Application of Smart Grid Communication Service Flow Modeling Based on Poisson Model in Grid Operation

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ABSTRACT

The early Poisson distribution and Markov autoregressive models can no longer reflect the characteristics of smart grid business flow. The long correlation characteristics of burst flow are simulated by the heavy tail ON/OFF model with multi-source convergence, while the Poisson model with short correlation and no memory is used for random flow. The simulation results show that the synthesized flow still has a certain statistical self-similarity, and the coefficient $H$ decreases after synthesis and that the long correlation and burst of self-similar business flows will not be smoothed by the convergence and synthesis of the self-similar business flows with short correlation services. In the actual operation process, the station-level power grid will result in load aggravation and significantly affect the network performance when it acts in response to faults. Therefore, it is necessary to consider the changes of network performance under different burst degrees.

KEYWORDS

Burst, Communication, Flow, Grid, Modeling, Simulation, Smart

1. INTRODUCTION

The goal of a smart grid station level network is to realize the whole station monitoring, control, alarm, and information interaction. According to the system operation requirements, the main services in the network include data acquisition and monitoring control, operation locking, protection information management, etc. Its communication behavior and business data correspond to specific operation requirements, showing a certain degree of complexity. Monitoring experiments show that modern network traffic does not conform to the short correlation represented by Poisson distribution in the traditional model. Still, in fact, it is more in line with the long correlation in the statistical sense, which means that the burst transmission characteristics of network traffic are not the same.
as the traditional traffic model, and will not be easily smoothed (Debin, Ting, Li, & Yaowen, 2020; Domański, A., Domafska, J., Czachórski, T., & Klamka, J., 2017) due to the increase of statistical time scale. These complex characteristics of flow have a great influence on the design, analysis, and simulation of network. In the first mock exam, traditional flow models such as the Poisson Markov model cannot satisfy the real-time, accurate, and sudden information interaction requirements (Ni, J., Zhao, Y., & Shen, Z., 2017) in the actual operation of the network. Therefore, it is necessary to establish accurate mathematical models for its traffic according to various business characteristics. According to the research results of the literature (Wlodarski, P., 2020; Liang, Q., 2002; Gao L. B. & Su J. D., 2019), no matter how the network type, number of users, topology, service, and service type change, the actual network traffic generally has statistical self-similarity in most time scales.

Based on the study of data transmission characteristics of smart grid, this paper proposes a modeling method for station level communication traffic and analyzes the influence relationship between traffic and network performance through simulation.

The remainder of this paper is organized as follows. Section 1 presents the analysis of the service behavior of the smart grid station level network. Section 2 considers the communication model of the station level network, and nodes interact to generate business packets related to power grid operation and maintenance tasks. Section 3 presents the generation of self-similar business sequences. Loading of traffic model and communication simulation are given in Section 4. Finally, section 5 provides some concluding.

2. ANALYSIS OF SERVICE BEHAVIOR OF SMART GRID STATION LEVEL NETWORK

The main business data transmitted during the operation of the station level network can be divided into three categories: periodic, sudden, and random (Yang T., Hou Y. C. & Zhao L. Y., 2020; Hao W. J., Yang Q., & Li W., 2019; Liu E. W., 2010), as shown in Table 1.

Periodic messages such as monitoring host polling message, intelligent electronic device (IED) periodic upload or passive transmission to the station control layer switch message, such message transmission real-time requirements are high.

IED, fault and other event report and device status message (Wang L., 2017; Yan Y. H., 2010) uploaded by IED actively. Random messages, such as trip command, wave recording data sent between IED and monitor, event record file, etc (Dou X. B., 2010). Sudden messages (Lu Y., Li J., & Guo Q., 2018; Zhu Q., Y., 2014; Millán, G., 2021), such as event reports, control commands, displacement information, and file transmission generated after random events such as protection action and control, also have certain requirements for system delay.

Table 1. Characteristics of station-level network message classification

| Type                              | Source node | Target node               | Communication behavior                                                                 | Byte |
|-----------------------------------|-------------|---------------------------|----------------------------------------------------------------------------------------|------|
| Periodic message, high real-time requirements | IED         | Station level equipment   | Periodic timing message actively uploaded by IED, switch message passively transmitted to station control layer | 446  |
| Burst messages require high real-time performance | IED station level equipment | IED station level equipment | Protection action, event report, control command, displacement information, file transmission and other unexpected irregular messages | 190  |
| Random message                    | IED station level equipment | IED station level equipment | Trip command, customization, recording, event recording, document, etc. sent between monitoring equipment and IED | 512k |
Periodic message is generated by fixed time interval, message length is fixed, real-time requirement is high, and its data flow simulation is relatively simple. Random messages are triggered by external events (equipment failure, human operation), which can be simulated by Poisson distribution model. The burst service message consists of switch tripping and closing, protection action and control command, displacement information, and file transmission. This kind of service message is short (Liu A., & Sun B., 2019; Liu A., & Sun B., 2019; Nguyen M. T., & Kim K., 2020).

3. NODE TRAFFIC MODELING

In the communication model of station-level networks, nodes interact to generate business packets related to power grid operation and maintenance tasks. The business flow in the network comes from the aggregation of different nodes and different communication services, which has the typical burst and randomness in the failure period, and the business particularity in general. This paper will carry out traffic modeling according to its characteristics.

The principle is shown in Figure 1. From the Figure 1, In the model, according to the essential characteristics of network traffic behavior, communication service packets and corresponding aggregated traffic will be generated from three aspects to simulate the interactive data conforming to the characteristics of network traffic as much as possible. All kinds of services are converged in the node to get the required traffic sequence.

1. Periodic service flow: In the model, the service is formed by equal interval and fixed period, and the message size is the same. In order to simplify the simulation, the unified International Electrotechnical Commission (IEC)61850 standard message is adopted.

2. Random traffic flow: The arrival of random packets has the characteristics of noncorrelation, so Poisson distribution is used as the traffic arrival model. The arrival interval $T_n$ obeys the expected value of $\lambda$. The mathematical description is as follows (1):

$$T_n = 1 - e^{-\lambda t}, \geq \lambda, t \geq 0$$  \hspace{1cm} (1)

3. Emergent service: Self-similar mathematical model is used to describe it. According to the physical meaning of similar self-description, if the traffic is in the behavior state with burst

![Figure 1. Business flow generation process](image-url)
characteristics in the previous period, the probability that it is still in the burst characteristics in the subsequent period will be higher than the probability of nonburst. There is a long-range correlation statistical characteristic in the arrival time of burst traffic, which can be described by mathematical self-similarity. It is an important characteristic of traffic flow analysis.

Depending on the operational behavior of IED or station-level nodes, multi-service aggregation models or single-service models can be loaded as needed.

4. GENERATION OF SELF-SIMILAR BUSINESS SEQUENCES

Self-similar model can describe the burst traffic generated in the system. Self-similar traffic burst generation and batch arrival can easily lead to more congestion and queue delay in the short term. The traditional network design and performance analysis based on the Poisson model cannot describe traffic flow characteristics and correctly estimate the impact of communication traffic on network performance. Therefore, choosing appropriate mathematical tools, establishing accurate and easy to implement smart grid business flow model, and more targeted network planning and design have certain research significance (Zhong W., Yu N., Ai C., 2020; Popoola, S. I., Adebisi, B., Hammoudeh, M., Gui, G., & Gacanin, H., 2020; Wu, Q., Fan, X., Wei, W., & Wozniak, M., 2020).

4.1 Mathematical Definition of Self-Similarity

The sudden traffic flow of smart grid can be regarded as a discrete time series. Given that the discrete-time stochastic process \( X_t \) \( \sim \) \( \{x_j, t = 0,1,2,...\} \), \( x_j \) is the number of network traffic flow entities arriving in \( t \) unit time. Definition of \( m \) reaggregate sequence \( X^{(m)} \) on stationary time series \( X \), \( X^{(m)} = \{X_k^{(m)}, k = 0,1,2,...\} \), the new sequence generated by calculating the mean value of each aggregation time series:

\[
X_k^{(m)} = \frac{1}{m} \sum_{i=km-(m-1)}^{km} x_i
\]  

The \( k \) order auto-correlation function \( r(k) \) of the aggregation time series is observed. If the sequence correlation coefficient after clustering in each scale block is consistent with the original sequence, that is, the statistical characteristics of the process after compression, such as mean \( \mu = E[X_t] \), variance \( \sigma^2 = E[(X_t - \mu)^2] \), auto-correlation function \( r(k) = E[(X_t - \mu)(X_{t+k} - \mu)]/\sigma^2, k = 1,2,3,... \)

The data process is a self-similar process.

The generalized stationary self-similar process is mathematically described as follows: the discrete random process \( X \) with parameter \( \beta (0<\beta<1) \) is self-similar process, and if \( m = 1,2,... \), variance \( \text{Var}(x^{(m)}) = \text{Var}(x)/m^\beta \), auto-correlation function \( r^{(m)}(k) = r_x(k) \), and \( H = 1-\beta/2 \) at each time aggregation sequence scale.

In the formula, \( H \) is the Hurst self-similarity coefficient, and the auto-correlation function shall satisfy \( R(k) = H(2H-1)k^{2H-2} \). When \( 0.5<H<1 \), the sequence \( X \) is a self-similar sequence, \( H = 1-\beta/2 \). The closer the value of this parameter is to 1, the higher the self-similarity of this process will be.

4.2 Generation Method of Self Similar Traffic

The ON/OFF model with heavy tailed distribution can be used to simulate the occurrence of self similar traffic (Priya, M. D., Suganya, T., Malar, A. C. J., Dhiyvaprabha, E., Prasad, P. K., & Vardhan, L. V., 2020; Abbasloo, S., Xu, Y., & Chao, H. J., 2020; Zheng, J., Yang, L., Pan, C.,...
It is found by data analysis that the distribution of file length, ON/OFF cycle length, network terminal working time, waiting time, file transmission time and packet generation interval in the communication network are all in line with a Heavy-tailed distribution characteristic of infinite variance, which is an important root cause of self-similarity of traffic. Therefore, the generation of self-similar flow sequences can be approximated by Heavy-tailed distribution.

Heavy-tailed distribution is mathematically described as:

$$P(X>x) \sim x^{-\alpha}, \quad x \to \infty, \quad 0<\alpha<2 \tag{3}$$

The tail of this distribution follows the rule of the energy distribution and decays hyperbolically, which decays much more slowly than the tail of the distribution with exponential decay. The parameter $\alpha$ is called the shape parameter and describes the weight of the trailing distribution. The smaller the parameter $\alpha$, the heavier the trailing of the distribution curve. Pareto distribution is a typical heavy-tailed distribution, and the mathematical description of its distribution function is as follows:

$$F(x) = 1 - \left(\frac{k}{x}\right)^\alpha, \quad f(x) = \frac{\alpha}{k} \left(\frac{k}{x}\right)^{\alpha+1}; \quad (x>k, \quad \alpha>0) \tag{5}$$

mean value: $E(x) = \left(\frac{\alpha}{\alpha - 1}\right)^{\alpha-1}, \quad (\alpha>1) \tag{6}$

When $\alpha \leq 2$ is in the formula, the Pareto distribution has an infinite variance, while if $\alpha<1$, the distribution has an infinite mean. As $\alpha$ decreases, the probability is mostly concentrated in the tail. In the process of data transmission duration, if any one of the ON or OFF duration distributions is a heavy-tailed distribution, then the convergence flows of the infinite service sources will show self-similar characteristics. The degree of self-similarity is closely related to $\alpha$: The smaller the $\alpha$ value is ($1<\alpha<2$), the greater the degree of self-similarity is $H=(3-\alpha)/2$.

ON/OFF model describes the most basic behavior of network data sources, can explain the cause of self-similar traffic and can be applied to the specific layer of the network to deal with specific problems. The research results on the influence of self-similar services on network performance show that the self-similar characteristics of business flows make the analysis of network performance more complex than the traffic model with short correlation characteristics. As the degree of self-similarity increases, network performance will perform worse in packet loss rate, throughput, and delay performance.

### 5. LOADING OF TRAFFIC MODEL AND COMMUNICATION SIMULATION

#### 5.1 Establishment of Communication Network Simulation Model

Traffic modeling is closely related to network system performance simulation and evaluation, which is a very important link. This paper studies the business flow model of a smart grid station-level network and analyzes the network performance, including throughput, average network response time, packet loss rate, etc., by changing different business flow parameters. OPNET MODELER14.5 software is used for simulation, and the model building is divided into the network, node, and process layers.
5.2 Simulation Experiment Description

5.2.1 Network Model Construction

Assuming that the simulated station-level communication network is a 16-node unit, without considering operational tasks, hierarchical relations, priority levels, and other factors, the established network topology is shown in Figure 2. It includes 15 IDE nodes, 1 monitoring node S1, and a channel switching rate of 100Mbit/s.

5.2.2 The Node Model

The subnet node model is shown in Figure 3. Self-similar source and Possion source nodes are defined to generate self-similar burst traffic with long correlation characteristics and memory-free Poisson random traffic flow, respectively. The Poisson sequence can be obtained by the Possion model of the source node, and the heavy-tailed ON/OFF sequence gives the self-similar sequence with multi-source convergence. The Queue module in the node model is responsible for the statistical queuing processing of the aggregate sequence.

As shown in Table 2, IED0-IED14 nodes are set at a fixed interval of 0.02s, S1 is the target node, and the reported data is sent periodically. Set S1 node and the source module of IDE1-IDE8 to generate random business packets with a Poisson distribution, and the packet generation interval $\lambda$ is 10ms, and the packet size obeys the negative exponential distribution of 0.3kbyte/s on average. Self-similar source models of IDE4-IDE14 and S1 were set with Pareto$(k, \alpha)$ ON/OFF duration distribution and a simulation time of 5min.

In the experiment, by changing the value of the shape parameter $\alpha$ of the ON/OFF duration distribution, different self-similarity coefficients $H$ were obtained so as to investigate the variation rule of network performance under various burst intensities.

5.3 Analysis of Simulation Results

The network performance indicators under different $\alpha$ values are shown in Table 3. According to the corresponding results in Table 3, as the $H$ value gradually increases from 0.6 to 0.9, the burst

Figure 2. The topological structure of station-level subnet
Table 2. Simulation parameter settings

| Business types     | Packet size (kB) | Contract interval (s) | Distribution function |
|--------------------|------------------|-----------------------|-----------------------|
| Cyclical service   | 0.5              | $\lambda=0.02$        | Fixed interval        |
| Random service     | 0.3              | $\lambda=0.01$        | Poisson distribution  |
| Emergent service   | 0.5              | ON/OFF distribution   | The theory of $H$     |
|                    |                  | Pareto(0.1,1.6)       | Self-similar distribution |

Table 3. Network performance indexes under different $\alpha$ values

| ON/OFF timedistribution | The theory of $H$ | Network latency (ms) |
|-------------------------|-------------------|----------------------|
| Pareto(0.1,1.6)         | 0.60              | 0.113                |
| Pareto(0.1,1.4)         | 0.80              | 0.116                |
| Pareto(0.1,1.2)         | 0.90              | 0.122                |
intensity gradually increases, leading to a gradual decline in the overall performance indicators of the network, such as average delay, packet loss rate, and load.

Figure 4 shows the network average delay performance results under different self-similarity coefficients $H$. The blue, red and green curves represent the change of $H$ delay from 0.6 to 0.9, respectively. When $H$ value is 0.9, the network delay reaches 0.122ms, and the network performance is the worst. This is because the self-similarity of burst traffic will bring long correlation and slow decay variance characteristics to the traffic sequence, resulting in the change of cell loss rate in the process of forwarding queuing in the form of heavy tail. And the limited capacity of the buffer will cause the change of the traffic-related structure, which will lead to the decline of various performance indicators.

5.4 Autocorrelation Analysis of Synthetic Sequence

As shown in Figure 5, this paper conducted autocorrelation analysis and statistics on the aggregation service sequence in the “queue” module. During the experiment, 15,000 continuous sample data
packets were counted each time, and the variance-time graph test method was combined to conduct statistical correlation analysis on the sample data. The obtained H-value test results of the synthesized business flow are shown in Table 4.

From the data in Table 4, it can be seen that the self-similarity coefficient H of all kinds of business convergence sequences is still distributed in (0.5, 1). It can be seen that the traffic volume obtained from node synthesis still has statistical self-similarity in a certain time scale, and the H value decreases after synthesis.

5.5 Simulation Conclusion

1. The experimental results show that the long-term correlation and burst of self-similar traffic flows will not be soothed by the convergence and synthesis of self-similar traffic flows and the statistical characteristics of self-similar traffic flow after synthesis still have strong self-similarity. The simulated traffic flow sequence generated by the model can well conform to the basic characteristics of the statistical characteristics of the station level network traffic flow, which verifies the validity of the traffic flow generation model.

2. The periodical message load of the station-level network is low, which has little impact on network performance. However, the response actions (such as the transmission of a large number of files) made in the event of random events (failure) will cause load aggravation and significantly affect network performance. Therefore, it is necessary to consider the performance of the station-level networks under different burst degrees to guide the network planning and design reasonably.

6. CONCLUSION

In this paper, the relevant business behavior and statistical characteristics of the smart grid during operation are analyzed, and a traffic modeling and network simulation method combining with its business behavior characteristics is presented. Experiments show that this method can better reflect the communication characteristics of station-level smart grids and reveal the network performance rules under different burst intensities. It can provide a reference for the analysis of network traffic characteristics, protocol design, and network configuration planning of smart communication networks.

The periodic message load of the station-level network is low, which has little impact on the network performance. However, in case of random events (failure), the response actions, such as the transmission of a large number of files and the transmission of various signals and commands, will aggravate the load and significantly affect the network performance. And because of the special working indicators of the smart grid, there are strict requirements on the real-time and reliability of information flow transmission. Therefore, it is necessary to consider the variation of station level

| Self-similar source | Possion source | Composite traffic flow $\hat{H}$ |
|---------------------|----------------|---------------------------------|
| $H = 0.7577$        |                | $H = 0.7131$                    |
| $H = 0.8040$        |                | $H = 0.7354$                    |
| $H = 0.8520$        |                | $H = 0.8219$                    |
| $H = 0.8570$        | $\lambda = 0.02s$ | $H = 0.8327$                    |
| $H = 0.8738$        |                | $H = 0.8431$                    |
| $H = 0.9076$        |                | $H = 0.8602$                    |
network performance under different burst degree, so as to guide the network planning and design reasonably. The future work is to improve the model of the smart grid while analyze the characteristics of the system more comprehensively.

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