

Intelligent Wireless Monitoring Technology for 10kV Overhead Lines in Smart Grid Networks

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Abstract

Promoted by the rapid development of information technology, 10kV overhead line has been widely used in the majority of cities, and it is of great significance to monitor the distribution network effectively, in order to ensure the normal operation of the system. Most of traditional distribution network monitoring methods are based on manual work, which causes inconvenience to the distribution network fault location, repair, maintenance and real-time monitoring, and reduces the efficiency of the distribution network emergency repair and the reliability of power supply. Aiming at the automatic monitoring problem of 10kV overhead network, this paper adopts an intelligent wireless monitoring technology, where a monitoring node is employed to monitor the network transmission status through wireless links. We evaluate the system monitoring performance by using the metric of outage probability, depending on the wireless data rate over wireless channels. For the considered system, we derive analytical outage probability, in order to measure the system performance in the whole range of signal-to-noise ratio (SNR). The simulation results are finally presented to verify the analytical expressions on the system monitoring outage probability in this paper.

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Keywords: 10kV overhead line, outage probability, analytical expression, simulations.

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1. Introduction

Promoted by the rapid development of wireless communication technology [1–3] and edge computing [4–6] as well as electronic technology and computer network technology, the 10kV overhead line has been enhanced by improving fault alarm data, real-time operational data, equipment parameters and other information integrated processing and integration. The characteristics of the collected data can be sent to the detection and control center, for the normal operation of power distribution network monitoring, the monitoring and fault localization [7, 8]. Through the implementation of this system, the modernization of power distribution network operation and management is realized, and the safety, reliability and economic operation of power distribution network are ensured.

The urban distribution network adopts the neutral ungrounded operation mode, and adopts the power

supply mode combining radiation and ring network. After years of urban network transformation, the automation degree of 10kV distribution network operation equipment has been improved significantly. However, the development of urban construction and social economy has put forward higher requirements for the reliability of power supply. At present, there are still many defects in the distribution network information automation and problem detection, described as follows.

Firstly, the automatic fault location function cannot be realized. Once a fault occurs, it needs to be manually searched along the line. At present, the structure of urban distribution network is complicated, and the coexistence of overhead and cable lines brings much difficulty to the fault search. Secondly, it is difficult to realize the detection and location of single phase fault of small current grounding system. In distribution networks, the interphase short-circuit fault of a line can be easily detected by the concomitant overcurrent phenomenon and subsequent circuit breaker trip.

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At present, the single-phase ground fault in the distribution network can only be detected by the “zero-sequence overvoltage” signal in the substation, and the specific fault line cannot be accurately judged. In most cases, the outage detection method of disconnecting the power supply line is used to judge the fault one by one, which is tedious and reduces the reliability of the power supply.

The future city 10kV distribution network should be able to real-time monitor the circuit operation, on-line fault, ground fault, over current, short circuit when the load current is cross the line, and so on, to transfer the characteristics of the data to the dispatching control center and realize regional fault detection and location, which can quickly isolate ground fault and restore power. Firstly, the smart grid monitoring system can monitor various states of line operation in real time and provide decision-making basis for safe power supply. Secondly, real-time monitoring of permanent faults such as circuit short-circuit, grounding and power outage and reporting the fault current can quickly locate the fault point and improve the efficiency of distribution and emergency repair [9, 10]. Thirdly, it is important to shorten the power outage time and reduce unnecessary losses to users. Lastly, it is also important to improve the level of automation and informatization.

By applying smart grid monitoring system installed by online monitoring point road and standeth in the dispatching control center, we can realize the normal operation of urban distribution network monitoring and control, all-weather monitoring, automatic positioning at the line fault, improve the reliability of power supply, with more high-quality, efficient service society.

In order to achieve the goal of automatic monitoring on the 10kV overhead network, this paper considers an intelligent wireless monitoring framework, where a monitoring node is employed to monitor the status of network transmission through the wireless links. The system monitoring performance is evaluated by using the metric of outage probability, depending on the wireless data rate over wireless channels. For the considered system, an analytical expression of the outage probability is derived, in order to evaluate the system performance in the whole range of signal-to-noise ratio (SNR). The simulation results are finally presented to verify the analytical expressions on the system monitoring outage probability in this paper.

2. System model

The intelligent wireless monitoring system model is shown in Fig. 1. As seen in Fig. 1, we consider an intelligent wireless monitoring technology for 10kV overhead lines in smart grid networks. S-D is a data transmission link, while S-M is the monitored link of the power distribution network in which S, D and

M are the source, destination and monitoring node, respectively. Notations z_1 and z_2 denote the channel of the link from the source S to D and to M, respectively [11–13]. According to the given system model, the transmission data rate from S to D can be expressed as [14, 15]

$$d_1 = W_B \log_2(1 + SNR_{z_1}), \quad (1)$$

with

$$SNR_{z_1} = \frac{P}{\sigma^2} |z_1|^2, \quad (2)$$

where B is communication bandwidth of the wireless monitoring, P represents the transmit power at the source, and σ^2 is the variance of the AWGN noise. Moreover, the monitoring data rate of the wireless link can be expressed as,

$$d_2 = W_B \log_2(1 + SNR_{z_2}), \quad (3)$$

with

$$SNR_{z_2} = \frac{P}{\sigma^2} |z_2|^2. \quad (4)$$

In addition, the distribution of $|z_1|^2$ and $|z_2|^2$ are, [16, 17]

$$f_{|z_1|^2}(x) = \frac{1}{\eta_1} e^{-\frac{x}{\eta_1}}, \quad (5)$$

$$f_{|z_2|^2}(y) = \frac{1}{\eta_2} e^{-\frac{y}{\eta_2}}. \quad (6)$$

Based on the equations (1) and (3), the monitoring data rate can be described by [18, 19],

$$d_2 - d_1 = W_B \log_2 \left(\frac{1 + \tilde{P}|z_2|^2}{1 + \tilde{P}|z_1|^2} \right), \quad (7)$$

with

$$\tilde{P} = \frac{P}{\sigma^2}. \quad (8)$$

Subsequently, the monitoring outage probability is exploited to measure the stability of the monitoring process, which is expressed by [20, 21]

$$P_{out} = \Pr(d_2 - d_1 < \lambda_t), \quad (9)$$

$$= \Pr \left(W_B \log_2 \left(\frac{1 + \tilde{P}|z_2|^2}{1 + \tilde{P}|z_1|^2} \right) < \lambda_t \right), \quad (10)$$

$$= \Pr \left(\frac{1 + \tilde{P}|z_2|^2}{1 + \tilde{P}|z_1|^2} < 2^{\lambda_t/W_B} \right), \quad (11)$$

where λ_t represents the threshold of the monitoring rate. Then, this equation can be further derived as [22–24]

$$P_{out} = \Pr \left(|z_2|^2 < \frac{(1 + \tilde{P}|z_1|^2) 2^{\lambda_t/W_B} - 1}{\tilde{P}} \right). \quad (12)$$

Considering the PDFs of $|z_2|^2$ and $|z_1|^2$, the outage probability can be written as

$$P_{out} = \int_0^{+\infty} \int_0^{\frac{(1+\tilde{P}y)2^{\lambda_t/W_B}-1}{\tilde{P}}} \frac{1}{\eta_1} e^{-\frac{x}{\eta_1}} \frac{1}{\eta_2} e^{-\frac{y}{\eta_2}} dx dy \quad (13)$$

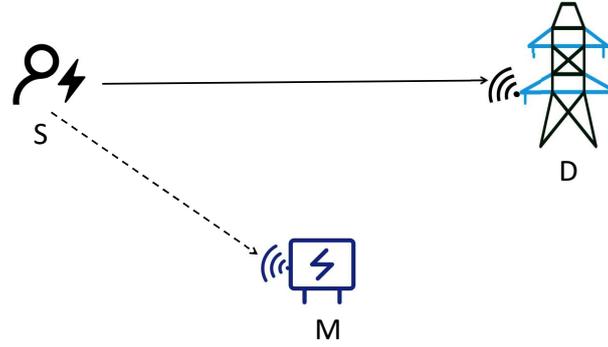


Figure 1. System model of the intelligent wireless monitoring technology for 10kV overhead lines.

where $x = |z_1|^2$ and $y = |z_2|^2$. In further, the outage probability can be calculated as,

$$P_{out} = \int_0^{+\infty} \frac{1}{\eta_1} e^{-\frac{x}{\eta_1}} \left[1 - e^{-\frac{(1+\bar{P}x)2^{\lambda_t/W_B+1}}{\eta_2 \bar{P}}} \right] dx, \quad (14)$$

$$= 1 - \int_0^{+\infty} \frac{1}{\eta_1} e^{-\frac{(2^{\lambda_t/W_B-1})}{\eta_2 \bar{P}}} e^{-\frac{(\eta_2+2^{\lambda_t/W_B}\eta_1)}{\eta_1 \eta_2} x} dx, \quad (15)$$

$$= 1 - e^{-\frac{(2^{\lambda_t/W_B-1})}{\eta_2 \bar{P}}} \frac{\eta_2}{\eta_2 + \eta_1 2^{\lambda_t/W_B}}. \quad (16)$$

From the above monitoring outage probability in (16), we will proceed to give some asymptotic analysis, in order to obtain some insights on the system design of the communication in the considered 10KV overhead lines. Specifically, when the transmit SNR \bar{P} becomes larger, we can use the approximate of $e^{-x} \simeq 1$ for small value of x , and approximate P_{out} as,

$$P_{out} \simeq 1 - \frac{\eta_2}{\eta_2 + \eta_1 2^{\lambda_t/W_B}}, \quad (17)$$

$$= \frac{\eta_1 2^{\lambda_t/W_B}}{\eta_2 + \eta_1 2^{\lambda_t/W_B}}. \quad (18)$$

When the zero threshold is considered with $\lambda_t = 0$, we can further have,

$$P_{out} \simeq \frac{\eta_1}{\eta_2 + \eta_1}. \quad (19)$$

From the above asymptotic expression of P_{out} , we can find that the system monitoring performance is significantly affected by the wireless transmission channels, indicating that we should enhance the monitoring channel quality as high as possible in practice, in order to maintain the system operation of

the communication in the considered 10KV overhead lines.

In the next section, we will provide some simulation results to verify the analytical results.

3. Simulation

In this part, we perform some simulations to verify the proposed work in this paper. Without loss of generality, the links in the network experience Rayleigh fading, and the wireless bandwidth of data transmission is set to $W_B = 0.5$. The noise of AWGN at the receiver is set to unity with $\sigma^2 = 1$. We will examine the effect of system parameters, such as P , λ_t , η_1 and η_2 , on the system monitoring outage probability P_{out} , in order to reveal the monitoring mechanism for the proposed system.

Table 1 and Fig. 2 demonstrate the monitoring outage probability of the considered system versus P and λ_t , where $\lambda_t \in \{1, 1.5, 2\}$, $\eta_1 = 1$, $\eta_2 = 5$, and P varies from 0dB to 30dB. From this table and figure, we can find that the analytical monitoring P_{out} is near the simulated P_{out} . Specifically, with $P = 5$ dB and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.5084 and 0.5073, respectively. With $P = 10$ dB and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.4785 and 0.4768, respectively. With $P = 20$ dB and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.4634 and 0.4609, respectively. Such results verify the derived analytical expression on the P_{out} for the considered system. Moreover, one can also find that the system monitoring performance becomes better with a larger P , as the increased transmit power can help monitor the system data transmission more efficiently. In further, the system outage increases with a larger λ_t , as an increased threshold will make the monitor much harder in practice.

Table 2 and Fig. 3 illustrate the monitoring outage probability of the considered system versus η_1 and λ_t , where $\lambda_t \in \{1, 1.5, 2\}$, $P = 10$ dB, $\eta_2 = 8$, and η_1 varies

Table 1. Numerical monitoring outage performance versus P and λ_t .

Methods	λ_t	P/dB						
		0	5	10	15	20	25	30
Simulation	1.0	1.0000	0.5084	0.4785	0.4676	0.4634	0.4601	0.4578
	1.5	1.0000	0.7086	0.6663	0.6513	0.6421	0.6368	0.6328
	2	1.0000	0.8712	0.8253	0.8057	0.7955	0.7900	0.7858
Analysis	1.0	1.0000	0.5073	0.4768	0.4662	0.4609	0.4576	0.4554
	1.5	1.0000	0.7093	0.6656	0.6497	0.6414	0.6363	0.6329
	2.0	1.0000	0.8697	0.8236	0.8051	0.7951	0.7888	0.7846

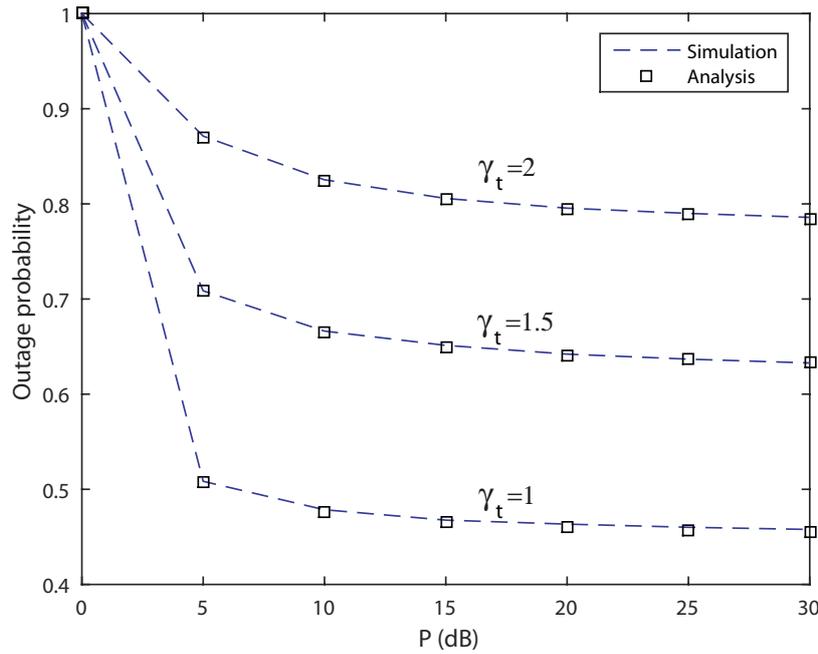


Figure 2. Monitoring outage performance versus P and λ_t .

Table 2. Numerical monitoring outage performance versus η_1 and λ_t .

Methods	λ_t	η_1						
		1	2	3	4	5	6	7
Simulation	1.0	0.3562	0.5119	0.6125	0.6802	0.7262	0.7558	0.7923
	1.5	0.5388	0.6951	0.7670	0.8164	0.8493	0.8656	0.8889
	2	0.7260	0.8298	0.8815	0.9064	0.9230	0.9355	0.9469
Analysis	1.0	0.3579	0.5184	0.6147	0.6789	0.7248	0.7592	0.7860
	1.5	0.5419	0.6946	0.7709	0.8168	0.8473	0.8691	0.8855
	2.0	0.7237	0.8342	0.8816	0.9079	0.9246	0.9362	0.9447

from 1 to 7. From this table and figure, we can also see that the analytical monitoring P_{out} is almost the same as the simulated one. In particular, with $\eta_1 = 1$ and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.3562 and 0.3579, respectively. With $\eta_1 = 3$ and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.6125 and 0.6147, respectively. With $\eta_1 = 5$ and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.7262 and 0.7248, respectively. Such results show the effectiveness of the derived analytical expression on the P_{out} for the

considered system. Moreover, we can also find that the system monitoring performance becomes worse with a larger η_1 or λ_t , as the increased η_1 or λ_t will make the monitor much harder in practice.

Table 3 and Fig. 4 illustrate the monitoring outage probability of the considered system versus η_2 and λ_t , where $\lambda_t \in \{1, 1.5, 2\}$, $P = 10\text{dB}$, $\eta_1 = 1$, and η_2 varies from 2 to 8. From this table and figure, we can also see that the analytical monitoring P_{out} matches well with the simulated one. In particular, with $\eta_2 = 2$

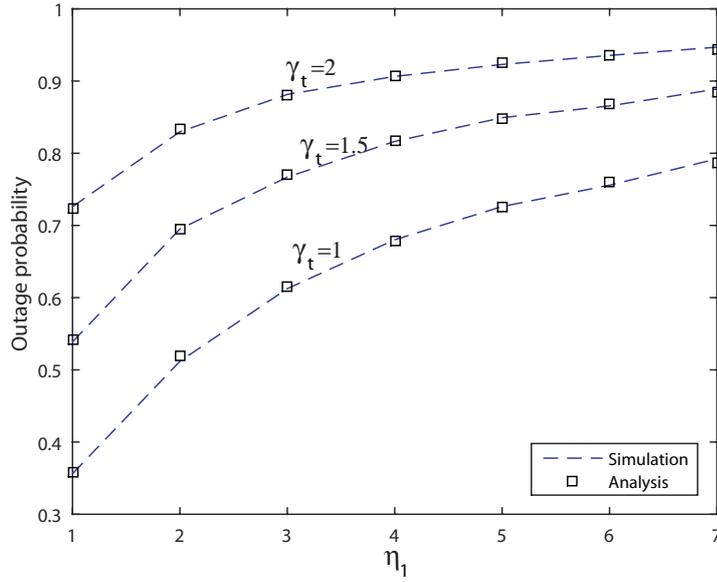


Figure 3. Monitoring outage performance versus η_1 and λ_t .

Table 3. Numerical monitoring outage performance versus η_2 and λ_t .

Methods	λ_t	η_2						
		2	3	4	5	6	7	8
Simulation	1.0	0.7176	0.6178	0.5361	0.4746	0.4266	0.3986	0.3564
	1.5	0.8607	0.7804	0.7210	0.6744	0.6237	0.5679	0.5392
	2	0.9483	0.8965	0.8615	0.8253	0.7918	0.7551	0.7283
Analysis	1.0	0.7131	0.6122	0.5361	0.4768	0.4293	0.3903	0.3579
	1.5	0.8591	0.7840	0.7202	0.6656	0.6186	0.5777	0.5419
	2.0	0.9475	0.9042	0.8625	0.8236	0.7876	0.7544	0.7237

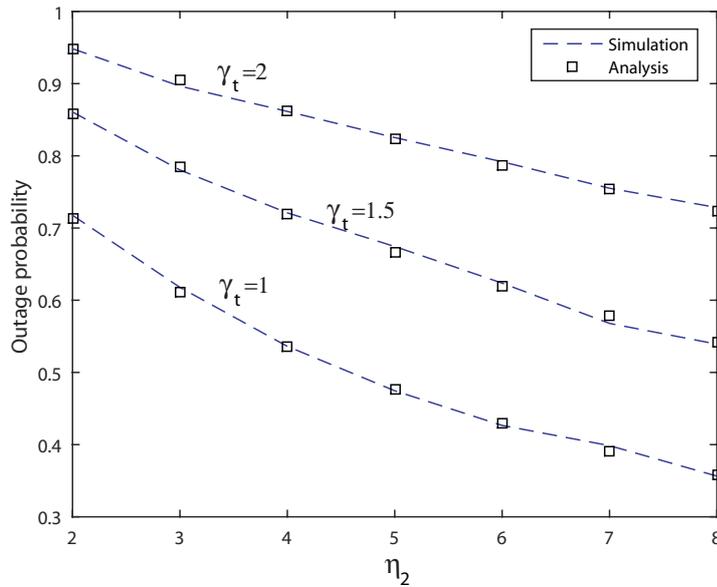


Figure 4. Monitoring outage performance versus λ_t and η_2 .

and $\lambda_t = 1$, the simulated P_{out} and analytical P_{out} are 0.7176 and 0.7131, respectively. With $\eta_2 = 5$ and $\lambda_t =$

1, the simulated P_{out} and analytical P_{out} are 0.4746 and 0.4768, respectively. With $\eta_2 = 8$ and $\lambda_t = 1$, the

simulated P_{out} and analytical P_{out} are 0.3564 and 0.3579, respectively. Such results show the effectiveness of the derived analytical expression on the P_{out} for the considered system. Moreover, we can also find that the system monitoring performance improves with a larger η_2 , as this can help make the monitor easier in practice.

4. Conclusions

In this paper, we studied a new intelligent wireless monitoring technology for 10kV overhead lines in smart grid networks. This monitoring system was modeled by two communication branches, where one branch was for data transmission, while the other was for monitoring. The system monitoring performance was evaluated by using the metric of outage probability, depending on the wireless data rate over wireless channels. For the considered system, an analytical expression of the outage probability was derived, in order to evaluate the system performance in the whole SNR regime. The simulation results were finally presented to verify the analytical expressions on the system monitoring outage probability.

4.1. Data Availability Statement

The data of this work can be obtained through the email to the authors: Jiangang Lu (JiangangLucsg@ieee.org), Zhan Shi (ZhanShiCSG@hotmail.com), and Xinzhan Liu (XinzhanLiu2022@hotmail.com).

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4.2. Copyright

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