A Reflected Impedance Estimation Technique for Inductive Power Transfer

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***Abstract*—This paper proposes a technique to estimate the equivalent reflected impedance on the transmit side of an inductive power transfer (IPT) system, produced by an inductively coupled load. This technique consists of analysing changes in the drain voltage waveform of the switching devices to estimate the reflected impedance, and hence not require feedback information from the receive side or the coupling between the coils. The correlation between the drain voltage waveform and the reflected impedance is done by training a model with machine learning techniques. The proposed impedance estimation method is demonstrated using circuit simulations and is verified experimentally, with an IPT transmitter driven by a load independent Class EF inverter operating at 13.56 MHz. The IPT receiver consists of an ac-load which allows changes in the residual reactance. The model trained from experimental data is capable of estimating the equivalent reflected impedance with an accuracy (coefficient of determination) of 0.9899 for the real part and 0.9743 for the imaginary part.**

I. Introduction

Inductive Power Transfer systems enable the possibility of transmitting power without a physical connection, a feature that is convenient and in cases necessary. [1] The possibilities of IPT are very broad [2], [3], especially in the field of transportation, where different approaches give solutions for applications ranging from wireless charging for large electric vehicles [4], to small drones [5]. The latter, is an example of lightweight low-power ($<150\,\mathrm{W}$) IPT systems that operate at MHz frequencies, and such range is the focus of the work presented here.

The design of an IPT system that operates at MHz frequencies often relies on soft-switching resonant converters at both ends to achieve good end-to-end efficiency. The behaviour of these converters depend on how the two ends of the system are coupled. Often, the receiving side is modelled with a voltage or current source representing the effect produced by the alternating magnetic field on the receive coil; and similarly, a reflected load models the effect produced by receive side on the transmit side.

Employing this modelling principle, broadly described for WPT in [6], allows defining a range of operation for both the reflected load at the transmit side, and the voltage (or current) source at the receive side. Defining this range of operation allows the system to be optimised for variable coupling and loading conditions [7]. An example of a multi-MHz IPT system that is optimised for variable coupling and load can be found in [5], where a drone without a battery was wirelessly powered at a broad range of coupling and loading conditions by designing the resonant converters at both ends of the system for those ranges. Knowledge of the reflected impedance was key in that work to allow for spatial freedom and variable power demand since the reflected impedance, not always purely resistive, had to be confined to the range of tolerance of the inverter.

The work presented here, as in or previous work done to detect foreign objects [8], investigates changes on the inductively coupled circuits by analysing the drain voltage waveform of a transistor with machine learning techniques.

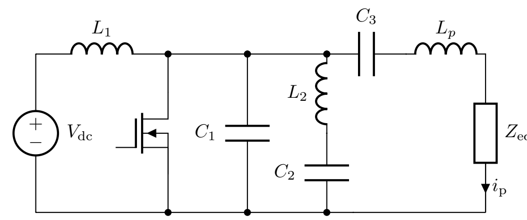

Fig. 1. Class EF inverter circuit topology driving an inductively coupled reflected impedance (Z_{eq}).

II. Load-independent Class EF Inverter

The Class EF inverter, a single-switch resonant topology shown in Fig. 1, allows for load-independent tuning by selecting the values of the passive components following the guidelines formulated in [9]. The solutions that are considered load-independet, achieve zero-voltage-switching (ZVS) over the entire restive load range, and in addition, when employed on an IPT system, the amplitude of the transmit coil current is load-independent and defined by V_{dc}.

The load-independent feature can be noticed in the drain voltage waveforms in Fig. 2. For the cases of no-load and maximum resistive load (+5 Ω), the turn-on voltage inherently converges to zero, and therefore achieves ZVS. Reflected reactances, however, detune the inverter and affect the load-independent operation. As can be seen in Fig. 2, the shape of the waveform changes depending on the type of load coupled. Inductive, capacitive and resistive loads affect the waveforms in different forms which are identifiable.

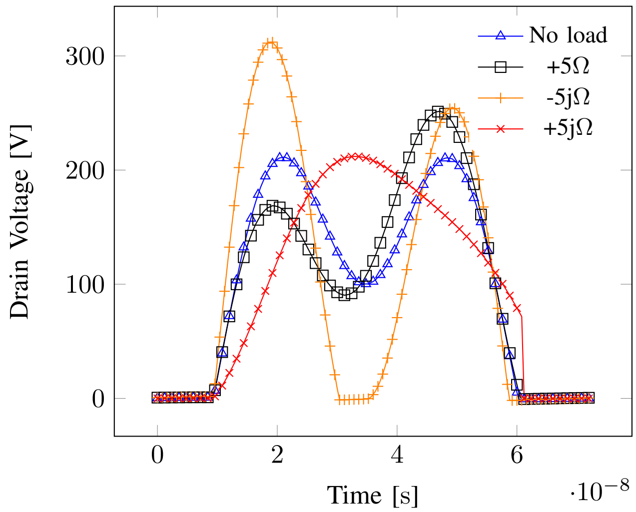

Fig. 2. Inverter's theoretical drain voltage waveform under various loading conditions.

III. Reflected Impedance Estimation

The drain voltage waveforms in Fig. 2 suggest the possibility of estimating the reflected impedance on an IPT transmitter that uses the load-independent Class EF inverter. The drain voltage is the signal chosen in this study not only because of its clear load-dependence, but also because, first, ZVS (or non-ZVS) operation can be identified; and second, the topology has a capacitance between the drain and the source of the transistor which absorbs the capacitance of the probe, making it relatively easy to measure and not affect the tuning of the system.

The proposed method consists of gathering the drain voltage waveform signals with different and well characterised loads, to then train a model that can recognise these loading conditions using machine learning techniques. The performance of the model are evaluated by using untrained data.

A. Data Acquisition and Augmentation

Before the training process, data were required to be prepared and configured. In simulation, the result output setting was used to select the sampling rate and data resolution. In order to compare the simulation and the experimental results, the sampling rate and resolution of the simulations were configured to be the same as the Teledyne LeCroy HDO4034 oscilloscope, which is 2.5 GHz, and 12 bit respectively. A full cycle of the drain voltage waveform was captured one hundred times for each value of equivalent reflected impedance. Additionally, random phase shifts and noise sources were added to the simulated waveform signals. The purpose of this data augmentation process is to ensure the robustness of the estimation model.

B. Model Training and Evaluation

Two common machine learning algorithms were considered to train the model, support vector machine (SVM) and convolutional neural network (CNN). SVM, well described in [10],

TABLE I

Simulation and Experimental Component Values

Parameter	Value (simulation)	Value (experiments)
V_{dc}	100 V	100 V
C$_1$	279 pF	156 pF + C_{OSS}
C$_2$	214 pF	176 pF
C$_3$	143 pF	130 pF
L$_1$	80 µH	80 µH
L$_2$	231 nH	267 nH
L$_p$	1130 nH	1118 nH

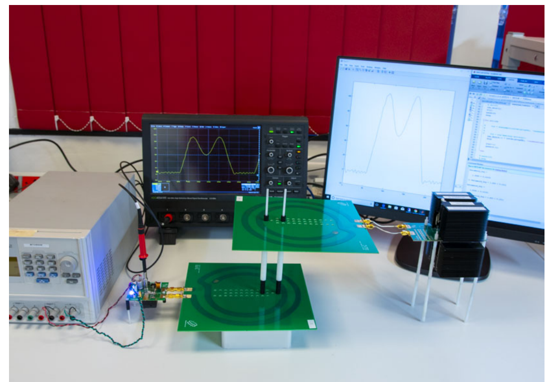

Fig. 3. Photograph of the experimental setup.

is commonly used in classification applications and in regression models, e.g. stock market prediction [11], [12]. SVM can be used to train a model to estimate the equivalent reflected impedance of an IPT system, however the system we proposed should be capable of achieving this regardless of the phase of the drain waveform. Therefore, an SVM-based approach would require data pre-processing before training. In order to avoid the data pre-processing, CNN was selected to train the estimation model, since it can achieve pattern recognition without being affected by shifts in position [13], i.e. phase. CNN has been used in various classification applications such as medical signal processing [14] and face recognition [15].

The training data were divided into three subsets: 85 % of the training data were used to train the CNN model, 10 % as the validation data set during the training process, and the last 5 % as the final test to evaluate the performance of the trained model. The network layers were configured manually based on the performance of the model.

IV. Verification of the Reflected Impedance Estimation Model

A. Circuit Simulation

The proposed technique was first verified by simulating a load-independent Class EF inverter operating under different loading conditions. The parameters used are described in Table. I.

The inverter was simulated with a reflected resistance ranging from 0 to 10 Ω, and a reflected reactance from −5 to 5 Ω, both with steps of 100 mΩ. The drain-voltage waveforms

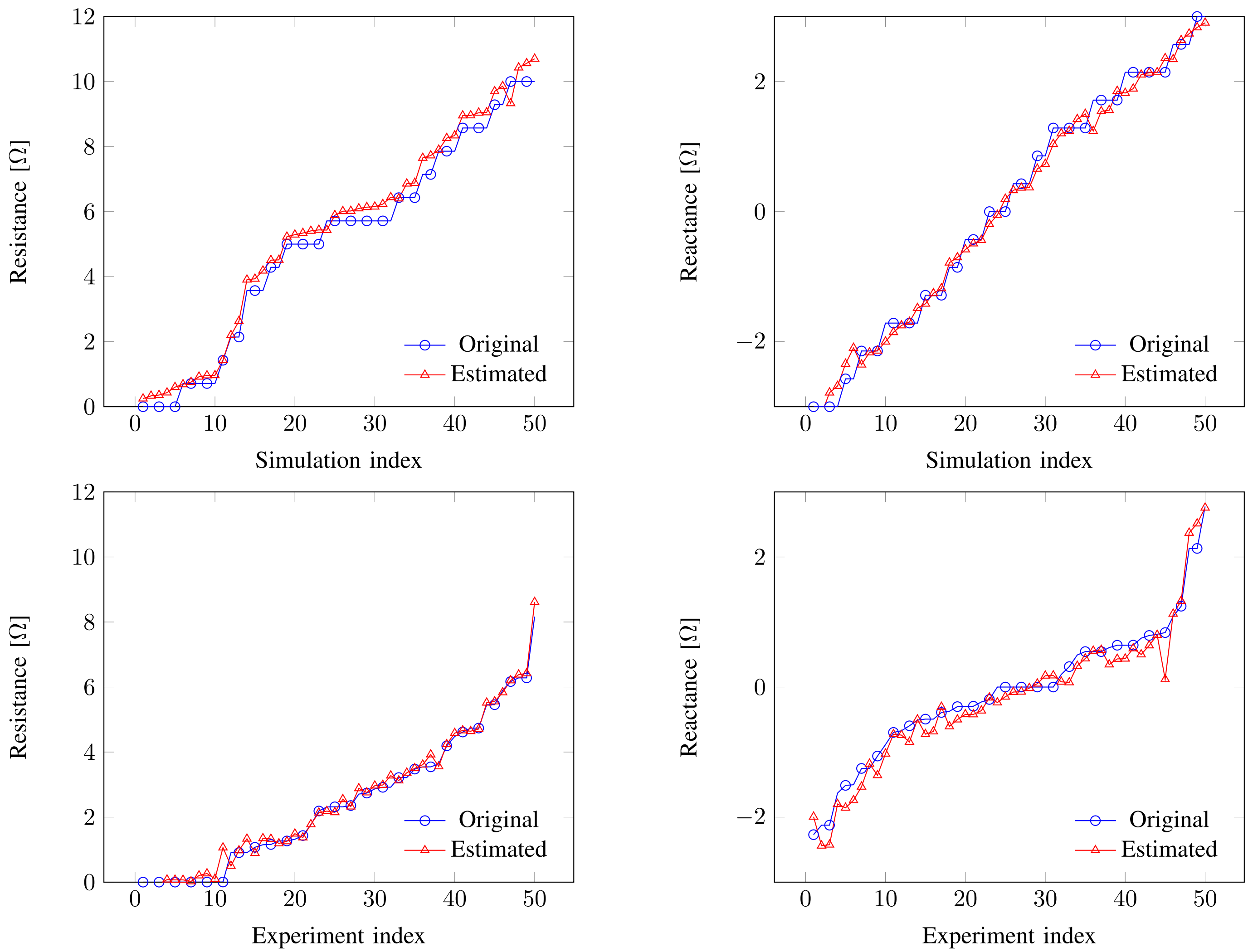

Fig. 4. Impedance estimation model results from a simulated and an experimental environment.

were recorded when the system reached steady-state for each reflected load and then labelled accordingly. These data were then used to train and verify the model. The reflected load estimation result using the simulated drain voltage waveform is shown in Fig. 4. The estimation accuracy (coefficient of determination) is 0.9942 for the real part of the impedance, and is 0.9905 for the imaginary part.

B. Experimental Verification

A similar approach was done on a real IPT setup capable of powering a load of up to $150\,\mathrm{W}$ at $13.56\,\mathrm{MHz}$. A photograph of the experimental setup can be seen in Fig. 3 and the design values of the inverter implemented can be found in Table I. The coils and the inductively coupled load used to train the model, are described in [16].

The reflected load on the transmit side was altered by changing coupling and the receive side capacitance that resonates the coil. As can be seen in Fig. 3, this systems allows for a precise separation and alignment, which was characterised in [16]. Data were obtained for coil separations of 12-$20\,\mathrm{cm}$ with steps of $1\,\mathrm{cm}$, and the tuning of the receive side was changed as done in [16]. Four loads which reflect a negative reactance and three which reflect a positive reactance were used at the coil separations mentioned. The reflected reactance allowed by this setup was rougly from -2 to $2\ \Omega$, and the reflected resistance from 0 to $8\ \Omega$.

The load-estimation results are shown in Fig. 4. The estimation accuracy (coefficient of determination) is 0.9899 for the real part of the impedance, and is 0.9743 for the imaginary part.

V. Conclusions

This paper presents a technique to estimate the equivalent reflected impedance on the transmit side of an IPT system, by using a CNN machine learning model which is trained using solely data from the drain voltage waveform of a transistor. A model was generated from circuit simulations and another one was generated using and oscilloscope and a 150 W IPT system that operates at $13\,56$ MHz. Both models were able to estimate the reflected resistance and reactance on the transmit side with an accuracy higher than $r^2 = 0.97$.

ACKNOWLEDGEMENT

The authors would like to acknowledge the following funding sources: EPSRC Challenge Network in Automotive Power Electronics, ref: IAA18/Mitcheson [IMP], the Department of Electrical and Electronic Engineering of Imperial College London, PINN Programme by the Ministry of Science and ICT of Costa Rica MICITT, University of Costa Rica, and EPSRC grant ref: EP/R004137/1 Converter Architectures.

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