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DESIGN OF AN OPTIMIZED LOCATION-AWARE RESOURCE SHARING AND POWER CONTROL SCHEME FOR M2M COMMUNICATION

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Abstract

In fifth-generation (5G) cellular networks, a Machine-to-Machine (M2M) communication is considered a promising approach to minimize interference and power consumption. The localization of unknown machines in M2M communication is important to achieve improved energy efficiency in cellular networks. Therefore, a hybrid location-aware framework was developed in this paper to reduce the interference and power consumption in M2M communication. The proposed technique utilizes a Received Signal Strength (RSS)-based localization algorithm to identify the location and signal strength of an unknown user. Here, the system choice the communication mode selection based on the distance and signal strength between the M2M pair. An Ant colony optimization (ACO)-based resource allocation scheme was applied for different modes to optimize the interference, data rate, and power consumption. Consequently, a Distributed gradient descent (DGD) algorithm was utilized in the proposed technique to minimize the transmission power of each user equipment (UE) in the communication system. The proposed model was modeled in MATLAB software and the outcomes are estimated. The comparative assessment evidences that the proposed technique effectively minimizes the power consumption, interference, and transmit power of UE.

Keywords: Machine-to-Machine communication, Cellular networks, Ant colony optimization, Distributed gradient descent.

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1. INTRODUCTION

Long-term-evolution advanced (LTE-A) is instigated in fourth-generation (4G) communication systems to enhance the network capacity [1]. Fifth generation (5G) cellular communication system aims to provide a thousand times more network capacity than the 4G technology [2]. In addition, it targets to increase the system throughput by twenty-five times more and reduce network traffic delay by five times more than the 4G network. However, the LTE-A approach cannot offer these services in 5G network [3]. Hence, M2M communication was introduced to deliver these conveniences in 5G networks [4]. The LTE-A technology allows two close user equipment to interconnect with each other directly with restricted contribution of cellular base stations (BSs) to eradicate the depletion of radio resource blocks [5]. In the Internet of Things (IoT) application, millions of UEs link together to provide intelligence in communication. In recent times, effective M2M communications technique is important to facilitate intelligent and useful benefits in IoT applications [6]. An intelligent M2M communication system effectively improves the network coverage, minimizes energy utilization, reduces delay, and increases the battery life of UEs [7]. In addition, it plays a vital role in numerous environmental circumstances like smart healthcare systems, transportation systems, natural disasters, etc. Thus, M2M communication has earned more attention in recent years because of its numerous benefits [8]. However, in M2M communications the amount of network traffic is increasing, which minimizes the users quality of service (QoS). In addition, the M2M communication performance is restricted because of the huge distance between the M2M pairs [9]. To resolve these challenges in the conventional cellular architecture, recent studies concentrated on the communication mode selection algorithm.

The studies concluded that the communication mode selection prior to data transmission enhances the performances like throughput, spectrum efficiency, and energy efficiency (EE) [10]. Typically, based on the network circumstances, the M2M pair functions in two modes namely direct and indirect [11]. If the M2M pairs are close to each other, the UEs directly communicate with other UEs, which is termed direct mode [12]. On the other hand, in the case of long-distance communication, the channel circumstances become weak and the data transfer happens by utilizing the cellular base states, this type of data transfer is termed an indirect mode [13-14]. In M2M communication, the utilization of direct mode- offers less tranmission power and minimizes the delay compared to the indirect mode communication [15]. Because of these benefits, direct mode communication acts as an effective choice for short-range communication systems [16]. But, the M2M communication based on the direct mode requires half of the available physical resources compared to the indirect mode. Thus, direct mode communication doubles the spectral efficiency of the system [17].

In addition, the indirect mode facilitates better performances in long-distance M2M communication. In addition, it is observed that these modes of communication operate upon licensed and unlicensed radio spectrum [18]. The usage of the unlicensed spectrum helps to overcome the huge user traffic, and the deployment of unlicensed spectrum eliminates the interference and increases the data rate of the user [19]. The spectrum and energy efficiency are the key factors, which play a crucial role in the design of 5G communications [20]. Energy efficiency is important for UEs because of its restricted battery capacity, therefore the reduction of power consumption of UEs increases their energy efficiency. However, in 5G networks, the utilization of M2M communication significantly improves spectral efficiency (SE) and EE. In addition, various intelligent techniques are integrated into M2M communication technology to mitigate the inference. However, M2M communication faces challenges in effectively sharing the radio spectrum and power allocation between the M2M UEs (MUEs) and cellular UEs (CUEs). In this article, a hybrid location-assisted framework was developed M2M communication approach was developed to resolve these issues.

The contribution of the proposed work is described as follows,

- This paper presents a location-aware framework for M2M communication over cellular networks. Here, RSS-based localization algorithm was integrated in the developed model to estimate the location of an unknown device.
- A communication mode selection module was designed, which operates based on the threshold distance and signal strength among devices; thus, it enables the UE to choose its communication mode automatically.
- An ACO-based resource allocation scheme was designed to share the available resources between the devices in two different modes. The integration of ACO enables the system to share resources based on their demands and optimizes the data rate, interference, and power consumption.
- A DGD-based power control mechanism was developed to optimize the transmit power each user equipment, thereby minimizing the inference, transmission power, and increases the energy efficiency.
- Finally, the projected framework is instigated in MATLAB tool, and the results are analyzed in terms of throughput, energy efficiency, and transmission power.

The organization of the presented work is described as follows, the literature related to the M2M communication was described in 2nd section, the system design is mathematically explained in 3rd section, the developed framework is explained in 4th section, the results of the proposed technique were examined in 5th section, and the research conclusion is described in 6th section.

2. RELATED WORKS

Few research articles associated to the proposed work are reviewed below,

Sree Krishna Das and Md Farhad Hossain [21] designed an energy management approach based on location of devices to minimize interference in the M2M communication system. This method utilizes a water filling and Lagrange decomposition techniques to manage transmission power of devices. The simulation outcomes illustrate that the developed model achieved optimal source sharing in an orthogonal cellular system. However, this model considers only the distance between the M2M pairs

Sree Krishna Das and Ratna Mudi [22] proposed a hybrid localization infrastructure based on differences and angle of arrival. The method utilizes the Kalman filter to detect the non-line of sight propagation error. The developed model enhances SE and EE by detecting the location of unknown devices in cellular networks. The developed scheme earned better device detection accuracy compared to the existing techniques. However, the utilization of the Kalman filter makes the system more complex and difficult to implement.

Sree Krishna Das *et al* [23] suggested a resource allocation methodology to boost the user experience. This method utilizes the reinforcement learning approach to estimate the optimal power allocation, which maximizes the attainable rate performance among M2M pairs. In addition, it increases the network capacity, and SE, and reduces interference. The convergence of the designed model is analyzed, which minimizes the computational complexity. However, the power consumption in cellular networks is more.

Yali Wu *et al* [24] presented a hybrid non-orthogonal random access with data communication protocol for M2M communication. This method utilizes the power back-off approach to modify the machine-type communication user to resolve the power issues in a cellular network. The optimal resource allocation increases the throughput and resource utilization. The proposed technique is less complex and prevents frequent computation. However, this method cannot mitigate cellular interference.

Zarin Tarannum Azim *et al* [25] proposed a deep Q network approach to minimize the difficulty in optimizing the reconfigurable intelligent surface (RIS) in M2M communications. This method effectively optimizes the location and level shift of RIS in M2M communication over cellular networks. The implementation results demonstrated that the proposed model attained a greater sum rate than the existing methods. Moreover, the QoS at the M2M receiver side is minimized in this approach.

Sree Krishna Das and Md Farhad Hossain [26] proposed a distance-based communication mode selection framework using the non-orthogonal resource allocation approach. In the presented framework, the UE choose its communication type based on the threshold distance between the M2M pairs. The results of the developed model was analyzed as throughput, and resource block utilization. In addition, the designed framework minimizes the traffic load in the cellular networks. However, it failed to address the power consumption challenge in M2M communication.

Nedaa Alhussien and T. Aaron Gulliver [27] presented a dual-phase optimal resource distribution model for M2M communications. The initial phase aims to satisfy the QoS demands, and the second phase aims to reduce the traffic in M2M cellular networks. The simulation outcomes demonstrated that the proposed model effectively decreases the delay and traffic in the system. However, the proposed technique face issues like computational complexity, high power consumption, and poor resource utilization.

3. SYSTEM MODEL

An M2M cellular communication system consists of a BS, user equipment, and a wireless channel. In a cellular network, the BS is the central node, which provides a wireless communication connection between the UEs and the core network. The UE is a device that communicates with the BS over the wireless channel. Typically, the wireless channel between the BS and UEs is designed as a time-varying fading with path loss. Fig 1 displays the system model of M2M communication.

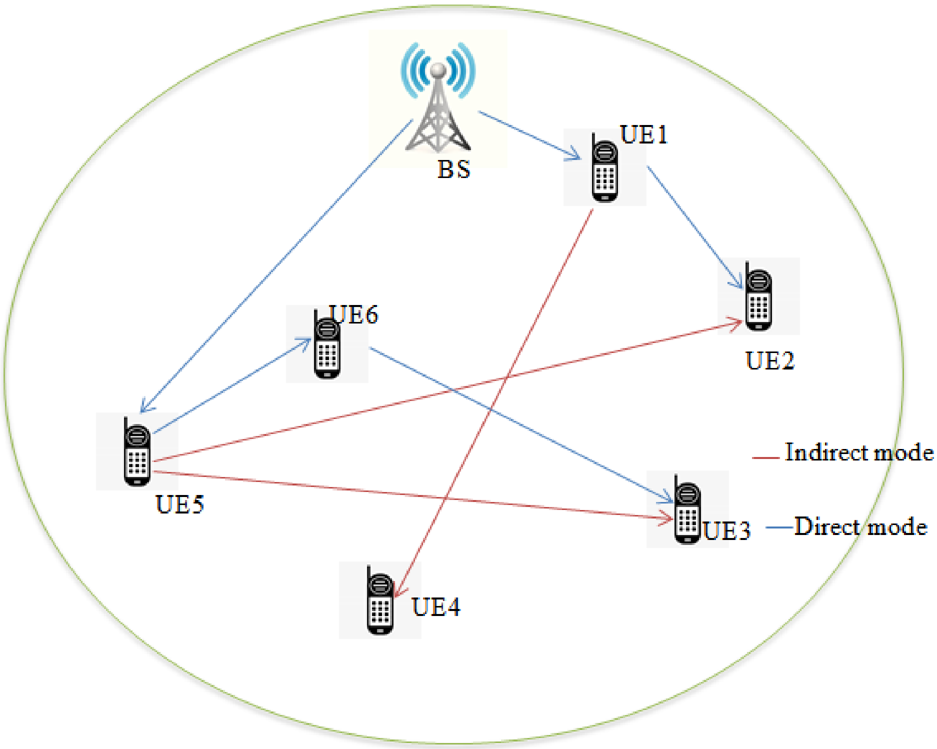

Fig.1 System Model of M2M communication

Here the wireless channel between the UEs and BS is modeled using a Rayleigh fading channel. The received signal at i^{th} UE is modeled as in Eqn. (1).

$$R_{si} = \sqrt{(p_i) q_i}\, x_i + n_i \qquad (1)$$

Where R_{si} defines the received signal at i^{th} UE, p_i indicates the transmit power of i^{th} UE, q_i refers to the channel gain between the BS and i^{th} UE, x_i is the transmitted symbol from i^{th} UE, and n_i represents the additive white Gaussian noise at i^{th} UE. The channel gain is represented in Eqn. (2).

$$q_i = \alpha_i * \sqrt{(d_i)^{(-\gamma)}} \qquad (2)$$

In which, d_i refers to the distance between the BS and i^{th} UE, α_i refers to the fading coefficient, and γ indicates the path loss exponent.

4. PROPOSED APPROACH FOR M2M COMMUNICATION

In M2M communication, the network model integrating the location of an unknown machine is important to mitigate interference. In the proposed work, the Received Signal strength (RSS)-based localization algorithm is applied to estimate the location of an unidentified user or device. Based on the location of the machine, the developed estimates the distance and signal strength. In the proposed work, the communication mode selection depends on the threshold distance and signal strength. Based on these two criteria's, the communication mode is selected as either direct mode or indirect mode. Then an ACO-based resource allocation module was developed to share resources between the devices for different models. This approach optimizes the data rate, power consumption, and interference in the communication system. Further, a DGD-based power control mechanism was designed to adjust the transmit power of each user's equipment, thereby minimizing interference and power consumption. The proposed framework is detailed in Fig 2.

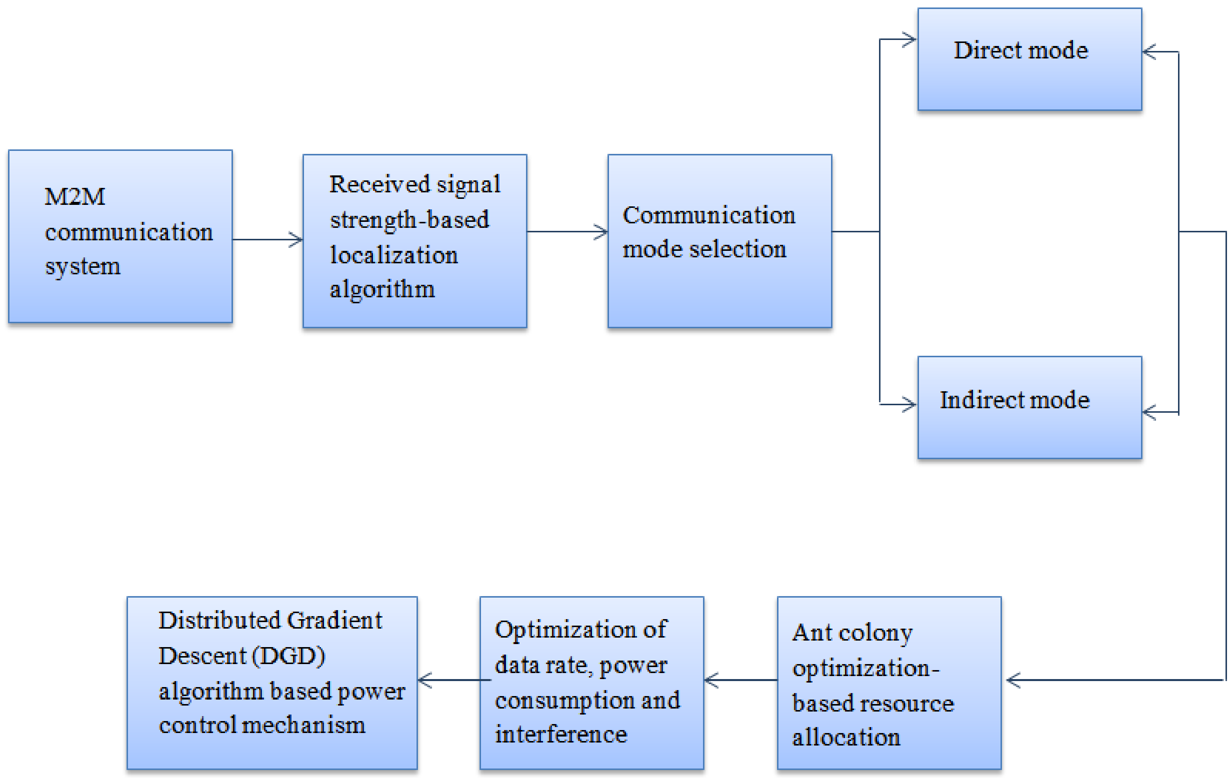

Fig. 2 Proposed Framework

4.1 Location estimation

In the proposed work, the Received Signal strength (RSS)-based localization algorithm was used to determine unknown device location. The basic principle behind RSS-based location estimation is to utilize the signal strength measurements from the multiple BSs to determine unknown device location. The received signal strength is the function of the distance between the unknown machine and the BS, and other factors like path loss, shadowing, and fading. Consider, a M2M communication system consisting of N several BSs. Let the number of measurements made at each base station be M. Assume $Y_{i,j}$ e the received signal strength at the base station i for the j^{th} measurement. The RSS-based localization approach estimates the location of an unknown device by solving the optimization problem and it is expressed in Eqn. (3).

$$\text{minimize} \quad \|y - f(x)\|^2 \qquad (3)$$

Where y denotes the $N \times M$ vector containing the receive signal strength, $f(x)$ refers to the $N \times 1$ vector of the expected signal strength at the unknown machine location, and x indicates the 2×1 vector consisting of the unknown coordinates of the unknown machine. The expected signal strength at the unknown machine location is expressed in Eqn. (4).

$$f_i(x) = P_t - PL_i(x) \qquad (4)$$

Where $PL_i(x)$ indicates the path loss from the base station i to the unknown machine location x, P_t denotes the transmitted power, and $f_i(x)$ refers to the expected signal strength of the unknown machine at the base station i. The path loss from the base station i to the unknown machine location x is expressed in Eqn. (5).

$$PL_i(x) = A_i + 10\, n_i \log 10(\mathrm{d}_i(x)) + X_i \qquad (5)$$

Where A_i denotes the reference path loss at a distance of 1 meter from the base station and it can be measured at a known distance from the base station, n_i indicates the path loss exponent, $\mathrm{d_i}(x)$ refers to the distance between the BS i and an unknown machine x, and X_i represents the Gaussian random variable representing the shadowing effect.

4.2 Communication mode selection

In M2M communication systems, the communication mode is selected based on the device's location. Typically, there are two different communication modes namely, direct and indirect mode. The communication mode is selected based on the distance threshold and the signal strength between the devices. In direct mode, the devices directly interconnect with each other without going through the cellular network. This mode is used when the devices are close to each other and the signal strength is strong enough to establish a reliable connection. In indirect mode, the M2M devices communicate through the cellular network, either directly or via intermediate nodes. This mode is used when the devices are far apart from each other or the signal strength is weak. Let d' be the distance between two M2M devices, and $\mathrm{d'_{th}}$ be the threshold distance, $\mathrm{S'}$ be the signal strength, and $\mathrm{S'_{th}}$ be the threshold signal strength. The communication mode selection is formulated in Eqn. (6)

$$C_{MS} = \begin{cases} if\left(d' \le d_{\mathrm{th}}\ or\ S' \ge S'_{\mathrm{th}}\right);\ Direct\ \text{mode} \\ if\left(d' > d_{\mathrm{th}}\ or\ S' < S'_{\mathrm{th}}\right);\ Indirect\ \text{mode} \end{cases} \tag{6}$$

Where C_{MS} denotes the communication mode selection function. If the distance between the devices is smaller than or equivalent to threshold distance or the signal strength is larger than or equal to the threshold value, the user selects direct mode. On the other hand, if the distance between the devices is higher than the threshold value or the signal strength is lower than the threshold value, the function selects an indirect mode.

4.3 Location-aware resource allocation

Location-aware M2M communication represents the communication between the devices, whose location and signal strength parameters are known. In cellular networks, the MUEs and the CUEs share the resources like bandwidth, power, etc., with each other. In the proposed model, ACO approach was utilized to optimally allocate and share resources between the MUEs and CUEs. Here, is the resource sharing between the MUEs and CUEs for both direct and indirect communication modes. ACO is a meta-heuristic optimization tecnique inspired by the foraging behavior of ants. In ACO-based resource-sharing schemes, a colony of virtual ants is utilized to estimate the optimal resource allocation among the devices in the network. The algorithm works by simulating the behavior of real ants, which communicate with each other using pheromone trails to estimate the shortest trail to a food source. In the context of location-aware resource allocation in M2M communication systems, ACO is utilized to determine the optimal allocation of resources among MUEs and CUEs in the network. The ACO algorithm is used to determine the shortest trail between the source and destination devices based on their locations and signal strength. Consider a scenario in which MUEs and CUEs share a resource over the cellular network. The resource can be either a frequency band or a time slot. In an ACO-based resource-sharing scheme, the ant agents are utilized to carry the pheromone trail from one device to another. The pheromone trail denotes the numerical value, which represents the level of resource demand, and in each iteration, the pheromone trail is updated based on the availability and demand of resources. The pheromone trail is expressed in Eqn. (6).

$$R_D(i, j) = 1/d(i, j) \tag{6}$$

In which, R_D is the pheromone trail between the device i and j represents the resource demand, and $d(i, j)$ indicates the distance between the device i and j. Further, the model allocates the available resource based on the pheromone trail of the devices. The devices that have laid down more pheromone trails are given a higher priority for resource access. The resource allocation is expressed in Eqn. (8).

$$R_A(i, j) = \left(R_D(i, j)^{\alpha} / \sum\left(R_D(i, k)\right)^{\alpha}\right) \quad (8)$$

In which, $R_A(i, j)$ defines the allocated resource between devices $i\ j$, α refers to the weighting factor, and $\sum\left(R_D(i, k)\right)^{\alpha}$ indicates the sum of the pheromone trail left by the device i for all k. In direct communication mode, the ACO technique determines the optimal resource allocation for a pair of devices communicating directly with each other. The algorithm considers the factors like locations of the two devices, their signal strength, and other parameters to calculate the optimal transmit power, data rate, and interference level. The data rate interrelates the bandwidth and the signal-to-noise ratio of the channel. The data rate of i^{th} direct mode user is expressed in Eqn. (9).

$$D_{Ri} = B_w \times log(1 + S_{nr}) \quad (9)$$

Where D_R represents the data rate of the i^{th} MUE, B_w indicates the bandwidth, and S_{nr} refers to the SNR. The interference in the M2M communication depends on the number of devices using the same resource and their transmit power levels. Let us consider L many devices using the same resource. The interference calculation is expressed in Eqn. (10).

$$I_n = P_t \times sum\left(d_r^{-2}\right) \quad (10)$$

Where I_n denotes the interference that occurred in direct communication mode, P_t refers to the transmit power, and d_r represents the distance between each device and the resource, and the sum is taken over all direct mode users. The power consumption of the i^{th} user is expressed in Eqn. (11).

$$P_{cp} = \sum_{i=1}^{L} P_{ci} \quad (11)$$

Where P_{cp} refers to the power consumption, and P_{ci} indicates the power consumed by each direct mode user. Similarly, the data rate, power consumption, and inference are estimated in an indirect communication mode.

In indirect communication mode, the ACO algorithm finds the optimal resource allocation for a group of devices communicating with each other through a relay node. The algorithm considers device locations, signal strength between the devices and the relay node, and other parameters to determine the optimal power consumption, data rate, and interference level for each device in the network. In indirect communication mode, devices communicate with each other through intermediate nodes in a network. Let us assume that there are two devices, one MUE and one CUE, which are sharing a resource through one intermediate node. The data rate calculation is expressed in Eqn. (12).

$$D_{Ri}^{ID} = B_{wdi} \times log(1 + S_{nr1}) \times log(1 + S_{nr2}) \quad (12)$$

Where D_{Ri}^{ID} denotes the data rate of the i^{th} indirect mode user, B_{wdi} represents the bandwidth utilized by the system, S_{nr1} refers to the SNR between the MUE and the intermediate node, and S_{nr2} represents the SNR between the intermediate node and the CUE. In indirect mode communication, the interference is influenced by the number of intermediate nodes and their transmit power levels. In indirect mode, the total interference is expressed in Eqn. (13).

$$I_n^{ID} = P_{dt} \times sum\left(d_{tr}^{-2}\right) \quad (13)$$

Where I_n^{ID} indicates the interference in the indirect mode communication, P_{dt} denotes the intermediate users transmit power and d_{tr} refers to distance between the intermediate node and the indirect mode user. The power consumption in indirect communication mode is expressed in Eqn. (14).

$$P_{cp}^{ID} = \sum_{i=1}^{L} P_{cpi} + \sum_{i=1}^{L} P_{tpi} \tag{14}$$

Here P_{cp}^{ID} is the power consumption, P_{cpi} indicates the power consumed by the indirect mode user, and P_{tpi} refers to the power consumed by the intermediate user. The total data rate, inference, and power consumption and is expressed in Eqn. (15), (16), and (17).

$$D_R^T = D_{Ri} + D_{Ri}^{ID} \tag{15}$$

$$I_n^{ID} = I_n + I_n^{ID} \tag{16}$$

$$P_{cp}^T = P_{cp} + P_{cp}^{ID} \tag{17}$$

Where D_R^T indicates the total data transmission rate, I_n^{ID} refers to the total interference and P_{cp}^T denotes the overall power consumption. This method considers the locations of M2M devices and optimizes the resource allocation process to reduce interference and power consumption while maximizing the data rate. Specifically, the scheme can allocate resources to devices that are close to each other, reducing the transmission power required and minimizing interference.

4.4 Optimal power control mechanism

An optimal power management module was created in the developed approach to change the transmit energy of each M2M devices based on their distance from the BS. The power control mechanism enables the system to reduce interference and system efficiency. In cellular networks, M2M devices assign a particular transmit power by the network operator. However, the assigned power will not be optimal for all devices because the signal strength fluctuates based on the distance between the device and the BS. If the distance between BS and device is large, it is important to improve its communication power to maintain a reliable connection. This leads to increase in interference and the energy utilization. Therefore, to resolve this issue, the DGD-based power control technique was designed in the presented work to adjust the transmit power of each UE based on their location from the BS. Basic principle behind this mechanism is to decrease the transmit power while maintaining the required signal strength at the receiver. This algorithm minimizes energy consumption and mitigates interference. The objective of the DGD-based power control mechanism is to reduce total power consumption and maintain a QoS level. Consider a cellular network with K UEs and a single BS. Let d_k denotes the distance between the BS and k^{th} UE. The received power at the BS from k^{th} UE is expressed in Eqn. (18).

$$R_{pk} = \frac{P_k}{{d_k}^{\delta}} \tag{18}$$

Where R_{pk} indicates the received power at the BS, P_k indicates the transmit power of k^{th} UE, and δ refers to path loss exponent. The aim of DGD is to decrease the total power utilization of all devices (UEs) subject to a minimum signal-to-interference-plus-noise ratio (SINR) limitation for each device. The SINR restriction is represented in Eqn. (19).

$$\chi_k \le \frac{\varphi_k}{I_{nr}} \tag{19}$$

Where χ_k refers to the SINR demand for k^{th} UE, φ_k indicates the noise power, and I_{nr} represents the interference from all other UEs. To solve the optimization problem, each UE updates its transmission power based on the gradient of the Lagrangian function concerning its power, using information from its neighbors. The Lagrangian function is expressed in Eqn. (20).

$$L_f = \frac{\sum\{k=1\}^K P_k}{d_k{}^{\delta}} + \sum\{k=1\}^K \beta_k\left(\frac{\chi_k - \varphi_k}{I_{nr}}\right) \quad (20)$$

Where L_f indicates the Lagrangian function, β_k refers to the Lagrange multiplier for the SINR constraint of the k^{th} device. The gradient of the Lagrangian function concerning P_k is represented in Eqn. (21).

$$\frac{\partial L_f}{P_k} = \frac{1}{d_k{}^{\delta}} - \frac{\beta_k\,\varphi_k}{\left(R_{pk}(I_{nr})^2\right)} \quad (21)$$

Further, k^{th} UE updates its transmission power and it is expressed in Eqn. (22).

$$P_k(t+1) = \max\{0, P_k(t) - S_{ts}\,\partial L_f/\partial P_k\} \quad (22)$$

Where t refers to the iteration index, and S_{ts} denotes the step size. The power control algorithm converges to an achievable solution, which satisfies the SINR constraint for all UEs while minimizing the total power consumption. The convergence rate depends on the choice of step size, the topology of the network, and the path loss exponent δ.

5. RESULTS AND DISCUSSION

In this article, a hybrid localization-assisted framework was designed to minimize power consumption and interference in the M2M communication system. The proposed approach includes localization, communication mode selection, optimal resource allocation, and power control. This approach integrates the ACO and DGD algorithms to optimize the transmit power, interference, and data transmission rate. The developed model was implemented in the MATLAB tool, version R2020a. The outcomes of the proposed technique were analyzed in terms of transmission power, energy efficiency, and throughput. Finally, a comparative assessment was carried out to validate the performance of the presented framework.

5.1 Performance comparison

The proposed strategy was implemented in MATLAB and the performance are evaluated based on user equipment and randomly located base stations. In the developed strategy, a total 50 number of resource blocks are assumed. Moreover, the key metrics are computed under different parameters such as transmission power, energy efficiency, and throughput. The results are compared with existing techniques like Joint Resource Allocation based Clustering (JRA-C) algorithm [28], Adaptive Routing Protocol (ARP) [29], and Location-based Discovery Heterogeneous Network (L-DHN) architecture [30].

5.1.1 Transmission power

Transmission power is the amount of power required to transmit a signal from a User Equipment (UE) device to a base station in a cellular network in M2M (Machine-to-Machine) communication. The transmission power is a crucial parameter in wireless communication systems, as it determines the signal strength and the coverage area of the UE device. In addition, it defines the distribution of energy from its base station of generation to a position where it is adapted to perform the possible work.

Table.1 Performance comparison of transmission power

Sl. no	Threshold distance	Transmission power (dBm)			
		JRA-C	ARP	L-DHN	Proposed
1	50	-53.4	-30.31	-83	-143
2	60	-49	-21.62	-72	-129
3	70	-46.5	-13	-70	-115

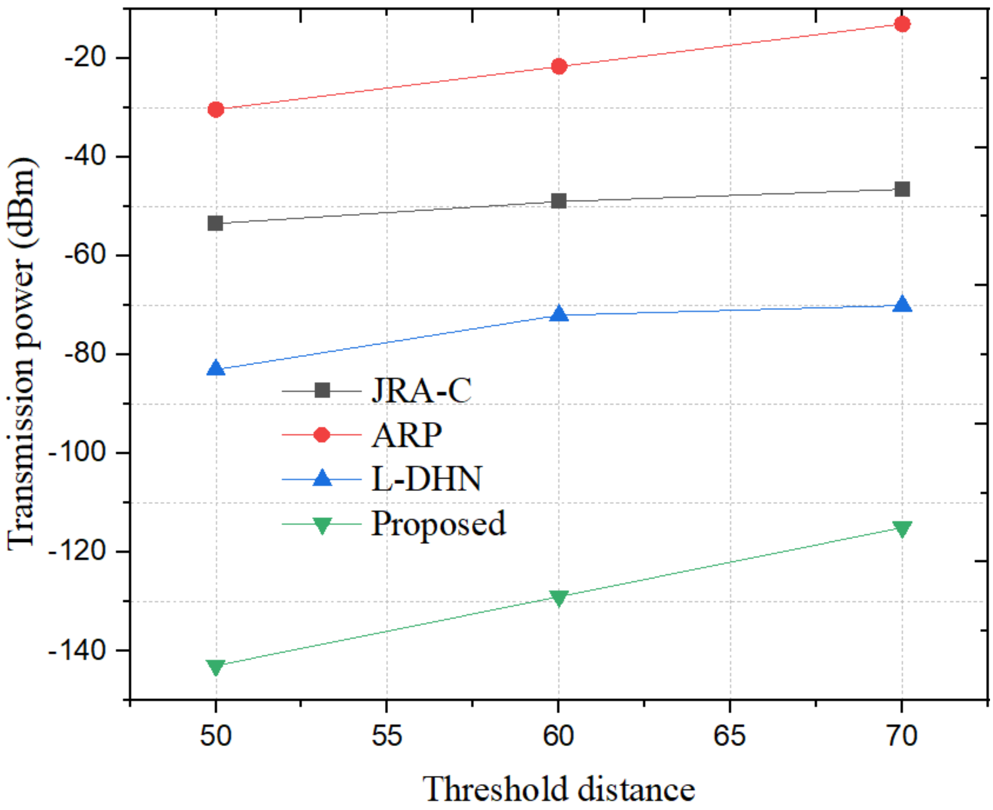

Fig.3 Transmission power validation

Fig 3 presents the validation of transmission power with respect to the threshold distance. Here, UEs increase the transmission power simultaneously, and then the per-user energy efficiency is increased faster. Therefore, the M2M communication has interference with the linearly increased system performance. Table 1 tabulates the transmission power comparison. The transmission power earned by the presented technique is evaluated with the traditional methodologies such as JRA-C, ARP, and L-DHN. This shows that the existing approaches have a low transmission power rate when compared to the presented approach. The rate of transmission power obtained by existing algorithms like JRA-C, ARP, and L-DHN are -46.5 dBm and -13 dBm, and -70 dBm respectively for a 70m threshold distance. However, the presented approach attained a transmission power rate is -115 dBm for a 100m threshold distance.

5.1.2 Energy efficiency

Energy efficiency refers to the amount of information that can be communicated per unit of energy consumption. Therefore, the EE is considered as an essential parameter to evaluate and optimize the energy consumption, and network performances, respectively. Typically, the EE determined in terms of bits per Joule, which represents the number of bits transferred per unit of energy consumption. Moreover, the increased EE denotes the reduction of noise power in the system. Consequently, a larger amount of noise power can cause the performance of lower energy efficiency. Validating the outcomes attained from three existing techniques and the proposed mechanism provides the finest performance than the developed one.

Table.2 Performance comparison of energy efficiency

Sl. no	Threshold distance	Energy efficiency (bits/joule)			
		JRA-C	ARP	L-DHN	Proposed
1	50	56	14.6	8.2	19
2	70	60	21.4	11.7	41.5
3	80	61	25.2	13.6	44.8
4	90	67	32.4	15	53.1
5	100	68	36.6	18	55

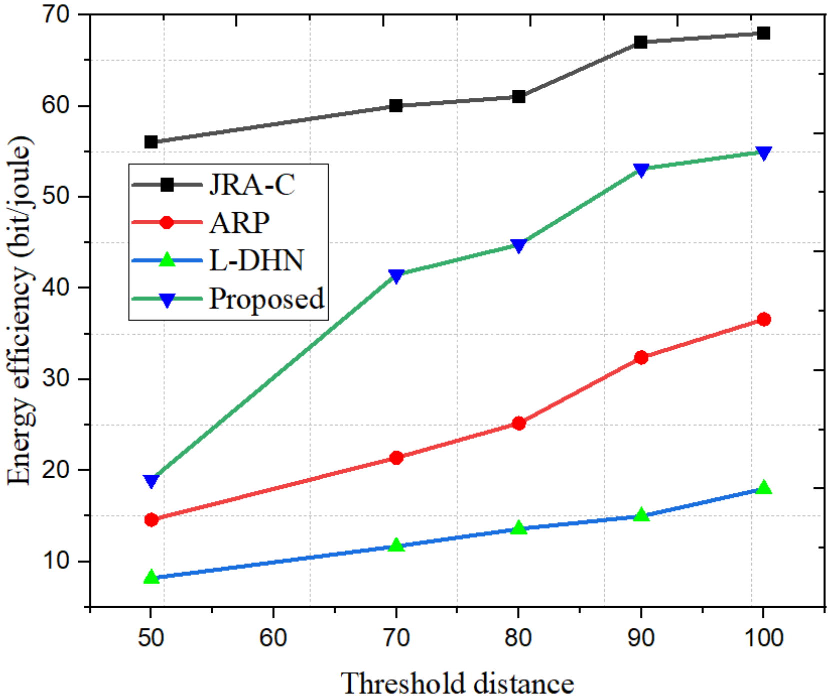

Fig.4 Comparison of Energy efficiency

The energy efficiency earned by the presented framework is validated with conventional methods like JRA-C, L-DHN, and ARP. The comparative analysis of energy efficiency value is presented in Fig 4. and Table 2. This describes that the existing approaches attained low energy efficiency score when compared to the presented approach. The percentage of energy efficiency scores obtained by existing algorithms like JRA-C, ARP, and L-DHN are 68 bit/joule, 36.6 bit/joule, and 18 bit/joule respectively for 100m threshold distance. However, the presented approach attained a greater energy efficiency score of 55 bits/joule for a 100m threshold distance. Furthermore, the EE can be enhanced by reducing the energy consumption of the UE devices and optimizing the transmission parameters.

5.1.3 Throughput analysis

Throughput refers to the rate at which information is transmitted between the UE devices and the base station. In M2M communication, throughput analysis is essential to determine the system performance and to optimize the network resources. The throughput is typically measured in terms of bits per second (bps), which represents the number of bits transmitted per second. The network capacity to transmit and receive the information is termed in the name of throughput. Moreover, attaining more ratio of the throughput can simply enhance the capacity of data transmission. In a location-aware network, the complex structure might accomplish a very less ratio of throughput. Moreover, fig. represents throughput versus the number of UEs in various modes and operations. Here, the throughput rate is increased with respect to per user simultaneously the number of UEs increases.

Table.3 Performance comparison of throughput

Sl. no	Number of UEs	Throughput (KBPS)			
		JRA-C	ARP	L-DHN	Proposed
1	4	271	628	998.4	712
2	8	272.92	662	876.53	537
3	12	280.55	580	745.88	481
4	16	283.32	495	699.8	327
5	20	313.39	496	644	237

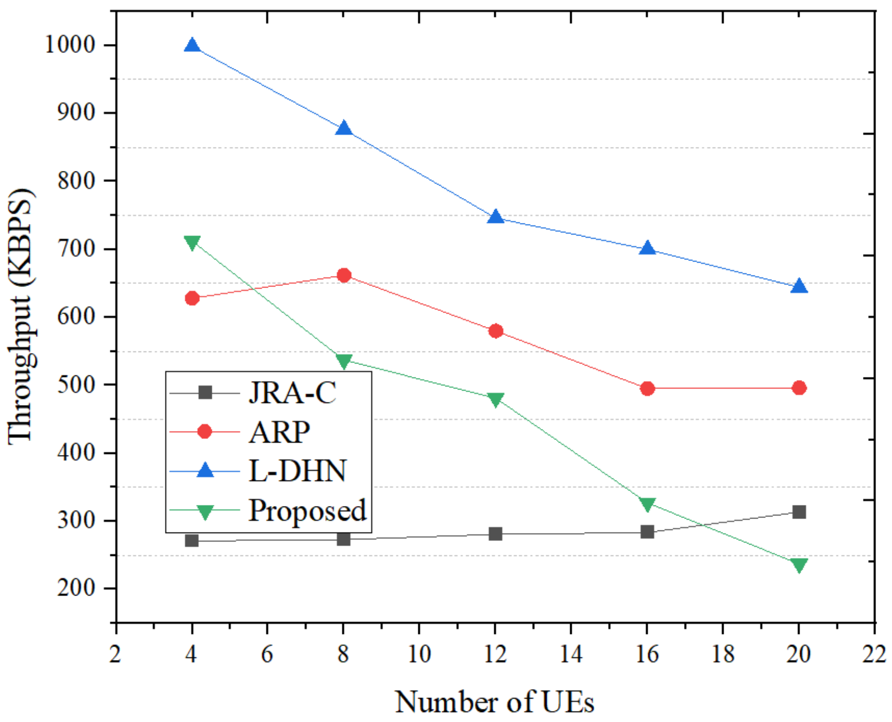

Fig.5 Comparison of throughput

The throughput rate obtained by the presented framework is evaluated with traditional approaches like JRA-C, ARP, and L-DHN. The comparative analysis of throughput rate value is presented in Fig 5. and Table 3. This demonstrates that the conventional approaches have a lower throughput rate when compared to the presented approach. The throughput rate value obtained by existing algorithms like JRA-C, ARP, and L-DHN is 271 KBPS, 628 KBPS, and 998.4 KBPS respectively for 4 number UEs. However, the presented approach has attained a higher throughput rate of 712 KBPS for 20 number UEs.

6. CONCLUSION

This paper presents an optimized localization-assisted power control and communication mode selection framework for the M2M communication system to decrease power utilization and interference. Initially, the proposed work estimates the location of the machine using the RSS approach and evaluates the distance and signal strength between the M2M pairs. In the proposed framework the communication mode was selected based on the signal strength and threshold distance between the M2M pairs. An ACO-based resource allocation scheme was analyzed for different communication modes to optimize the data rate, interference, and power consumption. Furthermore, a DGD-based power control strategy was designed to optimize the transmission power of all devices in the communication system. The developed model outcomes are analyzed in terms of throughput, EE, and transmission power and validated with the existing techniques like JRA-C, ARP, and L-DHN. The implementation outcomes demonstrates that the proposed framework decreases the power consumption, and interference, efficiently.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

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Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

Competing Interests : Not applicable

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