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ARTICLE

Optimization Model Proposal for Traffic Differentiation in Wireless Sensor Networks

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ABSTRACT

Wireless sensor networks (WSNs) are characterized by heterogeneous traffic types (audio, video, data) and diverse application traffic requirements. This paper introduces three traffic classes following the defined model of heterogeneous traffic differentiation in WSNs. The requirements for each class regarding sensitivity to QoS (Quality of Service) parameters, such as loss, delay, and jitter, are described. These classes encompass real-time and delay-tolerant traffic. Given that QoS evaluation is a multi-criteria decision-making problem, we employed the AHP (Analytical Hierarchy Process) method for multi-criteria optimization. As a result of this approach, we derived weight values for different traffic classes based on key QoS factors and requirements. These weights are assigned to individual traffic classes to determine transmission priority. This study provides a thorough comparative analysis of the proposed model against existing methods, demonstrating its superior performance across various traffic scenarios and its implications for future WSN applications. The results highlight the model's adaptability and robustness in optimizing network resources under varying conditions, offering insights into practical deployments in real-world scenarios. Additionally, the paper includes an analysis of energy consumption, underscoring the trade-offs between QoS performance and energy efficiency. This study presents the development of a differentiated services model for heterogeneous traffic in wireless sensor networks, considering the appropriate QoS framework supported by experimental analyses.

KEYWORDS

Wireless Sensor Networks (WSNs); traffic differentiation; traffic classes; Quality of Services (QoS); multi-criteria optimization; Analytical Hierarchy Process (AHP)

1 Introduction

Traffic characteristics in Wireless Sensor Networks (WSNs) are only partially determined due to their complex nature. These networks often experience unevenly distributed traffic, where data flows from numerous sensor nodes to a few destination points. It is challenging to ensure adequate Quality of Service (QoS) due to unpredictable traffic behavior and heterogeneous traffic characteristics. Consequently, there is a pressing need for differentiating services within WSNs. This research is motivated by the necessity to develop a multi-criteria model to ensure adequate QoS, ultimately leading to the requirement for differentiating services.

WSNs play a crucial role in the Internet of Things (IoT) due to their broad range of applications and their similarity to IoT networks, both of which utilize battery-powered nodes for monitoring processes [1]. IoT relies on the data traffic generated by WSNs, utilizing their wireless sensor nodes to efficiently transmit and gather information. This data flow enables real-time monitoring, control, and diverse applications of interconnected devices in the IoT ecosystem. Different IoT applications have varying QoS requirements; for instance, some applications demand strict delay constraints, while others are more tolerant. To address these needs, various service scheduling methods have been proposed for buffer management [2]. These methods include allocated buffer access for each traffic class and a shared buffer with a defined priority for each class.

Understanding traffic behavior in WSNs allows for more effective traffic management. For instance, a better strategy for implementing routing protocols and managing sensor nodes can be developed if the nature of the large amounts of data exchanged between the sensors is understood. This understanding ensures optimal bandwidth distribution across service classes by preventing the over-allocation of resources to high-priority classes. Once the necessary bandwidth has been allocated to the high-priority class, the remaining bandwidth can be distributed among the lower-priority classes. This approach is suitable for packet networks that support various traffic types competing for limited network resources, each with specific QoS requirements [3]. Service differentiation is achieved by applying QoS mechanisms at the access point of the analyzed network.

The primary aim of this research is to present a new service differentiation model for WSNs with heterogeneous traffic characteristics and QoS parameters. Based on the aforementioned considerations, the research question was formulated: How can we determine the weight factor values to assign priority to certain traffic classes? To answer this question, an optimization model was developed that determines weight values for individual traffic classes. The contributions of this research include: proposing an optimization model that addresses the existing challenges in traffic classification and resource allocation, which impacts QoS parameters and energy consumption; enhancing priority assignment schemes to certain types of traffic differentiated into classes by their relevant characteristics; and improving QoS and reducing delay using a novel Analytical Hierarchy Process (AHP) and Multi-Criteria Decision-Making (MCDM)-based approach.

This paper is structured as follows: Section 2 presents an overview of class-oriented models of traffic differentiation in WSNs to ensure QoS. Section 3 details the proposed model, including its network, queuing, and traffic class structure. This section also includes an analysis of multicriteria optimization methods, specifically the AHP method, and its application in determining weight components for specific traffic classes. Section 4 focuses on modeling heterogeneous traffic and identifying the most critical QoS parameters for different traffic types. These parameters serve as input for the AHP multi-criteria analysis, which determines their importance under varying traffic conditions. Section 5 presents a detailed comparative analysis with existing methods, showcasing the advantages and limitations of the proposed AHP model, supported by experimental and energy consumption analyses that validate its effectiveness and performance. Finally, Section 6 provides concluding remarks and suggestions for future research directions.

2 Related Work

Quality of Service (QoS) solutions provided through service differentiation algorithms within Wireless Sensor Networks (WSNs) have been suggested in various studies [4,5]. The strategy of differentiating services has emerged as a common approach for achieving QoS in real-time WSN applications. Beginning with pioneering works on service-based differentiated QoS, as seen in [4], subsequent research in this domain has demonstrated the tailored design of QoS approaches to accommodate WSN resource limitations [4,6]. Although the proposed mechanisms include various types of service differentiation, such as QoS-aware routing, scheduling based on priority schemes, assurance of QoS with a certain probability, and MAC protocols, research in this area is mainly based on different types of data and requirements for network QoS levels. Considering many other real-time QoS solutions in WSNs, it's evident that the service differentiation strategy predominantly prioritizes delay-sensitive packets [5], aiming to serve real-time packets in their arrival process to the destination point with minimal delays. However, there have been limitations in papers [7–9] that deal with the different QoS requirements of various traffic classes.

Delay-tolerant WSNs [10] are characterized by long-term and sporadic connections. A fundamental aspect of QoS requirements in delay-tolerant applications, such as automotive networks [11], revolves around ensuring reliable data transmission and compensating for unstable connections using storage and forwarding network functions. Research efforts in this domain predominantly focus on routing protocols [8,12], which aim to reduce data transmission delays. The method proposed in [13] efficiently schedules CoAP (Constrained Application Protocol) packets on sensor nodes by employing a classification mechanism to categorize CoAP requests and responses across the network. Additionally, it manages the timing and aggregation of received messages on the sensor nodes, achieving outcomes such as reduced energy consumption and network traffic.

Machine learning algorithms, specifically the Classification and Regression Tree (CART) algorithm, play a crucial role in optimizing resource allocation for WSNs by intelligently managing resources for classification and decision-making, as shown in [14]. This proposed scheme enhances accuracy, computational efficiency, and transmission effectiveness in resource allocation at the cluster level, with potential extensions to gateway, edge, and cloud levels. It addresses challenges such as fading and interference for diverse applications in heterogeneous WSNs. The paper [15] addresses QoS in WSNs through cross-layered architecture and statistical analysis, showing improvements in latency, throughput, energy efficiency, and reliability, while also discussing the role of machine learning in enhancing these metrics. In contrast, the performance of a heterogeneous data traffic network categorized as high and low priority is described in [16] by WSN integration on the Internet. However, the QoS requirements for timely and reliable packet transmission were not considered.

An enhanced class-based dynamic priority (E-CBDP) algorithm is proposed as a mechanism for scheduling uplink packets, which gives human-to-human (H2H) communication higher priority over M2M traffic [17]. Moreover, a dynamic priority queuing model is modified in [18] to assess the efficiency of various traffic types. Within this model, a priority jump strategy is introduced to enhance transmission opportunities for packets belonging to low-priority users.

A novel mechanism for effective traffic prioritization is introduced in [19]. Data packets generated from each wireless body area network are effectively placed in four separate queues, taking into account their criticality to ensure QoS-aware delivery. A scheduling mechanism based on the IEEE 802.15.6 standard is developed. Additionally, a traffic scheduling scheme for audio/video sensor networks, designed to meet the different QoS requirements of these delivery forms, is proposed in [20]. A typical architecture of audio/video sensor networks is presented, along with the concept of DiffServ (Differentiated Services) within this architecture. Two basic delivery methods are described. To meet the requirements of guaranteed real-time communication, a model without priority queues (NPPQ—Non-Preemptive Priority Queuing) was used to arrange two types of data packets. The average waiting time of these two types of data packets was also analyzed using the M/M/1 queuing model, and the performance of this model was compared with a model where bandwidth differentiation is present [21].

The paper [22] proposed a game theory-based admission control algorithm for efficient resource allocation in wireless mesh networks. Similarly, the traffic engineering model in [23] uses a dynamic queuing mechanism to assign priorities and ensure QoS in next-generation wireless sensor networks, thereby enhancing overall network performance.

3 Methodology

The methodology for the proposed traffic differentiation model in WSNs involves several steps to ensure efficient traffic management based on QoS parameters, as follows: (1) traffic classification using predefined parameters, (2) packet labeling based on their class, (3) packet directing to appropriate queues using the AHP-based model, and (4) weight factors and bandwidth allocations for each class to manage packet flow and ensure QoS.

3.1 Model Description

The model proposed in this paper presents traffic differentiation in WSNs, using multi-criteria optimization to manage traffic based on QoS parameters. The model is described through three key aspects: network structure, queuing system, and traffic classes. Each of these aspects is explained in detail, including methods for determining weight values for each traffic class, implementation of queuing systems, and algorithms for resource allocation to ensure bandwidth assurance. These details are discussed further in the following sections.

3.1.1 Network Structure

Service differentiation is considered a general principle for developing models that ensure appropriate QoS in WSNs and applications. Since the typical DiffServ approach could not be easily translated into the WSN environment [16], several models have been developed to achieve this goal. The most frequently applied integration approach involves modeling based on the implementation of a node-gateway as an interface between the WSN and the Internet [24].

Fig. 1 illustrates the network model of the traffic differentiation approach in a WSN. WSN nodes are assumed to have bidirectional communication with the network access point (gateway), with no direct communication among sensors. Each node generates different types of traffic that belong to classes k_1, k_2, and k_3 which are sent to the gateway, which serves as the access point in this network.

Upon reaching the access point, packets are organized into buffer rows. Within the access point, a scheduler and an appropriate queue mechanism are implemented, utilizing weighted values assigned to specific traffic classes. The primary objective is to achieve optimal resource allocation in the transmission process for packets with diverse QoS requirements.

Resource allocation optimization is performed by applying a multi-criteria AHP optimization method. Connections, i.e., individual traffic classes, are defined by the obtained AHP weights and link capacity value C. Based on these results, it is possible to assess the QoS performance of the access network.

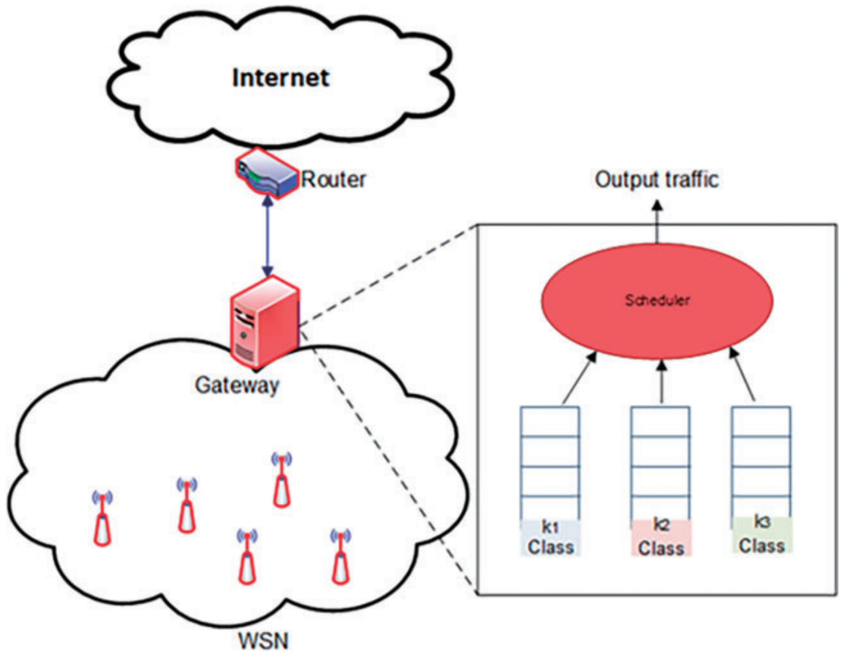

Figure 1: Traffic differentiation network model

3.1.2 Queuing System

The queuing model determines the behavior of packets waiting to be transmitted in the buffer at the access point (AP). Different types of traffic arrivals are placed in separate queues based on the differentiation principle applied at the AP. To achieve traffic class differentiation, it is assumed that each WSN node labels each packet with a specific traffic class label, directing them to the appropriate queues. Packet identification based on these labels determines the individual traffic class of each packet. If the number of traffic classes increases, there may be a need to increase the number of buffers, which are created separately for each traffic class.

Fig. 2 illustrates the queuing model of this system. Packet flows from different traffic classes are served based on the assigned weight factors for each queue. These weight factors are determined according to QoS traffic requirements, including parameters such as delay, loss, and jitter.

Consider a system with three traffic classes k_1, k_2, and k_3 and a final buffer with capacity K. This means that K is the maximum number of packets in the queue, and any subsequent packet will be rejected upon arrival. Packets of classes k_1, k_2, and k_3 arrive in the system with rate λ_{ki} (where $i = 1, 2, 3$), and service rate μ. For each row i the service rate μ is assigned with some weight factor $w_i > 0$. The weight factor w_i are probabilistic, satisfying the following relation: $w_0 + w_1 + w_2 + w_3 = 1$.

If we analyze a link with capacity C as a server that processes incoming packets at a certain rate, the capacity C represents the maximum data transfer rate. Incoming traffic represents the flow of data arriving at the link, and the service rate μ\muμ is the rate at which the link can transmit data, which in this case is equal to the link capacity C. The weight factors w_i will determine the share of capacity that will be available to each traffic class k_i.

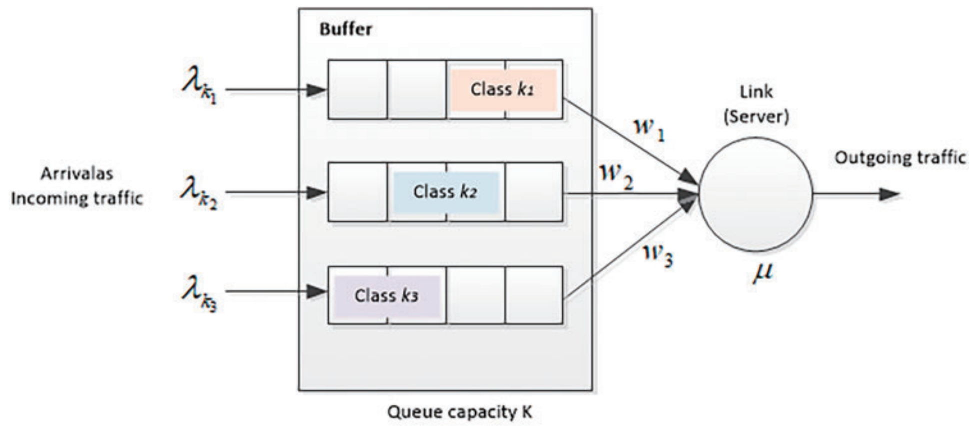

Figure 2: Queue system of the proposed model

Each queue has a limited waiting time value, and interarrival times are exponentially distributed with a mean value that depends on the service rate intensity, which characterizes the outgoing connection capacity to the network access point. These assumptions allow for the application of the M/M/1 queuing theory model to analyze the appropriate distribution of weight factors for individual traffic classes.

3.1.3 Traffic Classes

Considering the heterogeneous traffic in wireless sensor networks, different types of traffic are assumed, such as:

- k_1 class: High Priority Traffic (HP),
- k_2 class: Medium Priority Traffic (MP),
- k_3 class: Low Priority Traffic (LP).

Traffic class k_1 has the highest priority. Applications of this traffic class may include alarm data or any other form of real-time data that is delay intolerant, such as voice data. This type of data is characterized by low delay values and no packet loss, so it is retained in the buffer.

Furthermore, delay-tolerant traffic is defined by class k_2, with certain restrictions. For this traffic type, low delay is not crucial, as long as the transmission of information to the user is reliable. Otherwise, class k_3 is characterized by selected background applications where data transfer can be delayed or suspended during peak network conditions.

An important note is that in most WSNs, a single node does not always have the same sensors. This means that one node can support different traffic classes, while another node may only support two traffic class types. This indicates that QoS requirements should be precisely defined. The queuing model was developed with consideration of the QoS requirements important for different traffic types. Typically, QoS requirements for real-time traffic are defined using delay constraints, while QoS requirements for delay-tolerant traffic are defined using packet loss tolerance.

The QoS parameters (see Table 1), analyzed in the process of categorizing traffic types into certain classes, are highlighted by RFC 4594 [25]. This RFC is intended as a framework to support DiffServ in any network, including wireless networks.

Table 1: QoS parameters according to RFC 4594 [25]

Traffic class	Traffic characteristics	Loss tolerance	Delay tolerance	Jitter tolerance	Access category
k_1	Small packets of fixed size, constant emission rate	Very low	Very low	Very low	AC_VO (Voice)
k_2	Constant and variable rate, inelastic and non-bursty flow	Very low	Medium	Low	AC_VI (Video)
k_3	Variable rate, bursty long–duration elastic flow	Low	Medium-High	Yes	AC_DA (Data)

The proposed model supports real-time traffic (Expedited Forwarding-EF) and traffic that has a certain tolerance to delay (Assured Forwarding-AF). The EF category includes k_1 traffic class, which is real-time and high priority, while the AF category includes k_2 and k_3 classes which tolerate delays with medium and low priority, respectively. The EF traffic has strict time constraints, whereas the AF traffic can accept a predefined percentage of potential losses. Additionally, both real-time and delay-tolerant traffic can be further subdivided based on varying levels of importance, aligning with their respective reliability requirements [25]. Traffic class k_2 require lossless delivery, while class k_3 can tolerate some packet losses.

3.2 MCDM Techniques Analysis

The consideration of QoS parameters in the IoT environment is fundamentally influenced by selecting a service capable of providing suitable resources. QoS evaluation is treated as a multi-criteria decision-making problem when applying an appropriate optimization method. Based on the previously defined model of heterogeneous traffic differentiation in WSNs, three traffic classes are identified, each with specific requirements for QoS parameters: loss, delay, and jitter. The following discussion will focus on the application of a multi-criteria optimization method to determine suitable packet allocation weighting factors for resource allocation algorithms.

QoS modeling has been extensively researched within the IoT domain. Hence, it is necessary to establish a system that can effectively manage the increasing traffic demands while maintaining the required QoS level [26]. Developed QoS models utilize various methods to quantify QoS values, serving as metrics for service evaluation and selection. Given the event-driven nature of IoT traffic, selecting an appropriate resource to handle incoming traffic is critical. For such resource selection, a QoS evaluation model is employed as an objective tool in the decision-making process.

An MCDM model was proposed for a heterogeneous access network [27], where incoming service requests include preferences based on decision factors that determine the most appropriate network. Thus, the categorization of traffic into classes can be analyzed as an MCDM problem. MCDM guides decision-makers in choosing the optimal alternative from several options, determined by various criteria or attributes, whether clearly defined or ambiguous. In this case, the objective of employing MCDM techniques is to evaluate and rank alternatives (classes) based on QoS parameters (criteria).

Various MCDM techniques have been developed and applied to decide on the best alternative in WSNs. These include the Analytic Hierarchy Process (AHP) [28], Fuzzy Analytic Hierarchy Process (FAHP) [29], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [30], ELimination and Choice Expressing Reality (ELECTRE) [31], and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [32]. Among these, AHP stands out as the most popular and widely used technique due to its simplicity and the characteristics of its calculation results [33,34]. Table 2 presents a comparative analysis of various MCDM techniques.

Table 2: Comparison of multi-criteria decision-making methods

Decision-making technique	Criteria ranking	Complexity	Suitable for QoS parameters weight values use	References
PROMETHEE	Yes	Yes, in the case of a significant number of criteria (>7)	Simultaneous handling of qualitative and quantitative parameters.	[32,35]
ELECTRE	Yes	Yes	Simultaneous treatment with qualitative and quantitative parameters as heterogeneous QoS attributes.	[31,34,36,37]
TOPSIS	Yes	Partly	Frequently used as hybrid with AHP.	[30,34,38–42]
AHP	Yes	Yes, in the case of a large set of attributes	Suitable for use in the process of normalizing weight values of QoS parameters.	[30–33,42–45]
SAW	Yes	No	Limited use of the method in terms of accuracy when treating services of similar performance.	[34,46,47]

The AHP method was proposed as a method for service quality evaluation in [40,43], considering criteria related to services, networks, and users. These criteria include: type of service, minimum bandwidth, packet loss, delay, throughput, bit rate, cost, transmission power, received signal strength, load, mobile unit battery condition, and other user preferences. The key advantages of AHP compared to other methods include its flexibility and intuitiveness for the decision-maker, as well as the ability to check inconsistencies in decision-making [45]. Data entry in the comparison process is relatively simple for users.

3.3 AHP Method

AHP (Analytic Hierarchy Process) is one of the most commonly used methods in scenarios requiring the selection and ranking of alternatives based on multiple attributes. These attributes, which characterize potential alternatives, have different degrees of importance and are expressed on various scales. The AHP method facilitates decision-making and priority setting through qualitative and quantitative decision analysis.

Originally proposed by Thomas Saaty in the 1970s, the AHP method is designed for qualitative and quantitative analysis and evaluation of systems. The core principle involves defining a problem, which is then decomposed into a hierarchical structure. Each hierarchical level contains manageable elements, which can be further subdivided into more specific sets of elements. This procedure continues until the most granular elements of the problem are identified at the lowest hierarchical level. A key feature of AHP is its flexibility in constructing hierarchies to meet the specific needs of decision-makers. Metrics are used to assign scores to pairs of elements relative to a higher-level element, establishing priorities among elements at each hierarchical level. The comparison of elements is based on considering two criteria. These comparisons are conducted using the Fundamental Scale of Absolute Numbers ('1–9 scale') [45].

In the context of this study, AHP is utilized to assign weights to different traffic classes, i.e., alternatives, by using criteria such as delay, losses, and jitter. The process of assigning weights involves pairwise comparisons and consistency checks to ensure reliable prioritization of traffic classes. The primary objective of this model is to optimize resource allocation for the available capacity c_i to specific traffic classes, which are transmitted using total capacity C and are determined by the weight factor w_i. Capacity c_i is defined as follows:

$$c_i = w_i \cdot C \tag{1}$$

The weight factors w_i will be calculated using the multi-criteria optimization method AHP, as described earlier. The proposed model is presented in the flowchart shown in Fig. 3:

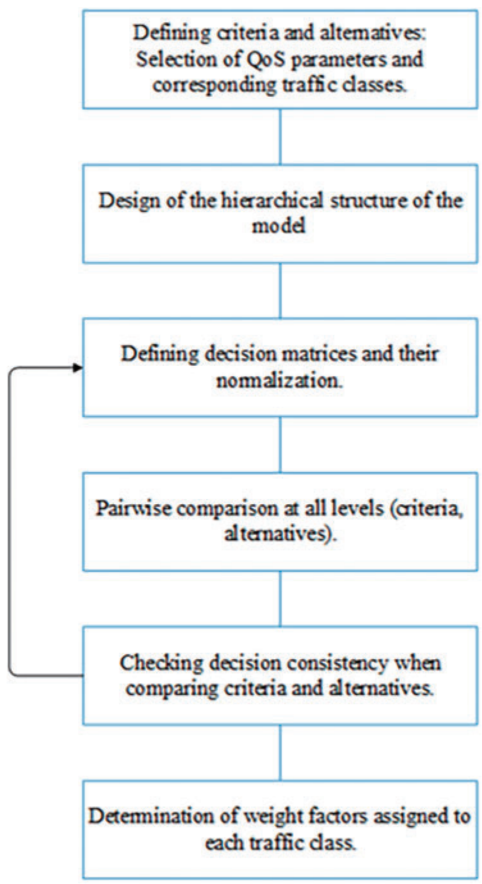

Figure 3: Flowchart for the proposed model

The flowchart in Fig. 3 consists of several phases:

1. Defining three traffic classes (k_1, k_2, and k_3) based on QoS requirements (delay, losses, jitter) as per RFC 4594.
2. Designing the hierarchical structure with one common goal at the highest level, criteria (delay, losses, jitter) at the next level, and traffic classes at the lowest level.
3. Pairwise comparison matrices for the criteria are constructed to determine their relative importance.
4. Weight calculation for each traffic class, producing priority vectors based on the criteria.

Each of these phases will be elaborated upon in the following sections.

4 Results

The results obtained from the implementation of the proposed traffic differentiation model in WSNs are presented. Performance metrics, including delay, packet loss, and jitter, are evaluated to demonstrate the effectiveness of the model. Additionally, a comparative analysis of these metrics across different traffic classes is provided to highlight the model's ability to prioritize and manage network traffic efficiently using the AHP method.

4.1 Defining Criteria and Alternatives

In the first phase of solving the optimization problem, we consider a queuing system in which three traffic classes, denoted as k_1, k_2, and k_3, are defined based on traffic type characteristics for a wireless sensor network. The assignment of traffic to each class is determined based on its fundamental characteristics as described in RFC 4594 [25]. The optimization goal is to assign priorities to each traffic class, resulting in weight factors for bandwidth allocation for individual traffic classes. Packets of each traffic class are served according to specific weight factors assigned to the corresponding packet queues of that class. These weight factors are determined by the QoS parameters of different traffic types. Thus, QoS parameters such as delay, loss, and jitter serve as decision criteria when determining the weight factor values. The resulting alternatives from the decision-making process are the traffic classes k_1, k_2, and k_3.

4.2 Design of Hierarchical Structure

When creating the hierarchical structure (Fig. 4), factors with relevant details and their contributions to the solution are considered. Given that a set of goals, criteria, and alternatives has been defined for the model in the previous phase, the hierarchical representation of the problem will serve as a comprehensive overview of complex relationships, aiding in the decision-making process.

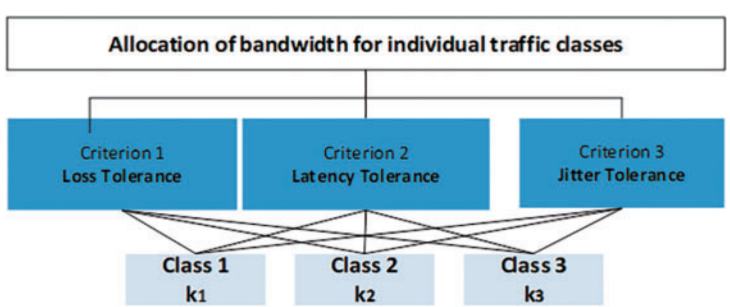

Figure 4: Hierarchical decision-making model at all levels

This hierarchical structure is further divided into sub-hierarchies, with only one common element at the highest level: the goal. The next level is characterized by setting criteria, i.e., quality parameters related to tolerance for delay, loss, and jitter. The task of prioritization involves comparing criteria and alternatives in the context of recognizing the influence of elements across hierarchical levels. After assessing the impact of all elements, priorities are determined for the entire hierarchical structure.

4.3 Comparison of Criteria

A set of pairwise comparison matrices is developed using three criteria, as shown in Table 3. All higher-level elements (criteria-QoS parameters) are compared with each other when creating the decision matrix. Lower-level elements (alternatives-traffic classes) are compared with elements at the higher level, thereby creating pairwise comparison matrices. The "1–9 scale" [45] is used for these comparisons, indicating the importance or dominance of one element over another in the context of the criteria or alternatives being compared.

Table 3: Comparison of criteria

Criteria	Delay	Losses	Jitter
Delay	1	1/9	1/5
Losses	9	1	5
Jitter	5	1/5	1

The comparison indicates the importance or dominance of one element over another with respect to the criterion type.

After the pairing process, a number from the scale is entered into the decision matrix, indicating the appropriate assessment. For example, entering the number 9 in the position (losses, delay) means that losses are 9 times more important than delay. Conversely, the value 1/9 is displayed in the position (delay, losses). The decision matrix A takes the following form:

$$A = \begin{bmatrix} 1 & 1/9 & 1/5 \\ 9 & 1 & 5 \\ 5 & 1/5 & 1 \end{bmatrix} \tag{2}$$

Multiplying A by itself determines the matrix of the first iteration $A(1)$, whose values are used to determine the first priority vector, i.e., the normalization vector. After determining the first priority vector, the process of multiplying matrix A by itself would be repeated, along with the process of determining the second priority vector. By observing the difference between these two vectors, the need for further iterations is assessed. When there is no significant difference between the vectors of successive iterations, the process is terminated, and the matrix $A(1) = A \times A$ has the following form:

$$A(1) = \begin{bmatrix} 2.99 & 0.26 & 0.95 \\ 43 & 2.99 & 11.8 \\ 11.8 & 0.95 & 3 \end{bmatrix} \tag{3}$$

Normalization is carried out to achieve uniformity and enable the comparison of data. Based on the determined values of the priority vector (normalization) (see Table 4), it is observed that the most important criterion is the criterion of losses.

Table 4: Normalization vector $\boldsymbol{w_n}$

A(1)	Delay	Losses	Jitter	Rows value sum	Normalization of rows value sum	Normalization vector ($\boldsymbol{w_n}$)
Delay	2.99	0.26	0.95	4.20	4.20/77.74	**0.05**
Losses	43	2.99	11.8	57.79	57.79/77.74	**0.74**
Jitter	11.8	0.95	3	15.75	15.75/77.74	**0.20**
Σ				**77.74**		

4.3.1 Comparison of Alternatives

Considering the process of determining the priority vectors for individual criteria (delay, losses, and jitter), the next step is to determine the priority vector for alternatives, namely, traffic classes k_1, k_2, and k_3. First, we define the criteria.

I. Criterion *Delay*: Traffic classes k_1, k_2, and k_3 are characterized by very low, medium, and medium to high delay tolerance, respectively. This indicates a high sensitivity of class k_1 and medium to high sensitivity of classes k_2 and k_3 to this QoS parameter.
II. Criterion *Losses*: Traffic classes k_1, k_2, and k_3 are characterized by very low, very low, and low loss tolerance, respectively. This indicates the extremely high sensitivity of classes k_1 and k_2, as well as the high sensitivity of class k_3 to this QoS parameter.
III. Criterion *Jitter*: Traffic classes k_1, k_2, and k_3, are characterized by very low, low, and moderate jitter tolerance, respectively. In that sense, the extremely high sensitivity of class k_1, high sensitivity of class k_2, and low sensitivity of class k_3 to the jitter parameter are noticed.

Table 5 represents the ratios of assigned importance to individual classes concerning the criteria: delay, losses, and jitter. As we compare the criteria, we will also compare the alternatives and derive the priority vectors for different traffic classes. Considering that we have three criteria (D, L, and J) for three alternatives (k_1, k_2, and k_3), this matrix can be written in general form as follows:

$$i\,(1) = i \times i \quad \text{where} \quad i = D, L, J \tag{4}$$

Table 5: The importance of individual classes concerning the parameters: delay, losses, and jitter

Alternative		k_1	k_2	k_3
Delay (D)	k_1	1	4	6
	k_2	1/4	1	2
	k_3	1/6	1/2	1
Losses (L)	k_1	1	1	2
	k_2	1	1	2
	k_3	1/2	1/2	1
Jitter (J)	k_1	1	2	4
	k_2	1/2	1	2
	k_3	1/4	1/2	1

The fundamental decision matrix i (Table 6) for matching the mentioned alternatives in terms of the considered criteria is a prerequisite for calculating the matrix $i(1)$, as well as for deriving the corresponding priority vector (normalization) (Table 7) for the individual traffic classes, taking into account the different criteria.

Table 6: The fundamental decision matrix $i(1), i = D, L, J$

i	$i\,(1) = i \times i$
D	$D\,(1) = D \times D = \begin{bmatrix} 3.02 & 11.00 & 20.00 \\ 0.84 & 3.00 & 5.50 \\ 0.46 & 1.68 & 3.02 \end{bmatrix}$
L	$L\,(1) = L \times L = \begin{bmatrix} 3.00 & 3.00 & 6.00 \\ 3.00 & 3.00 & 6.00 \\ 1.50 & 1.50 & 3.00 \end{bmatrix}$
J	$J\,(1) = J \times J = \begin{bmatrix} 3.00 & 6.00 & 12.00 \\ 1.50 & 3.00 & 6.00 \\ 0.75 & 1.50 & 3.00 \end{bmatrix}$

Table 7: Normalization vectors $\boldsymbol{w_d}, \boldsymbol{w_l}, \boldsymbol{w_j}$

D(1)	k_1	k_2	k_3	Rows value sum	Normalization of rows value sum	Normalization vector (w_d)
k_1	3.02	11	20	34.02	34.02/48.53	**0.70**
k_2	0.84	3	5.5	9.34	9.34/48.53	**0.19**
k_3	0.465	1.68	3.02	5.17	5.17/48.53	**0.11**
Σ				48.53		
L(1)	k_1	k_2	k_3	Rows value sum	Normalization of row sum value	Normalization vector (w_l)
k_1	3	3	6	12.00	12.00/30.00	**0.40**
k_2	3	3	6	12.00	12.00/30.00	**0.40**
k_3	1.50	1.50	3.00	6.00	6.00/30.00	**0.20**
Σ				30.00		
J(1)	k_1	k_2	k_3	Rows value sum	Normalization of row sum value	Normalization vector (w_l)
k_1	3.00	6.00	12.00	21.00	21.00/36.75	**0.57**
k_2	1.50	3.00	6.00	10.50	10.50/36.75	**0.29**
k_3	0.75	1.50	3.00	5.25	5.25/36.75	**0.14**
Σ				36.75		

Normalization vectors obtained by above mentioned criteria (w_d, $w_{l,}w_j$) are listed as follows in Table 7.

4.4 Determining the Goal Priority Vector

In the optimization process, determining goal priorities occurs in the step before the last. In the previous matrices, local priorities, i.e., the priority vectors for criteria and alternatives, have been determined (Table 7). Each column of the priority vector for an individual alternative concerning the selected criterion is multiplied by the corresponding row where the priority of each criterion is defined, resulting in the goal priority vector shown in Eq. (5).

The goal priority vector is determined as the product of the values of the criterion priority vector and the alternative priority vector. This vector ultimately provides the optimization solution for the given goal, as well as the defined criteria and alternatives. The best alternative (the traffic class with the highest priority) under the specified conditions is the one with the highest value in the goal priority vector. Table 8 provides an overview of the priority vector for individual classes concerning the criteria.

Table 8: Priority vectors of individual classes based on criteria

Alternative	Delay	Losses	Jitter
k_1	0.70	0.40	0.57
k_2	0.19	0.40	0.29
k_3	0.11	0.20	0.14

Eq. (5) represents the combination of priority vectors for individual classes based on the defined criteria (delay, loss, and jitter). The first matrix in this equation contains the normalized vectors W_d (normalized delay vector), W_l (normalized loss vector) and W_j (normalized jitter vector) representing the priority of each class according to each criterion. The second matrix (normalized vector W_n), contains the weight factors of each criterion determined based on their significance in optimization. The product of these matrices yields the target priority vector W_i in the following form:

$$\begin{array}{c} \\ k_1 \\ k_2 \\ k_3 \end{array} \begin{bmatrix} \boldsymbol{W_d} & \boldsymbol{W_l} & \boldsymbol{W_j} \\ 0.70 & 0.40 & 0.57 \\ 0.19 & 0.40 & 0.29 \\ 0.11 & 0.20 & 0.14 \end{bmatrix} \begin{bmatrix} \boldsymbol{W_n} \\ 0.05 \\ 0.74 \\ 0.20 \end{bmatrix} = \begin{bmatrix} \boldsymbol{W_i} \\ 0.45 \\ 0.37 \\ 0.18 \end{bmatrix} \tag{5}$$

The highest importance in the comparison of criteria is assigned to the criterion of losses in the mutual comparison of individual criteria, as shown by vector priority W_n in the second matrix. It has a weight factor value of 0.74. This is followed by the weight factor values for the other criteria: delay and jitter, which are 0.20 and 0.05, respectively. Therefore, the criterion that predominantly determined the value of the goal priority vector W_i in the decision-making process was the losses criterion, as shown in the previous matrix. Traffic class k_1, which is most sensitive to the defined QoS parameters (delay, losses, and jitter), also has the highest priority, with a weight value of 0.45. Traffic classes k_2 and k_3 have medium and lower priorities, with weight factor values of 0.37 and 0.18, respectively.

When developing this model, we consider the process of establishing specific types of connections through an appropriate link with a finite capacity C. Three types of connections are established, which we treat as three classes of traffic: k_1, k_2 and k_3. Results show that the connections characterizing the traffic class k_1 reserve $c_1 = 0.45\,C$, class k_2 use $c_2 = 0.37\,C$, while the connections of class k_3 reserve $c_3 = 0.18\,C$ of the link capacity C.

4.5 Estimation of Decision Consistency

When comparing individual criteria, the consistency of the decision-maker's assessments is checked to verify the correctness of the obtained weight factor values. The determination of decision consistency is done according to the following expression:

$$\boldsymbol{\lambda_{max}} = \frac{\mathbf{1}}{\boldsymbol{n}} \sum\nolimits_{i=1}^{n} \frac{(\boldsymbol{A} \cdot \boldsymbol{W})_i}{\boldsymbol{W}_i} \tag{6}$$

where are: $\boldsymbol{\lambda_{max}}$–the largest eigenvalue of the matrix, n–the size of the matrix, A–decision matrix, and W–vector of criteria priorities.

We calculate the vector of the normalized sum as follows:

$$(A \cdot W)_i = \begin{bmatrix} 1.00 & 0.11 & 0.20 \\ 9.00 & 1.00 & 5.00 \\ 5.00 & 0.20 & 1.00 \end{bmatrix} \begin{bmatrix} 0.05 \\ 0.74 \\ 0.20 \end{bmatrix} = \begin{bmatrix} 0.171 \\ 2.190 \\ 0.598 \end{bmatrix} \tag{7}$$

The consistency vector:

$$\frac{(A \cdot W)_i}{W_i} = \begin{bmatrix} 0.171/0.054 \\ 2.190/0.743 \\ 0.598/0.203 \end{bmatrix} = \begin{bmatrix} 3.17 \\ 2.95 \\ 2.95 \end{bmatrix} \tag{8}$$

The principal eigenvalue is:

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(AW)_i}{W_i} = \frac{1}{3}\,(3.17 + 2.95 + 2.95) = 3.02$$

Furthermore, we determine the Consistency Index (CI) as follows:

$$\boldsymbol{CI} = \frac{(\boldsymbol{\lambda_{max}} - \boldsymbol{n})}{(\boldsymbol{n} - \mathbf{1})} = \mathbf{0.01} \tag{9}$$

and Consistency Ratio (***CR***) as follows:

$$\boldsymbol{CR} = \frac{\boldsymbol{CI}}{\boldsymbol{RI}} = \mathbf{0.02} \tag{10}$$

where RI is the Random Consistency Index, which is obtained by referring to the standard RI values for the corresponding matrix size. For this table, the value of $RI = 0.52$ for matrix size $n = 3$ is determined.

The Consistency Ratio (CR) of the decision-making process is calculated (Eq. (10)) to verify the correctness of the obtained weight factor values for individual criteria and the priorities of alternatives. The results show that the CR for all factors within the matrix is within an acceptable range of values, i.e., $CR = 0.02 < 0$. This indicates that the assessments in comparing individual criteria are acceptable, thus verifying the consistency of the decision-maker's evaluations.

5 Discussion and Analysis

5.1 Comparative Analysis with Existing Models

A broader comparative analysis between the proposed AHP model and various existing traffic differentiation and QoS models in WSNs is summarized in Table 9.

Table 9: Comparative analysis of AHP model with existing traffic differentiation and QoS models

Aproach	Resource allocation	QoS management	Computing costs	Energy efficiency	Integration in dynamic conditions	Real-time adaptability	Scalability	Ref.
CSMA/CA	Contention-based	Single parameter	Medium	Low	High	High	High	[4]
TDMA	Fixed slots	Single parameter	Low	Medium	Low	Low	Low	[5,6]
Priority scheduling	Priority queues	Single parameter	Medium	Medium	Medium	Medium	Medium	[5,17,19–20]
Fuzzy logic systems	Fuzzy rules	Multi-parameter	High	Low	High	High	Medium	[29,30,40]
MCDM	Weighted criteria	Multi-parameter	High	Low	High	High	High	[33,34]
Game-theory	Nash equilibria	Multi-parameter	High	Medium	High	High	High	[22]
Machine learning	Predictive allocation	Multi-parameter	Very high	Low	High	High	High	[14,18,48]
Proposed AHP model	Weighted criteria	Multi-parameter	Medium to high	High	High	High	High	

The proposed AHP model offers notable improvements over traditional WSN traffic optimization methods. Unlike TDMA-based methods, which are inefficient under variable traffic conditions due to fixed slot allocations, the AHP model dynamically adjusts to traffic variations, enhancing adaptability. Compared to CSMA/CA-based methods, which manage dynamic traffic well but suffer from energy inefficiency due to collisions, the AHP model ensures both adaptability and energy efficiency. Priority-based scheduling, while effective for different traffic classes, lacks scalability and real-time adaptability. The AHP model overcomes these limitations by integrating multiple criteria for resource allocation, thereby improving both scalability and real-time performance. Fuzzy logic and other MCDM methods offer advanced QoS management but are computationally intensive. In contrast, the AHP model achieves similar QoS improvements with lower computational overhead, optimizing resource use without excessive processing power. Game theory and machine learning models provide strategic and predictive resource allocation but require significant computational resources.

5.2 Energy Consumption Analysis

In this section, we address the complexity inherent in the AHP model and its impact on energy consumption within resource-constrained environments such as WSNs. To analyze the impact of AHP on energy consumption, we consider how different QoS parameters, such as delay, jitter, and packet loss, affect the overall energy usage of WSN nodes.

- **Delay:** Increased delay results in higher energy consumption because nodes must keep their communication interfaces active for longer periods, leading to faster battery drain.

- **Jitter:** High jitter leads to more frequent retransmissions or buffering, which consumes additional energy for packet processing and reordering.
- **Packet Loss:** Packet loss necessitates retransmissions, directly increasing energy usage and further straining the limited energy resources of WSN nodes.

The energy consumption analysis in this study was conducted using a formula that aligns with the energy consumption model proposed in [48]. Specifically, the model calculates the energy consumption (Eqs. (11) and (12)) of each network node by considering key QoS parameters (delay, jitter, and packet loss) and their respective impacts on power usage. The formula used is:

$$P_{con} = N \cdot (P_{tx} + P_{rx} + P_{delay} \cdot delay + P_{jitter} \cdot jitter + P_{loss} \cdot loss) \tag{11}$$

$$E_{con} = P_{con} \cdot T \tag{12}$$

where:

- E_{con} represent energy consumption (J)
- P_{con} represent power consumption (mW)
- N is the total number of nodes
- P_{tx} and P_{rx} denote the power consumption for data transmission and reception, respectively.
- P_{delay}, P_{jitter} and P_{loss} correspond to the power consumption values associated with delay, jitter, and packet loss, respectively
- T–Time (s)

5.3 Experimental Analysis

The primary objective of the experimental analysis was to evaluate the performance of the proposed AHP traffic differentiation model against existing models, specifically Weighted Fair Queuing (WFQ) and First-In-First-Out (FIFO). The analysis focused on key QoS metrics—delay, packet loss, and jitter—across different traffic classes in WSNs. By simulating these scenarios, the study aimed to validate the efficacy of the AHP model in optimizing traffic management and enhancing energy efficiency under various network conditions.

5.3.1 Simulation Environment and Setup

To systematically assess the performance of the AHP model, the simulation was conducted using MATLAB, a tool for network analysis and simulation. The simulation environment is configured as detailed in Table 10.

The model assumes a static network with uniform traffic distribution. Power consumption parameters are derived from typical values observed in WSNs. This model was applied across all traffic classes and scheduling methods (AHP, FIFO, and WFQ), enabling a comparative analysis of different QoS parameters. Random variations were introduced to reflect real-world network conditions, allowing for a realistic assessment of each model's performance.

5.3.2 Quantitative Results and Analysis

The performance of each traffic differentiation model was evaluated based on the average delay, packet loss, and jitter observed across the different traffic classes. The results are summarized in Table 11 below.

Table 10: Simulation parameters

Simulation parameter	Description
Link capacity	0.1 Mbps (Maximum bandwidth available)
Simulation time	100 s
Time vector	Discretized into 1000 intervals
Traffic models	AHP, WFQ, FIFO
QoS metrics analyzed	Delay, Packet loss, Jitter
Bandwidth allocations	**AHP:** $k_1 = 45\%$, $k_2 = 37\%$, $k_3 = 18\%$ **WFQ:** $k_1 = 50\%$, $k_2 = 30\%$, $k_3 = 20\%$ **FIFO:** k_1, k_2, $k_3 = 33\%$ each
Number of nodes	**50**
Power consumption	$P_{tx} = 0.9\ WP_{rx} = 0.7\ W$, $P_{delay} = 0.1\ W/ms$, $P_{jitter} = 0.05\ W/ms$, $P_{loss} = 0.2\ W/\%$

Table 11: Quantified performance metrics for AHP, WFQ, and FIFO models

QoS metric	Traffic class	AHP	WFQ	FIFO
Delay (ms)	k_1	45	50	33
	k_2	37	30	33
	k_3	18	20	33
Packet loss (%)	k_1	2.2	2.4	1.63
	k_2	1.8	1.5	1.64
	k_3	0.9	1	1.62
Jitter (ms)	k_1	5	5	5
	k_2	5.1	5	5.1
	k_3	5	4.9	4.9
Energy consumption (J)	k_1	423.7	419.7	410.2
	k_2	426.3	416.3	411.2
	k_3	417.93	417.92	417.89

The following figures (Figs. 5–8) illustrate the comparison of delay, packet loss, jitter, and energy consumption among three different scheduling algorithms (AHP, WFQ, FIFO) across three traffic classes k_1, k_2, and k_3.

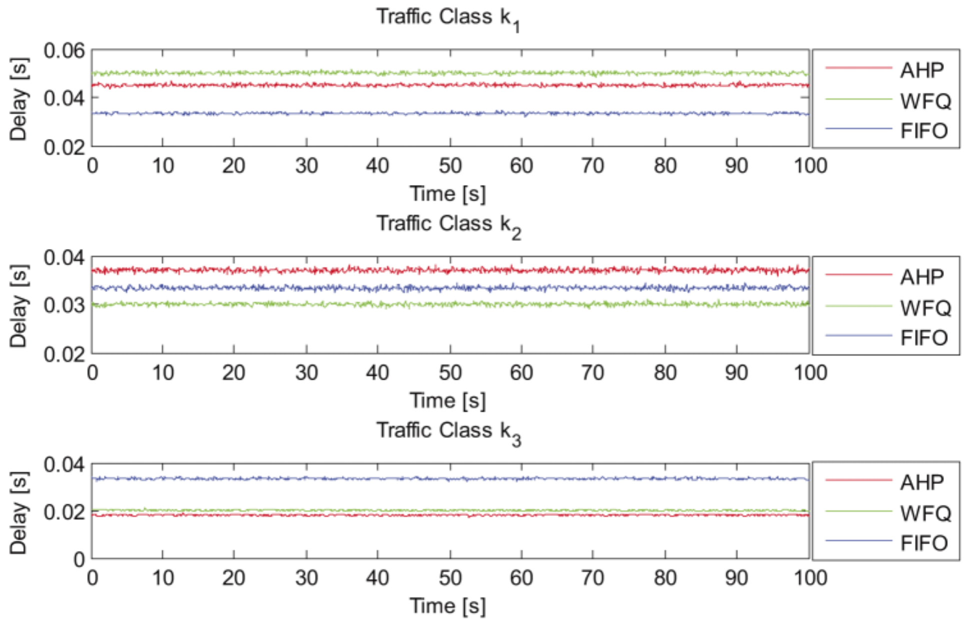

Figure 5: Delay comparison for three scheduling algorithms (AHP, WFQ, FIFO) across traffic classes

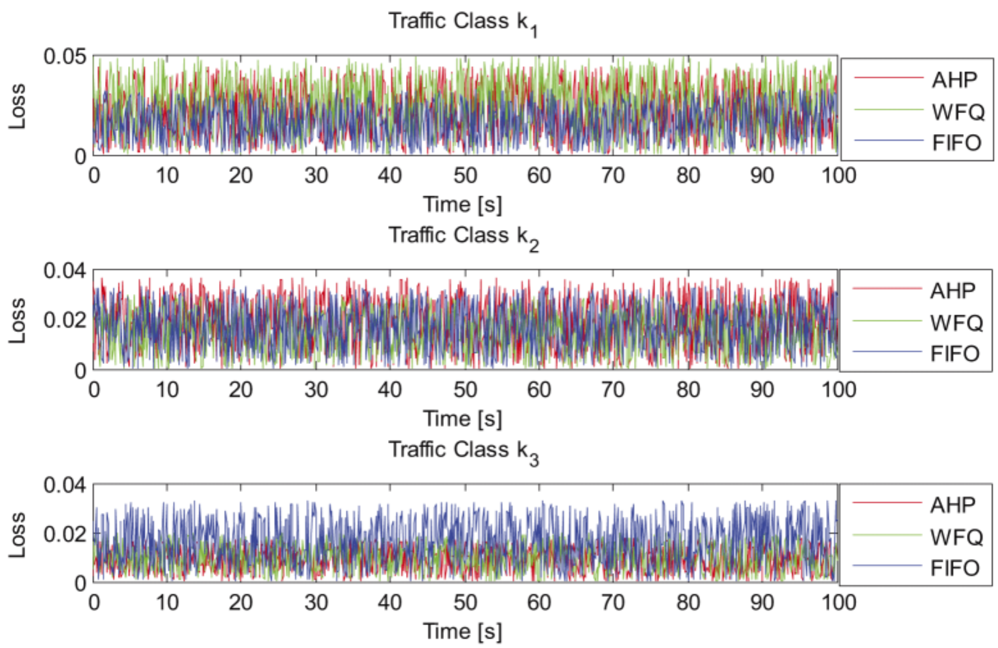

Figure 6: Packet loss comparison for three scheduling algorithms (AHP, WFQ, FIFO) across traffic class

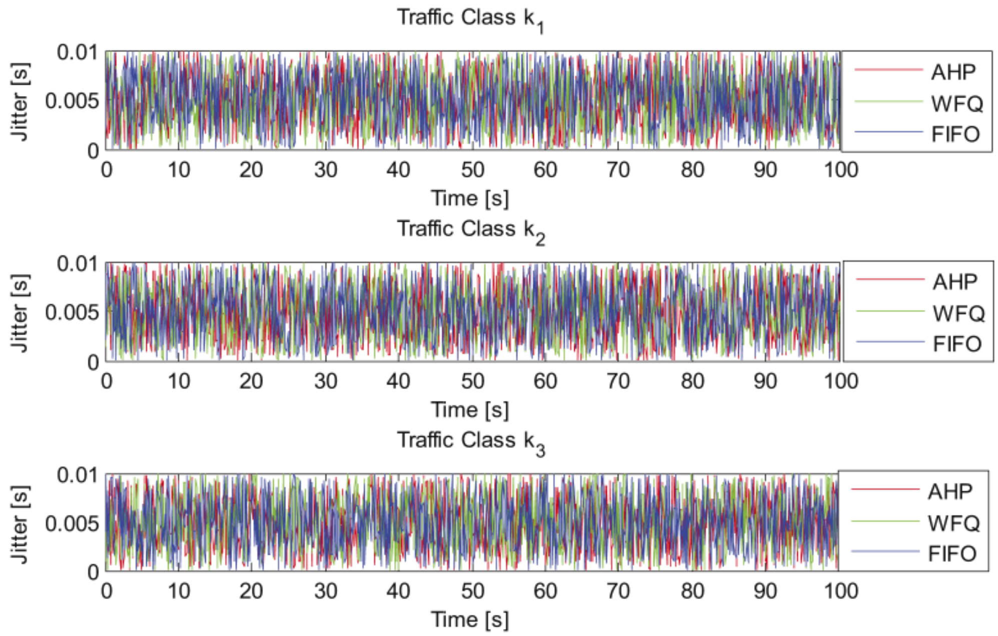

Figure 7: Jitter comparison for three scheduling algorithms (AHP, WFQ, FIFO) across traffic classes

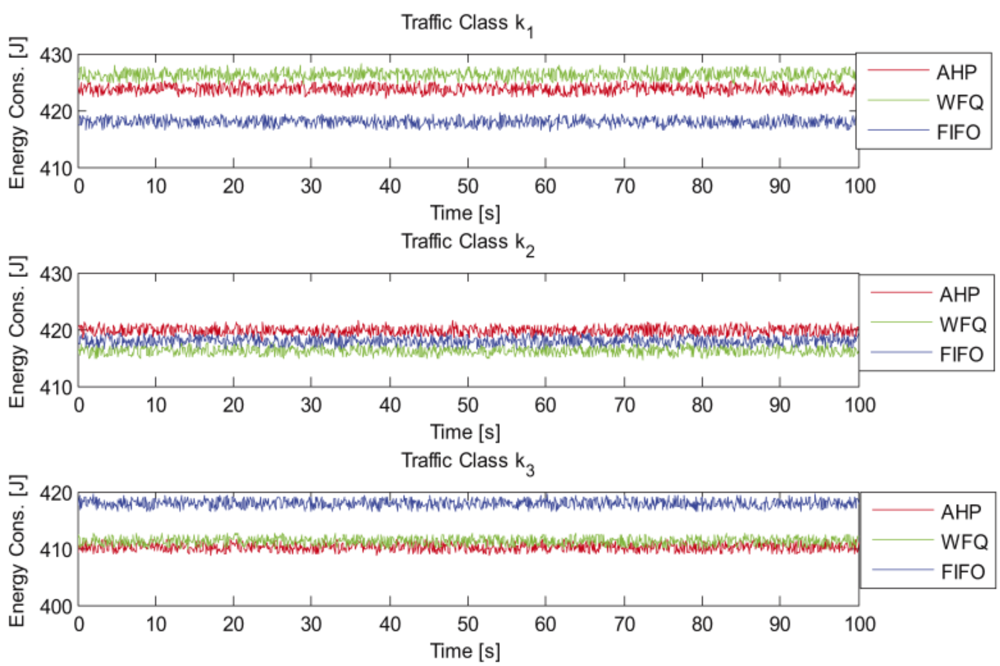

Figure 8: Energy consumption comparison for three scheduling algorithms (AHP, WFQ, FIFO)

In the comparative analysis of traffic differentiation models in WSNs, the AHP model exhibits varied performance across different traffic classes. Specifically, the average delay is low for k_1, moderate for k_2, and highest for k_3, with packet loss following a similar trend, showing increased loss in lower-priority classes. Jitter remains consistently low across all classes. In contrast, the WFQ model's average delay corresponds to bandwidth allocation, resulting in the highest delay for k_3. Packet loss is moderately higher compared to the AHP model, though the distribution is more balanced. Jitter remains uniform and low. The FIFO model shows nearly equal average delay across all classes, which is slightly higher than that in prioritized models. Packet loss is lower and more evenly distributed, while jitter varies slightly but remains generally low. This simulation underscores the impact of traffic prioritization on QoS metrics, demonstrating the distinct effects of each model on handling different traffic classes in WSNs.

When analyzing the performance of AHP, WFQ, and FIFO QoS models across parameters such as delay, packet loss, jitter, and energy consumption, each model has its strengths and weaknesses.

- **Delay:** AHP provides the best performance and lowest delay for high-priority traffic (k_1) compared to WFQ and FIFO, making it superior for time-sensitive applications where minimizing latency is critical.
- **Packet Loss:** AHP excels in reducing packet loss, particularly for lower-priority traffic (k_3). In scenarios where network congestion is a concern, AHP's ability to manage and distribute resources effectively helps minimize the loss of data packets.
- **Jitter:** All models (AHP, WFQ, and FIFO) are effective in maintaining stable and predictable data transmission, with jitter consistently low across all three models. This stability is important for applications that rely on smooth and continuous data flow, such as audio or video streaming.
- **Energy Consumption:** FIFO stands out in terms of energy efficiency. Unlike AHP and WFQ, FIFO treats all traffic equally, which reduces the computational complexity involved in prioritizing packets. As a result, it consumes less energy, making it the best choice for environments where conserving battery life is crucial.

AHP's ability to prioritize traffic effectively makes it the best overall model for managing delay and packet loss, especially in networks where timely and accurate data delivery is crucial. For instance, in critical infrastructure monitoring or emergency response systems, AHP ensures that the most important data is transmitted quickly and reliably. Although AHP consumes more energy than FIFO, the trade-off is justified by its superior performance in reducing delay and packet loss. In scenarios where maintaining high-quality service is more important than energy efficiency, AHP is the optimal choice.

WFQ offers balanced performance across all parameters, making it a good choice for networks that require fair resource allocation among different traffic types, particularly when energy constraints are moderate.

FIFO is ideal when energy efficiency is the top priority. It is best suited for scenarios where the network can tolerate slightly higher delays and packet loss, such as in applications where extending battery life is more critical than optimizing QoS parameters.

The experimental results indicate that the AHP model outperforms the WFQ and FIFO models, particularly in managing delay and packet loss for high-priority traffic classes. The AHP model exhibits:

- **Lower delay:** Especially for higher-priority traffic (k_1), indicating efficient resource allocation that reduces latency.
- **Reduced packet loss:** Particularly in critical traffic scenarios, demonstrating better congestion management.

– **Consistent jitter:** The AHP model maintains low jitter levels, which is crucial for time-sensitive data transmissions.
– **Moderate energy consumption:** While AHP consumes more energy compared to FIFO, this trade-off is justified by its superior performance in reducing delay and packet loss. For applications where service quality is more critical than energy efficiency, AHP represents the optimal choice.

5.4 Limitations of the Study

Despite its advantages, the AHP model presents certain limitations:

– **Complexity:** The AHP model involves matrix operations and multi-criteria decision-making, which generally leads to higher computational complexity. This complexity increases with the number of criteria and alternatives, potentially resulting in longer processing times.
– **Energy Constraints:** Higher computational complexity can lead to increased energy consumption due to more intensive processing at the nodes. However, the optimized resource allocation might offset this by reducing the need for retransmissions and improving overall efficiency.
– **Adaptability:** While highly adaptable, further optimizations are needed to enhance performance across diverse network types and conditions.
– **Simplified Simulation Conditions:** The simulation assumes fixed link capacity and static traffic patterns, which may not accurately reflect real-world network conditions with varying loads and dynamic environments.
– **Static Model Assumptions:** Bandwidth allocations for AHP, WFQ, and FIFO models are static and do not adapt to changing network conditions, limiting their applicability to more complex, real-world scenarios.
– **Numerical Precision and Generalizability:** Results may be affected by numerical rounding errors and may not be directly generalizable to other network types or larger systems due to the simplified assumptions and focus on basic performance metrics.

Future work will focus on refining the AHP model to reduce computational overhead, improve energy management, and broaden its adaptability for a wider range of WSN applications. Special attention will be given to optimizing energy usage to ensure that the model remains effective in energy-constrained environments, such as remote or battery-powered sensor networks.

6 Conclusion and Future Research Direction

In this study, we developed a model for classifying and managing heterogeneous traffic in Wireless Sensor Networks (WSNs) using the Analytical Hierarchy Process (AHP). The model effectively categorizes traffic into three classes (k_1, k_2, and k_3) based on their QoS requirements, such as delay, losses, and jitter. Each class is assigned a specific portion of the available bandwidth, ensuring efficient resource allocation and meeting the QoS demands of various applications.

The proposed AHP model demonstrates several advantages over traditional methods, such as TDMA, CSMA/CA, and priority-based scheduling. It offers dynamic adaptability to traffic variations, improves energy efficiency, and supports real-time adaptability. Additionally, the model's scalability and low computational overhead make it suitable for resource-constrained environments like WSNs.

The study also includes experimental results that validate the effectiveness of the proposed model under various network conditions. However, certain limitations were noted, including the need for further optimization to reduce computational complexity and energy consumption in highly dynamic network conditions. Future research could explore integrating the AHP model with machine learning and game theory approaches to enhance resource prediction and QoS management.

Overall, the AHP model provides a robust solution for traffic differentiation in WSNs, optimizing the use of available resources while maintaining the desired QoS levels. Future work should focus on refining the model for diverse network scenarios and minimizing its computational requirements to better support real-world applications. Further exploration could focus on modifying different QoS parameters within the AHP model and observing the effects on overall network performance and resource allocation efficiency. Implementing adaptive techniques that reduce the frequency of AHP calculations during periods of low network activity can conserve energy. For example, AHP could be invoked only during peak traffic periods, while simpler models like FIFO or WFQ are used otherwise. Limiting AHP calculations to critical decision-making processes while relying on less energy-intensive methods for routine operations can also help manage energy consumption more effectively.

This model can be applied in smart traffic management systems, where it prioritizes real-time data such as traffic flow, congestion alerts, and emergency vehicle routes. By efficiently managing and transmitting this critical information, the model helps optimize traffic flow, reduce congestion, and improve overall transportation efficiency in smart cities. Additionally, the AHP model can be applied in various other domains, such as environmental monitoring, smart agriculture, and healthcare systems. This model prioritizes critical data, and its particular value is in scenarios requiring rapid response to real-time data.

The results of this study can also serve as input data for developing analytical models for WSNs, which can be used in future research to analyze QoS performance metrics.

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