Combined 3D FEA and Machine Learning Design of Inductive Polyphase Coils for Wireless EV Charging

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***Abstract*—Wireless power transfer (WPT) technologies are currently researched and developed for charging the batteries of electric unmanned air and ground vehicles. This paper presents systems with special polyphase inductive coils, which generate rotating fields and achieve high power density and efficiency. The complex geometry is modeled and studied with 3D electromagnetic finite element analysis (FEA). In order to reduce the substantial computational effort, machine learning techniques are proposed for surrogate modeling. A deep learning algorithm is introduced to capture the physics-based relationships between geometry and electromagnetic properties in inductive coils for wireless charging. Parametric models are systematically generated and analyzed by 3D FEA to create a data base with hundreds of designs, which are then used as training and testing data for the machine learning model. A multi-input univariate output for the mutual inductance between the transmitter and receiver for an example two-phase WPT system is established. The outputs of the deep learning model are satisfactorily validated with 3.3% NRMSE and a R^2 value of 0.985.**

***Index Terms*—Wireless power transfer, meta-modeling, inductive coil design, machine learning, deep learning.**

I. Introduction

Flexibility in charging availability for battery-powered systems such as electric vehicles and portable electronics can allow for improved utilization of deployed weather-dependent renewable energy generation. Solar PV and wind power plants, two of the most popular renewable sources for generation, fluctuate greatly depending on the time of day and weather conditions with peaks during the midday or nighttime, respectively [1]. Temporal mismatch between the typical load curve and renewable generation potential may result in excess generation, requiring energy curtailment if export options are unavailable. Integration of wireless charging systems, such as depicted in Fig. 1, may allow for gradual charging from renewable energy sources throughout the day, extending battery life and offsetting demand for charging from peak times or charging on the go, reducing battery size and critical materials used, and considerably extending driving range.

Wireless charging systems deliver power over small to long distances, i.e. cm to km, through high-frequency excitation of inductive or capacitive coils. Challenges for the design and development of high-efficiency wireless charging systems include resonant compensation tuning and power electronic systems design, loss minimization for high-power operation, and sizing of coils for rated operation. Application for electric vehicles, for example, are often in the 80-91kHz range of excitation, requiring high-frequency inverters, and across airgaps from 150-200mm, necessitating sufficient coil size and excitation to deliver power in the kWs [2]. With the adoption of EVs, coordinated electric vehicle charging will become essential for grid management [3]. Potential standalone benefits of wireless charging include the capability to operate without human intervention, improved safety of operation with proper shielding and detection, and ease of use [4]. Wireless power transfer systems have the potential for rapid integration of EV batteries for V2G technologies that reduce peak grid loads [5].

Implementation of wireless charging to a variety of fields such as transportation electrification and miniaturized vehicles to optimally use excess generated renewable energy would require coil sizes and shapes of varying sizes depending on the operational constraints and rated power. While analytical methods exist for the sizing of symmetric rectangular and circular coils, unconventional designs with increased geometric complexity require computational and time-intensive electromagnetic simulations or rapid experimental prototyping to determine key parameters. Recent literature has proposed an alternative approach for electromagnetic device sizing using artificial intelligence to uncover key relationships between geometric and electric parameters with neural networks, particle swarm optimization, and evolutionary algorithms [6].

This paper develops a method, depicted in Fig. 4, for the physics-informed design of high-frequency wireless charging coils combining both neural networks trained on 3D FEA results and analytical equations for coil sizing derived from fundamental principles. Examples of machine learning applied to wireless power transfer from literature are reviewed, including algorithms and methodologies employed to maximize performance with coil and ferrite geometry optimization. A complex two-phase rotating field coil geometry, shown in Fig. 2, is proposed for 85kHz charging of an electric vehicle, showcasing the capability of the proposed method to predict non-trivial field properties. Results from multiple ANSYS Maxwell 3D FEA [7] parametric studies of the example two-phase rotating-field coil are used to create a set of design candidates used to train a neural network correlating input geometrical parameters with output mutual inductance.

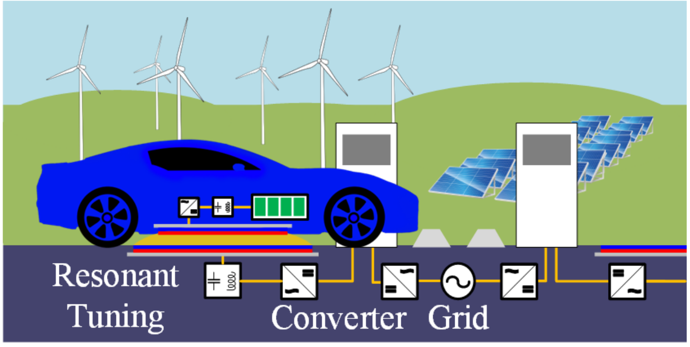

Fig. 1. Example application of a wireless power transfer system for electric vehicle charging to fully utilize renewable energy sources with near continuous vehicle charging availability.

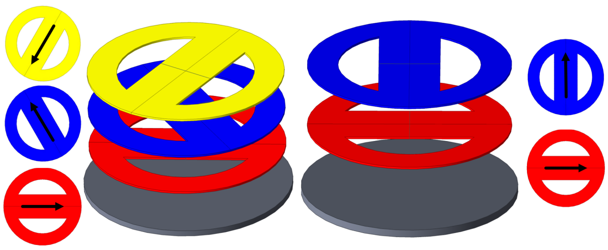

Fig. 2. Exploded view of 3D FEA models for three-phase and two-phase rotating-field wireless power transfer coil geometries for electromagnetic analysis with the direction of current excitation per phase.

II. Review of WPT Coil Design employing Machine Learning

Machine learning has recently been proposed as a design method for static and dynamic wireless power transfer systems to optimize multiple constraints and reduce computation times. Implementation of generative neural networks can allow for fast learning of electromagnetic design configurations for dynamic inductive power transfer systems. Curtis *et al.* have proposed generative neural networks as being capable of modeling a wide range of complex geometries while minimizing volume, magnetic cores, and stray magnetic fields [8]. A combination of artificial neural networks (ANN) and generative design techniques have been explored by Inoue *et al.* as an effective multi-objective design optimization method incorporating generational modeling for higher solution convergence during the analysis of possible candidates [9]. Particle swarm optimization (PSO) algorithms have been used in parallel with ANNs and 3D FEA to determine optimal wireless charging coil structure considering the efficiency, secondary power, and electromagnetic leakage [10].

Kim *et al.* have previously proposed an optimization of spiral coils at a high Q factor that estimates the turns and coil pitch size based on the outer diameter, wire thickness, and operating frequency, which were then validated through experimentation of fabricated prototypes [11]. The use of ANSYS Maxwell to simulate a synthetic dataset of sample models to train machine learning algorithms for inductive coil design has been validated through physical experimentation of prototypes [9, 11–13]. A combination of generative design, convolution networks, and deep learning techniques can generate images of the coil structure that are not limited by the number of turns or shape of the coils [14]. Modeling inductive coils through images may enable better representations of intricate coil structures compared to conventional methods.

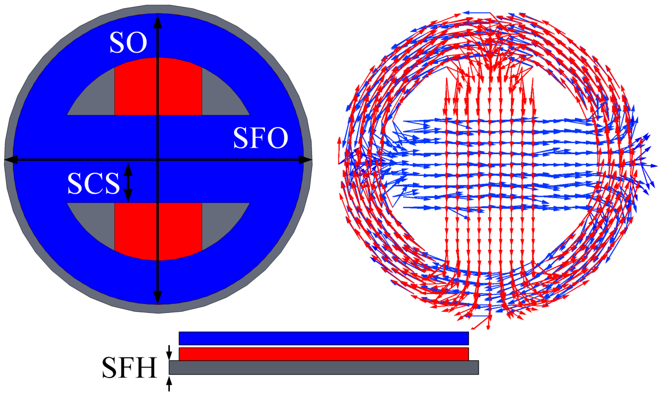

Fig. 3. Top view of the simulated two-phase WPT coils with the sizing parameters varied for machine learning application.

Evolutionary machine learning optimization-based methods are typically recommended for large-robust datasets but may not be highly effective at solving large-scale optimizations with smaller datasets. Deep reinforcement learning (DRL) may be an alternative, which has been reported to outperform computation times, design convergence, and spread performance of evolutionary algorithms [15]. Similarly, Jang *et al.* proposed a reinforced learning algorithm to derive the optimal numbers of turns to maximize the power efficiency of spiral inductive coils using deep learning [16]. Another method to analyze high dimensional datasets explored by Tucci *et al.* was to optimize the topology of electromagnetic systems through meta-modeling deep learning neural networks in conjunction with an autoencoder [17]. Wang *et al.* utilized meta-modeling in combination with a multi-objective optimization program to design double-D coils with LCC-LCC topology to reduce computation times and minimize the required training samples.

Artificial intelligence has been applied to developing wireless coil ferrite shielding and the fast design of on-road wireless charging tracks. Choi *et al.* have proposed optimizing the magnetic coupling between coils based on nonlinear ferromagnetic core structures through highly innovative reinforcement learning programs [18]. The proposed machine learning method made it possible to design an optimal structure under different parameters simultaneously, including the coupling coefficient and flux density. Machine learning has been proposed as a potential method to determine the optimal design structure and cost of implementing dynamic on-road wireless charging tracks by Shanmugam *et al.* [19]. Their machine learning algorithm produced a high 93% efficiency design by optimizing mutual inductances considering core structure, cross-coupling effects, and track length. Du and

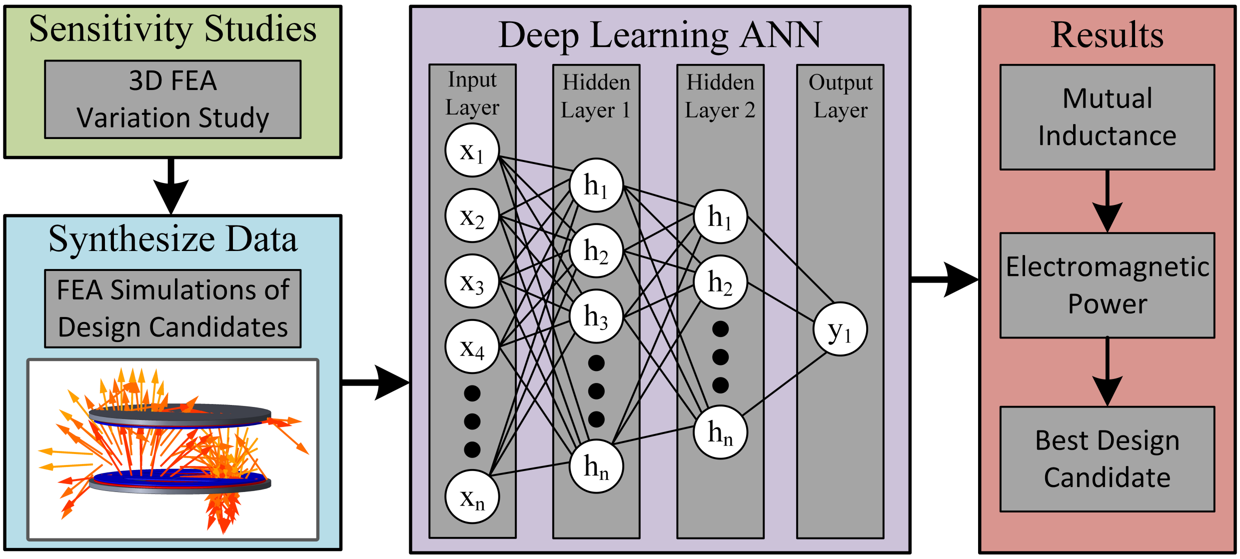

Fig. 4. Flow diagram for the proposed machine learning meta-modeling process. Design candidates were created based on ranges of feasible parameter values and simulated to create training and testing data for the deep learning algorithm. Outputs of the machine learning model include the best candidate for maximizing mutual inductance between the primary and secondary coils which can be used to determine the secondary power.

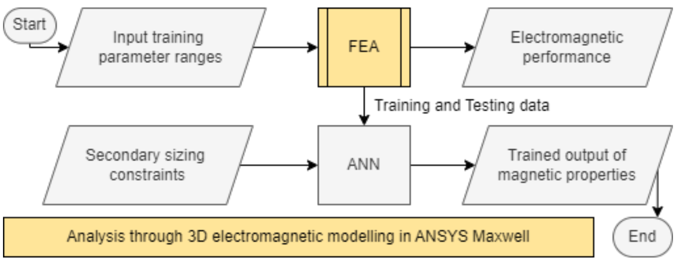

Fig. 5. Flowchart for proposed machine learning meta-modeling method. Simulated design candidates are used to train and test a machine learning model that will predict electromagnetic performance based on sizing variables.

Dujic recently proposed the optimization of a circular PCB coil geometry using a neural network based on 2D FEA results to predict coil inductances and resistances and compare designed coil efficiency and area-based power density[13]. The designed artificial neural network resulted in an error of less than 5% in self and mutual inductances compared to the 2D simulations and an experimental coil pair.

Machine learning has been demonstrated as an effective method of quickly modeling inductive coils to determine electromagnetic properties that reduce computation times and create innovative designs. Synthetic datasets created by simulating a wide range of design candidates in 3D FEA have been a critical step in previous proposals for training models and are expanded upon in this paper with polyphase designs. This paper contributes to the machine learning-based wireless coil design by exploring the use of an ANN for meta-modeling the performance of unconventional polyphase rotating field coils.

III. Multi-phase Wireless Power Transfer

Polyphase rotating-field inductive wireless charging coils, such as those depicted in Fig. 2, can create a uniform magnetic field distribution with near constant power output and high area-related power density, as detailed in Pries *et al.* [20]. The selected geometry is a bipolar configuration similar to that explored in Lewis *et al.*, which benefits from high copper area utilization and minimum flux leakage between poles [21]. The two-phase rotating field topology, depicted in Fig. 3, was selected to investigate the capability of the proposed method to predict the output of a geometrically and electromagnetically complex coil design. The direction of current excitation is illustrated in Fig. 2 with geometric rotation shifted by 180° and electrical excitation shifted by 90°.

TABLE I
Independent Secondary Coil Sizing Variables and Corresponding Limits for the 2-Phase Rotating Field Coil.

Var.	Description	Min.	Max.
SO	Coil outer diameter [mm]	60	150
SFO	Ferrite outer diameter [mm]	100	120
SFH	Ferrite height [mm]	1	6
SCS	Coilspan = $\frac{2w_t}{SO}$ [p.u.]	0.4	0.8

Self and mutual inductances between coils are simulated in 3D FEA to determine the electromagnetic performance of a wireless power transfer system. The following matrices are simulated mutual inductances between phases of the coil pair in three-phase and two-phase coils, respectively:

$$\begin{bmatrix} M_{SAPA} & M_{SAPB} & M_{SAPC} \\ M_{SBPA} & M_{SBPB} & M_{SBPC} \\ M_{SCPA} & M_{SCPC} & M_{SCPC} \end{bmatrix} = \begin{bmatrix} -46.33 & 22.77 & 22.93 \\ 22.50 & -46.31 & 23.05 \\ 22.25 & 22.78 & -46.46 \end{bmatrix} \mu H, \tag{1}$$

$$\begin{bmatrix} M_{SAPA} & M_{SAPB} \\ M_{SBPA} & M_{SBPB} \end{bmatrix} = \begin{bmatrix} -43.64 & -0.09 \\ 0.02 & -43.57 \end{bmatrix} \mu H, \tag{2}$$

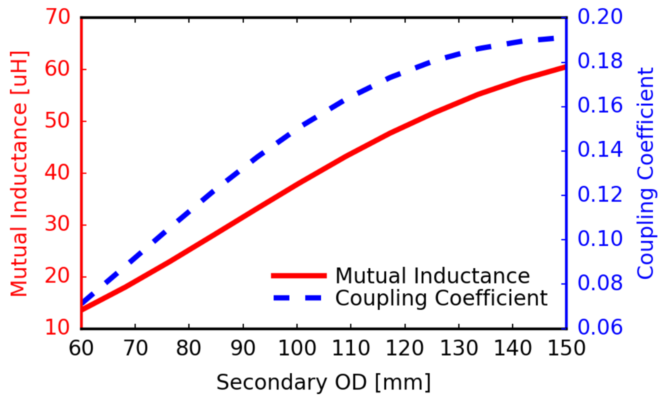

Fig. 6. Maxwell 3D FEA results for the mutual inductance and coupling coefficient over the secondary OD. An ideal secondary outer diameter would be at the knee of the curve.

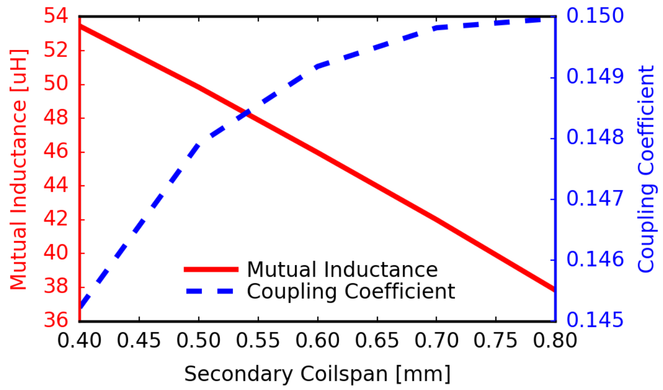

Fig. 7. Parametric study of coil magnetic properties based on secondary coilspan. Increases to coil surface area decreases mutual inductance and self inductance at different rates, resulting in a higher coupling coefficient.

where M is the mutual inductance with subscripts S and P denoting secondary or primary coil-side and A, B, and C defining the phase. The most interesting finding from these results is that while the three-phase coil matrix (1) has mutual inductance between the phases and the primary/secondary, the two-phase coil (2) has negligible coupling between phases of the primary and secondary coil. Additionally, the mutual inductance values between the primary and secondary of the two-phase coil are naturally balanced compared to the three-phase coil, simplifying necessary compensation. While not as power-dense as higher phase number systems and with varying power output, the two-phase system benefits from electromagnetic isolation between phases in the primary and secondary and can use a higher voltage excitation than higher phase alternatives.

Through a combination of references and parametric studies, the output power of a two-phase system can be determined from curve fitting resulting in the following equation:

$$P = j\omega I_s^H \underline{M}_{ps} I_p \approx K_p \omega M_{ps} I_s I_p, \qquad (3)$$

where K_p is a scaling coefficient dependent on the number of phases, $\underline{M}_{ps}$ is the mutual inductance between the primary

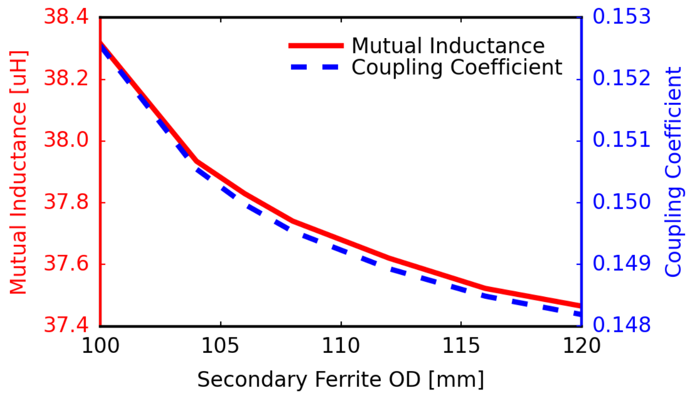

Fig. 8. Electromagnetic performance based on secondary ferrite outer diameter. Suitable shielding is necessary for minimal stray magnetic fields and higher coupling between coils.

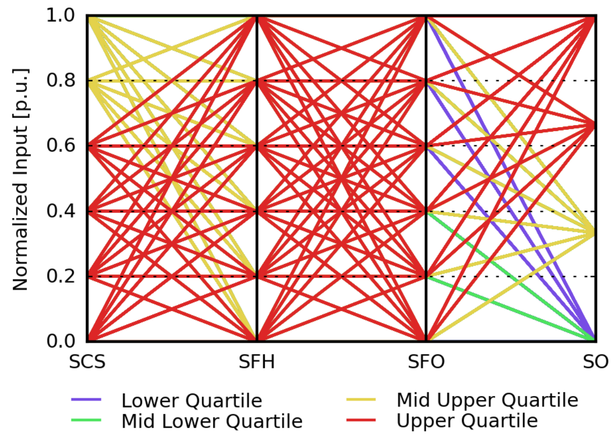

Fig. 9. Inputs vs their normalized values for each prediction quartile. Illustrating that mutual inductance heavily depends on the secondary outer diameter and secondary coilspan.

and the secondary, I_p is the primary-side coil current, and I_s is the secondary-side coil current [22]. The relationship is similar to that reported in previous papers on 3-phase systems and was verified with circuit simulation including a reduced order model (ROM) of the 2-phase coil resulting in a scaling coefficient of approximately 2.4.

The maximum voltage in coil windings is a limiting design factor that determines the maximum number of turns, and overall power output with the current excitation magnitude. The induced voltage in the primary can be estimated with the following equation from Mohammad *et al.* [23]:

$$V_{lp} = \omega I_p L_p N_t^2, \qquad (4)$$

where V_{lp} is the induced voltage in the primary, L_p is the self-inductance per turn, and N_t is the number of turns. A series of parametric studies were simulated in electromagnetic 3D FEA, which confirmed that induced voltage scales linearly with frequency and current. The inductance per turn, however, is non-linearly dependent on geometry, requiring FEA or analytical equations to compute. Approximate sizing of WPT

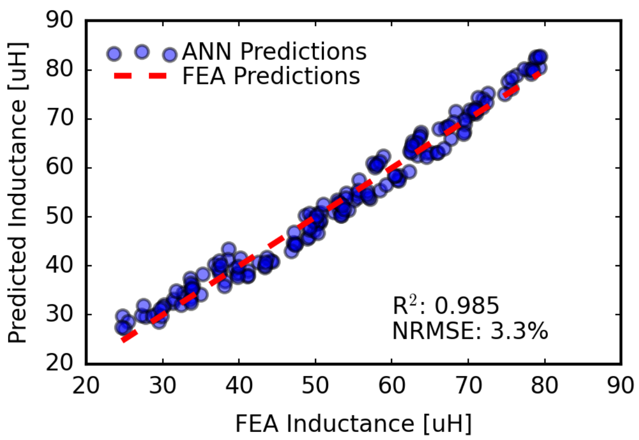

Fig. 10. Regression curve between ANN predicted and FEA simulated mutual inductance in the test dataset. Results indicate a high level of accuracy with an R^2 value of 0.985 and a normalized root mean squared error of 3.3%.

coils including the number of turns and necessary current for a rated power could then be performed at different scales using the calculated inductance per turn such as with the ANN proposed in this paper.

IV. Artificial Neural Network Case Study Results and Discussion

An example two-phase rotating-field coil was designed for 85kHz operation with multiple parametric studies calculating mutual inductance and coupling coefficient using an artificial neural network trained on 3D electromagnetic FEA results. Simulations for the coil were performed at a size of 100mm outer diameter with an airgap of 30mm between coils, 1/5th the scale of that needed for a stationary electric vehicle with a 150mm airgap and a coupling coefficient of 0.2. A base of 36 turns was selected as it is approximately the maximum number in an equivalent coil made out of a printed circuit board (PCB). Parametric studies for the variables listed in Table III, which were selected due to their impact on inductance per turn.

Parametric studies were conducted in ANSYS Maxwell 3D FEA to determine the effect of variables on inductance per turn. The correlation between mutual inductance and the four parameters was calculated and found that the secondary OD and secondary coilspan had the largest impact on inductance per turn, as shown in Fig. 6 and Fig. 7, which exhibit large variations in inductance with an amount of non-linearity. Modifying properties of the ferrite, as seen in Fig. 8, resulted in non-linear variation of mutual inductance which is potentially due in part to saturation of the core material. A depiction of the normalized weights of each input is presented in Fig. 9 with colors coordinating the differences in the resulting quartile of impact on the simulated mutual inductance. Highly optimal designs follow the upper quartile paths for weighing the inputs, an example with high mutual inductance could be achieved by following the upper quartile branches resulting in normalized inputs of 0.4, 1.0, 0.8, and 1.0 for the SCS, SFH, SFO, and SO, respectively. Results indicate that the mutual inductance does not vary significantly based on the ferrite shielding sizing compared to the coilspan and coil outer diameter.

An artificial neural network was constructed using the TensorFlow Python library and trained using more than 800 designs for the wireless power transfer coils using the algorithm shown in Fig. 5 [24]. From the initial designs, 20% were used for testing the performance of the neural network for predicting mutual inductance. The regression curve is shown in Fig. 10 between the perfect prediction and the results from the ANN trained on FEA results. The results indicate a high level of accuracy with an R^2 value of 0.985 and a normalized root-mean-squared error (RMSE) of 3.3%. Effective prediction of the inductance per turn may be used with (3) and (4) to approximate the size of the number of turns and current excitation for a rated power.

Machine learning predictions are highly satisfactory with simulated 3D FEA results. Surrogate modeling methods are validated by testing secondary coil sizing variables in the deep learning model and ANSYS simulation. Mutual inductance of -43.57μH and -43.46μH were determined through FEA simulation and machine learning respectively indicating high model accuracy with simulated results. Larger or more focused datasets may be created in 3D FEA to account for the wider application of machine learning to wireless charging applications. Further development of the method would benefit from refinement with experimental measurements validating FEA and meta-model results for the mutual inductance. Effective meta-modeling may allow for quick generation of thousands of design candidates, sizing in a variety of wireless charging applications, and optimization using a meta-model in the loop in place of detailed electromagnetic simulations.

V. Conclusion

A deep learning ANN for surrogate modeling of unconventional rotating field polyphase coils is proposed to reduce computation times substantially, create innovative designs, and facilitate the implementation of complex wireless charging systems at varying sizes for improved usage of renewable energy. Unconventional and non-symmetrical wireless power transfer systems require computationally and time-intensive electromagnetic simulation methods to optimize multiple non-linear characteristics while meeting sizing constraints. A specialized machine learning model is developed to determine the mutual inductance between geometrically complex two-phase coils, considering the secondary coil outer diameter, coilspan, and ferrite shielding to reduce computation times significantly.

The proposed deep learning model is trained and tested using a synthetic dataset created by simulating hundreds of design candidates in ANSYS Maxwell 3D FEA with varying sizing parameters selected based on multiple parametric studies. Deep learning outputs are highly accurate with simulated 3D FEA results with a NRMSE of 3.3% and high R^2 value of 0.985. The proposed model creates innovative secondary coil designs for rapid integration into existing systems with standardized transmitting coils at varying sizes for maximum renewable energy utilization.

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