OPTIMIZATION STRATEGIES FOR NODE SELECTION AND ENERGY ALLOCATION IN WPTN

Huajun CHEN[1], Lina YUAN[2*], Haolin WANG[3], Jing GONG[4]

With the rapid development of Internet of Things (IoT) technology, wireless power networks have become key to supporting their continuous operation. This paper delves into the energy collection process of wireless powered transfer network (WPTN), with a particular focus on the impact of nonlinear energy collection models on network performance. Studies indicate that nonlinear models more accurately reflect the complexity of energy conversion in the real world but also pose challenges to network stability and efficiency. In response to these challenges, a novel node selection mechanism algorithm is proposed. This algorithm comprehensively considers various practical constraints such as user location, energy demand, and communication distance. By establishing an optimization model and employing heuristic search strategies, it effectively selects the optimal set of nodes to achieve the optimization of energy collection and data transmission. Furthermore, this paper explores how to maximize the overall system energy efficiency while ensuring fairness among users. By designing reasonable energy allocation strategies and optimization algorithms, it achieves a balanced satisfaction of user energy demands and the maximization of network energy efficiency. MATLAB tools were also utilized for simulation analysis, and the results verified the effectiveness and superiority of the proposed algorithms under different scenarios. Overall, this research provides a theoretical foundation and practical guidance for node selection and energy allocation in WPTN, which is of significant importance for promoting the sustainable development of IoT technology.

Keywords: WPTN; Energy Collection; Node Selection; Energy Allocation; Optimization Strategies; MATLAB Simulation

1. Introduction

With the rapid proliferation of Internet of Things (IoT) technology, hundreds of millions of devices have been deployed across various sectors, ranging from small-scale smart homes to vast industrial monitoring systems. The majority of these devices rely on battery power, and the frequent replacement of batteries is not only costly but also burdensome to the environment [1-2]. Wireless Powered

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Transfer Network (WPTN), as an emerging technology, offers the potential to wirelessly supply energy to these devices, demonstrating significant application prospects [3-4]. The core of WPTN lies in the efficiency and reliability of energy collection. The energy collection process typically involves capturing energy from the environment, such as solar, wind, and vibrational energy, and then converting it into electrical energy for device use through energy converters. However, energy collection in actual environments is nonlinear and influenced by various factors, such as changes in environmental conditions and the efficiency degradation of energy converters [5-6]. Therefore, studying the impact of nonlinear energy collection models on network performance is crucial for enhancing the stability and efficiency of the network.

Research on energy collection models can be traced back to early models of solar cells and wind turbines. As technology has advanced, researchers have begun to focus on more complex nonlinear models. For example, [7-8] theoretically examined the energy harvested from radio signals by wireless mobile nodes and proposed a practical yet feasible nonlinear energy harvesting model using stochastic geometry. [9-10] characterized the performance of nonlinear WPT using multiple RF sources and proves the joint convexity of harvested power under certain conditions and demonstrated the benefits of exploiting this convexity for cooperative WPT enhancement through an example design. In WPTN, node selection is a key step in achieving efficient energy distribution. [11-12] used clustering algorithms to optimize the node selection process, reducing communication overhead and improving network coverage. [13] theoretically examined the energy harvested from radio signals by wireless mobile nodes and proposed a practical yet feasible nonlinear energy harvesting model using stochastic geometry. [14] characterized the performance of nonlinear WPT using multiple RF sources and proves the joint convexity of harvested power under certain conditions and demonstrated the benefits of exploiting this convexity for cooperative WPT enhancement through an example design. In WPTN, node selection is a key step in achieving efficient energy distribution. In addition, [15] used clustering algorithms to optimize the node selection process, reducing communication overhead and improving network coverage. [16] featured an algorithm for selecting optimal mobile consensus nodes, enhancing node reputation and stability by 6.8% and 17.5%, while cutting message counts by 33.9%. [17] introduced a neighbor selection method based on regional proximity to speed up block propagation while minimizing the risk of eclipse attacks and present a block propagation model to explain the method's effectiveness and evaluates its migration impact on different network sizes.

Energy distribution strategies require a balance between satisfying user fairness and maximizing energy efficiency. [18] designed an auction theory-based energy distribution algorithm that achieves dynamic energy allocation through a bidding mechanism. On the other hand, [19] proposed a deep learning-based energy distribution strategy that uses neural networks to predict user energy demands, thereby achieving more precise energy distribution. Simulation is an important means of verifying the effectiveness of algorithms. MATLAB, as a powerful simulation tool, is widely used in simulation research on Wireless Energy Propagation Networks. For instance, [20] used MATLAB to simulate the proposed energy distribution algorithm, verifying its performance under different scenarios.

Despite the progress made in existing research, there are still some challenges and gaps. First, most existing studies focus on linear energy collection models, with relatively less research on nonlinear models. Second, existing node selection and energy distribution algorithms often ignore various constraints in practical applications. Furthermore, the trade-off between algorithm fairness and energy efficiency maximization is also an issue that requires further research. In response to the deficiencies in existing research, this paper analyzes the characteristics of nonlinear energy collection models and establishes corresponding mathematical models; it proposes a node selection mechanism algorithm that comprehensively considers various constraints such as user location, energy demand, and communication distance; a dynamic energy distribution strategy is designed to achieve both user fairness and the maximization of overall system energy efficiency; MATLAB is used for simulation analysis to verify the effectiveness of the proposed strategy.

The rest of this paper is organized as follows: Chapter 2 describes the system model and problem statement of the Wireless Energy Propagation Network in detail; Chapter 3 introduces the node selection and energy distribution strategy; Chapter 4 provides the results of the MATLAB simulation analysis; Chapter 5 summarizes the paper and discusses future research directions.

2. System Model and Problem Description

2.1 WPTN Model

The WPTN is designed to provide a continuous energy supply to a wide array of devices that may include sensors, actuators, or other forms of IoT devices. The architecture of the WPTN typically consists of three main components:

(1). Energy Source: The device responsible for emitting energy signals, which can be either stationary or mobile.

(2). Energy Relays: Intermediate nodes that may exist to enhance or forward energy signals.

(3). Energy Harvesting Devices: Devices that receive energy and convert it into electrical energy.

The architecture of the WPTN can adopt various topological forms, including star, ring, or mesh, depending on the application scenario and coverage area.

2.1.1 User Model and Energy Transfer Process

The user model pertains to the characteristics and behavior of energy harvesting devices. Each device $d \in D$ has the following attributes:

(1). Energy Requirement: The minimum energy needed for the device to operate normally, denoted as $E_{d_{\text{demand}}}$.

(2). Energy Harvesting Capacity: The maximum energy that the device can collect in a unit of time, expressed as $E_{d_{\text{harvest}}}$.

(3). Location: The position of the device within the network, affecting its efficiency in receiving energy.

(4). Communication Needs: The demand for the device to send and receive data.

The energy transfer process can be described by the following formulas:

$$P_{\text{rx}} = P_{\text{tx}} \cdot G_{\text{tx}} \cdot G_{\text{rx}} \cdot \lambda^2 / (4\pi d)^2 \cdot PL(d), \tag{1}$$

$$E_{\text{collected}} = \eta \cdot P_{\text{rx}} \cdot t, \tag{2}$$

$$\eta = \eta_0 \cdot (1 - e^{-\alpha \cdot P_{\text{rx}}}), \tag{3}$$

where P_{tx} is the transmission power, G_{tx} and G_{rx} are the gains of the transmitting and receiving antennas, respectively. λ is the signal wavelength, d is the distance between the transmitter and the receiver. $PL(d)$ represents the path loss as a function of distance d, modeled as $PL(d) = PL_0 \cdot \left(d/d_0\right)^{\alpha}$. Here, PL_0 is the path loss at the reference distance d_0, and α is the path loss exponent. Additionally, the wireless channel includes additive white Gaussian noise (AWGN) with power N_0, which affects the signal-to-noise ratio (SNR) at the receiver. t is the energy transfer time, η is the energy conversion efficiency at the receiver, which accounts for the efficiency of converting the received energy into electrical energy, η_0 is the maximum energy conversion efficiency, and α is the efficiency decay coefficient.

2.1.2 Network Performance Metrics

The performance of a WPTN can be evaluated through three key metrics:

(1). Energy Coverage: The proportion of the network area that receives an adequate amount of energy.

(2). Energy Efficiency: The amount of energy required by the network to transmit a unit of data.

(3). Reliability: The probability that the network successfully transmits data within a specified time frame.

2.2 Analysis of Non-linear Energy Harvesting Models

In a WPTN, the efficiency and stability of energy harvesting are crucial for ensuring network performance. Non-linear energy harvesting models take into account the complexities of the actual energy conversion process, including environmental factors, device aging, and the physical limitations of energy converters. These factors cause the energy harvesting efficiency to decrease as the input power increases, exhibiting non-linear characteristics.

2.2.1 Establishment of Non-linear Models

Non-linear energy harvesting models are typically described using piece-wise functions. The following is a typical model for non-linear energy conversion efficiency:

$$\eta(P) = \begin{cases} \alpha \cdot P & \text{if } P \le P_{\text{th}}, \\ \beta + \gamma \cdot \log(P) & \text{if } P > P_{\text{th}}, \end{cases} \tag{4}$$

here the energy conversion efficiency, denoted as $\eta(P)$, is a function of the input power P. There exists a threshold power level, denoted as P_{th}, beyond which the efficiency transitions into a non-linear region. The parameters α, β, and γ were defined as the coefficients used to characterize the non-linear energy conversion efficiency. However, to enhance the clarity and replicability of the work, we have provided more specific information regarding these parameters. The parameters α, β, and γ are determined based on the specific energy harvesting devices and environmental conditions. For instance, α represents the initial conversion efficiency at low power levels, β is the power level at which the efficiency starts to saturate, and γ describes the rate at which the efficiency approaches saturation in the high-power region. The values of these parameters can be obtained through experimental calibration or by referring to the specifications provided by the device manufacturers. Here is an example of how these parameters can be determined: For a specific type of energy harvesting device, experiments were conducted to measure the energy conversion efficiency under different input power levels. The results showed that when the input power is below 10 mW, the conversion efficiency increases linearly with a slope of 0.8 (α = 0.8). When the input power reaches 10 mW (β = 10 mW), the efficiency begins to saturate and approaches a maximum value of 0.9 with a saturation rate of 0.1 (γ = 0.1). These values can be used to model the non-linear energy conversion efficiency for this particular device.

2.2.2 Model Characteristic Analysis

The establishment of the non-linear model provides a theoretical foundation for analyzing the energy harvesting process. The following characteristics are the focus of the analysis:

1. Saturation Behavior: When the input power exceeds a certain threshold

P_{th}, the conversion efficiency no longer increases linearly but tends to saturate.

2. Efficiency Decay: As the input power increases, the conversion efficiency may decrease due to overheating or other physical factors.

3. Stochastic Fluctuations: Environmental changes and device aging may lead to random fluctuations in the energy conversion efficiency.

The non-linear energy harvesting model has a significant impact on the performance of the WPTN. Firstly, uncertainty in energy supply: the non-linear model increases the uncertainty of energy supply, posing challenges to the stability and reliability of the network. Secondly, energy allocation strategy: new algorithms need to be developed to adapt to the changes in energy harvesting efficiency and optimize energy allocation. Lastly, network design: the design of the network must consider non-linear characteristics to ensure that all devices can meet their energy demands.

2.3 Optimization Problem Definition

In the WPTN, the core of the optimization problem is to achieve effective energy allocation and reasonable node selection to meet the overall performance requirements of the network. This includes maximizing system energy efficiency, ensuring fairness among users, and meeting specific Quality of Service (QoS) requirements. This section will detail the mathematical model of the optimization problem, the objective function, constraints, and solution methods.

The goal of the optimization problem is multifaceted and requires a comprehensive consideration of three aspects. First, maximizing system energy efficiency: enhancing the network's ability to transmit data while reducing energy consumption. Second, ensuring user fairness: guaranteeing that all users receive the necessary energy supply. Third, meeting QoS requirements: allocating resources reasonably according to the service quality requirements of different users.

2.3.1 Objective Function

The objective function is the core of the optimization problem and is typically defined as:

$$\begin{aligned} &\max_{\mathbf{x}} && U(\mathbf{x}) \\ &\text{subject to} && g_i(\mathbf{x}) \le 0, \quad i = 1, 2, \ldots, m, \end{aligned} \tag{5}$$

here, $U(\mathbf{x})$ represents the system performance metrics, such as energy efficiency and fairness. $\mathbf{x}$ is the vector of decision variables, including power allocation and user selection. $g_i(\mathbf{x})$

2.3.2 Constraint Conditions

Constraint conditions reflect the practical limitations in network design, which include:

(1). Energy Supply Constraint: The energy received by each user must not exceed their energy harvesting capacity.

$$E_{\mathrm{rx},d} \le E_{\mathrm{harvest},d}, \forall d \in D. \tag{6}$$

(2). Communication Distance Constraint: The communication distance between the user and the energy source should be within the effective range.

$$d_{sd} \le d_{\max}, \forall s \in S, \forall d \in D. \tag{7}$$

(3). User Fairness Constraint: Ensure that all users can meet their basic energy requirements.

$$E_{\mathrm{rx},d} \ge E_{\mathrm{demand},d}, \forall d \in D. \tag{8}$$

(4). Total Energy Constraint: The total energy consumption of the network must not exceed the total energy supply provided by the energy source.

$$\sum_{s \in S} P_{\mathrm{tx},s} \cdot t \le E_{\mathrm{total}}. \tag{9}$$

2.3.3 Optimization Algorithms and Performance Metrics

Solving optimization problems typically requires the use of specific algorithms, which mainly fall into four categories. First, Linear Programming (LP): suitable for cases where both the objective function and constraints are linear. Second, Integer Programming (IP): used when decision variables need to be integers, such as in user selection problems. Third, Nonlinear Programming (NLP): applicable when the objective function or constraints are nonlinear. Fourth, Heuristic Algorithms: employed to obtain approximate solutions when the problem size is large or the solution is complex.

The performance of optimization algorithms is usually assessed based on three metrics: First, Convergence Speed: the number of iterations or time required for the algorithm to reach an optimal or stable solution. Second, Quality of the Solution: the degree to which the solution obtained by the algorithm approaches the global optimum. Lastly, Robustness: the performance of the algorithm in the face of model parameter changes or uncertainties.

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3. Node Selection and Energy Allocation Strategy

3.1 Node Selection Algorithm

3.1.1 Mathematical Model of the Node Selection Algorithm

The node selection problem can be formulated as an optimization issue, with the following being a basic mathematical model. Initially, an objective function is established:

$$\max_{\mathbf{S}} \quad f(\mathbf{S}) = \sum_{d \in \mathbf{S}} w_d \cdot C_d, \tag{10}$$

where the selected set of nodes is denoted as $\mathbf{S}$, w_d represents the weight of device d, which could reflect its importance or priority in the network. C_d is the energy harvesting capability of device d. The constraints are then formulated as follows:

(1). Total Energy Demand Constraint:

$$\sum_{d \in \mathbf{S}} E_{\text{demand},d} \leq E_{\text{total}}, \tag{11}$$

(2). Communication Coverage Constrain:

$$\bigcap_{d \in \mathbf{S}} \text{Coverage}_d \geq \text{Required Coverage}, \tag{12}$$

here $E_{\text{demand},d}$ is the energy demand of device d, representing the minimum energy required for the device to function properly. E_{total} is the total energy supply of the network, indicating the overall amount of energy available for distribution among the devices. Coverage_d is the communication coverage range of the device, defining the area within which the device can effectively communicate and receive energy.

3.1.2 Design and Implementation of the Node Selection Algorithm

When designing the node selection algorithm, it is necessary to adhere to four principles. First, Optimization Principle: the algorithm should seek the optimal set of nodes to maximize network performance. Second, Fairness Principle: the algorithm should ensure that all users receive the necessary energy supply. Third, Adaptability Principle: the algorithm should adapt to changes in the network environment and user demands. Fourth, Efficiency Principle: the algorithm should maintain performance while having a low computational complexity. The design of the node selection algorithm closely follows the mathematical model to address the optimization problem. Formula (13) plays a crucial role in the node scoring process. The scoring is based on the energy harvesting capability and energy demand of each user, which are key variables in our mathematical model. The linear combination in Formula (13) allows for a straightforward yet effective evaluation of each user's priority in node selection, directly linking to the objective function in Formula (10) and considering the practical constraints of the network. The steps are as follows:

(1). Demand Analysis: Collect and analyze the energy requirements of all users $E_{\text{demand},d}$.

(2). Capability Assessment: Evaluate the energy harvesting C_d and communication capabilities of each user.

(3). Node Scoring: Assign a score to each user based on their capabilities and other metrics Score_d.

$$\text{Score}_d = w_d \cdot C_d - \lambda \cdot E_{\text{demand},d}, \tag{13}$$

Among them, λ is the coefficient used to balance the energy harvesting capability and energy demand.

(4). Node Ranking: Rank users based on scores, selecting the user with the highest score.

(5). Set Construction: Construct a set of nodes according to the ranking results and check if all constraints are met.

The implementation of the node selection algorithm needs to consider three key points: First, data structure: Choose the appropriate data structure to store user information and node sets. Second, algorithm process: Clarify each step and decision point of the algorithm. Third, efficiency optimization: Optimize the algorithm process to reduce unnecessary calculations and iterations.

To evaluate the performance of the node selection algorithm, three metrics need to be considered. First, convergence speed: The time required for the algorithm to reach the optimal or stable solution. Second, solution quality: The closeness of the solution obtained by the algorithm to the global optimal solution. Third, robustness: The performance of the algorithm when facing changes in the network environment.

3.2 Energy Allocation Strategy

The energy allocation strategy is the core of ensuring the efficient operation of WPTN. Reasonable energy allocation can not only enhance the overall energy efficiency of the network but also ensure the quality of service (QoS) for users. The objective function of energy allocation typically aims to maximize the overall utility of the network while meeting the following conditions:

(1). Meet the minimum energy demand: Each user obtains at least the minimum energy required.

(2). Fairness: All users receive a relatively fair energy allocation.

(3). Maximize the total network utility: On the basis of meeting the above conditions, as much as possible to improve the total utility of the network.

3.2.1 Mathematical Model of Energy Allocation

The energy allocation problem can be formulated as the following optimization problem. First, establish the objective function:

$$\max_{\mathbf{P}} \sum_{d \in D} U_d(P_d), \tag{14}$$

in which $U_d(P_d)$ represents the utility function of device d, and P_d is the energy allocated to device d. Subsequently, the constraints are formulated as follows:

(1). Total Energy Constraint:

$$\sum_{d \in D} P_d \leq P_{\text{total}}, \tag{15}$$

(2). Minimum Energy Requirement Constraint:

$$P_d \geq P_{\min,d}, \forall d \in D, \tag{16}$$

(3). Non-negativity constraint

$$P_d \geq 0, \forall d \in D, \tag{17}$$

where P_{total} represents the total energy supply of the network, and $P_{\min,d}$ represents the minimum energy requirement of device d.

3.2.2 Dynamic Energy Allocation Algorithm

Dynamic energy allocation necessitates the real-time adjustment of the energy distribution plan to accommodate changes in the network state. A simple strategy for dynamic adjustment can be outlined as follows:

(1). Initialization: Allocate a base level of energy to each user $P_d^{(0)}$.

(2). Monitoring and Forecasting: Continuously monitor the energy harvesting status and user demands, and forecast future trends.

(3). Adjustment: Based on the forecast results, adjust the energy allocation:

$$P_d^{(t+1)} = P_d^{(t)} + \Delta P_d, \tag{18}$$

herein, ΔP_d represents the energy adjustment amount for device d during the time interval from t to $t+1$.

3.2.3 Algorithm Design and Performance Evaluation

Algorithm design should take into account three factors. First, the selection of the utility function: The utility function should reflect the preferences and demands of users for energy. Second, the optimization method: Choose an appropriate optimization method, such as the Lagrange multiplier method, convex optimization, or heuristic algorithms. Third, fairness constraints: Ensure that the algorithm takes into account fairness among users when allocating energy. Evaluating the performance of energy allocation algorithms requires considering the following metrics.

(1). Energy Efficiency:

$$\text{Energy Efficiency} = \frac{\text{Total Data Transferred}}{\text{Total Energy Consumed}}. \tag{19}$$

(2). Fairness:

$$\text{Fairness} = \frac{\sum_{d \in D} (P_d - \bar{P})^2}{D}. \tag{20}$$

here $\bar{P}$ represents the average energy allocation amount.

(3). Stability:

$$\text{Stability} = \frac{1}{T}\sum_{t=1}^{T} \text{Var}[P_d^{(t)}]. \tag{21}$$

here T is the total time period, $\text{Var}[P_d^{(t)}]$ denotes the variance in energy allocation at time t.

3.3 Algorithm Performance Analysis

Algorithm performance analysis is a critical component in assessing the effectiveness of node selection and energy allocation strategies. It not only helps us understand the performance of the algorithm under ideal conditions but also reveals the robustness and scalability of the algorithm when facing real-world network environments. When conducting algorithm performance analysis, the following metrics are crucial:

(1). Convergence Speed: The number of iterations or time required for the algorithm to reach an optimal or stable solution.

(2). Solution Quality: The closeness of the solution obtained by the algorithm to the global optimal solution.

(3). Computational Complexity: The computational resources required for the execution of the algorithm, usually related to the scale of the problem.

(4). Memory Usage: The storage space required during the execution of the algorithm.

(5). Robustness: The performance of the algorithm when facing changes in model parameters or uncertainties.

3.3.1 Theoretical Analysis

Theoretical analysis not only offers preliminary insights into the algorithm's performance but also demonstrates how the mathematical model is translated into the implemented algorithm. For instance, the convergence analysis of the node selection algorithm shows that the algorithm can efficiently reach an optimal solution by leveraging the linear relationship defined in Formula (13). This indicates that even with a linear model, the algorithm can achieve satisfactory performance in terms of convergence speed and solution quality, which is comparable to more complex AI-based algorithms but with lower computational overhead. For node selection and energy allocation algorithms, the following theoretical analyses are necessary:

(1). Convergence Analysis: Proving that the algorithm can converge to an optimal or stable solution.

(2). Complexity Analysis: Analyzing the time and space complexity of the algorithm.

(3). Sensitivity Analysis: Assessing the algorithm's sensitivity to parameter changes.

Below is an example of the algorithm's convergence speed analysis:

$$\text{Convergence Rate} = \frac{f(x^{(k)}) - f(x^{(*)})}{f(x^{(0)}) - f(x^{(*)})}, \tag{22}$$

herein, $f(x^{(k)})$ represents the objective function value at the k-th iteration, $f(x^{(*)})$ denotes the optimal objective function value, and $f(x^{(0)})$ signifies the initial objective function value.

3.3.2 Complexity Assessment

The computational complexity of an algorithm is typically represented by the Big O notation. For instance, if our algorithm includes a nested loop, its time complexity might be $O(n^2)$, where n is the number of nodes in the network. Below is an example illustrating the time complexity:

$$\text{Time Complexity} = O(n^2). \tag{23}$$

This indicates that the execution time of the algorithm grows quadratically with the increase in network size.

3.3.3 Robustness Analysis

Robustness analysis evaluates how the algorithm performs under various uncertainties. The proposed algorithm, based on the mathematical model and implemented through Formula (13), exhibits good adaptability to parameter variations. This is crucial for the practical deployment of WPTN, where environmental factors and device variations can significantly impact energy harvesting efficiency. Unlike some AI-based algorithms that may require extensive retraining under different conditions, our algorithm maintains stable performance with minimal adjustments, making it more suitable for real-time applications in dynamic network environments. This typically involves simulating various network conditions and observing the variations in algorithm performance. A measure of robustness is defined as:

$$\text{Robustness} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{f(x^{(i)})}{f(x^{(*)})} - 1\right)^2, \tag{24}$$

here N is the number of simulated scenarios, and $f(x^{(i)})$ is the performance of the algorithm in the i -th scenario.

4. Numerical Simulation Analysis

The simulations were conducted on a computer with an Intel Core i7 processor and 16GB RAM. The Matlab implementation utilizes matrix operations and built-in optimization functions to efficiently solve the problem. During the simulation, the memory usage was monitored, and it was found that the algorithm consumes approximately 500MB of RAM for the problem size of 10 users. The computation time for each simulation run is approximately 10 seconds, demonstrating the efficiency of the proposed algorithm. Before initiating a simulation, it is imperative to establish the simulation parameters and performance metrics that will guide the assessment of the network's operation. The key parameters to be defined are as follows:

(1). Simulation Duration: The total time span of the simulation is set at 100 seconds, denoted as “simulation_times=100 s”.

(2). Number of Users: The network will consist of 10 user equipments (UEs), represented by “N=10”.

(3). Base Station Power: The maximum transmittable power by the base station (BS) is capped at 1 watt, expressed as “BS_power =1 watts (W)”.

(4). Wireless Channel Model: The wireless channel is modeled with path loss $PL(d) = PL_0 \cdot (d/d_0)^{\alpha}$, where PL_0=40 dB at d_0=1 m, and α=2.5 for indoor environments.

(5). Noise Power: The noise power at the receiver is modeled as N_0 =−174 dBm/Hz, considering a bandwidth of 1 MHz.

(6). Energy Harvesting Efficiency: This parameter quantifies the efficiency with which the user equipment can harvest energy from the received power. It is modeled as a function of the received power, “eta=@(P) 0.8 * P^0.7”.

(7). Communication Distance: The spatial separation between the user equipment and the base station is determined randomly for each user, generated using the formula “distance=rand(num_users, 1)”.

The performance metrics to be evaluated encompass:

(1). Energy Consumption: This metric will track the total energy expended throughout the simulation.

(2). Throughput: This measures the rate at which data is successfully transmitted across the network.

(3). User Fairness: This ensures that network resources are equitably allocated among users.

These parameters and metrics are critical for evaluating the efficiency and effectiveness of the network under simulation. They provide a comprehensive framework for understanding the system's behavior and for making informed decisions regarding network optimization and resource management.

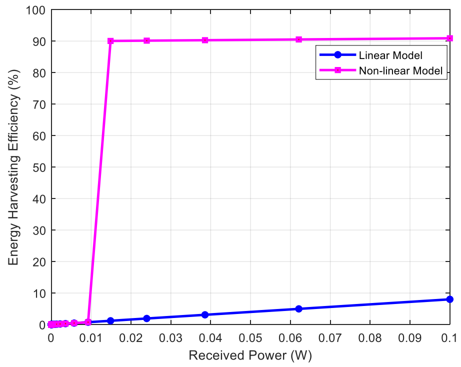

Fig. 1. Comparison of Non-linear and Linear Energy Collection Efficiency with Received Power

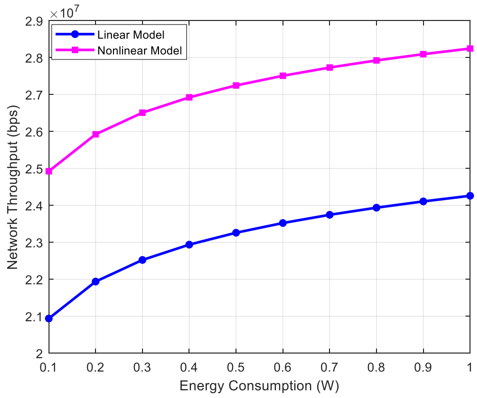

Fig. 2. Comprehensive Comparison of Energy Consumption and Network Throughput of Non-Linear and Linear Energy Harvesting Models

Fig. 1 reveals distinct characteristics of the Linear and Nonlinear energy harvesting models across different power levels. At low power levels, both models exhibit identical energy collection efficiency, which increases linearly with received power. This indicates that the nonlinear effects are negligible in this region, and both models operate similarly without significant deviations. However, as the received power increases into the high-power range, the nonlinear model demonstrates superior performance. Its energy harvesting efficiency surpasses that of the linear model and approaches a saturation point. This saturation behavior reflects the practical limitations of energy conversion in real-world devices, where efficiency cannot grow indefinitely with power. The nonlinear model's ability to maintain higher efficiency in the high-power range highlights its advantage in practical applications, as it effectively avoids the unrealistic, unbounded efficiency growth predicted by the linear model. This makes the nonlinear model more suitable for high-power scenarios, ensuring stable and efficient energy harvesting while preventing potential issues like equipment overload.

Fig. 2 demonstrates energy consumption and network throughput comparison of Nonlinear and Linear energy harvesting models. As can be seen from Fig.2, at the same energy consumption levels, the Nonlinear Model generally achieves higher network throughput than the Linear model. For example, when energy consumption is around 0.5W, the throughput of the Nonlinear Model is approximately 2.651×10^7 bit per second (bps), which is noticeably higher than the 2.326×10^7 bps of the linear model. This indicates that the Nonlinear Model can provide better network performance under the same energy consumption conditions, making it more efficient in utilizing energy for data transmission. The Linear Model requires more energy to achieve a similar increase in throughput. As energy consumption increases further, the Nonlinear Model's throughput continues to rise at a faster rate compared to the Linear Model, highlighting its superiority in converting energy into effective network throughput.

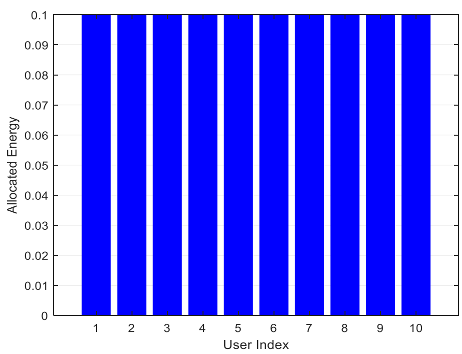

Fig. 3. Energy Allocation Among Selected Users

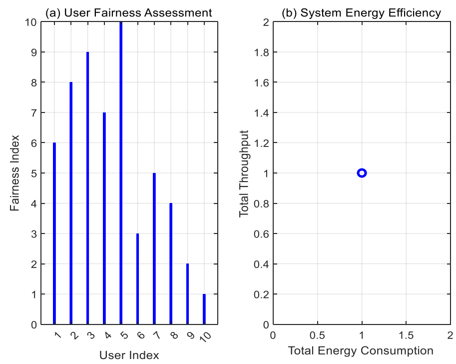

Fig. 4. User Fairness Assessment and System Energy Efficiency Analysis

Fig. 3 illustrates the amount of energy allocated to each selected user. The X-axis represents the index of the selected users, and the Y-axis indicates the amount of energy allocated to each user, measured in watts (W). The simulation results show that the heights of all bars are essentially uniform, which validates the effectiveness of the uniform allocation strategy. If there are differences in height, it may indicate that other factors are influencing the energy allocation, such as the users' energy requirements, communication distances, or other priority rules.

Fig. 4 presents an illustration of user fairness and system energy efficiency, composed of two sub-figures, each occupying half the space of the subplot. Fig. 4(a) displays the fairness index for each user, with each bar representing a user's fairness index; the shorter the bar, the fairer the energy allocation to that user. The fairness index is assessed by calculating the standard deviation of the energy allocated to the user—the smaller the standard deviation, the more uniform the energy distribution and the better the fairness among users. If the bars in the bar chart are short and of similar length, it indicates that the algorithm has achieved a high level of fairness among users. Longer or more varied bars may point to unfair phenomena in energy allocation, which require further investigation into the causes. Fig. 4(b) represents the relationship between total energy consumption and total throughput. The X-axis indicates the total system energy consumption measured in W, and the Y-axis indicates the system's total throughput. It is assumed that the total throughput is directly proportional to the total energy consumption, but this may not be the actual case, as the actual throughput may be influenced by many other factors.

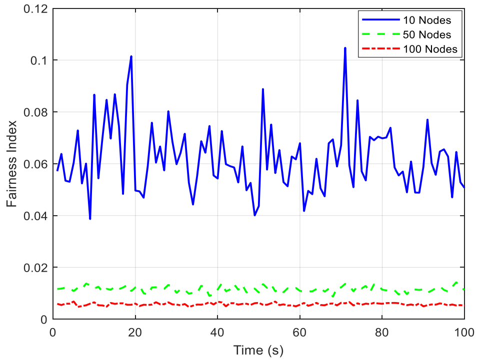

Fig. 5 Fairness Index Over Time for Non-linear Method

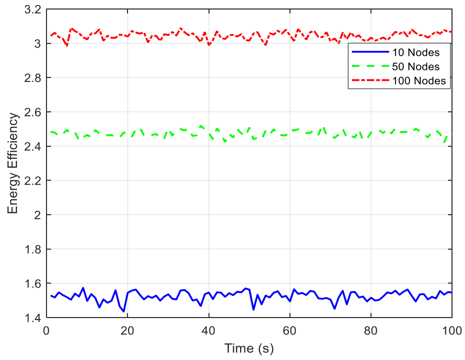

Fig. 6 Energy Efficiency Over Time for Non-linear Method

Fig. 5 depicts how fairly energy is allocated among users over a 100-second simulation period for Non-linear Method in WPTN scenarios with 10, 50, and 100 nodes. The fairness index, calculated as the standard deviation of energy allocation, shows that a lower value indicates more equitable distribution. The blue line (10 nodes) has the lowest index, highlighting the simplest energy distribution. The green line (50 nodes) shows a higher index due to increased allocation complexity. The red line (100 nodes) demonstrates the most challenging distribution but remains acceptable. Overall, the strategy ensures reasonable energy allocation fairness across varying network densities.

Fig. 6 illustrates the energy efficiency for Non-linear Method in WPTN over 100 seconds for 10, 50, and 100 nodes. Energy efficiency is the ratio of throughput to energy consumption. The blue line (10 nodes) shows the highest efficiency, as fewer nodes lead to less energy consumption and higher throughput. The green line (50 nodes) indicates lower efficiency due to increased consumption but optimized throughput. The red line (100 nodes) has the lowest efficiency due to the highest consumption, yet it maintains an acceptable level. Despite efficiency decreasing with more nodes, the trend stabilizes, proving the allocation strategy's effectiveness and scalability in enhancing energy efficiency across different network densities.

5. Conclusion and Future Work

This paper presents a comprehensive study on optimizing node selection and energy allocation in Wireless Powered Transfer Networks (WPTN). The key findings include an in-depth analysis of nonlinear energy harvesting models, which provide a more accurate representation of real-world energy conversion processes. A novel node selection algorithm was proposed, considering practical constraints such as user location, energy demand, and communication distance, enhancing network efficiency. Additionally, a dynamic energy allocation strategy was developed to maximize system energy efficiency while ensuring fairness among users. Extensive MATLAB simulations have validated the effectiveness of these strategies, demonstrating superior energy efficiency and network performance.

Despite the significant contributions, the study has identified limitations that suggest avenues for future research. The models used are simplified and may not capture the full complexity of real-world network operations. Future studies should incorporate more detailed models to enhance the accuracy of findings. The parameters in the simulations are based on theoretical estimates and may not reflect actual conditions; thus, future work should utilize empirical data to refine these parameters. The proposed algorithms show promise but could be further optimized, particularly in terms of computational efficiency and adaptability to dynamic network conditions. Lastly, the strategies need real-world testing to assess practical viability and gather empirical data for model refinement. In conclusion, while there is room for further exploration, this paper has made substantial contributions to the field of WPTN, setting a solid foundation for future work aimed at advancing the efficiency and sustainability of IoT networks.

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