Fast Design Optimization Method Utilizing a Combination of Artificial Neural Networks and Genetic Algorithms for Dynamic Inductive Power Transfer Systems

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ABSTRACT Multiple parameters with large nonlinear characteristics must be considered simultaneously to design the coil dimensions of static inductive power transfer (SIPT) systems. The design of dynamic inductive power transfer (DIPT) systems is more challenging due to the large number of parameters needed to be considered. In the conventional artificial neural network (ANN)-based design approach, optimal coil dimensions are found using ANN that has learned the nonlinear characteristics between coil dimensions and magnetic characteristics using the finite element method (FEM). However, this approach requires a large amount of training data, and it is difficult to reach an optimum design if there are many design criteria. In order to overcome these challenges, this paper proposes a design optimization method using two approaches: improving the time efficiency of ANN training data collection by superposing the magnetic fields from the coils and improving the input value of ANN using a genetic algorithm. Design results predicted by the ANN are compared with FEM simulation, circuit simulations, and experimental results to verify the validity of the proposed algorithm. The FEM and circuit simulation results and the ANN prediction results match with errors of 10.2% or less for all design requirements. Experimental results are provided for a 3 kW DIPT system with four transmitter coils and an automated test rail. Comparison results between ANN predicted values and experimental values match with an error of less than 12.7%.

INDEX TERMS Artificial neural networks, genetic algorithms, multi-objective optimization, wireless power transmission.

I. INTRODUCTION Electric vehicles (EVs) are rapidly growing in popularity with their promise of reducing emissions and operating costs. However, EVs have challenges compared to conventional internal combustion engine (ICE) vehicles, such as the limited driving range, long charging time, heavy battery weight, and high battery price. Dynamic inductive power transfer (DIPT) systems have been proposed and studied to address the issues. In a DIPT system, transmitter coils are embedded in the road to supply electric power to EVs wirelessly. DIPT is expected to reduce the battery’s weight and cost and improve the vehicle range and charging time [1], [2], [3], [4], [5].

To perform design optimization of an inductive power transfer (IPT) system, engineers need to consider many vital specifications, such as output power, stray magnetic fields, variation of coupling due to misalignment, coil losses, magnetic core volume, and copper winding volume [6], [7], [8], [9], [10], [11], [12], [13], [14]. In addition, DIPT requires...
further considerations beyond static inductive power transfer (SIPT) systems, such as the distribution of transmitted power on transmitter coils along the road and the average output power received by moving vehicles [15], [16], [17], [18], [19], [20], [21], [22].

To overcome the challenges in the design process for IPT systems, the Pareto front-based multi-objective optimization method has been discussed in previous works [23], [24], [25], [26]. The Pareto front is a performance boundary given by the set of designs in which an increase in one of the performances results in a decrease in the other. This method performs characteristic value mapping with a design parameter sweep using the loss model and FEM model to determine an optimized design point. In this method, the coupling coefficient and the stray magnetic fields are obtained by FEM simulation after determining the coil geometry. Due to the large air gap between the loosely coupled primary and secondary coils, as well as the presence of ferrite to shape the fields, it is difficult to define an exact mathematical model to represent the relationship between the geometric parameters of the coils for the IPT systems such as the various lengths, widths, and heights, and the magnetic parameters such as the inductances, coupling coefficients, and stray fields. As a result, the multi-objective design optimization methods for IPT systems rely heavily on FEM simulations to calculate these magnetic parameters. Using FEM simulations to perform parametric sweeps is time-consuming, especially when the user needs to run thousands of simulations to achieve the desired resolution.

In order to reduce the calculation time for the stray magnetic fields, optimization methods using the superposition of stray magnetic fields have also been proposed [27], [28]. In these methods, the stray magnetic field is obtained with each turn of the coils and represented as any number of turns and currents using the superposition of magnetic fields. These methods can significantly reduce the stray magnetic field calculation time. However, these methods are unsuitable for flexible design optimizations of IPT systems if they include magnetic core size and winding geometries because they require a large inductance matrix and a current-magnetic field coefficient vector for each magnetic core geometry.

As an alternative to the optimization method above, artificial neural network (ANN)-based approaches have been proposed [29], [30], [31], [32]. The ANNs generate the Pareto fronts and select the optimal designs from given specifications and goals. In the literature [32], the ANNs predict the inductance and coupling coefficient of inductors from a 2-D FEM model of an inductor. The trained ANN learns the nonlinear characteristics of inductors and can depict a Pareto-front line by quickly predicting and plotting a large amount of data. This method is excellent for optimizing IPT systems since neural networks can represent nonlinear relationships between input and output variables. However, there are two challenges in systems with many input and output variables, such as DIPT, as shown in Fig. 1.

The first challenge is that a vast amount of training data is required. In the conventional approach, ANN learns the nonlinear relationship between coil dimensions and magnetic characteristics from FEM data. A vast amount of FEM data is required to learn relationships if there are many input variables.

The second challenge is too many design criteria to reach the optimal design. Even if an ANN can learn nonlinear relationships, too many design requirements will take too much time to find an optimal design point that satisfies all design criteria.

To overcome the two challenges, this paper proposes a new fast design optimization method utilizing a combination of ANNs and genetic algorithms (GAs) for DIPT systems. The motivation of this paper is to find the Pareto front and perform multi-objective optimization in a short time. Section II presents an overview of the proposed algorithm in which superposition can help ANNs learn stray magnetic field data quickly, and GAs in the feedback step select input variables effectively. The proposed method demonstrates design optimization in Section III. In Section IV, simulations verify the validity of the optimized design. In Section V, the validity of the optimized design is verified experimentally.

II. THE PROPOSED DESIGN OPTIMIZATION PROCESS

In this section, a method to efficiently collect ANN training data by superposition of the magnetic fields of the transmitter and receiver coils in order to overcome the challenge 1 mentioned in the previous section is proposed. Furthermore, a method to improve input value by a GA to overcome the challenge 2 is proposed.

A. ASSUMPTION OF THE OPTIMIZATION PROBLEM

The coil model to be optimized is shown in Fig. 2. There are ten design variables, including the width of coil winding, the coil length, the distance between two transmitter coils, and the number of turns, listed in Table 1.
As the receiver coil moves from above the center of the transmitter coil to the edge according to the vehicle traveling direction, the coupling coefficient between the transmitter coil and receiver coil changes significantly from maximum to minimum. Since this coupling coefficient profile significantly affects the average output power, it is necessary to accurately simulate the coupling coefficient profile. In this paper, the coupling coefficient profiles are calculated in an FEM model with five receiver positions from $y_0$ to $y_4$ depicted in Fig. 2(a).

Since the transmitter coil is symmetrical about the center points $x_0$ and $y_0$, symmetry was used to calculate the coupling coefficient profile of the entire transmitter coil with respect to the vehicle’s traveling direction. Additionally, it is assumed that all of the multiple transmitter coils have the same magnetic profiles and that adjacent transmitter coils do not affect the magnetic characteristics of each other. The coupling coefficients between each transmitter coil are ignored in this paper to simplify the analysis.

The conventional ANN-based design optimization flow is shown in Fig. 3. In step 1, ten random values, one for each design variable, are input into the FEM simulator. In step 2, the FEM simulator calculates magnetic characteristics from the input design variables. In step 3, ANN learns the nonlinear relationship between coil dimensions and magnetic characteristics. In step 4, the design variables are input into the trained ANN that is fixed. In step 5, a large number of design points are output from the trained ANN. In step 6, the optimal design point that satisfies all design criteria is found from a large number of design points. The design criteria selected in this paper are listed in Table 2.

Although many more design criteria exist for an actual DIPT system, 12 parameters that mainly affect system characteristics are selected. The coil interval $l_{\text{interval}}$ is represented as
\[
l_{\text{interval}} = l_{ty} + 2w_{ty} + p.
\]
If the coil interval is increased, the number of inverters and compensation circuits on the transmitter side can be reduced, hence the system cost can be reduced. However, longer coil tends to cause higher loss and higher stray fields.

The difference of coupling coefficient $k_{\text{diff}}$ is defined as
\[
k_{\text{diff}} = \frac{|k_{x0,y0} - k_{x1,y0}|}{\max(|k_{x0,y0}|, |k_{x1,y0}|)},
\]
where $k_{x0,y0}$ and $k_{x0,y1}$ are the coupling coefficients at $(x_0, y_0)$ and $(x_1, y_0)$, respectively. A small $k_{\text{diff}}$ improves the output power reduction in misalignment conditions in the lateral direction but requires larger transmitter coils.
The power ripple $P_{\text{ripple}}$ is the difference between the maximum power and the minimum power when the receiver coil passes over the transmitter coils and is expressed by

$$P_{\text{ripple}} = \left( 1 - \frac{P_{\text{dip}}}{P_{\text{peak}}} \right) \times 100 \% \quad (3)$$

where $P_{\text{dip}}$ is the lowest output power and $P_{\text{peak}}$ is the peak output power. Reducing the power ripple can be expected to reduce the size of filters and compensation circuits on the receiver side. However, a small $P_{\text{ripple}}$ tends to increase the size of the transmitter coil and decrease the length of the transmitter coil interval.

Reducing the transmitter and receiver coil’s current and voltage is expected to reduce the costs of the Litz wire and the compensation circuits. However, low currents and voltages make it difficult to transmit high power.

**B. SOLUTION 1: REDUCTION OF ANN TRAINING DATA COLLECTION TIME BY SUPERPOSITION OF MAGNETIC FIELDS**

In solution 1, the ANN learns the stray magnetic field data with only the transmitter coil and with only the receiver coil separately. The turn numbers of the transmitter and receiver coils are a single turn, respectively. The currents that flow in the transmitter and receiver coils are unit currents. The trained ANN predicts the nonlinear characteristics of the stray magnetic field at an arbitrary current and an arbitrary number of turns using the superposition of magnetic fields. An FEM simulation model used to calculate stray magnetic fields is shown in Fig. 4. The SAE standard [7] is considered to design stray magnetic fields with the assumption that the width of the vehicles is 1.6 m. A position 800 mm away from the center of the receiver coil in the horizontal direction is defined as the measurement point of the stray magnetic field. The height of the measurement point is half the vertical gap between the receiver and transmitter coils.

The calculation methods for stray magnetic fields are compared in Fig. 5. The conventional stray magnetic field calculation method is shown in Fig. 5(a). The conventional method calculates the total value of the stray magnetic field when an arbitrary current flows through an arbitrary number of turns of the transmitter and receiver coil. The proposed stray magnetic field calculation method is shown in Fig. 5(b). The superposition of the magnetic fields can be used to calculate the total value of the stray magnetic fields for any number of turns and currents. Therefore, the ANN can predict the stray magnetic field at an arbitrary current and number of turns by learning the stray magnetic fields from the one-turn transmitter and receiver coils. Rather than calculating the stray magnetic field for any combination of turns and current by FEM, it is more time-efficient to train the ANN by using superposition after calculating the stray field of only the unit current and unit winding by FEM. Additionally, since stray magnetic fields are calculated with superposition, the currents can be calculated given whatever circuit topology is used and simultaneously can be optimized in the circuit to meet stray magnetic field limits as well as maximize efficiency. Typically, these two processes are done separately [23]. If it is assumed that three points of training data are required for one input variable, the proposed method can reduce the time required for data collection to about 1/40. A mid-range desktop personal computer (Intel Core i7-9700 K with 32 GB RAM) completes one FEM simulation in a minute. Therefore, the proposed method reduced the time required for data collection from about 40 months to about one month.

**C. SOLUTION 2: GENETIC ALGORITHM TO IMPROVE THE RANDOM INPUT**

Solution 2 uses a genetic algorithm (GA) to improve the random input variables to the ANN. The comparison between the conventional ANN-based method and the proposed ANN- and GA-based method is shown in Fig. 6. The conventional ANN-based method to output design points is shown in Fig. 6(a). The ten design variables are randomly input to the fixed trained ANN, and the magnetic characteristics are output from the ANN. Design points satisfying 12 design criteria are found from a large number of design points. This conventional method is challenging because many unnecessary design points are output from the random input values. The proposed method with the combination of ANN and GA is shown in Fig. 6(b). The GA improves the random input values to the ANN. By finding the input value area that can output...
appropriate design points, ANN can more effectively output design points that satisfy 12 design criteria.

III. DESIGN OPTIMIZATION

In this section, a proposed algorithm combining ANN and GA is constructed, and an optimal design point is extracted by the algorithm.

A. CONSTRUCTION OF ANN

The input variables are assumed as follows:

\[ l_{tx}, l_{ty}, \omega_{tx}, \omega_{ty}, \alpha_{i}, p, l_{r}, w_{r}, N_{t}, N_{r}. \]

The three-dimensional components of the magnetic fields due to the unit current from the transmitter coil and the three-dimensional components of the magnetic fields due to the unit current from the receiver coil are calculated separately by FEM. The magnetic fields are calculated in both cases with and without misalignment. In order to calculate the power transmission distribution of the coil, five measurement points are set along the vehicle traveling direction, and the magnetic parameters are calculated.

As the output of ANN, 90 magnetic parameters are assumed as follows:

Output : \( L_{t,x,y} \), \( L_{t,x,y} \), \( k_{s,y} \).

\[ \text{Re} \left( B_{t,x,y} \right), \text{Im} \left( B_{t,x,y} \right), \text{Re} \left( B_{r,x,y} \right), \text{Im} \left( B_{r,x,y} \right) \]

where \( L_{t,x,y} \) and \( L_{r,x,y} \) are the self-inductance of the transmitter and receiver coils, and \( k_{s,y} \) is the coupling coefficient between the transmitter and receiver coils. \([x_{i}, y_{j}]\) is represented by

\[ [x_{i}, y_{j}] = [x_{0}, y_{0}], [x_{0}, y_{1}], [x_{0}, y_{2}], [x_{1}, y_{0}], [x_{0}, y_{3}], [x_{0}, y_{4}], [x_{1}, y_{0}]. \]

\[ \text{Re} \left( B_{t,x,y} \right), \text{Im} \left( B_{t,x,y} \right), \text{Re} \left( B_{r,x,y} \right), \text{Im} \left( B_{r,x,y} \right) \] are three dimensional vector values and represented as follows:

\[ \text{Re} \left( B_{t,x,y} \right) = \left[ \text{Re} \left( B_{x,t,x,y} \right), \text{Re} \left( B_{y,t,x,y} \right), \text{Re} \left( B_{z,t,x,y} \right) \right] \]

\[ \text{Im} \left( B_{t,x,y} \right) = \left[ \text{Im} \left( B_{x,t,x,y} \right), \text{Im} \left( B_{y,t,x,y} \right), \text{Im} \left( B_{z,t,x,y} \right) \right] \]

where \( I_{t} \) and \( I_{r} \) are the real and imaginary part of the magnetic fields when \( I_{t} \) is 1 A(rms) and \( I_{r} \) is 0 A(rms) in the receiver position \([x_{i}, y_{j}]\). \text{Re} \left( B_{r,x,y} \right) \) and \text{Im} \left( B_{r,x,y} \right) \) are the real and imaginary part of the magnetic field when \( I_{r} \) is 0 A(rms) and \( I_{t} \) is 1 A(rms) in the receiver position \([x_{i}, y_{j}]\). By splitting the magnetic field \( B_{x,y} \) when the receiver position is \([x_{i}, y_{j}]\) can be obtained for any combination of current \( (I_{t}, I_{r}) \) as follows:

\[ B_{x,y} = \left\{ \left[ \text{Re} \left( B_{t,x,y} \right) N_{t}I_{t} + \text{Re} \left( B_{r,x,y} \right) N_{r}I_{r} \right]^{2} + \left[ \text{Im} \left( B_{t,x,y} \right) N_{t}I_{t} + \text{Im} \left( B_{r,x,y} \right) N_{r}I_{r} \right]^{2} \right\}^{1/2} \]

where \( N_{t} \) and \( N_{r} \) are the number of turns in transmitter and receiver coils. When the magnetic field is split into real and imaginary components, and the \( x, y, \) and \( z \) components are also split, the magnetic fields for each component is proportional to the number of turns \( (N_{t}, N_{r}) \) and the currents \( (I_{t}, I_{r})[\text{27}, \text{28}, \text{33}, \text{34}] \) Splitting stray fields is required to calculate the total stray fields since the phase angle between the transmitter and receiver currents is different by 90 degrees. The reflected magnetic fields from coil winding and aluminum plates must also be considered as stray fields with varying phase angles. The maximum value of the magnetic fields \( B_{x,y} \) is defined as

\[ B_{\text{stray}} = \max \left\{ B_{x,y} \right\}. \]
input and output layers, and each hidden layer has 100 nodes. By minimizing the loss function, weights between each node and the bias of each node are optimized. As the loss function, root mean square error (RMSE) is used, and the RMSE is defined by

\[
RMSE = \sqrt{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2},
\]

where \(n\) is the number of nodes on the output layer \((n = 90)\), \(Y\) is the normalized output parameters of FEM, and \(\hat{Y}\) is the normalized predicted output parameters.

Nodes on each hidden layer have activation function \(\sigma\). The type of activation function can be chosen according to the nonlinear model the user wants to fit. On the hidden layer one, the activation function at node one is represented as

\[
\sigma \left( \mathbf{z}^{(1)} \right) = \sigma \left( u_{11}^{(1)} x_1 + u_{21}^{(1)} x_2 + \ldots + u_{m1}^{(1)} x_m \right)
\]

where \(m\) is the number of input variables \((m = 8)\), the activation function can be chosen from any nonlinear function such as the sigmoid function, hyperbolic tangent function, and arc tangent function. A comparison of activation functions is shown in Fig. 7. The sigmoid function maps the input values in the range \((0, 1)\) as shown in Fig. 7(a). Therefore, it is mostly used for multi-class classification. The hyperbolic tangent function and arc tangent function provides an output that is zero-centered. Hence, large negative values are mapped to negative outputs [35] as shown in Fig. 7(b). The arc tangent function is slightly flatter than the hyperbolic tangent function, as shown in Fig. 7(c). Hence, it has a better tendency to differentiate between similar inputs [36]. This paper uses the arc tangent function as the activation function since the relationship between coil dimension and magnetic characteristics in DIPT systems tends to be moderate.

By minimizing the error between the output of the ANN and FEM data from the same input value in iteration calculation, weights between each node are optimized using the back-propagation algorithm [37], [38]. The ANN can represent the nonlinear relationship because the hidden layers have nonlinear activation functions. If a linear function is used for the activation function, the fitting result is essentially the same as the linear regression.

In this paper, the double-sided LCC compensation network [39], [40], [41], [42] is assumed for the IPT system. The circuit topology is shown in Fig. 8. The circuit makes the transmitter coil current constant regardless of the coupling coefficient between the transmitter and receiver coils. For this reason, the LCC compensation network is appropriate for DIPT systems since the coupling coefficient changes in a wide range. In addition, the compensation network is suitable for battery charging applications such as EV charging since the load on the receiver side is charged with a constant current.

The rms receiver current \(I_{r}\) is represented as

\[
I_{r} = \frac{P_{out,x,0,y0}}{\omega L_{k,x,0,y0} \sqrt{L_{x,x,0,y0} L_{r,x,0,y0}}} 
\]

where \(I_{r}\) is the rms current of the transmitter coil, \(P_{out,x,0,y0}\) is output power when the receiver coil is above the center of the transmitter coil, and \(\omega\) is the angular switching frequency of the system. Therefore, output power when the receiver position is at \(y_r = y_1, \ldots, y_4\) is calculated as

\[
P_{out,x,0,yi} = \omega L_{k,x,0,yi} L_{x,x,0,y0} L_{r,x,0,y0} \quad (i = 1, 2, 3),
\]

\[
P_{out,x,0,y4} = 2 \omega L_{k,x,0,y4} L_{x,x,0,y0} L_{r,x,0,y0}. 
\]

The output power \(P_{out,x,0,y4}\) is doubled because the receiver coil is induced by the two primary coils when the receiver coil is at the edge of the primary coil [43]. Using (16) and (17), the average output power \(P_{ave}\) is calculated as

\[
P_{ave} = \left( P_{out,x,0,y0} + 2P_{out,x,0,y1} + 2P_{out,x,0,y2} 
+ 2P_{out,x,0,y3} + P_{out,x,0,y4} \right) / 8. 
\]

The approximated coil loss is calculated by

\[
P_{loss} = \frac{\omega L_{x,x,0,y0} I_{r}^2}{Q_{coil,t}} + \frac{\omega L_{r,x,0,y0} I_{r}^2}{Q_{coil,r}}
\]

where \(Q_{coil,t} = Q_{coil,r} = 400\) is assumed as a general case of the coil quality factors. Once the input voltage \(V_{dc}\), the output voltage \(V_{bat}\), and the transmitter current \(I_{t}\) are determined, the values of the compensation circuits are uniquely determined as

\[
L_{1,s} = \frac{2\sqrt{2}V_{dc}}{\pi \omega I_{t}},
\]

\[
C_{1,p} = \frac{\pi I_{t}}{2\sqrt{2} \omega V_{dc}},
\]

\[
C_{1,s} = \frac{\pi I_{t}}{\omega \left( \pi \omega L_{x,x,0,y0} - 2 \sqrt{2} V_{dc} \right)},
\]

\[
C_{r,s} = \frac{\pi P_{out,x,0,y0}}{\omega^2 \left( \pi L_{r,x,0,y0} P_{out,x,0,y0} - 2 \sqrt{2} V_{bat} M_{x,0,y0} \right)}.
\]
TABLE 3. Design specifications for the DIPT system

| Description                        | Parameter | Value | Unit |
|------------------------------------|-----------|-------|------|
| Input dc voltage                   | $V_{dc}$  | 100   | V    |
| Output dc voltage                  | $V_{bat}$ | 100   | V    |
| Output power at the center         | $P_{out,x0,y0}$ | 3.3 | kW   |
| Switching frequency                | $f_s$     | 85    | kHz  |
| Air gap                            | $g$       | 250   | mm   |
| Transmitter current                | $I_t$     | 20–100| A(rms)|

**B. FITTING OF ANN**

The design specifications for the DIPT system are shown in Table 3. Input and output voltages and output power at the center of the primary side coil are defined as $V_{dc} = 100$ V, $V_{bat} = 100$ V, and $P_{out,x0,y0} = 3.3$ kW. Although the proposed algorithm can design systems with different $V_{dc}$ and $V_{bat}$, the same voltages are used since an experimental system that recirculates power is planned. The low input and output voltage are used to simplify the prototype system’s safety setup since the prototype’s purpose is to compare the experimental results and ANN predictions. The transmitter current $I_t$ is also swept in the range of 20 to 100 A(rms) to find the best driving point. The ANN is trained using the 4600 FEM data points for the training data. 100 FEM data points are used for the validation data. The ranges of the random geometric input values are defined in Table 1.

The graph of the root mean square of training error and validation error versus the number of iterative calculations when the number of the training data is 200 is shown as an example in Fig. 9. The training error means the difference between the predicted data and training data used to fit the ANN. The validation error means the difference between the predicted data and new data, which is used to verify the accuracy of the trained neural network for new data. In Fig. 9, the verification error in the graph turns to increase after the dashed line, but the training error continues to decrease. This means that ANN overfitting occurs in the region where the number of iterative calculations is greater than the dashed line [32]. In other words, the ANN only fits the training data accurately and cannot output accurate data when new data comes. In order to prevent overfitting, the iterative calculations are stopped at the point where the validation data is minimum, and the prediction error is defined as the accuracy of the ANN using this number of data.

The graph of the number of data versus prediction error is shown in Fig. 10. When the number of data is 4700, the validation error of the ANN is less than 4%. This means that
the trained ANN can predict magnetic characteristics from new coil dimensions within a 4% error.

C. CONSTRUCTION OF GA

The algorithm flow of the constructed genetic algorithm is shown in Fig. 11. At each generation of the GA, the trained ANN is used to calculate each potential design solution’s magnetic characteristics quickly. A random geometric design represented as a vector of 10 parameters is selected from the ranges defined in Table 1 and called an initial population. The size of the population is 5000. Magnetic characteristics are output through the fixed ANN from the initial population.

Design outputs are extracted to find an optimal solution based on the design criteria listed in Table 2. The design solutions that satisfy design criteria 1 and 2 are defined as the 1st group. The design solutions that satisfy the design criteria 3 and 4 out of the 1st group are defined as the 2nd group. In the same way, the 3rd group, 4th group, 5th group, and 6th group are defined. Hence, the 6th group satisfies all the design criteria from 1 to 12. The 5000 pairs of design points are selected from the 1st group to the 6th group, and the members of the selected subset are called parents. At the time, the incentives are applied for the probability of being selected as a parent from each group as follows: the members in the $s$-th group have $s^2$ times more probability.

The new set of geometry parameters is created through crossover and mutation from the selected parents [44], [45], and the members of the created subset are called children. The ratio of two parents-parameters out of ten variables is randomly determined using the 1-point crossover method [46]. As mutation elements, three out of ten variables of the coil geometry after the combination of parents parameters are randomly selected and changed randomly in the $\pm 30\%$. The created children become the input variables to the fixed ANN in the next generation. The process is iterated until the number of design points in the 6th group converges. The number of design points extracted after 33 generations is 579 plots in this paper.

D. THE EXTRACTION PROCESS OF AN OPTIMIZED DESIGN POINT

The comparison of the obtained Pareto fronts by the conventional and proposed methods is shown in Figs. 12 and 13. Both scatter plots are output using the fixed ANN trained on the data obtained using the method of superposition in Solution 1. Both algorithms finished plotting in about ten minutes using a mid-range desktop personal computer (Intel Core i7-9700 K with 32 GB RAM). The design results of the conventional method are shown in Fig. 12. In the conventional method, 500 000 random design values are input. There was no design point in the final design criteria. Hence, the optimum design point could not be found since the Pareto front could not be obtained in the last two planes, as shown in Fig. 12(e) and (f). The result of the proposed method after 33 generations is shown in Fig. 13. The proposed method outputs 579 points of data for the final design criteria and finds Pareto fronts for all planes to choose an optimal design point since
GA improves the input parameter space instead of the purely random input. Hence, the proposed method using ANN and GA was able to find the optimum design point that could not be found by the conventional method. The design point that the red arrows indicate in Fig. 13 is chosen as the optimized design point. A design point with good performance in all aspects was manually selected based on all the Pareto fronts of Fig. 13 in an iterative process when the indicated design point was chosen. For this reason, the selected design point in the Pareto planes is located close to but not precisely on the Pareto fronts. For systematically identifying an optimal design, calculating the distance between the design points and each Pareto front on a standardized surface and balancing the distance on each plane could be one of the approaches. The simulation and experimental results of the design are shown in the following sections.

IV. VERIFICATION IN FEM AND CIRCUIT SIMULATION

In this section, the errors between the predicted value and the calculated value are evaluated using FEM and a circuit simulator in order to verify the accuracy of the ANN prediction values. The overview of the optimized coils is shown in Fig. 14. Input values after the design optimization are shown in Table 4. The turn number of the transmitter and receiver coils are 3 and 5. The distance between adjacent coils is 29.2 mm, the coil interval is 879.2 mm, the receiver coil volume is 2277.2 cm$^3$, and the core volume of the transmitter coils per meter is 3142.1 cm$^3$/m.

The graph of the coupling coefficient between the transmitter coils and the receiver coil with respect to the receiver position is shown in Fig. 15. The dashed lines are the FEM simulation result, and the markers are the predicted values of the ANN. The ANN can predict the FEM result of the coupling coefficient with a 1% error or less error in the entire region where the transmitter coil moves. The comparison between the ANN predictions and FEM, including other magnetic characteristics, is shown in Table 5. Self-inductance, the coupling coefficient, and the stray magnetic field are all predicted with an error of 7% or less.

A comparison between ANN predictions and circuit simulation results is shown in Table 6. Matlab Simulink and PLECS are used for the circuit simulation. The output power
is fixed at 3300 W in the ANN algorithm. Since the constructed ANN algorithm considers only the coil loss and not the total loss, the output power is the same as the input power. It was confirmed that coil loss, voltage, and current could be predicted with an error of 10% or less.

The simulation result of the output power with respect to the receiver coil position is shown in Fig. 16. The ANN can predict the circuit simulator results of output power with reasonable accuracy over the entire moving range of the receiver coil position. The error of the power ripple is 0.3%, and the error of the average power is 3.5%.

V. EXPERIMENTAL RESULTS

In this section, the accuracy of the prediction values of the ANN is evaluated using an experimental prototype system.

A. PROTOTYPE SYSTEM

The prototype coils are shown in Fig. 17. The transmitter and receiver coils are shown in Fig. 17(a) and (b), respectively. High-density polyethylene (HDPE) sheets were used for the coil formers to make the designed coils precisely. A side view of the prototype coils is shown in Fig. 17(c). The ferrite cores, Litz-wires, and coil formers are stacked in this order on a 2 mm aluminum plate. MnZn ferrite core (PC95, TDK) with 5 mm thickness is used for wireless coils. All wireless coils and inductors were made from 2325-strand AWG 38 Litz-wire. A general-purpose full-bridge inverter is used on the primary side to provide the ac excitation. It contains two silicon carbide (SiC) half-bridge MOSFET modules (CAS325M12HM2) with a rating voltage of 1.2 kV. The same SiC MOSFET modules are used for the diode rectifier.

A rail system is constructed to measure the average power and power ripple when the receiving coil moves at a constant speed. The constructed rail system is shown in Fig. 18. The receiver coil is mounted on the cart and can be moved at a constant speed by belts mounted on the rails and the electric motor. The cart can move at a maximum speed of 10 km/h and has a maximum payload of 200 kg. In order to accurately measure the stray magnetic field, glass fiber was used for the frame material of the base of the rail.

B. MEASUREMENT METHODS

A DWPT system that has an individual inverter for each transmitter coil is assumed in this paper. Therefore, efficiency and stray field measurements have been conducted with a single inverter and a single transmitter coil. The circuit configuration used in the experiment is shown in Fig. 19. The power feedback via a dc wire allows the circulating of the transferred power within the system instead of dissipating the power in a resistive load. While the transferred power is circulated, total losses are drawn from the external dc supply. Therefore, the dc current $I_{\text{loss}}$ and the dc supply voltage $V_{\text{dc}}$ can be measured.
to calculate the total power losses. The transferred power is calculated using the measured feedback current $I_{fb}$. The values for the compensation components are listed in Table 7.

The measurement method of the strength of the stray magnetic fields is shown in Fig. 20. The magnetic field is measured at 800 mm away from the center of the receiver coil when there is a lateral misalignment of 200 mm between the receiver and the transmitter coil. The measurement height is the middle point between the transmitter and receiver coil.

The schematic diagram for power ripple and average output power is shown in Fig. 21. In order to simplify the measurement of average output power and power ripple, a parallel connection of the four transmitter coils to one inverter is used instead of attaching an individual inverter for each transmitter coil.

The top view of the constructed experimental system is shown in Fig. 22. The receiver coil is moved from coil 1 to 4 at a speed of 6 km/h.

C. EXPERIMENTAL RESULTS
The voltage and current waveforms of the prototype system when the output power is 3 kW with a single transmitter coil are shown in Fig. 23. The inverter’s voltage and current waveforms are shown in Fig. 23(a). The load is inductive since the inverter current is positive when the inverter voltage changes from positive to negative. The diode rectifier’s voltage and current waveforms are shown in Fig. 23(b). The diode is switched according to the positive and negative current, and the rectifier voltage is inverted. The voltage and current waveforms of the transmitter and receiver coil are shown in Fig. 23(c) and (d), respectively. The measured transmitter and receiver current have been 56.6 A(rms) and 28.9 A(rms) and matched with an accuracy of 5.4% or less.

The measurement result of the stray magnetic fields is shown in Fig. 24. The solid line is the experimental value, and the marker is the predicted value of ANN. The stray magnetic field reached a maximum value of 19.0 $\mu$T(rms) at 85 kHz. The ANN predicted value of 17.4 $\mu$T(rms) matched...
the experimental value with an error of 8.4%. In all frequency bands, the stray magnetic field was below the SAE standard value of 27 μT(rms).

Power ripple measurement results are shown in Fig. 25. The solid line is the experimental value, and the markers are the predicted values of ANN. The measured power ripple was 35.5%. The error was 12.7% compared to the ANN prediction value of 40.0%. There are two reasons why the experimental value is smaller than the ANN predicted value. First, the peak value becomes smaller in the experimental value than the predicted value since the ANN predicted value does not consider the circuit loss in the output power value. Second, the experimental value has a smoother power distribution since the coupling coefficient between the adjacent transmitter coils is not considered in the ANN prediction. In order to predict the power ripple with higher accuracy, it is necessary to consider the circuit loss and the coupling coefficient between the transmitter coils.

A list of comparisons between ANN prediction and experimental values is shown in Table 8.
All items except coil loss are within 12.7% error. The reason why the power ripple error is relatively large is as described above. The coil loss error is large because the coil quality factor $Q$ is different. In the ANN prediction value, 400 was used as a constant for the coil quality factor. However, in the experimental values, the quality factors of the transmitter coils and receiver coil were 242.7 and 319.6, respectively. For this reason, the experimental value is much larger than the predicted value of ANN. The prediction error of the coil loss causes a 1.7% error in the dc-dc efficiency of the system. If the 1-2% error of the dc-dc efficiency is acceptable, the proposed method can be utilized with accurately predicted power transfer capability, coupling coefficient, stray field, maximum current, and voltage value. Suppose a higher prediction accuracy of dc-dc efficiency is required. In that case, the proposed method can iterate the optimization using calculated coil quality factors from the previous iteration since the accurate coil quality factors can be calculated by acquiring the magnetic field on the Litz wire and ferrite core surface [34], [47]. The error of the coil loss is improved from 29.9% to 3.8% if the accurate coil quality factors are used for transmitter and receiver coils.

VI. CONCLUSION
This paper proposes an optimal design method combining ANN and GA for the design optimization of DIPT systems. The proposed algorithm uses the superposition of calculated stray magnetic fields to collect training data for ANN. As a result, the data collection time has been decreased from about 40 months to one month. In addition, the proposed algorithm uses a GA-based input value improvement method so that the trained ANN can efficiently output design points that satisfy many design criteria simultaneously. The conventional approach could not find any optimal design; however, the proposed method found 579 points. Design results predicted by the ANN have been compared with FEM simulation, circuit simulation, and experimental results to verify the validity of the proposed algorithm. The FEM and circuit simulation results and the ANN prediction results match with errors of 10.2% or less for all design criteria. As for the comparison between ANN prediction and experimental values, the values except for the coil loss match each other with an error of less than 12.7%. If a higher prediction accuracy of coil loss is required, the proposed method can be modified to include calculating and optimizing the coil quality factors.

REFERENCES
[1] B. J. Limb et al., “Economic viability and environmental impact of in-motion wireless power transfer,” IEEE Trans. Transport. Electrific., vol. 5, no. 1, pp. 135–146, Mar. 2019.
[2] C. C. Mi, G. Buja, S. Y. Choi, and C. T. Rim, “Modern advances in wireless power transfer systems for roadway powered electric vehicles,” IEEE Trans. Ind. Electron., vol. 63, no. 10, pp. 6533–6545, Oct. 2016.
[3] A. A. Mohamed, C. R. Lashway, and O. Mohammed, “Modeling and feasibility analysis of quasi-dynamic WPT system for EV applications,” IEEE Trans. Transp. Electrific., vol. 3, no. 2, pp. 343–353, Jun. 2017.
[4] J. M. Miller, P. T. Jones, J.-M. Li, and O. C. Onar, “ORNL experience and challenges facing dynamic wireless power charging of EV’s,” IEEE Circuits Syst. Mag., vol. 15, no. 2, pp. 40–53, Apr.–Jun. 2015.
[5] L. Hutchinson, B. Wateron, B. Anvar, and D. Naberezhnykh, “Potential of wireless power transfer for dynamic charging of electric vehicles,” IET Intell. Transport Syst., vol. 13, no. 1, pp. 3–12, 2019.
[6] D. McRobbie, “Concerning guidelines for limiting exposure to time-varying electric, magnetic, and electromagnetic fields (1 Hz-100 KHz),” Health Phys., vol. 100, no. 4, 2011, Art. no. 442.
[7] J. Schneider, “Wireless power transfer for light-duty plug-in/electric vehicles and alignment methodology,” SAE International J2954 Taskforce, 2016.
[8] U. K. Madawala, M. Neath, and D. J. Thrimawithana, “A power-frequency controller for bidirectional inductive power transfer systems,” IEEE Trans. Ind. Electron., vol. 60, no. 1, pp. 310–317, Jan. 2013.
[9] H. H. Wu, A. Gilchrist, K. D. Sealy, and D. Bronson, “A high efficiency 5 kW inductive charger for EVs using dual side control,” IEEE Trans. Ind. Informat., vol. 8, no. 3, pp. 585–595, Aug. 2012.
[10] Z. U. Zahid et al., “Modeling and control of series-series compensated inductive power transfer system,” IEEE Trans. Emerg. Sel. Topics Power Electron., vol. 3, no. 1, pp. 111–123, Mar. 2015.
[11] J.-Y. Lee and B.-M. Han, “A bidirectional wireless power transfer EV charger using self-resonant PWM,” IEEE Trans. Power Electron., vol. 30, no. 4, pp. 1784–1787, Apr. 2015.
[12] B. X. Nguyen et al., “An efficiency optimization scheme for bidirectional inductive power transfer systems,” IEEE Trans. Power Electron., vol. 30, no. 11, pp. 6310–6319, Nov. 2015.
[13] K. Colak, E. Asa, M. Bojarski, D. Czarkowski, and O. C. Onar, “A novel phase-shift control of semibridgeless active rectifier for wireless power transfer,” IEEE Trans. Power Electron., vol. 30, no. 11, pp. 6288–6297, Nov. 2015.
[14] S. Inoue, R. Nimri, A. Kamineni, and R. Zane, “High-resolution design optimization for IPT including stray field and coupling coefficient,” in Proc. IEEE Appl. Power Electron. Conf. Expo., 2021, pp. 1573–1579.
[15] H. Li, Y. Liu, K. Zhou, Z. He, W. Li, and R. Mai. “Uniform power IPT system with three-phase transmitter and bipolar receiver for dynamic charging,” IEEE Trans. Power Electron., vol. 34, no. 3, pp. 2013–2017, Mar. 2019.
[16] H. Feng, T. Cai, S. Duan, J. Zhao, X. Zhang, and C. Chen, “An LCC-compensated resonant converter optimized for robust reaction to large coupling variation in dynamic wireless power transfer,” IEEE Trans. Ind. Electron., vol. 63, no. 10, pp. 6591–6601, Oct. 2016.
[17] D. M. Vilathgamuwa and I. Sampath, “Wireless power transfer (WPT) for electric vehicles (EVs)—present and future trends,” in Plug in Electric Vehicles in Smart Grids. Berlin, Germany:Springer, 2015, pp. 33–60.
[18] Z. Zhang, H. Pang, A. Georgiadis, and C. Cecati, “Wireless power transfer–An overview,” IEEE Trans. Ind. Electron., vol. 66, no. 2, pp. 1034–1058, Feb. 2019.
[19] G. Di Capua et al., “Analysis of dynamic wireless power transfer systems based on behavioral modeling of mutual inductance,” Sustainabil-ity, vol. 13, no. 5, 2021, Art. no. 2556.
[20] D. Patil, M. K. Mcondon, J. M. Miller, B. Fahimi, and P. T. Bal- sara, “Wireless power transfer for vehicular applications: Overview and challenges,” IEEE Trans. Transport. Electrific., vol. 4, no. 1, pp. 3–37, Mar. 2018.
[21] Y. J. Jang, E. S. Suh, and J. W. Kim, “System architecture and mathematical models of electric transit bus system utilizing wireless power transfer technology,” IEEE Syst. J., vol. 10, no. 2, pp. 495–506, Jun. 2016.
[22] S. Inoue, R. Nimri, A. Kamineni, and R. Zane, “A new design optimization method for dynamic inductive power transfer systems utilizing a neural network,” in Proc. IEEE Energy Convers. Congr. Expo., 2021, pp. 1496–1501.
[23] R. Bosshard, J. W. Kolar, J. Mühlthaler, I. Stevanović, B. Wunsch, and F. Canales, “Modeling and $\eta$ - $\alpha$-pereo-ration of inductive power transfer coils for electric vehicles,” IEEE Trans. Emerg. Sel. Topics Power Electron., vol. 3, no. 1, pp. 50–64, Mar. 2015.
[24] S. Bandypadhyay, V. Prasash, P. Bauer, and J. Ferreira, “Multi-objective optimisation of a 1-kW wireless IPT systems for charging of electric vehicles,” in Proc. IEEE Trans. Electrific. Conf. Expo, 2016, pp. 1–7.
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[25] R. Bosshard and J. W. Kolar, “Multi-objective optimization of 50 kV/85 kHz IPT system for public transport,” IEEE Trans. Emerg. Sel. Topics Power Electron., vol. 4, no. 4, pp. 1370–1382, Dec. 2016.

[26] R. Bosshard, U. Iruretagoyena, and J. W. Kolar, “Comprehensive evaluation of rectangular and double-D coil geometry for 50 kV/85 kHz IPT system,” IEEE Trans. Emerg. Sel. Topics Power Electron., vol. 4, no. 4, pp. 1406–1415, Dec. 2016.

[27] M. Lu and K. D. Ngo, “A fast method to optimize efficiency and stray magnetic field for inductive-power-transfer coils using lumped-loops model,” IEEE Trans. Power Electron., vol. 33, no. 4, pp. 3065–3075, Apr. 2018.

[28] M. Lu and K. D. Ngo, “Circuit models and fast optimization of litz shield for inductive-power-transfer coils,” IEEE Trans. Power Electron., vol. 34, no. 5, pp. 4678–4688, May 2019.

[29] G. Tsekouras, S. Kiurtzis, A. Kladas, and J. Tegopoulos, “Neural network approach compared to sensitivity analysis based on finite element technique for optimization of permanent magnet generators,” IEEE Trans. Magn., vol. 37, no. 5, pp. 3618–3621, Sep. 2001.

[30] A. Sadeghian and J. Lavers, “Implementation of knowledge-based system for iron core inductor design,” IEEE Trans. Magn., vol. 40, no. 6, pp. 3495–3504, Nov. 2004.

[31] S. Shimokawa et al., “Fast 3-D optimization of magnetic cores for loss and volume reduction,” IEEE Trans. Magn., vol. 54, no. 11, Nov. 2018, Art. no. 8400904.

[32] T. Guillod, P. Papamaniolos, and J. W. Kolar, “Artificial neural network (ANN) based fast and accurate inductor modeling and design,” IEEE Open J. Power Electron., vol. 1, pp. 284–299, 2020.

[33] E. Waffenschmidt, “Homogeneous magnetic coupling for free positioning in an inductive wireless power system,” IEEE J. Emerg. Sel. Topics Power Electron., vol. 3, no. 1, pp. 226–233, Mar. 2015.

[34] M. Lu and K. D. T. Ngo, “Synergetic optimization of efficiency and stray magnetic field for planar coils in inductive power transfer using matrix calculation,” in Proc. IEEE Appl. Power Electron. Conf. Expo., 2017, pp. 3654–3660.

[35] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016, [Online]. Available: http://www.deeplearningbook.org

[36] J. Kamruzzaman and S. M. Aziz, “A note on activation function in multilayer feedforward learning,” in Proc. Int. Joint Conf. Neural Netw., 2002, vol. 1, pp. 519–523.

[37] C. Serpico and C. Visone, “Magnetic hysteresis modeling via feedforward neural networks,” IEEE Trans. Magn., vol. 34, no. 3, pp. 623–628, May 1998.

[38] S. Cingetti, M. Marchesi, and A. Serri, “A neural network model of parametric nonlinear hysteretic inductors,” IEEE Trans. Magn., vol. 34, no. 5, pp. 3040–3043, Sep. 1998.

[39] S. Li, W. Li, J. Deng, T. D. Nguyen, and C. C. Mi, “A double-sided LCC compensation network and its tuning method for wireless power transfer,” IEEE Trans. Veh. Technol., vol. 64, no. 6, pp. 2261–2273, Jun. 2015.

[40] W. Li, H. Zhao, J. Deng, S. Li, and C. C. Mi, “Comparison study on SS and double-sided LCC compensation topologies for EV/PHEV wireless chargers,” IEEE Trans. Veh. Technol., vol. 65, no. 6, pp. 4429–4439, Jun. 2016.

[41] Y.-B. Yu, D.-H. Tran, and W. Choi, “Implementation of the constant current and constant voltage charge of inductive power transfer systems with the double-sided LCC compensation topology for electric vehicle battery charge applications,” IEEE Trans. Power Electron., vol. 33, no. 9, pp. 7398–7410, Sep. 2018.

[42] Y. Chen, H. Zhang, C.-S. Shin, C.-H. Jo, S.-J. Park, and D.-H. Kim, “An efficiency optimization-based asymmetric tuning method of double-sided LCC compensated WPT system for electric vehicles,” IEEE Trans. Power Electron., vol. 35, no. 11, pp. 11475–11487, Nov. 2020.

[43] A. Kamineni, G. A. Covic, and J. T. Boys, “Analysis of coplanar intermediate coil structures in inductive power transfer systems,” IEEE Trans. Power Electron., vol. 30, no. 11, pp. 6141–6154, Nov. 2015.

[44] J. H. Holland, Adaptation in Natural and Artificial Systems: An Introduction Analysis With Applications to Biology, Control, and Artificial Intelligence. Cambridge, MA, USA: MIT Press, 1992.

[45] S. Katoch, S. S. Chauhan, and V. Kumar, “A review on genetic algorithm: Past, present, and future,” Multimedia Tools Appl., vol. 80, no. 5, pp. 8091–8126, 2021.

[46] A. J. Umbarak and P. D. Sheth, “Crossover operators in genetic algorithms: A review,” ICTACT J. Soft Comput., vol. 6, no. 1, pp. 1083–1092, 2015.

[47] T. Guillod, J. Huber, F. Krusmer, and J. W. Kolar, “Litz wire losses: Effects of twisting imperfections,” in Proc. IEEE 18th Workshop Control Model. Power Electron., 2017, pp. 1–8.

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