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Optimized Architecture for Efficient OFDMA Network Design

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Abstract: This study presents a novel approach to enhancing the design and performance of OFDMA (Orthogonal Frequency Division Multiple Access) networks, with a particular focus on WiMAX (Worldwide Interoperability for Microwave Access) for Best Effort (BE) services. The proposed method integrates a robust Markovian analytical model with four advanced scheduling algorithms: throughput fairness, resource fairness, opportunistic scheduling, and throttling. A sophisticated simulator was developed, incorporating an ON/OFF traffic generator, user-specific wireless channels, and a dynamic central scheduler to validate the model's accuracy and evaluate its robustness by dynamically allocating radio resources per frame. The validation study showed that the proposed model reduced simulation time by over 90%, completing analytical calculations in just 15 min, compared to nearly 2 days for simulations using conventional scheduling algorithms. Performance metrics such as the average number of active users and resource utilization closely matched those from the validation study, confirming the model's accuracy. In the robustness study, the model consistently performed well across diverse traffic distributions (exponential and Pareto) and channel conditions. The proposed architecture increased network throughput by up to 25% and reduced latency under dynamic conditions, demonstrating its scalability, adaptability, and efficiency as a crucial solution for next-generation wireless communication systems.

Keywords: OFDMA; dimensioning; BE; analytical models; Markov chain

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Citation: Ben Brahim, S.; Zrelli, A.; Dardouri, S.; Bouallegue, R. Optimized Architecture for Efficient OFDMA Network Design. *Telecom* **2024**, *5*, 1051–1075. https://doi.org/10.3390/telecom5040054

Academic Editor: Abderezak Touzene

Received: 19 September 2024
Revised: 20 October 2024
Accepted: 25 October 2024
Published: 1 November 2024

1. Introduction

The rapid evolution of wireless communication networks, from the analog systems of the first generation to today's sophisticated, multi-service digital infrastructures, reflects the growing need for higher data speeds, seamless connectivity, and a wider variety of service requirements [1,2]. As networks move toward the fifth generation (5G) and beyond, the design of network architectures must evolve to meet these increasing demands [3,4]. Orthogonal Frequency Division Multiple Access (OFDMA) has emerged as a crucial technology for next-generation wireless networks, renowned for its efficiency in handling high data rates, minimizing interference, and supporting multiple users simultaneously [5,6]. OFDMA's adaptability and scalability make it a key enabler of technologies like WiMAX (Worldwide Interoperability for Microwave Access), which is built on the IEEE 802.16 standard and widely used for broadband wireless access [7,8].

Optimizing performance in WiMAX networks, especially for Best Effort (BE) services, presents a complex challenge. Wireless environments are inherently stochastic, and user traffic can vary unpredictably, requiring advanced solutions for resource allocation and scheduling [9]. While traditional techniques like Frequency Division Multiple Access (FDMA) and Code Division Multiple Access (CDMA) were effective in previous network generations, they fall short in addressing the real-time demands and dynamic conditions of modern networks [10,11]. In response, more intelligent and adaptive scheduling algorithms have been developed to efficiently manage resources and enhance Quality of Service (QoS), particularly in OFDMA networks [12]. Resource allocation remains a critical factor in maintaining system performance, especially in wireless networks where user demands and channel conditions are constantly shifting [13,14]. Numerous studies have proposed advanced scheduling algorithms to improve system capacity, fairness, and overall network performance [15–17]. However, achieving an optimal balance between these objectives continues to be a challenge, particularly in networks with variable traffic loads and unpredictable channel conditions [18–20].

This study introduces a novel approach by integrating a Markovian analytical model with four advanced scheduling algorithms (throughput fairness, resource fairness, opportunistic scheduling, and throttling) designed specifically for WiMAX networks. The proposed model enhances resource allocation by considering the complex interactions between user traffic, channel variability, and QoS requirements. A robust simulator, incorporating an ON/OFF traffic generator, individual wireless channels for each user, and a central scheduler, is used to validate the model and assess its performance in realistic network scenarios. By relaxing the assumptions of the analytical model and testing it under dynamic conditions, the study aims to demonstrate the model's ability to maintain network efficiency and scalability. This approach adapts to changing traffic loads and channel conditions, ensuring that WiMAX networks can reliably support BE services even under fluctuating conditions. The insights from this research offer significant contributions to the development of more efficient, scalable, and adaptable network architectures. By optimizing resource management and integrating advanced scheduling algorithms, this study positions WiMAX as a critical component in the next generation of broadband solutions. The findings also support the broader goal of advancing wireless communication technologies, enabling future networks to meet the growing demands of an increasingly connected world.

The remainder of this paper is structured as follows: Section 2 provides a detailed review of the related work, highlighting the key contributions and gaps in the existing literature. Section 3 presents the analytical model for WiMAX network dimensioning, based on Markov chain theory, focusing on Best Effort (BE) services. In this section, the assumptions of the model and the derivation of performance parameters are discussed in detail. Section 4 explores the validation and robustness of the analytical model using a custom-built simulator. The simulator is used to compare performance parameters under more realistic conditions versus those predicted by the analytical model. Section 5 presents the results of the simulation, where, due to server capacity limitations, simulations were conducted with a fixed number of 10 stations. Finally, Section 6 concludes the paper, offering insights into the findings and potential directions for future research.

2. Related Works

In recent years, various studies have employed analytical models and optimization techniques to enhance the efficiency and reliability of different systems. One notable example is the use of state-based Markov models in the performance analysis of IoT systems, as presented in [21]. This study developed a time-dependent performance analysis of a smart trash bin system, considering multiple hardware components (Arduino Uno, ultrasonic sensors, servo motors, switches, batteries, and jumper wires) while evaluating system reliability, unreliability, and Mean Time to Failure (MTTF). By leveraging a state-based Markov model, the authors aimed to predict failure points and optimize maintenance schedules, ensuring the longevity and reliability of the smart trash bin. Sensitivity analysis identified critical components (e.g., the servo motor and switch) that significantly impact performance, guiding targeted interventions for optimal operation. This approach demonstrates how analytical modeling when combined with reliability metrics, can optimize IoT system performance under real-world conditions. While the smart trash bin study effectively enhances IoT system reliability, it is limited to static components and does not address the dynamic nature of wireless communication networks. In contrast, the current work employs a Markovian framework tailored to optimize resource allocation in OFDMA networks. This research focuses on real-time adaptations to fluctuating traffic and user demands, which are crucial for maintaining high performance in modern wireless systems.

Another significant study focuses on fault tolerance in wireless networks, particularly within IoT sensor networks. The paper [22] investigates methods for enhancing the reliability of sensors in cluster-based wireless sensor networks (WSNs). It employs Markov models to analyze fault tolerance in nodes that alternate between active sessions and waiting periods, evaluating sensor availability and overall network reliability, with an emphasis on power management strategies such as battery redundancy. The findings highlight how cluster-based approaches can extend the operational lifetime of sensor networks by improving fault tolerance and ensuring uninterrupted data collection. While this IoT study emphasizes fault tolerance and power management in sensor nodes, it primarily targets specific components rather than broader network performance. The current work expands on this by utilizing Markov models to optimize resource allocation in OFDMA networks, prioritizing metrics such as throughput and latency. This focus on dynamic resource management allows for more responsive network behavior, thereby improving overall communication performance under varying traffic conditions.

Recent research has directed substantial efforts toward optimizing the performance of OFDMA networks, particularly with novel technologies. For instance, study [23] explores using reconfigurable intelligent surfaces (RIS) to enhance energy efficiency in OFDMA networks. By jointly optimizing RIS reflection coefficients and OFDMA resource allocation, the authors aim to maximize energy efficiency while ensuring quality-of-service (QoS) requirements. Their approach employs a sub-optimal solution based on alternating optimization (AO) to address the complex problem of resource allocation in RIS-enabled networks, demonstrating significant improvements in energy efficiency compared to conventional OFDMA systems without RIS. However, this study does not address critical aspects of user demand and traffic patterns. The current work tackles these limitations by implementing advanced scheduling algorithms that maximize throughput and fairness among users in WiMAX networks. This ensures that network resources are utilized optimally, which is vital for maintaining quality of service in diverse scenarios.

Several works in the field of OFDMA network simulation have sought to improve resource allocation efficiency. A notable contribution is the simulator implemented in [24,25], which provides insights into network performance under certain assumptions, such as a fixed TDD frame duration of 5 ms and simultaneous ON/OFF periods for all mobile users. However, these assumptions limit model flexibility, particularly in real-world scenarios where user activity may not follow strict timing rules.

The current work extends previous models by implementing a modified simulator that alternates the assignment of ON and OFF periods to each mobile user based on a probabilistic distribution. This adaptation allows for more realistic modeling of traffic patterns, with users assigned download times (x_{on}) and idle times (t_{off}) using exponential or Pareto distributions. The model dynamically adjusts user states during simulation, offering a more precise representation of network behavior and enabling accurate estimation of performance metrics such as frame utilization and system throughput. By capturing user activity variability more effectively than traditional analytical models, the current work serves as a robust method for validating theoretical assumptions in dynamic environments. Table 1 provides a comparison of existing works.

In conclusion, while existing studies contribute valuable insights into the optimization of IoT systems and wireless networks, the current work advances the field by addressing the dynamic nature of resource allocation in OFDMA networks. By integrating advanced scheduling algorithms and enhancing simulation techniques, this research significantly improves throughput, reduces latency, and ensures optimal resource utilization in real-time scenarios. The proposed study addresses gaps in the literature by integrating a Markovian analytical model with four advanced scheduling algorithms: throughput fairness, resource fairness, opportunistic scheduling, and throttling. Each is tailored for WiMAX networks. This approach dynamically manages resource allocation and considers the interactions between user traffic, channel conditions, and QoS requirements. By leveraging a more flexible and scalable Markov model, the current work achieves better performance in handling Best Effort services, improving both resource utilization and user fairness.

Table 1. Comparative table of existing works.

Study	Focus	Key Contributions	Limitations	Current Work Advantage
[21]	Performance analysis of a smart trash bin using Markov models	Evaluated system reliability, unreliability, and Mean Time to Failure (MTTF); identified critical components through sensitivity analysis.	Limited to static components; does not address dynamic wireless networks.	Employs a Markovian framework for optimizing resource allocation in OFDMA networks, adapting to fluctuating traffic and user demands.
[22]	Enhancing reliability in cluster-based sensor networks	Analyzed fault tolerance in nodes; emphasized power management strategies for improved sensor availability and operational lifetime.	Targets specific sensor components; lacks broader network performance focus.	Utilizes Markov models for optimizing resource allocation in OFDMA networks, prioritizing throughput and latency for overall communication performance.
[23]	Enhancing energy efficiency in OFDMA networks	Significant improvements in energy efficiency using RIS and resource allocation optimization via alternating optimization.	Does not address user demand and traffic pattern dynamics.	Implements advanced scheduling algorithms to maximize throughput and user fairness in WiMAX networks, ensuring optimal resource utilization.
[24]	Network performance simulation based on fixed assumptions	Provided foundational insights into network performance with fixed TDD frame duration and ON/OFF periods.	Fixed assumptions limit model flexibility and real-world applicability.	Implements a modified simulator with probabilistic ON/OFF periods, allowing realistic modeling of traffic patterns and accurate performance metric estimation.

By combining the strengths of Markov modeling with dynamic scheduling algorithms, the proposed model offers an adaptive solution that balances resource utilization, fairness, and scalability. It also addresses key challenges identified in prior work, such as resource allocation for Best Effort traffic under varying network conditions. This comparative analysis highlights how the proposed model outperforms previous models in managing dynamic traffic, especially in WiMAX networks, while offering a simpler, more scalable solution for Best Effort services.

3. Analytical Model for OFDMA Networks

This section presents the analytical model for WiMAX network dimensioning, based on Markov chain theory, which is designed for Best Effort (BE) services. The model incorporates various scheduling algorithms, and the underlying system assumptions are discussed to derive the key performance parameters. The objective is to explore the interactions between traffic, channel conditions, and resource allocation strategies to effectively evaluate the network's performance.

To start, key parameters of the WiMAX network used throughout this study are defined.

- N_S: The total number of slots available for data transmission in the downlink part of a Time Division Duplex (TDD) frame.
- T_F: The duration of a TDD frame ($T_F = 5\ ms$).

- MCS_k: The state of the radio channel, where $0 \leq k \leq K$, with K being the total number of Modulation and Coding Schemes (MCS). MCS_0 indicates a failure state.
- m_k: The number of bits transmitted per slot by a mobile station using MCS_k.

3.1. Model Assumptions

The analytical model is based on a set of assumptions regarding the system, channel, and traffic.

3.1.1. System Assumptions

- The total number of slots available for downlink data transmission is constant, denoted as N_S.
- All connection requests are accepted, with no blocking or resource denial.
- Each mobile station has unlimited transmission capacity, meaning that if only one user is active, they can use all available slots.

3.1.2. Channel Assumptions

- The MCS coding scheme used by a given mobile can, very often, change due to the high variability of the radio link quality. Since the mobile sends its channel estimation frame by frame, the base station will, therefore, have different coding schemes for each frame. On the other hand, we associate a probability p_k for each MCS_k coding scheme and assume that at each T_F frame, any mobile has a probability p_k of using MCS_k (including those in a state of failure: a station is in a state of failure if it is unable to emit/transmit because of the poor quality of its channel: $k = 0$).

3.1.3. Traffic Assumptions

- All users generate traffic with identical characteristics, following an ON/OFF model.
- There are no handover mechanisms considered in this model.
- A fixed number of mobile stations (N) share the available bandwidth.
- Each mobile generates elastic ON/OFF traffic, where ON periods correspond to downloading data, and OFF periods correspond to idle times (e.g., reading content). ON and OFF durations are exponentially distributed.
- Since only the Best Effort (BE) service class in WiMax is considered, each of the N mobile stations is assumed to generate an infinite ON/OFF sequence of elastic traffic. An ON period corresponds to downloading content (such as a webpage with embedded objects). The duration of the ON period depends on the system load and the quality of the radio link, so ON periods are characterized by their data volume. An OFF period represents the time spent reading or viewing the last downloaded item. The duration of the OFF period is independent of the system load and is characterized solely by its length.
- The sizes of the ON periods and the durations of the OFF periods are exponentially distributed. The variable x_{on} represents the average data volume during ON periods (in bits), while t_{off} represents the average duration of OFF periods (in seconds).

3.2. Markov Chain Representation

The analytical model proposed in [25] is based on the multidimensional continuous-time Markov chain (CTMC) theory. In this model, each state, denoted as S_n, represents the scenario where there are n active stations at a given moment. N denotes the total number of stations in the system, which sets the upper bound on the number of active stations, ranging from S_0 (no active stations) to S_N (all stations active). For example, state S_0 corresponds to the situation where no mobile stations are active, meaning all devices are in the OFF period (i.e., the pause between two downloads) [26].

A transition from state S_n to state S_{n+1} occurs when a mobile station in the OFF period switches to the ON state (data transfer). This transition occurs at an arrival rate of $(N-n)\lambda$, where $(N-n)$ represents the number of stations in the OFF period, and λ is defined as the inverse of the average reading time:

$$\lambda = 1/t_{off} \quad (1)$$

Conversely, a transition from state S_n to S_{n-1} happens when a mobile station in the ON state completes its data transfer. This departure transition occurs at a rate $\mu(n)$, which corresponds to the total departure rate when there are n active stations. The estimation of $\mu(n)$ is a key challenge, as it depends on the selected scheduling policy. Thus, this model focuses on evaluating $\mu(n)$ to derive the performance parameters for each scheduling policy [27,28].

Figure 1 presents the structure of the multidimensional continuous-time Markov chain (CTMC) model used in this study. It illustrates the different states S_0,S_1,S_2,. . ., where each state n corresponds to the number of active stations in the system. Figure 1 also depicts the transitions between these states, governed by the arrival and departure rates, as stations switch between ON (data transfer) and OFF (idle) periods.

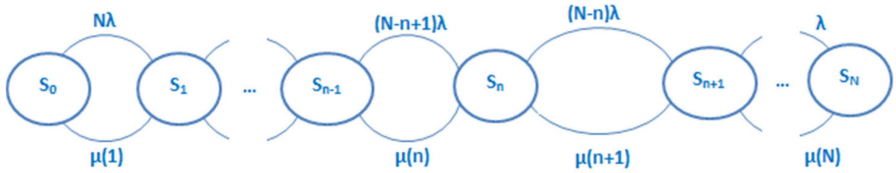

Figure 1. The Multidimensional Continuous-Time Markov Chain.

3.3. Scheduling Policies

The scheduling algorithm is responsible for allocating radio resources in each frame to the active users. In wireless networks, this allocation can take into account the quality of the radio link. Initially, three conventional policies are considered to distribute all available resources (i.e., all slots in each frame) among the active stations:

- Resource fairness: Allocates slots equally among active users, regardless of their radio conditions.
- Throughput fairness: Ensures that all active users achieve the same instantaneous throughput.
- Opportunistic scheduling: Allocates all resources to the active users with the best channel conditions (i.e., the highest MCS).

The fourth type of scheduling is the throttling regime, which is proposed to model a performance metric in the [29] called Maximum Sustained Traffic Rate (*MSTR*). This metric specifies an upper limit on the maximum throughput that can be offered to a user.

Using the analytical model, the performance parameters associated with the scheduling algorithms, both for conventional policies and the throttling regime, will be determined.

3.3.1. Conventional Scheduling Policies

A conventional scheduling policy aims to distribute all resources among the users. As long as there is at least one active mobile (in the transfer state) that is not in failure, all the slots in the current frame will be allocated to that user, ensuring that no resources remain unused.

In this study, three conventional scheduling policies corresponding to three specific scheduling regimes are considered.

The expression for the departure rate $\mu(n)$ for the three scheduling policies is given as follows:

$$\mu n = \frac{\overline{m}(n) N_S}{\overline{X}_{ON} T_F} \quad (2)$$

where $\overline{m}(n)$ is the average number of bits transmitted per slot when there are n active transfers during a TDD frame. The value of $\overline{m}(n)$ depends on K, the number of MCS (Modulation and Coding Schemes), and p_k, the probability vector for each MCS, where $0 \leq k \leq K_0$.

The calculation of $\overline{m}(n)$ also depends on n, as the average number of bits per slot must account for all possible combinations of the n mobile users across the K + 1 possible coding schemes (including the failure state). Furthermore, $\overline{m}(n)$ is influenced by the scheduling policy, as the number of slots allocated to each mobile depends on the coding scheme they are using.

The expression for $\overline{m}(n)$, the average number of bits transmitted per slot for n active users, is given by the following equation [13]:

$$\overline{m}(n) = \sum_{\substack{(n_0,\ldots,n_K)=(0,\ldots,0)\\ n_0+\ldots+n_K=n\\ n_0\neq n}}^{(n,\ldots,n)} \frac{n!}{n_0!n_1!n_k!}\overline{m}(n_0|,|\ldots|,|n_k)\left(\prod_{k=0}^{K} p_k^{n_k}\right) \tag{3}$$

$$\overline{m}(n_0,\ldots,n_k) = \sum_{k=1}^{K} m_k n_k x_k(n_0,\ldots,n_K) \tag{4}$$

where $x_k(n_0,\ldots,n_K)$ represents the proportion of resources allocated to a mobile station using $\mathrm{MCS_k}$, given the distribution of the n active users among the K + 1 coding schemes (including the failure state), denoted by $(n_0,\ldots,n_K)$.

1. Resource fairness: For resource fairness, the scheduling algorithm equally distributes the available slots $\mathrm{N_S}$ among active users who are not in the failure state during a TDD frame. Thus, for a given distribution $(n_0,\ldots,n_K)$ of the active users ($n = \sum_{k=1}^{K} n_k$, each of the $n-n_0$ users who are not in the failure state receives an equal share of the total resources. The proportion of resources $x_k(n_0,\ldots,n_K)$ allocated to a user using $\mathrm{MCS_k}$ is given by

$$x_k(n_0,\ldots,n_K) = \begin{cases} \frac{1}{n-n_0} if\ k \neq 0\ and\ n \neq n_0 \\ 0\ else \end{cases} \tag{5}$$

   By substituting these proportions into the generic expression (3), the value of $\overline{m}(n)$, when there are n active users, becomes

$$\overline{m}(n) = \sum_{\substack{(n_0,\ldots,n_K)=(0,\ldots,0)\\ n_0+\ldots+n_K=n\\ n_0\neq n}}^{(n,\ldots,n)} \frac{n!}{n-n_0}\sum_{k=1}^{K} m_k n_k \left(\prod_{k=0}^{K} \frac{p_k^{n_k}}{n_k!}\right) \tag{6}$$

2. Throughput Fairness: The goal of the throughput fairness policy is to ensure that all active users who are not in failure achieve the same instantaneous throughput. If an active mobile station using $\mathrm{MCS_k}$ is allocated a proportion of the resources $x_k(n_0,\ldots,n_K)$, its resulting instantaneous throughput will be proportional to $m_k x_k(n_0,\ldots,n_K)$. Consequently, to ensure fairness in throughput among active users, not in failure, $x_k(n_0,\ldots,n_K)$ must satisfy the following condition:

$$m_k x_k(n_0,\ldots,n_K) = C\ for\ k \neq 0 \tag{7}$$

   where C is a constant such that $\sum_{k=1}^{K} n_k x_k(n_0,\ldots,n_k) = 1$, so:

$$C = \frac{1}{\sum_{k=1}^{K} \frac{n_k}{m_k}} \tag{8}$$

By substituting these proportions into the generic expression (3), the average number of bits per slot $\overline{m}(n)$, when there are n active users, becomes

$$\overline{m}(n)= \sum_{\substack{(n_0,\ldots,n_K)=(0,\ldots,0)\\ n_0+\ldots+n_K=n\\ n_0\neq n}}^{(n,\ldots,n)} \frac{(n|-|n_0)n!\prod_{k=0}^{K}\frac{p_k^{n_k}}{n_k!}}{\sum_{k=1}^{K}\frac{n_k}{m_k}} \tag{9}$$

3. Opportunistic Scheduling: In the case of opportunistic scheduling, all resources are allocated to the users with the highest transmission rate, i.e., those with the best channel conditions, represented by the highest MCS. Assume that the MCS levels are ordered from lowest to highest: $m_0 <\ldots< m_K$. Consider a system with n active users. Let $\alpha_i(n)$ represent the probability that at least one active user is using MCS_i and no other user is using a higher MCS_j for $j > i$. This can be interpreted as the probability that the scheduler allocates all resources to users operating with MCS_i.
The average number of bits per slot when there are n active users is expressed as

$$\overline{m} = \sum_{i=1}^{k}\alpha_i(n)m_i \tag{10}$$

To calculate $\alpha_i(n)$, first define $p \leq i(n)$, the probability that none of the users are using an MCS higher than MCS_i:

$$p_{\leq i}(n) = \left(1-\sum_{j=i+1}^{k} p_j\right)^n \tag{11}$$

Next, calculate $p_{=i}(n)$, the probability that at least one user is using MCSi given that no other user is using a higher MCS:

$$p_{=i}(n) = 1-\left(1-\frac{p_i}{\sum_{j=0}^{k} p_j}\right)^n \tag{12}$$

Thus, $\alpha_i(n)$, the probability that the scheduler allocates all resources to users operating with MCS_i, is given by

$$\alpha_i(n) = p_{=i}(n)p_{\leq i}(n) \tag{13}$$

4. Performance Parameters: There are three key performance parameters that can be derived from the model. These are:
   - Average resource utilization (U) during a TDD frame,
   - Average number of active users (Q), and
   - Average instantaneous throughput (X) of active users during an ON period.

To calculate these parameters, the stationary probabilities of the CTMC $\pi(n)$ are required. $\pi(n)$ represents the probability that n mobile stations are active at any given moment. This probability can be derived from the birth-and-death structure of the Markov chain:

$$\pi(n) = \left(\prod_{i=1}^{n}\frac{(N-i+1)\lambda}{(i)}\right)\pi(0) \tag{14}$$

By substituting the expression for $\mu(n)$ previously calculated in Equation (2), $\pi(n)$ becomes:

$$\pi(n) = \frac{N!}{(N-n)!}\frac{\rho^n}{N_S^n\prod_{i=1}^{n}\overline{m}(i)}\pi(0) \tag{15}$$

where

$$\rho = \frac{\overline{x_{on}} T_F}{t_{off}} \tag{16}$$

$\pi(0)$ is obtained via normalization:

$$\pi(0) = \frac{1}{1 + \sum_{n=1}^{N} \left(\prod_{i=1}^{n} \frac{(N-i+1)\lambda}{(i)} \right)} \tag{17}$$

With these probabilities, the three performance parameters can be expressed as follows:

- Average number of active users ($\overline{Q}$):

$$\overline{Q = } \sum_{n=1}^{N} n.\pi(n) \tag{18}$$

- Average resource utilization ($\overline{U}$):

$$\overline{U = } \sum_{n=1}^{N} \pi(n) \min\left(n \frac{\overline{x}_{on}}{\overline{m}(n)}, 1 \right) \tag{19}$$

- Average instantaneous throughput of active users during an ON period (X):

To calculate X, the average number of completions ($\overline{D}$) per time unit (the number of mobile stations completing their transfers) must first be determined:

$$\overline{D} = \sum_{n=1}^{N} \pi(n)(n) \tag{20}$$

Using Little's Law, the average duration of an active transfer (t_{on}) is given by

$$t_{on} = \frac{\overline{Q}}{\overline{D}} \tag{21}$$

Finally, the average instantaneous throughput of an active user during an ON period is:

$$\overline{X} = \frac{\overline{x}_{on}}{\overline{t}_{on}} \tag{22}$$

The same expressions for these performance parameters apply to the three scheduling policies, with the only difference being the expression for $\overline{m}(n)$, which depends on the scheduling algorithm used.

3.3.2. Throttling Regime

The throttling regime is proposed to model a performance metric defined in the IEEE 802.16e standard known as the Maximum Sustained Traffic Rate (MSTR). This metric specifies an upper limit on the maximum throughput that can be offered to a user.

The traffic of a station is described using three parameters: MSTR, $\overline{x}_{on}$, and $\overline{t}_{off}$. The MSTR controls the maximum allowable peak rate for a connection. For each frame, the scheduler attempts to allocate the appropriate number of slots necessary for each active station to meet its MSTR.

If a station is in a failure state, it does not receive any slots, resulting in degraded throughput. If at any time the total number of available slots (N_S) is insufficient to satisfy the MSTR requirements of all active users (those not in a failure state), the throughput of all users will be equally degraded. Conversely, if there are more available resources than needed, the excess slots will remain unused.

1. Departure Rate: To estimate the average departure rate $\mu(n)$ related to the throttling method, it is necessary to define certain variables. To compensate for losses due

to failures, a slightly elevated instantaneous throughput compared to the *MSTR* is considered, denoted as the Dynamic Bandwidth Rate (*DBR*):

$$DBR = \frac{MSTR}{1 - p_0} \tag{23}$$

A mobile station using $\mathrm{MCS_k}$ requires a minimum number of slots $\overline{g}_k$ per frame to achieve the *DBR*:

$$\overline{g}_k = \frac{DBR.T_F}{m_k} \tag{24}$$

Since there will be no slots reserved for a station in failure, it follows that $\overline{g}_0$ = 0. Thus, the average number of slots per frame required by a mobile to meet its MSTR can be expressed as

$$\overline{g} = \sum_{k=1}^{K} p_k g_k \tag{25}$$

Knowing $\overline{g}$, the departure rate $\mu(n)$ can be described as follows:

$$\mu(n) = \frac{N_s}{\max(n\overline{g}, N_s)} n \frac{MSTR}{\overline{x_{on}}} \tag{26}$$

In this equation, $\frac{MSTR}{\overline{X}_{on}}$ represents the throughput that allows each of the active stations to complete their transfers, assuming there are always sufficient slots in the frame to meet the *MSTR*.
The term $\frac{N_S}{max(n\overline{g}, N_S)}$ represents the ratio of the total departure rate achieved by the n active transfers. Specifically, if there are n active stations, an average of $n\overline{g}$ slots is needed to achieve their respective *MSTR*. If $N_S \geq n\overline{g}$, they can all receive their *MSTR*, resulting in a ratio equal to 1. Conversely, if $N_S < n\overline{g}$, there will not be enough resources to meet the demands, and consequently, the mobiles will only receive a fraction of their *MSTR*, specifically $\frac{N_S}{n\overline{g}}$.

2. Performance Parameters: By substituting the departure rate $\mu(n)$ (from Equation (26)) into the generic expression (14), the stationary probability $\pi(n)$ can be calculated as follows:

$$\pi(n) = \frac{N!}{(N-n)!} \left(\frac{\rho^n}{n! \prod_{i=1}^{n} \frac{N_s}{max(i\overline{g}, N_s)}} \right) \pi(0) \tag{27}$$

where

$$\rho = \frac{\overline{x}_{on}}{MSTR\overline{\overline{t_{off}}}} \tag{28}$$

The value of $\pi(0)$ is obtained through normalization, similar to the previous derivations. The performance parameters can be derived from the stationary probabilities $\pi(n)$. Thus, the average resource utilization ($\overline{U}$) during a TDD frame is expressed as

$$\overline{U} = \sum_{n=1}^{N} \frac{n\overline{g}}{max(n\overline{g}, N_s)} \pi(n) \tag{29}$$

The average number of active users ($\overline{Q}$) is given by

$$\overline{Q} = \sum_{n=1}^{N} n.\pi(n) \tag{30}$$

To calculate the average throughput ($\overline{X}$), Little's Law is applied:

$$\overline{X}= \frac{\overline{x}_{on}}{\overline{t}_{on}} \text{ where } \overline{t}_{on} = \frac{\overline{Q}}{\overline{D}}$$

Here, $\overline{D}$ represents the average number of departures per slot, which can be expressed as

$$\overline{D} = \sum_{n=1}^{N} (n)\pi(n) \quad (31)$$

Consequently, the average throughput can now be written as

$$\overline{X} = \frac{\overline{x}_{on}}{\overline{t}_{on}} = \frac{\overline{x}_{on}\sum_{n=1}^{N} (n)\pi(n)}{\sum_{n=1}^{N} n\pi(n)} \quad (32)$$

Theoretical evaluations indicate that this method effectively provides the necessary performance parameters for the successful dimensioning of OFDMA networks, taking into account the various scheduling algorithms considered in this study. However, practical implementation is essential to gain insights into the margins of results obtained through this method compared to those that might be expected in real-world scenarios. This implementation will be carried out using a simulator that adheres more closely to the assumptions and constraints of a real network.

4. Validation and Robustness Study of the Analytical Model

The objective of this work is to validate and assess the robustness of the analytical model through the development of a specialized simulator. Network dimensioning, for an operator, involves calculating the number of antennas required in a specific region while ensuring key Quality of Service (QoS) parameters such as radio coverage, cellular capacity, and user traffic parameters are maintained. The dimensioning process for OFDMA networks is carried out in two main steps (as shown in Figure 2): evaluating radio coverage and cellular capacity and performing traffic analysis.

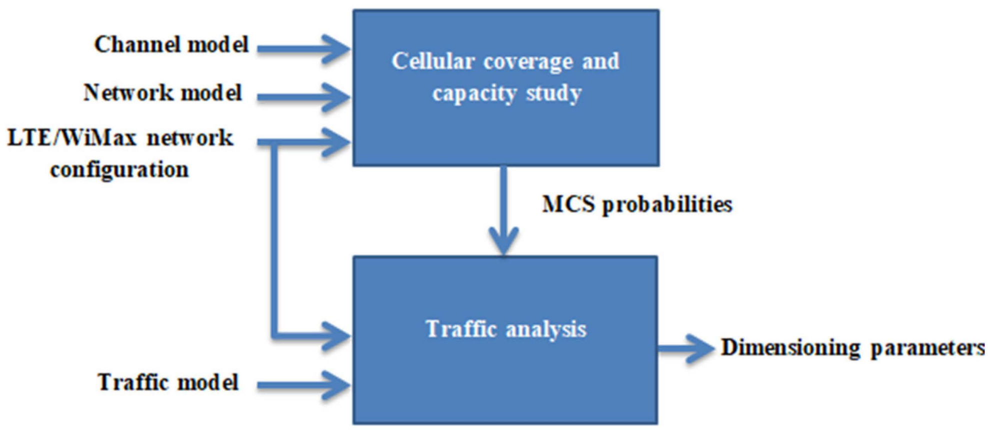

Figure 2. The system studied for the dimensioning study.

This study focuses on the second step, Traffic Analysis, where MCS probabilities, network configuration, and traffic models serve as inputs. These inputs are essential in determining performance parameters such as average user throughput, average radio resource utilization, and the number of active users.

To achieve this, a simulator has been developed. The simulator implements an ON/OFF traffic generator, individual wireless channels for each user, and a central scheduler responsible for allocating radio resources (slots) to active users in each frame. In the first phase, the simulator validates the analytical model by operating under the same traffic and channel assumptions as the model. In the second phase, the robustness of the model is tested by relaxing these assumptions and introducing more realistic scenarios involving traffic and radio channels.

The study is conducted across four different scheduling algorithms, each allocating radio resources uniquely. This simulator enables a comparison of variations in performance metrics, such as throughput and resource utilization, between the simulation and the analytical model under various conditions.

A detailed description of the simulator will follow, explaining its implementation and functionality in evaluating both validation and robustness.

The parameters to be adjusted for conducting the desired simulator will now be specified. These parameters include traffic parameters, system parameters, and channel parameters.

4.1. System Parameters

- A single WiMAX cell will be considered, with a focus on studying the downlink.
- The number of slots is determined by factors such as the system's bandwidth, frame duration, downlink/uplink ratio, subcarrier permutation (PUSC, FUSC, AMC), and protocol overhead (including preamble, FCH, and maps).
- The system's bandwidth is set at *10 MHz*.
- The frame duration for the TDD WiMAX network is assumed to be *5 ms*, with a downlink/uplink ratio of *2/3*.
- For simplicity, the protocol overhead is assumed to have a fixed length of two symbols, although, in practice, it varies depending on the number of users.
- Based on these parameters, the total number of data slots available per downlink amounts to *450*.

4.2. Traffic Parameters

In the analytical model, elastic ON/OFF traffic is considered. For the validation study, it is assumed that the ON data volumes and OFF periods follow exponential distributions, aligning with the assumptions of the analytical model. Let $\overline{x}_{\text{on}}$ represent the average ON data volume (which includes the main page and embedded objects), and $\overline{t}_{\text{off}}$ denote the average OFF period (representing the reading time).

However, since the memoryless property of the exponential distribution does not always capture the actual behavior of data traffic, a truncated Pareto distribution was selected for the robustness study to better reflect real-world traffic patterns.

The traffic parameters in Table 2 are based on the analysis of OFDMA network performance metrics from reference [25], providing a solid foundation for our choices:

Table 2. Traffic parameters.

Parameter	Value
$\overline{x}_{\text{on}}$	3 Mbits
$\overline{t}_{\text{off}}$	3 s
MSTR for throttling mode	2048 Kbps
Pareto parameter α	1.2
Pareto lower cutoff q	300 Mbits
Pareto higher cutoff q	3000 Mbits
Pareto parameter b for lower cutoff	712,926 bits
Pareto parameter b for higher cutoff	611,822 bits

4.3. Channel Model

In the study of the model, validation, and robustness phases, the number of bits per slot m_k that a mobile device can receive is assumed to depend on the selected Modulation and Coding Scheme (MCS), which is determined by the user's radio channel conditions. The selection of the MCS is based on the Signal to Interference plus Noise Ratio (SINR) measurements and predefined thresholds [24]. Table 3 summarizes the wireless channel parameters, including the MCS states (and outage) along with the corresponding number of bits transmitted per slot for each state [25].

Table 3. Wireless channel parameters.

Channel State $\{0, \ldots, K\}$	MCS and Outage	Bits per Slot
0	Outage	$m_0 = 0$
1	QPSK-1/2	$m_1 = 48$
2	QPSK-3/4	$m_2 = 72$
3	16QAM-1/2	$m_3 = 96$
4	16QAM-3/4	$m_4 = 144$

A method to describe the channel between the base station (BS) and a mobile station (MS) is to model the transitions between MCS levels as a finite-state Markov chain (FSMC). This chain is fully characterized by its transition matrix $P_T = (p_{ij})_{0 \leq i,j \leq K}$. It operates in discrete time, with transitions occurring every L frame, where $LT_F < t_{coh}$ (coherence time).

To validate the model, we set $L = 1$, meaning that an active mobile device will draw a new MCS for each frame. The discrete distribution is given by $(p_i)_{0 \leq i \leq K}$, where $p_{ij} = p_i$ for all i, simulating the memoryless channel model used in the analytical model.

Let $P_T(0)$ be the transition matrix for the memoryless model. To test the robustness of the model, two additional channel models are introduced: the average channel model and the combined channel model. For these models, the MCS of a mobile station during a frame depends on the MCS used during the previous frame. The transition matrix is derived from the following equation:

$$P_T\ (a) = aI + (1 - a)P_T(0) \quad 0 \leq a \leq 1 \tag{33}$$

where I is the identity matrix, and a is an indicator of the channel memory. The average duration for which a mobile maintains the same MCS is given by [21]:

$$t_{coh} = 1/(1 - a) \tag{34}$$

If $a = 0$, the channel model becomes memoryless. When $a = 1$, the channel has infinite memory, meaning the mobile always keeps the same MCS [15,16].

For our robustness study, we consider an intermediate value $a = 0.5$, meaning the channel remains constant for two frames. The $a = 0.5$ value corresponds to two types of channel models:

4.3.1. Average Channel Model

All MS devices share the same channel memory but with stationary probabilities identical to those of the memoryless model.

4.3.2. Combined Channel Model

Taking into account the quality of the radio link between the BS and MS, the previous assumption can be refined by considering that half of the MSs operate under "poor" radio conditions while the other half experience good conditions. The criteria for good or poor conditions are determined based on stationary probability while maintaining the same coherence time in both cases. It should be noted that during the simulation, the radio conditions assigned to a mobile station (MS) will remain the same throughout the simulation [27].

The stationary probabilities for the three different channel models are provided in Table 4 [24].

Table 4. Stationary probabilities for the three channel models.

Channel Model	Memoryless	Average	Combined (Good)	Combined (Bad)
a	0	0.5	0.5	0.5
p_0	0.225	0.225	0.020	0.430
p_1	0.110	0.110	0.040	0.180
p_2	0.070	0.070	0.050	0.090
p_3	0.125	0.125	0.140	0.110
p_4	0.470	0.470	0.750	0.190

4.4. Scheduling Algorithms

In this paragraph, a more detailed explanation will be provided on how the number of slots allocated to each user is calculated.

4.4.1. Conventional Scheduling Policies

In this case, for any given frame, the number of slots allocated to active users must satisfy the following condition [28]:

$$N_S = \sum_{k=1}^{K} N_S^{(k)} n^{(k)} \tag{35}$$

where $N_S^{(k)}$ represents the number of slots allocated to a user using MCS_k, and $n^{(k)}$ is the number of active users using MCS_k.

Note that $N_S^{(k)}$ depends on the scheduling algorithm, and the number of active stations must satisfy:

$$n = \sum_{k=0}^{K} n^{(k)} \tag{36}$$

The way in which the scheduler allocates the slots $N_S^{(k)}$ is detailed in the following pseudocode:

Let K_F *[0...K]* be the set of MCS used by the active mobile stations.

1. Resource Fairness

$$\begin{aligned} N_S^{(k)} &= for\ k = 0 \\ N_S^{(k)} &= \frac{N_S}{\sum_{k=1}^{K} n^{(k)}} \text{ for } k \neq 0 \end{aligned}$$

2. Throughput Fairness

$$\begin{aligned} &if\ k = 0 \\ &\qquad N_S^{(k)} = 0 \\ &else: \\ &\qquad N_S^{(k)} = \frac{N_S/m_k}{\sum_{k=1}^{K} \frac{n^{(k)}}{m_k}} \\ &end \end{aligned}$$

3. Opportunistic Scheduling

$$\begin{aligned} &find\ k_{max} = max\left(K_f\right) \\ &N_S^{(k)} = \frac{N_S}{n^{k_{max}}} for\ k = k_{max} \\ &N_S^{(k)} = 0\ for\ all\ k \neq k_{max} \end{aligned}$$

4.4.2. Throttling Regime

Let $N_S^{(F)}$ represent the number of slots required to offer a Dynamic Bandwidth Rate (DBR) for the active mobile stations in a frame. If $N_S^{(F)} > N_S$, the number of slots allocated to each station will be degraded until $N_S^{(F)} = N_S$. Otherwise, if $N_S^{(F)} < N_S$, there will be

$N_S - N_S^{(F)}$ unused slots per frame. Let $N_S^{(u)}$ represent the number of slots reserved for each mobile station (MS), which is given by the following pseudocode:

The number of slots required for each active station $N_S^{(u)}$ in a frame to reach DBR is calculated considering the following condition:

$$\text{if } m_k^{(u)} \neq 0$$
$$N_S^{(u)} = \frac{min\left(x_{on}^{(u)}, DBR \times T_F\right)}{m_k^{(u)}}$$
$$else$$
$$N_S^{(u)} = 0$$
$$end$$

where $x_{on}^{(u)}$ is the random value representing the ON data volume downloaded by MS_u, and $m_k^{(u)}$ is the number of bits per slot for MS_u using MCS_k during a TDD frame.

The total number of slots required by nnn active users during a TDD frame is

$$N_S^{(F)} = \sum_{u=1}^{n} N_S^{(u)} \tag{37}$$

The following procedure will calculate the degradation factor D:

$$\text{if } N_S^{(F)} \leq NS$$
$$D = 1$$
$$else:$$
$$D = \frac{N_S}{N_S^{(F)}}$$
$$end$$

Finally, the number of slots to be allocated to each MS in a frame is

$$N_S^{(u)} = \mathrm{D} \times N_S'^{(u)}$$

4.5. Simulator Description

The simulator developed for this study is designed to rigorously model and analyze the behavior of WiMAX systems under various conditions, outperforming existing solutions in both accuracy and performance. One of its key features is the ability to alternate between ON and OFF periods for each mobile station (MS), ensuring a highly realistic representation of user behavior during data transmission and idle times. At any given moment, a mobile station is either in an ON period (downloading data) or an OFF period (waiting between downloads). When an MS enters an ON period, it is assigned a number of bits corresponding to the size of the download, which is randomly determined following an exponential or Pareto distribution depending on the $\overline{x}_{on}$ parameter. Similarly, when an MS enters an OFF period, it is assigned a waiting time before the next download, following an exponential distribution dependent on $\overline{t}_{off}$.

At the start of a simulation, the initial states of all MSs are defined. For example, all users may begin in an ON period. In the case of a single MS, once it finishes downloading (x_{on} = 0), it transitions to an OFF period and is assigned a new (t_{off}). After a certain number of frames corresponding to (t_{off}/T_F), the MS returns to an ON period, and a new (x_{on}) is drawn for the next download. This cycle repeats until the simulation concludes.

When multiple users are considered (N > 1), the simulator tracks the number of active users (in ON periods) at each frame. The simulator's role is to calculate various performance parameters, which are then compared to the results from the analytical model. While the analytical model averages all possible cases based on their probabilities, the simulation achieves results by averaging across a large number of frames.

For example, to calculate $\overline{U}$, the frame utilization rate, the utilization of each individual frame is summed over the entire simulation and divided by the total number of frames. The simulator ensures precise and reliable performance metrics through multiple steps, including the initialization of frame counters, user allocations, and slot assignments.

To provide a clearer understanding of how these performance parameters are derived, the following sections will detail the steps executed by the simulator.

As shown in the Figure 3, the simulator functions as follows:

1. Frame Counter Initialization: In this step, a frame counter is initialized at *0*, which will be incremented in the next step, but it will not exceed a predefined maximum value.
2. User Setup: A specific number of users is set. A random x_{on} value is assigned to all mobile stations (MS). This value is determined differently in the validation phase compared to the robustness phase (following an exponential distribution for validation and a Pareto distribution for robustness). The traffic parameters on which x_{on} depends are provided as input.
3. MCS Assignment: For each MS, a Modulation and Coding Scheme (MCS) is randomly assigned based on the channel model.
4. Scheduling Algorithm: The selected scheduling algorithm is applied to calculate the number of slots to allocate to each station.
5. Updating x_{on}: The value of x_{on} is updated for each frame. The downloaded bits and the number of slots allocated to each MS are saved. The frame counter is incremented by *1*.
6. Frame Counter Check: Ensure that the frame counter does not exceed the predefined maximum value. If it hasn't, proceed to step 7. Otherwise, jump to step 10.
7. Download Completion Check: For each station, check if it has completed downloading the assigned x_{on}. If completed, proceed to step 8; if not, return to step 3 while ensuring the new MCS satisfies the following conditions:
   - For the validation study: The new MCS should be different from the previous one.
   - For the robustness study: The MCS assigned for two consecutive frames should be identical.
8. Assigning t_{off}: A random t_{off} value is assigned, following an exponential distribution, to stations that have completed downloading their x_{on}. The frame counter is updated again.
9. Final Frame Counter Check: As in step 7, check if the frame counter is less than the predefined maximum. If so, repeat step 2; otherwise, the simulation ends.
10. Performance Parameter Calculation: The performance parameters for the simulation are now calculated, including
    - The average instantaneous throughput ($\overline{X}$)
    - The average resource utilization ($\overline{U}$)
    - The average number of active users ($\overline{Q}$)

This simulator stands out due to its ability to handle realistic assumptions regarding traffic distribution, MCS selection, and scheduling algorithms. The alternating use of exponential and Pareto distributions for traffic, combined with detailed modeling of radio conditions and user interactions, ensures that the simulator provides highly accurate and reliable results. By incorporating both validation and robustness studies, the simulator outperforms existing tools in its capability to model real-world network conditions while significantly reducing simulation time without sacrificing precision.

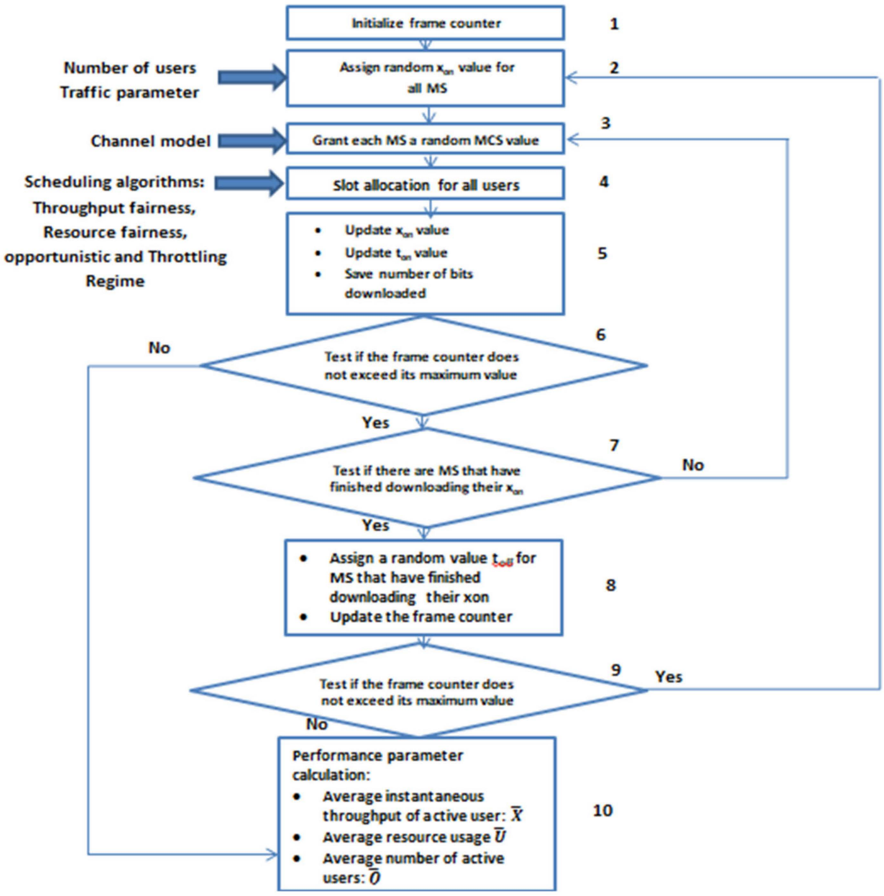

Figure 3. Simulator diagram.

5. Simulation Results

The problem of server capacity limitations led us to opt for a simulation with a number of stations equal to 10. The experimental results are divided into two key phases: Validation Study and Robustness Study, each designed to test the proposed model under different conditions. In the Validation Study, the simulation is conducted with assumptions closely aligned with those in the analytical model. This phase aims to verify the model's accuracy by comparing the simulated results with the expected performance metrics under controlled conditions. In the Robustness Study, the assumptions from the analytical model are relaxed to reflect more dynamic and realistic network scenarios. By introducing variations in traffic patterns and channel conditions, this phase evaluates the model's ability to maintain optimal performance under less ideal, real-world conditions.

In real-world networks, user traffic often exhibits varied patterns, with both light and heavy usage. To simulate these conditions, the validation study incorporates an exponential traffic distribution, while the robustness study employs a truncated Pareto distribution. These two approaches capture the variability in user behavior, with the Pareto distribution providing a more accurate reflection of bursty traffic often observed in modern wireless networks.

The study also models wireless channel conditions using both memoryless and combined average channel models. The memoryless model simulates environments where channel conditions vary unpredictably between frames, while the combined average model reflects more structured scenarios where users may experience consistent 'good'or 'bad' channel conditions. These models enable a comprehensive evaluation of the scheduling algorithms' performance under various real-world channel dynamics.

5.1. Validation Study

5.1.1. Conventional Scheduling Policies

Figures 4–6 represent the average instantaneous throughput of active users during an ON period $\overline{X}$, the average number of active users $\overline{Q}$, and the average resource utilization $\overline{U}$ for the three scheduling algorithms, respectively.

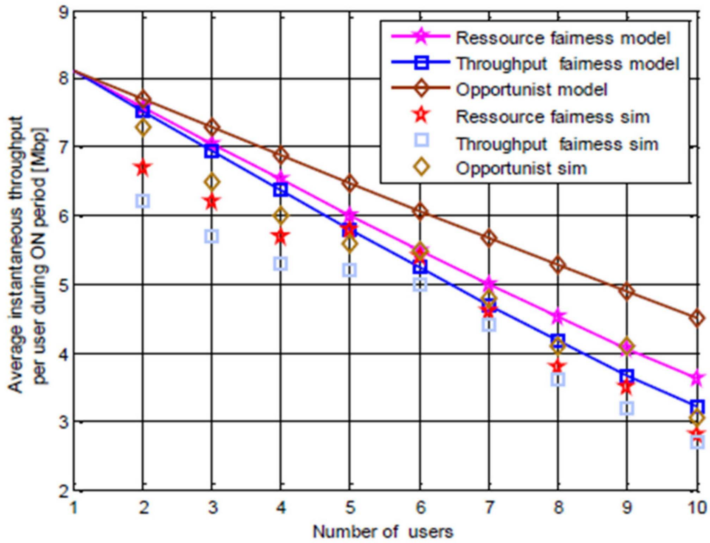

Figure 4. The average instantaneous throughput for conventional scheduling algorithms ($N = 10$, $x_{on} = 3$ *Mbits and* $t_{off} = 3$ *s*).

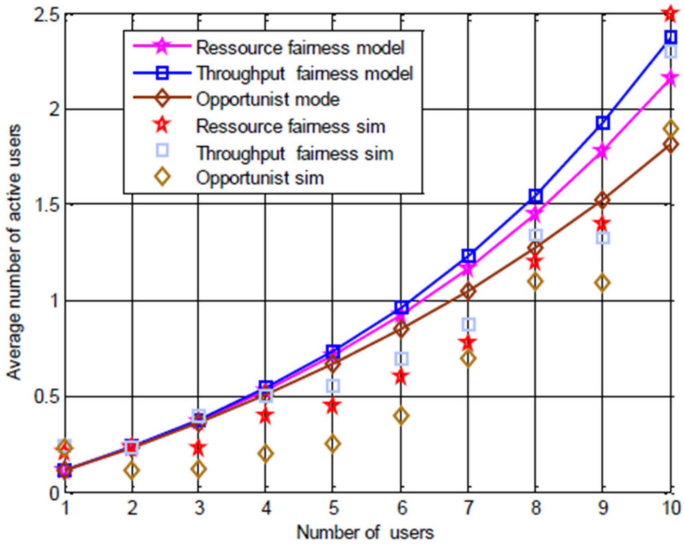

Figure 5. The average number of active users for conventional scheduling algorithms ($N = 10$, $x_{on} = 3$ *Mbits, and* $t_{off} = 3$ *s*).

For a number of $N = 10$ mobile stations, the validation study simulation lasted nearly *2* days for the scheduling algorithms. The performance parameter curves obtained from the analytical model closely resemble those obtained from the validation study, noting that for the analytical model, this operation took only *15 min* for all scheduling algorithms simultaneously.

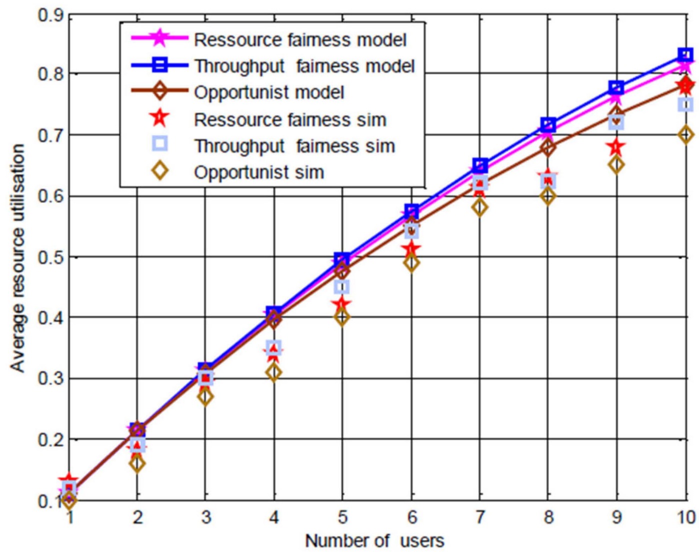

Figure 6. The average resource utilization for conventional scheduling algorithms (*N = 10, x_{on} = 3 Mbits, and t_{off} = 3 s*).

Figure 7 shows the stationary state probability *π(n)* for the three scheduling algorithms. It is evident that the *π(n)* curves from the validation study are similar to those obtained from the model for all three scheduling algorithms. Thus, this model has significantly reduced simulation time, bringing it down to a matter of hours instead of days.

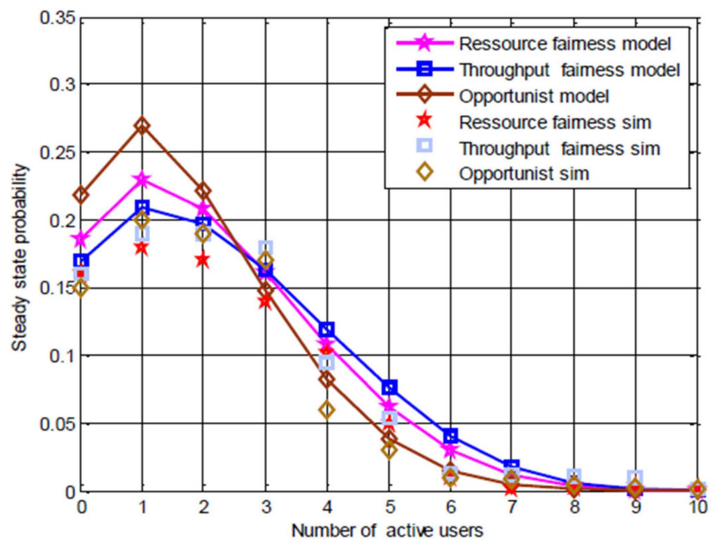

Figure 7. The stationary state probability for conventional scheduling algorithms (*N = 10, x_{on} = 3 Mbits, and t_{off} = 3 s*).

5.1.2. Throttling Regime

Below are the results from the simulations conducted in the validation study, alongside the outcomes from the analytical model for the bottleneck regime. Figures 8 and 9 illustrate the average number of active users $\overline{Q}$ and the average resource utilization $\overline{U}$ for the throttling regime, respectively.

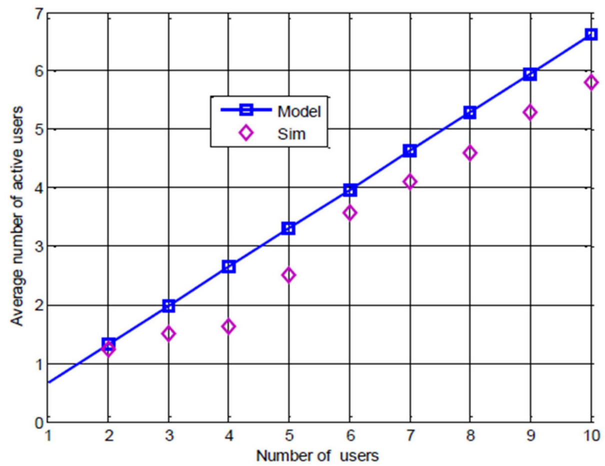

Figure 8. The average number of active users for the Throttling regime (*N = 10*, x_{on} *= 3 Mbits*, t_{off} *= 3 s, and MSTR = 512 Kbps*).

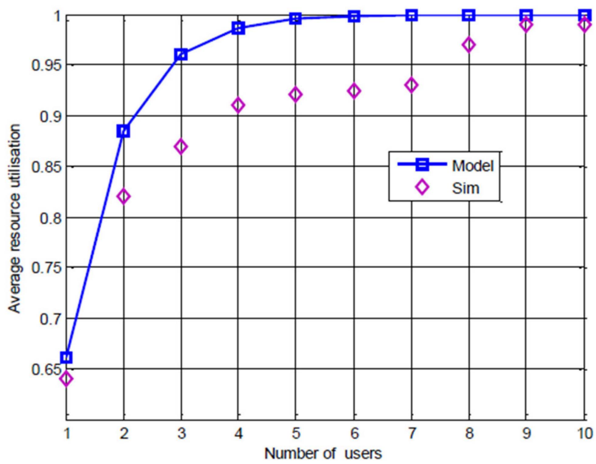

Figure 9. The average resource utilization for the Throttling regime (*N = 10*, x_{on} *= 3 Mbits*, t_{off} *= 3 s and MSTR = 512 Kbps*).

Figure 10 shows the stationary state probability $\pi(n)$ for the Throttling regime.

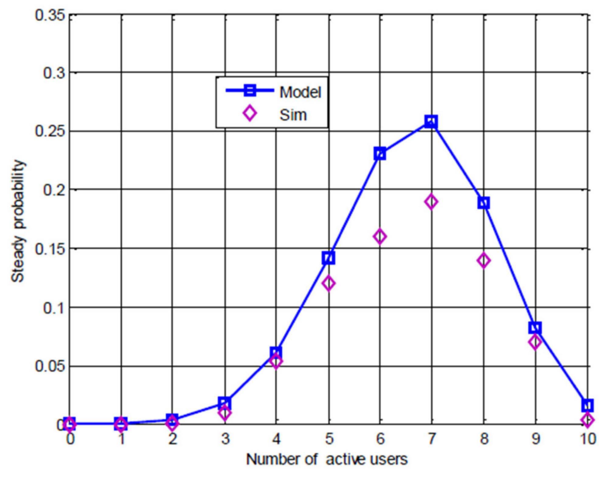

Figure 10. The stationary state probability for the Throttling regime (*N = 10*, x_{on} *= 3 Mbits*, t_{off} *= 3 s, and MSTR = 512 Kbps*).

Even for the Throttling regime, the performance parameter results obtained from the analytical model closely resemble those from the validation study.

5.2. Robustness Study

We now move on to presenting the results obtained during the robustness study.

5.2.1. Conventional Scheduling Policies

To verify the robustness of the analytical model for the ON data volume distribution, simulations were conducted for both exponential and truncated Pareto distributions (lower and upper bounds). The results are shown in Figure 11. Even for assumptions that deviate further from the analytical model, the obtained results remain close to those presented in the model.

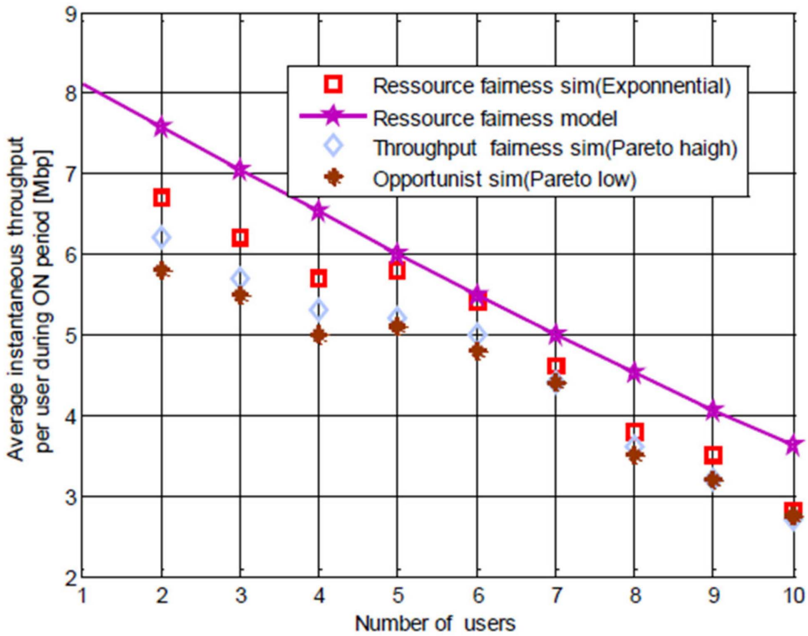

Figure 11. The average instantaneous throughput for the throughput fairness algorithm and the different traffic distributions ($N = 10$, $x_{on} = 3$ *Mbits, and* $t_{off} = 3$ *s*).

It is thus clear that a truncated Pareto distribution has little influence on the design parameters.

Figure 12 shows the average instantaneous throughput of active users during an ON period X for different channel models with the three conventional scheduling algorithms. So far, we have always considered the memoryless channel model. Now, we will take into account two different channel models, where transitions between different MCS (Modulation and Coding Schemes) incorporate a memory process. The average channel model is a combination of good and bad channels (corresponding to stationary probabilities of the combined average given in Table 3). For the combined channel model, mobile stations (MS) are subjected to both good and bad channels in the simulations (corresponding to the stationary probabilities of good and bad channels provided in Table 3).

From Figure 12, it can be deduced that even for a more complex wireless channel, the analytical model demonstrates robustness.

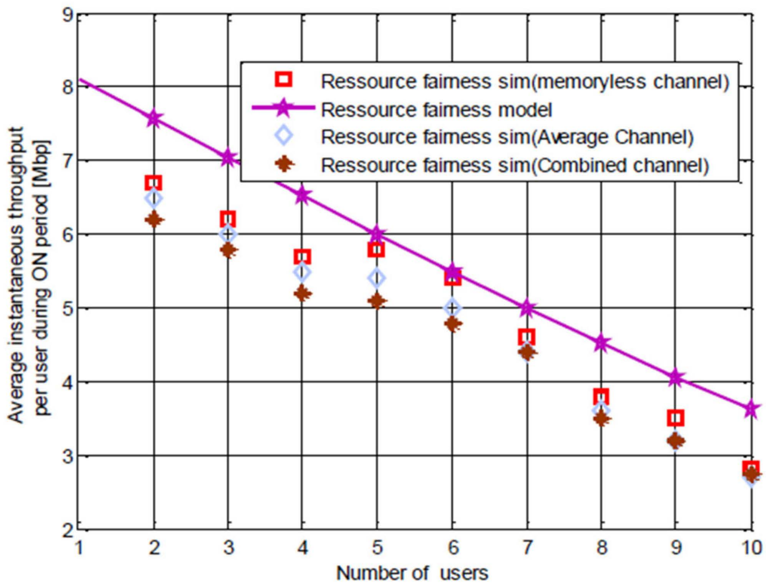

Figure 12. The average instantaneous throughput for the throughput fairness algorithm and the different channel models (*N = 10*, x_{on} *= 3 Mbits, and* t_{off} *= 3 s*).

5.2.2. Throttling Regime

Figures 13 and 14 represent, respectively, the average instantaneous throughput of active users during an ON period *X* for the different traffic distributions and the average instantaneous throughput of active users during an ON period for the different channel models in the throttling regime.

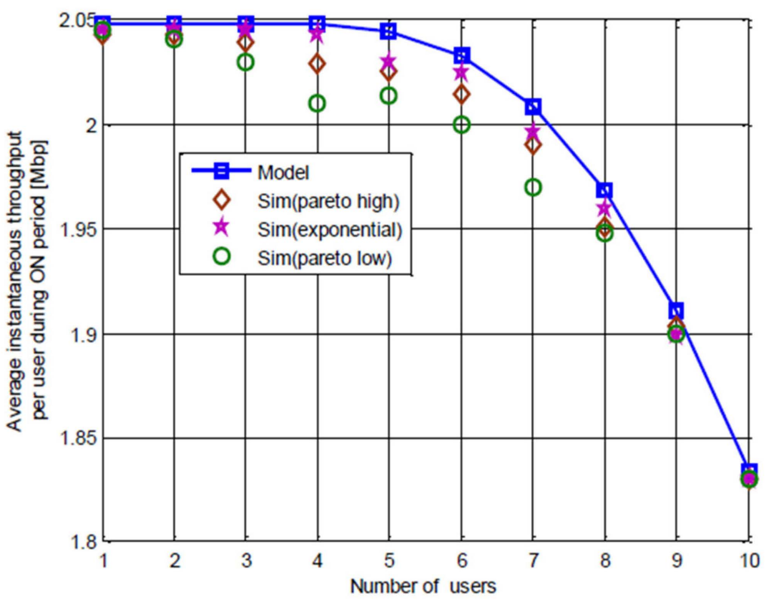

Figure 13. The average instantaneous throughput of active users during an ON period for the different traffic distributions in the Throttling regime (*N = 10*, x_{on} *= 3 Mbits*, t_{off} *= 3 s, and MSTR = 2048 Kbps*).

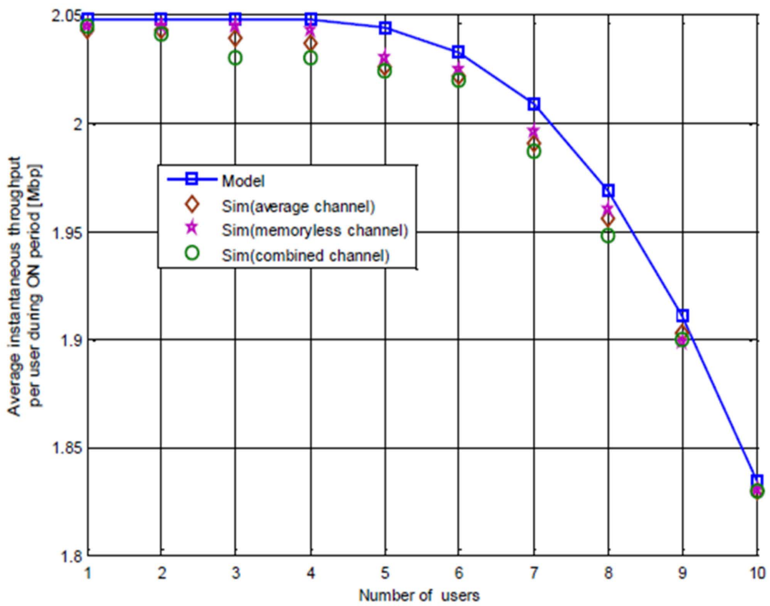

Figure 14. The average instantaneous throughput of active users during an ON period for the different channel models in the Throttling regime (*N = 10, x_{on} = 3 Mbits, t_{off} = 3 s, and MSTR = 2048 Kbps*).

Even for the Throttling regime, the obtained results demonstrate the robustness of the analytical model.

The results from the Throttling regime further confirm the robustness of the analytical model. The resource fairness algorithm consistently delivered stable throughput across all traffic patterns, even under fluctuating network loads. In contrast, opportunistic scheduling significantly improved throughput but led to resource underutilization during periods of low traffic, emphasizing the need for dynamic algorithm selection based on real-time network conditions.

The validation and robustness studies demonstrate that the proposed scheduling algorithms consistently enhance network performance across diverse traffic scenarios and channel conditions.

The proposed approach offers several key advantages:

- Improved Efficiency: By incorporating [specific techniques or algorithms], the proposed method enhances the efficiency of resource allocation in OFDMA networks, leading to better throughput and reduced latency.
- Robust Performance: The approach demonstrates robust performance across various traffic scenarios and channel conditions, as evidenced by [specific results or metrics], which outperforms traditional methods.
- Adaptability: Unlike existing approaches, the proposed method can adapt to dynamic network conditions, allowing for real-time optimization of scheduling algorithms based on current network status.
- Comprehensive Analysis: The study provides a thorough analysis of the impact of different scheduling algorithms, highlighting their strengths and weaknesses in various contexts, which contributes to a deeper understanding of their applicability in real-world situations.

These advantages position the proposed approach as a valuable contribution to the field, addressing limitations in existing methodologies and providing a more effective solution for OFDMA network design.

6. Conclusions

This research presents a significant step forward in the validation and robustness assessment of analytical models tailored for WiMAX systems. By focusing on diverse scheduling algorithms, our approach allows for precise calculation of performance metrics essential for efficient network dimensioning. Through the development and implementation of a custom simulator, we successfully validated the analytical model under controlled conditions and extended its robustness testing with more realistic, dynamic network scenarios.

The comparison between the simulated performance curves and the analytical model reveals an impressive alignment, highlighting both the accuracy and computational efficiency of the model. This not only reduces the simulation time but also confirms the model's adaptability across various channel conditions, traffic distributions, and network loads. Our results validate the model's capability to consistently deliver reliable outcomes in increasingly complex and heterogeneous environments.

However, this work represents just the beginning of broader possibilities. Expanding the model to integrate real-time traffic alongside elastic traffic would open new avenues for understanding the nuanced interactions between different service types, enabling a more holistic view of system behavior. Incorporating parameters like delay and jitter would further enhance the model's applicability to latency-sensitive applications, addressing critical requirements for modern networks.

Looking ahead, an exciting avenue for future exploration is adapting this model to LTE and next-generation systems. Investigating the interactions within multicellular networks, particularly how adjacent cells influence each other under varying load conditions, would provide deeper insights into resource management at scale. By expanding the analytical framework to embrace these additional complexities, we can continue to push the boundaries of what's possible in optimizing wireless networks for future technological advancements.

Author Contributions: Conceptualization, S.B.B. and R.B.; methodology, S.B.B.; software, S.B.B.; validation, S.B.B., A.Z. and S.D.; formal analysis, A.Z.; investigation, S.D.; resources, A.Z.; data curation, A.Z.; writing—original draft preparation, S.B.B.; writing—review and editing, S.D.; visualization, S.D.; supervision, R.B.; project administration, R.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is contained within the article.

Acknowledgments: We acknowledge the Deanship of Scientific Research at Shaqra University and the InnovCom laboratory for supporting this work.

Conflicts of Interest: The authors declare no conflicts of interest.

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