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5G-Based Transmission Power Control Mechanism in Fog Computing for Internet of Things Devices

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Abstract: Fog computing has become the revolutionary paradigm and one of the intelligent services of the 5th Generation (5G) emerging network, while Internet of Things (IoT) lies under its main umbrella. Enhancing and optimizing the quality of service (QoS) in Fog computing networks is one of the critical challenges of the present. In the meantime, strong links between the Fog, IoT devices and the supporting back-end servers is done through large scale cloud data centers and with the linear exponential trend of IoT devices and voluminous generated data. Fog computing is one of the vital and potential solutions for IoT in close connection with things and end users with less latency but due to high computational complexity, less storage capacity and more power drain in the cloud it is inappropriate choice. So, to remedy this issue, we propose transmission power control (TPC) based QoS optimization algorithm named (QoS-TPC) in the Fog computing. Besides, we propose the Fog-IoT-TPC-QoS architecture and establish the connection between TPC and Fog computing by considering static and dynamic conditions of wireless channel. Experimental results examine that proposed QoS-TPC optimizes the QoS in terms of maximum throughput, less delay, less jitter and minimum energy drain as compared to the conventional that is, ATPC, SKims and constant TPC methods.

Keywords: Fog computing; Internet of Things; QoS optimization; transmission power control; constant TPC; ATPC; SKim

1. Introduction

5G technology has become the center of attention in every corner of the world due to its highly resource allocation and flexible nature. In the meantime, Fog computing, edge/cloud computing and Internet of Things (IoT) and so forth, have revolutionizing many sectors such as, health, education, enterprises and industries by enhancing their resources that is, functional costs, power usage and quality management and so forth. Fog computing and IoT as a whole is portraying the clear image of the entire map and further will be explored, enriched and totally transformed from their previous conditions. It is analyzed that nearly 57% of the world's population will be facilitated by IoT system with high resources. But one of the challenging issues of the IoT devices and networks is the high-power drain and limited battery lifetime with regular recharging from the external sources. The wireless link or channel status varies with different conditions such as, interference from same network devices, internal noise and environmental factors and so forth, also natural hindrances for example, roofs and walls are degrading the signal strength at the larger level. Poor reliability is also adversely affecting the by increasing more delay and overhead of packets during transmission of packets. To enhance the channel quality in terms of high signal delivery and less placket loss ratio (PLR) in IoT enabled sensor networks, minimizing the power drain and extending the battery lifetime of the sensor based devices is the first and foremost priority. As sensor nodes from several manufacturers such as, TelosB, MicaZ and so forth, dissipates the more power than the other parts for example, CPU, hard-drive and ROM and so forth. In addition, it increases the contention in the network. For prolonging the network lifetime and increasing transmission reliability (i.e., reducing PLR), transmission power control (TPC) mechanism is most appropriate one because it increases/decreases power according to the need of the end user and predefined threshold levels by adopting the channel conditions. Key purpose of TPC strategy is to achieve optimal transmission power, a power level that does not break the already established link between a pair of nodes and avoid the contention in the network. The decision to change transmission power level based on link quality indicator (LQI) is not appropriate, because of less convincing to get rid of environmental disturbances and deviation from the predefined threshold levels. That is another entity received signal strength indicator (RSSI) is adopted accurately analyze the quality of the receiver's signal then adapt the transmission power in an on-demand fashion accordingly. This fluctuation in the power level in a dense network increases the interference resulting in a collision and ultimately high packet loss ratio (i.e., less reliability). This paper, therefore, investigates the impact of TPC on the quality of the entire network. It is also observed that when the fluctuation in wireless channel and difference in transmission power levels is longer than interference and re-transmission rate of packets increase. Hence, less quality of service and more power drain.

Furthermore, 5G based Fog computing and IoT have become the part and parcels of our everyday routine by examining and analyzing the entire environment to take the strong initiative for the present and future trends [1]. In order to realize the full benefits of the IoT, it will be necessary to provide sufficient networking and computing infrastructure to support low latency and fast response times in various applications. Cloud Computing in the key enabler for IoT applications due to its ample storage and processing capacity. Nonetheless, being far from end-users, cloud-supported IoT systems face several challenges including high response time, heavy load on servers and lack of global mobility.

We rigorously describe the TPC based mechanisms for QoS optimization in distinct networks with main focus at the 5G-enabled adaptive transmission power control algorithm for the QoS optimization and monitoring in the Fog computing by considering the static and dynamic channel characteristics. Many authors have already contributed significantly in revolutionizing the entire wireless and sensor worlds for efficient and closed communication between heterogeneous networks, especially, IoT, Fog and cloud computing and so forth. Whereas, very few have explored the QoS domain and still there is no proper and effective method to fix the QoS optimization and monitoring in the IoT and Fog computing with the transmission power control. Also, the static and dynamic behavior of the channel during QoS optimization in Fog and IoT networks needs to be considered. At the same time the rapid proliferation in the emerging market of the miniaturized IoT devices have facilitated the consumers on the one hand, while on the other hand, their power-hungry nature and limited battery lifetime have created several challenges in the Fog and IoT networks. So, keeping this demand into mind we have taken into account the notion of TPC-based QoS optimization in Fog computing by considering the static and dynamic wireless channel states.

As the number of connected devices increases exponentially, achieving higher network capacity and reliability with lower latency and energy consumption is challenging. It is estimated that the IoT will cause the Internet Protocol (IP) traffic to increase up to 300% by 2018 [1]. Although not all the network embedded devices (e.g., sensor nodes) will communicate simultaneously among each other and outside the network due to highly dense and multi-hop nature. Thus, it is crucial to investigate that how the QoS of IoT networks is affected with conventional methods and what changes are effectively made by the proposes algorithm.

Furthermore, remote deployment of an IoT network makes it difficult for the field technician to replace the battery sources, hence, prolonging the battery lifetime of the sensor nodes is very vital. This research aims to resolve the challenging problems, for instance, how to optimize the QoS in the Fog and IoT system by adopting the transmission power control strategy? To establish the strong and appropriate connection between the QoS metrics for example, throughput, delay, jitter and energy drain and TPC in the presence of the static and dynamic channel conditions? How to develop the state-of-the art Fog framework in-line with the IoT and TPC?

This paper contributes in two ways.

- We propose a novel 5G enabled Transmission Power Control (TPC) algorithm for QoS optimization titled (QoS-TPC). In addition, tradeoff between Transmission Power Control and QoS metrics such as, throughput, delay, jitter and energy consumption is established by considering the static and dynamic channel features. Besides, the proposed algorithm is compared with the conventional adaptive transmission power control (ATPC), SKims and constant TPC methods.
- Framework of the 5G-based TPC for QoS optimization in the Fog and IoT system is proposed, as shown in the Figure 1.

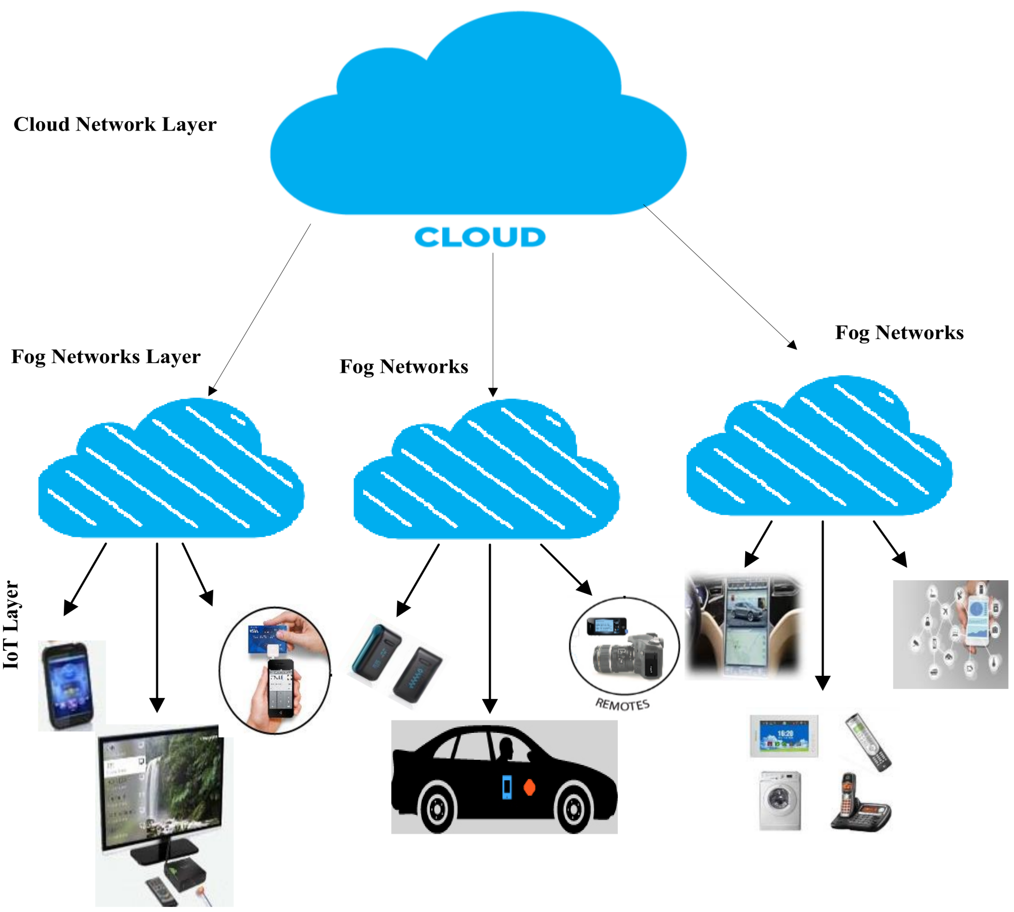


Figure 1. Proposed 5G-enabled Fog Computing and Internet of Things (IoT) based Architecture.

The rest of the paper is structured as follows. Section 2, reviews the rigorous literature about Fog computing, IoT system, QoS, 5G-based TPC and wireless channel and so forth. Section 3, proposes the 5G-based Transmission Power Control (TPC) algorithm for QoS optimization in Fog networks. Experimental results extracted in Section 4, paper is concluded in the Section 5.

2. Related Work

5G-based transmission power control (TPC) for Quality of service (QoS) provisioning is the key ingredient, while its optimization over the Fog and IoT system is the biggest hurdle to fulfil the needs of the network [1–5]. In the literature, various power management algorithms have been proposed such as, power control for the fair time slot allotment, adaptive and dynamic nature power control, duty-cycle enabled power control and so forth. Authors in [6–10] discuss that the dynamic power management (DPM) chooses the power levels in a random fashion to save the energy in the sensor networks but it has limitation to get the entire information of the past and future data which is very complex task. Similarly, the power control algorithm (PCA) in [11] adjusts the power levels by considering the needs of channel but the correlation between nodes is very weak that is why large portion of the power is dissipated in the control message transmission. While time slot control based principle offers the longer idle span, hence, more energy will be saved as compared to schemes in [12]. Authors in [13,14] design the sleep wake-up mechanism to save the more energy by increasing the sleep time of nodes, besides there is an automatic switching between these two states. Authors in [15], establish the trade-off between energy drain and he delay between transmitter and receiver nodes to manage the duty-cycle of the entire network. Authors in [16–19], design the closed-loop power control mechanism by adopting the various channel states but they do not focus at the QoS optimization in the Fog computing. Researchers in [20], present the signal to noise ratio based channel allotment scheme and they followed the work in the [21,22] for investigating the role of bandwidth and channel in effective resource allocation. Generally, in the sensor networks IoT and Fog computing reliability and TPC are inter-related and hence, the better QoS classifiers. Hence, it is very vital to build the track between QoS, channel, TPC, energy efficiency and the battery lifetime, for further details see Table 1.

Most of the traditional schemes are helpful to save the power and somehow QoS but still there is large room vacant to deal with the TPC based QoS optimization in the Fog and IoT in the presence of various wireless channel forms. Thus, a very few related works are discussed one by one. As APTC [3], develop the adaptive TPC algorithm to save the energy in the WBANs by considering the various body postures and scenarios, besides their work optimizes the channel parameters and compared with the traditional methods. But they do not focus at the joint TPC and QoS optimization approach for the Fog and IoT. Similarly, SKims [2], re-enforcement learning based TPC based method is very efficient to optimize the QoS in IoT networks but their power adaptation mechanism is very complex from computational point of view and not very effective. On the contrary our proposed TPC based QoS algorithm is very simple, effective and requires very few control packets while exchanging/transferring information between the transmitter and receiver. Moreover, their research do not broadly present the interconnection between TPC and various network metrics in the presence of the static and dynamic channel conditions. Last traditional algorithm is the constant TPC, which either saves more energy or shows more reliability and do not possess both qualities at a time, so it is not the potential candidate for the IoT and Fog computing environment.

All the aforementioned research works have worked in the diverse domains with the distinct goal and target to be achieved. Few of the emerging areas are described as, energy efficiency, resource allocations, TPC, QoS control, power monitoring and management in different direction that is, sensor networks, IoT, cognitive radios, cellular networks, wireless networks, wireless body area/sensor networks and so forth. But this paper presents very remarkable contribution by proposing 5G-based TPC algorithm for QoS optimization and adopting wireless channel's entire features, network metrics, Fog computing, IoT and so forth. Besides, 5G-based Fog computing and IoT framework is proposed.

Table 1. Summary of Existing Works.

Ref. No	Applications	Proposed Techniques	Component Being Optimized	Results
[1–5]	QoS optimization, TPC	Review	QoS metrics	QoS aware Fog computing and IoT
[6–10]	IoT-enabled Fog computing, QoS	TPC driven and MAC based	Data rate and throughput	TPC-aware QoS control
[11–15]	IoT, 5G, smart mobile security	TPC and data rate based	Security key, resource allocation	Low power consumption
[16–18]	IoT, Security and ECG	Algorithms, Architecture	Authentication key, Duty cycle	Minimize cost and energy consumption
[19–21]	IoMT, Telemedicine	Battery-friendly, rate control	Battery charge and modulation level	IoT longer media transmission
[22–25]	Wireless capsule, IoMT	Predictive techniques	Battery charge, data rates	Improve mobility, battery lifetime
[26–29]	IoT, DLM, wireless ad-hoc networks	Window-based algorithms, Battery models	Transmission rates	Battery-friendly and energy-efficient
[30–32]	Medical media, 5G	Energy optimization algorithms	Novel Frameworks	Smart medical healthcare system
[33–35]	IoT, PLM, Smart Cities, Industries	Ontology-based methods and architectures	Battery lifecycle	Smart PLM, Smart CPS
[36–38]	IoT, QoS, WSN, Security,	Dynamic game-based and energy management	TPC and data rate	To extend the lifecycle of medical devices
[39–45]	IoT, Energy Harvesting, PLM and WPT	Battery-friendly and Energy Harvesting	Battery charge	Lifetime of smart IoMT and BSN devices
[46–52]	IoT, EEG, Security in BAN	Routing-based power control techniques	To optimize QoS in PLM	To monitor IoT based healthcare
[53–61]	IoT, Artificial Intelligence, security QoS and Energy management Frameworks	Fuzzy-logic, HRV and energy-efficient techniques	To optimize, transmission power and battery charge	To obtain energy-efficient IoT based
[62–69]	IoT, BSN, ECG, PLM data sources	TPC, energy harvesting	To optimize, manage the TPC and duty-cycle	Smart healthcare

3. Proposed Transmission Power Control Mechanism

In this section we first propose the block diagram of the 5G-based TPC mechanism, then explain the TPC in detail with key focus at the QoS optimization in the Fog and IoT system.

3.1. Block Diagram

For the efficient and intelligent examination of the wireless channel, received signal strength indicator (RSSI) is considered as an emerging entity for the Fog computing and IoT-enabled nodes while fairly allocating the transmission power and hence the QoS optimization. It is estimated within the transceiver radio by attaining the normal value of the signal power over multiple symbol periods, that is, eight of the received information packet analogous to distinct body movements and gestures of individuals [1,2]. RSSI explains the strength of received power at the destination node and is evaluated by the time, transmission power (TP) and distance among other nodes. The reliability of channel is proportional to RSSI which is further used to characterize it. The sensor node at sender side transmits a packet after every 200 ms with TP levels in between 0 dBm and −25 dBm. Receiver sets RSSI threshold level of −100 dBm, which shows packet loss/worst channel condition. Moreover, the path loss calculation for both static and dynamic channel states are considered at the 2.4 GHz frequency. It is observed that there is relatively high path loss in dynamic channel condition and higher frequency, however, packet loss is very low in static case and lower frequency [2]. We used accelerometer sensors to detect static and dynamic channel states accordingly. Hence, this study proposes TPC based framework for considering dynamic and static cases to efficiently adapt the channel deviations for optimizing the QoS as shown in Figure 2. In the proposed framework, receiver obtains one data packet from transmitter then calculates RSSI; if its value exceeds RSSI target value, then acknowledgment (ACK) of short inter-frame space period (pSIFS) will be sent to transmitter side. Also signaling overhead is not taken into account, less power is consumed in a static case unlike the dynamic.

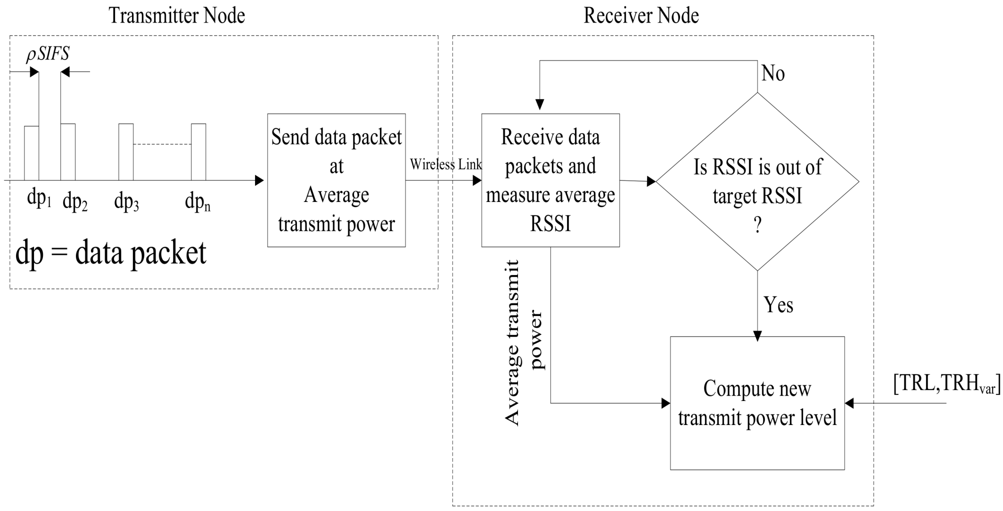


Figure 2. Block diagram of the 5G-based Transmission Power Control (TPC) in Fog and IoT system.

3.2. Transmission Power Control Based QoS Optimization

As Fog computing is one of the 5G's intelligent services and this sub-section proposes and presents in detail the 5G-enabled TPC algorithm for QoS optimization (QoS-TPC). Our proposed QoS-TPC can be run by the receiver as well as by the transmitter sensor nodes as following the QoS requirement of sensor nodes in Figure 3. For the sake of ease, we suppose that only receiver performs TPC. The entire working principle of the proposed QoS-TPC is discussed below.

First, the receiver computes the average RSSI ($\overline{R}$), (steps 2 and 4) for each latest and lowest (i.e., obtained after latest sample) received samples before determining transmission power (TP) level. Assume the TP and the corresponding RSSI at the receiver for the latest (i.e., current) sample is P_t and R_{latest} both in dBm respectively, similarly the lowest sample (i.e., received after latest sample) have transmission power and RSSI as $P_t - \Delta P_i$ and $R_{latest} - 1$ respectively, where $i = 1, 2, \ldots\ldots\ldots, N$ shows number of TP levels for CC2420 radio. After receiving the RSSI sample, the BS updates the average RSSI, $\overline{R}$, according to the Equations (1) and (2).

$$\overline{R} = R_{latest} + (1 - \alpha_1) \times R_{lowest} \tag{1}$$

$$\overline{R} = R_{latest} + (1 - \alpha_2) \times R_{lowest} \tag{2}$$

whereas, α_1 and α_2 are the average weights of RSSI sample exhibiting good and bad state channels, accordingly.

The BS compares the value of $\overline{R}$ with the known target RSSI (R_{target}) and then decides the TP level by using Equation (3).

$$\Delta P = \arg\left\{\Delta P_1, \Delta P_2, \ldots, \Delta P_N \overset{\min}{} \left(\sqrt{\left(R_{\text{target}} - \overline{R} - \Delta P_i\right)^2}\right)\right\}$$
$$s.t. \Delta P_i > R_{\text{target}} - \overline{R} \tag{3}$$

whereby, N is the number of TP levels and at least $\lceil \log 2(N) \rceil$ bits are required to exploit respective value for TPC.

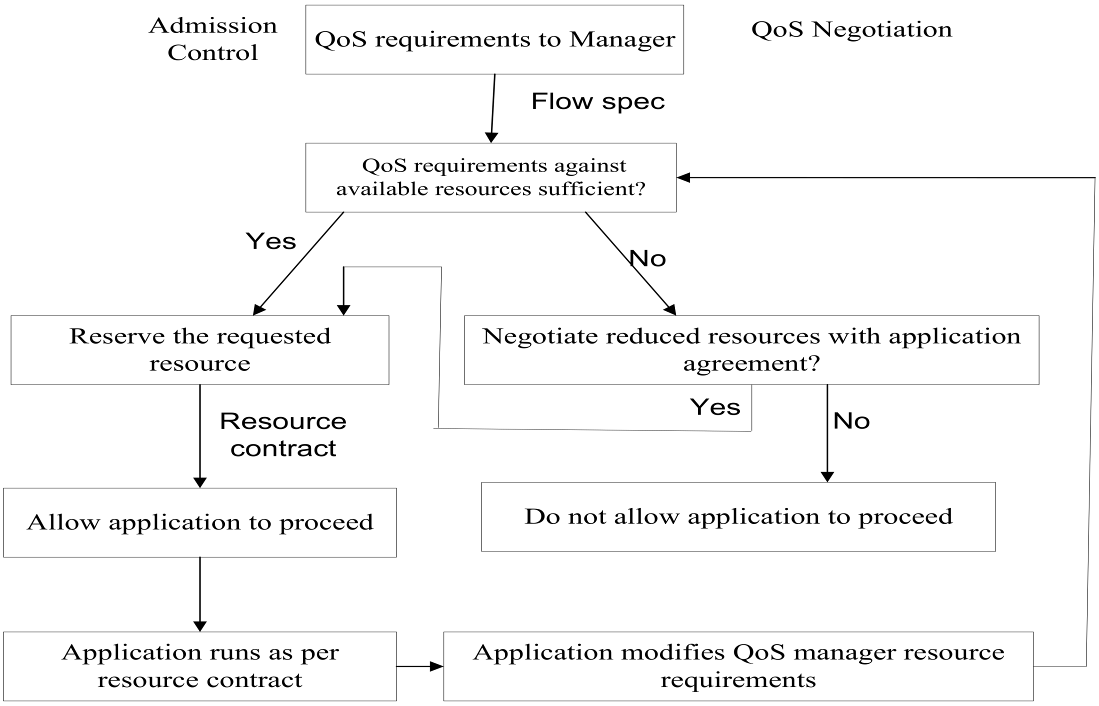


Figure 3. Flowchart of the Quality of Service (QoS) requirement in Fog and IoT systems.

The principle ingredients of the proposed QoS-TPC algorithms are the average RSSI ($\overline{R}$), target RSSI (R_{target}), α_1; coefficient of the good channel and coefficient of the bad channel α_2 with higher and lower threshold levels TRH, TRL, respectively.

Proposed 5G-based QoS-TPC algorithm adjusts the transmission power in an on-demand fashion by considering the entire features of the wireless channel in Fog and IoT system. If TRH greater than R_{target} (step 6), the transmission power is decreased (step 7) to save energy. On the other hand, if TRL falls below the R_{target} (step 6), the transmission power is increased (step 7) to improve channel reliability. Similarly, transmission power adaptation guarantees effective and reliable communication in Fog and IoT. Finally, we should also make sure that the power for each transmission shall neither exceed $P_{\max}$ nor drop below $P_{\min}$, (steps 11 and 14). Proposed QoS-TPC algorithm is simple and easy to implement because small computational complexity is introduced to the receiver and the transmitter sensor nodes. Furthermore, the proposed QoS-TPC does not require large signaling overhead because only few bits are needed for the acknowledgment data packets as shown in the Figure 4.

The key aim to adopt the lowest RSSI samples is to keep consistency in the data transmission by getting feedback information about the power levels. This is the first step to introduce the TPC, Fog and QoS optimization mechanism in the IoT. We verified through experimental results in MATLAB that proposed algorithm outperforms the conventional IoT TPC such as ATPC [3], SKims [2] and constant TPC methods in terms of energy saving, RSSI stability, packet loss ratio (PLR), throughput, delay and jitter as shown in Figures 4–6. Wireless channel with two experimental cases such as, static and dynamic is used and observed that proposed algorithm outperforms the traditional methods in terms of RSSI stability, acceptable reliability, average throughput, more energy saving, less delay and jitter values.

Pseudocode: 5G-based TPC algorithm for QoS optimization in Fog

R_{latest} : (RSSI Samples in the start)

R_{lowest} : (RSSI samples in the last)

$\overline{R}$: (RSSI Average)

R_{target} :(RSSI target)

if $R_{latest} > \overline{R}$

$\overline{R} = R_{latest} + (1-\alpha_1) \times R_{lowest}$

else $R_{latest} < \overline{R}$

$\overline{R} = R_{latest} + (1-\alpha_2) \times R_{lowest}$

endif

if $\overline{R} > TRH$ or $\overline{R} < TRL$

$$\Delta P = \arg\left\{ \overset{\min}{\Delta P_1, \Delta P_2, \ldots\ldots, \Delta P_N} \left(\sqrt{\left(R_{target} - \overline{R} - \Delta P_i\right)^2} \right) \right\}$$

$$s.t. \Delta P_i > R_{target} - \overline{R}$$

$$QoS\_Opt = \{\Delta P - \left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(R_i - R_{target}\right)^2}\right) - \frac{8 \times pl}{delay(pl)} - (WIN_{avg} + T_{Data} + T_{Ack} + 2T_{pSIFS} + 2\tau)\}$$

else $\{TRL \leq \overline{R} \leq TRH \pm QoS\_Opt\}$

$\Delta P = 0$

endif

(The sensor nodes in IoT will perform)

If $P_t + \Delta P > P_{max} + QoS\_Opt$

$P_t = P_{max} - QoS\_Opt$

else $P_t + \Delta P < P_{min} + QoS\_Opt$

$P_{min} \pm QoS\_Opt$

elseif $P_t = P_t + \Delta P - (QoS\_Opt)$

end

end

Figure 4. Proposed 5G-based TPC Algorithm for QoS optimization in the Fog Networks.

3.3. Performance Metrics for IoT SYSTEM

In this section, we present the trade-off between 5G-enabled transmission power and the different network metrics, such as throughput, delay, jitter and energy consumption level, for our proposed TPC-QoS algorithm and conventional TPCs, such as ATPC, SKims and Constant TPC methods, in the Fog and IoT system. We follow the IEEE 802.15.4 IoT's standard MAC with physical layer [3,23], each network entity will be discussed briefly. Main notations and symbols of this section are described as:

T_{PHR} = Transmission time of PHY header
T_P = Transmission time of preamble
R_{Data} = Data transmission rate

T_s = CSMA slot length
$T_{\rho SIFS}$ = Short inter-frame spacing time
T_{CCA} = Clear channel assessment time
MHR = MAC header
FTR = MAC footer
T_{Ack} = Acknowledgement
τ = Propagation delay

$$PLR = \frac{l}{s} \tag{4}$$

$$MaximumThroughput = \frac{8 \times pl}{delay(pl)} \tag{5}$$

$$delay(pl) = WIN_{avg} + T_{Data} + T_{Ack} + 2T_{\rho SIFS} + 2\tau \tag{6}$$

$$\begin{aligned} WIN_{avg} &= \tfrac{WIN_{\min}.T_s}{2} \\ &= \tfrac{WIN_{\min}.(T_{CCA}+20\mu \sec)}{2} \end{aligned} \tag{7}$$

3.3.1. Maximum Throughput

It is defined as the ratio of the payload size (pl), the total transmission delay that is, $delay(pl)$ as given in Equation (6).

3.3.2. Delay

It is defined as the time span when an event occurs while transmitting/receiving the first packet.

3.3.3. Jitter

Jitter is the deviation in delay, caused by random inter-arrival time spikes of the several transmitted and dropped/re-transmitted packets. In many cases it is defined as a measure of the variation in the packet's delay over time in the entire network.

3.3.4. Energy Consumption

Due to energy-constrained nature of sensor nodes in Fog and IoT system the life-time of these devices will be shortened, so to remedy this problem TPC is one of the efficient and effective solutions to optimize the QoS in Fog and IoT networks.

3.3.5. Packet Loss Ratio (PLR)

It is defined as the ratio of total number of lost packets (l) to the transmitted packets (s), it always measures in (%).

Furthermore, pl, WIN_{avg} and T_{Data}, are the payload size, average back-off time, and, transmission delay of the Physical Layer Protocol Data Unit (PPDU), accordingly. Besides, it is calculated based on the R_{target} (−85 dBm) and threshold levels (TRL = −88 dBm, TRH = −83 dBm) of the RSSI values.

$$T_{Data} = T_P + T_{PHR} + \frac{8 \times (MHR + x + FTR)}{R_{Data}} \tag{8}$$

The Δ in Equation (9), represents the deviation in RSSI value for proposed algorithm and conventional TPC methods, R_i is the RSSI latest samples, where $i = 1, 2, \ldots\ldots\ldots, n$ and R_{target} is the RSSI target.

$$\Delta = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(R_i - R_{target})^2}, n \text{ shows RSSI samples} \tag{9}$$

4. Experimental Environment

In this section, the performance of the typical conventional TPC methods, such as constant transmission power control, ATPC [3], the SKims method [2] and our proposed 5G-based QoS-TPC algorithm in IoT is compared and evaluated through simulations in MATLAB with respect to average values of RSSI and transmission power. We use the real-time data sets of two channel cases such as, dynamic and static provided by NICTA [22]. Table 2, presents detailed simulation parameters. In addition, we adopt average transmission power to analyze QoS optimization level of our proposed 5G-based QoS-TPC algorithm in comparison with conventional TPC methods and showed that the proposed algorithms significantly optimize the QoS in the IoT systems in terms of throughput, delay, jitter and energy saving (40.9%), hence it is the potential candidate, as shown in Figures 5 and 6.

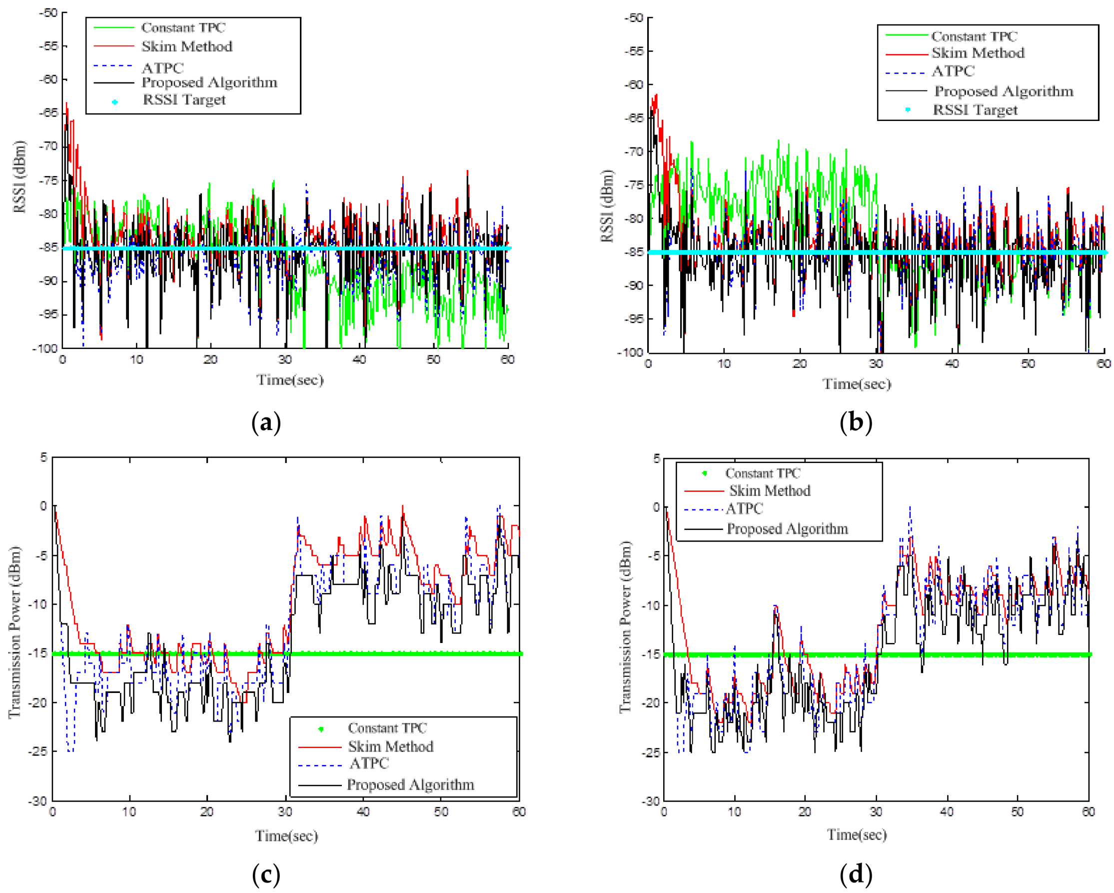


Figure 5. Transmission power level and Received Signal Strength Indicator (RSSI) in Dynamic and Static Channel states (a) and (**c**) Transmission power level, (**b**) and (**d**) RSSI of each data packet.

Figure 5 and Table 2, present the comparison of transmission power (dBm) and corresponding RSSI (dBm) values in the first 60 s between conventional TPC methods and our proposed TPC-QoS algorithm by considering two channel states that is, dynamic and static, respectively in frequency band 2.4 GHz. The analysis showed that the constant TPC adjusts the deviations in the channel by sacrificing more energy, so it provides more reliability and high energy consumption. Through experimental results it is clear that the proposed algorithm (transmission power= 5.67 (mW), RSSI value = −81.25 dBm, Avg. energy consumption (mJ) = 0.37, PLR = 3.63%, std.dev = 5.53 dBm), while the constant TPC (transmission power = 7.23 (mW), RSSI value = −69 dBm, Avg. energy consumption (mJ) = 3.28, PLR = 3.47%, std.dev = 8.80 dBm), ATPC (transmission power = 5.95 (mW), RSSI value = −80.29 dBm, Avg. energy consumption (mJ) = 1.27, PLR = 3.53%, std.dev = 5.60 dBm) and SKims (transmission power = 6.99 (mW), RSSI value = −78.67 dBm, Avg. energy consumption (mJ) = 1.55, PLR = 3.57%, std.dev = 5.79 dBm), at the dynamic channel state as shown in Figure 5a,b and Table 3.

Similarly, Figure 5c,d and Table 3, represents the transmission power and RSSI for the proposed algorithm (transmission power = 5.61 (mW), RSSI value = −80.96 dBm, Avg. energy consumption (mJ) = 0.34, PLR = 3.60%, std.dev = 5.43 dBm), while the constant TPC (transmission power = 7.01 (mW), RSSI value = −75.3 dBm, Avg. energy consumption (mJ) = 3.26, PLR = 3.40%, std.dev = 7.53 dBm), ATPC (transmission power = 5.83 (mW), RSSI value = −80.50 dBm, Avg. energy consumption (mJ) = 1.25, PLR = 3.50%, std.dev = 5.570 dBm) and SKims (transmission power = 6.96 (mW), RSSI value = −79.23 dBm, Avg. energy consumption (mJ) = 1.53, PLR = 3.48%, std.dev = 5.75 dBm), at static channel state. For further details see the Table 2.

Generally, there is more variation in dynamic case than the static one with proposed QoS-TPC algorithm and conventional TPC methods. Our proposed algorithm exhibits less TP, more RSSI stability, less packet loss ratio, less energy consumption than ATPC, SKims and constant TPC methods, in other words proposed QoS-TPC surpasses the typical conventional IoT TPC methods as shown in Table 3.

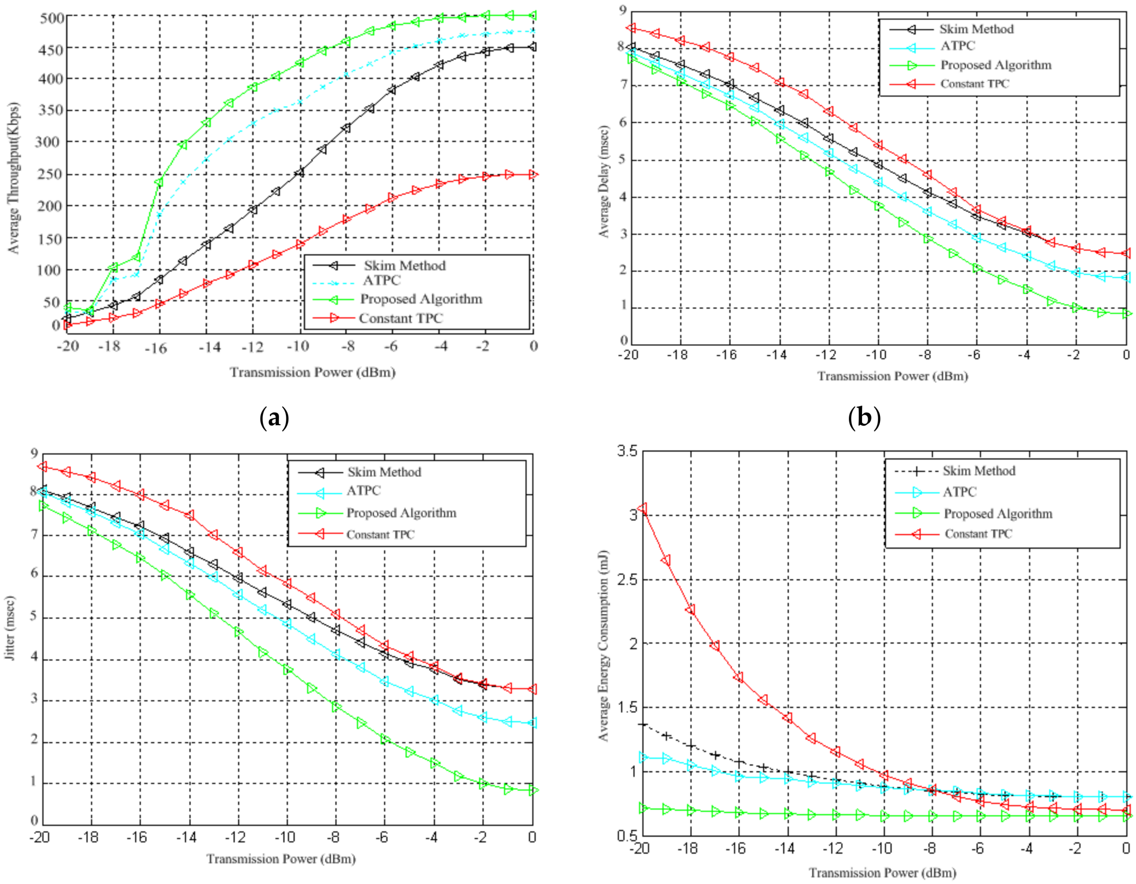
The Figure 6 and Table 2, show the performance of our proposed QoS-TPC algorithm and typical conventional IoT TPC methods in terms of network metrics such as, throughput, delay, jitter and energy consumption level. Figure 6a presents trade-off between transmission power (TP) and average throughput for our proposed algorithm and conventional TPC methods for IoT, in which it is verified that throughput increases with the increase of transmission power of 500 kbps, 450 kbps, 400 kbps, 250 kbps for proposed algorithm, ATPC, SKims and constant TPC methods respectively.

Experimental results show that proposed 5G-based QoS-TPC enhances performance by maximizing throughput about 500 kbps, while constant TPC has lowest throughput than other conventional TPC methods. Figure 6b, presents the relationship between TP and average delay for proposed algorithm and ATPC, SKims, constant TPC methods. The analysis shows that average delay decreases with the increase of TP and there is an average delay value of 7.5 ms for our proposed algorithm—the constant TPC method has a longer average delay of about 8.5 ms, while the ATPC and SKims methods exhibit 7.7 ms and 7.8 ms, respectively. Figure 6c illustrates the effect of TP on jitter for proposed algorithm and conventional TPC methods. Through simulation results in MATLAB it is observed that jitter decreases as the TP increases.

Apparently, proposed 5G-based QoS-TPC and ATPC method has almost same jitter of 7.4 ms and SKims method exploits 7.8 ms jitter value, while constant TPC method reveals jitter of 8.5 ms which is higher than proposed algorithm and other conventional TPC methods. Figure 6d, explores the relation between TP and average energy consumption for proposed algorithm and conventional IoT TPC methods. We analyzed that average energy consumption minimizes with the increase of TP.

It is evident from Figure 6 that the transmission power and average energy consumption of proposed QoS-TPC algorithm is less than the conventional TPC methods or in other words we can say that our proposed algorithm saves energy of 40.9% which is higher than ATPC, SKims and constant TPC methods. Nevertheless, proposed algorithm surpasses the conventional TPC methods.

Deviation in RSSI values for conventional TPC methods and our proposed algorithm with target RSSI (R_{target}) is determined by using Equation (9). We analyzed that ATPC and SKims TPC methods can maintain the RSSI at a relatively stable level and constant TPC method maintains RSSI at very low level while our proposed algorithm maintains RSSI at more stable level than all conventional TPC methods as shown in Table 3. Hence, we can say that our proposed 5G-based QoS-TPC algorithm outperforms in terms of RSSI stability, throughput, delay, jitter and energy saving (see Table 3 for detail) than conventional TPC methods. In Table 3, it is shown that there is slightly more RSSI deviation and packet loss ratio in dynamic case than the static one, which affects the transmit power level and RSSI stability of conventional TPC methods more than our proposed 5G-based QoS-TPC algorithm.



(**a**) (**b**)

(**c**) (**d**)

Figure 6. Transmission power vs. network metrics (**a**) Average throughput, (**b**) average delay, (**c**) jitter, (**d**) average energy consumption.

Table 2. Experimental Parameters.

Parameter	Value
TRH	−83 dBm
TRL	−88 dBm
R_{target}	−85 dBm
Carrier frequency	2.4 GHz
Channel Bandwidth	1 MHz
ΔPi	{−3,−2,−1,0,1,2,3,4}
Maximum Transmit power level	0 dBm
Minimum Transmit power level	−25 dBm
avgweight1	0.8
avgweight2	0.2
Channel Model	Real-time [28]
Data packet size	100 Bytes
Data packet interval	100 ms
Data Rate	250 Kbps
Noise figure	5 dB
Noise PSD	−174 dBm/Hz
Node speed	1.5 km/h
PAR	1
Pc	12.5 mW
T_{total}	100 ms
Number of packets	4000

Table 3. Summary of Experimental Results.

Algorithm	QoS Parameters	Wireless Channel	
		Experimental Analysis	
		Dynamic	Static
TPC Constant	Transmission power (mW)	7.23	7.01
	Average RSSI (dBm)	−69.0	−75.3
	Avg. energy_consump (mJ)	3.28	3.26
	PLR (%)	3.47	3.4
	Std.dev in RSSI (dBm)	8.8	7.53
ATPC Method	Transmission power (mW)	6.13	6.09
	Average RSSI (dBm)	−80.29	−80.50
	Avg.energy_consump (mJ)	6.27	0.25
	PLR (%)	3.53	3.5
	Std.dev in RSSI (dBm)	5.6	5.57
SKims Method	Transmission power (mW)	5.95	5.83
	Average RSSI (dBm)	−78.67	−79.23
	Avg. energy_consump (mJ)	1.55	1.53
	PLR (%)	3.57	3.48
	Std.dev in RSSI (dBm)	5.79	5.76
Proposed Algorithm (QoS-TPC)	Transmission power (mW)	5.67	5.61
	Average RSSI (dBm)	−81.85	−80.96
	Avg. energy_consump (mJ)	0.37	0.34
	PLR (%)	3.63	3.6
	Std.dev in RSSI (dBm)	5.53	5.43

5. Conclusions and Future Research Work

Due to the emerging and revolutionized role of 5G in every aspect of the human life, this paper proposes a 5G-based TPC algorithm for QoS optimization in the Fog computing and IoT system with static and dynamic wireless channel features at a frequency of 2.4 GHz. Transmission power is adapted according to the dynamic and static channel states. We examine and compare the performance of proposed 5G based QoS-TPC algorithm with traditional constant TPC, APTC and SKims methods in terms of transmission power, RSSI values and network metrics that is, throughput, delay, jitter and energy consumption and showed that constant TPC drains more energy with poor RSSI performance in both static and dynamic channel conditions. Besides, it is observed through experimental results that there is more variation in the dynamic case than in the static in the Fog computing and IoT systems. In addition, proposed 5G based QoS-TPC presents more stable RSSI value than traditional TPC methods, in the mean-time limitations of the orthodox methods are addressed with the supportive reasons while optimizing the QoS (i.e., minimum transmission power, more RSSI stability (i.e., less variation), less packet loss ratio, high throughput, less delay, less jitter and maximum energy saving of 40.9%. Finally, it can be said that the remarkable contribution of the proposed 5G-based QoS-TPC algorithm in optimizing the QoS is made unlike the conventional methods.

Following are the few limitations of the proposed QoS-TPC.

- PLR increase due to more energy saving, which is not suitable for the critical event analysis.
- High RSSI value is needed to perform well, which is no appropriate to QoS-sensitive applications
- Delay and jitter values are slightly increasing

We will use our proposed algorithm with Adaptive modulation and cooperative communication to save energy in IoT and Fog computing systems.

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