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OPTIMIZING INFORMATION SUPPORT TECHNOLOGY FOR NETWORK CONTROL: A PROBABILISTIC-TIME GRAPH APPROACH

In modern telecommunications and computer networks, efficient and reliable information collection is essential for effective decision-making and control task resolution. Current methods, such as periodic data transmission, event-driven data collection, and on-demand requests, have distinct advantages and limitations. ***The object of the paper:*** *The study focuses on developing a comprehensive model to optimize information collection processes in network environments.* ***Subject of the paper:*** *This paper investigates various information collection methods, including periodic data transmission, event-driven data collection, and on-demand requests, and evaluates their efficiency under different network conditions. This study* ***proposes*** *a flexible and accurate model that can optimize information support technologies for network control tasks. The key* ***tasks*** *include 1. Developing a probabilistic-time graph model to evaluate the efficiency of different information collection methods. 2. Analyzing model performance through mathematical relationships and simulations. 3. Comparing the proposed model with existing methodologies.* ***Results.*** *The proposed model demonstrated significant variations in the efficiency of the information collection methods. Periodic data transmission increased network load, while event-driven data collection was more responsive but could miss infrequent changes. On-demand requests balanced timely data needs with resource constraints but faced delays due to packet loss. The probabilistic time graph effectively captured these dynamics, providing a detailed understanding of the trade-offs.* ***Conclusions.*** *This study developed a flexible and accurate model for optimizing information support technologies during network control tasks. The model's adaptability to varying network conditions has significant practical implications for improving network efficiency and performance. Future research should explore the integration of machine learning techniques and extend the model to more complex network environments.*

Keywords: *information support technology; network control; probabilistic-time graph; telecommunications; computer networks.*

1. Introduction

1.1. Motivation

In telecommunications and computer networks, efficient and reliable information collection is essential for effective decision-making and control processes [1]. The increasing complexity and scale of modern networks make it increasingly challenging to ensure timely and accurate data transmission [2]. This research was motivated by the need to address the limitations of existing information collection methods and improve network systems' overall performances.

Current techniques such as periodic data transmission, event-driven data collection, and on-demand requests have advantages and disadvantages [3]. Periodic data transmission ensures regular updates; however, it can cause network congestion due to the high volume of data [4]. Event-driven data collection responds quickly to changes, enhancing real-time decision-making, however, it may miss infrequent yet important events [5]. On-demand requests allow for data retrieval as needed, balancing the need for timely information while maintaining network resource constraints; however, such requests can be delayed by packet losses and other network issues [6].

The variability and unpredictability of network conditions further complicate these challenges. Factors such as traffic load, node availability, and error rates can change significantly, requiring a flexible and robust approach to information collection that can adapt to different conditions and maintain high performance [7].

Improving information collection methods has significant practical implications. Enhanced efficiency and reliability in data transmission can lead to better decision-making, more effective network management, and improved service quality [8]. For businesses and industries that depend on network infrastructure, such improvements can result in cost savings, increased productivity, and a competitive edge [9].

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The increasing importance of applications like the Internet of Things (IoT), smart cities, and autonomous systems underscores the need for reliable and timely data. Failures in information collection for such applications can cause major disruptions, safety risks, and financial losses. Thus, developing a model that optimizes information support technologies is crucial for advancing these fields and ensuring their success.

1.2. State of the Art

Network control and information collection have seen significant advancements in recent years. Various methodologies have been developed to address the challenges of efficient and reliable data transmission in dynamic network environments. These methodologies can be broadly classified as periodic data transmission, event-driven data collection, and on-demand requests.

Periodic data transmission is a widely used method for regularly collecting data..This approach ensures that the control centre receives consistently updated information, which is critical for maintaining up-to-date knowledge of the network's state. However, this method can lead to network congestion and increased load because data are transmitted regardless of whether there are significant changes in the network. This can result in inefficiencies and delays in responding to critical network state changes [10].

Event-driven data collection triggers data transmission based on specific changes in the network state. The proposed method is more efficient in responding to real-time events because it only sends data when a predefined event occurs. This can reduce unnecessary data transmission and network load. However, event-driven methods can miss infrequent but important changes, leading to gaps in the information available to the control centre [11]. A recent study by Surenther et al. [12] demonstrated that integrating machine learning can enhance the responsiveness and accuracy of event-driven data collection in wireless sensor networks.

On-demand requests involve the control centre retrieving information as required. This method balances the need for timely data with network resource constraints, , where data are only requested when necessary. While this approach can reduce network load compared to periodic transmission, it is susceptible to delays if the request or response packets are lost or corrupt during transmission [13]. Urooj et al. [14] proposed advanced techniques for improving the reliability and efficiency of on-demand data requests in 5G networks, highlighting the benefits of heuristic-assisted multi-objective optimization.

Several studies have compared these methods to identify their strengths and weaknesses. For example, Li [15] explored improving network controllability processes and emphasized the importance of selecting appropriate data collection methods based on network conditions. Similarly, Surenther et al. [12] examined the data transmission efficiency of wireless sensor networks and highlighting the role of machine learning in optimizing energy consumption and data accuracy.

Recent advancements have also seen integration of emerging technologies such as machine learning and artificial intelligence integration into information collection methods. These technologies can enhance the adaptability and efficiency of data transmission by predicting network conditions and optimizing data collection strategies. For example, Rachakonda et al. [16] demonstrated that machine learning techniques can dynamically adjust data collection strategies in IoT environments, significantly improving efficiency and reliability.

Moreover, new research by Li et al. [17] has highlighted the importance of addressing privacy and security challenges in information collection for next-generation networks, emphasizing the need for robust and secure data transmission methods. Another study by Tso et al. [13] reviewed server resource management strategies for data centres and provided insights into optimizing information collection and transmission in large-scale network environments.

The increasing complexity of network environments and increasing demand for reliable and efficient data collection have driven research towards developing more sophisticated models. These models provide a nuanced understanding of the trade-offs involved in different information collection strategies, which will lead to more resilient and responsive network systems.

This research seeks to contribute to the ongoing efforts to enhance network control and information collection processes by synthesising these methodologies and integrating modern technological advancements. The proposed model addresses the limitations of existing methods and provides a flexible, robust framework for optimizing information support technologies in dynamic network environments.

1.3. Objectives and Structure

The model proposed in this paper addresses these challenges by integrating probabilistic and time-based analyses to evaluate the efficiency of different information collection strategies. By considering factors such as packet loss probability, availability of network nodes, and likelihood of conflicts during data transmission, the proposed model provides a comprehensive framework for optimizing information support technologies.

Previous studies have highlighted the importance of timely and reliable data collection for network control [9]. However, existing models often lack the flexibility to adapt to varying network conditions and do not adequately account for the probabilistic nature of data transmission errors and conflicts [10]. This study aims to fill this gap by presenting a detailed probabilistic-time graph model that can adjust dynamically to different information collection methods and network states.

The primary contributions of this paper include:

1. A detailed probabilistic-time graph model for collecting information in network control tasks.
2. An analysis of the impact of different information collection methods on network efficiency and data collection time.
3. Comparison of the proposed model with existing methodologies, demonstrating its advantages in terms of flexibility and accuracy.

The methodology section of this paper describes the mathematical foundation of the model, including the derivation of key probabilistic functions and construction of probabilistic time graphs. The results section presents a series of simulations and comparative analyses that illustrate the model's effectiveness under various network conditions. Finally, this section explores the implications of the findings for network control strategies and suggests potential areas for future research.

By providing a robust and adaptable model for information-support technology, this study contributes to ongoing efforts to enhance the efficiency and reliability of network control processes, ultimately leading to more resilient and responsive network environments.

In this paper, Section 2, Materials and Methods, outlines the methodologies employed in this study, including the probabilistic-time graph model and its application to various information collection methods. This section also details the mathematical foundations and probabilistic functions used in the analysis. Section 3, Results and Discussion, presents the results of the simulations and comparative analyses, highlighting the performance of the proposed model under different network conditions. This section interprets these results, examines their implications for network control strategies, and compares them with existing methodologies. Finally, the Conclusions section summarizes the key outcomes of the study, highlighting practical applications and suggesting directions for future research.

2. Materials and Methods

2.1. System Overview

The information support stage is the first stage of control. To reduce the time required to collect information about the state of network elements, performing this process in parallel for all controlled objects is preferable. The time interval required to obtain data from the most remote object determines the total time required for information collection.

Information about the network state can be collected either at the initiative of the switching centre, which handles network control tasks periodically according to a set schedule, or at the initiative of all nodes whose state changes may affect the network's performance. In the first case, information was collected via a special request from the control centre. In other cases, the request is not transmitted, and the information is provided at the initiative of the switching nodes. In this scenario, information about a switching node's state change should be transmitted when this change is detected. With periodic transmission, there may be a delay in providing updated data equal to half the information transmission period.

Upon request, information is collected by sending a call packet $f_{call}(z)$ to the requested node. The controlled node responds with reply packet $f_{ans}(z)$, which includes, in addition to the address of the control centre, all necessary information required to assess the node's state. This information is crucial, so its receipt must be acknowledged. When transmitting a call packet, it may be lost (function $f_{call}^{lost}(z)$), received with a distorted address of the called or calling subscriber (functions $f_{call}^{adr_1}(z)$ and $f_{call}^{adr_2}(z)$ respectively), correctly received (function $f_{call}^{rt}(z)$), and recognized with probability P_{det}. The packet can be accepted if the subscriber is free (probability P_{free}). If a call packet is lost or received with a distorted address, no acknowledgement is sent, and the message is retransmitted after interval T_{TA}. If the subscriber was busy or the call packet was not recognized (probability P_{undet}), the call is repeated after the interval T_{TA}. If the call packet is received by another subscriber (distorted address of calling subscriber A_1) and the subscriber is free, a reply packet will be sent. Network error detection causes a time interval ΔT upon correct receipt of a packet, and the call packet is lost.

Upon correct receipt of the call packet (function $f_{call}^{rt}(z)$), a reply packet will be issued, which may be correctly received (function $f_{ans}^{rt}(z)$), lost (function $f_{ans}^{lost}(z)$), received with a distorted address (function $f_{ans}^{adr_2}(z)$), detected error (function $f_{ans}^{de}(z)$), received with distorted information field (function $f_{ans}^{err}(z)$), outdated data (function $f_{ans}^{od}(z)$), or incomplete data (function $f_{ans}^{id}(z)$).

If the call and reply packets are received correctly, and the subscriber is free (P_{free}), the control task is resolved. In the case of lost reply packets (f_{ans}^{lost}), detected errors (f_{ans}^{de}), or address distortion ($f_{ans}^{adr_2}$), the call packet is retransmitted after an interval T_{TA}.

When information about the network state is transmitted at the initiative of the controlling switching node, a call packet is not issued. The information collection process proceeds similarly to the process described above.

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2.2. Probabilistic-Time Graph Model

Let the probabilities of using information collection methods via call packets, state changes, and periodic schedules be denoted as P_1, P_2, and P_3, respectively, where these probabilities can take values of 1 or 0. The generalized probabilistic-time graph characterizing the information collection process for the three indicated methods is shown in Figure 1. This graph also indicates the waiting time for data issuance in the network state during periodic transmission ΔT_{cycle}.

In Figure 1, the following designations are introduced:

$$
\begin{aligned}
&f_{st1} = f_6 \cdot f_{ans}^{rt}(z);\ f_{st2} = f_6 \cdot f_{ans}^{err}(z);\\
&f_{st3} = f_6 \cdot f_{ans}^{od}(z);\ f_{st4} = f_6 \cdot f_{ans}^{id}(z)\\
&f_{st5} = f_1 \cdot f_3 + f_6 \cdot f_5 + f_2 \cdot f_4\\
&f_{st6} = (1 - P_c) \cdot (P_2 + P_3 \cdot z^{\Delta T_{cycle}}) \cdot f_{ans}^{rt};\\
&f_{st7} = (1 - P_c) \cdot (P_2 + P_3 \cdot z^{\Delta T_{cycle}}) \cdot f_{ans}^{err}(z);\\
&f_{st8} = (1 - P_c) \cdot (P_2 + P_3 \cdot z^{\Delta T_{cycle}}) \cdot f_{ans}^{od}(z);\\
&f_{st9} = (1 - P_c) \cdot (P_2 + P_3 \cdot z^{\Delta T_{cycle}}) \cdot f_{ans}^{id}(z);
\end{aligned}
\tag{1}
$$

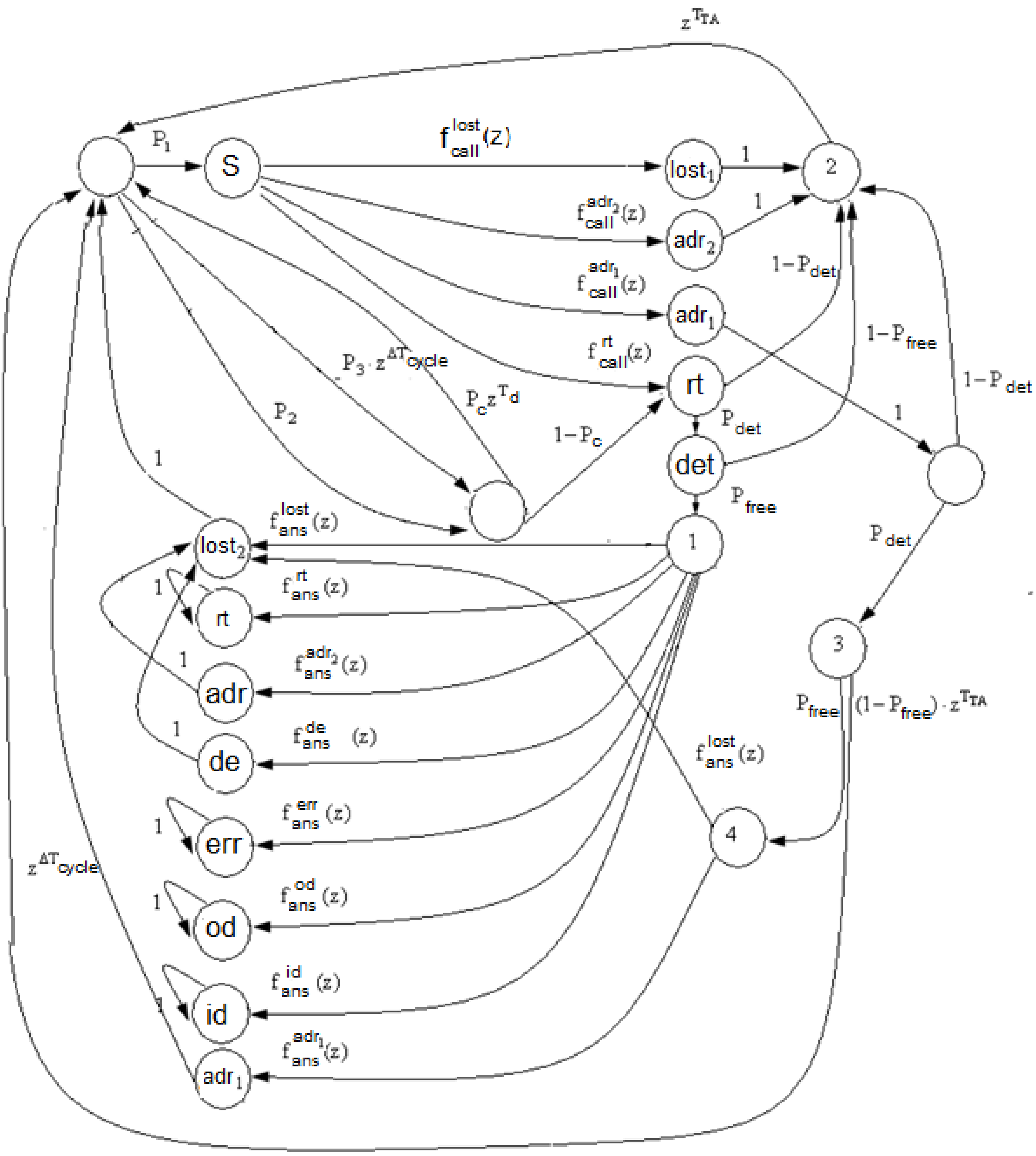

Fig. 1. The probabilistic-time graph of the information collection stage

The graph shown in Figure 1, through equivalent transformations, is presented in the form shown in Figure 2.

In Figure 2, the following expressions are indicated:

$$f_1(z) = f_{call}^{lost} + f_{call}^{adr_2} + f_{call}^{rt} \cdot [(1 - P_{det}) + P_{det} \cdot (1 - P_{free}) + f_{call}^{adr_1} \cdot (1 - P_{det})];$$

$$f_2(z) = f_{call}^{adr_1} \cdot P_{det};$$

$$f_3(z) = z^{T_{TA}};$$

$$f_4(z) = (1 - P_{free}) \cdot z^{T_{TA}} + P_{free} \cdot f_{ans}^{lost} \cdot z^{T_{TA}} + P_{free} \cdot f_{ans}^{adr_1} \cdot z^{T_{TA}};$$

$f_5(z) = P_{lost} \cdot z^{T_{TA}}$, где $P_{lost} = f_{ans}^{lost} + f_{ans}^{adr_2} + f_{ans}^{de}$;

$$f_6(z) = f_{call}^{rt} \cdot f_{det} \cdot f_{free};$$

$$f_{ans}^{rt}(z) = f_{ans}^{rt} \cdot (1 - P_{od} - P_{id} - P_{lost} - P_{undet}) \cdot z^{T_d};$$

$$f_{ans}^{err}(z) = f_{ans}^{rt} \cdot P_{undet} \cdot z^{T_d};$$

$$f_{ans}^{id}(z) = f_{ans}^{rt} \cdot P_{id} \cdot z^{T_d};$$

The graph shown in Figure 2, through equivalent transformations, is presented in the form shown in Figure 3.

The graph shown in Figure 3 was transformed into the form shown in Figure 4.

The arc functions in this graph are denoted in the same manner as in Figure 4. The functions of the information-collection stage arcs are determined by the following formulas:

$$f_1(z) = \left[\frac{P_1 \cdot f_{st1}}{1 - f_{st5}} + \frac{f_{st6}}{1 - f_{st5} \cdot P_1}\right] \cdot \frac{1}{1 - (P_2 + P_3 \cdot z^{\Delta T}) \cdot z^{T_d}};$$
$$f_2(z) = \left[\frac{P_1 \cdot f_{st2}}{1 - f_{st5}} + \frac{f_{st7}}{1 - f_{st5} \cdot P_1}\right] \cdot \frac{1}{1 - (P_2 + P_3 \cdot z^{\Delta T}) \cdot z^{T_d}}; \quad (2)$$
$$f_3(z) = \left[\frac{P_1 \cdot f_{st3}}{1 - f_{st5}} + \frac{f_{st8}}{1 - f_{st5} \cdot P_1}\right] \cdot \frac{1}{1 - (P_2 + P_3 \cdot z^{\Delta T}) \cdot z^{T_d}};$$
$$f_4(z) = \left[\frac{P_1 \cdot f_{st4}}{1 - f_{st5}} + \frac{f_{st9}}{1 - f_{st5} \cdot P_1}\right] \cdot \frac{1}{1 - (P_2 + P_3 \cdot z^{\Delta T}) \cdot z^{T_d}}.$$

The generating function of this graph is given by

$$F(z) = f_1(z) + f_2(z) + f_3(z) + f_4(z). \quad (3)$$

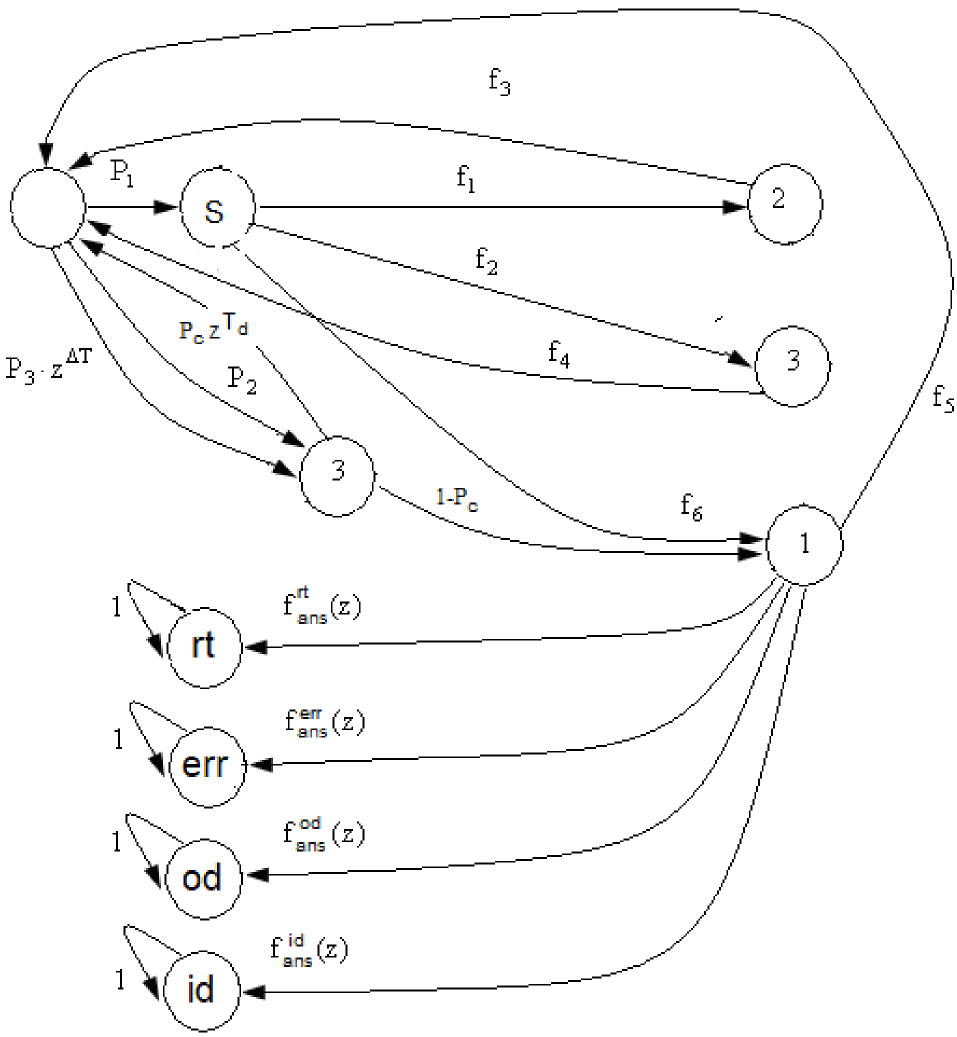

Fig. 2. The transformed probabilistic-time graph

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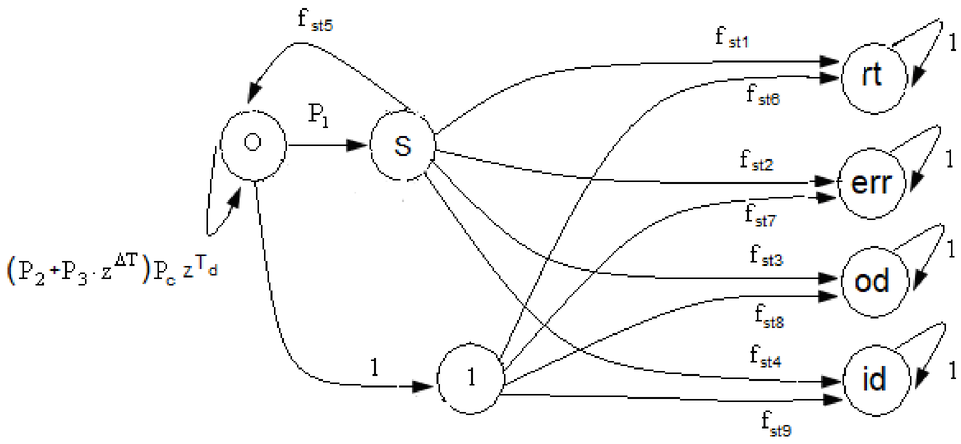

Fig. 3. The transitional probabilistic-time graph

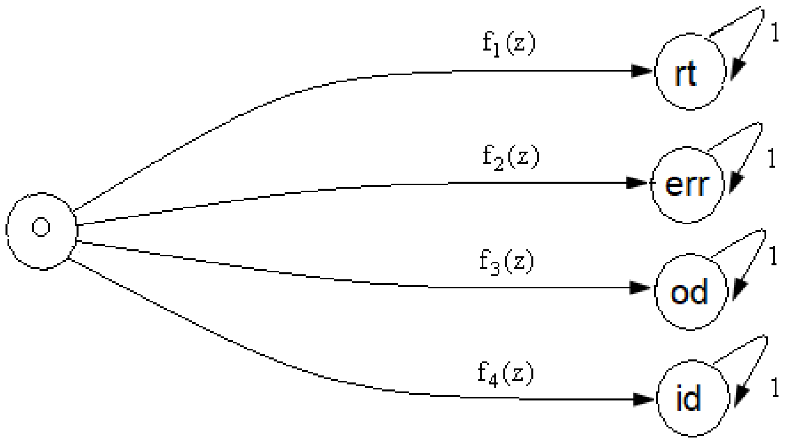

Fig. 4. The transformed probabilistic-time graph

The average time required to collect information about the network state is

$$T_{avgcoll} = \frac{dF(z)}{dz}|_{z=1}. \quad (4)$$

The probabilities of correct collection, collection with error, outdated information, and incomplete information are respectively given as follows

$$P_{collrt} = f_1(z)|_{Z=1}; P_{collerr} = f_2(z)|_{Z=1};$$
$$P_{collod} = f_3(z)|_{Z=1}; P_{collid} = f_4(z)|_{Z=1}.$$

Expressions (2-4) and their data represent the model for collecting information about the network state for control tasks. In this model, depending on the values of P1, P2, and P3, which can be either 1 or 0, methods for information collection by request, by state changes of elements, or periodically are implemented.

2.3. Methodology of Determining the Arc Functions of Probabilistic-Time Graphs in Information Collection Technology

A call packet is transmitted in multi-object control based on the "point-to-multipoint" principle. This multi-route transmission method sends the same message simultaneously to subordinate switching nodes. The users use the received messages to solve various tasks simultaneously. The length of the transmitted message should ensure a short delivery time. Response packets in multi-object control are transmitted based on the "multipoint-to-point" principle.

The characteristic of the "multipoint-to-point" transmission method is that a message from M sources is transmitted through M channels to a single user. The transmitted messages are different, and their transmission times into the channel are generally not synchronized. The user processes the received messages simultaneously in parallel or uses them to solve a specific control task.

From the described features of the two information exchange methods, it is clear that they share much in common, differing only in the process of using the received results. Therefore, the mathematical models of these methods are practically identical but have some peculiarities.

As discussed previously, the network structure model is represented as an undirected graph. It is assumed that the network includes multiple switching nodes N connected by arcs. Each arc is characterized by its length lij and capacity Cij. All of these data are presented as length matrix h=|lij| and capacity matrix C=|Cij|.

A node is characterized by the buffer storage capacity (BSC) Wj, the service rate for incoming requests μj, the incoming request rate λi, and the reliability coefficient Krj (readiness coefficient).

The message stream is transmitted along several (M) routes to M users ("point-to-multipoint") or to a single user ("multipoint-to-point"). Each message follows its route, differing from others according to channel characteristics and the number of transit nodes. There are βα network sections on the α-th route. Accordingly, the traffic distribution and control problem can be solved by considering the following indicators:

- message delivery time Td;
- probability of delivery within a specified time P(Td ≤ Tdt);
- efficiency of channel resource usage $K_{use_j} = \frac{C_{\alpha OUT}}{C_\alpha}$, where CαOUT is the data transmission rate over channel α;
- ensuring the equality of the output flow intensity λOUTj and the input flow intensity of the node $\lambda_{\sum IN_j}$ with the constraint Perr≤Pacpt err, where Pacpt err is the allowable error probability in message delivery.

In the control process, it is necessary to ensure minimal delivery time and maximum delivery probability within the specified time, the maximum value of the network resource usage coefficient, and $\lambda_{OUT_j} = \lambda_{\sum IN_j}$.

Due to possible buffer storage overflow, some messages at the switching node may be lost (intensity λ_{lost_j}). The output flow intensity of node j is then determined by the following expression:

$$\lambda_{OUT_j} = \lambda_{\sum IN_j} - \lambda_{lost_j}. \quad (5)$$

In multi-route transmission, each message must have its own header. The redundancy due to these headers is denoted as

$$r_{rdn} = 1 + \frac{k_H}{n}, \quad (6)$$

where kH is the header length, and n is the message length.

The packet transmission time along the chosen path τTRFα includes the transmission time along the track sections TTRFα, the delay time at the switching node TDELαi, and signal propagation time TPROPAGαi. The track contains β sections, we get:

$$\tau_{TRF\alpha} = T_{TRF\alpha} \cdot r_{rdn} + \sum_{i=1}^{\beta-1} T_{DEL\alpha i} + \sum_{i=1}^{\beta} T_{PROPAG\alpha i}$$

The transmission time TTRFα is determined by the message duration n and the modulation rate in the channel (data transmission rate over channel βα), i.e.

$$T^T_{TRF_\alpha} = \frac{n}{\beta_\alpha}. \quad (7)$$

The distance between the transit nodes and the signal propagation speed determines the propagation time.

A computer network represents a queuing system. According to this theory, the delay time at switching nodes depends on the arrival flow law. It is often assumed that the flow is stationary and follows the Poisson distribution. In this case, the delay time at the node is determined as follows:

$$T_{DELj} = \frac{\rho_j}{\mu_j - \lambda_j} = \frac{\rho_j}{\mu_j \cdot (1-\rho_j)}, \quad (8)$$

where $\rho_j = \frac{\lambda_j}{\mu_j}$.

The probability of packet loss at the j-th switching node due to BSC overflow in a simple flow is determined by the following formula:

$$P_{lostj} = \frac{1-\rho_j}{1-\rho_j^{\,w_j+1}} \cdot \rho_j^{\,w_j}. \quad (9)$$

Individual fragments and entire messages may be lost during transmission due to BSC overflow at transit switching nodes. Consequently, the loss probability over the entire route will be:

$$P_{lost\alpha 1} = 1 - \prod_{i=1}^{\beta} (1 - P_{losti}). \quad (10)$$

The message delivery time to M users is equal to the maximum transmission time of one message along route α

$$T_d = \max(\tau_{TRF\alpha}). \quad (11)$$

As a result, the arc functions during the transmission of a call packet will be:

$$f_{call}^{lost}(z) = P_{lost\alpha} \cdot z^{T_d};\ f_{call}^{rt}(z) = P_{rt} \cdot z^{T_d};$$
$$f_{call}^{adr_1}(z) = f_{call}^{adr_2}(z) = P_{err_{adr}} = 1 - (1-p)^{n_{adr}}; \quad (12)$$

$$P_{rt} = (1-p)^n;\ P_{err_{adr}} = 1-(1-p)^{n_{adr}},$$

where n_{adr} is the length of the address field, and p is the probability of single-bit error.

Response packets in multi-route control are transmitted based on the "multipoint-to-point" principle. Therefore, at the control centre, overloads may occur during the reception of these packets, leading to conflicts between the received response packets. Upon detecting such conflicts, response packets are retransmitted. It can be assumed that the incoming response packets follow the Poisson distribution. In this case, the probability of conflict occurrence is determined by the following formula:

$$P_c = 1 - e^{-2\rho_1}, \tag{13}$$

where ρ_1 is the channel load coefficient; $\rho_1 = \sum_{i=1}^{N} \lambda_i \cdot T_{ans_i} + \sum_{i=1}^{N} \lambda_{\pi_i} \cdot T_{ans_i}$; λ_π, λ is the intensity of the transmitted and retransmitted packets; N is the number of switching nodes that transmit response packets.

The transmission method's efficiency, defined by the relative number of response packets delivered in the first attempt, is expressed as follows:

$$\rho = \rho_1 \cdot e^{-2\rho_1}, \tag{14}$$

In this case, ρ_{max}=0.18.

In the graph in Figure 1, the possibility of conflict occurrence and resolution is taken into account by the following function:

$$f_c(z) = \frac{(1-P_c)}{1-P_c \cdot z^{T_{TA}}} \cdot (1-P_1). \tag{15}$$

When receiving response packets, the message is used only after its preparation for simultaneous control task solving. Denote the data preparation time for control tasks as τ_{prep}.

Therefore, the message delivery time can be determined by the expression:

$$T_d = \max_{\alpha}\Big\{T_{TRFj} \cdot r_{rdn} + \sum_{i=1}^{\beta-1} T_{DEL\alpha i} + \sum_{i=1}^{\beta} T_{PROPAG_{\alpha i}}\Big\} + \tau_{prep}. \tag{16}$$

Thus, the arc functions during the transmission of the response packet are expressed as follows:

$$P_{undet}(z) = [1-(1-p)^n] \cdot \frac{1}{2^{K_{sd}}}; \qquad P_{det}(z) = [1-(1-p)^n] \cdot \left(1-\frac{1}{2^{K_{sd}}}\right);$$

$$f_{ans}^{lost} = P_{lost} \cdot z^{T_d}; \quad f_{ans}^{adr} = P_{err_{adr}} \cdot z^{T_d}; \quad f_{ans}^{rt} = (1-p)^n \cdot z^{T_d};$$

$$f_{ans}^{err} = P_{undet} \cdot z^{T_d}; f_{ans}^{det} = P_{det} \cdot z^{T_d}; f_{ans}^{od} = f_{ans}^{id} = (1-p)^n \cdot z^{T_d}.$$

3. Results

Graphs were constructed based on the relationships derived to compare the information support options. These graphs show the dependency of the relative average information collection time on the state of the communication channel (probability of a single-bit error), the probability of subscriber availability, and the probability of a potential conflict.

An informed choice of the information support option can be made using the developed model and obtained mathematical relationships.

Figures 5 and 6 show the dependency of the relative information collection time on the error probability in the channel for the three information support options, constructed according to expressions (2) – (4), with the subscriber availability probabilities Pfree=0.8 and Pfree=1, respectively.

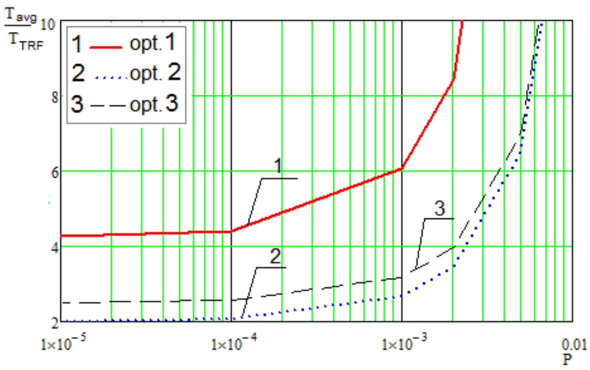

Fig. 5. The dependance $\frac{T_{avg}}{T_{TRF}} = f(p)$ with P_{free}=0.8

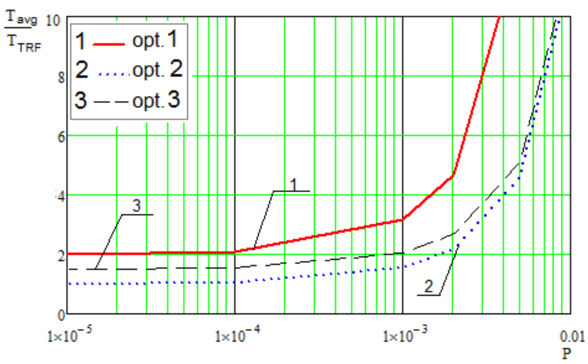

Fig. 6. The dependance $\frac{T_{avg}}{T_{TRF}} = f(p)$ with P_{free}=1

These graphs demonstrate that the information collection time increased significantly with probability p > 104 when using any of the analyzed options. The information collection time on request was more than twice that of the other options. The subscriber availability probability significantly affects the collection time (Figure 7, 8). For P_{free}=0.8 and $p=10^{-3}$, the information collection time for the second and third options was almost comparable to the same characteristic of the first option with P_{free}=1 (Figures 5, 6).

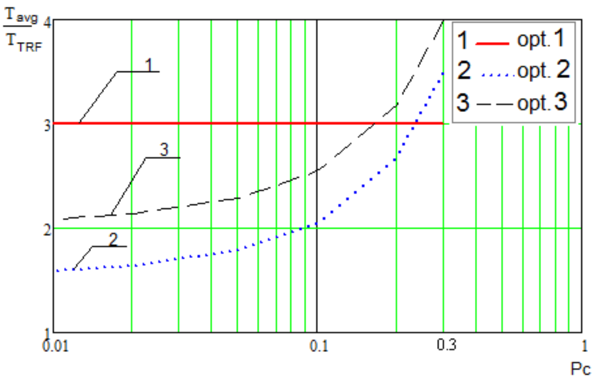

Fig. 7. The dependance $\frac{T_{avg}}{T_{TRF}} = f(P_c)$ with $p=10^{-3}$

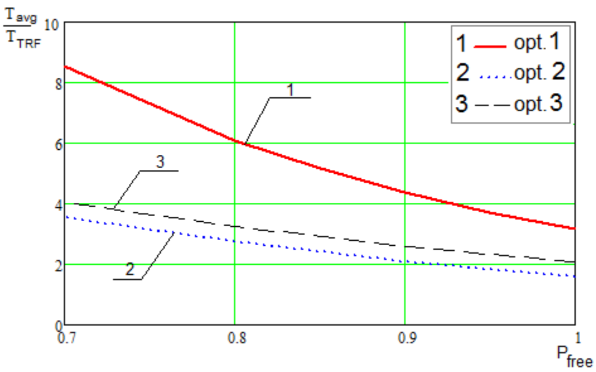

Fig. 8. The dependance $\frac{T_{avg}}{T_{TRF}} = f(P_{free})$ with $p=10^{-3}$

There is a similar dependency between the information collection time and the probability of service packet recognition P_{det}. Because many service packets are in the network, measures must be taken to distinguish and recognize them with a probability of no less than 0.9.

The probability of conflict occurrence significantly influences the time required for information collection (P_c), which depends on the network load. As shown in Figure 7, when P_c>0.1, the information support time for the second and third options began to increase rapidly and exceeded the characteristics of the first option (Figure 7).

When selecting an information support method, it is essential to consider the time and network resources consumed in the information collection process. Network resources are used only during information exchange between control and control centres. In the first data collection option, the need for information exchange arises at the initiative of the control centre. In contrast, in the second option, it is at the initiative of the controlled centres. The third option involves periodic transmission of updated data. Since the probability of adjusting the network control process under normal operating conditions is not very high, we assume that the network resources consumed for information collection in the third option will be greater than those in the first and second options.

In the second information support option, the information collection time, and consequently the consumed network resources, is slightly less than that in the first option. However, the control centre determines the necessity of using the first option. Therefore, for information support, it is necessary to provide the possibility of collecting information both on request and when the state of network elements changes.

4. Discussion

The proposed probabilistic-time graph model for optimizing information support technologies in network control tasks demonstrated notable variability in the efficiency of different information collection methods. This study analyzes periodic data transmission, event-driven data collection, and on-demand requests, each of which exhibits distinct advantages and limitations under various network conditions.

Periodic data transmission ensures regular updates however, it can cause network congestion due to the high volume of data. This finding is consistent with existing literature and highlights the challenge of increased network load associated with periodic transmission methods. For instance, a recent study by Al-Fuqaha et al. [18] discussed the significant network load caused by periodic data transmission, emphasizing the need to balance data timeliness and network efficiency. Our study demonstrates illustrates that the information collection time increases significantly when the error probability in the channel exceeds 10^{-4}.

Event-driven data collection responds more to real-time changes, thereby reducing unnecessary data transmission. However, it may miss infrequent but significant state changes. This aligns with the observations in recent studies, where event-driven methods are praised for their responsiveness but are noted for their potential to overlook rare events. Research by Akkaya and Younis [19] highlighted the efficiency of event-driven data collection in wireless sensor networks but pointed out the risk of missing sporadic but crucial data changes. The proposed model demonstrates that event-driven methods maintain lower average information collection times under various network conditions, particularly when subscriber availability is high.

On-demand requests balance the need for timely data while maintaining network resource constraints. They are effective in minimizing network load but are susceptible to delays due to packet loss or corruption. The

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effectiveness of this method in balancing timely information retrieval with resource constraints is supportedby studies on dynamic network environments. Zhang et al. [20] discussed the benefits and challenges of on-demand data collection in IoT networks, particularly focusing on packet loss and delay issues. The findings of this study indicate that on-demand requests exhibit increased collection times when the probability of subscriber availability is less than 1.

The study by Inzillo et al. [21] reveals significant improvements in energy efficiency and network performance through adaptive array technologies. Implementing adaptive beamforming techniques reduces energy consumption and enhances packet delivery ratios, which is critical for maintaining efficient and reliable network control. This aligns with the current study's findings that adaptive methods can optimize network performance by dynamically adjusting to network conditions.

Großwindhager et al.'s [22] research on dependable IoT systems for networked cars underscores the importance of reliability and security in IoT applications. The study emphasizes the need for dependable wireless communication and localization, achieved through adaptive algorithms and robust protocol testing. These insights are relevant to the current study, highlighting the necessity of reliable and timely information collection methods for efficient network control.

The model's flexibility in adapting to varying network conditions has significant practical implications for improving network efficiency and performance. By enabling dynamic selection among different information collection methods, the model can optimize resource utilization and enhance decision-making processes in network management. This adaptability is particularly relevant in modern telecommunications and computer networks, where conditions can change rapidly and unpredictably.

Network administrators can use the proposed model to evaluate the trade-offs of each information collection method based on real-time network conditions. The proposed approach can lead to more efficient use of network resources, reduced data collection times, and improved overall network performance. The insights provided by the probabilistic-time graph model can inform network control strategies and help mitigate the limitations of current methodologies.

Future research should explore integrating machine learning techniques to predict network conditions and dynamically adjust information collection strategies. Machine learning can enhance a model's ability to adapt to real-time changes, which improves its efficiency and reliability. In addition, extending the model to accommodate more complex network topologies and heterogeneous environments would provide a broader understanding of its applicability. Understanding how the model performs under various conditions is crucial as networks become increasingly diverse. Research on the impact of emerging technologies, such as 6G networks and the Internet of Things, on information collection methods is also crucial for future advancements. A recent paper by Dang et al. [23] discussed the challenges and opportunities of 6G networks, emphasizing the need for advanced information-collection models.

The proposed model must develop robust security and privacy mechanisms. As network environments increase in complexity, ensuring the security and privacy of data transmission is critical. Future studies could investigate methods to integrate these considerations into the model to enhance its practical utility and reliability. Ziegeldorf et al. [24] highlighted the importance of incorporating security and privacy features into IoT networks and provided insights that could be applied to the current model.

This study presents a comprehensive and adaptable model for optimizing information support technologies for network control tasks. By incorporating probabilistic and time-based analyses, the proposed model provides a detailed understanding of the trade-offs involved in different information collection methods. The results highlight the model's potential to improve network efficiency and performance, and they have significant practical implications for network control strategies. Future research directions include integrating machine learning techniques, extending the model to more complex environments, and developing robust security mechanisms.

Conclusions

This study presents a comprehensive model for information support technology aimed at optimizing control task resolution in network environments. The model integrates probabilistic and time-based analyses to evaluate the efficiency of various information collection methods, including periodic data transmission, event-driven data collection, and on-demand requests.

The proposed model demonstrates that the efficiency of information collection significantly varies depending on the method employed. Periodic data transmission while ensuring regular updates can increase network load and reduce unnecessary data transmission. Event-driven data collection responds more to real-time changes but may miss infrequent yet significant state changes. On-demand data requests balance the need for up-to-date information with network resource constraints but are susceptible to delays if packets are lost or corrupted.

The probabilistic-time graph model effectively captures the dynamic nature of network conditions and provides a robust framework to evaluate different information collection strategies. By considering factors such as packet loss probability, node availability, and conflict likelihood, the proposed model provides a detailed understanding of the trade-offs involved in each method. This study highlights that network conditions, such as the probability of single-bit errors, subscriber availability, and potential conflicts, significantly impact the information collection time and the overall network efficiency. For example, high error probabilities and low subscriber availability can drastically increase the time required to collect data, thereby affecting the timeliness and reliability of the control task resolution.

The proposed model offers greater flexibility and accuracy when adapting to varying network conditions than existing methodologies. Traditional models often cannot dynamically adjust to real-time changes and probabilistic transmission errors. Integrating probabilistic-time graphs into the proposed model addresses these limitations, providing a more comprehensive and adaptable network control approach.

The findings of this study have significant practical implications for network control strategies. Network administrators and engineers can use the proposed model to make informed decisions about the most suitable information collection methods based on current network conditions. This can lead to more efficient use of network resources, reduced data collection times, and improved overall network performance.

Although the proposed model provides a robust framework for optimizing information support technologies, further research is required to refine and expand its applicability. Future studies could explore the integration of machine learning techniques to predict network conditions and dynamically adjust information collection strategies. In addition, the proposed model can be extended to consider more complex network topologies and heterogeneous network environments.

This study has developed a novel and effective model for providing information support technology for network control tasks. By incorporating probabilistic and time-based analyses, the proposed model offers a detailed and adaptable framework for optimizing information collection methods, ultimately enhancing the efficiency and reliability of network control processes. The insights gained from this research can guide the development of more resilient and responsive network environments, thereby contributing to the advancement of telecommunications and computer network technologies.

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Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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ОПТИМІЗАЦІЯ ТЕХНОЛОГІЇ ІНФОРМАЦІЙНОЇ ПІДТРИМКИ УПРАВЛІННЯ МЕРЕЖЕЮ: ПІДХІД НА ОСНОВІ ЙМОВІРНІСНО-ЧАСОВИХ ГРАФІВ

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У сучасних телекомунікаційних та комп'ютерних мережах ефективний та надійний збір інформації є важливим для прийняття рішень та розв'язання задач управління. Методи, що існують, такі як періодична передача даних, збір даних на основі подій та запити на вимогу, мають свої переваги та обмеження. **Об'єктом статті** є розробка комплексної моделі для оптимізації процесів збору інформації в мережевих середовищах. **Предметом статті** є методи збору інформації, включаючи періодичну передачу даних, збір даних на основі подій та запити на вимогу, та оцінюється їх ефективність за різних умов мережі. **Метою** цього дослідження є розробка гнучкої та точної моделі, яка може оптимізувати технології інформаційного забезпечення для завдань управління мережею. Основні **задачі** дослідження включають: 1. Розробка ймовірнісно-часової графової моделі для оцінки ефективності різних методів збору інформації. 2. Аналіз продуктивності моделі за допомогою математичних співвідношень та симуляцій. 3. Порівняння запропонованої моделі з існуючими методологіями. **Результати:** Запропонована модель показала значні варіації в ефективності методів збору інформації. Періодична передача даних збільшувала навантаження на мережу, тоді як збір даних на основі подій був більш оперативним, але міг пропускати рідкісні зміни. Запити на вимогу балансували між необхідністю своєчасних даних та обмеженнями ресурсів, але стикалися із затримками через втрату пакетів. Ймовірнісно-часовий граф ефективно відображав ці динаміки, забезпечуючи детальне розуміння компромісів. **Висновки:** В рамках дослідження розроблено гнучку та точну модель для оптимізації технологій інформаційного забезпечення в завданнях управління мережами. Здатність моделі адаптуватися до різних умов мережі має значні практичні наслідки для покращення ефективності та продуктивності мереж. Майбутні дослідження повинні дослідити інтеграцію методів машинного навчання та розширити модель для більш складних мережевих середовищ.

Ключові слова: технологія інформаційного забезпечення; управління мережею; ймовірнісно-часовий граф; телекомунікації; комп'ютерні мережі.

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