

## Energy-Efficient Resource Allocation in WPT-Based IoT Networks - A Survey

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### ABSTRACT

*With the significant growth of Internet of Things (IoT) devices, wireless power transfer (WPT) emerges as a promising technology for energetically recharging devices wirelessly. However, effective use of transferred wireless power relies on strategic allocation of communication resources, such as transmission power, time slots, subcarriers, and antennas. This study offers a comprehensive survey of the state-of-the-art in energy-efficient resource allocation for WPT-enabled IoT networks. The necessary background on WPT techniques, architectures, IoT network paradigms, resource allocation fundamentals, and key performance metrics is presented. Analytical models relating resources to energy efficiency metrics are reviewed. Resource management solutions under both perfect and imperfect channel state information conditions are surveyed and compared. Techniques like convex approximation, non-linear programming, game theory, and stochastic optimization are employed to address these challenges. Although existing literature offers valuable insights, key open challenges persist, such as distributed solutions, network lifetime optimization, integration of practical traffic and energy harvesting models, and security investigation. This survey summarizes existing work, highlights open issues, and proposes directions for future research on this significant topic.*

### ARTICLE INFO

Article History

Received: February, 2023

Received in revised form: March, 2023

Accepted: May, 2023

Published online: June, 2023

### KEYWORDS

Energy-Efficient, WPT-Based, IoT,  
Networks

### INTRODUCTION

The Internet of Things (IoT) paradigm has fuelled the explosive growth of interconnected smart devices and sensors. It is estimated that over 50 billion IoT devices will be deployed by 2025, leading to massive-scale networks (Ansere et al., 2020). IoT devices are used in various applications, such as smart homes, healthcare, environmental monitoring, smart cities, and industrial automation (Gandotra & Jha, 2017). However, these devices are typically powered by compact batteries with limited energy storage and lifetime. Frequent battery replacement is costly and inconvenient (Jing et al., 2017). This issue is further exacerbated by the massive scale of IoT networks spanning large geographic areas.

Wireless Power Transfer (WPT) has emerged as a promising solution to energetically replenish IoT devices over-the-air

(Zewde & Gursoy, 2018). WPT techniques allow wireless charging of devices by leveraging radio frequency (RF) signals. However, effective utilization of the wirelessly transferred energy is contingent on strategically allocating communication resources like transmission power, time slots, spectrum, and antennas (Wang, Lin, et al., 2021). With exploding energy costs and carbon footprints of Information and Communication Technology (ICT) systems, energy-efficient resource management has become critical (Mao et al., 2016). Optimizing the allocation of resources can help maximize key performance metrics like Energy Efficiency (EE), network lifetime, throughput, and fairness (Krikidis et al., 2014). Various optimization frameworks leveraging tools like non-linear programming, convex optimization, and cooperative games have been applied to solve these challenging problems (Chang et al., 2019;

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Ding et al., 2014; P. Liu et al., 2019). Both perfect and imperfect Channel State Information (CSI) scenarios have been investigated. However, many open challenges remain, such as handling massive network scales, integration with practical traffic patterns and Energy Harvesting (EH) models, distributed solutions, and standardization of models and metrics. In this comprehensive survey, the state-of-the-art in energy-efficient resource allocation for WPT-based IoT networks is reviewed. The necessary background on WPT techniques, architectures, IoT network paradigms, resource allocation fundamentals, and key performance metrics is provided. Commonly used analytical models for EE, EH, and consumption are then presented. Resource management solutions under both perfect and imperfect CSI conditions are surveyed and compared. Finally, open issues are highlighted, and directions for future

research are suggested. This paper aims to provide a consolidated overview of scalable and efficient resource allocation techniques to unlock the potential of WPT for sustainable and perpetual operation of IoT networks.

### OVERVIEW OF WPT TECHNIQUES

The various techniques used for WPT can be broadly classified into radiative and non-radiative methods as shown in Figure 1. (Ponnimbaduge Perera et al., 2018). Non-radiative or near-field techniques like magnetic resonant coupling require the receiver to be in close proximity of the energy transmitter. On the other hand, radiative or far-field techniques can power devices remotely over longer distances using electromagnetic waves in RF bands. Radiative WPT is better suited for IoT networks due to the distributed nature of devices (Barman et al., 2015).

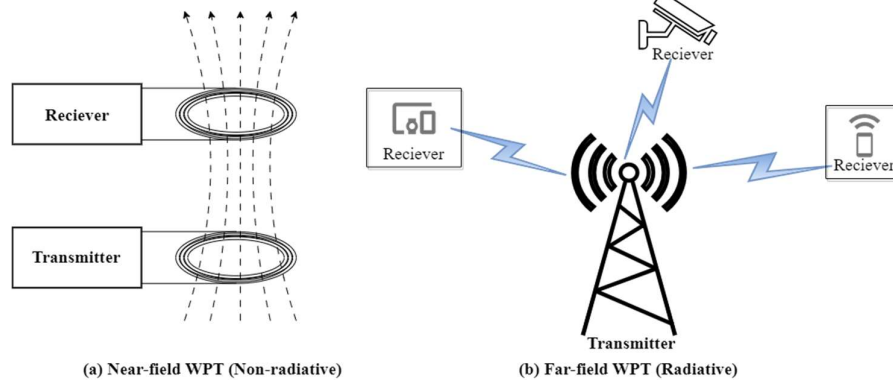


Figure 1: Wireless Power Transfer Techniques

Two main radiative WPT approaches are microwave radiation and RF radiation (Zeng et al., 2017). Microwave radiation uses higher frequency bands (2.4-5.8 GHz) and requires directive antennas for long-range power transfer. RF radiation operates in lower bands like HF, VHF, and UHF for omni-directional power transfer to nearby devices. RF radiation is more suitable for IoT systems with low power requirements compared to microwave radiation. Based on omni-directional or focused propagation, WPT techniques can be categorized as near omni-directional powering and focused beamforming (Ponnimbaduge Perera et al., 2018). Focused beamforming allows directional power transfer to intended users but requires accurate beam alignment.

### WPT Architectures for IoT

The integration of WPT with IoT networks has enabled several architectures (Baroudi, 2019; Bi et al., 2016). In Wireless Powered Communication Networks (WPCN) (K. Zheng et al., 2021), devices first harvest RF energy from Hybrid Access Points (HAPs) and then use that harvested energy for data transmission. These HAPs are equipped with antennae to generate RF signals in specific bands. They may also employ multiple antennas to perform energy beamforming to focus signals toward target devices (G. Yang et al., 2015). In WPT-enabled cellular IoT architecture (Z. Yang et al., 2018), Cellular networks like LTE and the upcoming 5G readily provide wide-area connectivity for IoT. These

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cellular Base Stations (BSs) can also provide wireless charging capability to provide RF energy to IoT devices in their coverage area (Huang & Lau, 2014). Others may employ the use of dedicated Access Points (APs) or Power Beacons (PBs) deployed in IoT environments solely to provide wireless charging to devices, (Wu et al., 2019). The long-range BSs act as hubs to collect data from devices scattered across large geographies. Licensed cellular spectrum ensures reliability and security. The BSs can also be equipped with wireless charging capabilities to periodically replenish device batteries (Huang & Lau, 2014).

In Peer-to-Peer (P2P) architectures such as Device-To-Device (D2D) networks, IoT devices directly cooperatively charge each other (Krikidis, 2014). Devices take turns acting as energy transmitters and energy receivers based on their current energy reserves and demands. IoT devices communicate directly with each other without going through any fixed infrastructure (Clerckx et al., 2019) The devices self-organize based on proximity and form ad hoc connections for localized services. This enables features like content sharing, distributed coordination, and P2P wireless charging between devices. D2D networks are highly flexible and avoid single points of failure. However, frequent topology changes make resource allocation challenging (Doppler et al., 2009). Communications are also limited to short ranges within personal area networks or neighbourhood area networks. Longer-range access to the cloud would require additional gateways. Wireless Sensor Networks (WSNs) interconnect a large number of spatially distributed sensor nodes using multi-hop mesh networking (K. Zheng et al., 2021). Such WSN devices can also opportunistically scavenge ambient RF signals from TV, radio, cellular and Wi-Fi networks to power themselves (Krikidis et al., 2014).

Satellite connectivity provides an alternative way to network remotely located IoT devices, especially in rural and remote areas (Routray & Hussein, 2018). Long-range IoT services can be delivered through communication satellite links. Low-earth orbit satellites also hold promise for achieving global IoT coverage. Since satellite coverage is from the sky, WPT takes the form of unidirectional downlink charging from the sky to ground

devices (Routray & Hussein, 2018). However, satellite bandwidth is limited. Channel dynamics due to mobility also pose challenges. A heterogeneous mix of IoT networking paradigms can coexist based on the geographic scale, connectivity range and wireless charging needs.

## RESOURCE ALLOCATION FUNDAMENTALS

Optimizing the allocation of communication resources is crucial for improving the EE of WPT-enabled IoT networks. The main resources allocated include (Chang et al., 2019; Krikidis et al., 2014):

- i. **Transmission Power** - Transmission power control involves optimizing the amount of RF energy used for wireless charging as well as data transmission (Park & Clerckx, 2014). Higher transmit power increases received signal strength, resulting in more harvested energy and better link capacity. However, RF energy rapidly decays with distance due to path loss. Increasing power also boosts interference and energy consumption (Wang, Lin, et al., 2021). Algorithms are needed to balance these trade-offs for maximum EE across the network.
- ii. **Time Slots** - Time slot allocation divides the timeline into intervals for wireless charging and data communication (Hameed et al., 2021). Dedicated time slots for energy transfer also referred to as harvest-then-transmit time slots avoid interference between charging signals and data transmissions. The duration of each slot can be optimized based on traffic loads and energy demands (Luo et al., 2013). SWIPT maximizes the usage of the available spectrum c. But sufficient time slots for charging must be ensured for battery replenishment.
- iii. **Spectrum** - Efficient allocation of frequency channels or bandwidth between WPT and communication links is necessary to avoid interference (Clerckx et al., 2019). Dedicated bands can be assigned for wireless charging. The remaining

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spectrum can be divided between IoT device access links and cellular/backhaul connections. Contention-based protocols or orthogonal slicing like Orthogonal Frequency Division Multiple Access (OFDMA) manage spectrum sharing. Cognitive Radio (CR) techniques also enable opportunistic spectrum utilization by sensing ambient transmissions.

- iv. **Antenna** - By leveraging antenna arrays and beamforming, the RF signals for WPT can be more precisely steered toward target devices (Hameed et al., 2021). This maximizes received signal intensity for efficient wireless charging. Exploiting the spatial dimension also reduces interference and enhances network capacity. Massive Multiple-Input Multiple-Output (MIMO) configurations with large antenna scales further improve spatial focusing.

#### Key Performance Metrics and Mathematical Models

Major metrics for evaluating and comparing resource allocation algorithms include (Jing et al., 2017; Ramezani & Jamalipour, 2017):

- i. **Energy Efficiency**: Given by the number of information bits successfully transmitted per unit of energy consumed across the network. Measured in bits/joules.
- ii. **Network Lifetime**: The total time duration a WPT-based IoT network can remain operational before nodes deplete their batteries.
- iii. **Throughput**: The end-to-end data rate (bits/second) considering all communication links in the IoT network.
- iv. **Fairness**: Comparative energy charging or data transmission performance achieved between individual nodes.

#### Energy Efficiency Metrics and Models

Mathematical modelling helps formulate resource allocation problems to optimize WPT-based IoT network performance.

Accurate modelling of the EH process is important to ensure the predicted throughput and power consumption match real-world measurements.

#### A. Definitions of Energy Efficiency Metrics

For a WPT-based IoT network with  $N$  nodes, the total EE is given by Equation (1) (Wu et al., 2016):

$$EE_N = \left( \frac{\sum_{n_i=1} R_i}{\sum_{n_i=1} P_i} \right) \quad (1)$$

Where  $R_i$  is the data throughput (bps) of node  $i$ , and  $P_i$  is the power consumption (Watts) of node  $i$ .

The throughput  $R_i$  depends on channel conditions, resource allocation, and interference. It is typically modelled using Shannon's capacity formula (Buzzi et al., 2016) as shown in Equation (2):

$$R_i = B \log_2 (1 + SINR_i) \dots (2)$$

Where  $B$  is the allocated bandwidth (Hz) for node  $i$ , and  $SINR_i$  is the signal-to-interference-plus-noise ratio given by Equation (3) (Xiang et al., 2014):

$$SINR_i = \frac{P_i}{(\sigma^2 + I_i)} \dots (3)$$

Here  $P_i$  is the transmit power of node  $i$ ,  $\sigma^2$  is the noise power, and  $I_i$  is the interference.

#### B. Energy Harvesting Models

Energy harvesting refers to the conversion of ambient RF signals into usable electrical energy for powering devices (Ulukus et al., 2015). Key energy harvesting models include:

- i. **Linear energy harvesting model**: The output DC power  $P_{DC}$  is linearly proportional to the input RF power  $P_{RF}$  as shown in Equation (4) (Zeng et al., 2017):

$$P_{DC} = \eta P_{RF} \dots (4)$$

Where  $\eta$  is the energy conversion efficiency. This model holds when the input RF power is relatively low.

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- ii. Non-Linear Energy Harvesting (NEH) models: At higher input power levels, the conversion efficiency becomes non-linear and starts saturating (Wei et al., 2022). Two common non-linear models are shown in Equation (5) and (6):
- iii. Sigmoid model (Clerckx et al., 2019):

$$P_{DC} = \frac{P_{\max}}{(1 + e^{-(aP_{RF} + b)})} \dots(5)$$

Where  $P_{\max}$  is the maximum harvestable DC power, and a, b are curve-fitting parameters.

- iv. Logistic model (Wang, Lv, et al., 2021):

$$P_{DC} = c_1 \tanh(c_2 P_{RF}) \dots(6)$$

Where  $c_1$  and  $c_2$  are constants obtained through curve fitting.

### C. Energy Consumption Models

The sources of power expenditure in wireless nodes include (P. Liu et al., 2019):

- i. Transmission power: Consumed by power amplifiers, RF antennas, and associated circuitry during data transmission and WPT.
- ii. Signal processing power: Dissipated in carrying out digital and analog signal processing operations like coding, decoding, modulation, synchronization, channel estimation etc.
- iii. Circuit power: Consumed by electronic components like mixers, filters, analog-to-digital converters, phase-locked loops etc. This fixed power is drawn regardless of transmission activity.
- iv.

### D. Trade-offs between Energy Efficiency and Other Metrics

A holistic approach is required that seeks to maximize EE subject to certain constraints on throughput, latency, and fairness based on Quality-of-Service (QoS) needs. While improving EE is important, it often requires balancing trade-offs with other performance metrics (K. Zheng et al., 2021).

- i. Throughput Trade-off:

Higher data rates require transmitting at higher power levels, which reduces EE. For a given power budget, solely maximizing throughput causes the energy consumed per bit to increase, deteriorating the bits/Joule metric (L. Dai et al., 2019; Zhou et al., 2013). This requires joint optimization of rate and power using appropriate constraints and utility functions.

- ii. Latency Trade-off:

To lower latency in wireless networks, transmission powers must be increased to enable quicker encoding/decoding and reduce retransmissions. However, higher transmit power directly reduces EE. Techniques like cooperative relaying can potentially improve both latency and efficiency (Shi et al., 2014). But in general, a trade-off exists between minimizing latency and maximizing EE.

- iii. Fairness Trade-off:

Energy efficiency metrics like network lifetime consider the overall system performance. However, optimizing system-wide efficiency often starves individual nodes and links. Improving fairness in terms of throughput, charging time or battery level requires deviating from the network-centric optimal operating point (Clerckx et al., 2019). This deteriorates the aggregate utilization of resources.

### Resource Allocation with Perfect CSI

With perfect CSI, the channel-state information is assumed to be known accurately without estimation errors or quantification noise. Research on optimizing resource allocation under this idealized assumption includes:

### A. Power Allocation Algorithms

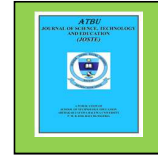
Transmit power allocation is one of the most critical resources that impacts EE. With perfect knowledge of channel gains, optimal power control policies can be derived to maximize EE. In (P. Liu et al., 2019), the authors designed an energy-efficient power allocation method for mmWave beam-space MIMO-NOMA systems, where there may be multiple users in each selected beam. First, according to the Beam Selection results, the work got the precoding matrix through Zero-Forcing (ZF) beamforming method. Second, the work formulated the EE maximization optimization problem as a fractional programming problem.

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Through sequential Convex Approximation (SCA) and Second-Order Cone (SOC) transformation, the original optimization problem was transformed to a convex optimization problem. By using iterative optimization algorithm, the power allocation results were achieved. The work in (B. Liu et al., 2019) proposed a framework for energy-efficient cooperation in Mobile Edge Computing (MEC)-enabled CR networks. The framework integrates MEC, CR, and WPT technologies to optimize the EE of wireless devices. Cooperative relaying was used to obtain spectrum for offloading, and optimization problems were formulated to maximize the practical EE in both partial offloading and local computing scenarios. A two-phase method was proposed to handle the non-convex problems, and semi-closed-form solutions were obtained.

An energy-efficient power allocation and splitting algorithm for mmWave beam space MIMO-NOMA with SWIPT was designed in (Chen et al., 2021). The work, studied the integration of SWIPT in mmWave beam space MIMO-NOMA system. To improve the EE while guaranteeing the minimum rate and harvested energy requirements at each IoT node, the EE maximization via power allocation at the BS and power splitting at each IoT node is analysed. The joint optimization problem was non-convex and intractable due to the presence of intra-beam and inter-beam interference. To tackle it, the work employed a two-layer iterative algorithm by leveraging Dinkelbach method and Alternating Optimization (AO) framework. These works demonstrate that with perfect CSI, global optimal power control policies can be derived by converting the non-convex problems into tractable convex forms using tools like fractional programming and successive convex approximation. Power allocation provides direct control over energy transfer and consumption. But optimal allocation is challenging with interference and non-linear harvesting efficiency (Zewde & Gursoy, 2018).

## B. Joint Time and Power Allocation

Alongside optimizing transmit power, the time slots for WPT and Wireless Information Transfer (WIT) can also be adapted to improve EE in IoT networks. For a WPCN, work in (Wu et al., 2016), jointly optimized the power control and time allocation. The goal was to investigate

the maximum achievable EE of the network while taking into account the initial battery energy of each user. The authors first studied the EE maximization problem in the WPCN without any system throughput requirement and showed that the EE maximization problem for the WPCN can be cast into EE maximization problems for two simplified networks via exploiting its special structure. For each problem, the authors derived the optimal solution and provided the corresponding physical interpretation, despite the non-convexity of the problems. Exploiting fractional programming theory, the resulting non-convex problem was transformed into a standard convex optimization problem. Finally, the optimal solution structure was characterized to derive an efficient iterative algorithm for obtaining the optimal solution. (Z. Yang et al., 2018) explored optimal strategies for minimizing energy consumption in a cellular network with NEH, using both NOMA and Time Division Multiple Access (TDMA) via joint power control and time-allocation. They considered the receiver sensitivity, on which energy conversion starts beyond a threshold, and explicitly take into account the circuit energy consumption of both machine type communication devices (MTCDs) and machine type communication gateways (MTCGs).

The work in (Pu et al., 2020) presented an energy efficient resource allocation algorithm for massive MIMO systems powered by WPT with proportional fairness. In the system, multiple Sensor Nodes (SNs) harvest energy from the PB by WPT, and then the SNs communicate with the BS by exploiting the harvested energy. A proportional fair energy efficient resource allocation algorithm that combines time and power allocation was proposed to maximize the EE. Compared with the minimum EE maximization algorithm and the total user's EE maximization algorithm, simulation results showed that the proposed algorithm can obtain a good trade-off between the total EE of the system and minimum EE of the users. The authors assumed perfect CSI and did not consider interference. The measured outcomes were system EE and total user's EE. The time slot duration assignment needs to balance energy harvesting and data transmission phases. Joint time and power allocation improves flexibility but introduces

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coupling constraints. Optimal schedules under causality constraints are NP-hard.

### C. Joint Spectrum and Power Allocation

Efficient allocation of frequency channels or bandwidth alongside optimizing transmit power is also essential for improving EE. A joint subchannel and power allocation optimization was investigated in (H. Dai et al., 2017) for D2D communication with WPT in a cellular network. The objective was to maximize weighted EE by leveraging a game theoretic approach. They first proved that an exact potential game applies to the resource allocation problem and there exists the best Nash equilibrium (NE) which is the optimal solution of the optimisation problem. Then, aiming to the optimisation problem, a robust and distributed learning algorithm was proposed and proven that it can converge to the best NE. For a SWIPT network, the work in (Zhou et al., 2013) the authors investigated the design of joint subchannel and power allocation in downlink OFDM systems. The authors derived an optimal solution for TDMA and OFDMA information transmission with power splitting applied at each receiver. They provided insights into the trade-offs between harvested EE, achievable rate and peak and/or total transmission power constraint. It was shown that time-switching outperforms power-switching when both the minimum harvested energy and achievable rate are sufficiently large. Joint adaptation of time, spectrum and power dimensions enabled by perfect CSI helps unlock substantial performance gains in wireless powered networks. Spectrum allocation avoids interference but limits frequency reuse. Cognitive sharing holds promise but requires sensing overhead (Yin et al., 2015).

### D. Energy Efficient Beamforming

Leveraging multiple antennas for spatial beamforming and signal focusing is another important technique for improving the EE of wireless powered networks. The work in (Wang, Lv, et al., 2021) investigated energy-efficient resource allocation problem in massive MIMO-NOMA networks with practical NEH. A joint power, time and antenna selection allocation scheme under the NEH model was designed. An EE maximization problem was

formulated to effectively determine the optimal resource allocation strategies. As the formulated problem was non-trivial, non-linear fraction programming method was applied to convert the problem into a convex optimization problem, and then it was solved by Lagrange dual decomposition approach. Simulation results demonstrated that the effectiveness of the proposed solution is acceptable. In (Chu et al., 2018), the authors studied the use of Wireless Powered Sensor Networks (WPSN) in IoT systems with goal is to maximize the system EE and sum throughput of the sensor network, and the paper proposed solutions for two different scenarios: For the first scenario, the paper proposed a global optimal solution to jointly design the energy beamforming and time allocation. For the second scenario, the paper exploited the hierarchical energy interaction between the power station and the sensor network, which is known as energy trading, and proposed a quadratic energy trading based Stackelberg game, linear energy trading based Stackelberg game, and social welfare scheme.

A Rate-Energy (R-E) trade-off beamforming algorithm was proposed in (Zhang & Ho, 2013) for a MISO SWIPT system. The study examined two scenarios: one with separated receivers and another with co-located receivers. For the case of separated receivers, the paper derived the optimal transmission strategy to achieve different trade-offs for maximal information rate versus energy transfer, which are characterized by the boundary of a so-called R-E region. For the case of co-located receivers, the paper showed an outer bound for the achievable R-E region due to the potential limitation that practical EH receivers are not yet able to decode information directly. Under this constraint, the paper investigated two practical designs for the co-located receiver case, namely time switching and power splitting, and characterized their achievable R-E regions in comparison to the outer bound. Energy-focused beamforming designs enabled by perfect CSI and multiple antennas help improve the RF charging efficiency, reduce interference, and enhance energy-efficient operation. Beamforming improves efficiency but requires accurate CSI. Hybrid analog/digital architectures help reduce feedback overhead.

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### E. Optimization Techniques

The resource allocation problems aimed at maximizing EE are typically non-convex due to the fractional objective functions and non-linear coupling between numerators and denominators. However, with perfect CSI, various optimization techniques can be leveraged to transform these challenging problems into tractable convex forms.

#### i. Game Theory:

Game theory enables distributed solutions where wireless links compete with each other and converge to an equilibrium maximizing individual utility across efficiency and throughput (Chu et al., 2018; H. Dai et al., 2017; Ding et al., 2014).

#### ii. Successive Convex Approximation:

The original non-convex problem is iteratively approximated as a convex program at each step. This yields locally optimal resource allocation policies (Chen et al., 2021; P. Liu et al., 2019).

#### iii. Alternating Optimization:

Here the optimization variables are divided into separate groups optimized alternately. It converges to a stationary point satisfying the Karush-Kuhn-Tucker (KKT) optimality conditions (Chen et al., 2021).

#### iv. Lagrange Dual Decomposition:

Lagrange dual decomposition works by decomposing a large optimization problem into smaller sub-problems that are easier to solve. The basic idea is to introduce Lagrange multipliers for the constraints in the original problem and solve sequentially (Wang, Lv, et al., 2021). The above techniques successfully exploit the perfect CSI assumption to transform the EE maximization problems into equivalent or approximate convex forms solvable by efficient algorithms. It is noteworthy that joint optimization across multiple domains improves EE in WPT based IoT networks at the cost of higher complexity. We next survey resource allocation under imperfect CSI.

### V. Resource Allocation with Imperfect CSI

- i. The prior section assumed perfect knowledge of the CSI at the transmitters. However, in practical IoT networks, various factors introduce CSI imperfections (Prasad et al., 2017):

#### A. Impact of Imperfect CSI

In practical wireless powered IoT networks, various factors such as inaccurate channel estimation, time-varying channel, delay, quantization error, and feedback error lead to imperfections in the CSI available at the transmitters (H. Dai et al., 2017):

- i. Channel estimation errors: The channel sensing process introduces noise and interference which degrades the accuracy of estimated CSI. Limited sensing duration also causes errors.
- ii. Quantization errors: The estimated CSI needs to be quantized before being fed back to the transmitter. This finite precision quantization leads to errors.
- iii. Feedback delay: In mobile networks, the CSI variations between channel sensing and data transmission due to mobility or environmental changes lead to outdated CSI.
- iv. Channel aging: The coherence time of the channel limits the duration over which the estimated CSI remains relevant. Time-varying channels cause aging.

These CSI imperfections lead to a mismatch between the actual channel gains during transmission and the estimated channel gains used for resource allocation optimizations. This reduces the achieved throughput, EE, and overall network performance compared to the perfect CSI case.

#### B. Robust Resource Allocation Algorithms

To account for the impact of imperfect CSI, robust optimization techniques can be leveraged for energy-efficient resource allocation. Stochastic optimization methods model the CSI uncertainty stochastically based on its statistical distribution. Lyapunov optimization and Markov modelling are applied to maximize expected performance (Abubakar

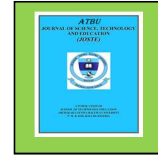
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*et al.*, 2022). Lyapunov optimization technique, does not require the statistical knowledge of the channel and energy (Xu et al., 2017). A dynamic computation offloading strategy for energy-efficient MEC systems powered by renewable energy sources via EH technologies was proposed in (Mao et al., 2016). The paper formulated the Execution Cost Minimization (ECM) problem and proposes a low-complexity online Lyapunov Optimization-Based Dynamic Computation Offloading (LODCO) algorithm that jointly decides the offloading decision, the CPU-cycle frequencies for mobile execution, and the transmit power for computation offloading. In (Kim et al., 2020), the authors proposed a novel waveform scheduling algorithm for a MISO WPT system. The authors formulated a stochastic optimization problem that maximizes the average of the sum of output DC voltages of receivers while satisfying the minimum average output DC voltage requirements of all receivers. They developed a low-complexity approximated algorithm to solve this non-convex optimization problem. The proposed algorithm outperforms existing algorithms in terms of the weighted-sum of the output DC voltages.

Learning-based techniques can directly learn efficient resource allocation policies from data. Deep-Q learning was applied in (Li et al., 2020) for Wireless Powered IoT networks assisted by Unmanned Aerial Vehicles (UAVs). The paper formulated the resource management problem as a Markov Decision Process (MDP) and presented a new deep Q-learning based resource management (DQL-RM) scheme to derive the optimal resource management strategy in UAV-assisted Wireless Powered IoT networks.

Robust beamforming techniques optimize precoder and combiner matrices to minimize interference under CSI errors. In (Ansere et al., 2020), the authors investigated resource allocation in energy-efficient IoT networks with imperfect CSI. The authors proposed a novel optimization model that jointly optimizes user selection, power allocation, and the number of activated BS antennas to maximize EE while guaranteeing quality of service requirements. (Boshkovska et al., 2017) proposed a joint time allocation and power control scheme for MIMO-WPCNs that takes into account uncertainty regarding CSI and

provides robustness against imperfect CSI knowledge. The proposed scheme exploits multiuser diversity and provides a substantial performance gain compared to baseline schemes. The paper also investigated the non-trivial trade-off between sum throughput and resource allocation fairness for wireless power users. Simulation results showed that the proposed scheme outperforms benchmark schemes based on NEH models and imperfect CSI knowledge. In (Wang, Lin, et al., 2021), authors develop an Energy-Efficient Resource Allocation Scheme in massive MIMO-NOMA networks with WPT using a distributed alternating direction method of multipliers (ADMM) approach. The authors proposed a joint power, time, antenna selection, and subcarrier allocation scheme for perfect and imperfect CSI under QoS requirements. Non-linear fraction programming method is used to convert the problem to be convex then a distributed ADMM-based approach is employed to solve the problem. Robust designs provide resilience but often require higher complexity and feedback overhead.

## VI. Open Challenges and Future Directions

While existing literature has provided valuable insights into resource allocation for improving energy efficiency, several key challenges remain open:

### A. Distributed Solutions

Most existing works have focused on centralized algorithms for resource allocation where a central controller has global network knowledge. However, centralized approaches do not scale well to large networks with thousands of distributed IoT devices (Hameed et al., 2021). More future research needs to develop distributed and localized solutions where resource allocation decisions are made at individual nodes based on local CSI and limited message passing. For example, game theory and pricing mechanisms could incentivize devices to optimize their own utility while improving overall system efficiency. Hierarchical solutions could also decompose the network into smaller regions for distributed optimization (Chu et al., 2018). A key challenge lies in balancing optimality with signalling overhead.

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### B. Wireless Charging Congestion

In dense IoT deployments, many devices may contend for wireless charging from the same set of limited PBs leading to severe congestion issues (Pu et al., 2020). For example, devices closer to the charger may hog energy, starving more distant nodes. This requires solutions to balance efficiency with fairness during such charging congestion (Faisal et al., 2019). Potential approaches include scheduling based on charging priority, backoff mechanisms similar to Carrier Sense Multiple Access (CSMA) and pricing methods to discourage energy hogging (Ding et al., 2014). However, distributed coordination is difficult, especially when devices have limited energy to communicate their charging needs. AI/Machine Learning techniques could help match supply with urgent charging demands (Li et al., 2020).

### C. Network Lifetime Optimization

While existing works focus on EE, optimizing the operational network lifetime is equally important for self-sustainable WPT networks. New performance metrics that combine efficiency and perpetual operation merits research. This could build on works that maximize the minimum battery level across nodes (Chen et al., 2021). Lifetime also needs to be jointly optimized alongside metrics like throughput and latency based on application needs.

### D. Practical Energy Harvesting Models

Most prior literature assumes simplistic linear EH models that are agnostic to the underlying RF-to-DC conversion circuitry (Marshall et al., 2019). However, practical non-linear models and implementations exhibit more complex behaviours like saturation and sensitivity thresholds (Niyato et al., 2017). Integrating such practical non-linear models based on simulation and experiments will lead to more accurate system performance analysis. Coping with hardware imperfections is also crucial.

### E. Standardization

Currently, there is a lack of universally standardized models and performance metrics for WPT-based networks. Each work uses custom definitions suited to their specific context and assumptions. Developing unified frameworks on modelling, metrics like efficiency, and validation testbeds will enable better experimental analysis and rapid comparative assessment of new techniques. Efforts towards standardization and harmonization of terminology, models and benchmarks merits dedicated investigation.

These challenges and future directions are summarized in Table 1.

**Table 1:** Summary of challenges and future directions.

Challenges	Directions	Description
<b>A. Distributed Solutions</b>	Develop Distributed and Localized Solutions	<ul style="list-style-type: none"> <li>Existing works have primarily focused on centralized algorithms for resource allocation.</li> <li>Future research should concentrate on developing distributed and localized solutions.</li> <li>Techniques like game theory and pricing mechanisms can be employed to encourage devices to optimize their utility while enhancing overall system efficiency.</li> <li>Hierarchical solutions that segment the network into smaller regions can also be explored.</li> </ul>

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<p><b>B. Wireless Charging Congestion</b></p>	<p>Balance Efficiency and Fairness in Charging Congestion</p>	<ul style="list-style-type: none"> <li>• Wireless charging congestion can arise when multiple devices vie for charging resources from a limited power budget (PBs).</li> <li>• Solutions that strike a balance between efficiency and fairness during charging congestion are needed to address the issue.</li> <li>• Approaches such as priority-based scheduling, backoff mechanisms similar to Carrier Sense Multiple Access (CSMA), and pricing methods to discourage energy hogging are potential solutions.</li> <li>• Achieving distributed coordination, especially when devices have limited energy for communication, poses challenges.</li> <li>• Techniques from AI/Machine Learning could potentially aid in matching supply with urgent charging demands.</li> </ul>
<p><b>C. Network Lifetime Optimization</b></p>	<p>Explore Metrics and Joint Optimization for Network Lifetime</p>	<ul style="list-style-type: none"> <li>• Optimizing the operational network lifetime is crucial for sustainable Wireless Power Transfer (WPT) networks.</li> <li>• Research efforts should be directed towards defining and combining performance metrics that account for both efficiency and perpetual operation.</li> <li>• Approaches that maximize the minimum battery level across nodes, as well as joint optimization of lifetime with other metrics like throughput and latency based on application requirements, merit investigation.</li> </ul>
<p><b>D. Practical Energy Harvesting Models</b></p>	<p>Integrate Practical Non-Linear Models for Energy Harvesting</p>	<ul style="list-style-type: none"> <li>• Many prior works have relied on simplistic linear energy harvesting (EH) models that do not capture the complexities of real-world systems.</li> <li>• Research should focus on integrating practical non-linear EH models that consider behaviors like saturation and sensitivity thresholds.</li> <li>• These models, based on simulations and experiments, can lead to more accurate performance analyses.</li> <li>• Additionally, addressing the challenges posed by hardware imperfections is vital for realistic modeling.</li> </ul>
<p><b>E. Standardization</b></p>	<p>Establish Universally Standardized Models and Metrics</p>	<ul style="list-style-type: none"> <li>• Currently, the absence of universally standardized models and performance metrics for WPT-based networks hinders comparability and consistency across works.</li> <li>• Efforts should be dedicated to developing unified frameworks that cover modeling, efficiency metrics, and validation testbeds.</li> <li>• Standardization would enable better experimental analyses and allow for rapid comparative assessment of new techniques. The standardization of terminology, models, and benchmarks is essential to advance the field cohesively.</li> </ul>

**CONCLUSIONS**

In this comprehensive survey, we provided an overview of the state-of-the-art in energy-efficient resource allocation for WPT-

enabled IoT networks. EE is critical to address the massive scale of IoT devices with limited energy reserves. Effective use of transferred wireless power can significantly enhance

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network lifetime and reduce maintenance overhead.

We first provided necessary background on WPT techniques, IoT network architectures, resource allocation techniques, and performance metrics for IoT networks. We then presented commonly used analytical models relating resources to the EE metric in bits/Joule. Next, we reviewed joint resource allocation optimizations under both perfect and imperfect CSI knowledge. Convex approximation, non-linear programming, game theory and stochastic control are among the techniques leveraged to solve these challenging problems.

While existing literature has provided valuable foundational work, we also highlighted key open challenges and future directions. Developing distributed solutions, handling wireless charging congestion, optimizing network lifetime, incorporating practical traffic and EH models, and investigating security are important areas needing further research. Cross-layer optimization and integration of machine learning tools is also essential to achieve intelligent, robust and scalable solutions.

In conclusion, energy-efficient resource management will play a pivotal role in sustainable deployment of perpetual WPT-based IoT networks spanning massive scales, especially for remote and inaccessible environments. As an emerging research area, it offers rich opportunities for impactful contributions through rigorous analytical modelling, protocol design, and experimental validations tailored for this emerging IoT paradigm. We hope that this survey provides useful insights and directions to stimulate further research in this important area.

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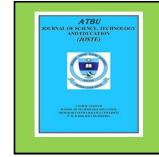
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