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Online Document Transmission and Recognition of Digital Power Grid with Knowledge Graph

Yuzhong Zhou[1], Zhengping Lin[1], Liang Tu[1,*], and Qiansu Lv[2]

[1]Electric Power Research Institute of China Southern Power Grid Company, Guangzhou, China
(e-mail: yuzhong_zhou@hotmail.com, zhengping_lin@hotmail.com, Liang_Tu1@hotmail.com).
[2]Electronic Power Research Institute of Guizhou Power Grid Co. Ltd., Guizhou, China
(e-mail: qiansulvcsg@hotmail.com).

Abstract

Inspired by the ever-developing information technology and scalable information systems, digital smart grid networks with knowledge graph have been widely applied in many practical scenarios, where the online document transmission and recognition plays an important role in wireless environments. In this article, we investigate the online document transmission and recognition of digital power grid with knowledge graph. In particular, we jointly consider the impact of online transmission and recognition based on computing, where the wireless transmission channels and computing capability are randomly varying. For the considered system, we investigate the system performance by deriving the analytical expression of outage probability, defined by the transmission and recognition latency. Finally, we provide some results to verify the proposed studies, and show that the wireless transmission and computing capability both impose a significant impact on the online document transmission and recognition of digital power grid networks.

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1. Introduction

Thanks to the new information techniques such as cloud computing and scalable information systems [1, 2], digital grid system has emerged as a new energy ecosystem [3–5], which is particularly important for the application of electrification of urban mobility. In particular, the emergence of knowledge graph, Internet of Things, artificial intelligence, and blockchain also provides some new perspectives for the development of digital smart grid networks. Nowadays, digital grid system has worked as the core driving force, providing data as the key production factor, modern power energy network and the new generation information network as the basis, through the deep integration of digital technology and energy enterprise business and management, and constantly improving the level of digitalization, networking and intelligence [6]. It has the characteristics of flexibility, openness, interactivity, economy and sharing, making the power grid more intelligent, safe, reliable, green and efficient. Different from traditional vertical and closed IT architectures, the digital grid adopts a cloud based, microservice based, and internet-based open architecture. This can help realize real-time applications of massive data and intelligent processing of business processes, achieve rapid response, rapid iteration, and flexible trial and error, meet the high concurrency requirements of business loads, and have a wide range of business applications and good user experience.

The current digital power system can realize multi-modal sensor measurement data access, effectively support multi-dimensional real-time state monitoring of new energy power generation [7], improve the level of grid transparency, and provide a more comprehensive and accurate data basis for accurate power prediction on the generation side [8]. The traditional power analysis methods, such as electromechanical model and state equation, are no longer applicable to the complicated network and electromagnetic transient process that are

*Corresponding author. Email: Liang_Tu1@hotmail.com

changing rapidly when a large number of new energy sources are connected. Relying on the advanced computing technology for big data in cloud computing and edge computing, it will help analyze the model with tens of millions of dimensions in the future, and achieve rapid and efficient analysis of power systems.

In this article, we investigate the online document transmission and recognition of digital power grid with knowledge graph. In particular, we jointly study the impact of online transmission and recognition based on computing, where the wireless transmission channels and computing capability are randomly varying. For the considered system, we evaluate the system performance by deriving an analytical expression for the system outage probability, defined by the transmission and recognition latency. Finally, we provide some results to verify the proposed studies, and show that the system performance is affected by both the wireless transmission quality and computational capability. The results in this paper provide some references to the development of information technology and scalable information systems.

2. System model of the online document transmission and recognition of digital power grid based on knowledge graph

In this section, the online document transmission and recognition of digital power grid with knowledge graph is considered. Specifically, the document is transmitted from source S to destination D over wireless channel q. In practical application scenarios, channel q may vary depending on the specific application scenarios [9–11]. Without loss of generality, we assume that the wireless channel experiences Rayleigh flat fading, and hence $|q|^2$ follows an exponential distribution with the average gain of ρ [12–14]. The transmission data rate of the channel is defined as [15–17]

$$R_t = w \log_2\left(1 + \frac{P|q|^2}{\zeta}\right), \tag{1}$$

where w is the bandwidth of wireless transmission, P is the transmission power of the online document, and ζ is the noise of AWGN. The probability density function (PDF) of $z = |q|^2$ is expressed as [18, 19]

$$f_z(z) = \frac{1}{\rho} e^{\frac{-z}{\rho}}. \tag{2}$$

With the transmission data rate R_t, the transmission delay of the online document can be calculated as [20–22]

$$t_1 = \frac{M}{R_t}, \tag{3}$$

$$= \frac{M}{w \log_2\left(1 + \frac{P|q|^2}{\zeta}\right)}, \tag{4}$$

where M is the length of the online document. After the transmission, the associated recognition and processing delay is defined as [23–25]

$$t_2 = \frac{M}{\theta_c}, \tag{5}$$

where $\theta_c \in [\theta_{min}, \theta_{max}]$ is the computational capability at the edge node, in which θ_{min} and θ_{max} denote the minimum and maximum computing capability, respectively. Hence, the total delay of the system can be expressed as [26–28]

$$t_{total} = \frac{M}{w \log_2\left(1 + \frac{P|q|^2}{\zeta}\right)} + \frac{M}{\theta_c}, \tag{6}$$

where the first term on the right-hand side (RHS) of (6) denotes the transmission delay, while the second term is the recognition and processing delay. From t_{total}, we proceed to analyze the system performance by studying the system outage probability, in the following section.

3. Performance analysis of the online document transmission and recognition of digital power grid based on knowledge graph

In this part, we turn to analyze the system performance of the online document transmission and recognition of digital power grid. According to the online transmission and recognition latency, the outage probability of the online document transmission and recognition of digital power grid can be expressed as [29, 30]

$$P_{out} = \Pr(t_{total} > \eta), \tag{7}$$

$$= \Pr\left(\frac{M}{w \log_2\left(1 + \frac{P|q|^2}{\zeta}\right)} + \frac{M}{\theta_c} > \eta\right), \tag{8}$$

where η is a predetermined latency threshold. As it is difficult to directly obtain an analytical expression for P_{out}, we firstly solve the conditional outage probability on a given computing capability θ_c as

$$P_{out}(\eta|\theta_c) = \Pr(t_{total} > \eta|\theta_c), \tag{9}$$

$$= \Pr\left(\frac{M}{w \log_2\left(1 + \frac{P|q|^2}{\zeta}\right)} > \eta - \frac{M}{\theta_c}\middle|\theta_c\right), \tag{10}$$

$$= \Pr\left(|q|^2 < \frac{\zeta}{P}\left(2^{\frac{M\theta_c}{w(\eta\theta_c - M)}} - 1\right)\middle|\theta_c\right). \tag{11}$$

With the analytical PDF of $|q|^2$ in (2), the conditional outage probability can be further derived as

$$P_{out}(\eta|\theta_c) = \int_0^{\frac{\zeta}{P}\left(2^{\frac{M\theta_c}{w(\eta\theta_c - M)}} - 1\right)} \frac{1}{\rho} e^{-\frac{v}{\rho}} dv, \tag{12}$$

$$= 1 - e^{-\frac{\frac{\zeta}{P}(2^{\frac{M\theta_c}{w(\eta\theta_c - M)}} - 1)}{\rho}}. \tag{13}$$

From the above conditional outage probability $P_{out}(\eta|\theta_c)$, we can write the system overall outage probability P_{out} as

$$P_{out} = \int_0^{+\infty} P_{out}(\eta|\theta_c) f_{\theta_c}(\theta_c) d\theta_c. \quad (14)$$

As θ_c is subject to the uniform distribution in the interval of $[\theta_{min}, \theta_{max}]$, we can further have

$$P_{out} = \int_{\theta_{min}}^{\theta_{max}} P_{out}(\eta|\theta_c) f_{\theta_c}(\theta_c) d\theta_c, \quad (15)$$

$$= \int_{\theta_{min}}^{\theta_{max}} P_{out}(\eta|\theta_c) \frac{1}{\theta_{max} - \theta_{min}} d\theta_c, \quad (16)$$

$$= 1 - \frac{1}{\theta_{max} - \theta_{min}} \int_{\theta_{min}}^{\theta_{max}} e^{-\frac{\frac{\zeta}{P}\left(2^{\frac{M\theta_c}{w(\eta\theta_c - M)}} - 1\right)}{\rho}} d\theta_c. \quad (17)$$

From the theory of advanced mathematics, we can obtain an analytical expression of approximate outage probability as

$$P_{out} = \sum_{n=1}^{N} \frac{\triangle}{N} P(\eta|\theta_{min} + n\triangle) \frac{1}{\triangle}, \quad (18)$$

$$= 1 - \frac{1}{N} \frac{1}{\theta_{max} - \theta_{min}} \sum_{n=1}^{N} e^{-\frac{\frac{\zeta}{P}\left(2^{\frac{M(\theta_{min}+n\triangle)}{w(\eta(\theta_{min}+n\triangle)-M)}} - 1\right)}{\rho}}, \quad (19)$$

where N is the number of terms in the equidistant partitions of the integral region, and $\triangle$ is the length of each partition. Note that the approximation accuracy improves with a larger number of N, as more terms can help decrease the interval in the numerical integration, which is helpful for the approximation accuracy. However, a larger number of N will increase the computational complexity linearly. Hence, a trade-off should be taken into account based on both the accuracy and complexity.

4. Numerical and Simulation results

In this part, we perform some simulations to verify the derived analysis on the online document transmission and recognition of digital power grid based on knowledge graph. Without loss of generality, the wireless channel for the online document transmission is subject to Raleigh flat fading [31, 32] with the unity average channel gain, i.e., $\rho = 1$. Moreover, the computing capability at the edge node is subject to uniform distribution [33, 34], which is often used to model the practical computing capability, including the edge computing and cloud computing application scenarios. In particular, $\theta_{min} = 20$MHz and $\theta_{max} = 30$MHz are set for the computing capability. The wireless bandwidth is set to 8MHz for the online document transmission, and we set 1000 terms for the approximation calculation in the analytical outage probability, i.e., $N = 1000$.

Table 1 and Fig. 1 depict the outage probabilities of the online document transmission and recognition versus η and P, where the value of ζ was set to 5, $M = 10$, the number of the sampling values for the channels was set to 50,000, $\eta \in \{1, 1.5\}$ and $P \in \{20, 25, 30, 35, 40\}\, dB$. From this table and this figure, we can find that for various values of η and P, the analytical P_{out} is almost equal to the simulated P_{out}. In particular, in the case of $\eta = 1$ and $P = 20$dB, the analytical P_{out} is 0.1545 and the simulated P_{out} is 0.1547. In the case of $\eta = 1$ and $P = 30$dB, the analytical P_{out} is 0.0165 and the simulated P_{out} is 0.0167. In the case of $\eta = 1$ and $P = 40$dB, the analytical P_{out} is 0.0019 and the simulated P_{out} is 0.0017. Such agreement validates the derived analytical P_{out} for the considered system. Moreover, the system outage probability becomes better when P increases, as a larger transmit power can help reduce the transmission latency efficiently. In further, the value of P_{out} decreases with a larger η, as this can tolerate more latency in the transmission and processing of online files.

Table 2 and Fig. 2 depict the outage probabilities of the online document transmission and recognition versus η and ζ, where $P = 30$dB, $M = 10$, the number of the sampling values for the channels was set to 50,000, $\eta \in \{1, 1.5\}$ and $\zeta \in \{1, 2, 3, 4, 5\}$. From this table and this figure, we can also observe that for various values of η and ζ, the analytical P_{out} is almost equivalent to the simulated value. Specifically, in the case of $\eta = 1$ and $\zeta = 1$, the analytical P_{out} is 0.0038 and the simulated P_{out} is 0.0034. In the case of $\eta = 1$ and $\zeta = 3$, the analytical P_{out} is 0.0097 and the simulated P_{out} is 0.0101. In the case of $\eta = 1$ and $\zeta = 5$, the analytical P_{out} is 0.0169 and the simulated P_{out} is 0.0167. Such fitness also verifies the derived analytical expression of P_{out} for the considered system. Moreover, the system outage probability deteriorates when ζ increases, as a stronger noise can enlarge the transmission latency significantly. In further, the value of P_{out} decreases with a larger η, leading to an increased tolerated latency for the transmission and processing of online files.

In Table 3 and Fig. 3, we show the experimental results for the system P_{out} versus η and M. In these experiments, the value of P was set to be $30dB$, the number of the sampling values for the channels was set to 50,000, $\zeta = 5$, and $M \in \{8, 9, 10, 11, 12\}$. As shown in Table 3, one can see that the simulation result and analytical result have the similar values for various values of η and M. For example, when $\eta = 1.0$ and $M = 8$, the simulation result is 0.0.0090, while the analytical result is 0.0.0090, and they are equal to each other. When $\eta = 1.5$ and $M = 12$, the simulation result is

Table 1. Analytical and simulation outage probability versus P and η.

Methods	η	P/dB				
		20	25	30	35	40
Simulation	1.0	0.1545	0.0517	0.0165	0.0054	0.0019
	1.5	0.0576	0.0180	0.0055	0.0016	0.0005
Analysis	1.0	0.1547	0.0518	0.0167	0.0053	0.0017
	1.5	0.0588	0.0190	0.0060	0.0019	0.0006

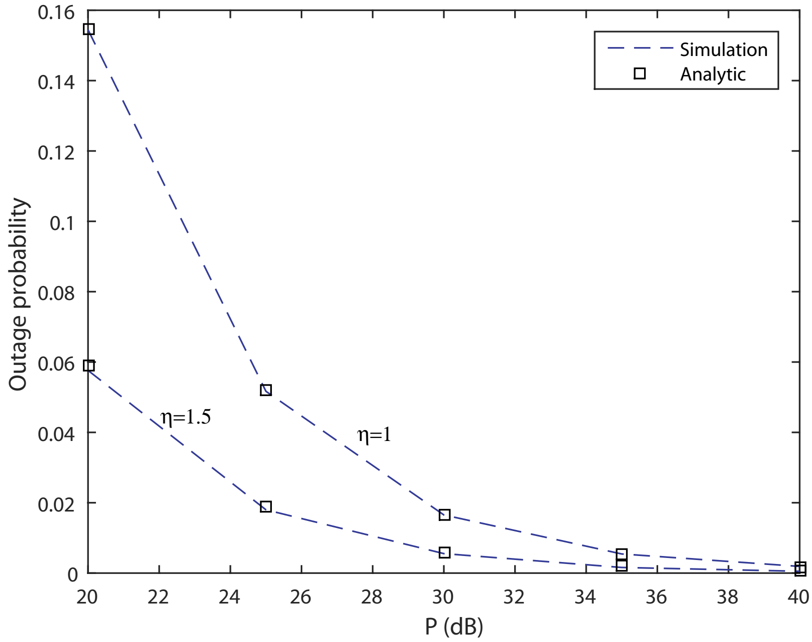

Figure 1. System outage probability versus P and η.

Table 2. Analytical and simulation outage probability versus ζ and η.

Methods	η	ζ				
		1	2	3	4	5
Simulation	1.0	0.0038	0.0068	0.0097	0.0135	0.0169
	1.5	0.0015	0.0026	0.0041	0.0048	0.0060
Analysis	1.0	0.0034	0.0067	0.0101	0.0134	0.0167
	1.5	0.0012	0.0024	0.0036	0.0048	0.0060

0.0089, while the analytical result is also 0.0090, where the difference between them is just 0.0001. According to these results, it can be concluded that the analytical results are verified by the simulation results, which also demonstrate the effectiveness of the analysis on the system P_{out} versus the parameter M. In Fig. 3, two curves versus η are drew, including $\eta = 1.0$ and $\eta = 1.5$. The curve with $\eta = 1.0$ is above the curve $\eta = 1.5$, as a larger threshold indicates an enhanced delay tolerance, and an increased delay tolerance can help improve the system performance. In addition, the results for both curves show that the outage probability of the system grows up as M becomes larger. This result shows that a larger file can degrade the transmission and recognition of the system.

5. Conclusions

We investigated the key issue of online document transmission and recognition in the digital power grid with knowledge graph. In particular, we analyzed the joint impact of online transmission and recognition based on computing, where the randomness of both wireless transmission and edge computing were taken into account. For the considered system, we evaluated the system performance by deriving the analytical outage probability, measured by the transmission and recognition latency. We further demonstrated some

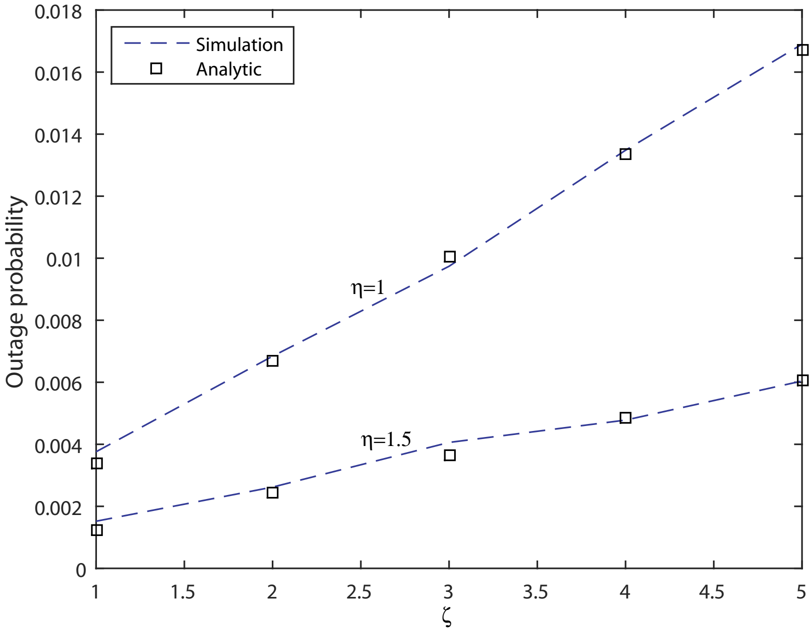

Figure 2. System outage probability versus ζ and η.

Table 3. Analytical and simulation outage probability versus M and η.

Methods	η	M				
		8	9	10	11	12
Simulation	1.0	0.0090	0.0122	0.0173	0.0238	0.0343
	1.5	0.0039	0.0050	0.0063	0.0073	0.0089
Analysis	1.0	0.0090	0.0122	0.0167	0.0235	0.0344
	1.5	0.0040	0.0049	0.0060	0.0074	0.0090

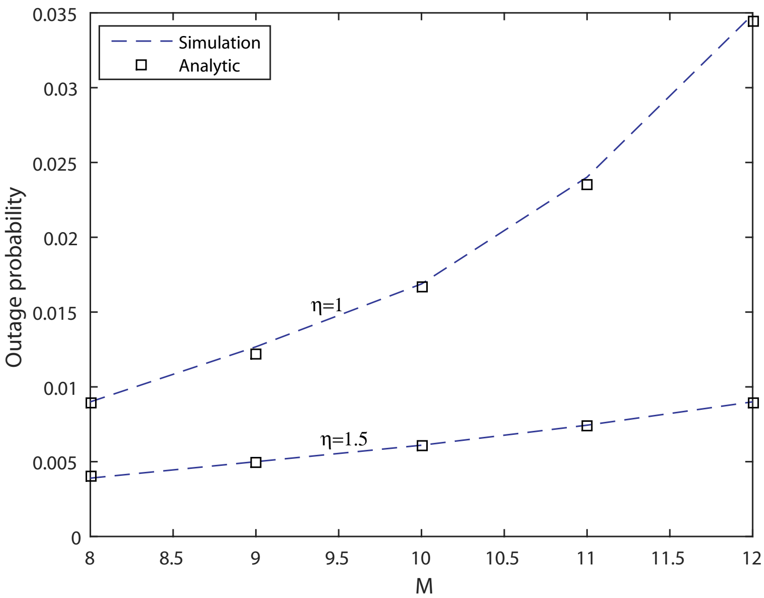

Figure 3. System outage probability versus M and η.

results to verify the proposed studies, and show that the system performance can be improved by an enhanced wireless channel quality or computing capability. The results in this paper could provide some important references to the development of wireless communications and scalable information systems.

5.1. Data Availability Statement

The data of this work can be obtained through the email to the authors: Yuzhong Zhou (yuzhong_zhou@hotmail.com), Zhengping Lin (zhengping_lin@hotmail.com), Liang Tu (Liang_Tu1@hotmail.com), and Qiansu Lv (qiansulvcsg@hotmail.com).

5.2. Copyright

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