

Optimized Bagged Broad Learning Framework for Enhanced Modeling of Transcutaneous Energy Transfer

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Transcutaneous Energy Transfers (TETs) are innovative devices designed to wirelessly transfer energy from an external source to an artificial organ (AO) implanted within the body, utilizing inductive coupling between external transfer and internal receiver coils. A critical objective in TET design is to minimize device size while ensuring reliable and efficient power delivery to the AO across varying operational conditions, such as changes in coil alignment and distance. On the other hand, broad learning system (BLS) models, grounded in pseudo-inverse theory and compressed sensing, offer a robust alternative for regression tasks, supported by mathematical proofs of their universal approximation property. By employing horizontal architecture comprising feature nodes and enhancement nodes, BLS models deliver a powerful framework for capturing intricate patterns, presenting a compelling option for deep learning applications. To address the limitations of single BLS in terms of generalization ability and robustness to noise, this study proposes an optimized bagged BLS (BagBLS) model combined with Tree-structured Parzen Estimator hyperparameter to TETs modeling. The consistently high coefficient of determination scores obtained from BagBLS studies indicates the degree to which our methodology captures the underlying patterns in the TETs data.

Index Terms— Modeling, transcutaneous energy transfers, artificial neural networks, machine learning, regression.

I. INTRODUCTION

TRANSCUTANEOUS Energy Transfers (TETs) are wireless devices that use inductive coupling to transmit energy from the outside of the body to an implanted artificial organ (AO) without the need for wires trespassing the body's skin. They use coils in the transmitter and the receiver, which act as high-frequency transformers without a magnetic core surrounding the coils to guide the magnetic flux. The lack of a magnetic core and the fact that the receiver coil is underneath the skin pose a challenge for transmitting power since the coils may be positioned at different distances from each other, changing the coupling factor. Bigger coils may have better coupling factors, but they are uncomfortable for patients using them to charge the AO. Thus, an effective TET design must be as small as possible and still capable of providing enough energy to the AO over varying coil distances. To do this, researchers applied optimization techniques supported by Finite Element Method (FEM) [1]. FEM-based optimization and modeling are inherently computationally intensive, often necessitating the integration of data-driven models to enhance modeling efficiency and accuracy.

Among models based on deep learning, the Broad Learning System (BLS) [2] has been recognized as an attractive choice due to its ability to effectively deal with nonlinear interactions. BLS is a shallow artificial neural network construction approach that combines pseudo-inverse matrix computing with a random vector functional network structure [3]. It involves direct links between the input and output layers, in addition to hidden neurons with randomly assigned weights. However, the randomness of successive mappings may lead to instability in a single BLS and inadequate generalization, which can be dealt with through

ensemble learning.

To improve modeling consistency and generalization, the authors propose a bagged BLS approach (BagBLS), which combines BLS's abilities with the bagging ensemble learning strategy. This hybrid method makes use of BLS's effectiveness and non-linear modeling characteristics while also merging bagging's stability and reduced variance, making it appropriate for difficult regression tasks.

The interaction between the optimization process and FEM with BagBLS slows everything significantly. Thus, one possibility for addressing this issue is to substitute FEM with conceptual models such as the BagBLS. Then, the TET procedure for optimization can be used by BagBLS to supply insights for any TET arrangement. Following [1], the model must offer power, no-load voltage, load voltage, and load current at various coil distances. This information should be appropriate for each set of inputs of a TET configuration that includes the number of turns, wire gauge, and frequency. The TET coils were simulated by using FEM simulations to create reliable models with the combination of configurations illustrated in Table I.

TABLE I
TET CONFIGURATIONS WITH THEIR SAMPLE VALUES

Variable of the configuration	Sample values
Primary Coil Number of turns (N_1)	[31, 62, 124, 248]
Primary Coil Number of Layers (L_1)	[1, 2, 3]
Primary Coil Wire Gauge (AWG_1)	[16, 19, 22, 26] AWG
Secondary Coil Number of turns (N_2)	[12, 24, 48, 96]
Secondary Coil Number of Layers (L_2)	[1, 2, 3]
Secondary Coil Wire Gauge (AWG_2)	[20, 26, 29, 32] AWG
Frequency ($Freq$)	[53.25, 106.5, 213, 426] kHz
Distance ($Dist$)	[4, 8, 12, 16, 20] mm

Since AOs behave as constant power loads, the BagBLS model needs to determine load voltage and current for a specific load resistance that matches the AO's power demand. If a TET structure is unable to supply the required power, the model should instead report values of voltage and current for the load resistance that achieves the maximum possible power. This dual-output requirement implies that the BagBLS must differentiate between configurations that meet or fall short of the AO's power demands, producing two distinctive sets of outputs. This approach ensures that TET designs operate most accurately and practically.

To deal with this issue, a potential solution is to replace the FEM software with metamodels such as BagBLS. The TET optimization process can then use the BagBLS-generated model to give insights into any TET configuration in the form of a surrogate model. The model must offer power, no-load voltage, load voltage, and load current at various coil distances, as suggested in [1]. This data should be appropriate for each set of inputs (TET configuration) consisting of the number of turns, wire gauge, and frequency.

This paper approaches the TET problem with a novel BagBLS framework combining conventional BLS, bagging strategy, and hyperparameter optimization via Tree-structured Parzen Estimator (TPE) using the Optuna library [4] in Python language. TPE is a Bayesian optimization method that efficiently explores the hyperparameter space by simulating the probability distribution of high-performing setups. This approach promises that the BagBLS model operates effectively while requiring little computing overhead, solving any challenges associated with manual or grid-based hyperparameter tuning. The remainder of this digest is organized as follows: In Section II, the methodology and results are briefly presented. Afterward, the conclusion and directions of future research are drawn in Section III.

II. METHODOLOGY AND RESULTS

The first step to obtaining a model with BagBLS is by simulating the system with different combinations of configuration shown in Table I. These simulations were the input to create the models for the load voltage, current, and power (V_2 , I_2 , P), the source current (I_1), and the no-load voltage (V_o). The BagBLS were generated in three different situations: (i) for the configurations that may not supply the power required by the AO, (ii) for the configurations that supply the required power, and (iii) for all configurations together. Two models were generated for electrical quantities.

The setup of the Google Colab for the TET modeling experiments was a 2.30 GHz Haswell Central Processing Unit with 2 cores and 12 GB of Random Access Memory to evaluate the regressors using Python programming language.

Result analysis was performed on the splitting of 80% of samples in the training dataset, 20% of samples in the validation dataset, and 20% of samples in the test dataset for each fold in the adopted 5-fold cross-validation scheme. Optuna TPE was designed for hyperparameter optimization using 200 trials with the objective function given by the

maximization of the R^2 (coefficient of determination) mean for the validation set. The traditional BLS and the proposed BagBLS presented high R^2 values as shown in Table II (with best results highlighted in bold) and could be useful to save computation time during the TET design. The TET configurations were simulated to generate the required power of 13 W. The optimized BagBLS was achieved with a regularization parameter (λ) of 0.026, 51 feature nodes (m), 43 enhancement nodes (k), 6 layers (n), and a learning rate (α) of 0.062, utilizing the GELU (Gaussian Error Linear Unit) activation function and trained with bagging comprising 21 estimators and a maximum sample ratio of 0.8152.

TABLE II
 R^2 VALUES (TEST DATASET) OF THE OPTIMIZED REGRESSION MODELS

Variables	BLS	BagBLS
V_2	0.9219	0.9452
I_2	0.8879	0.9137
P	0.9674	0.9892
I_1	0.9738	0.9974
V_o	0.9314	0.9781

III. CONCLUSION AND FUTURE RESEARCH

This study evaluates a novel BagBLS framework for modeling parameters of TETs. A brief comparative analysis between the standard BLS and the proposed BagBLS highlights the superior performance of the latter, which integrates the strengths of ensemble learning, the flexibility of BLS, and the efficiency of TPE-based hyperparameter optimization. The results demonstrate the potential of the BagBLS for predictive accuracy and robust TET modeling.

For further studies, evaluating multi-objective hyperparameter optimization strategies [5] represents an opportunity for boosting the performance of the BLS and its variants including approaches that might enable the simultaneous optimization of multiple objectives, including processing efficiency and generalization capability.

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REFERENCES

- [1] D.W. Ferreira, L. Lebensztajn, L. Krähenbühl, F. Morel, and C. Vollaie, "A design proposal for optimal transcutaneous energy transmitters," *IEEE Trans. Magn.*, vol. 50, no. 2, pp. 997-1000, 2014.
- [2] C. L. P. Chen and Z. Liu, "Broad learning system: an effective and efficient incremental learning system without the need for deep architecture," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 1, pp. 10-24.
- [3] Y. -H. Pao and Y. Takefuji, "Functional-link net computing: theory, system architecture, and functionalities," *Computer*, vol. 25, no. 5, pp. 76-79, 1992.
- [4] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A next-generation hyperparameter optimization framework," in *Proc. 25th ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, Anchorage, AK, USA, vol. 158, 2019.
- [5] M. A. Costa e Silva, L. S. Coelho, and L. Lebensztajn, "Multiobjective biogeography-based optimization based on predator-prey approach," *IEEE Trans. Magn.*, vol. 48, no. 2, pp. 951-954, 2012.