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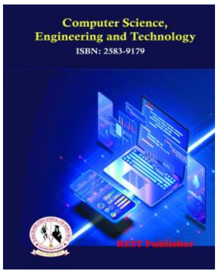


# Adaptive Current Control based Artificial Neural Network in Drone Recharging Stations for Resonant Wireless Power Transfer

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***Abstract.*** *The rapid growth of the drone market presents both opportunities and challenges, particularly in the area of energy management. One of the main limitations in drone operation is the restricted flying range, necessitating frequent battery recharges. A scalable and efficient solution for persistent operation is the establishment of a network of wireless recharging stations, particularly located on building rooftops. Resonant wireless power transfer (WPT) is an ideal technology for this purpose, enabling non-contact energy transfer. However, the variability in the coupling factor between thedrone and the recharging pad due to misalignments poses a significant technical challenge, leading to potential inefficiencies in power transfer. This work proposes an innovative solution using anArtificial Neural Network (ANN) controller to dynamically adjust the current in response to the fluctuating coupling factor. By leveraging machine learning, the ANN can predict and compensate for misalignments, ensuring stable and efficient power delivery in a multi-pad charging station. Simulations conducted using the Simscape Power Systems module in Simulink demonstrate the effectiveness of the proposed ANN-based tuning mechanism in maintaining optimal charging performance. This approach offers a promising path toward enabling large-scale, autonomous drone recharging stations, paving the way for continuous and efficient drone operations across various industries.*

## 1. INTRODUCTION

The rise of drone technology in recent years has been a game-changer across many industries, ranging from logistics and surveillance to agriculture and entertainment. The demand for drones continues to surge, driven by their capabilities, efficiency, and convenience in performing tasks that would otherwise be time-consuming or dangerous. However, one of the critical challenges that the drone industry faces is energy management, particularly the limited flight range due to battery constraints. This limitation forces drones to frequently return to base stations or charging docks, disrupting the operational flow and limiting their ability to provide persistent service. As the drone market grows, finding scalable and efficient energy solutions becomes increasingly essential. One promising approach is to establish wireless recharging stations that can support the continuous operation of drones, eliminating the need for manual recharging while reducing downtime.

Wireless Power Transfer (WPT), especially resonant WPT, has emerged as a feasible solution for this purpose. Resonant WPT relies on electromagnetic fields to transfer energy without the need for direct physical contact between the drone and the charging pad. This method has several advantages over traditional wired charging solutions, including reduced wear and tear on charging components, enhanced convenience, and the possibility of creating charging stations at various locations, including building rooftops. By creating a network of wireless charging stations, drones could automatically recharge on-the-fly, expanding their operational range and potentially enabling round-the-clock operations in applications that demand high availability, such as delivery systems or surveillance networks.

Despite the potential advantages of WPT, several technical challenges need to be addressed to ensure its effectiveness, particularly in the context of autonomous drone operations. One of the most significant hurdles is the variability in the coupling factor between the drone and the wireless charging pad. The coupling factor determines the efficiency of energy transfer between the two systems, and itis highly sensitive to misalignments, changes in distance, and orientation of the drone relative to the charging pad. Small misalignments in positioning, which are inevitable in real-world scenarios, can lead to suboptimal energy transfer, resulting in lower charging efficiency, longer recharging times, and potential overheating of the components involved. These inefficiencies pose a major challenge to the scalability and viability of wireless charging networks for drones, particularly when there are multiple charging pads in a station.

Addressing this challenge requires an intelligent and adaptive solution capable of dynamically adjusting to the fluctuating coupling factors and ensuring consistent power transfer. This is where the concept of integrating Artificial Neural Networks (ANNs) into the control mechanism of WPT systems becomes relevant. An ANN can act as a smart controller that learns from the variations in the coupling factor and adjusts the power input to the charging pad accordingly, thus compensating for misalignments in real-time. By leveraging machine learning, the ANN controller can predict the optimal charging conditions based on the current positioning of the drone and make the necessary adjustments to ensure efficient power delivery. This approach not only enhances the overall charging efficiency but also optimizes the system for various operational scenarios, such as multi-pad charging stations where multiple drones may be charging simultaneously.

The proposed solution involves developing an ANN-based controller that tunes the current fed to the charging pad, responding dynamically to changes in the coupling factor. The ANN can continuously monitor the charging process and make real-time adjustments to maximize energy transfer while minimizing losses. The machine learning model would require training on a set of data that reflects different misalignments, distances, and orientations of the drone relative to the charging pad. Once trained, the model can be deployed to control the charging process in real-world scenarios, where it will continually learn and adapt to new conditions, making it an ideal solution for the highly dynamic and unpredictable environment of drone recharging.

To test the viability of this approach, simulations were carried out using the Sim Scape Power Systems module in Simulink, which allowed for the modeling of the wireless power transfer system and the integration of the ANN controller. The simulations demonstrated the effectiveness of the ANN-based tuning mechanism in maintaining optimal charging performance, even under varying misalignment conditions. The results revealed that the proposed solution could significantly improve the efficiency of the charging process compared to conventional methods, reducing the time required for recharging and minimizing energy losses due to suboptimal alignment.

The implications of this research are far-reaching, as it opens the door to a new era of autonomous drone recharging stations that could support large-scale drone operations across industries. A network of rooftop charging stations, powered by resonant WPT and controlled by intelligent ANN-based systems, could provide the backbone for continuous drone operations in urban environments, eliminating the need for manual intervention or stationary charging docks. Such a system could revolutionize industries that rely on drones, including delivery services, emergency response teams, agricultural monitoring, and infrastructure inspections, where drones need to operate continuously over long distances or for extended periods.

Furthermore, the ANN-based control mechanism proposed in this work is highly adaptable and scalable, meaning it can be applied not only to small drones but also to larger, more energy-demanding models. This flexibility is crucial as drone technology continues to evolve, with new applications requiring increasingly sophisticated energy management solutions. The ability to scale the technology to meet the needs of both small and large drone fleets will be key to the widespread adoption of autonomous drone systems in commercial and industrial settings.

In conclusion, the rapid growth of the drone market necessitates the development of efficient and scalable solutions for energy management, particularly for persistent drone operations. Wireless power transfer, coupled with resonant charging systems, offers a promising path toward creating autonomous recharging stations that can support continuous drone flights.

However, addressing the challenge of misalignments between the drone and the charging pad requires an intelligent solution that can dynamically adjust to changes in the coupling factor. The integration of Artificial Neural Networks into the control mechanism of wireless charging systems provides a robust and adaptable solution that can optimize power transfer in real-time. Simulations confirm the effectiveness of this approach in improving charging efficiency, paving the way for large-scale, autonomous drone recharging stations that can revolutionize industries dependent on drones forcritical tasks. The proposed system offers a scalable and practical solution to the challenges of drone energy management, enabling the development of a new generation of autonomous drones capable of performing continuous, high-efficiency operations across a wide range of applications.

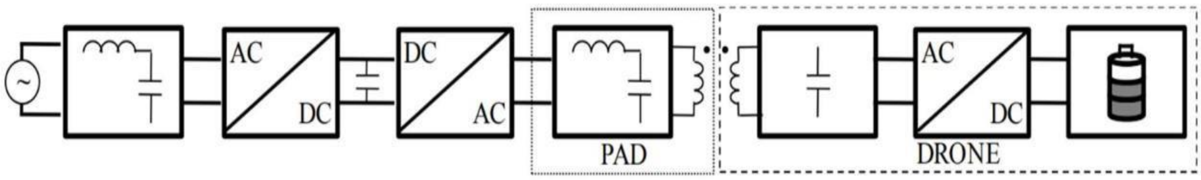


**FIGURE 1**. Recharge system. Only one pad-drone couple is represented in the figure. All pads are connected in parallel.

## 2. SINGLE-INVERTER MULTI-PAD WPT CHARGING STATION

The recharge system is shown in Fig. 1, where the inverter supplies the pads that, in turn supply the drones (only one pad-drone couple is represented in the figure). Fig. 2 details a generic pad structure where: VG is the input voltage (it is the voltage at the inverter output terminals), the coupled coils (CCs) are partially represented by their primary circuit self-inductance and winding resistance, and by the mutual inductance. The capacitor CT1 compensates for the primary circuit self-inductance, while the filter LF-CF is used for tuning the current of the CCs primary circuit. Finally, Z represents the whole impedance downstream from the filter. Lithium Ion batteries are the best candidates for the considered application since they provide high energy density and lightweight [22]. Typically, the battery charging is initially performed at constant current and increasing voltage. When the voltage reaches the nominal value, it is kept constant and the current rapidly decreases. Consequently, the absorbed power changes during the recharge period with a peak, PPK, during the transition from constant current to constant voltage. In the following, it is assumed that a drone is recharged at a constant power equal to PPK to simplify the description of the current tuning mechanism adopted to ensure that it is recharged in a fixed time interval regardless of the coupling factor. Notwithstanding, the idea behind this mechanism can be mixed with charging systems accounting for the actualcharging profile as it is explained in the following sections. In the circuit of Fig. 2, the current, IF, flowing towards Z can be expressed as a function of the voltage drop, VF, across CF:

$$I_F = \frac{V_G - V_F}{j\varpi L_F} - j\varpi C_F V_F$$

At resonance the value, IFR, of this current is independent from Z:

$$I_{FR} = -j\,\frac{V_G}{\varpi_R L_F}$$

$$\varpi_R = \frac{1}{\sqrt{L_F C_F}}$$

**FIGURE 2**. shows the drone model where VS is the voltage source whose value depends on both IFR and the mutual inductance.

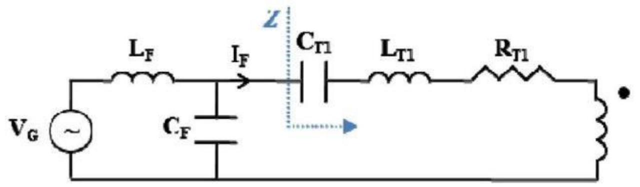


Fig.2. Electrical circuit representing a pad.

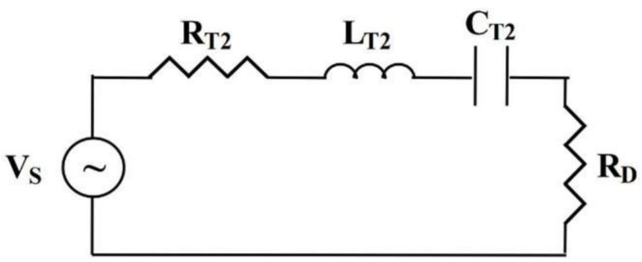


**FIGURE 3**. Electrical circuit representing a drone. The resistance RD is the drone equivalent resistance appearing from the

rectifier input port.

In Fig. 3, LT2 and RT2 represent, respectively, the secondary circuit self-inductance and winding resistance of the CCs. Finally, CT2 is the compensation capacitor and RD is the drone equivalent resistance appearing from the rectifier input port. At resonance, assuming the self-inductance of both primary and secondary circuit equal to LT, and considering the generic coupling factor k, VS can be expressed by:

assuming both winding resistance equal to RT, the power absorbed by the drone is:

$$V_s = j\varpi_R k L_T I_{FR} = k \frac{L_T}{L_F} V_G$$

$$P_D = \frac{R_D}{(R_D + R_T)^2} V_S^2 = \frac{R_D}{(R_D + R_T)^2} k^2 \left(\frac{L_T}{L_F}\right)^2 V_G^2$$

Assuming that the pads are equivalent to each other as well as the drones, the absorbed power depends only on the coupling factor once the system components and the pads' source voltage have been chosen. The coupling factor changes as the landing position changes, thus the drones well aligned with the pad can be recharged in a time interval smaller than the misaligned ones. If the system is designed for ensuring that PD is equal to PPK for the average-coupling factor, kAVG, then the power delivered to the drone is lower than PPK when there is a poor alignment while it is greater than PPK when there is a good alignment. Therefore, it is necessary a strategy for compensating the variable value of the coupling factor. In (4), the values of the drone equivalent resistance, the secondary circuit self-inductance, and the winding resistance cannot be adjusted, while the filter inductance and the input voltage could be tuned. More specifically, tuning the filter inductance asks for the use of an inductor with variable inductance that, in turn, asks for a capacitor with variable capacitance in order to hold the resonance condition. The input voltage can be tuned through the inverter control signal by changing the amplitude modulation ratio (AMR). Therefore, the latter solution is the simplest one but it is more expensive because it asks for the use of an inverter for each pad with a different control signal that depends on the misalignment. The use of a variable inductance enables to use only one inverter for the whole recharge station. In this case, the reference inductance, LFR, value is calculated by considering the average value of the coupling factor:

$$L_{FR} = \sqrt{\frac{R_D}{P_{PK}}} \frac{1}{R_D + R_T} k_{AVG} L_T V_G^2$$

For a given k, the value of LF has to be changed according to the following expression in order to ensure a charging power equal to PPK:

$$L_F = \frac{k}{k_{AVG}} L_{FR}$$

From an operating point of view, when the recharge starts the LF value is equal to the reference inductance and the power absorbed by the drone battery, PD, k, is estimated. After that, the inductance is changed according to the following expression:

$$L_F = \sqrt{\frac{P_{D,k}}{P_{PK}}} L_{FR}$$

where PD, k is the power absorbed by the battery when the inductance is equal to the reference value and the misalignment leads to the coupling factor k. Therefore, the inductance is increased to reduce the current and, consequently, the transmitted power when the one estimated towards the drone is greater than the target value (i.e. PD, k > PPK since k > kAVG). Otherwise, when the absorbed power is too low (i.e. PD, k < PPK since k < kAVG) the inductance is reduced to increase the current in the primary circuit in order to transmit a greater power to the secondary. There are many methods that may be adopted for obtaining variable inductance [23]. Some methods specifically designed for WPT systems have been also proposed in the last years [24]. Finally, a capacitor with variable capacitance [25] is also necessary, thus the capacitance value can be modified in order to hold the filter working at the resonance. As said before, the proposed method can be easily readapted when the actual charging profile is considered instead of using PPK. In this case, the reference inductance can be represented by a function of the power to be delivered to the drone during the charging period. Equation (5) still holds valid, but PPK is substituted with the power related to the charging profile, PD(t). Moreover, a DC/DC converter has to be connected between the rectifier and the battery in order to force the charging profile. Finally, the implementation of the proposed current sharing mechanism asks for a wireless communication system between the pad and the drone [26].

## 3. ARTIFICIALNEURALNETWORK(ANN)CONTROLLERFORDYNAMICPOWER ADJUSTMENT

The introduction of the Artificial Neural Network (ANN) controller into the system provides a sophisticated solution to the challenge of maintaining efficient power transfer in wireless power transfer (WPT) systems, especially in the context of drone recharging stations. In a typical wireless charging scenario, the power transfer efficiency is highly dependent on the alignment and positioning of the drone relative to the charging pad. Misalignments—whether due to slight shifts in position or changes in orientation—result in variations in the coupling factor, which directly affects the efficiency of energy transfer. This, in turn, can cause longer recharging times, suboptimal charging performance, and potentially wasted energy.

To address these challenges, the proposed ANN controller leverages machine learning techniques to dynamically adjust the charging current in real time. By continuously monitoring the drone’s position and alignment relative to the charging pad, the controller can predict and compensate for any misalignments or fluctuations in the coupling factor, ensuring that the system operates optimally at all times.

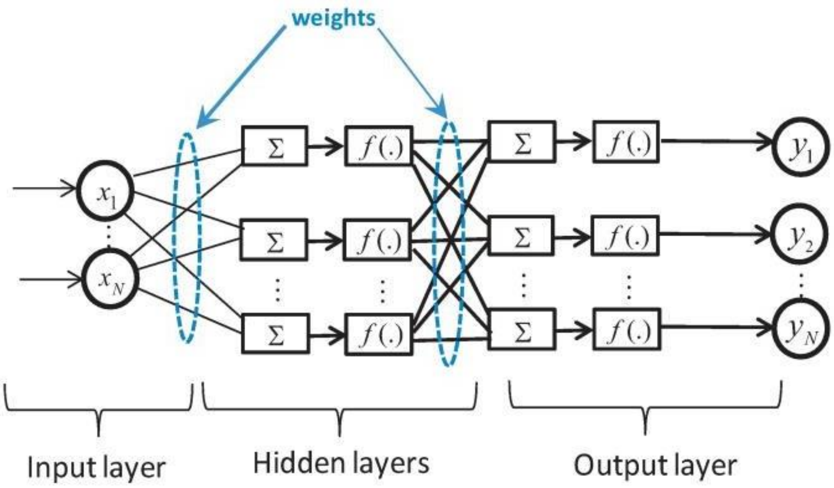


**FIGURE** 4. ANNneuralstructure.

**Key Functions of the ANN Controller:**

**Real-time Position and Alignment Monitoring:** The ANN controller's first task is to continuously monitor the drone's position relative to the charging pad. This is accomplished by analyzing real-time data, such as the distance between the drone and the pad, as well as the orientation and angle at which the drone is hovering. Advanced sensors or position tracking systems can feed this information to the controller, enabling it to assess how the alignment is changing over time.

**Learning and Adaptation:** One of the most significant advantages of using an ANN is its ability to learn from historical data and adapt over time. Initially, the ANN is trained using a set of data that simulates different alignment scenarios, varying the drone's position, angle, and distance from the charging pad. The network learns the relationship between these parameters and the power transfer efficiency, allowing it to predict how changes in alignment will affect the energy transfer.

As the system is used in real-world conditions, the ANN continuously refines its understanding by learning from each charging session. This allows the controller to adapt to new scenarios and optimize power transfer for various drone models, charging pad designs, and environmental conditions.

**Dynamic Current Adjustment:** The core functionality of the ANN controller is to adjust the current fed in to the charging system based on real-time feedback about the coupling factor. When the coupling factor is high (i.e., the alignment is optimal), the controller ensures that the system operates at its maximum power transfer rate. Conversely, when the coupling factor drops due to misalignment, the ANN predicts the necessary adjustments to the current in order to compensate for the loss inefficiency.

By dynamically adjusting the current, the ANN controller ensures that the charging system remains stable and efficient even under suboptimal alignment conditions. The ability to make these adjustments in real time is crucial for ensuring that the drone can charge as quickly and efficiently as possible without the need for manual intervention.

**Prediction and Compensation for Misalignments:** One of the primary challenges in WPT for drone recharging is dealing with misalignments, which are often unpredictable and can change throughout the charging process. The ANN controller predicts the impact of these misalignments on the charging efficiency and compensates accordingly. By using historical data and real-time sensor feedback, the ANN can recognize patterns in the drone's positioning and make accurate predictions about how the misalignment will affect power transfer.

**Multi-pad Charging Station Optimization:** In the case of a multi-pad charging station where multiple drones maybe charging simultaneously, the ANN controller can manage the charging process across multiple pads. By communicating with each charging pad in the station, the controller can dynamically allocate power resources and prioritize drones that may require more efficient charging based on their alignment. The ANN can also ensure that the power output is evenly distributed among the charging pads, preventing any one drone from drawing excessive power or undercharging due to misalignments. This ability to optimize power distribution in a multi-pad setup is essential for scaling the system to support large fleets of drones in urban environments.

**Training the ANN Controller**

Training the ANN controller is a crucial step in developing an effective solution. The training process involves feeding the network with a variety of simulated scenarios that capture the potential variations in drone positioning, alignment, and environmental factors. The goal is to help the ANN learn the complex relationships between the drone's position, the coupling factor, and the optimal current for power transfer.

**Training Process Steps:**

**Data Collection:** A large dataset is generated that simulates different drone positions, angles, and distances relative to the charging pad. This data could include a variety of misalignments, including horizontal shifts, vertical displacements, and angular deviations. The corresponding coupling factors are calculated, along with the power transfer efficiency for each scenario.

**ANN Model Selection:** The type of ANN architecture used depends on the complexity of the problem. A feedforward neural network or a convolutional neural network could be used, depending on the nature of the data and the level of accuracy required. The network is designed to take inputs such as the drone's position and angle and output the optimal current required for efficient charging.

**Training:** The data is used to train the ANN, teaching it to recognize patterns in the input data and predict the most effective current adjustments for different alignment conditions. The training process involves adjusting the weights and biases of the network to minimize the error in power transfer predictions, typically by using optimization algorithms like gradient descent.

**Validation and Testing:** Once trained, the ANN is validated using a separate dataset that it has not encountered before. This step is crucial to ensure that the network generalizes well to new, unseen conditions. After validation, the model is tested under various real-world conditions to confirm its performance in ensuring optimal power transfer during drone recharging.

**Simulation and Performance Evaluation**

The effectiveness of the ANN controller is evaluated through simulations using tools like Simscape Power Systems in Simulink. These simulations allow the wireless power transfer system, along with the ANN controller, to be modeled and tested under various scenarios. The results of the simulations provide valuable insights into how the system performs in real-world conditions and how well the ANN controller can maintain stable and efficient charging performance.

**Key metrics that are typically evaluated during the simulation include:**

**Charging Efficiency:** The percentage of energy successfully transferred to the drone relative to the total energy consumed by the charging system. The higher the efficiency, the less energy is wasted due to misalignments.

**Power Transfer Stability:** The ability of the system to maintain a consistent power delivery despite fluctuations in the coupling factor.

**Recharge Time:** The time it takes for the drone to fully recharge under varying alignment conditions. A key objective of the ANN controller is to minimize recharge time while maintaining energy efficiency.

The ANN controller presents a transformative solution for addressing the challenges of wireless power transfer in drone recharging systems. By intelligently adjusting the charging current based on real-time feedback about the drone's position and alignment, the ANN ensures that power transfer remains stable and efficient, even under suboptimal conditions. This dynamic, adaptive approach is essential for creating scalable, autonomous drone recharging stations that can support continuous drone operations across a variety of industries. With the ability to predict and compensate for misalignments, the ANN controller promises to significantly improve the efficiency and reliability of drone recharging systems, paving the way for large-scale deployment of wireless charging networks in urban environments and beyond.

## 4. MATHEMATICALANALYSISOF THE ANN CONTROLLER FOR WIRELESS POWER TRANSFER (WPT) SYSTEMS

The wireless power transfer (WPT) system in the context of autonomous drone recharging involves the use of resonant inductive coupling to transfer energy from the charging pad to the drone's onboard battery. The efficiency of this transfer is highly sensitive to the alignment between the drone and the charging pad, which in turn affects the coupling factor. A misalignment leads to a fluctuation in the coupling factor, influencing the efficiency of power transfer. The Artificial Neural Network (ANN) controller can mitigate this fluctuation by dynamically adjusting the current supplied to the charging system, based on the real-time feedback received from the drone's position relative to the charging pad.

The mathematical analysis involves modeling key components of the WPT system, the behavior of the coupling factor, and the adjustment process driven by the ANN. Let's explore the mathematical formulation of these components in greater detail.

**Resonant Inductive Coupling and Power Transfer Efficiency**

The efficiency of resonant wireless power transfer is primarily governed by the coupling factor kkk, which varies with the relative distance and alignment between the drone and the charging pad. The total power transferred from the charging pad to the drone's receiver coil is given by the formula:

$$P_{\text{transfer}} = \frac{V_{\text{primary}} V_{\text{secondary}}}{R_{\text{load}}} \cdot k^2$$

where:

a. P transfer is the power transferred to the drone's battery,

b. V primary is the voltage on the charging pad (primary coil),

c. Vsecondaryisthevoltageinducedonthedrone'sreceivingcoil(secondarycoil),

d. R load is the load resistance (which can represent the internal resistance of the battery or the drone's power electronics),

e. K is the coupling factor, a measure of how effectively the two coils are coupled through resonant inductive fields.

The coupling factor k itself depends on the relative positioning, orientation, and distance between the primary (charging pad) and secondary (drone) coils. For simplicity, k can be modeled as a function of the relative alignment, represented as:

$$k = f(\Delta x, \Delta y, \Delta z, \theta)$$

where:

f. Δx, Δy, Δzrepresentthedrone'sdisplacementalongthethreeCartesianaxesrelativetothecenterofthe charging pad, and

g. θ represents the angular misalignment between the drone and the pad.

For resonant coupling systems, k typically follows an inverse square law in relation to the distance between the coils. When there is a misalignment, the coupling factor decays more rapidly, and the power transfer efficiency drops.

**Dynamic Adjustment of Current Using ANN**

The key role of the ANN controller is to adjust the current supplied to the charging pad to compensate for variations in the coupling factor caused by misalignments. The controller continuously monitors the drone's position and alignment, adjusting the current I primary I_{\text{primary}} I primary fed into the primary coil (charging pad) to maintain optimal power transfer.

Let's consider the ANN as a function that takes the misalignment parameters (displacements and angle) as input and adjusts the primary current in a way that compensates for the fluctuation in the coupling factor.

Let the output of the ANN be denoted as the adjustment factor α\alphaα, which modifies the current supplied to the primary coil:

$$I_{\text{primary}}(t) = I_{\text{ref}} \cdot \alpha(t)$$

where:

- I primary (t)I_{\text{primary}}(t)I primary(t) is the time-varying current to the primary coil (charging pad),
- IrefI_{\text{ref}}I ref is the reference or base current corresponding to ideal alignment (no misalignment),
- α(t)\alpha(t)α(t)is the adjustment factor computed by the ANN attimettt, based on the drone's position and orientation feedback.
- The adjustment factor α(t)\alpha(t)α(t)is determined by the ANN through the following relationship:

$$\alpha(t) = f_{\text{ANN}}(k(t), \Delta x(t), \Delta y(t), \Delta z(t), \theta(t))$$

where:

h. fANN f_{\text{ANN}}fANN represents the trained ANN function,

i. k(t)k(t)k(t) is the current coupling factor attimettt,

j. Δx(t), Δy(t), Δz(t)\Deltax(t),\Deltay(t),\Deltaz(t)Δx(t),Δy(t),Δz(t)are the displacements of the drone attimettt,

k. θ(t)\theta(t)θ(t)is the angular displacement or misalignment attimettt.

Since the coupling factor k(t)k(t)k(t) varies as a function of drone position and orientation, the ANN dynamically adjusts α(t)\alpha(t)α(t) to compensate for these fluctuations, ensuring that the current fed to the primary coil is always optimized for the best possible power transfer efficiency.

**Training the ANN**

Training the ANN involves minimizing the error in power transfer efficiency and loss, which can be formulated as an optimization problem. The objective is to find the optimal ANN weights WWW that minimize the power loss P loss P_{\text{loss}}P loss over a training set of misalignment scenarios. The loss function LLL is given

$$L(W) = \sum_{i=1}^{N} \left( \left( P_{\text{transfer}}(i) - \hat{P}_{\text{transfer}}(i) \right)^2 + \lambda \cdot (\Delta k(i))^2 \right)$$

where:

l. NNN is the number of training samples,

m. Ptransfer(i)P_{\text{transfer}}(i)Ptransfer(i)istheactualtransferredpowerfortheiii-th sample,

n. P^transfer(i)\hat{P}_{\text{transfer}}(i)P^transfer(i)isthepredictedtransferredpowerbasedonthe ANN's output, Δk(i)\Delta k(i)Δk(i) is the error in coupling factor for the iii-th sample,

o. λ\lambdaλisaregularizationtermtopreventoverfittingandensurestability.

p. The ANN is trained to minimize the loss function L(W)L(W)L(W), which is typically done using gradient descent or other optimization algorithms. Once the ANN is trained, it can be used to predict the optimal adjustment factor α(t)\alpha(t)α(t) during real-time operations.

## 5. WPTSYSTEMSIMULATION BYMEANSOFSIMSCAPEPOWER SYSTEMS MODULE IN SIMULINK

The proposed strategy to deal with the misalignment issues has been simulated through the Sims cape Power Systems™ module in Simulink®. Fig. 4 shows the equivalent circuit of the power converter used for the simulation runs.

**TABLE 1**. Quantities And Values Of The Simulations runs

| **Components and parameters** | | | | |
|---|---|---|---|---|
| ***Symbol*** | ***Value*** | | ***Symbol*** | ***Value*** |
| $V_{DC}$ | 40 V | | AMR | 0.8 |
| $f$ | 200 kHz | | $R_T$ | 0.5 Ω |
| $L_{T1}$ - $L_{T2}$ | 5 μH | | $C_{T1}$ - $C_{T2}$ | 127 nF |
| $k_{AVG}$ | 0.1 | | $k_1$ | 0.06667 |
| $k_2$ | 0.03333 | | $k_3$ | 0.1 |
| $L_{FR}$ | 412.6 nH | | $L_{F1}$ - $L_{F2}$ - $L_{F3}$ | 825 nH |
| $C_{FR}$ | 1.535 μF | | $C_{F1}$ - $C_{F2}$ - $C_{F3}$ | 767 nF |
| $R_B$ | 10 Ω | | $C_B$ | 10 μF |
| $R_D$ | 8.11 Ω | | $P_{PK}$ | 82 W |

Table 1 contains the values of the components and the other considered quantities. The value of RD has been computed by using the following equation [27], where RB is the battery resistance:

$$R_D = \frac{8}{\pi^2} R_B$$

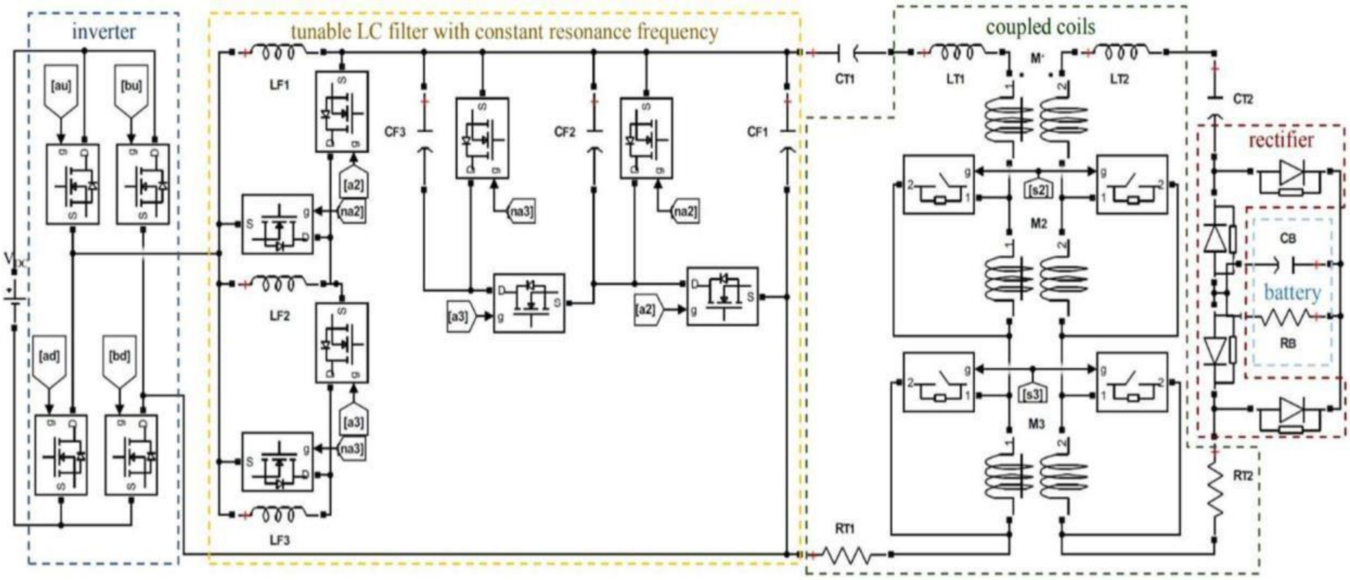


**FIGURE 5.** Circuit simulated by means of the Sims cape Power Systems ™module in MATLAB®-Simulink®

The coupling factor variation has been emulated by means of multiple CCs whose primary (and secondary) circuits are connected in series. The upper CCs emulate the lowest value of coupling factor. A couple of ideal switches are connected in parallel with each additional CCs. When these switches are set to closed status, the CCs are short-circuited and then they do not contribute to the overall coupling factor. Otherwise, the status of the switches is set to open when the contribution onthe coupling factor of the related CCs has to be considered. The variable inductance and capacitance are obtained by the parallel connection of inductors and capacitors, respectively.

A couple of MOSFETs is associated to each additional inductor to enable its connection or disconnection from the main circuit. MOSFETs products are planar [28]-[31] or Super Junction [32], [33], but in low voltage applications, the planar are of concern. More specifically, one MOSFET is connected in series with the inductor and the other in parallel.

They are operated by opposite control signals. When the first is turned on, the second one is tuned off, then the inductor is connected to the main circuit enabling to increase the current towards the primary circuit of the CCs. On the other hand, when a current reduction is necessary, the MOSFET in series is turned off to disconnect the inductor and the other MOSFET is turned on to enable the inductive energy dissipation.

A capacitor is associated to each inductor to ensure that the filter always operates at the resonance. Therefore, a MOSFET is connected in series with the capacitor and another one in parallel and theyare operated through the same signal controlling the MOSFETs of the related inductor. More specifically, CF2 and LF2 are both connected in parallel with, respectively, CF1 and LF1 when signal a2=1.

Similarly, CF3 and LF3 are also connected when signal a3=1 (in this case it is necessary - but it is not sufficient - that a2=1). When a drone lands on a pad, there is not any knowledge of the alignment. Therefore, any initial value for the filter inductance and capacitance could be adopted provided thatthe resonance is guaranteed. The configuration LFR-CFR (i.e. the one to be set when a coupling factor equal to the average one occurs – basic scenario) has been chosen as the initial one. Thisconfiguration is obtained by connecting LF2 and CF2 while leaving disconnected both LF3 and CF3 (signal a2=1and a3=0).

Three scenarios have been emulated. The basic one has been obtained by keeping open the upper couple of ideal switches (i.e. s2=0) and closed the lower ones (i.e. s3=1). The scenario with a worse alignment has been emulated by keeping closed both couples of ideal switches (i.e. s2=s3=1). When the control system detects this scenario by means of elaborating the received information about the power delivered to the drone, it connects LF3 and CF3 to increase the current through the primary circuit, thus counterbalancing the poor alignment. The control system obtains this effect by setting a3=1

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The scenario with a better alignment than the main one has been emulated by leaving open both couples of ideal switches (i.e. s2=s3=0). Conversely, to the previous scenarios, the control system disconnects LF2 and CF2toreduce the current when it detects a power transfer exceeding the reference one. In this case it sets a2=0 (consequently, a3=0). Figs. 5-7 show the waveforms of the current in the primary circuit (IF) of the coupling inductors, and the current (IB) through the resistor RB emulating the battery.

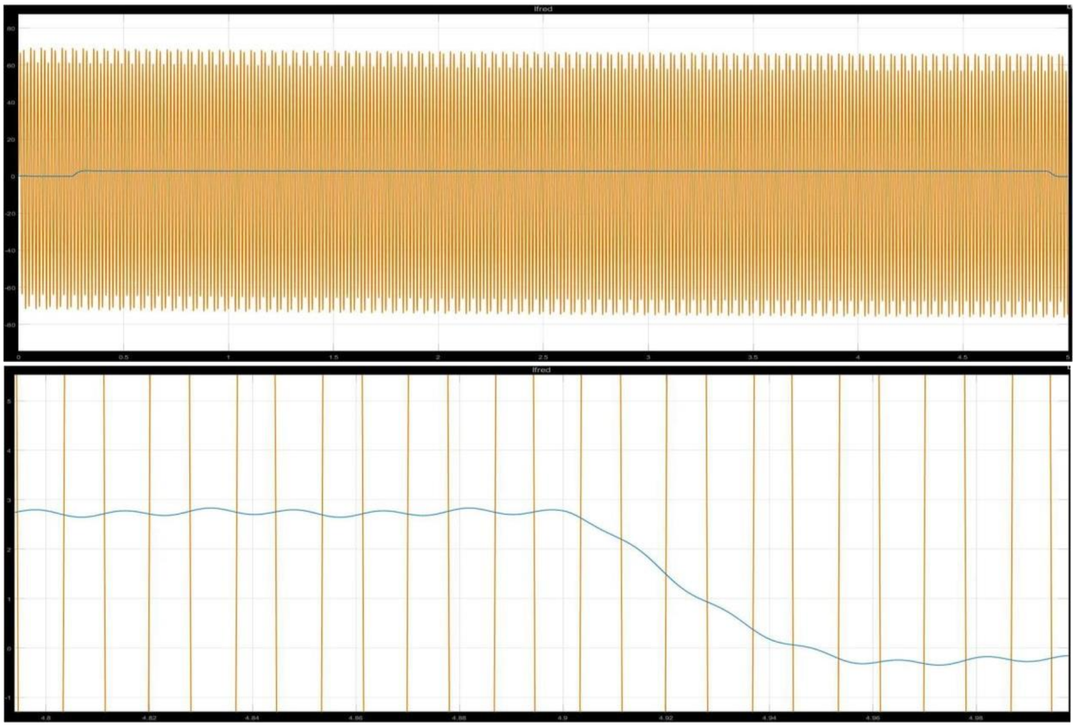

**FIGURE 6.** Current wave forms (IF red–IB blue) when k=kAVG.

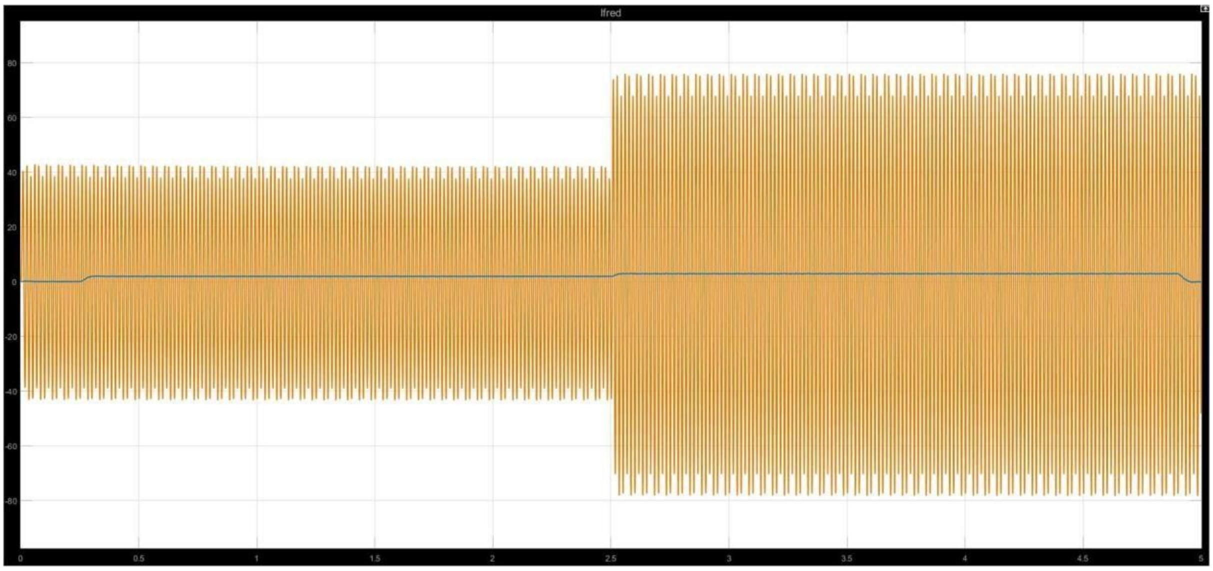


**FIGURE 7.** Current wave forms (IF red–IB blue) when k<kAVG.

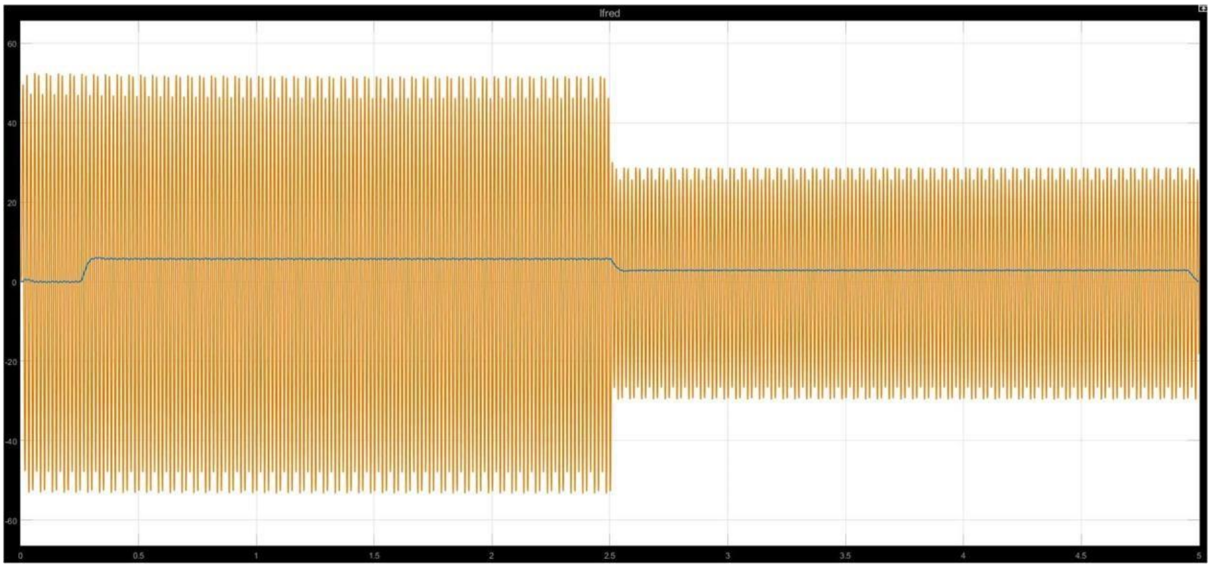


**FIGURE 8**.Current wave forms(IFred–IBblue)whenk>kAVG

In particular, Fig. 8 shows the simulation of the basic scenario where it is not necessary any change into the circuit in order to adapt the parameters since the alignment leads to a coupling factor equal to the average one. For the reason that the two currents have very different values, Figs.5(b) and(c) show the zoomed view of the two simulated traces. The steady-state current through RB is about 2.87A, which implies an absorbed active power equal to PPK. Fig.6showsthe simulation of the case with a poor alignment, which requires the control intervention in order to adapt the circuit structure.

It can be seen, in this figure, that the initial current into the primary circuit is equal to the basic scenario, thus confirming that it does not depend on the circuit downstream from the filter, while the current into the load is less than the required one. Subsequently into the figure, it is shown that because of the adaptive approach, the current is increased by means of modifying the filter inductance capacitance looking to deliver the desired power to the load.

Again, since the two currents have very different values, Figs. 6(b), (c), (d), and(e) show the zoomed view of the two simulated traces. The final steady-state current through RB is still about 2.87A, which impliesanabsorbed active power equal to PPK, and such a value confirms that it is equal to the basic case. The current wave forms for the scenario with a better alignment are depicted in Fig.7.

Once again, the results confirm the expected behavior of the recharging system, which requires the control intervention in order to adapt the circuit structure. It can be seen, in this figure, that the initial current into the primary circuit is equal to the basic scenario, while the current into the load is greater than the require done.

Subsequently into the figure, it is shown that because of the adaptive approach, the current is decreased by means of modifying the filter inductance-capacitance looking to deliver the desired power to the load. Once again, since the two currents have very different values, Figs. 7 (b), (c), (d), and (e) show the zoomed view of the two simulated traces. The final steady-state current throughRBisadjustedtoabout2.87A, which comply with the active power equal to PPK of the basic case.

# 6. CONCLUSION AND FUTURE SCOPE

This paper proposed an innovative solution to address the energy management challenges in the rapidly growing drone market, particularly the issue of restricted flying range due to frequent attery recharges. A scalable and efficient solution for persistent drone operation is the establishment of wireless recharging stations, especially those located on building roof tops. The study highlighted the potential of resonant wireless power transfer (WPT) as an ideal technology for non-contact energy transfer. However, the variability in the coupling factor due to misalignments between the drone and recharging pad remains a key challenge, leading to inefficiencies in power transfer.

To overcome this issue, the paper introduced an Artificial Neural Network (ANN) controller that dynamically adjusts the current in response to fluctuating coupling factors. By using machine learning, the ANN can predict and compensate for misalignments, ensuring stable and efficient power delivery in a multi-pad charging station. Simulations conducted in Sims cape Power Systems in Simulink demonstrated the effectiveness of the proposed ANN-based tuning mechanism, which maintained optimal charging performance despite misalignment. This approach holds significant promise for enabling large-scale, autonomous drone recharging stations, supporting continuous and efficient drone operations in various industries.

**Future Scope**

Future research could focus on optimizing the performance of the ANN controller by incorporating more advanced machine learning techniques, such as reinforcement learning or deep learning, to further enhance the system's adaptability and efficiency under dynamic operational conditions.

Expanding the scope of simulations to account for real-world environmental factors, such as varying weather conditions and obstacles in the charging environment, would provide a more comprehensive understanding of the system's robustness and reliability.

Additionally, the development of hard ware proto types and real-world testing will be crucial to validate the feasibility and scalability of the proposed solution in operational drone fleets. Integrating the ANN-based WPT system with drones' autonomous navigation and docking capabilities could enable fully automated recharging stations, eliminating the need for manual intervention.

Further, there search could explore the integration of renewable energy sources, such as solar panels on rooftop charging pads, to enhance the sustainability of the wireless recharging stations. Investigating the economic feasibility and cost-effectiveness of deploying large-scale wireless recharging infrastructure could provide valuable insights into the practical viability of this technology in commercial and industrial drone operations.

Lastly, expanding the wireless power transfer system to support higher power levels and multiple dronessimultaneouslycouldpavethewayforthewidespreadadoptionofautonomousdronefleetsin logistics, surveillance, and other sectors.

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