



Research Article

OPTIMAL CHANNEL ASSIGNMENT AND SCHEDULING IN WIRELESS MULTIMEDIA SENSOR NETWORKS THROUGH ADAPTIVE DEEP NEURAL NETWORK-BASED DATA FLOW ALLOCATION

Ronald Chiwariro and Lokaiah Pullagura

Department of Computer Science and Engineering, Faculty of Engineering and Technology
JAIN (Deemed-to-be University), Bangalore, India

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ABSTRACT

An improved throughput capacity region can be achieved in wireless networks by equipping them with multiple channels. However, such an approach inevitably brings the issue of solving the coupled channel assignment and scheduling problem. This can be solved by equipping each network node with multiple radio interfaces that can operate on multiple non-overlapping channels. The availability of multiple orthogonal channels in a wireless network can lead to substantial performance improvement by alleviating contention and interference. In this paper, an intelligent channel assignment and channel scheduling algorithm on WMSN is proposed. The suggested model will mainly cover two phases: the data flow allocation, and then Channel Assignment and Scheduling. Data Flow Allocation will be performed by an ensemble of Adaptive Deep Neural Networks based on the available channel queues. Further, the Channel Assignment and Scheduling will be accomplished by the Improved Sail Fish Optimization. This optimal Channel Assignment and Scheduling will be performed by an objective model considering the back-off time, stability, packet drop rate, and throughput. Through theoretical analysis and simulation experiments, it is proved that the proposed algorithm is throughput guaranteed when compared to other state-of-the-art algorithms on Wireless Multimedia Sensor Networks.

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INTRODUCTION

Wireless networks have gained tremendous popularity in the past 15 years. Recently there has been an explosion of wireless devices, and traffic has grown 20,000% in the last five years [10]. One of the major categories of wireless networks is Wireless Multimedia Sensor Networks (WMSNs) that is comprised of small embedded video motes capable of extracting the surrounding environmental information, locally processing it and then wirelessly transmitting it to the parent node or sink [9] [14]. It is comprised of video sensors, a digital signal processing unit and a digital radio interface. The availability of low-cost hardware such as complementary metal-oxide semiconductor (CMOS) cameras and microphones has fostered the development of WMSNs, i.e., networks of wirelessly interconnected devices that are able to ubiquitously retrieve multimedia content such as video and audio streams, still images, and scalar sensor data from the environment [11]. In addition to the ability to retrieve multimedia data, WMSNs will also be able to store, process in real-time, correlate and fuse multimedia data originating from heterogeneous sources. Wireless multimedia sensor networks will not only enhance existing sensor network applications such as tracking, home automation, and environmental monitoring, but they will also enable several new applications

[12]. WMSNs will be enabled by the convergence of communication and computation with signal processing and several branches of control theory and embedded computing [13]. Traditional protocol design in WSNs commonly focuses on a single network layer or the link layer. To cope with the interdependent and intricate relations of different network layers, a cross-layer design is expected which can jointly optimize routing, transmission scheduling, power control and channel assignment.

The main objective of multi-channel scheduling is to schedule the transmissions of the data over multiple channels to the users [17]. The important measures in choosing a scheduling algorithm are throughput, latency, fairness, and complexity. The major focus of existing work is mostly on the throughput and delay performance of the scheduling algorithm in Stanford University Access Hybrid WDM/TDM Passive Optical Network (SUCCESS-HPON) [15], but there is hardly any support for fairness and Quality of Service (QoS) guarantee. The multi-channel scheduling and its applications rely on the ability of the whole system to provide some sort of quality of service guarantee [19]. There are several measures that are to be considered when choosing a scheduling algorithm. The most important are fairness, latency and complexity [16] [14]. In multi-channel Scheduling, it is the scheduling algorithm

*Corresponding author: Ronald Chiwariro

Department of Computer Science and Engineering, Faculty of Engineering and Technology
JAIN (Deemed-to-be University), Bangalore, India

that is key to achieving high performance [20]. The major focus is on the delay and throughput performance of the whole system, there is hardly any support for fairness and QoS guarantee [18].

The availability of multiple orthogonal channels in a wireless network can lead to substantial performance improvement by alleviating contention and interference. However, this also gives rise to non-trivial channel coordination issues [21]. The situation is exacerbated by variability in the achievable data rates across channels and links. Thus, scheduling in such networks may require substantial information exchange and lead to non-negligible overhead. This provides a strong motivation for the study of scheduling algorithms that can operate with limited information while still providing acceptable worst-case performance guarantees [22]. Computing an optimal schedule, even in a single-channel network, is almost always intractable, due to the need for global information, as well as the computational complexity. Appropriate scheduling policies are of utmost importance in achieving good throughput characteristics in a wireless network [23]. However, previous wireless scheduling policies typically assume a single, fixed transmission rate for all users. As a result, channel scheduling algorithms designed for a single-rate environment may not be appropriate in multi-channel WLANs [24] [25].

LITERATURE REVIEW

In 2019, Xu *et al.* [1] presented distributed algorithms for multichannel single-interface wireless sensor networks with both single-hop and multi-hop multipath scenes, named, respectively, Low Duty Cycling (LDCS) and ME of LDCS. It was theoretically demonstrated that the proposed algorithms could achieve guaranteed throughput capacity regions that were comparable with other distributed maximal-matching-based algorithms (such as Single path (SP), Multi-path (MP), and tuple-based MS) with low implementation complexity. LDCS utilize a rate-proportional-based mechanism to allocate datagrams locally and applies random access technique based on probability to complete the channel assignment and scheduling. Such design has avoided executing the maximal-matching-finding process and attained lower complexity that was independent of the number of links and channels. Under the proposed algorithms, random access and back-off time techniques were introduced to keep the complexity low and independent of the number of links and channels. Through theoretical analysis and simulation experiments, it was proved that the proposed algorithms are throughput guaranteed, and in some network scenarios, the achieved capacity region could be larger than that of other comparable distributed algorithms.

In 2016, Yigit *et al.* [2] proposed a Link-Quality-Aware Capacitated Minimum Hop Spanning Tree (LQ-CMST) as well as the Priority and Channel-Aware Multi-Channel (PCA-MC) scheduling algorithm for smart grid applications. Furthermore, the effect of different modulation and encoding schemes on the performance of the proposed algorithms has been evaluated under harsh smart grid channel conditions. Comparative performance evaluations through extensive simulations have shown that the proposed algorithms significantly reduce communication delay and the choice of encoding and modulation schemes was critical to meet the requirements of envisioned smart grid applications. Overall, our main contribution was to investigate the performance of

multi-channel WSNs for smart grids and to quantify how priority and channel-aware communication will perform under different network traffic loads and the harsh smart grid channel conditions.

In 2015, Li *et al.* [3] investigated the Optimal Routing problem jointly with Scheduling, Channel and Power Assignment (OR + SCP) in Multi-Power Multi-Radio (MPMR) WSNs. The Concurrent Transmission Link Sets (CTLs) were introduced and then formulated the OR + SCP problem based on CTLs as a linear programming problem, which is proven to be NP-Hard. Furthermore, an Advanced Link Conflict Graph (ALCG) was proposed to reduce the high complexity of identifying all CTLs. However, the complexity of the optimal routing problem has increased with the increase in the number of power levels and network size. We thus provide a polynomial time heuristic scheme for (OR + SCP) with a routing strategy based on max-flow LP. Considering the limited processing ability of sensor nodes, it was difficult to compute the LP equations on sensor nodes. Therefore, an efficient distributed routing algorithm was designed based on a random walk which does not compute the LP equations and works well in large-scale WSNs. The simulation results have shown that this proposed algorithm can improve data transmission efficiency, and significantly reduce data transmission delay and energy consumption.

In 2009, Mohsenian and Wong [4] proposed a Distributed Congestion-Aware Channel Assignment (DCACA) algorithm for Multi-Channel Wireless Mesh Networks (MC-WMNs). The frequency channels were assigned according to the congestion measures which indicate the congestion status at each link. Depending on the selected congestion measure (e.g., queueing delay, packet loss probability, and differential backlog), various design objectives can be achieved. Our proposed distributed algorithm was simple to implement as it only requires each node to perform a local search. Unlike most of the previous channel assignment schemes, our proposed algorithm has assigned not only the non-overlapped (i.e., orthogonal) frequency channels but also the partially-overlapped channels. In this regard, the channel overlapping and mutual interference matrices were introduced which model the frequency overlapping among different channels. Simulation results have shown that in the presence of elastic traffic (e.g., TCP Vegas or TCP Reno) sources, our proposed DCACA algorithm has increased the aggregate throughput and also decreases the average packet round-trip compared with the previously proposed Load-Aware channel assignment algorithm. Furthermore, in a congested IEEE 802.11b network setting, compared with the use of three non-overlapped channels, the aggregate network throughput can further be increased by 25% and the average round-trip time can be reduced by more than one-half when all the 11 partially-overlapped channels were used.

In 2017, Gao *et al.* [5] proposed a novel deadline-driven Link Quality Aware Channel Assignment scheme (LACA), where link quality, deadlines and collisions were jointly considered. LACA prioritizes links with urgent deadlines and heavy collisions. Besides, LACA has allowed the exploitation of spare slots for retransmissions on lossy links, which can further reduce the retransmission delay. Extensive simulation experiments have shown that compared to the existing approaches, LACA can better utilize the wireless spectrum and achieve a higher packet delivery ratio before the deadline.

In 2015, Gálvez *et al.* [6] addressed the issue of joint routing, channel assignment, scheduling and link rate allocation in multi-rate multi-channel wireless networks with the goal of increasing network capacity. Many wireless standards have supported a variety of modulation and coding schemes, which have allowed devices to choose from several transmission rates. Typically, the highest possible rate was used for transmission, but the potential for increased spatial reuse and capacity exists when using lower rates due to higher interference tolerance. This problem of selecting link rates was further complicated in a multi-channel network. Channel assignment has affected the sets of interfering links, and as such also influences the optimal choice of link rates. And there was also an interdependency between routing and both rate and channel assignment. In this work, the joint problem was analyzed, and due to its hardness, proposed a fast heuristic algorithm Joint Multi-Rate (JMR) to solve it. This algorithm was evaluated through numerical experiments in a wide variety of configurations, showing the potential for improved capacity via link rate allocation depends on a variety of factors which relate to the capability and need of exploiting spatial reuse, which includes the transmission power, the number of channels and the network architecture and topology. In this work, architecture was also proposed for wireless mesh networks with increased capacity and under which optimized rate allocation was shown to notably increase performance. Finally, the solutions were found by JMR under the NS-3 simulator using the 802.11a protocol stack, where it was shown that physical and MAC layer limitations reduce the performance gain of JMR.

In 2009, Lin and Rasool [7] developed fully distributed algorithms that have jointly solved the channel-assignment, scheduling, and routing problem. Our algorithms were online algorithms, i.e., they do not require prior information on the offered load to the network and can adapt automatically to the changes in the network topology and offered load. Our algorithms were shown provably efficient. That is, even compared with the optimal centralized and offline algorithm, our proposed distributed algorithms could achieve a provable fraction of the maximum system capacity.

Furthermore, the achievable fraction that can guarantee was larger than that of some other comparable algorithms in the literature.

In 2016, Roh and Lee [8] studied a joint channel assignment, link scheduling, routing, and rate control problem for the Wireless Mesh Network (WMN) with multiple orthogonal channels and multiple directional antennas. This problem is inherently hard to solve since the problem was formulated as a Mixed Integer Nonlinear Problem (MINLP). However, despite its inherent difficulty, have developed an algorithm to solve the problem by using the generalized Benders decomposition approach [2]. The simulation results have shown the proposed algorithm provides the optimal solution to maximize the network utility, which was defined as the sum of utilities of all sessions.

Problem Statement

In wireless networks, an improved throughput capacity region can be achieved by equipping with multiple channels. However, such an approach inevitably brings the issue of solving the coupled channel assignment and scheduling problem. Some common challenges now with the development of WMSNs are considered that also require to be addressed, which are high bandwidth demand, heterogeneous multimedia reliability, coverage area, in-network processing, application-specific QoS constraints, etc. Numerous methods are proposed in the channel scheduling approaches in wireless networks that have diverse features and challenges as given in Table 1. LDC [1] attains better throughput performance and achieves lower complexity. However, this model is restrictive in maintaining the network. LQ-CMST and PCA-MC [2] can efficiently minimize communication delay and improves the performance of the network. Though, it is not suitable for integrating with weighted fair scheduling schemes. OR+SCP [3] is proposed for minimizing the computational complexity, end-to-end transmission delay and energy consumption.

Conversely, it can cause a longer interference range. DCACA [4] attains increased aggregate throughput and minimizes the average packet round-trip time. However, it attains the congestion-aware channel assignment problem. LACA [5] improves the Packet Delivery Ratio (PDR) and efficiently prioritizes the paths.

Table 1 Features and challenges of conventional channel scheduling approaches in wireless networks

Author [citation]	Methodology	Features	Challenges
Xu <i>et al.</i> [1]	LDCS	<ul style="list-style-type: none"> It attains better throughput performance. It achieves lower complexity. 	<ul style="list-style-type: none"> This model is restricted in maintaining the network.
Yigit <i>et al.</i> [2]	LQ-CMST and PCA-MC	<ul style="list-style-type: none"> It can efficiently minimize communication delays. It improves the performance of network. 	<ul style="list-style-type: none"> It is not suitable for integrating with weighted fair scheduling schemes.
Li <i>et al.</i> [3]	OR + SCP	<ul style="list-style-type: none"> It minimizes computational complexity. It minimizes end-to-end transmission delay and energy consumption. 	<ul style="list-style-type: none"> It can cause the longer interference range.
Mohsenian and Wong [4]	DCACA	<ul style="list-style-type: none"> It attains increased aggregate throughput. It minimizes the average packet round-trip time. 	<ul style="list-style-type: none"> However, it attains the congestion-aware channel assignment problem.
Gao <i>et al.</i> [5]	LACA	<ul style="list-style-type: none"> It improves the packet delivery ratio. It efficiently prioritizes the paths. 	<ul style="list-style-type: none"> The major limitation of this work is the global optimum.
Gálvez <i>et al.</i> [6]	JMR	<ul style="list-style-type: none"> It minimizes spatial reuse. It can attain maximum capacity. 	<ul style="list-style-type: none"> It needs to enhance the physical layer and CSMA.
Lin and Rasool [7]	Distributed Algorithms	<ul style="list-style-type: none"> It effectively solves the problem of optimizations. It attains faster solutions. 	<ul style="list-style-type: none"> It impacts the actual system performance.
Roh and Lee [8]	Generalized Benders decomposition approach	<ul style="list-style-type: none"> It obtains optimal solutions. It improves the network utility. 	<ul style="list-style-type: none"> Though, it cannot transmit with multiple links.

Though, the major limitation of this work is the global optimum. JMR [6] is developed to minimize spatial reuse and attain maximum capacity. On the other hand, it needs to enhance the physical layer and CSMA. Distributed algorithms [7] effectively solve the problem of optimizations and attain faster solutions. It impacts the actual system performance. The generalized Bender's decomposition approach [8] obtains optimal solutions and improves the network utility. Though, it cannot transmit with multiple links. Hence, these challenges are observed for developing a new model in WMSN.

METHODOLOGY

The capacity of wireless networks can be substantially increased by equipping each network node with multiple radio interfaces that can operate on multiple non-overlapping channels. The availability of multiple orthogonal channels in a wireless network can lead to substantial performance improvement by alleviating contention and interference. However, this also gives rise to non-trivial channel coordination issues. The situation is exacerbated by variability in the achievable data rates across channels and links. Thus, scheduling in such networks may require substantial information exchange and lead to non-negligible overhead. This provides a strong motivation for the study of scheduling algorithms that can operate with limited information while still providing acceptable worst-case performance guarantees. In this paper, an intelligent channel assignment and channel scheduling algorithm on WMSN will be proposed. The proposed model will mainly cover two phases: one will be the Data Flow Allocation, and the other will be the Channel Assignment and Scheduling. In the first phase, Data Flow Allocation will be performed by the Adaptive Deep Neural Network (ADNN), which will be done based on the available channel queues. Further, the Channel Assignment and Scheduling will be accomplished by the improved Sail Fish Optimization (SFO) [26]. This optimal Channel Assignment and Scheduling will be performed by an objective model considering the back-off time, stability, packet drop rate, and throughput.

In multichannel scenarios, it is truly difficult to guarantee the throughput performance (characterized by capacity region) in a distributed manner. The objective of this issue is to maintain the system stable with finite queue lengths inside a specific capacity region. The implementation of scheduling algorithms should be combined with data flow allocation and channel assignment because of channel diversity. Toward this direction, a provably efficient Single Hop algorithm and its Multipath extension have been developed for Multi-Channel Multi-Interface (MC-MI) networks.

In SP and MP, each link maintains multiple per-channel queues as well as one common link queue. Arriving packets first enter the common link queue and are then assigned to each channel via executing a data flow allocation mechanism, as illustrated in Figure 1 and the transformation process in Figure 2. According to the per-channel queues, maximal scheduling is carried out to determine the set of forwarding queues. At the same time, aiming at achieving reliable throughput capacity region under SP or MP, each link collects queue length and channel rate information from the neighbourhood before allocating data flow.

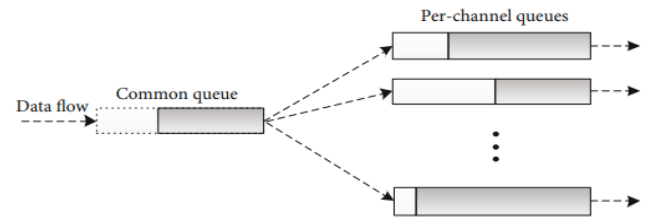


Figure 1 Relay-forwarding framework in SP and MP

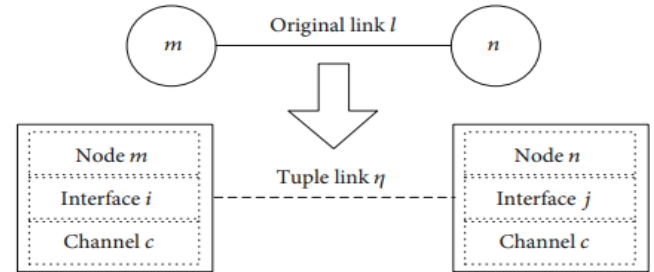


Figure 2 Transformation Process

Table 2 List of Notations

Variable	Notation
L, C, S	Set of all links, channels and users.
I_l	Set of links interfering with l over the same channel.
$I_{cha}(l), I_{int}(l)$	Channel/interface interference set.
K_1, K_2	Link/interface/channel interference degree.
r_l^c	Rate of link l on channel c .
$A_l(n), A_s(n)$	The Number of packets arriving at link l and user s at time slot n .
(l, c)	Channel queue maintained by link l on channel c .
$\mathcal{E}_{(l,c)}$	Set of all channel queues that interfere with (l, c) .
$q_l^c(n)$	Queue length of (l, c) .
$A_{l(n)}^c$	The number of packets assigned by link l to channel c at time slot n .
$D_{l(n)}^c$	The number of packets served by link (l, c) in time slot n .

Proposed Model

At each time slot in the proposed algorithm, packets are assigned to channel queues immediately after arriving based on our data flow allocation mechanism without extra relay-forwarding common queue, which leads to a reduced transmission delay. For channel assignment and scheduling, the algorithm employs random access and back-off time techniques instead of executing the maximal matching process. The algorithm consists of two parts and the stability is given as follows:

Data Flow Allocation. For data flow allocation, a rate proportional-based policy is designed as

$$A_{l(n)}^c = A_{l(n)} \frac{r_l^c}{\sum_{d \in C} r_l^d} \quad (1)$$

The allocation process is implemented locally and is shown in Figure 3. Each link does not require information on other links in the data flow allocation phase, which can decrease the overhead effectively.

Channel Assignment and Scheduling. After data allocation, channel assignment and scheduling mechanisms are used to make the decision of whether a queue should be scheduled or not. The random access and back-off time techniques are employed. To be specific, each time slot is divided into two sub-slots: a scheduling slot and a transmission slot, either of which has a fixed length. The scheduling slot is further

divided into M mini-slots. Such time slot division is shown in Figure 4. According to the back-off time technique, each queue selects a mini-slot with probability as

$$\begin{cases} Pr\{I_l^c = M + 1\} = e(-p^c) \\ Pr\{I_l^c = m\} = e(-p^c)^{(m-\frac{1}{M})} - e(-p^c)^{(\frac{m}{M})}, \quad m = 1,2,3, \dots, M \end{cases} \quad (2)$$

where I_l^c represents the backoff time picked by (l,c) and the parameter p^l is computed as

$$p_l^c = \alpha \frac{q_l^c(n)/r_l^c}{\max_{(j,d) \in \mathcal{E}(l,c)} \left[\sum_{(k,c') \in \mathcal{E}(j,d)} q_k^{c'}(n)/r_k^{c'} \right]}, \quad (3)$$

where $\alpha = \log M$. In formula (2), if a queue chooses $M+1$ as its backoff time, it will remain static in the current time slot. Instead of waiting for the entire scheduling slot, a queue enters the transmission slot to send messages immediately after the selected backoff time expires as long as no one in its interference set has already picked a smaller backoff time. If two or more queues select the same mini-slot, all of them fail to accomplish the transmission successfully because of collision.

Stability Region. For the purpose of analyzing stability, we use the below equation.

$$V(n) = \max_{l \in L, c \in C} \left[\sum_{(j,d) \in \mathcal{E}(l,c)} \frac{q_j^d(n)}{r_j^d} \right], \quad (4)$$

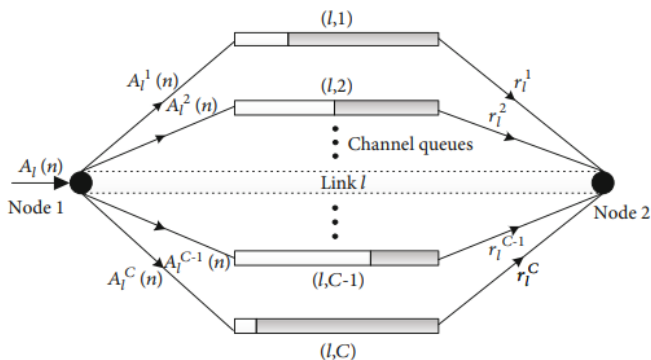


Figure 3 Adaptive Deep Neural Network Data Flow allocation based on Channel Queues

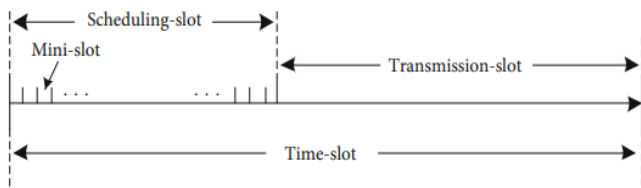


Figure 4 Channel Assignment and Scheduling

The algorithm utilizes a rate-proportional-based mechanism to allocate datagrams locally and applies random access technique based on probability to complete the channel assignment and scheduling. Such a design avoids executing the maximal-matching-finding process and attains lower complexity that is independent of the number of links and channels.

RESULTS AND DISCUSSION

Experimental Setup

The proposed Channel Assignment and Scheduling in WMSN is carried out in MATLAB, which is a numeric computing platform used to analyze the data and develop algorithms. The

system configuration of the implementation includes MATLAB 2018a software running on Windows 11 Operating system with 8GB RAM Internal memory. The performance of the proposed model is compared with the conventional models by analyzing back-off time, stability, packet drop rate, and throughput. A description of the result obtained for channels 1 and 2 from the proposed WMSN is elaborated in this section.

Experimental Analysis for Channel 1

Figure 5 a, b and c denotes the WMSN with 50 nodes with iterations 1, 700 and 1500. Furthermore, Figure 5 d, e, and f denote the WMSN with 100 nodes with iterations 1, 700 and 1500. The blue colour in the image represents the primary users and the magenta colour in the image represents the secondary users.

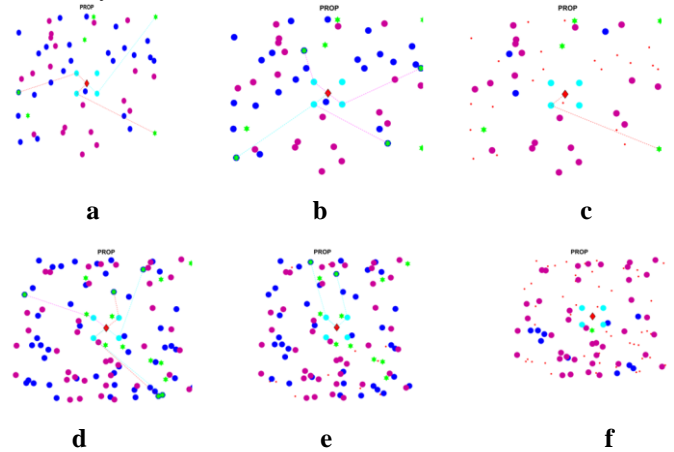


Figure 5 Experimental analysis for channel 1 a) 50 nodes with iteration 1, b) 50 nodes with iteration 700, c) 50 nodes with iteration 1500, d) 100 nodes with iteration 1, e) 100 nodes with iteration 700 and f) 100 nodes with iteration 1500.

Experimental Analysis for Channel 2

Figure 6 a, b and c de notes the WSMN with 50 nodes and Figure 6 d, e and f denote WSMN with 100 nodes and similar iterations.

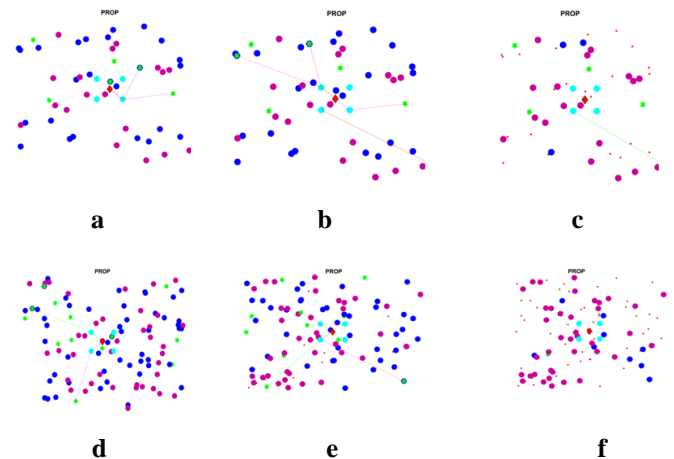


Figure 6 Experimental analysis for channel 2 a) 50 nodes with iteration 1, b) 50 nodes with iteration 700, c) 50 nodes with iteration 1500., d) 100 nodes with iteration 1, e) 100 nodes with iteration 700 and f) 100 nodes with iteration 1500.

Performance Analysis

This section elaborates on the performance of the proposed WMSN for channel 1 and channel 2. The performance is done

using the evaluation metrics, such as Back Off-Time (ms), Normalized energy, Packet drop rate stability and throughput

Performance Analysis for Channel 1

The performance analysis of Channel 1 for the proposed WMSM is illustrated in Figure 7. From the figure, it is clear that the proposed model attains the highest performance in the 1500th iteration. At population 100 and 1st round the back-off time of the proposed WMSM is found to be 0.136338ms. The proposed WMSM attains the normalized energy of 0.549575J, the packet drop rate of 1, and stability of 50 at the first iteration.

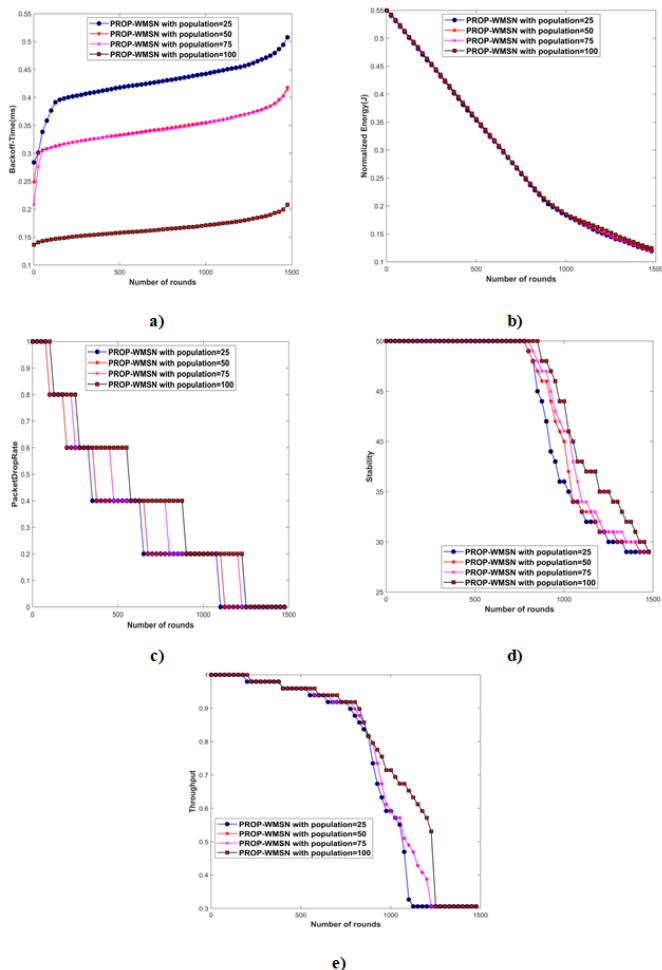


Figure 7 Performance analysis for Channel 1 a) Back Off-time, b) Normalized energy, c) Packet Drop Rate, d) Stability and e) Throughput

Performance Analysis for Channel 2

The performance analysis of Channel 2 for the proposed WMSM is illustrated in Figure 8. From the figure, it is clear that the proposed model attains the highest performance in the 1500th iteration. At population 100 and 1st round the back-off time of the proposed WMSM is found to be 0.148963ms. The proposed WMSM attains the normalized energy of 0.55122J, the packet drop rate of 1, and stability of 50 at the first iteration.

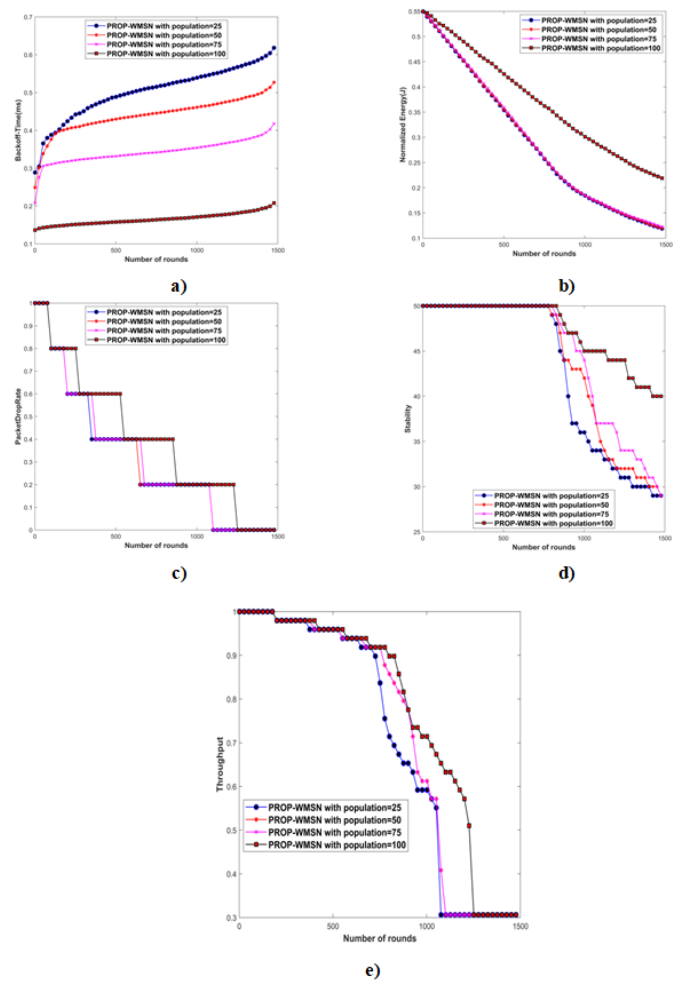
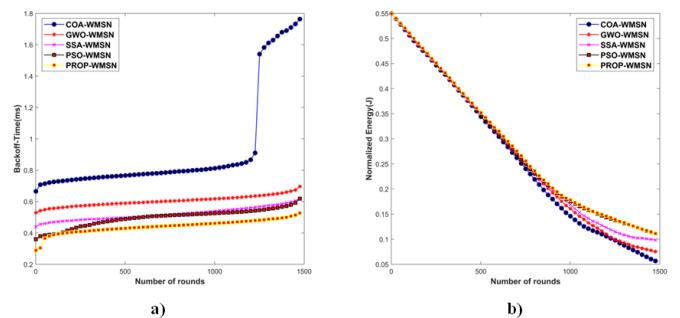


Figure 8 Performance analysis for Channel 2 a) Back off-time, b) Normalized energy, c) Packet Drop Rate, d) Stability and e) Throughput

Comparative Analysis

The comparative analysis of the WMSN model for Channel 1 and Channel 2 is illustrated in Figures 9 and 10. The result obtained by the comparative model at the 1500th iteration is provided in Tables 3 and 4 respectively. For the comparative analysis, the existing models such as Coyote Optimization Algorithm (COA)-WMSN, Grey Wolf Optimization (GWO)-WMSN, Sparrow Search Algorithm (SSA)-WMSN and Particle Swarm Optimization (PSO)-WMSN were used as the benchmark.

Comparative Analysis for Channel 1



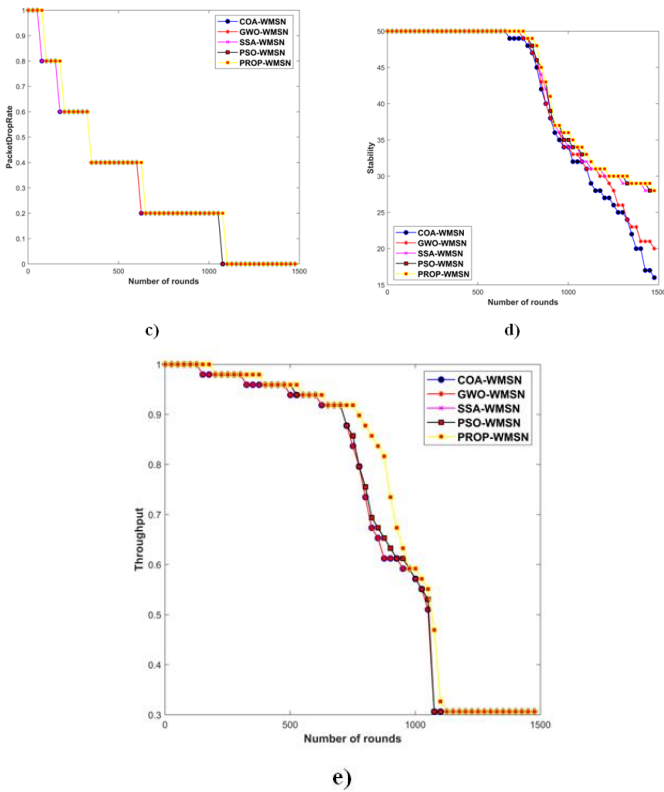


Figure 9 Comparative analysis for channel 1 in terms of a) Back Off-Time, b) Normalized energy, c) Packet Drop Rate, d) Stability and e) Throughput.

Table 3 Comparative results of WMSM for Channel 1

Methods	Back off-Time (ms)	Normalized energy (J)	Packet drop rate (At var 36)	Stability (At var 60)	Throughput (At var 60)
GOA-WMSN	1.87962	0.052689	0.2	16	0.27551
GWO-WMSN	1.16469	0.073883	0.2	20	0.27551
SSA-WMSN	0.99619	0.098002	0.2	28	0.306122
PSO-WMSN	0.831425	0.108298	0.2	28	0.306122
Proposed WMSN	0.653935	0.108793	0.2	28	0.306122

The table demonstrates that the proposed model attains quite satisfactory performance in Channel 1 conditions in terms of back-off-time, normalized energy, packet drop rate, stability and throughput. This performance is attributable to the data being trained first by the Adaptive Ensemble Deep Neural Network, after which the scheduling is carried out via Improved Sail Fish optimisation. It is therefore recommended that this approach be used in applications that mainly involve WMSNs. These are mostly real-time and do not require any delay. It automatically offers great efficiency in non-real-time traffic.

Comparative Analysis for Channel 2

Table 4 Comparative results of WMSM for Channel 2

Methods	Back off-Time	Normalized energy	Packet drop rate (at var 4)	Stability (at var 60)	Throughput (At var 50)
GOA-WMSN	84.76012	0.051207	0.6	18	0.306122
GWO-WMSN	60.29041	0.09683	0.8	28	0.306122
SSA-WMSN	59.96117	0.108298	0.8	28	0.306122
PSO-WMSN	57.52428	0.108793	0.8	28	0.306122
Proposed WMSN	1.87962	0.116111	0.8	28	0.306122

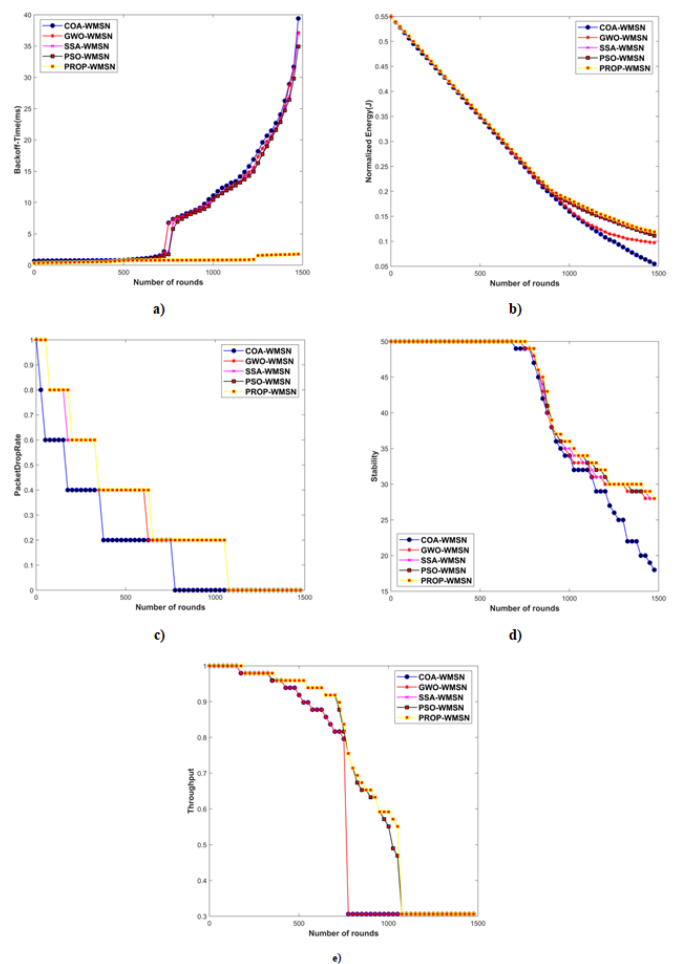


Figure 10 Comparative analysis for channel 2 in terms of a) Back Off-Time, b) Normalized energy, c) Packet Drop Rate, d) Stability and e) Throughput.

The table shows that the suggested approach achieves relatively excellent performance utilising the same conditions offered by Channel 2 in terms of back-off-time, normalised energy, packet drop rate, stability, and throughput. This performance is attributable to the data that came before it from an Ensemble of Adaptive Deep Neural Networks, which uses Improved Sail Fish optimisation to schedule tasks. Therefore, it is advised that this method be applied in applications that primarily make use of WMSNs. Most of these operate in real-time and don't need a wait. It automatically provides excellent efficiency in non-real-time traffic.

CONCLUSION

This paper proposed a model that aims to improve the Quality of Service in Wireless Multimedia Sensor Networks in various environments. To accomplish this, the proposed solution undergoes two phases: Data Flow Allocation which was addressed by an Adaptive Deep Neural Network, followed by Channel Assignment and Scheduling using an Improved Sail Fish Optimisation. The objective model considered the back-off time, stability, packet drop rate, and throughput. The performance evaluation shows that the proposed solution can be considered for improving throughput in varying application environments. However, further developments can improve the attained results. We propose the consideration of various Adaptive Deep Neural Networks with different trained models and also using transfer learning. This will yield the most effective combination of the Neural Networks' ensemble.

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