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Research Article

Optimizing Energy Efficiency in Multidevice Communication with Artificial Intelligence Assistance

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This paper seeks to improve mobile communications performance by integrating artificial intelligence (AI) techniques. The study is centered on device-to-device (D2D) communication, which has emerged as a significant aspect in the 5th generation of mobile networks (5G) and is expected to be extended to the 6th generation (6G). Based on the fuzzy system, the proposed solution tackles the critical issue of energy harvesting in D2D communication. The solution presents a support system that selects the best relay for the transmitter-receiver communication to minimize energy consumption and maximize the network's lifetime. Minimizing energy consumption optimizes the network's lifetime, thus providing a reliable and efficient communication system. The approach taken in this study offers a novel perspective in addressing the energy harvesting challenge in D2D communication. It is expected to have a significant impact on the performance of mobile communications.

1. Introduction

As per Cisco's newly renamed Annual Internet Report [1], the total number of networked devices around the world is projected to reach 29.3 billion by 2023, exceeding the human population by more than three to one. This represents a significant increase from the 18.4 billion connected devices in 2018. A new generation of cellular networks is required (5G). Customers require a network that can accommodate a wide range of access requirements with high speed, low latency, guaranteed quality of service, and the ability to manage multiple connected devices [2].

To meet customer expectations, the 5G network must meet certain demands, including a ten to hundred times higher data rate per user, more than a thousand times higher volume of mobile data per unit area, a significantly increased number of connected devices, a ten-fold increase in battery life for low-power devices, and a fivefold reduction in end-to-end latency [3, 4].

Device-to-device (D2D) communication is a type of wireless communication where two mobile devices can communicate directly without going through a central network. This allows for faster, more efficient, and more reliable communication compared to communication through a central network, particularly in areas where the central network is congested or inaccessible.

With D2D communication, devices can exchange data, files, music, and video in real time. This technology can also be used for location-based applications, social networking services, and multimedia content delivery.

D2D communication can be implemented over wireless technologies such as 4G or 5G cellular networks, Wi-Fi, and personal communication services (PCS).

Minimizing energy consumption is important in device-to-device (D2D) communication because it can greatly impact the overall efficiency and performance of the network. In D2D communication, devices communicate directly with each other, bypassing the need for a central network infrastructure [5]. This eliminates the need for transmitting data through intermediate nodes, making communication faster and more efficient. However, this direct communication also puts a greater strain on the battery life of the devices, as they are constantly transmitting data. Minimizing energy consumption can help extend the battery life of devices, allowing them to communicate for longer periods without needing to be recharged [6–9].

This paper proposes a novel approach to address the need for reducing energy consumption in D2D communication networks and enhancing network performance. Our study aims to reduce the energy consumption of connected devices in D2D communication networks while ensuring that the network can meet the growing demands of customers and maintain high-performance standards.

The study presents a comprehensive system model and problem formulation for D2D communication. This will include a detailed description of how D2D communication operates and the specific problem that our study is trying to address. A key study component introduces a fuzzy model, a mathematical tool that models uncertainty and vagueness in real-world problems. The fuzzy model consists of three stages: fuzzification, fuzzy inference, and defuzzification. During fuzzification, the data from the system is transformed into a fuzzy representation; during fuzzy inference, the data is analyzed using predefined rules; and during defuzzification, the output is transformed back into a numerical representation for analysis.

We will also provide information on the simulation parameters used in the study, which will give readers an understanding of the conditions under which the study was conducted and the limitations and assumptions of the study. The results and discussion section will present and analyze the study's findings, providing a detailed examination of the results and their implications for the field of D2D communication.

Finally, the conclusion will summarize the main results and contributions of the study, providing a concise overview of the key results and highlighting the implications of the findings for future research in the field of D2D communication. The proposed approach not only addresses the issue of energy consumption in D2D communication networks but also ensures that the network can meet the growing demands of customers while maintaining high-performance standards, making it a significant contribution to the field.

2. Related Works

The works [10, 11] delve into resource allocation and power management in intracellular D2D communication networks. Reference [10] emphasizes reducing energy consumption by implementing efficient resource allocation and power management strategies. On the other hand, Kim [11] adopts a different approach to improving energy efficiency in D2D networks. Both studies aim to optimize the performance of D2D communication systems by minimizing energy waste and maximizing energy efficiency.

The literature in [12] investigates resource allocation for LTE D2D communication networks, using mathematical programming algorithms to minimize energy consumption while maintaining a high quality of service. The study aims to find the optimal allocation of resources that balances energy consumption and quality of service.

The work provided in [13] introduces a graph-based power management method to minimize energy consumption in D2D communication networks. The method allocates resources and efficiently manages power consumption, reducing energy waste and maximizing energy efficiency.

Conversely, authors in [14] examine the impact of different channel allocation policies on energy consumption in D2D communication networks. The study sheds light on the relationship between channel allocation and energy consumption and how this relationship can be leveraged to optimize the energy efficiency of D2D networks.

In [15], the authors propose an energy-efficient channel reusing scheme for multi-D2D (device-to-device) links in communications. It first analyzes the energy efficiency of a single D2D link in both noncooperative mode (NCM) and cooperative mode (CM), showing that the D2D link's efficiency is mainly determined by the location of the cellular user equipment (CUE) that shares resources with the D2D pair. Based on this analysis, a location-based algorithm (LBA) is proposed to select the optimal CUE for each D2D pair, aiming to maximize the overall energy efficiency of all D2D links. Numerical results demonstrate that the proposed LBA effectively improves the D2D system's overall energy efficiency while ensuring the target rate for each D2D link. Moreover, the proposed LBA does not require channel state information (CSI) for all the involved links, significantly reducing feedback overhead and computational complexity.

A proposed method to minimize energy consumption using game theory in D2D communication networks is deliberated in [16, 17]. The study explores how game theory can be applied to optimize resource allocation and power management in D2D networks to reduce energy consumption and improve energy efficiency.

Concerning the research in [18], this paper focuses on providing real-time monitoring and response services for smart cities in an environmentally-friendly manner. The authors propose integrating green communication techniques, particularly device-to-device (D2D) communication, to improve data rates and reduce energy consumption. The research aims to optimize uplink subcarrier assignment and power allocation in D2D-based cellular networks, minimizing energy costs while meeting data rate requirements. The complexity of the problem is addressed by decomposing it into subproblems for subcarrier assignment and power allocation, using a heuristic algorithm, and transforming constraints into a convex optimization problem.

In [19], the authors investigate the impact of network coding on energy consumption in D2D communication networks. The study proposes a method to improve energy efficiency by reducing energy consumption through network coding techniques. The goal is to minimize energy waste and maximize energy efficiency in D2D communication networks.

The optimization of energy consumption in D2D communication networks is a critical research area that has received considerable attention in recent years. Researchers have explored various techniques, such as resource allocation and power management strategies, to reduce energy waste and improve energy efficiency in D2D networks. The studies discussed in this review highlight the importance of considering various factors, such as network topology, communication range, channel allocation policies, and traffic load, when optimizing energy consumption in D2D networks.

Overall, the literature shows that there is still much room for improvement in terms of energy optimization in D2D communication systems.

3. System Model and Problem Formulation

In this section, we will explore the definition of a D2D communication system model that considers different topologies and D2D management in terms of control and discovery.

We will thoroughly analyze our methodology for selecting the most suitable relay for DR-DC communication. We will closely examine the transmitted power consumed, focusing on energy efficiency. Finally, we will thoroughly describe our energy harvesting strategy for D2D communication.

3.1. D2D Communication Model. In device-to-device communication, various topologies are used. Specifically, D2D communications are classified into four distinct categories by many authors and specialists, as shown in Figure 1 [20–22].

(i) DR-OC (device relaying with operator controlled link establishment): This is a D2D communication mode where a device located in a poorly covered area or on edge can relay information to the base station via other neighboring devices. The base station manager controls the link and allocates resources, either partially or completely [20, 21].

(ii) DC-OC (direct D2D communication with operator controlled link establishment): In this case, the source and destination devices communicate directly without the need for routing data through a base station. However, the base station still plays a role in establishing control links for efficient radio resource management [20, 21].

(iii) DR-DC (device relaying with device controlled link establishment): In this mode, D2D communication operates similarly to DR-OC but without the involvement of a base station. The source and target devices coordinate communication and rely on relay devices for data transmission [20, 21].

(iv) DC-DC (direct D2D communication with device controlled link establishment): In this mode, the source and target devices communicate directly without needing a base station to control the connection [20, 21].

3.2. D2D Communication Management and Discovery. This classification involves mobile devices and the network in supporting D2D communications.

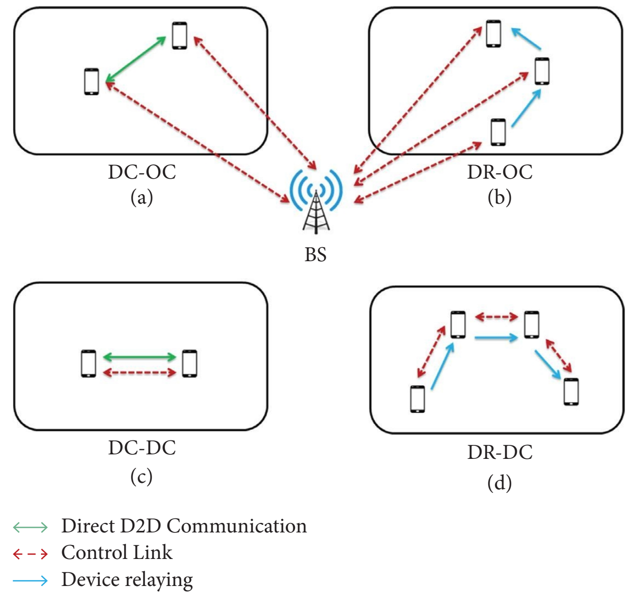

FIGURE 1: D2D communication topologies.

(i) D2D control: There are three types of control in D2D communication: full control, light control, or hybrid control. With full control, the operator network fully manages the communication, including authentication and resource allocation. With light control, the D2D terminals can communicate with each other with minimal network intervention, with the network only responsible for terminal authentication when connected. Hybrid control involves critical aspects being managed by the network, such as authentication and radio resource allocation, while noncritical aspects are managed autonomously by the D2D equipment.

(ii) D2D discovery: This task is crucial for D2D communications, where devices search for neighboring devices to initiate communication. The discovery process can be split into two steps: discovery initiation and discovery control.

(iii) The initiation step occurs when two users want to share content. The control step occurs when both users are already engaged in cellular communication and come within close range of each other [23, 31].

The focus of this study is the DR-DC case, deemed the most energy-efficient D2D communication topology, intending to find a net power gain in a network of five devices.

These devices are named, respectively, as UE_A, UE_B, and UE_{Ri}. with $i \in \{1, 2, 3\}$.

The notations used in the rest of this work are given in Table 1:

The parameters listed in Table 1 are as follows:

(i) UE_A represents the source device that transmits its own data.

(ii) UE_B represents the destination device that receives data from UE_A.

(iii) UE_{Ri} represents the relay device, which relays data from UE_A to UE_B.

Table 1: Defined notations.

Symbol	Description
UE_A	User equipment A
UE_B	User equipment B
UE_R	User equipment R_i (relais)
d_{AB}	Distance between UE_A and UE_B
d_{ARi}	Distance between UE_A and UE_{Ri}
d_{BRi}	Distance between UE_B and UE_{Ri}
D_{UEA}	Data transmitted by UE_A
D_{UEB}	Data transmitted by UE_B
D_{UERi}	Data transmitted by UE_{Ri}

In the DR-DC topology, UE_A transmits its data D_{UEA} to UE_B via the relay node UE_{Ri}.

This considers four transmissions inside the network, defined as follows:

(1) UE_B sends a discovery signal to UE_{Ri}

(2) UE_{Ri} sends a discovery signal to UE_A

(3) UE_A sends its data D_{UEA} to UE_{Ri} and

(4) UE_{Ri} sends data from UE_A (D_{UEA}) to UE_B

The considered tested topology is illustrated in Figure 2.

This figure presents the DR-DC communication scheme as proposed in this paper.

The forthcoming section will show how someone will describe and discuss different situations.

3.3. Problem Formulation. As previously mentioned, the objective is to develop a viable strategy to maximize the network's lifetime in D2D communication. This entails implementing energy-saving measures for devices within the network. Achieving this goal depends on accurate and effective management to optimize the network's parameters. Key parameters include network lifetime and energy consumption by the equipment.

The presence of an obstacle such as a wall does not affect energy losses in the simulation since the simulation scenario remains unchanged compared to the classical case, and the approach used has no impact on the space utilized.

To address these factors, we propose a DR-DC communication scheme that utilizes a fuzzy logic procedure to select the appropriate relay, thus ensuring a longer network lifetime.

To accomplish this objective, we present the following detailed algorithm, which consists of a small number of straightforward steps:

Step 1

(i) The distance between the two observed devices (UE_A–UE_{Ri}) must be calculated. Afterward, any terminals that have a distance exceeding 100 m should be discarded. This maximum distance's length is justified in [12]. In other words, these terminals could exist at a position more than 100 m or perhaps they have not yet been discovered.

(ii) Next, we will determine the distance between UE_R and UE_B.

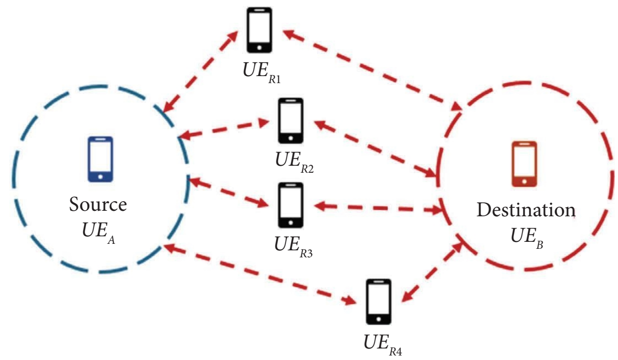

Figure 2: Proposed topology.

To do this, we first establish the Cartesian coordinate system for UE_A, UE_B, and UE_{Ri} *devices*. We move UE_R along a line that is parallel to the line connecting UE_A and UE_B. The coordinates for UE_A, UE_B, and UE_R are (0, 0), (d_{AR}, 0), and (x_R, d), respectively. With this information, we can then calculate the distance between UE_{Ri} and UE_B as follows in the following equations:

$$d_{AR} = \sqrt{\left(x_A - x_R\right)^2 + \left(y_A - y_R\right)^2} = \sqrt{x_R^2 + d^2}, \quad (1)$$

$$d_{BR} = \sqrt{\left(x_B - x_R\right)^2 + \left(y_B - y_R\right)^2} = \sqrt{\left(d_{AB} - x_R\right)^2 + d^2}. \quad (2)$$

Step 2. We will calculate the transmission power provided by each terminal. The first assumption is that the bandwidth for transmitting data remains constant over time. To determine the potential gain in energy efficiency within a D2D network, we must assess the overall energy consumption of the network; we must analyze the overall network's energy consumption.

First, we use Shannon's capacity formula because, as shown in the literature, such a rule gives the relationship between the data transmitted rate coming from the user equipment j (Dj) and the needed power by the user equipment j for a transmission of that data rate Dj (Pj), as given in [18, 19]:

$$C = W.\log_2\left(1 + \frac{S}{N}\right), \quad (3)$$

where W is the width of the bandwidth, S the signal strength, and N is the power of additive white Gaussian noise (AWGN)

$$S = P_j|h|^2 k r^{-\alpha}, \quad (4)$$

where k is a constant related to antenna gain, h represents channel fading at transmitter and receiver (Assuming that fading follows the same law at both the transmitter and receiver), r is the distance between the transmitter and the receiver, and α is the path loss exponent.

We can see that the power expression can be deduced from this Shannon's rule as it follows:

$$\frac{C}{W} = \log_2\left(1 + \frac{S}{N}\right). \tag{5}$$

Furthermore, we have the following expressions for the power of the different devices:

$$P_j = \frac{N}{|h|^2 k} d_r^\alpha \Phi\left(C_j\right), \tag{6}$$

where $j \in \{U_{\text{UEA}}, U_{\text{UEB}}, U_{\text{UERi}}\}$

Furthermore, we have the following expressions for the power of the different terminals:

$$P_{\text{UEA}} = \frac{N}{|h|^2 k} d_{AR}^\alpha \Phi\left(C_{\text{UEA}}\right), \tag{7}$$

$$\begin{aligned} P_{\text{UEB}} &= \frac{N}{|h|^2 k} d_{BRi}^\alpha \Phi\left(C_{\text{UEB}}\right), \\ P_{\text{UERi}} &= \frac{N}{|h|^2 k} d_{ARi}^\alpha \Phi\left(C_{\text{UERi}}\right). \end{aligned} \tag{8}$$

Thanks to equations (5)–(7), we can find

$$\begin{aligned} P_T &= \frac{N}{|h|^2 k} \left[\Phi\left(C_A\right).\left(d_{ARi}^\alpha + d_{BRi}^\alpha\right) + \Phi\left(C_B\right).\left(d_{ARi}^\alpha + d_{BRi}^\alpha\right)\right], \\ P_j &= \frac{N}{|h|^2 k.r^{-\alpha}} \left[\exp\left(\ln 2.C_j\right) - 1\right] = \frac{N}{|h|^2 k.r^{-\alpha}} \Phi\left(C_j\right), \end{aligned} \tag{9}$$

where

$$C_j = \frac{D_j}{W}\left(\frac{\text{enbit/s}}{Hz}\right) et\ \Phi\left(C_j\right) = \exp\left(\ln 2.C_j\right) - 1, \quad j \in \{U_{\text{UEA}}, U_{\text{UEB}}, U_{\text{UER}i}\}. \tag{10}$$

We aim to determine the overall energy efficiency gain for the entire network. This total entire network's power consumption could be expressed as follows:

$$P_T = P_{\text{UEA}} + P_{\text{UEB}} + P_{\text{UER}i}, \tag{11}$$

where P_{UEA} is the total power consumed by UE_A, P_{UEB} is the total power consumed by UE_B, and $P_{\text{UER}i}$ is the total power consumed by UE_{Ri}.

P_T^{Ri} is the total powers for the DR-DC topology.

$$P_T^{Ri} = \frac{N}{|h|^2 k}.\Upsilon\left(d_{ARi}, d_{BRi}\right).\left(\Phi\left(C_A\right) + \Phi\left(C_{\text{beacon}}\right)\right), \tag{12}$$

where $\Upsilon(x, y) = x^\alpha + y^\alpha$, d_{ARi}, and d_{BRi} are, respectively, the distances between UE_A and UE_{Ri}, and UE_B and UE_{Ri}.

In the DR-DC topology, the transmission of D_{UEA} data from UE_A to UE_B occurs through the UE_R relay device in four steps:

(i) UE_B sends a beacon to UE_R

(ii) UE_R sends a beacon to UE_A

(iii) UE_A sends its D_{UEA} data to UE_R

(iv) UE_R sends the data from UE_A (D_{UEA}) to UE_B

The timing process of these transmissions is illustrated in Figure 3.

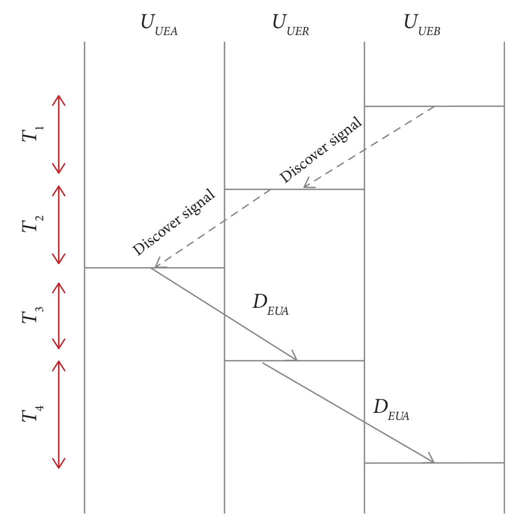

Figure 3: Time processes of DR-DC topology transmissions.

The total energy consumed by the DR-DC topology can be deduced from the temporal processes involved. By analyzing the power consumed during the transmission from node A to node B, from node B to node R, from node R to node A, and from node R to node B, as well as the duration of each transmission, we can calculate the total energy consumed by the network using the following equation:

$$E_T = P_{B \longrightarrow R}^x.T_1 + P_{R \longrightarrow A}^x.T_2 + P_{A \longrightarrow R}^x.T_3 + P_{R \longrightarrow B}^x.T_4, \tag{13}$$

where E_T represents the total energy consumed by all UEs. $P_{B \longrightarrow R}^x$ is the power consumed during the transmission from node B to node R. T_1 is the duration of the transmission from node B to node R. $P_{R \longrightarrow A}^x$ is the power consumed during the transmission from node R to node A. T_2 is the duration of the transmission from node R to node A. $P_{A \longrightarrow R}^x$ is the power consumed during the transmission from node A to node R. T_3 is the duration of the transmission from node A to node R. $P_{R \longrightarrow B}^x$ is the power consumed during the transmission from node R to node B. T_4 is the duration of the transmission from node R to node B.

Figure 4 represents the total energy consumption of mobile devices (smartphones) at each moment in the classical case, meaning it provides a discrete representation of energy consumption, displaying values at specific moments in time.

Step 3. This step involves implementing a fuzzy decision support system (FDSS) approach.

To ensure a reliable and efficient connection, adopting a fuzzy decision support system approach in the selection process of the most qualified relay is necessary. The FDSS will consider various important factors such as signal strength, distance, reliability, and other relevant characteristics of the relays.

By processing this information through a set of fuzzy rules, the FDSS will recommend the best relay to use for the requested connection. This approach allows for a more

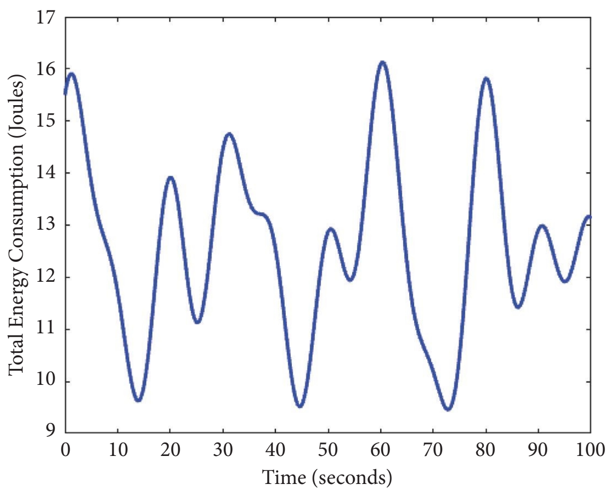

Figure 4: Total energy consumption in DR-DC communication.

nuanced and sophisticated evaluation of the relays, considering both certain and uncertain information.

Implementing an FDSS approach in the relay selection process will greatly improve the overall performance and quality of the requested connection.

4. Fuzzy System Model

Fuzzy logic is a mathematical theory that extends classical (or binary) logic by allowing variables to have degrees of truth rather than just being true or false. The "degree of truth" concept is represented as a value between 0 and 1, where 0 represents false and 1 represents true. This enables fuzzy logic to handle uncertainty and imprecision more flexibly and naturally.

Fuzzy logic is used in various fields, such as artificial intelligence, control systems, decision-making, and expert systems. It can be used to model human reasoning, where knowledge about a particular problem may be incomplete or ambiguous.

Fuzzy logic operates on linguistic variables, which are variables that can take on values described by words or phrases rather than numbers. These linguistic variables are then transformed into fuzzy sets, which describe the degree of membership of a value in a particular set. These fuzzy sets are then manipulated using fuzzy rules, which describe the relationship between inputs and outputs in a way that resembles human reasoning [24–28].

Overall, fuzzy logic provides a more intuitive and flexible way of dealing with uncertainty and imprecision compared to classical logic, making it a valuable tool in various fields.

The internal workings of a decision support system (DSS) will utilize fuzzy logic analysis to reach the desired outcome, as shown in Figure 5.

In this scenario, the inputs of the decision support system are the transmission power ($I1$) and the distance ($I2$) between equipment that could be selected to play the relay role. These inputs are analyzed using fuzzy logic analysis, as shown in the schematic representation of the system in Figure 6.

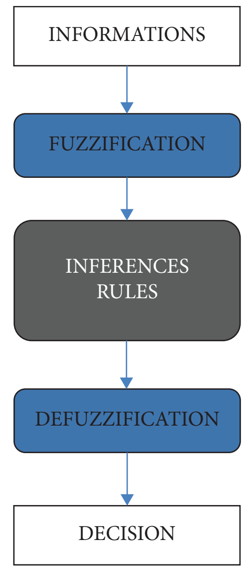

Figure 5: General structure of a decision support system including fuzzy logic.

The input of transmission power is represented by ($I1$), and the input of distance is represented by ($I2$). The inputs are processed through the fuzzy logic approach to reach the desired result. The purpose of using fuzzy logic analysis in this system is to provide a clearer understanding of the relationship between the transmission power and distance when selecting equipment to play the relay role [29].

4.1. Fuzzification. In a fuzzy model with two fuzzy variables (distance and emission power), fuzzification transforms the numeric inputs of distance and emission power into fuzzy sets, representing the degree to which each input belongs to a given fuzzy set. This can be accomplished using relevance functions, which assign a relevance degree between 0 and 1 to each possible input [30].

For example, suppose the distance can vary between 0 and 50 meters, and the emission power can vary between 10 mW and 100 mW. In that case, we can define fuzzy sets such as "Short Distance" (distance less than 25 m), "Average Distance" (distance between 12 m and 25 m), and "Long Distance" (distance between 25 m and 50 m).

Similarly, we can define fuzzy sets for emission power, such as "Low Power" (power less than 25 mW), "Average Pawer" (power between 25 mW and 75 mW), and "Maximum Power" (power greater than 75 mW).

The creation of fuzzy linguistic variables, the execution of fuzzification, and the selection of the ideal number of division levels are decisions stemming from an iterative procedure that encompasses multiple simulations. These choices are founded on a combination of theoretical expertise, practical familiarity, and empirical assessments, all with the intention of ensuring that the model effectively caters to the specific requirements of the problem at hand.

Fuzzification, in turn, involves utilizing relevance functions to allocate a degree of relevance to each input, namely distance and emission power, based on their

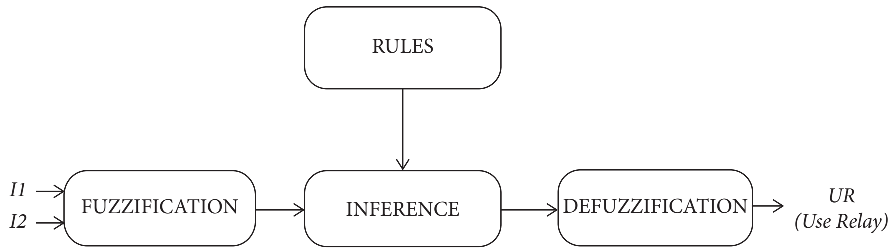

Figure 6: Illustration representing the logic system.

membership in the respective fuzzy sets. The outcome of fuzzification produces two relevance functions that characterize the importance of each input for each fuzzy set.

4.2. Fuzzy Inference. Fuzzy inference in this model refers to the process of using fuzzy logic to reason about the relationship between the inputs and the desired output. The fuzzy inference process involves mapping the inputs, represented by fuzzy sets, to the output space using a set of rules defined by the system designer. The rules specify how the input fuzzy sets should be combined to form the output fuzzy set. This process is often referred to as "fuzzification."

The fuzzy inference engine evaluates the rules by using a combination of fuzzy set operations, such as intersection and union, to determine the degree to which each rule is satisfied by the inputs. The output fuzzy set is obtained by aggregating the results of all the rules. This fuzzy output set is then defuzzified to obtain a single, crisp output.

In this model, fuzzification transforms the inputs *I*1 (transmission power) and *I*2 (distance of equipment selected as a relay) into fuzzy sets. The fuzzy sets are then processed through the fuzzy inference engine, which uses a set of rules to combine the input fuzzy sets and generate an output fuzzy set.

Finally, the output fuzzy set is defuzzified to obtain a crisp output representing the desired result.

This system has two inputs, *I*1 and *I*2, which are transformed into linguistic variables, and an output, *UR*. The fuzzy sets related to the information are shown in Table 2.

Table 3 summarizes the various fuzzy rules that define the logical relationship between the input variables and the output variables.

Instead, rules are typically selected in a way that best reflects the logic of the system and provides relevant results for the specific problem being addressed.

The rules are combined using AND and OR operations, where the AND operator acts on the variables within a rule, while the OR operator connects different rules. There are several ways to perform these operations in inference, and they relate to the membership functions, including [24].

(i) MAX-MIN inference method (Mamdani)

(ii) MAX-PROD inference method (Larsen)

(iii) SOM-PROD inference method (Sugeno)

In this case, we opted for the min-max method due to its ease of implementation. This method associates "min" with logical "AND" and "max" with logical "OR."

Table 2: The information is associated with fuzzy sets.

Information	Description
LP	Low power
AP	Average power
MP	Maximum power
SD	Short distance
AD	Average distance
LD	Long distance
NU	Not used
MU	Moderation used
HU	Heavily used

Table 3: Fuzzy rule table.

	LP	AP	MP
SD	MU	MU	MU
AD	NU	HU	MU
LD	NU	MU	HU

Figures 7–9 illustrate, respectively, the input variables *I*1 (*P*), *I*2 (*D*), and the output variable *UR*.

The input variable *I*1 (*P*) represents the power consumption of the relay node in device-to-device communication. The fuzzy logic algorithm uses this variable to determine the most energy-efficient relay node for data transmission. The higher the value of *I*1 (*P*), the greater the energy consumption of the relay node, and vice versa. The goal is to choose the relay node with the lowest power consumption to transmit data and minimize energy waste, thus improving the system's overall energy efficiency.

Input variable *I*2 refers to the distance (*D*) between the transmitter and the potential relay node. It represents the physical proximity of the relay node to the transmitter, and it is used as an input in the fuzzy logic system to determine the suitability of a particular node as a relay. The closer the relay node is to the transmitter, the more likely it is to be selected as the relay, as it will result in a lower path loss and a stronger signal.

The output variable UR refers to the uncertainty level of the proposed energy harvesting and connectivity-maintaining algorithm based on fuzzy logic. It determines the appropriate relay node to be selected based on energy consumption and the distance between the transmitter and receiver. The output variable UR is calculated using the fuzzy logic rules, which consider the input variables *I*1 (power) and *I*2 (distance). The output variable UR determines the relay node with the lowest energy consumption and the best connectivity, ensuring that the energy and connectivity requirements are met.

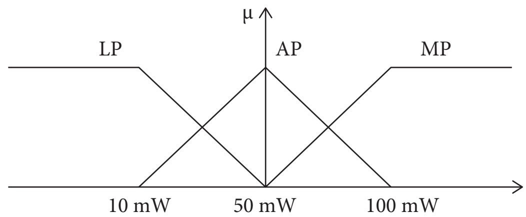

Figure 7: Input variable *I*1 (*P*).

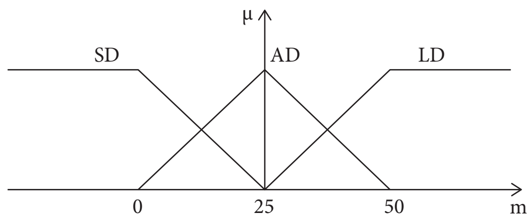

Figure 8: Input variable *I*2 (*D*).

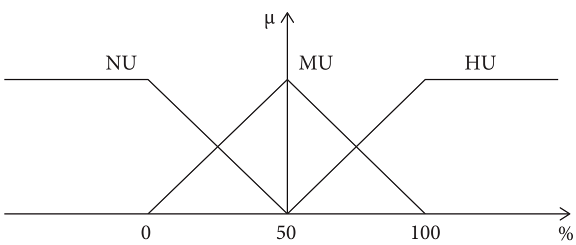

Figure 9: Output variable *UR*.

The frequent use of the MAX-MIN inference method is due to its practicality, which makes it easier to implement.

4.3. Defuzzification. Defuzzification is the final process in a fuzzy logic system where the fuzzy output obtained from the fuzzy inference step is transformed into a precise numerical decision. Its objective is to provide an accurate value that can be used to select the appropriate relay based on the transmission power (*I*1) and distance (*I*2) characteristics.

Once the input variables *I*1 and *I*2 are provided to the system, a fuzzy logic analysis is performed to generate a fuzzy output. This fuzzy output represents different degrees of membership to different possible relays based on the transmission power and distance characteristics.

Next, defuzzification is performed using the centroid method. In this method, the aggregated fuzzy set is represented by a curve of fuzzy members, where each fuzzy member represents the degree of membership of a precise value in the fuzzy set. The centroid of this curve is calculated by considering the degrees of membership and their corresponding precise values.

The centroid represents a selected relay using a precise numerical value corresponding to the optimal relay. It is calculated by taking a weighted average of the precise values, where the weights are determined by the respective degrees of membership of the fuzzy members. Thus, fuzzy members with higher degrees of membership have a greater impact on the centroid.

Through defuzzification and the use of the centroid method, it is possible to determine the most appropriate relay for the role using the input variables *I*1 and *I*2. The precise numerical decision obtained can then be used to choose the ideal equipment for the relay role based on the transmission power and distance characteristics.

5. Simulation Parameters and Results

To meet the requirements of D2D communication with the relay application and minimize energy consumption in the network, fuzzy simulation parameters will be employed. These parameters will be used to simulate the behaviour of the sender (UE_A), receiver (UE_B), and three relays (UE_{R1}, UE_{R2}, and UE_{R3}).

The goal is to optimize the network's energy consumption while ensuring that the D2D communication requirements are met.

(1) Distance: The distance inputs can be defined in a range of 0 to 100 meters, with discrete values such as 10, 50, and 100.

(2) Power: The power inputs can be defined on a range of 25 to 100 mW, with discrete values such as 25, 50, and 100.

(3) Fuzzy rules: Fuzzy rules can be defined to reflect the optimal use decision of the relay based on distance and power. For example, if the distance is low and the power is high, the relay is not used, but if the distance is high and the power is low, the relay is used.

(4) Fuzzy membership functions: Fuzzy membership functions can be defined to represent the (distance) and (power) inputs.

For example, a fuzzy membership function for distance may have values of "Short Distance," "Average Distance," and "Long Distance" and a fuzzy membership function for power may have values of "Low Power," "Average Power," and "Maximum Power."

(5) Fuzzy inference algorithm: The fuzzy inference algorithm can be defined to produce an output using the inputs, fuzzy rules, and fuzzy membership functions. For example, the algorithm may use the max-min method to produce an output using the most relevant fuzzy rules.

In this study, we conducted a comprehensive comparison between the use of a smart fuzzy system and the classical case for DR-DR communication in a relay network. Our objective was to assess the impact of the fuzzy system on the total energy consumption within the network.

The study's results, which are displayed in Figure 10, provide strong evidence for the efficacy of using a fuzzy system in DR-DR communication networks. In a 3-relay network, for instance, the total energy consumption without the fuzzy system was observed to range between 10 and 17 joules. However, when a fuzzy system was implemented, the energy consumption was found to be between 7 and 15 joules, demonstrating a significant reduction. The same pattern was seen in a 5-relay network, where the total energy consumption without a fuzzy system was between 15 and

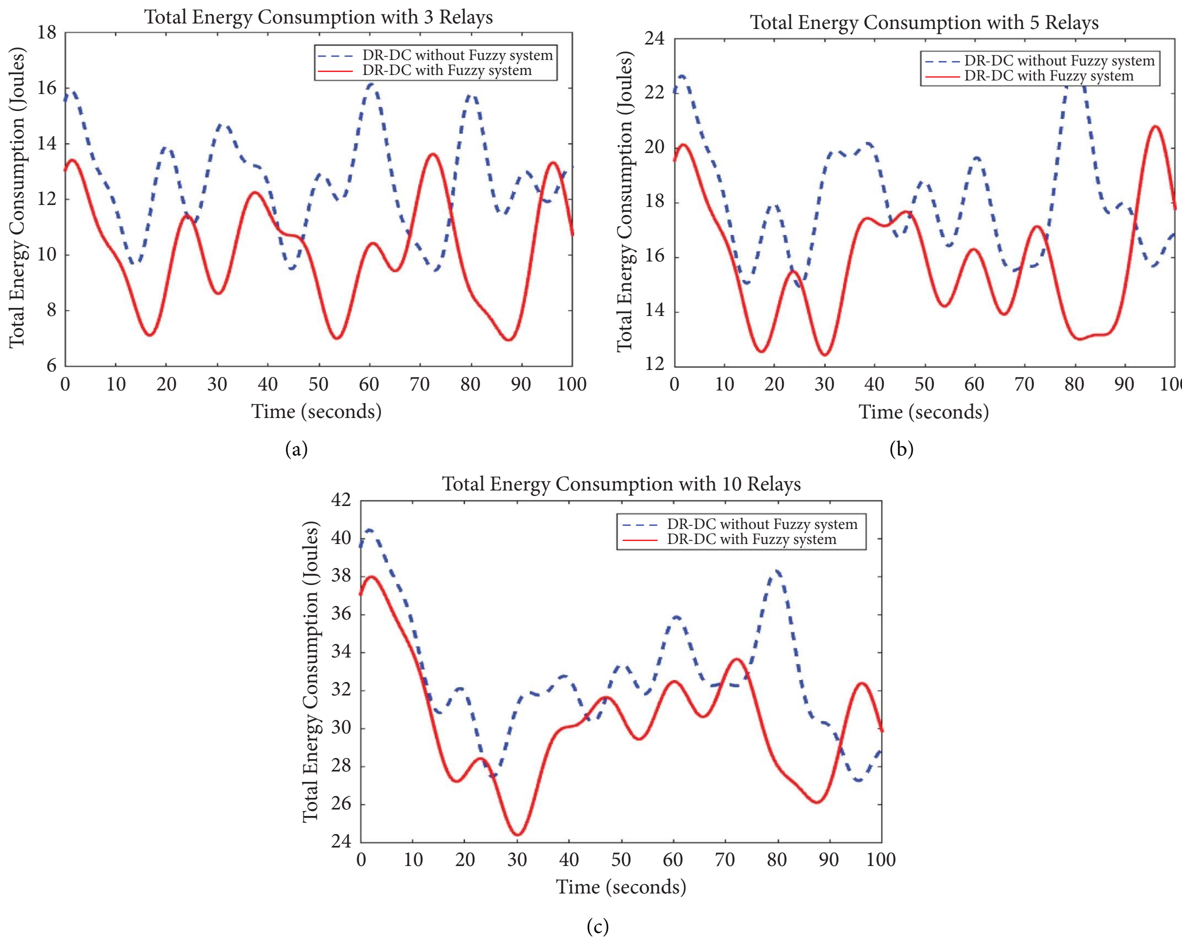

FIGURE 10: Comparison of energy consumption in DR-DC communication: without fuzzy system vs. with fuzzy system.

23 joules, while with a fuzzy system, it was between 12 and 21 joules. This trend held even in a 10-relay network, where the total energy consumption without a fuzzy system was between 27 and 41 joules, while with a fuzzy system, it was between 24 and 38 joules.

The study's results clearly indicate that using a fuzzy system can result in significant energy savings within DR-DR communication networks. In fact, the results showed that the total energy consumption was reduced by 11.76% for a 3-relay network, 8.69% for a 5-relay network, and 7.31% for a 10-relay network.

These findings highlight the potential for energy efficiency that can be achieved by implementing a fuzzy system in DR-DR communication networks.

The study examined the impact of a fuzzy system on the average energy gain in DR-DC communications. The results revealed that the average energy consumption was 21.16 joules without the fuzzy system. However, with the implementation of the fuzzy system, this average consumption was successfully reduced to 18.31 joules.

These findings, as depicted in Figure 11, clearly underline the effectiveness of the fuzzy system in reducing energy consumption in DR-DC communications. The fuzzy system enables significant energy savings by optimizing the network's energy performance. The decrease in average energy consumption from 21.16 to 18.31 joules represents a reduction of approximately 13.5%.

These findings demonstrate the significance of the fuzzy system in improving the energy efficiency of DR-DC communications. By employing advanced techniques such as the fuzzy system, it becomes possible to better utilize energy resources, reduce costs, and maintain high performance in communication networks.

Table 4 displays the differences in total energy consumption with and without a fuzzy system for various numbers of used relays. It provides a clear and concise presentation of the results obtained in the study, making it easy to understand the data. The table includes information on the number of relays, the total energy consumption without a fuzzy system in joules, the total energy consumption with a fuzzy system in joules, and the reduction in total energy consumption as a percentage.

The results highlight that the application of an intelligent system can facilitate more informed decision-making by using fuzzy logic to optimize operations or controls. More specifically, employing a fuzzy system for the judicious selection of an appropriate relay, thereby minimizing energy consumption and maximizing network lifespan, proves to be

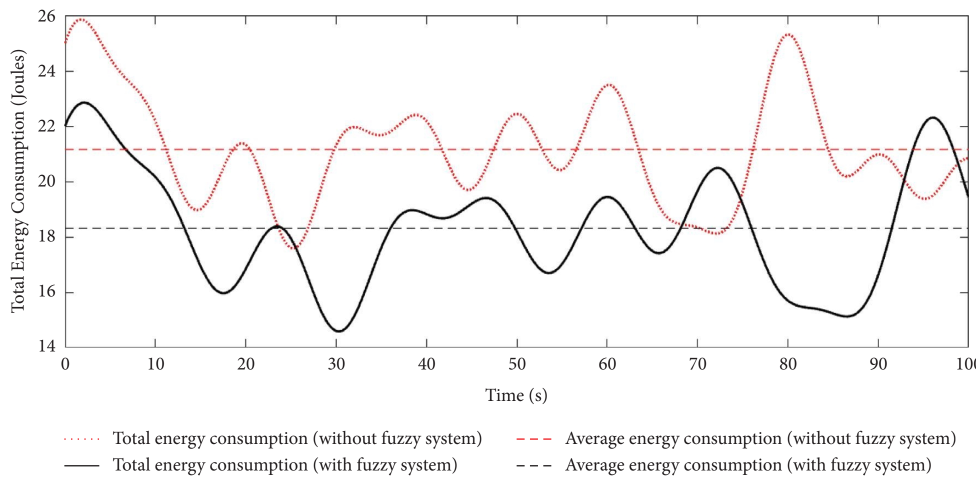

Figure 11: Average energy improvement in DR-DC communication: without fuzzy system versus with fuzzy system.

Table 4: Comparison of total energy consumption with and without a fuzzy system for different numbers of relays.

Number of relays	Total energy consumption without a fuzzy system (Joules)	Total energy consumption with a fuzzy system (joules)	Reduction in total energy consumption (%)
3	10 to 17	7 to 15	11.76
5	15 to 23	12 to 21	8.69
10	27 to 41	24 to 38	7.31

a promising approach. The obtained results demonstrate the value of this approach in reducing the overall energy consumption within a D2D network.

6. Conclusion

Device-to-device communication in the upcoming generations of 5G and 6G telecommunication systems is attractive. Despite increased network load, it will allow more users to communicate simultaneously with improved communication quality. We have proposed an energy and connectivity optimization algorithm based on fuzzy logic to meet this challenge.

Our algorithm effectively manages energy consumption and enhances the quality of sender-receiver communication, thereby maximizing the network's lifespan. The evaluation of our approach using Matlab yielded positive results, demonstrating significant improvements in reduced energy consumption, extended network lifespan, and shorter delivery time. This algorithm proves to be highly effective in optimizing energy management and connectivity in both 5G and 6G telecommunication systems. Furthermore, future studies can focus on further enhancing performance and efficiency. Overall, our fuzzy logic-based approach offers an effective solution for optimizing energy consumption and communication quality in 5G and 6G telecommunication systems, with simulation results validating the improvements in energy consumption, network lifespan, and delivery time. We have confidence in the performance of our algorithm and its potential to positively impact future telecommunication systems.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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