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Performance Analysis and Research of Knowledge Sharing System for Power Grid Networks

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Abstract

Knowledge sharing is a critical aspect of machine learning and knowledge management, which also plays an important role in regulating the power grid networks. Hence, it is important to investigate the performance of knowledge sharing in the power grid networks. Motivated by this, we firstly investigate a typical power grid network with a knowledge sharing node, where the transmit power of users is constrained by the knowledge sharing node. We then measure the system performance by evaluating the system outage probability (OP), where the analytical expression of OP is derived in detail. Finally, we present some simulation and numerical results on the OP for the considered power grid networks with knowledge sharing, in order to verify the proposed studies on the OP. In particular, these results show that the knowledge sharing can help enhance the system OP performance efficiently.

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Keywords: Performance analysis, knowledge sharing, power grid networks, outage probability.

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1. Introduction

Knowledge sharing is a critical aspect of machine learning and knowledge management [1–4]. Many researchers have studied the factors that affect knowledge sharing and the benefits that it can bring to information technology [5–8]. Researchers have also identified several factors that affect knowledge sharing in systems, which include trust, communication, incentives, leadership, culture, and technology. For example, trust between wireless nodes can create a safe environment for sharing knowledge, while incentives can motivate the nodes to share their expertise. Knowledge sharing can bring numerous benefits to information technology, including increased innovation, better decision-making, improved problem-solving, and enhanced machine learning. By sharing knowledge, wireless nodes can learn from one another and build on each other's expertise, leading to better overall performance [9–11]. Despite the potential benefits, there are also barriers to knowledge sharing that can prevent it from occurring. These barriers include a lack of time, resources, and motivation, as well as a mechasim that values individual achievement over collaboration. Researchers have also studied various methods for promoting knowledge sharing in wireless nodes. These include creating communities of practice, using knowledge management systems, and promoting informal communication channels such as social media and face-to-face meetings. In a word, the literature on knowledge sharing highlights the importance of creating a way that values collaboration and learning, while also providing the necessary incentives and resources to support knowledge sharing. By doing so, the wireless systems can benefit from the collective knowledge of their wireless nodes and improve the overall performance.

Motivated by the development of IoT networks, the use of digital technologies has enabled the smart grid to become a modernized electricity grid that enhances reliability, efficiency, and flexibility [12–14]. It comprises an interconnected network of electricity generation, transmission, and distribution systems that communicate with each other and electricity consumers in real-time. Energy storage, renewable energy sources, distribution automation, advanced metering infrastructure, and communication systems are various components that make up the smart grid network [15–17]. The primary goal of the smart

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grid network is to ensure the efficient, reliable, and secure delivery of electricity to consumers while simultaneously decreasing energy costs and greenhouse gas emissions. Additionally, the communication system is a crucial component of the smart grid network, allowing for real-time monitoring and control of the electricity grid.

To enable real-time monitoring and control of the electricity grid, smart grid networks employ various communication technologies, including wireless communication, power line communication, and fiber-optic communication [18–20]. Wireless communication is used for remote monitoring and control of electricity distribution systems, while power line communication is used for communication over the power lines. Fiber-optic communication is used for high-speed communication between substations and control centers. Cybersecurity is an important aspect of smart grid networks as they are vulnerable to cyber-attacks. Cyber-attacks on the smart grid can cause power outages, disrupt energy delivery, and compromise consumer data. Therefore, the smart grid network must be safeguarded against cyber-attacks [21–23]. This can be achieved by implementing security measures such as encryption, authentication, and access control.

Smart grid networks have various applications such as demand response, renewable energy integration, electric vehicle charging, and energy storage. Demand response enables electricity consumers to reduce their electricity consumption during peak periods, while renewable energy integration enables the integration of renewable energy sources into the electricity grid. Electric vehicle charging enables the charging of electric vehicles using the electricity grid, while energy storage enables the storage of electricity for later use. The collection and analysis of real-time data on electricity consumption is enabled by Advanced Metering Infrastructure (AMI), which is a vital component of the smart grid network. AMI consists of smart meters, communication systems, and data management systems. The data obtained from AMI can be utilized to enhance energy efficiency, cut energy costs, and enhance the reliability of the electricity grid. Despite its numerous benefits, implementing smart grid networks presents several challenges. These obstacles include expensive implementation costs, the absence of standards, interoperability difficulties, privacy concerns, and regulatory issues. Addressing these challenges is critical to the successful implementation of smart grid networks.

Motivated by the above literature overview, we firstly investigate a typical power grid network with a knowledge sharing node, where the transmit power of users is constrained by the knowledge sharing node. We then measure the system performance by evaluating the system outage probability (OP), where the analytical expression of OP is derived in detail. Finally, we present some simulation and numerical results on the OP for the considered power grid networks with knowledge sharing, in order to verify the proposed studies on the OP. In particular, these results show that the knowledge sharing can help enhance the system OP performance efficiently.

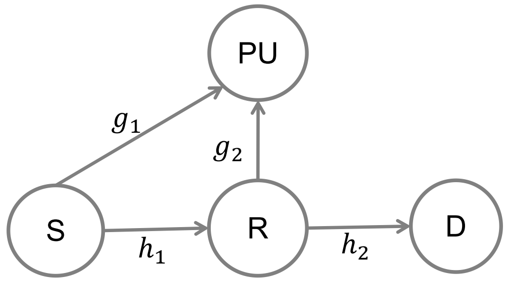

Figure 1. System model of a typical power grid network with a knowledge sharing node.

2. System model

Fig. 1 considers the system model of one cognitive wireless network with one transmit source S and one receive device D, which can communicate with each other through a relay R. Moreover, there is one primary user (PU) in the network, and the source and relay can share spectrum with the PU to improve the spectral efficiency of the network.

Because of the spectrum sharing, the source and relay may interfere with the primary user. Therefore, the transmit power of the source and relay is limited by the PU, which can be given respectively as

$$P_S = \frac{I_p}{|g_1|^2}, \tag{1}$$

$$P_R = \frac{I_p}{|g_2|^2}, \tag{2}$$

where I_p is the tolerable interference power of the PU, $|g_1|^2 \sim \exp(\beta_1)$ is the channel gain of the link from the source to the PU, and $|g_2|^2 \sim \exp(\beta_2)$ is the channel gain of the link between the relay and PU. When the source communicates with the receive device through the relay, the signal-to-noise ratio (SNR) from S to D can be given as

$$Y_S = P_S|h_1|^2, \tag{3}$$

where $|h_1|^2 \sim \exp(\alpha_1)$ is the channel gain of the link from the source to the relay. Similarly, the SNR from the relay to the receive device is

$$Y_R = P_R|h_2|^2, \tag{4}$$

where $|h_2|^2 \sim \exp(\alpha_2)$ is the channel gain of the link from R to D.

3. Performance Analysis

Outage probability is one of the important metrics to evaluate the wireless communication system. In this section, we provide an analytical expression for the outage probability to help analyze the system performance.

From (3) and (4), we can obtain the end-to-end SNR at the receive device as [24]

$$\Upsilon_D = \min(\Upsilon_S, \Upsilon_R) \tag{5}$$
$$= \min(P_S|h_1|^2, P_R|h_2|^2) \tag{6}$$
$$= I_p \min\left(\frac{|h_1|^2}{|g_1|^2}, \frac{|h_2|^2}{|g_2|^2}\right), \tag{7}$$

and the outage probability for the wireless communication can be written as [25–27]

$$P_{out} = \Pr(\Upsilon_D < \Upsilon_{th}) \tag{8}$$
$$= \Pr\left[\min\left(\frac{|h_1|^2}{|g_1|^2}, \frac{|h_2|^2}{|g_2|^2}\right) < \frac{\Upsilon_{th}}{I_p}\right] \tag{9}$$
$$= 1 - \Pr\left[\min\left(\frac{|h_1|^2}{|g_1|^2}, \frac{|h_2|^2}{|g_2|^2}\right) \geq \frac{\Upsilon_{th}}{I_p}\right] \tag{10}$$
$$= 1 - \Pr\left(\frac{|h_1|^2}{|g_1|^2} \geq \frac{\Upsilon_{th}}{I_p}, \frac{|h_2|^2}{|g_2|^2} \geq \frac{\Upsilon_{th}}{I_p}\right), \tag{11}$$

where Υ_{th} is a minimum threshold of the SNR. Since $|h_1|^2$, $|h_2|^2$, $|g_1|^2$, and $|g_2|^2$ are independent of each other, (3) can be re-written as [28–30]

$$P_{out} = 1 - \Pr\left(\frac{|h_1|^2}{|g_1|^2} \geq \frac{\Upsilon_{th}}{I_p}\right)\Pr\left(\frac{|h_2|^2}{|g_2|^2} \geq \frac{\Upsilon_{th}}{I_p}\right) \tag{12}$$
$$= 1 - \left[1 - \Pr\left(\frac{|h_1|^2}{|g_1|^2} < \frac{\Upsilon_{th}}{I_p}\right)\right]\left[1 - \Pr\left(\frac{|h_2|^2}{|g_2|^2} < \frac{\Upsilon_{th}}{I_p}\right)\right]. \tag{13}$$

Let $u_1 = |h_1|^2 \sim \exp(\alpha_1)$ and $v_1 = |g_1|^2 \sim \exp(\beta_1)$, we can obtain [31–34]

$$\Pr\left(\frac{|h_1|^2}{|g_1|^2} < \frac{\Upsilon_{th}}{I_p}\right) = \Pr\left(u_1 < \frac{\Upsilon_{th} v_1}{I_p}\right) \tag{14}$$
$$= \int_0^{\infty}\int_0^{\frac{\Upsilon_{th} v_1}{I_p}} f_{u_1}(u_1) f_{v_1}(v_1) \mathrm{d}u_1 \mathrm{d}v_1 \tag{15}$$
$$= \int_0^{\infty}\int_0^{\frac{\Upsilon_{th} v_1}{I_p}} \frac{1}{\alpha_1} e^{-\frac{u_1}{\alpha_1}} f_{v_1}(v_1) \mathrm{d}u_1 \mathrm{d}v_1 \tag{16}$$
$$= 1 - \int_0^{\infty} \frac{1}{\beta_1} e^{-\frac{v_1}{\beta_1}} e^{-\frac{\Upsilon_{th} v_1}{I_p \alpha_1}} \mathrm{d}v_1 \tag{17}$$
$$= \frac{\beta_1 \Upsilon_{th}}{\alpha_1 I_p + \beta_1 \Upsilon_{th}}. \tag{18}$$

Similarly, Let $u_2 = |h_2|^2 \sim \exp(\alpha_2)$ and $v_2 = |g_2|^2 \sim \exp(\beta_2)$, we can obtain

$$\Pr\left(\frac{|h_2|^2}{|g_2|^2} < \frac{\Upsilon_{th}}{I_p}\right) = \Pr\left(u_2 < \frac{\Upsilon_{th} v_2}{I_p}\right) \tag{19}$$
$$= \int_0^{\infty}\int_0^{\frac{\Upsilon_{th} v_2}{I_p}} f_{u_2}(u_2) f_{v_2}(v_2) \mathrm{d}u_2 \mathrm{d}v_2 \tag{20}$$
$$= \int_0^{\infty}\int_0^{\frac{\Upsilon_{th} v_2}{I_p}} \frac{1}{\alpha_2} e^{-\frac{u_2}{\alpha_2}} f_{v_2}(v_2) \mathrm{d}u_2 \mathrm{d}v_2 \tag{21}$$
$$= 1 - \int_0^{\infty} \frac{1}{\beta_2} e^{-\frac{v_2}{\beta_2}} e^{-\frac{\Upsilon_{th} v_2}{I_p \alpha_2}} \mathrm{d}v_2 \tag{22}$$
$$= \frac{\beta_2 \Upsilon_{th}}{\alpha_2 I_p + \beta_2 \Upsilon_{th}}. \tag{23}$$

By substituting (3) and (3) into (3), we can obtain

$$P_{out} = 1 - \left(1 - \frac{\beta_1 \Upsilon_{th}}{\alpha_1 I_p + \beta_1 \Upsilon_{th}}\right)\left(1 - \frac{\beta_2 \Upsilon_{th}}{\alpha_2 I_p + \beta_2 \Upsilon_{th}}\right) \tag{24}$$
$$= \frac{\alpha_1 \beta_2 I_p \Upsilon_{th} + \alpha_2 \beta_1 I_p \Upsilon_{th} + \beta_1 \beta_2 \Upsilon_{th}^2}{(\alpha_1 I_p + \beta_1 \Upsilon_{th})(\alpha_2 I_p + \beta_2 \Upsilon_{th})}. \tag{25}$$

Observing from (3), we can find that parameters α_1, α_2, β_1, β_2, I_p and Υ_{th} all affect the system outage probability. In order to verify the results of the proposed outage probability analysis, and reveal the effect of various parameters on the system outage probability, we provide some simulations in the following section.

4. Simulation

In this part, we provide some simulations to verify the effectiveness of the proposed analytical method. If not specified, we set $\alpha_1 = 2$, $\alpha_2 = 2$, $\beta_1 = 0.01$, and $\beta_2 = 0.01$. Besides, the tolerable interference power of the PU is set to 20dB, and the minimum threshold of the SNR is 20dB.

Fig. 2 and Table 1 present the outage probability versus Υ_{th} with $I_p = 10$dB and $I_p = 20$dB, where Υ_{th} changes from 0 to 10dB. From Fig. 2 and Table 1, we can see that the highly matched results between the analysis and the simulation confirms the accuracy of the proposed analytical method. Moreover, the outage probability increases as Υ_{th} increases. This is because that a higher value of Υ_{th} requires a higher SNR of the communication, which leads to an increase in the outage probability of the wireless transmission. In further, we also observe that the result with $I_p = 20$dB is better than that with $I_p = 10$dB. This phenomenon reveals that a higher tolerable interference power can help reduce the system outage probability and thus achieve a better system performance.

Table 1 Data for Fig. 2

Methods	I_p/dB	Y_{th}/dB					
		0	2	4	6	8	10
Simulation	10	0.001	0.0015	0.0025	0.004	0.0062	0.0098
	20	0.0853e-03	0.1587e-03	0.246e-03	0.4053e-03	0.6273e-03	0.98e-03
Analytical	10	0.001	0.0016	0.0025	0.004	0.0063	0.0099
	20	0.1e-03	0.1585e-03	0.2511e-03	0.398e-03	0.6307e-03	0.9993e-03

Table 2 Data for Fig. 3

Methods	α_1	I_p/dB					
		0	5	10	15	20	25
Simulation	1	0.1339	0.0457	0.0150	0.0048	0.0015	0.0005
	2	0.0931	0.0309	0.0099	0.0031	0.0010	0.0003
	3	0.0786	0.0258	0.0082	0.0026	0.0008	0.0003
Analytical	1	0.1342	0.0457	0.0148	0.0047	0.0015	0.0005
	2	0.0930	0.0309	0.0099	0.0032	0.0010	0.0003
	3	0.0783	0.0258	0.0083	0.0026	0.0008	0.0003

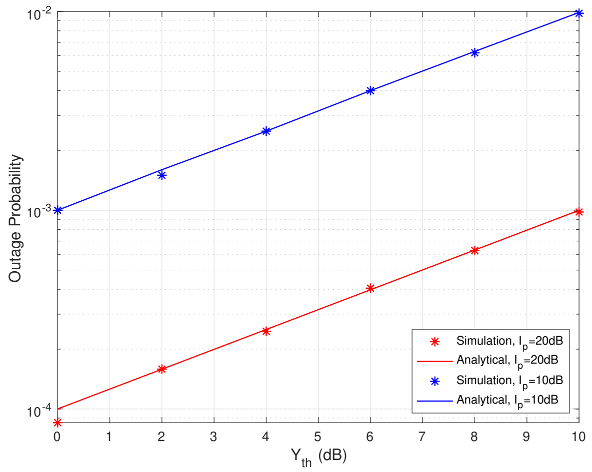

Figure 2. Outage probability versus Y_{th} with $I_p = 10$dB and $I_p = 20$dB.

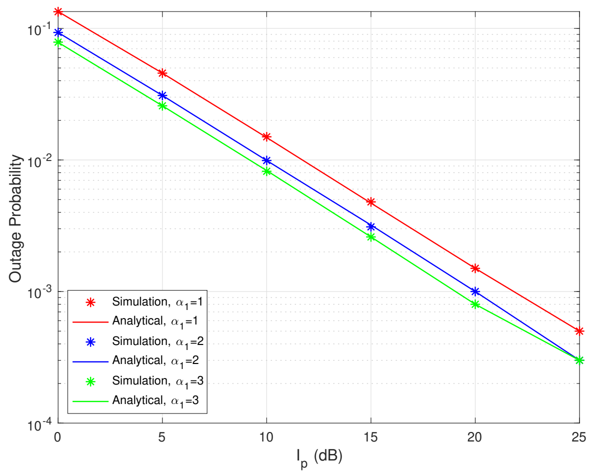

Figure 3. Impact of I_p on the outage probability with $\alpha_1 = 1$, $\alpha_1 = 2$ and $\alpha_1 = 3$.

Fig. 3 and Table 2 show the impact of I_p on the outage probability, where I_p varies from 0dB to 25dB, and α_1 takes value in the set $[1, 2, 3]$. As seen in Fig. 3 and Table 2, we find that the proposed analytical and simulation results are consistent, demonstrating the correctness of the analytical derivation. Moreover, we can see that as I_p increases, the outage probability decreases. The reason for this phenomenon is that, a larger tolerable interference power I_p helps improve the SNR of the transmission, resulting in a better communication performance. In addition, we also observe that as α_1 increases, the system performance improves. This is because that a larger α_1 yields a better channel condition from the source to the relay, which improves the SNR and promotes the system performance.

The influence of α_1 on the outage probability with $I_p = 10$dB and $I_p = 20$dB is shown in Fig. 4 and Table 3, where α_1 varies from 1 to 5. We can observe from this figure and table that, the analytical result is highly

Table 3 Data for Fig. 4

Methods	I_p/dB	α_1				
		1	2	3	4	5
Simulation	10	0.0148	0.0099	0.0083	0.0075	0.0069
	20	0.0016	0.0010	0.0008	0.0007	0.0007
Analytical	10	0.0148	0.0099	0.0083	0.0075	0.0070
	20	0.0015	0.0010	0.0008	0.0007	0.0007

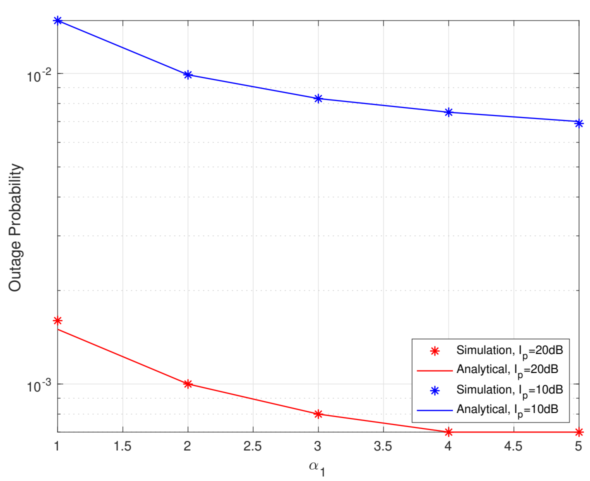

Figure 4. Influence of α_1 on the outage probability with $I_p = 10$dB and $I_p = 20$dB.

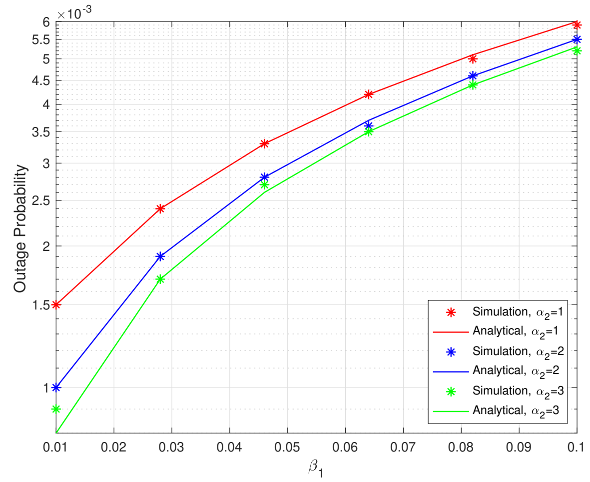

Figure 5. Impact of β_1 on the outage probability with $\alpha_2 = 1$, $\alpha_2 = 2$ and $\alpha_2 = 3$.

coincident with the simulation result. This illustrates the accuracy of the proposed analytical expression. Moreover, as α_1 increases, the outage probability decreases. This is because that a larger α_1 indicates a stronger channel gain from the source to the relay, which means a higher transmit SNR and results in a lower system outage probability. In further, the outage probability with $I_p = 20$dB is higher than that with $I_p = 10$dB. The reason is that a higher tolerable interference power I_p helps reduce the SNR and then improves the quality of the wireless communication.

Fig. 5 and Table 4 depict the impact of β_1 on the outage probability for the proposed analytical and simulation method, where β_1 ranges from 0.01 to 0.1, and α_2 takes value in the set [1, 2, 3]. From this figure and table, we can find that the proposed analytical results match well with the simulation results across all values of β_1 and α_2, thereby indicating the accuracy of the proposed analytical expression. Moreover, it is evident from the figure that all curves increase with a higher value of β_1, implying that the channel state has a significant impact on the system performance. Specifically, as β_1 increases, the SNR at the receiver deteriorates, resulting in a higher outage probability. In furthuer, a larger value of α_2 can improve the system performance, as it facilitates a better communication between the source and relay. Based on these results, it can be concluded that the proposed analytical expression accurately captures the system behavior and can be effectively used for performance evaluation.

5. Conclusion

Knowledge sharing was a critical aspect of machine learning and knowledge management, which also played an important role in regulating the power grid networks. Therefore, it was important to investigate the performance of knowledge sharing in the power grid networks. Motivated by this, we firstly investigated a typical power grid network with a knowledge sharing node, where the transmit power of users was constrained by the knowledge sharing node. We then measured the system performance by evaluating the system OP, where the analytical expression of OP was derived in detail. Finally, we presented some simulation and numerical results on the OP for the considered

Table 4 Data for Fig. 5

Methods	α_2	β_1					
		0.01	0.028	0.046	0.064	0.082	0.1
Simulation	1	0.0015	0.0024	0.0033	0.0042	0.0050	0.0059
	2	0.0010	0.0019	0.0028	0.0036	0.0046	0.0055
	3	0.0009	0.0017	0.0027	0.0035	0.0044	0.0052
Analytical	1	0.0015	0.0024	0.0033	0.0042	0.0051	0.0060
	2	0.0010	0.0019	0.0028	0.0037	0.0046	0.0055
	3	0.0008	0.0017	0.0026	0.0035	0.0044	0.0053

power grid networks with knowledge sharing, in order to verify the proposed studies on the OP. In particular, these results in this work showed that the knowledge sharing could help enhance the system OP performance efficiently.

5.1. Copyright

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