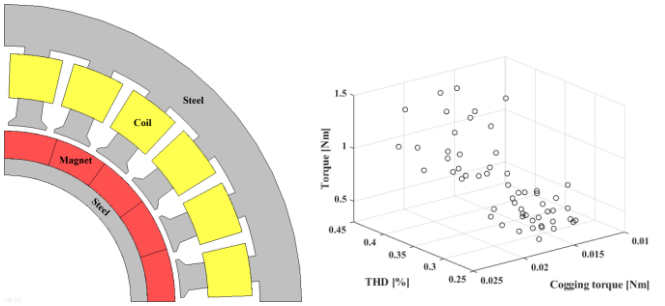


Fig. 2. Initial design model and extracted pareto front set. (a) Initial model (b) Pareto front set

IV. OPTIMAL DESIGN OF ROBOT JOINT MOTOR

The proposed algorithm is applied to the robot joint motor as shown in Fig. 2 (a) to achieve the objective of improving torque density and reducing torque ripple, using torque, B-EMF THD, and cogging torque as objective functions. The Fig. 2 (b) is the pareto front set of the motor derived through the optimization algorithm, and the optimal design is derived by selecting an appropriate solution according to the importance of the objective function among the solutions. The selection of the initial motor, design variables, and optimal design results will be covered in full paper due to the spatial limitations.

V. CONCLUSION

This paper proposes an optimization algorithm for improving torque density and reducing torque ripple of a motor for robot joints. The proposed algorithm reduces derivation time of optimal solution through machine learning based meta-model generation and improves the performance of the meta-model through the grid subdivision and dynamic sampling method. The performance of the algotithm is verified through the test functions, and the pareto front set is derived by applying it to the motor, and the optimal model is derived by selecting an appropriate solution. The detailed optimal design results will be presented in full paper due to spatial limitations.

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