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Hybrid Computation Approach for Performance Evaluation of Broadband Wireless Networks based on Tethered High-Altitude Unmanned Platforms

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Abstract: This paper discusses the advantages of implementation of a broadband wireless network based on a tethered drone, and describes a novel hybrid approach based on a combination of analytical modeling, simulation and machine learning to the computation of its performance characteristics. The paper presents the calculation results for the increase in the telecommunications coverage area (line-of-sight zone) and the parameters of the communication channel between the base station (BS) located on the drone and the ground station (GS) within line-of-sight. A stochastic polling model with batch packet servicing is proposed to evaluate the network performance. A description is given of the interaction protocol between the BS and the GS for obtaining initial data for carrying out numerical calculations.

Keywords: hybrid computation approach, combination of simulation and ML methods, tethered drone, wireless network, stochastic polling.

1. INTRODUCTION

Currently, autonomous unmanned aerial vehicles (UAVs) are widely used in both civil and defense industries. They are especially effective in creating modern broadband wireless networks and various communication systems [2, 16–19]. The main disadvantage of autonomous UAVs and, consequently, telecommunication networks based on them is the limited operating time (up to 1 hour), which is related to the short lifespan of the battery installed on the UAV's board. Therefore, such UAVs cannot be effectively used in systems requiring long operation times, such as security management systems and protection of critical facilities (nuclear power plants, airfields, long bridges and state border sections).

Sustained operation can be achieved through tethered UAVs (tethered unmanned aerial vehicles operating at high altitudes). Their propulsion systems and payloads are powered by ground-based energy sources transmitted through a tether cable. Tethered high-altitude UAVs stand between satellite systems and terrestrial systems, with their equipment (such as cellular base stations, radio relay, and radar systems) mounted on tall structures. In contrast to costly satellite systems, tethered UAVs offer significant cost advantages and provide better telecommunications and video coverage than ground-based telecom systems.

The latest reviews [3, 8] on the topic of tethered high-altitude platforms provide links to numerous articles on design methods and architecture of such platforms based on high-altitude balloons, airships and aircrafts. However, the topic of tethered high-altitude

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unmanned platforms, which use multi-rotor unmanned aerial vehicles (tethered drones) as a high-altitude module, is poorly covered. Tethered drones (tethered UAV or tUAV), the intensive development of which began in the last decade, are capable of solving many new problems in both the civil and defense industries [**?**, 5–7, 9]. The advantage of such networks is fast and flexible deployment, increased reliability of wireless communications, controlled mobility, reduced operating costs, etc. The design and implementation of broadband wireless networks based on tethered drones is a promising direction in the creation of next generation 5G/6G networks.

This paper evaluates the performance of a broadband wireless network based on a tethered drone using an original stochastic polling model. In contrast to well-known works [4, 14, 15], we consider a polling model with batch servicing of queues of packets from wireless network subscribers. The calculation of the maximum radio coverage, required power, and antenna gain factors for receiving and transmitting wireless network devices based on a tethered drone is also provided.

2. ARCHITECTURE OF BROADBAND WIRELESS NETWORK BASED ON TETHERED DRONE

A broadband wireless network using a tethered drone typically comprises of a radio cell centered around a base station equipped with either an omnidirectional or sector antenna, which connects to subscriber stations. These subscriber stations do not directly communicate with each other, only through the base station, forming a star-shaped network. Standards like IEEE 802.11 [1] and its variations have been established for effective wireless data transmission channel management.

Another aspect is the centralized management system of a broadband wireless network. The base station polls subscriber stations cyclically based on a polling table, optimizing network bandwidth usage, prioritizing data transmission, and reducing interference. Each cycle divides into two intervals for downlink (T_1) and uplink (T_2) data transmission. The cycle duration, including the downlink/uplink ratio, is set up before network operation.

During each time interval (T_1, T_2), fixed-duration slots are allocated. A control interval (T_3) in each slot transmits the polling table, dictating the sequence of data transmission for both the base station and subscriber stations. The number of slots assigned to each subscriber station may vary based on priority. Moving between cycles involves a guard interval (T_4) to ensure proper service completion, calculated at a rate of 3.5 microseconds per kilometer for the farthest subscriber.

To assess the performance of a wireless network utilizing a tethered drone, certain parameters will be considered for numerical evaluation in the upcoming section. These include:

- a cycle duration of 5000 microseconds;
- a slot duration of 250 microseconds;
- control and guard interval durations of 30 microseconds and 17.5 microseconds, respectively.

3. MATHEMATICAL MODEL OF STOCHASTIC BATCH POLLING FOR PERFORMANCE EVALUATION OF WIRELESS NETWORK BASED ON TETHERED DRONE

A suitable mathematical model for analyzing broadband wireless networks with centralized control is the stochastic polling model with a single server and $N (N \geq 2)$ queues from Q_1 to Q_N (see Fig. 3.1).

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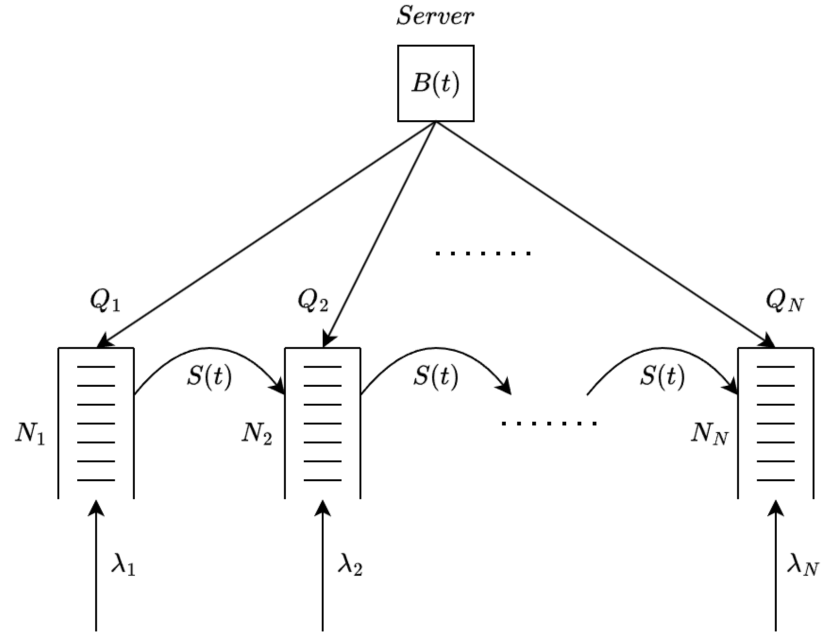

Fig. 3.1. Polling model

The arrival of packets at each queue is assumed to follow a Poisson process with rate λ_i, while each queue has a buffer size limited by N_i. Different from existing literature [4,14,15], we incorporate batch packet servicing in this wireless network scenario, with service times following an arbitrary distribution law $B(t)$. The server moves sequentially between queues, returning to the first after reaching the last, and switches between queues randomly based on distribution function $S(t)$.

Key performance metrics to be determined for the wireless network include the mean packet sojourn time and the packet loss probability within the system.

4. PERFORMANCE EVALUATION OF WIRELESS BROADBAND NETWORK PROTOCOL BASED ON TETHERED HIGH-ALTITUDE UNMANNED PLATFORM USING POLLING MODEL WITH BATCH SERVICE

For complex models such as the one presented in the current paper, it is difficult to obtain analytical results using traditional mathematical methods of queueing theory. Therefore, in this section, a new approach based on a combination of machine learning and simulation modeling is developed to evaluate the network performance and perform numerical analysis. Within the framework of this approach, a simulation model is developed to evaluate the characteristics of batch polling systems, which is then trained using various machine learning algorithms (e.g., decision tree and gradient boosting).

4.1. Performance Evaluation of Polling Systems with Batch Service Using Simulation

The Monte Carlo simulation method is a universal tool for studying the characteristics of complex systems. The simulation model developed within the current study, was implemented in C++ using the OMNeT++ platform, which is a modular component library and a computer network simulation environment. The structure of the simulation model is illustrated in Fig. 4.2.

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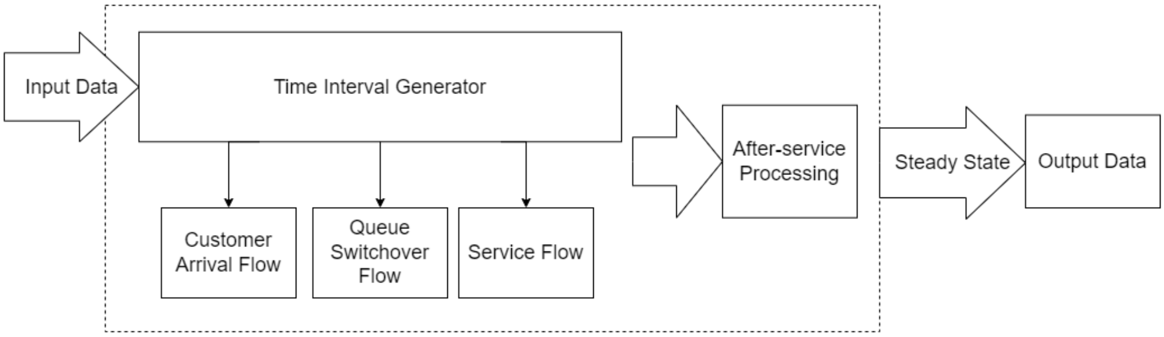

Fig. 4.2. Simulation model structure

The system's input parameters feed into the time interval generator, which creates packet arrival, queue switchover, and packet servicing flows. Results are transmitted to the user interface as a table once the system reaches a steady state.

In an illustration of a symmetric polling system with 10 queues, each queue has a 10 KB buffer size, and packets are 256 bytes each. The cycle length is 5000 microseconds, with fixed slot sizes of 250 microseconds. Two slots are allocated to each queue, with control and guard intervals of 30 and 17.5 microseconds, respectively. Analysis at data transmission rates of 5 MB/s, 10 MB/s, and 20 MB/s reveals trends in packet loss probability and mean sojourn time based on packet arrival rates (see Fig. 4.3 and Fig. 4.4).

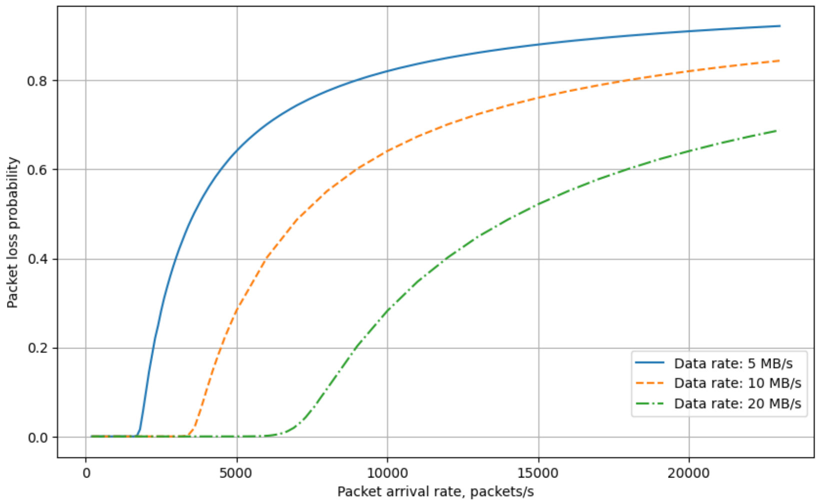

Fig. 4.3. Dependence of the packet loss probability on the packet arrival rate, number of queues – 10

Observations from Fig. 4.3 and Fig. 4.4 show that higher data transmission rates lead to increased packets serviced per queue visit, lowering packet loss probability and mean sojourn time, which are consistent across all queues due to system symmetry.

An example of an asymmetric polling system with 15 queues is also considered, maintaining similar system parameters. Despite different allocations of slots to queues, trends in packet loss probability and mean sojourn time with varying packet arrival rates and data transmission speeds echo those observed in symmetric systems (see Fig. 4.5 and Fig. 4.6).

However, since the queues in this example are allocated different numbers of slots, the packet loss probability and the mean packet sojourn time in different queues are different. An example is shown in Fig. 4.7 for the case of a data transmission rate of 5 MB/s. Since the first 5 queues are allocated 2 slots, the server will have more time to service packets in these

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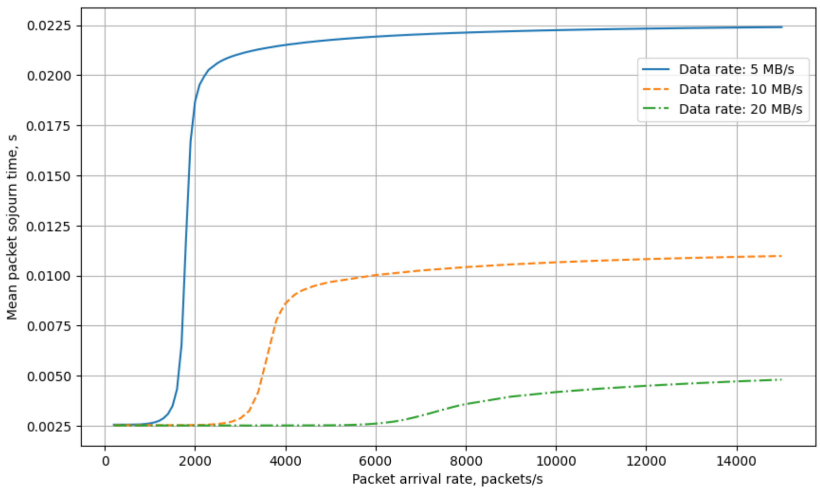

Fig. 4.4. Dependence of the mean packet sojourn time on the packet arrival rate, number of queues – 10

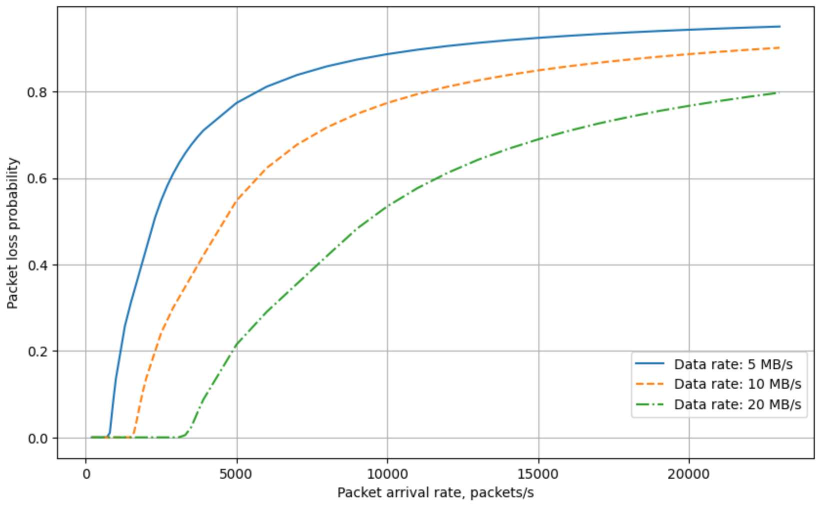

Fig. 4.5. Dependence of the packet loss probability on the packet arrival rate, number of queues – 15

queues, which will reduce the packet loss probability and the mean packet sojourn time in these queues compared to others.

Each simulation can last from a few seconds to several hours, depending on the values of the input parameters.

4.2. *Applying Machine Learning Methods to the Performance Evaluation of a Tethered Drone-Based Wireless Network*

When designing broadband wireless networks, in particular a network based on a tethered high-altitude unmanned platform, the initial data is usually unknown. To test many variants of the initial data, multiple calculations of performance characteristics are needed. Therefore, the use of simulation for multiple calculations leads to significant time costs. This drawback of simulation is overcome by using machine learning, where the calculation of results is almost instantaneous, from milliseconds to several seconds, and stable, regardless of the value of the input parameters. In the current paper, the decision tree model and the gradient boosting model were used to predict the mean packet sojourn time.

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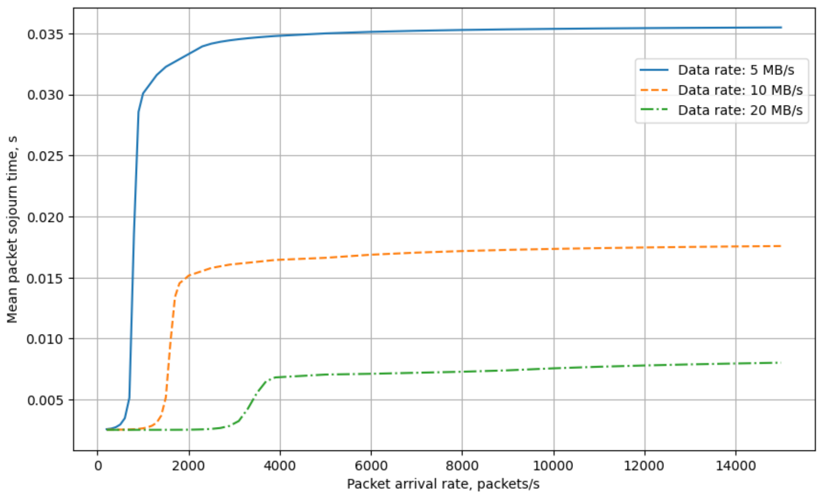

Fig. 4.6. Dependence of the mean packet sojourn time on the packet arrival rate, number of queues – 10

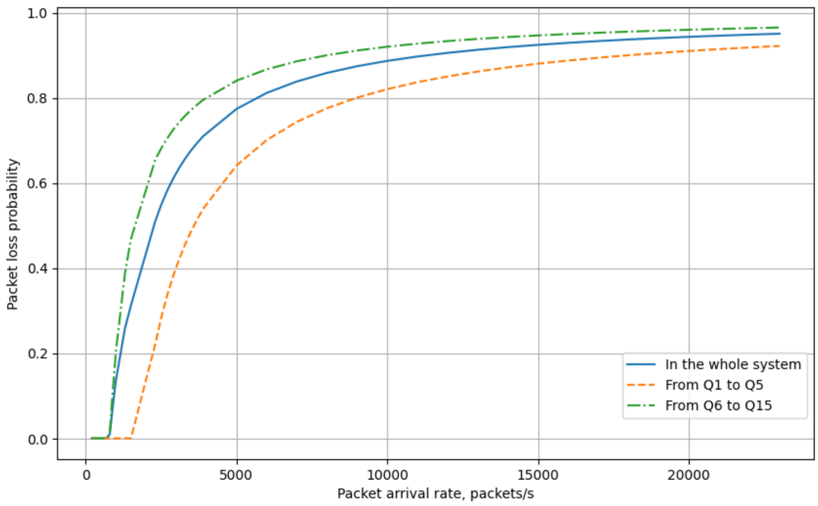

Fig. 4.7. Dependence of the mean packet loss probability in different queues on the packet arrival rate, number of queues – 15

To train and test the models, a dataset is collected, which consists of 20,000 points generated by the simulation model. These sets are divided into three parts: a training set, a validation set, and a test set, with ratios of 70%, 20%, and 10%, respectively. The dataset has 9 input parameter values and 1 output parameter, which is the average time packets spend in the system.

The range of input parameter values is shown in Table 4.1.

One of the most widely used models for solving both classification and regression problems is the decision tree model. It works by splitting the training data into subsets and then constructing a tree where each node represents a condition on one of the features, and each edge (branch) corresponds to the outcome of this condition. In this paper, the model is built in Python using the scikit-learn library. During training, the optimal value of the maximum tree depth is 11.

Gradient boosting is a powerful machine learning method for solving both classification and regression problems. The basic idea of this method is to sequentially add new trees to the ensemble, each of which is adjusted to the residuals of the previous tree in order to minimize

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Table 4.1. Range of input parameter values

Input parameters	Range
Number of queues	1 – 20
Arrival flow rate	500 – 20000 packets/s
Data transfer rate	0.5 – 20 MB/s
Packet sizes	64 – 1024 Bytes
Buffer size	10240 Bytes
Cycle duration	5000 μs
Slot duration	250 μs
Service interval duration	30 μs
Guard interval duration	17.5 μs

the loss function. Unlike a separate decision tree, gradient boosting often has higher accuracy and is resistant to overfitting due to its compositional approach and built-in regularization. Just like the decision tree model, the gradient boosting model is also built in Python using the scikit-learn library. The optimal value of the maximum tree depth is 10.

To optimize the training time, prevent overfitting and improve the generalization ability, the early stopping strategy with the parameter $patience = 10$ is applied. The main idea is to stop the model training process when the performance on the validation data set stops improving. The training time is 2.3 seconds for the decision tree model and 15.7 seconds for the gradient boosting model.

After training, the models are used to predict the results on the test set, the results of which are shown in Figures 4.8 and 4.9.

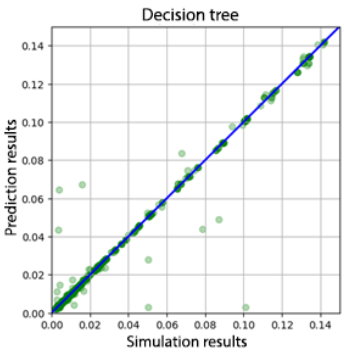

Fig. 4.8. Figure on left side

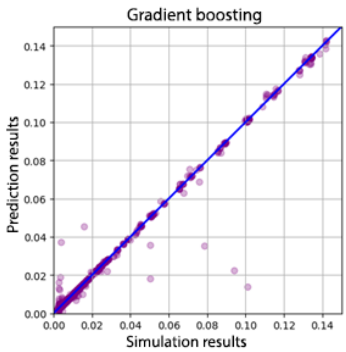

Fig. 4.9. Figure on right side

The blue line of the $y = x$ function indicates that the predicted result matches the modeling result. The greater the distance from a point to this line, the greater the prediction error. The accuracy metrics of this model on the test set are presented in Table 4.2.

Table 4.2. Accuracy metrics of models on the test dataset

Accuracy metrics	Decision tree	Gradient boosting
Mean Squared Error (MSE)	$3.11 \cdot 10^{-5}$	$2.68 \cdot 10^{-5}$
Mean absolute error (MAE)	0.0012	0.0007
Root Mean Square Error (RMSE)	0.0056	0.0052
R^2	0.9935	0.9944

As can be seen, the prediction results on the test dataset with the use of the gradient boosting model are slightly better than those with the use of the decision tree model.

Next, we use these two models to predict the mean packet sojourn time on the new dataset. The time required for each simulation and prediction with the same set of input parameters is presented in Table 4.3. The prediction results are presented in Figure 4.10.

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Table 4.3. Calculation time of results in seconds

Methods	Time, s
Simulation	82
Decision tree	$2.3 \cdot 10^{-4}$
Gradient boosting	$2.9 \cdot 10^{-4}$

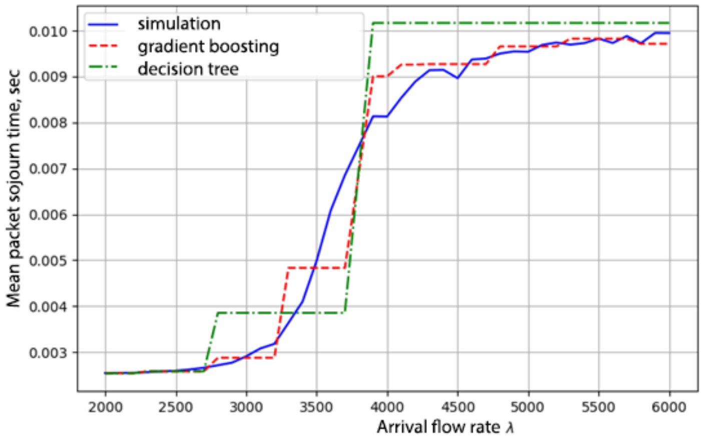

Fig. 4.10. Comparison of results

It can be seen that despite the longer training and prediction time, the gradient boosting model produces more accurate predictions compared to the decision tree model. Both models show relatively good prediction results compared to the results obtained from simulation modeling, while significantly reducing the computation time.

The theoretical results obtained at the stage of analytical modeling and simulation, presented in the previous sections, coincide with a fairly high degree of accuracy with the experimental studies conducted during a series of field experiments based on the ”Albatross” tethered high-altitude unmanned platform of long-term operation [10–13].

5. CONCLUSION

This paper presents the findings of a study evaluating the performance of a broadband wireless network utilizing a tethered drone, incorporating an innovative stochastic polling model. In contrast to existing research [4, 14, 15], this study considers a polling model that includes batch servicing of packets from wireless network subscribers. A detailed explanation of the protocol governing communication between the base station and subscriber devices in the broadband wireless network using a tethered drone is outlined, providing the necessary data for numerical calculations in the simulation model of the polling system with batch servicing. The simulation model enables the determination of key performance metrics for the broadband wireless network with centralized control. Furthermore, the study includes engineering calculations for maximum radio coverage, power requirements, and antenna gain coefficients for the receiving and transmitting devices in the wireless network employing a tethered drone. While simulation is time-consuming for testing multiple variants of initial data, machine learning offers a more efficient and stable solution for predicting performance characteristics. In this regard, the decision tree and gradient boosting models were used to accurately predict the mean packet sojourn time. The necessity of using the machine learning approach in addition to simulation is highlighted by its ability to provide instant and consistent results, regardless of input parameters, overcoming the time costs associated with simulation.

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