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# Research on Voltage Sag Loss Assessment Based on a Two-Stage Taguchi Quality Perspective Method

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**Abstract:** Voltage sags resulting from symmetrical or asymmetrical faults pose a significant threat to power quality. In response to this challenge, a voltage sag loss assessment method based on a two-stage Taguchi quality perspective approach is proposed to address the quantitative analysis of voltage sag economic losses. Initially, using the Taguchi quality perspective method, single-index quality loss functions are separately established for voltage sag magnitude and fault duration. Subsequently, by introducing a comprehensive load tolerance curve, sensitivity parameters within the quality loss function are accurately calculated. This yields a deterministic model for voltage sag assessment. Building upon this, the relative impact of the two indices on voltage sag loss is evaluated using the quality loss function. Consequently, a comprehensive loss model under the influence of multiple indices is formed by integrating two single-index evaluation models. The simulation results indicate that this method can effectively assess the economic losses of voltage sags under the combined influence of multiple factors. Compared to the original economic loss assessment method, it improves quantitative accuracy by approximately 3.72%. Moreover, the method reduces the computational complexity of loss assessment through the consolidation of intervals with similar sensitivity parameters.

**Keywords:** economic assessment; quality loss function; sensitivity parameters; Taguchi quality perspective; voltage sag

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## 1. Introduction

With continuous socio-economic development, the usage of power-sensitive equipment is increasing, and the voltage sag problem is receiving more and more widespread attention [1,2]. Due to lightning, wind, external damage, power equipment insulation level reduction, and other factors, asymmetric faults such as single-phase grounding, two-phase grounding, and two-phase short-circuit will inevitably occur in the power system. It is also possible to have a symmetrical fault of three-phase short-circuit. Furthermore, the resulting voltage drop will affect the normal operation of power-sensitive equipment [3] and may cause serious economic losses [4,5]. Assessing the losses caused by voltage sag incidents will aid in formulating effective response measures, enhancing the reliability and robustness of the power system, reducing economic losses for users, and ensuring the quality and availability of the power supply [6].

The economic fallout from voltage dips encompasses a spectrum of losses, spanning production line shutdowns, data losses, compromised product quality, and damages incurred due to equipment malfunctions [7]. In the context of assessments based on actual measurement data, [8] proposed a user-centric approach for analyzing the economic losses of power quality. In [9], process-immune time is incorporated into the consideration of economic losses due to distribution network faults, representing a further refinement of the loss model. From an economic indicator perspective, [10] established a consequence model for voltage sag fault levels in sensitive equipment. As a practical matter, [11] developed a model assessing the impact of seasonal weather on predicting disturbances in power quality in distribution networks, representing a practical advancement in loss prediction methods under specific environmental conditions. The study by [12] proposed a low data-dependent assessment method for interruption probability in industrial processes, overcoming challenges related to logical relationships among various equipment in industrial processes through a heuristic search algorithm-based interruption probability solving method. To move forward a single step, [13] suggested optimizing and adjusting simulated loss values using BETA parameter correction based on empirical data. Combining prediction results with sag tolerance characteristics, [14] classified voltage sag risk levels, providing an evaluation that benefits from both ample simulation data and a method driven by actual measurements, making it more closely aligned with objective reality. The authors of [15] introduced an approach using fuzzy probability and possibility distribution to handle uncertainty, evaluating equipment tripping by transforming rigorously enforced statistical data into a fuzzy possibility distribution function. The above-mentioned studies can be categorized into two main types: combined assessment methods and fuzzy comprehensive assessment methods. While the combination assessment method is noted for its subjectivity and limited logical relationships [16], the fuzzy comprehensive assessment method faces challenges stemming from an unclear mapping between risk indicators and economic losses, thereby compromising assessment accuracy [15]. These inherent difficulties significantly impact the precision of assessment outcomes. However, a paradigm shift occurs when the improved fuzzy comprehensive assessment method is integrated with the change curve of process parameters. This integration not only enhances the adaptability of assessment results but also provides novel insights for evaluating transient losses in voltage. This innovative approach augments the discourse on the critical facet of power system analysis, offering valuable perspectives for the assessment of voltage transients.

The choice of assessment model building method—the Taguchi method [17]—as an experiment design and quality optimization method [18], provides new ideas and solutions for voltage-transient loss assessment [19]. The advantage of using Taguchi's method to assess the economic loss of a voltage-dropout event is that, compared to traditional methods, Taguchi's method does not need to subdivide and calculate the losses one by one according to the classifications of direct loss, restoration loss, and other losses that are difficult to quantify, but only needs to focus on the maximum loss at the time of the interruption, and then it can convert the loss toward the system interruption loss according to the degree of deviation of the status of the dropout and the system interruption [20]. The degree of deviation is expressed as a sensitivity parameter. Existing studies have mainly used the method of discounting the transient loss to the interruption loss by the transient drop amplitude as a constant or univariate functional relationship [21]. Obviously, the voltage-dropout loss model under the influence of multiple factors is more in line with the reality. Problems in the existing research on voltage sag loss under the influence of multiple factors focus on simplifying assumptions and lack of data. For example, in the study, it is assumed that the relationship between dropout amplitude and duration is linear and the effects on losses are independent of each other, i.e., they are regarded as separate variables [22] and their effects on losses were considered separately in the assessment process. This approach of looking at the amplitude and duration of the temporary drop independently ignores the possible nonlinear relationship and interaction effects between the two, as well as the combined effect of the two on the losses in real situations. In addition, existing studies usually assume the sensitivity parameter of the mass loss function under different states in single-indicator assessment models as a certain value empirically, and for multiple-indicator models, the expansion of dimensionality makes that the single certain value determined by the original empirical value can no longer approximately satisfy the actual conditions under more constraints. Therefore, the value of the sensitivity parameter in the quality loss function becomes the main factor limiting the establishment of the multi-indicator model, and how to refine the model assumptions on the basis of determining the value of the parameter is the key to establishing an optimal assessment model and improving the accuracy of the assessment of voltage drop loss.

Based on this, this paper proposes an economic assessment method for voltage transients based on a two-stage Taguchi quality view approach, aiming to address the threat to power quality brought about by the inputs of sensitive equipment in industrial processes and the economic loss brought about by voltage transients to the normal operation of industrial processes. In this paper, the methodology introduces the Taguchi quality loss function in two stages: in the first stage, the Taguchi quality loss function is introduced, and the effects of the transient drop time and fault duration on the losses are modeled, respectively. By introducing the signal-to-noise ratio, the interrelationships and interactions between different influencing factors are considered, but due to the nonlinear relationship between the influencing factors, it still may not be possible to completely eliminate the effects brought about by the factors being independent of each other. Therefore, the Taguchi quality loss function is introduced again in the second stage to assess the magnitude of the influence of the two parameters on the loss, respectively, and a comprehensive quality loss model is established in the case of inconsistent magnitude of the influence of multiple indicators on the loss. Through the assignment of the multivariate quality loss function, the combined effect of multiple influencing factors on the loss is more accurately reflected. The experimental results show that the method can effectively assess the economic loss level of voltage dips in the target system under the joint influence of multiple indicators.

## 2. Taguchi's Method

### *2.1. Taguchi's View of Quality*

Taguchi's view of quality is an important branch of Taguchi's method. The Taguchi view of quality recognizes that the quality of a product or process begins at the design stage and continues to improve during manufacturing and service. Taguchi's view of quality emphasizes the economic benefits of quality, which can be achieved by improving quality, which can reduce product or process variability, increase efficiency and productivity, and reduce costs [23].

Product quality characteristics refer to the inherent features of a product, process, or system related to requirements. From the perspective of measurable characteristics, products can be categorized into three types based on different target values: "larger is better" characteristics, "smaller is better" characteristics, and "nominal best" characteristics. In other words, the ideal states for these characteristics are +∞, 0, and a certain specified value k, respectively. The number of quality characteristic dimensions for measurable characteristics can only be a non-negative number.

### *2.2. Quality Loss Function*

In order to achieve a quantitative description of the mapping relationship between the magnitude of the deviation of a quality characteristic from the target value and the resulting economic loss, Taguchi's quality loss function for the quality view, in general form, is

$$L_i(x) = K_i \cdot F_i(x - A_i) \tag{1}$$

where $i \in \{1, 2, 3\}$, representing the look-ahead, small, and visual characteristics, respectively; $x$ is the quality characteristic; $A_i$ is the target value; $x$-$A_i$ is the deviation of the quality characteristic from the target value; $F_i$ (-) is a functional expression describing this deviation; and $K$ is the maximum value of loss caused by the deviation of the quality characteristic $x$ from the target value.

$$A_i = \begin{cases} +\infty, i = 1 \\ 0, i = 2 \\ N^+, i = 3 \end{cases} \tag{2}$$

Common quality loss functions are:

(1) Mean square error loss function

The mean square error loss function calculates the squared error between the predicted value and the true value and averages it out, also known as the quadratic mass loss function.

$$L_i(x) = \begin{cases} K_1 \cdot (1/x^2), i = 1 \\ K_2 \cdot x^2, i = 2 \\ K_3 \cdot (x - A)^2, i = 3 \end{cases} \quad (3)$$

where $(x\text{-}A)^2$, $x^2$, and $1/x^2$ reflect the degree of proximity of the quality characteristics to the target value, i.e., the degree of fluctuation of the quality characteristics of the lookout, lookout small, and lookout large, respectively.

(2) Inverse normal mass loss function

The inverse probability mass loss function is a loss function used to evaluate classification models. The basic idea is to view the classification problem as a probability distribution function, where each sample has a probability value indicating the probability that it belongs to each category. For a classifier, its goal is to make the predicted probability distribution function as close as possible to the true probability distribution function. Its general form is:

$$L(x) = K\left[1 - \frac{\pi(x)}{m}\right] \quad (4)$$

where: $\pi(x)$ is the probability density of the random distribution of the mass characteristic $x$, and $m$ is the upper definite bound of $\pi(x)$.

For the normal distribution there is

$$\pi(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-A)^2}{2\sigma^2}} \quad (5)$$

Thus an upper definite bound for $\Pi$(x) can be computed:

$$m = \frac{1}{\sqrt{2\pi}\sigma} \quad (6)$$

Therefore, the inverse normal mass loss function is:

$$L(x) = K \cdot [1 - e^{-\frac{(x-A)^2}{2\sigma^2}}] \quad (7)$$

Unlike traditional loss functions, the inverse probability mass loss function focuses on assessing the difference between the predicted distribution and the true distribution, rather than the specific values of the predicted distribution. Specifically, it calculates the ratio between the predicted distribution and the true distribution for each category, which can be thought of as a weight for each category that is used to adjust for the effects of different categories in an unbalanced dataset.

In addition to the above two methods, there are other quality loss functions such as the cross-entropy loss method and the logarithmic loss method. In contrast to the above methods, the inverse normal quality loss function is advantageous in that it can handle unbalanced datasets and can focus more on the predictive performance of a few categories. In addition, it does not need to explicitly define the category weights because these weights can be automatically inferred from the data set.

### *2.3. Integrated Approach*

Signal-to-noise ratio $\eta$ is an important indicator to reflect the stability of product quality. $\eta$ represents dimensionless data; the larger the value, the more stable the product quality, and the smaller the loss caused.

Let us assume that the value of the quality characteristic of the product is a random variable, its mathematical expectation is $\mu$, its variance is $\sigma^2$, and there exists a target value

A. For the value of the product characteristic $x$, it is desirable that $\mu$ = A and that $\sigma^2$ is as small as possible.

$$\eta_i = \begin{cases} 10\log(\sigma^2+\mu^2), i=1 \\ 10\log(\frac{1}{\sigma^2+\mu^2}), i=2 \\ 10\log(\mu^2/\sigma^2), i=3 \end{cases} \tag{8}$$

The assignment is accomplished based on the signal-to-noise ratio values. The mathematical expectation of the $\eta$ value in the same row is taken as the reciprocal, the values obtained at different amplitudes are summed, and the values in each row are compared with the sum to obtain the magnitude of the contribution of the transient amplitude to the fluctuations.

$$\omega_i = \frac{1}{\eta_i} \Big/ \sum_{j=1}^{n} \frac{1}{\eta_j} \tag{9}$$

*2.4. Quality Loss Function Model with Multiple Indicators*

From the definition of the function and the objective reality, it may be assumed that the overall quality obeys an n-dimensional normal distribution, i.e., Y~$N_n$ ($\mu$, $\Sigma$), where $\mu$ is the overall mean vector and the positive definite matrix $\Sigma$ is the covariance matrix

$$\mu = \begin{pmatrix} \mu_1 & \mu_2 & \cdots & \mu_3 \end{pmatrix} \tag{10}$$

$$\Sigma = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{pmatrix} \tag{11}$$

Thus the $i$th quality feature $y_i$ also obeys normal distribution, i.e., $y_i$ ~N($\mu_i$, $\sigma_{ii}$). Therefore, according to the size of the signal-to-noise ratio, based on the size of the "contribution" of different quality indicators to the fluctuations, different weights $\lambda$ can be assigned, and the assignment method is the same as the $\omega$.

The loss function for the $i$th quality indicator is determined based on the economic significance of the indicator and its quality characteristics. Thus, the multivariate quality loss function is:

$$L(y_1, y_1 \cdots y_{\mathrm{n}}) = \sum_{i=1}^{n} \lambda_i L(y_i) \tag{12}$$

## 3. Tolerance Curves for Sensitive Equipment

The occurrence of voltage sag events with a specific duration and magnitude may or may not lead to a system interruption. The numerical probability of this occurrence is inherently linked to the proportion $\gamma$ of economic losses caused by incidents characterized by these features. Therefore, the economic loss situation can be characterized by solving for the probability of voltage sag events leading to a system interruption under different conditions.

Different sensitive equipment have different electrical characteristics, and accordingly the degree of tolerance to voltage dips is also different, so the sensitive load tolerance curve there is uncertainty region. According to the sensitive load tolerance curve, the sensitive equipment working area is divided into normal operation area, uncertainty area, and fault area shown in Figure 1. When the voltage sag eigenvalue index is above curve 1, the equipment is not affected by the transient drop, and the failure rate is 0. When the transient drop eigenvalue index is below curve 2, the equipment cannot operate, and the failure rate is 1. The intermediate region between curve 1 and curve 2 cannot determine the operation of the equipment, and it is necessary to assess its probability [24].

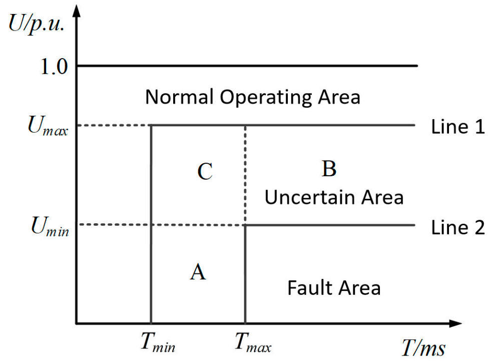


**Figure 1.** Uncertain region of sensitive load tolerance curve.

According to the different influencing factors, the uncertainty region can be further divided into three parts, $A$, $B$, and $C$, where the equipment failure rate in region $A$ is a one-dimensional function about the transient time T, and the failure rate is proportional to T. Thus the failure probability model for region $A$ can be obtained:

$$P_A = \frac{T - T_{\min}}{T_{\max} - T_{\min}}, (U, T) \in A \tag{13}$$

The equipment failure rate in region $B$ is a one-dimensional function about $U$, and the failure rate is inversely proportional to the square of $U$. Thus the failure probability model for region $B$ can be obtained:

$$P_B = \frac{U_{\max}^2 - U^2}{U_{\max}^2 - U_{\min}^2}, (U, T) \in B \tag{14}$$

The failure rate of region $C$ is a two-dimensional function with respect to $U$ and $T$. Thus the failure probability model for region $C$ is:

$$P_C = P_A P_B = \frac{T - T_{\min}}{T_{\max} - T_{\min}} \times \frac{U_{\max}^2 - U^2}{U_{\max}^2 - U_{\min}^2}, (U, T) \in C \tag{15}$$

Based on the above analysis, the failure rate of the sensitive equipment on the load side can be obtained as the severity of voltage dips on the load side, i.e.,

$$E = \sum P_i \alpha_i \tag{16}$$

where $\alpha_i$ is the percentage of sensitive device $i$ in the load side.

Based on the sensitive load withstand curve and the voltage withstand capability of the sensitive equipment, it is possible to calculate the probability that a transient event with a fault duration of any value and a transient drop amplitude of any value may lead to a system interruption, i.e., the value $\gamma$ of the ratio of the economic loss corresponding to the maximum loss when an interruption occurs within any given time and amplitude range.

There is a relationship between this ratio value and the sensitivity parameter [25]:

$$\sigma^2 = -\frac{(x - A)^2}{2 \ln(1 - \gamma)} \tag{17}$$

In summary, the solution of the key parameter $\sigma^2$ for calculating the voltage-transient loss in Taguchi's quality view can be realized by using the sensitive load tolerance curve and the voltage tolerance capability of the sensitive equipment.

## 4. Economic Evaluation Process of Voltage Dips

The process of economic evaluation of voltage transients is shown in Figure 2, as described below.

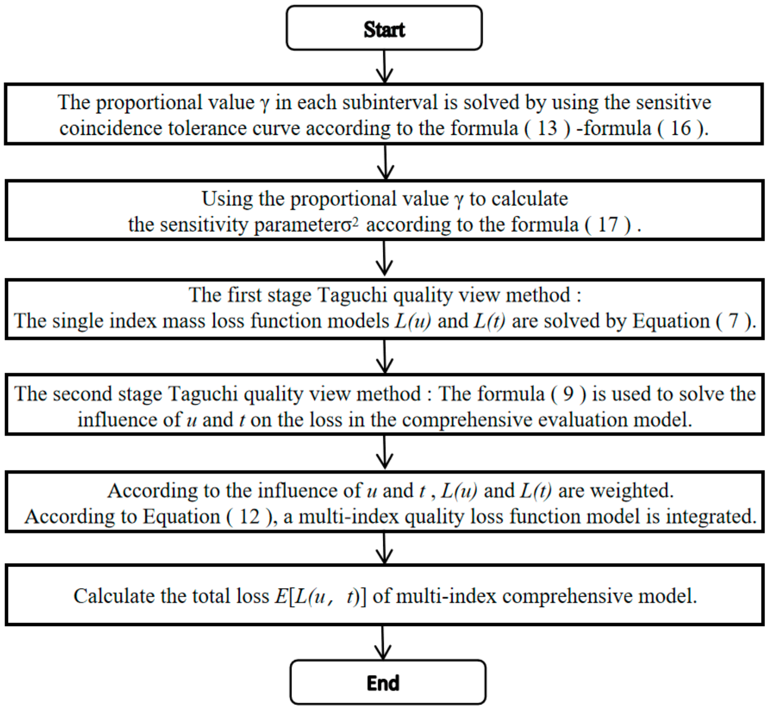


**Figure 2.** Flowchart for economic evaluation of voltage dips.

(1) In the first stage of Taguchi's quality view, based on Equation (7), the quality loss functions $L(u)$ and $L(t)$, are solved for the voltage-transient economic loss with respect to the transient amplitude and fault duration, respectively.

The solution steps include:

a. Establishment of single-index models: Utilizing the Taguchi quality perspective, single-index quality loss functions $L(u)/L(t)$ are developed separately for sag magnitude and fault duration. These functions are employed to depict the losses incurred by deviations from the target values at varying degrees.
b. Continuous processing: According to the voltage-transient density index of the target power system, obtain the continuous type probability distribution function $F(u)/F(t)$ and the probability density function $f(u)/f(t)$.
c. Discrete calculation: Firstly, select the unit length of transient drop amplitude and fault duration, and divide the evaluation range into several subintervals of equal length according to this setting; use the probability density function obtained from the continuous processing to calculate the mean and variance in each unit amplitude/time.
d. Weight calculation: Using Equations (8) and (9), substitute the mean and variance within each amplitude/time subinterval to calculate the weight $\omega$ of each amplitude/time subinterval.
e. Proportional value $\gamma$ solution: Using Formulas (13) to (15), calculate the probability of failure in each region of each sensitive load tolerance curve combined with the system of each sensitive load share, and use Formula (16) to further calculate the probability of failure in the system within the amplitude/time subinterval; that is, the range of interruptions occurring when the corresponding economic loss accounted for the proportion of the maximum loss of the value of the proportion of $\gamma$.

f. Sensitivity parameter $\sigma^2$ solution: Introduce the continuous function again and use Equation (17) to integrate and solve the sensitivity parameter of the mass loss function $L(u)/L(t)$ in each time t/amplitude $u$ subinterval.

g. Establishment of deterministic model: Incorporate the critical parameters obtained from the aforementioned steps into the quality loss functions $L(u)/L(t)$ to derive the single-index deterministic model.

(2) In the second stage of Taguchi's quality view, again utilizing Taguchi's quality view, the magnitude of the impact of the two parameters of transient drop amplitude and duration on the loss is quantified according to Equation (9), respectively. The combination of the two single-indicator assessment models is realized by assigning weights to each of them, so as to establish a comprehensive quality loss model under the influence of multiple indicators as shown in Equation (12).

The specific realization is as follows: the third use of the probability density functions $f(u)$ and $f(t)$, respectively, to calculate the transient drop amplitude and fault duration under the entire definition domain of the expectation, the variance, and thus the use of the signal-to-noise ratio and the calculation of weights. A quality loss function model with multiple indicators is established.

(3) The expected value of the voltage-dip economic loss function is then used to characterize the level of voltage-dip economic loss for that time period. Based on Equation (25), the economic loss under the joint influence of the amplitude of the sag and the duration of the fault is calculated.

## 5. Example Analysis

Tests were conducted using the IEEE 39-node test system, the structure of which is shown in Figure 3.

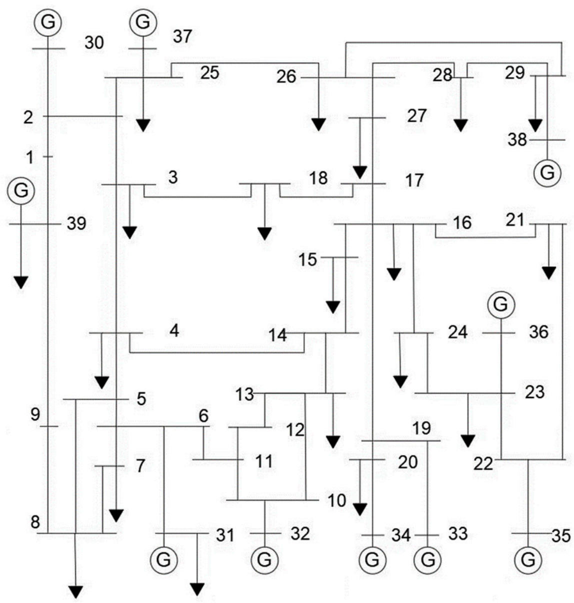

**Figure 3.** IEEE 39-node system architecture.

The load distribution parameter is set to be 0.5 and the number of Monte Carlo simulations is 5000 to obtain the voltage sag density metrics as shown in Table 1.

The total load of load point 15 is 140.5 MW, where the ratio of PC, ASD, PLC, and insensitive equipment is 1/15, 1/5, 1/5, 8/15, respectively. Knowing that the cost of interruption of sensitive loads counted under this ratio is USD 0.5363/kW, the maximum value of economic loss for load point 15 is USD 75,350.15.

**Table 1.** Voltage sag density index of load point 15.

| Voltage Sag Magnitude | Fault Duration/s | | | | |
|---|---|---|---|---|---|
| | **0.0~0.2** | **0.2~0.4** | **0.4~0.6** | **0.6~0.8** | **>0.8** |
| 0~10% | 0 | 0 | 0.023 | 0.031 | 0.012 |
| 10~20% | 0 | 0 | 0.041 | 0.078 | 0.031 |
| 20~30% | 0 | 0.003 | 0.073 | 0.121 | 0.061 |
| 30~40% | 0 | 0.005 | 0.073 | 0.102 | 0.069 |
| 40~50% | 0.003 | 0.007 | 0.064 | 0.138 | 0.081 |
| 50~60% | 0.017 | 0.027 | 0.217 | 0.462 | 0.254 |
| 60~70% | 0.074 | 0.105 | 0.409 | 0.750 | 0.384 |
| 70~80% | 0.125 | 0.241 | 0.700 | 1.106 | 0.649 |
| 80~90% | 0.161 | 0.331 | 0.576 | 0.698 | 0.352 |

## *5.1. Solving the Mass Loss Function*

The first stage of the Taguchi mass-viewing method is used to obtain the mass loss functions $L(u)$, $L(t)$ under the influence of transient drop amplitude and fault duration, respectively.

An example of this is the quality loss function $L(t)$ of the voltage-transient economic loss with respect to fault duration.

### 5.1.1. Continuous Type Conversion of Discrete Interval Data

Taking load point 15 as an example, its voltage sag density data are studied, and the continuum type probability distribution function under different transient drop amplitudes are fitted separately using numerical analysis, and from this, the probability density function of voltage sag is calculated.

$$\begin{aligned} f(t) = & -22.4336t^4 + 20.6672t^3 + 2.9340t^2 \\ & -2.0109t + 0.3474 \end{aligned} \quad (18)$$

Further, a continuous two-dimensional probability density function may be calculated based on a quality loss function $f(t)$ for voltage-transient economic losses with respect to fault duration and a loss function $f(u)$ with respect to transient amplitude:

$$f(u,t) = f(u) \cdot f(t) \quad (19)$$

The probability density metrics of voltage transients after the continuumization process are shown in Figure 4.

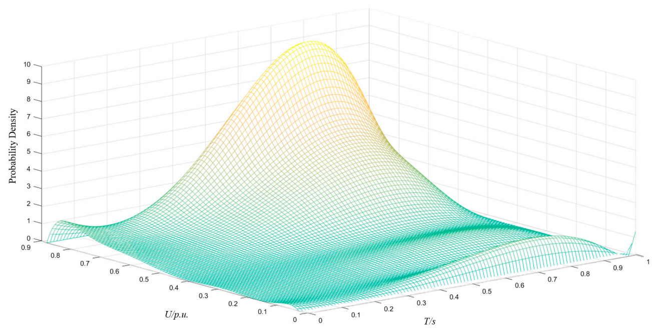


**Figure 4.** Continuous two-dimensional probability density function image.

Accordingly, we can visually analyze the trend of the probability of the occurrence of a transient-dropout accident with the transient-dropout amplitude and duration. As can be seen in Figure 4, the probability of voltage dips with low amplitude (0.6~0.9) is much larger than that with large amplitude (<0.6); the probability of a voltage dip being instantaneous (0~0.5 s) is much smaller than that of being temporary (0.5~1 s).

The distribution of voltage sag amplitude in Figure 4 is close to the probability density shown in Table 1, and the distribution trend is that most of the voltage sag amplitudes are above 0.6 and the duration is above 0.4 s, which shows that the fitting results are accurate.

#### 5.1.2. Calculation of Weights

It is worthwhile to select 0.1 p.u. and 0.2 s as the unit lengths of the transient drop amplitude and fault duration, respectively, and to divide the analyzed range of 0–0.9 p.u. and 0–1 s into 9/5 subintervals according to the transient drop amplitude/fault duration. The mean and variance of each subinterval are calculated by using the probability density function obtained from the continuum processing, and the weight $\omega$ of each unit amplitude is calculated accordingly; the related parameters in each subinterval of the transient amplitude calculated are shown in Table 2.

**Table 2.** Taguchi quality view parameters under different sag amplitude.

| Voltage Sag Magnitude | $EX_j$ | $DX_j$ | $\eta_j$ | $\omega_j$ |
|---|---|---|---|---|
| 0~10% | 0.045210 | 0.001603 | 9.055668 | 0.239014 |
| 10~20% | 0.133704 | 0.000837 | 13.293675 | 0.162817 |
| 20~30% | 0.257539 | 0.000728 | 19.592860 | 0.110470 |
| 30~40% | 0.343885 | 0.000798 | 21.707538 | 0.099709 |
| 40~50% | 0.461008 | 0.000794 | 24.277935 | 0.089152 |
| 50~60% | 0.557246 | 0.000779 | 26.007863 | 0.083222 |
| 60~70% | 0.653269 | 0.000826 | 27.132266 | 0.079773 |
| 70~80% | 0.754876 | 0.000818 | 28.428599 | 0.076136 |
| 80~90% | 0.824429 | 0.000161 | 36.251479 | 0.059706 |

#### 5.1.3. Calculation of Sensitivity Parameters

The regions of uncertainty in the operational status of each sensitive load are shown in Figure 5:

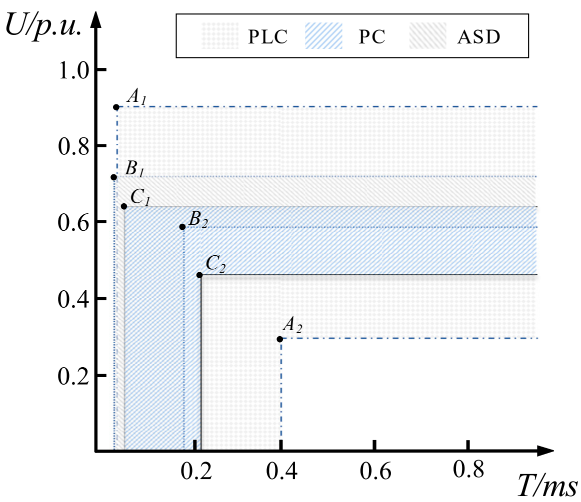


**Figure 5.** Uncertainty region of each sensitive load's operating status.

Of these, $A_1$ (0.02,0.90), $A_2$ (0.40,0.30), $B_1$ (0.015,0.71), $B_2$ (0.175,0.59), $C_1$ (0.04,0.63), and $C_2$ (0.205,0.46).

In Figure 5, the region enclosed by the two lines with turning points $A_1$ and $A_2$ (shaded square area) represents the uncertainty region of the sensitive device PLC. Similarly, the uncertainty regions for PC and ASD are indicated by two other shaded areas.

From the minimum and maximum values of the voltage tolerance amplitude of each sensitive load shown in Figure 5 and the minimum and maximum values of the equipment transient drop tolerance duration, the fault rate of each sensitive load in the region of uncertainty of the operating state calculated according to Equations (13) to (15) is shown in Table 3.

**Table 3.** Failure rates of sensitive loads in the region of uncertain operating conditions.

| Equipment Type | Failure Rate | | |
|---|---|---|---|
| | $P_A$ | $P_B$ | $P_C$ |
| PC | 0.1005 | 0.0894 | 0.0087 |
| ASD | 0.0800 | 0.0618 | 0.0049 |
| PLC | 0.1900 | 0.3500 | 0.0665 |

The probability that a device fails in each transient subinterval is:

$$G_i = S_i(A) \cdot P_A + S_i(B) \cdot P_B + S_i(C) \cdot P_C + S_i(e) \cdot 1 \tag{20}$$

where $i \in \{1, 2, 3\}$, representing PC, ASD, and PLC, respectively; $G_i$ denotes the probability of failure of the $i$th device in this staging range; $P_A$, $P_B$, and $P_C$ are the probabilities of failure of the device in the area of $A$, $B$, and $C$; $S_i$ $(A)$, $S_i$ $(B)$, $S_i$ $(C)$, and $S_i$ $(e)$ denote the magnitude of the proportion of the areas of A, B, C, and the area of the completely failed area to the total area in this staging range.

Since there are multiple loads in the system and the percentage of each load is different, the value of the discounted percentage of interruption loss $\gamma$ for the combined consideration of multiple loads can be calculated by the following equation:

$$\gamma = \sum_{i=1}^{4} G_i \cdot M(i) \tag{21}$$

where $M(i)$ represents the proportion of the $i$ middle load in the system.

The important parameters of the loss function under each amplitude subinterval calculated from Equation (21) and the sensitivity parameters obtained from Equation (17) are shown in Table 4.

**Table 4.** The parameters of mass loss function under different sag amplitudes.

| Voltage Sag Magnitude | $\gamma_j$ | ${\sigma_j}^2$ |
|---|---|---|
| 0~10% | 0.356347 | 0.378276 |
| 10~20% | 0.356347 | 0.378276 |
| 20~30% | 0.356347 | 0.378276 |
| 30~40% | 0.268961 | 0.531992 |
| 40~50% | 0.249164 | 0.581596 |
| 50~60% | 0.204019 | 0.730417 |
| 60~70% | 0.057408 | 2.819052 |
| 70~80% | 0.048089 | 3.381751 |
| 80~90% | 0.047054 | 3.458027 |

In summary, the loss function of voltage sag with respect to fault duration can be obtained as

$$L_1(t) = 75350.15 \times \sum_{j=1}^{9} \varpi_j \cdot (1 - e^{-\frac{t^2}{2\sigma_j^2}}) \tag{22}$$

From Table 4, it is noted that when the amplitude is in the range of 0 to 0.3 p.u., the sensitivity parameters of the three subintervals are the same, so they can be combined.

Similarly, the loss function of the voltage transient with respect to the transient amplitude is given as

$$L_2(u) = 75350.15 \times \sum_{k=1}^{5} \varpi_k \cdot (1 - e^{-\frac{(u-1)^2}{2\sigma_k^2}}) \tag{23}$$

where $\omega_k$ = [0.035515, 0.071567, 0.120867, 0.228174, 0.543877] and ${\sigma_k}^2$ = [5.855566, 1.046046, 0.555858, 0.555858, 0.555858]. Similarly, due to the same sensitivity parameters, the three subintervals within the fault duration of 0.4 to 1 s can be combined and processed.

### *5.2. Multi-Indicator Quality Loss Function Modeling*

The second stage of the Taguchi mass view is used to quantify the magnitude of the effect of the two parameters—transient drop amplitude and duration, respectively—on losses.

There are two important factors affecting the voltage-dropout loss in the model: dropout magnitude $x$, and fault duration $y$. Among them, $x$ has a look-ahead property with a target value of 1, and $y$ has a look-small property.

The magnitude of the effect of the variables $u$, $t$ on the transient loss calculated by using the Taguchi mass view method in combination with the expectation and variance of the transient loss amplitude calculated by the probability density function $f(u)$, $f(t)$ using Equations (8) and (9) is shown in Table 5.

**Table 5.** Algorithm parameters under multi-index.

| **Index** | ***EX*** | ***DX*** | $\eta$ | $\omega$ |
|---|---|---|---|---|
| $t$ | 0.631392 | 0.040943 | 3.569439 | 0.779779 |
| $u$ | 0.678700 | 0.025087 | 12.639008 | 0.220221 |

According to the influence of transient drop amplitude and fault duration on the transient loss, the transient drop amplitude and duration are given a weight of 0.779779 and 0.220221, respectively, and the weight is used to realize the combination of the two single-indicator models, which establishes a multi-indicator quality loss function model:

$$L(u,t) = 0.779779L_1(t) + 0.220221L_2(u) \tag{24}$$

Then the total loss of the node is

$$E[L(u,\mathrm{t})] = \iint\limits_D L(u,t)\cdot f(u,t)dtdu = \ \ 50521 \tag{25}$$

where $D$ denotes a region with a transient drop amplitude of 0 to 0.9 p.u. and a fault duration of 0 to 1 s.

### *5.3. Analysis of Results*

Taking into account both the voltage sag amplitude and duration's impact on sag losses, under the assumptions of the case study in this paper, the economic loss due to voltage sags is approximately USD 50,521. According to the reasoning process of the traditional method, if the characteristic matrix is transposed, meaning if duration is considered as the primary evaluation criterion, this method should be equivalent to the original method [25]. However, as is shown in Table 6, the results show that when using the traditional quality engineering theory to analyze this case study, the losses calculated based on sag amplitude (traditional method) or duration (variation of the traditional method) as the primary evaluation criteria are USD 48,643 and USD 79,343, respectively. It is evident that traditional methods yield significantly different loss calculation results for the same case study.

**Table 6.** Evaluation results of voltage sag losses under different methods.

| **Quality Engineering Theory and Methods** | | **Methodology of This Paper** |
|---|---|---|
| Voltage Sag Magnitude | Fault duration | 50,521 |
| 48,643 | 79,343 | |

This is because, in traditional assessment methods, simplifying assumptions are often made to streamline calculations. Firstly, the impact of sag duration and amplitude on losses is often independently considered. Secondly, the assessment model may only account for the influence of a single factor on voltage sag losses [20], or it might categorize sag duration into large intervals (instantaneous, temporary, short-term) and treat the influence factor of sag duration within each interval as a constant. In practical production, the majority of sag durations are less than 1 s. Therefore, when assessing losses for sag events within this time range, the influence factor of variable time is considered constant, essentially ignoring the impact of time changes on losses within this range.

The method proposed in this paper, from the perspective of model construction, comprehensively considers the impact of both sag duration and amplitude on economic losses, making the assessment more comprehensive.

From the computational results, the losses obtained using the method proposed in this paper fall between the values obtained using the traditional method (considering only the influence of sag amplitude) and its variation (considering only the influence of duration). Compared to the results of the traditional one-dimensional quality loss function, the relative error is 3.72%, and the deviation is less than 10%, within a reasonable range. This is because the method in this paper, based on the two-stage Taguchi quality perspective approach, accurately calculates the quality loss functions for each influence, considering the joint impact and relative importance of these two critical factors on losses. The essence of the method is to improve the accuracy of traditional methods and their variations, then obtain a weighted average of sag losses influenced by different factors. In practical applications, the correctness of the loss values obtained by this method can be verified by comparing them with the values obtained using traditional methods and their variations.

## 6. Conclusions

In this paper, for the problem of quantitative analysis of voltage-transient economic loss, a voltage-transient assessment method based on two-stage Taguchi's quality view is proposed on the basis of the simplified model assumed by the traditional one-dimensional mass loss function. The method not only overcomes the problem that the single multivariate mass loss function weakens the interrelationships among multiple influencing factors, but also gives an optimization scheme for the weakening assumption of the time factor in the traditional quality engineering theoretical approach. At the same time, the sensitivity conformity tolerance curve is used to realize the problem of taking values of sensitivity parameters in the construction of a multivariate loss function model.

The case analysis indicates that, through the aforementioned improvements, the accuracy of the assessment results has been enhanced by approximately 3.72%. In practical applications, the correctness of the loss values obtained through this method can be verified by comparing them with the losses calculated using traditional methods and their variations.

Simultaneously, in the assessment calculation process, by merging intervals with similar attributes and combining the use of discrete probability values and continuous probability density functions, the calculation precision was improved without excessively complicating the assessment process.

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## Nomenclature

| Symbols | Definitions |
|---|---|
| $A_i$ | target value |
| $F_i$ (-) | a functional expression describing this deviation |
| $K$ | the maximum value of loss caused by the deviation of the quality characteristic $x$ from the target value |
| $L_i$ (-) | loss function |
| $\pi(x)$ | the probability density of the random distribution of the mass characteristic $x$ |
| $m$ | the upper definite bound of $\pi(x)$. |
| $\eta$ | an important indicator to reflect the stability of product quality |
| $\omega_i$ | the contribution of the temporary decline value to the fluctuation |
| $\mu$ | population mean vector |
| $\Sigma$ | the covariance matrix |
| $\lambda$ | |
| $P_A$ | the fault probability of area A |
| $T$ | the transient time |
| $U$ | voltage |
| $E$ | the failure rate of the sensitive equipment on the whole load side |
| $\alpha_i$ | the percentage of sensitive device $i$ in the load side. |
| $\sigma^2$ | the sensitivity parameter |
| $\gamma$ | the value of the corresponding economic loss as a proportion of the maximum loss when an interruption occurs |
| $f$(-) | probability density function |
| $EX$ | mathematical expectation |
| $DX$ | variance |

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