11th International Conference on Power Electronics-ECCE Asia
May 22 - 25, 2023 / ICC Jeju, Jeju, Korea

Optimal Number of Turns Design of IPT for Maximum Power Efficiency base on Reinforcement Learning with DQN

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***Abstract*-- This paper proposes the method to find the optimal number of turns in IPT for a maximum power efficiency by using deep Q-learning network (DQN) based on reinforcement learning (RL) algorithm. Since it is barely possible to get an optimal number of turns for a transmitter (Tx) and a receiver (Rx), satisfying to operate at a maximum power efficiency, the most of Tx & Rx turns are normally wound until the coils are occupied over the cores. Moreover, it requires extremely long time to iteratively proceed to simulate all existing combinations of the Tx & Rx coil windings to derive the maximum power efficiency. To minimize the time to compute the number of coil-turns to get the maximum power efficiency, the proposed DQN algorithm can select the optimal coil turns having high Q-value through ε-greedy turn selection process. After a few episodes of the neural network system, the expected power efficiency by the proposed RL can reach to the maximum power efficiency by less than 20% of all possible combinations. The proposed RL algorithm has been evaluated by FEM simulation analysis, showing that the optimal number of turns for various WPT cases having different loads can be easily found.**

***Index Terms* -- Reinforcement learning (RL), WPT (Wireless power transfer), Inductive power transfer (IPT), DQN (Deep Q-learning network)**

I. Introduction

Recently, the need to use wireless charging technology for various applications such as smartphones, electric vehicles, and home appliances using wireless charging is increasing in the domestic and foreign markets [1]. The most important thing in the development of such wireless charging technology is to maximize charging efficiency under given physical and electrical conditions, and various studies have been conducted on how to maximize transmission efficiency under various charging conditions [1]-[8].

An equivalent circuit of an inductive power transfer (IPT) can be represented by magnetization inductance and leakage inductance, as shown in Fig. 1. A wireless power transmission system is a technology that transmits power from transmitter to receiver using high frequency magnetic field and can satisfy maximum efficiency and maximum power transmission conditions by removing reactance of Tx & Rx coils using resonance capacitors. If physical and electrical design conditions are given, the remaining major parameters are the number of turns for transmitter (Tx) & receiver (Rx) coils N_1 & N_2, and it is important to select the optimum number of transmitting and receiving turns Even if the resonant conditions of the Tx & Rx are completely satisfied.

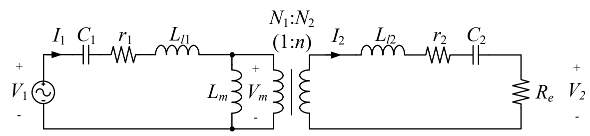


Fig. 1. Typical examples for series-series compensation IPT.

In case of Planar-shaped coils on the market, as shown in Fig. 2, it is common to wind them up until all sections of the core were covered [1]-[4]. However, if the number of turns is too small, the current should be large under the same ampere-turn condition; hence, the copper loss caused by the high current becomes severe. On the other hands, if the number of turns is large, the AC resistance component corresponding to the coil loss increases, which results in the decrement of the power efficiency [6]. Therefore, the only way to determine the optimal number of turns for Tx & Rx for a maximum power efficiency operation under given physical shapes and electrical conditions is to perform the finite-element-method (FEM) simulation analysis considering all the possible cases. Therefore, it is necessary to find the optimal number of turns, satisfying the maximum power efficiency operation with minimum computation time. This iterative approach, however, requires a lot of computation time [5]-[6].

In this paper, an algorithm that utilizes deep Q Network (DQN) reinforcement learning (RL) to find the optimal number of turns for a maximum power efficiency in minimal episodes is newly proposed. By the proposed RL algorithm to learn DQN, a neural network system with ε-greedy process was applied, and the algorithm was designed to follow the highest reward based on the input variables N_1 & N_2. the proposed DQN-based reinforcement learning algorithm is verified by simulation and experiment, showing that the optimal number of turns corresponding to the maximum efficiency can be derived from episodes by less than 20% of all possible coil turn cases.

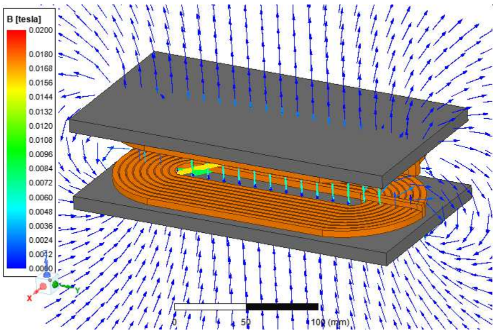


Fig. 2. An example of Simulation result for IPT system.

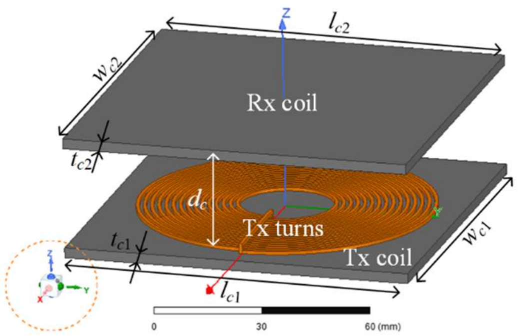


Fig. 3. FEM simulation model for the proposed IPT.

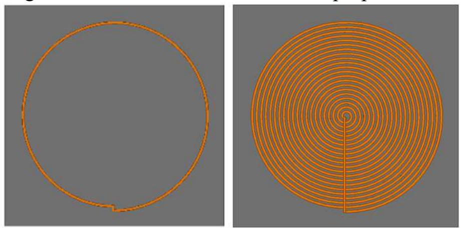


Fig. 4. Coil structure w.r.t $N = 1$(left) and $N = 21$(right)

II. Coil Modeling and RL Algorithm Design

A. Tx & Rx coil Modeling

To verify the performance of the proposed DQN algorithm design with 3D FEM simulation analysis, a 100 mm × 100 mm planar core structure is established for Tx & Rx cores, as shown in Fig. 3, where a gap between the Tx & Rx is set to 30 mm. Switching frequency is selected at 100 kHz and the thickness of the ferrite core is 3 mm, assuming that the core is not saturated. To identify the loss characteristics of ferrite cores available in market, it is assumed that the relative permeability of the ferrite cores used in this paper is 3200, and the loss-tangent is calculated as 0.07 [7]. Accordingly, the resistance values, including the copper and core losses can be obtained from the FEM simulation. For simplicity of analysis, it is assumed that the Tx & Rx coils in Fig. 3 are designed by symmetrical and the coil turns are wound from the outside to the inside, as shown in Fig. 4. Because the maximum number of coil winding is 21 turns, the total number of simulation cases for all possible combination is calculated as 441 in this paper. The detail physical parameters are summarized in Table I. To derive the optimal number of turns, typical examples for wireless power applications are summarized in Table II. Operating conditions e.g., power, voltage, and effective resistance, are mentioned, considering commercialized products in markets.

To derive the efficiency included in the proposed RL algorithm, the Tx & Rx sies are assumed to be fully resonated by series capacitors; thus, the coil efficiency can be found as follows [5].

$$\eta = \frac{(\omega_s M)^2 R_e}{r_1(r_1+R_e)^2 + (\omega_s M)^2 (r_2+R_e)} \tag{1}$$

From (1), r_1 and r_2 includes copper and core losses for Tx & Rx coils, respectively, and mutual inductance M is the same as nL_m, as shown in Fig. 1. Although the AC power efficiency in (1) mainly depends on M, r_1, and r_2, the effective load resistance R_e also determines the efficiency. As described in Table II, the range of effective load resistance is usually 4.8 ~ 5.6 Ω, considering the voltage and power conditions. Therefore, the proposed RL algorithm will be implemented based on this resistance information.

TABLE I
Design Parameter for the Proposed IPT

Parameters	Value	Parameters	Value
l_{c1}, l_{c2}	100mm	d_c	30mm
w_{c1}, w_{c2}	100mm	f_s	100kHz
t_{c1}, t_{c2}	3mm		

TABLE II
Design Application Examples for the Proposed IPT

Application	Electrical Parameters		
	V_e	R_e	P_L
Notebook	19.0V	5.6Ω	65W
Tablet	15.0V	5.0Ω	45W
Robotic Vacuum	21.6V	5.8Ω	80W
Monitor	12.0V	4.8Ω	30W

B. Design of Reinforcement Learning Algorithm for Optimal Number of Turns

Fig. 5 shows DQN based RL algorithm to derive the optimal number of turns for a maximum power efficiency. The proposed algorithm selects the number of coil windings of the Tx & Rx, according to the ε-greedy policy. This ε-greedy policy selects whether to explore or exploit by probabilistically, and the corresponding values of N_1 and N_2 combination becomes the FEM 3D simulation input. After the efficiency is calculated through the formula (1), the efficiency is set to reward and inserted to a neural network system with the current states of N_1 & N_2. After that, the neural network system can learn this process to update the neural network based on the reward and selected N_1 & N_2. A neural network system compares the actual value (reward) and the predicted value (output of the network) through the loss function and optimizer, as shown in Fig. 6 and learns so that the error between the two values is minimized. As the episodes increase, the weight and bias in the hidden layers of the neural network are gradually updated, and ultimately optimal states (N_1 & N_2) can be followed to achieve the maximum efficiency point.

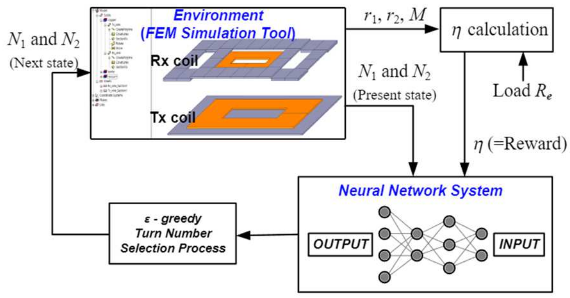


Fig. 5 Proposed RL algorithm for optimal turn design.

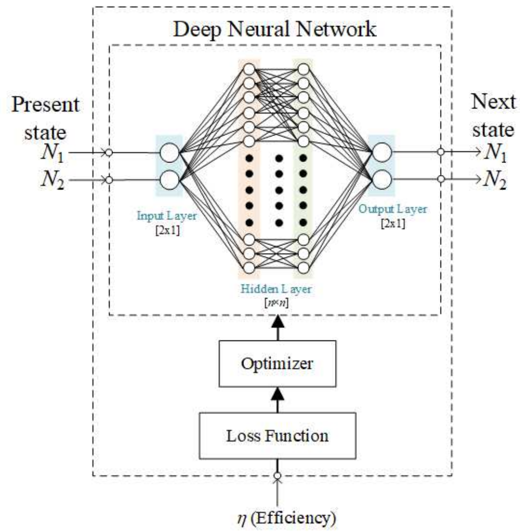


Fig. 6 Proposed neural network system.

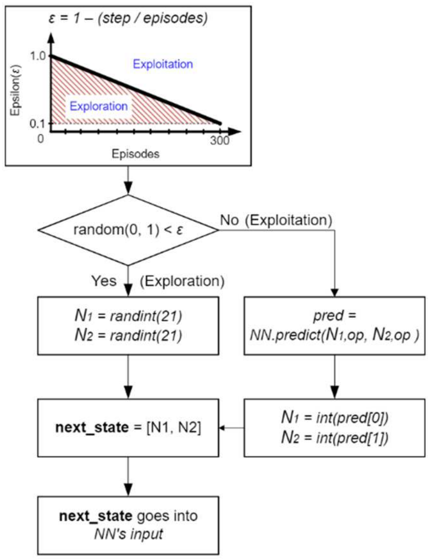
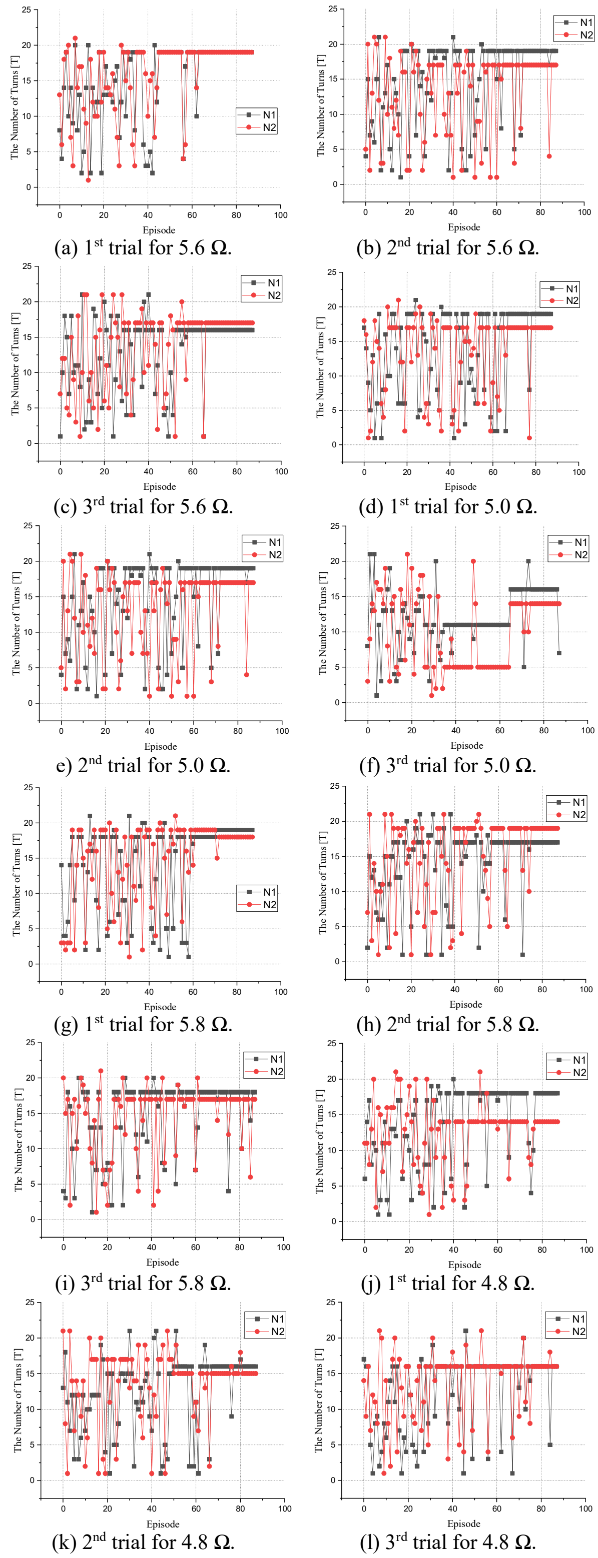


Fig. 7 The proposed ε-greedy turn selection process.



(a) 1st trial for 5.6 Ω. (b) 2nd trial for 5.6 Ω.

(c) 3rd trial for 5.6 Ω. (d) 1st trial for 5.0 Ω.

e) 2nd trial for 5.0 Ω. (f) 3rd trial for 5.0 Ω.

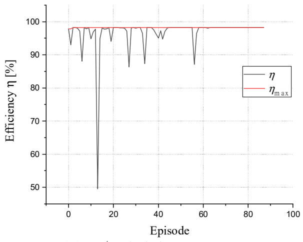
(g) 1st trial for 5.8 Ω. (h) 2nd trial for 5.8 Ω.

(i) 3rd trial for 5.8 Ω. (j) 1st trial for 4.8 Ω.

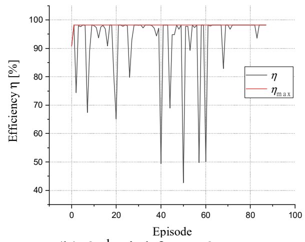
(k) 2nd trial for 4.8 Ω. (l) 3rd trial for 4.8 Ω.

Fig. 8 Analytic results of N_1 & N_2 w.r.t. episodes.

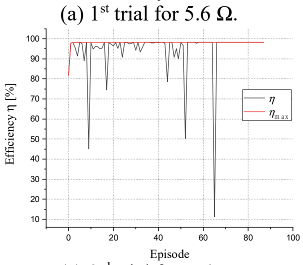
The ε-greedy policy is to determine the N_1 and N_2, depending on the value of ε, in this paper, as shown in Fig. 7. The value of ε gradually decreases from 1 to a specified minimum as the episodes increases, and a random value between 0 and 1 is compared to ε. If ε > random value, then exploration is selected, whereas if ε < random value, exploitation is selected. In the exploration, N_1 and N_2 are randomly selected and sent to the input of the neural network. On the other hands, in exploitation, N_1 and N_2 having the highest reward values based on the learned neural network are conservatively selected. In the early episodes, the probability of exploration is high. As the number of episodes increases, however, the probability of exploitation increases, leading to select the optimal



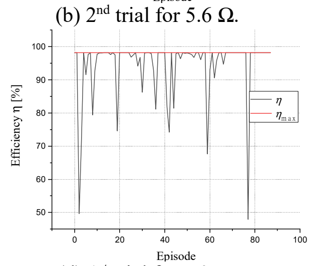
(a) 1[st] trial for 5.6 Ω.



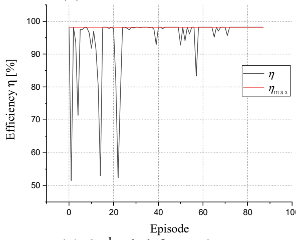
(b) 2[nd] trial for 5.6 Ω.



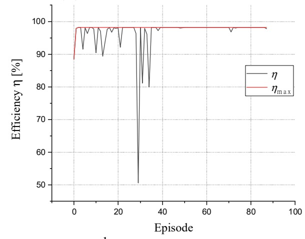
(c) 3[rd] trial for 5.6 Ω.



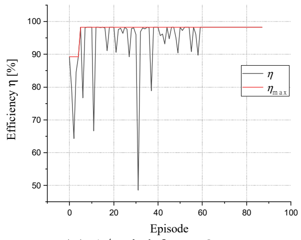
(d) 1[st] trial for 5.0 Ω.



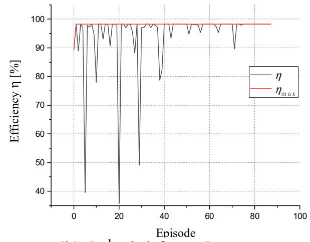
(e) 2[nd] trial for 5.0 Ω.



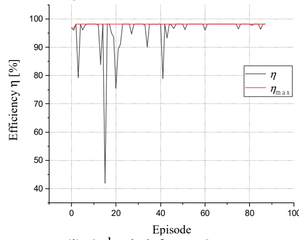
(f) 3[rd] trial for 5.0 Ω.



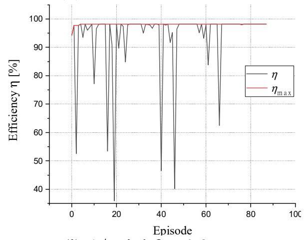
(g) 1[st] trial for 5.8 Ω.



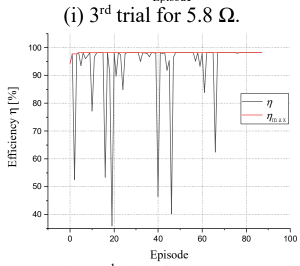
(h) 2[nd] trial for 5.8 Ω.



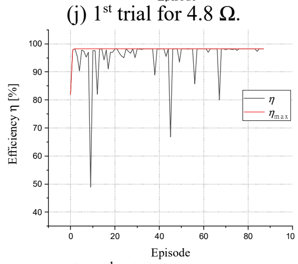
(i) 3[rd] trial for 5.8 Ω.



(j) 1[st] trial for 4.8 Ω.



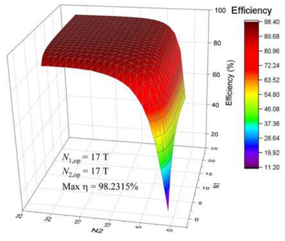
(k) 2[nd] trial for 4.8 Ω.



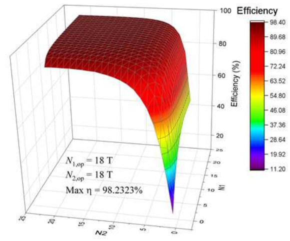
(l) 3[rd] trial for 4.8 Ω.

Fig. 9 Analytic results of efficiency w.r.t. episodes.

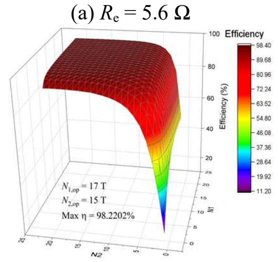
number of turns having the highest reward values; hence, the neural network can derive the optimal combination of N_1 and N_2 based on the learned neural network.



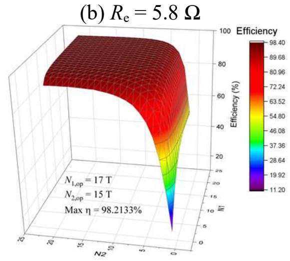
(a) R_e = 5.6 Ω



(b) R_e = 5.8 Ω



(c) R_e = 5.0 Ω



(d) R_e = 4.8 Ω

Fig. 10 Analytic results of efficiency w.r.t. episodes.

III. Simulation Evaluation

In this section, the FEM simulation results of the algorithm to derive the optimal N_1 and N_2 using ε-greedy are evaluated. 2. Considering the four cases in Table 2, the simulation results w.r.t. the load resistance for 1~3 trials are shown in Fig. 8. As identified from Figs. 7-9, the proposed algorithm follows the ε-greedy policy for all load resistances in Fig. 8. In early episodes, N_1 and N_2 are randomly selected to collect data to train the neural network, i.e., exploration. In later episodes, because exploration decreases and exploitation increases, the optimal N_1 and N_2 having the highest reward are preferred to be selected. Although each case and each trial have different tendency, the final selected N_1 and N_2 are usually saturated after 60~ 80 episodes, which are highly lower than the total N_1 and N_2 combinations.

Fig. 9 shows a graph of the evolution of the power efficiency w.r.t. the episodes. Similar with Fig. 8, the power efficiency is gradually converged to the maximum power efficiency by virtue of the algorithm's ε-greedy policy, as identified from Fig. 7. To evaluate the performance of the proposed RL algorithm, all the combinations were examined in advance to find a maximum power efficiency point, as shown in Fig. 10. After the total numbers of possible combinations between the Tx & Rx are implemented, the optimal number of turns having a maximum efficiency for each application in Table II can be found. The maximum ratio between the power efficiencies by the proposed RL and by all simulation implementations are summarized in Table 3. The maximum power efficiency by the proposed RL is compared with the maximum efficiency considering all combinations. The comparison shows that the maximum efficiency found by the algorithm is very close to the correct maximum efficiency.

IV. Experimental Verification

To verify that the simulation results obtained by the proposed RL algorithm for a maximum power efficiency,

TABLE III
SIMULATION RESULT BY THE PROPOSED ALGORITHM

R_e		Trial		
		1st	2nd	3rd
5.6 Ω	Proposed N_1, N_2	$N_1 = 19$ $N_2 = 19$	$N_1 = 19$ $N_2 = 17$	$N_1 = 16$ $N_2 = 17$
	Proposed η_{max}	98.22396%	98.23036%	98.22754%
	Max ratio	99.9923%	99.9989%	99.9960%
	Calculated N_1, N_2	$N_1 = 17, N_2 = 17$		
	Calculated η_{max}	98.23147%		
5.8 Ω	Proposed N_1, N_2	$N_1 = 19$ $N_2 = 18$	$N_1 = 17$ $N_2 = 19$	$N_1 = 18$ $N_2 = 19$
	Proposed η_{max}	98.22946%	98.23190%	98.22905%
	Max ratio	99.9971%	99.9996%	99.9967%
	Calculated N_1, N_2	$N_1 = 18, N_2 = 18$		
	Calculated η_{max}	98.23236%		
5.0 Ω	Proposed N_1, N_2	$N_1 = 19$ $N_2 = 17$	$N_1 = 17$ $N_2 = 15$	$N_1 = 16$ $N_2 = 14$
	Proposed η_{max}	98.21615%	98.22024%	98.20715%
	Max ratio	99.9958%	100%	99.9867%
	Calculated N_1, N_2	$N_1 = 17, N_2 = 15$		
	Calculated η_{max}	98.22024%		
4.8 Ω	Proposed N_1, N_2	$N_1 = 18$ $N_2 = 14$	$N_1 = 16$ $N_2 = 15$	$N_1 = 16$ $N_2 = 16$
	Proposed η_{max}	98.20644%	98.21604%	98.0431%
	Max ratio	99.9930%	99.9973%	99.9908%
	Calculated N_1, N_2	$N_1 = 17, N_2 = 15$		
	Calculated η_{max}	98.21330%		

an experimental set was constructed as shown in Fig. 11. A DC power supply was used on the Tx coil side and a DC electronic load on the Rx coil side to apply the DC voltage. To operate a switching frequency of 100 kHz, 0.1mm/120EA type Litz wire was adopted for Tx & Rx coil, and DC electronic load was set to 4.8Ω, which corresponds to Monitor among the various applications in Table 2. A 100 mm x 100 mm x 3 mm ferrite core was used, as shown in Fig. 12, and the coil was wound from the outside to the inside as the number of turns increases, allowing the number of turns to be varied from 21 to 1. The air gap between the Tx & Rx is set to be 30 mm. The experimental waveforms for the voltages and currents of the Tx & Rx coils are presented in Fig. 13. Because the inductance of the coil changes as the number of turns changes, the experiments were conducted by changing additional resonant capacitors to keep both the Tx & Rx coils be resonated. As a result, the phase difference between the primary and secondary currents is 90° for different number of Tx & Rx coil turns, as shown in Fig. 13.

The power efficiency was measured and calculated by measuring the information from a DC power supply and a DC electric load. Because such calculated power is DC-to-DC power efficiency, high frequency inverter loss in Tx side and rectifier loss in Rx side were excluded to derive

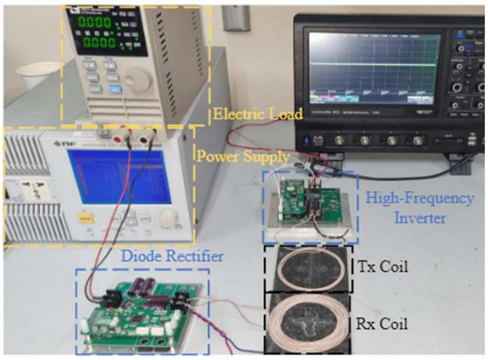


Fig. 11 Experimental setup to evaluate the proposed RL algorithms.

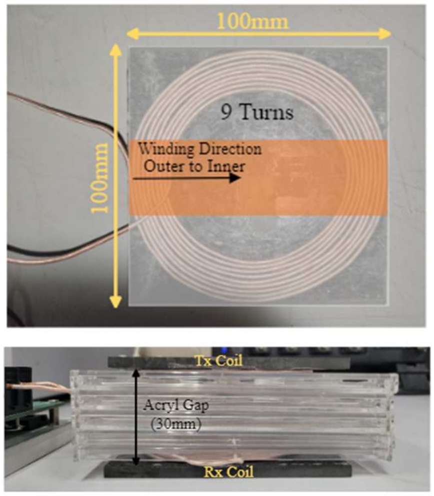
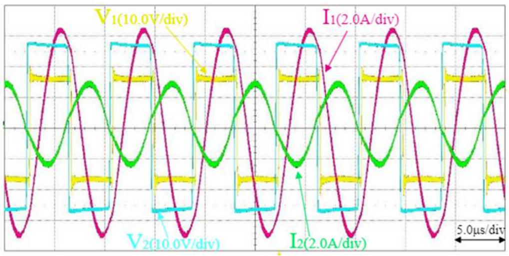
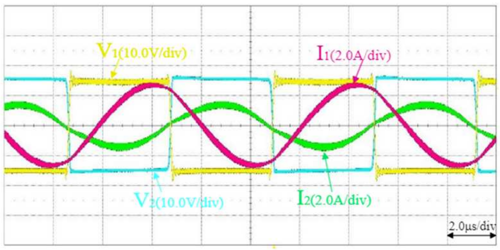


Fig. 12 Fabricated Tx & Rx coils.



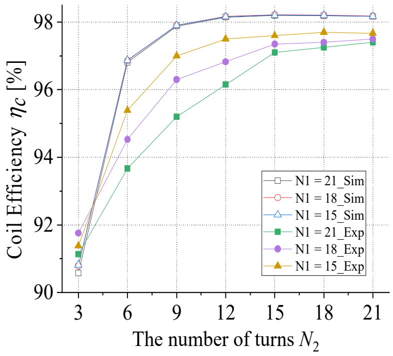
(a) $N_1 = 9$ and $N_2 = 21$



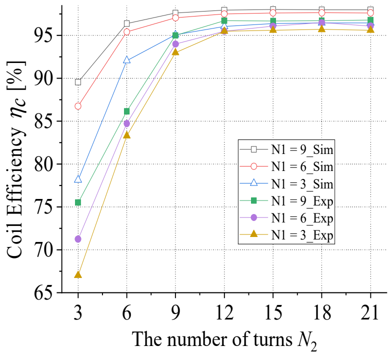
(b) $N_1 = 15$ and $N_2 = 15$

Fig. 13 Experimental waveforms of Tx & Rx coil.

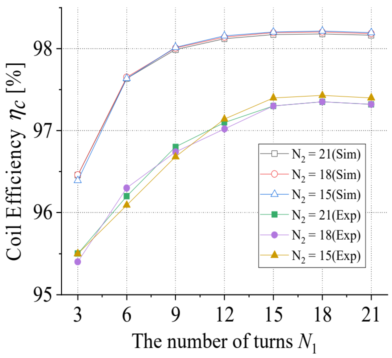
AC power efficiency by a PSIM simulation analysis. Based on this measurement method, the power efficiency results are shown in Fig. 14, where the simulation and experimental results are in good agreement with each other, considering the measurement errors and resonant conditions. Major discrepancy between the simulation and measurement results may come from the resistance loss modeling in the simulation analysis. Nevertheless, the overall tendency of the efficiency characteristics by



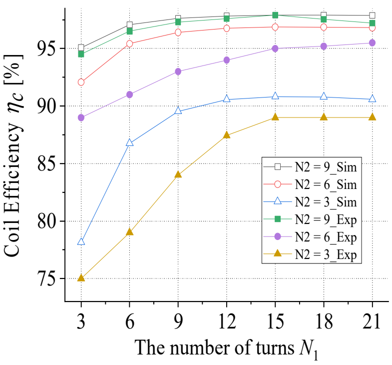
(a) Efficiency N_2 w.r.t N_1 for = 21, 18, 15.



(b) Efficiency N_2 w.r.t N_1 for = 9, 6, 3.



(c) Efficiency N_1 w.r.t N_2 for = 21, 18, 15.



(d) Efficiency N_1 w.r.t N_2 for = 9, 6, 3.

Fig. 14 Simulation and experiment results for efficiency

experiments are matched with simulation results by the proposed RL algorithm. As shown in Fig. 14, it is confirmed that the efficiency usually increases as the number of turns increases. When N_1 and N_2 are over 15 turns, however, the efficiency tends to be almost constant or even decreases. As a result, the maximum efficiency can be obtained at N_1 = 17 and N_2 = 15, which are the same results obtained from the proposed RL algorithm.

V. Conclusion

In this paper, it is found that the proposed RL algorithm can derive the optimal number of turns for a maximum power efficiency through Deep-Q Learning, and its performance has been verified by simulation and experiment. By virtue of the proposed RL algorithm, the optimal number of turns having maximum efficiency can be found by only 20% of the total episodes. Therefore, previous iterative computation time by FEM simulation analysis can be greatly reduced for designing IPT. The proposed RL algorithm is expected to be useful not only for selecting the optimal number of turns, but also for designing various nonlinear systems.

Acknowledgment

This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2022R1F1A1073409).

References

[1] Z. Zhang, H. Pang, A. Georgiadis and C. Cecati, “Wireless power transfer—An overview,” *IEEE Trans. Ind. Electron.*, Vol. 66, No. 2, pp. 1044-1058, Feb. 2019.

[2] J. Sallan, J. L. Villa, A. Llombart and J. F. Sanz, “Optimal design of ICPT systems applied to electric vehicle battery charge,” *IEEE Trans. Ind. Electron.*, Vol. 56, No. 6, pp. 2140-2149, Jun. 2009.

[3] K. Aditya and S. S. Williamson, “Design guidelines to avoid bifurcation in a series–series compensated inductive power transfer system,” *IEEE Trans. Ind. Electron.*, Vol. 66, No. 5, pp. 3973-3982, May. 2019.

[4] Eun S. Lee, “Frequency-modulation-based IPT with magnetic communication for EV wireless charging,” *IEEE Trans. Ind. Electron.*, vol. 70, no. 2, pp. 1398-1408, Feb. 2023.

[5] Eun S. Lee et al., “Optimal Number of Turns Design of the IPT Coils for Laptop Wireless Charging,” *IEEE Access*. vol. 9, pp. 19548-19561, Feb. 2021.

[6] Byeong H. Choi et al., “Optimal Dipole-Coil Ampere-Turns Design for Maximum Power Efficiency of IPT,” *IEEE Trans. Power Electron.*, vol. 35, no. 7, pp. 7317-7327, Jul. 2020.

[7] Eun S. Lee et al., “Calculation Methodologies of Complex Permeability for Various Magnetic Materials,” *Electronics*, vol. 10, pp.1-9, Sep. 2021.

[8] Byeong-Guk Choi and Yun-Su Kim, “New Structure Design of Ferrite Cores for Wireless Electric Vehicle Charging by Machine Learning,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 12, pp. 12162-12172, Dec. 2021.