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Dynamics Power Quality Cost Assessment Based on a Gradient Descent Method

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Abstract: The escalating demand for power load is increasingly prone to triggering power quality (PQ) issues, leading to severe economic losses. Aiming at reducing the economic losses, this paper focuses on the coordinated relationship between PQ and economic costs. Firstly, a multilayer multiple linear stepwise regression method is employed to screen PQ indicators, identifying harmonic and voltage deviation as the primary influencing factors of PQ. Secondly, a gradient descent optimization algorithm based on the Least Absolute Shrinkage and Selection Operator (LASSO) is proposed, enabling rapid computation of the minimum PQ cost. Finally, through validations of two case studies, the results confirm that the proposed method can rapidly calculate the minimum PQ cost based on real-time load demands, enabling the dynamic adjustment of PQ cost to meet the evolving needs of power system development.

Keywords: PQ cost; dynamic PQ index; LASSO; gradient descent; data driven

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1. Introduction

Due to rapid industrialization, there has been a significant increase in the diversity of electrical load types, particularly with the introduction of nonlinear and transient loads, leading to increasing energy demands. The integration of renewable energy resources into the grid with power electronics interfaces has further exacerbated power quality (PQ) issues, as it seeks to meet the rising energy demand.

PQ refers to the electrical power that drives an electrical load and its ability to function properly [1]. PQ issues affect the normal operation of electrical equipment, leading to economic consequences known as PQ cost, which significantly compromises the efficiency and cost-effectiveness of electrical systems [2]. The studies referenced in [3,4] demonstrate that the economic impact of PQ issues in the US amounted to USD 24 billion, while in EU-25 countries, it exceeded EUR 150 billion annually. System faults, types of loads, or environmental factors could cause PQ disturbances, such as voltage regulation issues, harmonics, noise, and frequency fluctuation. Some economic impacts caused by PQ disturbances were presented in Reference [5], focusing on a paper mill in eastern Croatia. Sharma et al. [6] focused on the quantification of economic loss caused by the poor PQ phenomenon, investigated several case studies, and proposed solutions towards poor PQ problems. The poor performance of PQ lead to significant financial losses for both companies and services [7], highlighting the critical importance of developing effective PQ management policies and rational methods.

The study of PQ events has become increasingly relevant, and references [8,9] conducted a comprehensive analysis of PQ challenges, proposing several approaches to analyzing power system signals in the presence of distortions caused by the power system [10].

The wavelet transform was first proposed for PQ events and has since become a hot research topic [11]. PQ issues encompass a range of disturbances, including short-term voltage interruptions, harmonic interference, voltage sags and swells, voltage fluctuations, flicker, and voltage unbalance [12,13]. PQ interferences could lead to interruptions in production processes, resulting in significant economic losses. Focusing on the challenges and harmonics affected by nonlinear loads, reference [14] investigated fuzzy-controlled photovoltaic and battery energy storage systems to improve the voltage situation. As power grids expand and renewable energy sources penetrate more deeply, it has become challenging to comprehensively evaluate PQ events using a single indicator. Consequently, there is a growing trend towards proposing comprehensive PQ management systems.

PQ events refer to sudden and occasional deviations from rated values or ideal waveforms in a very rapid process and constitute a significant portion of the economic cost associated with PQ. In recent years, with advancements in research, scholars have believed that different types of PQ events in power systems should be addressed with corresponding and rational management strategies. Aiming at this problem, Zhou et al. [15] established a model corresponding to the compressive treatment device and the related benefit measurement and clarified the correlation between economic benefits and device performance using the net present value method. Zhong et al. [16] used direct and indirect analysis methods for PQ economic investigation and concluded that a more precise conclusion could be obtained through direct analysis methods under the preconditions of data analysis detection and statistical analysis of data information. Yuan et al. [17] introduced a basic framework for the economic analysis of PQ in public distribution networks, detailed the evaluation method of PQ economic loss, and carried out a specific analysis using distribution network data. Under the backdrop of the COVID-19 pandemic, the study computed the direct financial cost resulting from fluctuations in network losses due to PQ issues, employing an observed case study and an investigatory method for PQ enhancement. This analysis demonstrated the influence of voltage unbalance on network losses, as discussed in Reference [18]. Sharma et al. [19] conducted an in-depth exploration assessing the economic benefits of grid storage using cost-efficiency methods, analyzed the influencing factors of energy storage efficiency in detail, and assessed the uncertainty of relevant parameters using the Monte Carlo method.

With an in-depth investigation in the field of PQ economic analysis, it was found that event-based PQ economic loss is a major component of the economic cost of PQ. Consequently, management policies should be tailored according to the different types of PQ problems in a power system. Reference [20] presents an investigative analysis on the application of wildfire monitoring sensors in monitoring PQ events. With the introduction of newly developed technologies into the investigation of electric power, deep learning methods are also being explored to address PQ issues, focusing on application [21], type of data, and learning technique [22]. Wei et al. [23] employed a principal component analysis with a support vector machine to monitor disturbances, reducing the curse of dimensionality in the original data, and also used an extreme learning machine to classify PQ events. Due to the traditional solution to PQ disturbance being time-consuming and not feasible, the hyperparameter optimization of machine learning algorithms was executed for detection and classification, in which noise was randomly prepared, and the simulation outperformed the other algorithms in accuracy in [24]. Gaussian mixture models were used to detect anomalies in PQ disturbance events to predict the occurrence of unusual clusters in weather condition in [25]. Ma et al. [26] proposed an optimal control method for a PQ-integrated compensation device for a distribution substation area, employing an intelligent control technique and a multilevel control strategy in order to achieve optimal control of the integrated PQ compensation device in the distribution substation area. Simulation verification and an example calculation were applied to verify the feasibility and effectiveness of the proposed method. Makasheva et al. [27] found that the main components of PQ cost were transient interruptions, voltage dips, and harmonic cost. Based on the data collected from recent surveys, the PQ cost during peak demand times was significantly higher than those during low demand times. A new coefficient for calculating time-varying PQ cost was introduced into the traditional static calculations, which allowed PQ cost to vary with real-time load demand and provided customers with more flexibility. Jin et al. [28] proposed a method for the economic evaluation of PQ using fuzzy neural networks, which was challenging to model accurately with traditional mathematical methods. Liu et al. [29] proposed a method for the economic evaluation of PQ based on the public information model and analyzed the economic cost of PQ. Additionally, the essential data needed for the economic evaluation of PQ were compiled and refined. Lei et al. [30] described the process of an economic evaluation of PQ management programs, which was divided into five steps, including the acquisition of raw data, data analysis, model building, calculation, and result analysis. The applicability of the four economic evaluation methods in PQ management was discussed in depth.

Although there is already a sophisticated evaluation system in place, there is a lack of real-time and accurate economic analyses. Thus, this paper proposes a gradient descent optimization algorithm based on the Least Absolute Shrinkage and Selection Operator (LASSO), integrating a new coefficient for PQ cost into traditional static calculations. This approach achieves dynamic coordination between PQ cost and real-time loads, enabling faster computation of the minimum PQ cost and thus enhancing the economic profitability of PQ. The main contributions of this paper are as follows:

- Screening of the important factors influencing PQ, such as voltage deviation and harmonics, as primary indicators of PQ cost.
- Introduction of a regression coefficient based on the minimum shrinkage operator and the gradient descent algorithm to dynamically calculate PQ cost.
- Presentation of case studies at home and abroad, demonstrating the effectiveness of the proposed scheme in reducing PQ cost.

The rest of the paper is organized as follows. The basic theories of multilevel multivariate linear stepwise regression and the formulation of PQ indicator assessments are introduced in Section 2. Case studies are presented in Section 3 to demonstrate the efficiency of the proposed method in reducing the economic loss in PQ. Section 4 concludes this paper.

2. Materials and Methods

2.1. Basic Theory of Multilevel Multivariate Linear Stepwise Regression

Due to the involvement of multiple factors in PQ issues, and the potential complex interrelationships and impacts among these factors, this study employs a multilayer multiple linear stepwise regression method for dynamic adjustment to accurately identify the primary factors with the most significant impact on PQ, aiming to enhance system stability and cost-effectiveness and achieve more efficient management of PQ.

Since Multiple Linear Regression (MLR) can be used to explore the quantitative relationship between individual explanatory variables and multiple explanatory variables, features can be extracted to solve multivariate covariate covariance problems. Considering that the explanatory variable is independent of the main influencing factors, it does not significantly impact other explanatory variables. In this case, multivariate linear stepwise regression can be used to eliminate non-major impact factors and construct the optimal regression model. The basic steps are outlined as follows:

- Introduction of the explanatory variables into the regression model for testing.
- Iteration over the above process until all results that pass the significance test (excluding non-significant variables) are filtered out.

The equation for the algorithm is described as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_k X_k + \mu \tag{1}$$

where Y is the dependent variable; X_1, X_2, ..., X_k are the independent variables; k is the number of explanatory variables; β_i is the regression coefficient; and μ is the unobservable disturbance term.

The stepwise regression method introduces or eliminates only one independent variable at each step, which depends on the F-test or correction coefficient of its partial regression sum of squares. Assume that there are $m-1$ variables. Then, introduce variable X_j to calculate the regression sum of squares SS_s and residual SS_r, calculating the regression sum of squares without the variable X_j and the corresponding partial regression sum of squares $SS_{s(-j)}$. The test statistic is thus as follows:

$$F_j = \frac{\frac{U}{1}}{\frac{SS_r}{(n-m-1)}},\ F_j \sim F_\alpha(1,\ n-m-1) \tag{2}$$

where α is the test degree, usually taken as 0.05 or 0.10. When $F_j > F_\alpha(1,\ n-m-1)$ is satisfied, X_j is brought into the equation; otherwise, it is discarded. Otherwise, the test method is the same as the process of eliminating meaningless independent variables in statistics, usually $\alpha_{in} < \alpha_{out}$. The coefficient of complex correlation and residual standard deviation are used to test the results of Multiple Stepwise Regression (MSR) and the precision of MSR. As the coefficient R approaches 1, the regression model exhibits a stronger explanatory power. A decrease in residual standard error S signifies an increase in the precision of the model.

Considering the high similarity in indicator weight sizes within the same type and the high variability of weight sizes across different types, indicators are prone to marginalization. To ensure the completeness of the evaluation index system, the multilayer MSR algorithm is iteratively applied. In each iteration, indicators within the same type are treated equivalently, and multiple rounds of filtering are conducted to obtain distinct categories of evaluation indicators. The flowchart of the algorithm is shown in Figure 1.

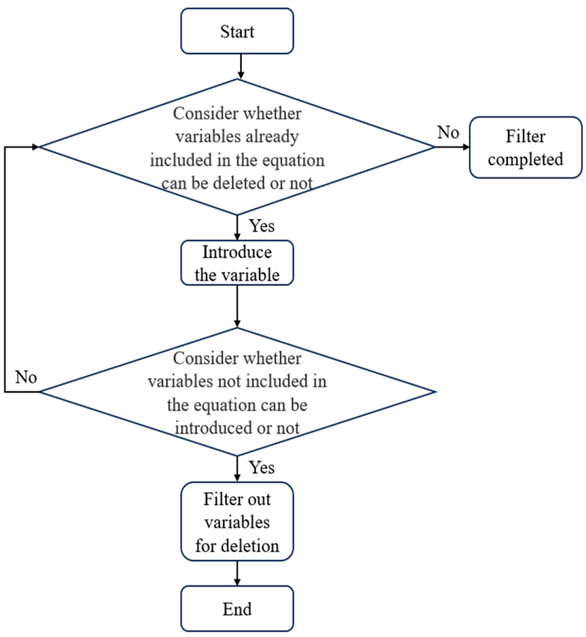

Figure 1. Multilayer multiple linear stepwise regression model steps.

2.2. Analysis of PQ Indicator Assessment

The PQ index assessment system is constructed as shown in Figure 2, where the indices are integrated into the multilayer multiple linear stepwise regression algorithm. Table 1 presents the initial layer of index determination, while Table 2 displays the outcomes of the iterative intermediate process.

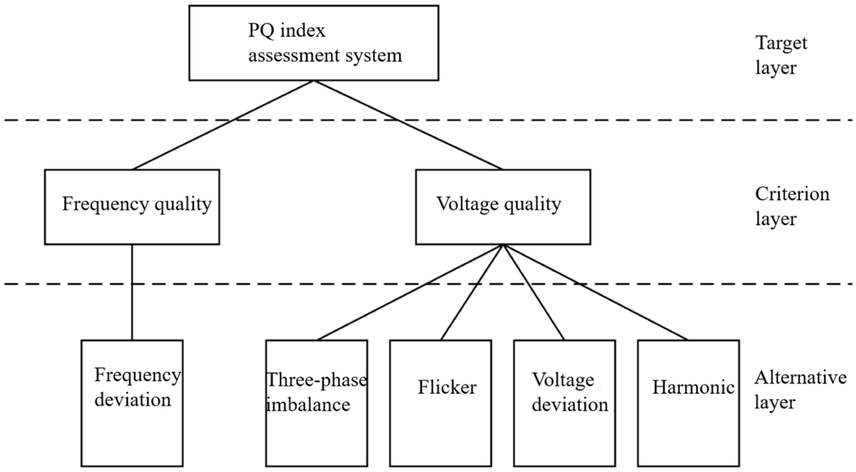

Figure 2. Data-driven PQ index assessment system.

Table 1. The results of the MSR analysis for the first-level evaluation indicators.

	Non-Standard Coefficient		Standard Coefficient	t-Value	p-Value	Collinearity Diagnostics	
	B	Standard Error	*Beta*			VIF	Tolerance
Constant	0	0	-	−1.349	0.214	-	-
Harmonic	1	0	0.269	242,297,617.960	0.00009	2.387	0.352
Voltage deviation	1	0	0.770	692,914,603.169	0.00011	2.387	0.352
R^2	-	-	-	1	-	-	-
Adjusted R^2	-	-	-	1	-	-	-
F	-	-	-	$F(2,8)$ = 1,147,838,455,382,284,928, p = 0.000	-	-	-
D-W value	-	-	-	1.231	-	-	-

Table 2. The first level of evaluation indicators gradually returns to the intermediate process of iteration.

Iterations	Class	Non-Standard Coefficient	Standard Error	t-Value	p-Value
1	constant	−6053.505	1899.424	−3.187	0.011
	harmonic	1.281	0.069	18.518	0
2	constant	0	0	−1.349	0.214
	voltage deviation	1	0	692,914,729.033	0
	harmonic	1	0	242,297,661.972	0

To ensure the credibility and transparency of the data, this study employed a method of sampling and random simulation on idealized data. Specifically, critical parameters were extracted from existing theoretical models, followed by random sampling, to generate experimental data. Such an approach effectively simulates real-world scenarios and provides a reliable foundation for subsequent analyses. Firstly, critical parameters were extracted from existing theoretical models of power quality, including voltage deviation, harmonic content, and frequency deviation. Then, these parameters were sampled using random sampling techniques, taking into account the range and distribution of these parameters in actual scenarios. Based on the sampled parameter values, a series of real and representative experimental data were generated using SPSS software in 19.0 version.

Combining relevant PQ indicators, utilizing an improved Analytic Hierarchy Process (AHP), a PQ index assessment system was established to ensure effective PQ. Each evaluation criterion in the system should align with objective facts of PQ while considering computational complexity and time constraints. Considering these factors comprehensively, this paper selected five key PQ indicators and constructed a data-driven PQ index assessment system, as illustrated in Figure 2.

The indicator layer was treated as the independent variable, as shown in Table 1, while PQ served as the dependent variable input for the stepwise regression. The variable with the highest weight was automatically assigned, where $R_2 = 1$ shows the significance of harmonics and voltage deviation in influencing PQ. Consequently, these factors were selected as the primary indicators in the first layer, as their values of 1 indicated a strong impact on PQ, affirming the efficacy of the algorithm.

Table 2 provides a comprehensive analysis of the regression coefficients and p-value for each iteration, utilizing a stepwise approach that integrates forward and backward selection techniques. The forward method begins by analyzing regression coefficients for each harmonic and voltage deviation, identifying the smallest p-value that meets the entry criteria for inclusion in the algorithm. Conversely, the backward method assesses all harmonic and voltage deviation regressions, targeting the largest p-value that satisfies the exit criteria for exclusion from the algorithm. The entry threshold is set at $p < 0.05$, while the exit threshold is $p > 0.1$ across 2 iterations.

Following this computational process, the evaluation indicators for the second and third layers are presented in Tables 3 and 4. It is observed that frequency deviation, three-phase unbalance, and flicker have relatively weaker impacts on PQ compared to the first layer of indicators. Among these, frequency deviation and three-phase unbalance are part of the second layer evaluation index, while flicker is categorized under the third-layer assessment index. The parameters for both layers are less than 0.05, indicating that the proposed method is well adapted.

Table 3. Results of MSR analysis of second-level evaluation indicators.

	Non-Standard Coefficient		Standard Coefficient	t-Value	p-Value	Collinearity Diagnostics	
	B	**Standard Error**	**Beta**			**VIF**	**Tolerance**
Constant	13,143.329	3433.134	-	3.828	0.00625	-	-
Frequency deviation	0.187	0.029	1.538	6.548	0.0001	15.669	0.064
Three-phase imbalance	47,344.137	19,162.294	0.58	2.471	0.0435	15.669	0.064
R^2	-	-	-	0.975	-	-	-
Adjusted R^2	-	-	-	0.968	-	-	-
F	-	-	-	$F(2,7) = 138.481$, $p = 0.000$	-	-	-
D-W value	-	-	-	1.625	-	-	-

Table 4. Results of stepwise regression analysis of third-level evaluation indicators.

	Non-Standard Coefficient		Standard Coefficient	t-Value	p-Value	Collinearity Diagnostics	
	B	**Standard Error**	**Beta**			**VIF**	**Tolerance**
Constant	60,145.241	10,949.610	-	−5.493	0.00114	-	-
Flicker	10.795	1.317	0.945	8.197	0.00005	1	1
R^2	-	-	-	0.894	-	-	-
Adjusted R^2	-	-	-	0.880	-	-	-
F	-	-	-	$F(1,8) = 67.188$, $p = 0.000$	-	-	-
D-W value	-	-	-	0.98	-	-	-

Based on the aforementioned information, the harmonic and voltage deviations are identified in the first layer as primary indicators of PQ costs, which will be further explored in terms of PQ dynamic adjustments.

2.3. Least Absolute Shrinkage and Selection Operator (LASSO) Theory

Dynamic PQ cost estimation theory combines the consumed cost in PQ and the minimum contraction operator with a gradient descent algorithm. Using the minimum contraction operator and improved gradient descent to train the target, the resultant trend of its training will be minimized to reach the minimum cost of PQ.

The PQ assessment model is constructed with the first layer of indicators, including harmonics and voltage deviation, and the two main indicators:

$$I = h(X) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 = \theta^T X \tag{3}$$

where x_1 and x_2 are independent variables, representing harmonics and voltage deviation. θ_0 is a bias term, θ_1 and θ_2 are the inverse of the weights, θ^T is the parameter combination of the transpose vector, and X is composed of (x_1, x_2) of the characteristic column vector. To solve the degree of influence of the main PQ indicators is to solve the optimization parameters θ_1 and θ_2. Taking $\frac{1}{2}$ of the mean square error of the objective function as the set target, the gradient descent method of i-th parameter is formulated as follows:

$$\theta_{i+1} = \theta_i - \rho \frac{1}{m} \sum_{t=1}^{m} x_{ti} \left(\sum_{j=1}^{n} \theta_j x_{tj} - y_t \right) \tag{4}$$

In Equation (4), ρ is the learning rate of gradient descent, m is the number of data, and n is the dimension of the sample data.

LASSO regression modeling is a compression estimation method that retains the advantages of subset shrinkage by constructing a penalty function, compressing some regression coefficients, and setting some regression coefficients to zero to obtain a finer model.

Suppose that after n samplings, the standard observable data are (x, y), where x and y are independent variables of dimension $n \times p$ $(n > p)$ and dependent variables of dimension $n \times 1$. Each observation is independent of each other, the i-th standard observation is $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})^T$, $i \in [1, 2, \ldots, n]$, and the i-th dependent variable is denoted as $y = (y_1, y_2, \ldots, y_n)^T$. Thus, the regression model is as follows:

$$y_i = \overset{\wedge}{\alpha} + \sum \beta_j x_{ij} + \varepsilon_i \tag{5}$$

where $\varepsilon_i \sim N(0, \sigma^2)$, the definition of $\overset{\wedge}{\alpha} = \overline{y}$, and the standard data as $\overline{y} = 0$, which can be described as follows:

$$y = \beta x + \varepsilon \tag{6}$$

where $\varepsilon \sim N(0, \sigma^2)$, representing a random perturbation term. β is an n-dimensional parameter vector, and to filter the significant factors, the following constraint is necessary:

$$\arg \min_{\{\beta_1, \beta_2, \cdots \beta_n\}} \|y - \beta x\|^2 \quad s.t \sum_j \frac{|\beta|}{\sum \beta_j^0} \leq s \tag{7}$$

In Equation (7), denote $s = \frac{t}{\sum \beta_j^0}$, $s \in [0, 1]$ and $t \geq 0$. Continually adjusting the t-value to reduce the overall regression coefficient of the algorithm and compressing the coefficients of non-significant variables to zero are the key to the LASSO regression method. Then, Equation (4) can be substituted into the constraints:

$$S_{\theta,t} = \arg \min_{\{\beta_1, \beta_2, \cdots \beta_n\}} \left\| \theta_i - \rho \frac{1}{m} \sum_{t=1}^{m} x_{ti} \left(\sum_{j=1}^{n} \theta_j x_{tj} - y_t \right) \right\|^2 \quad s.t \sum_j \frac{|\beta|}{\sum \beta_j^0} \leq s \tag{8}$$

where $S_{\theta,t}$ is the overall regression coefficient of the fusion of the minimum shrinkage operator and the gradient descent algorithm.

2.4. Analysis of Dynamic PQ Indicator Relationship

Through the analysis of Equation (8), the indicators of the standard regression coefficient in the PQ index assessment system are shown in Figure 3.

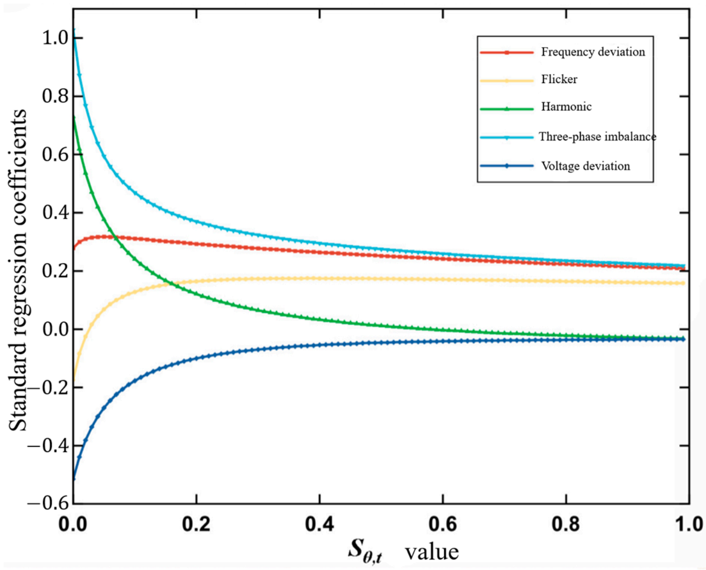

Figure 3. The regression coefficients of PQ cost with different evaluation indicators.

In Figure 3, it can be seen that the standard regression coefficients in the PQ index assessment system converge at a small value, indicating that the deviation is small and the effect of the indicators is significant. According to the multilayer multiple linear stepwise regression algorithm, the regression coefficients of the first layer of the main influence indicators are shown in Figure 4.

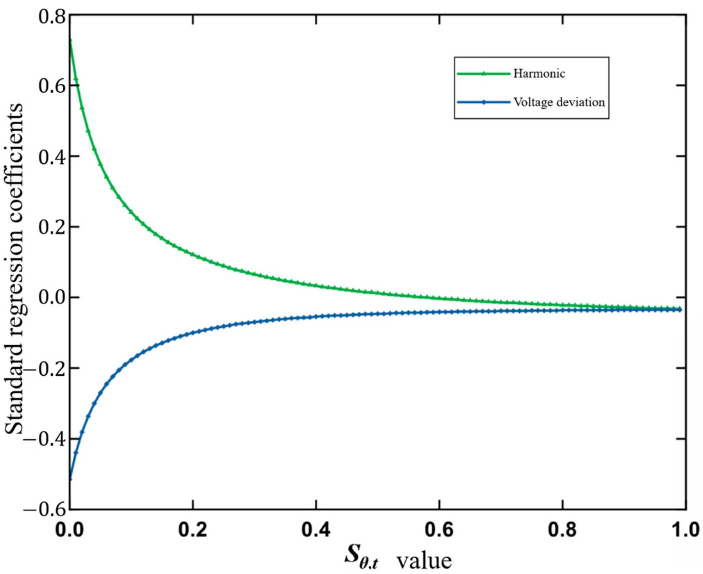

Figure 4. The regression coefficients of PQ cost with the primary evaluation indicators in the first layer.

2.5. PQ Gradient Descent Coefficient

To a certain extent, the requirements for PQ levels fluctuate with load demand. During periods of high customer loading demands, a substantial supply of PQ levels is provided to prevent any detrimental economic losses. Conversely, during periods of low customers loading demands, only a minimal amount of PQ levels is supplied. Hence, by examining the correlation between PQ levels and load demand, the temporal cost of PQ can be determined through the analysis of daily load curves. As an illustration, consider the segmented daily load curve spanning 3 h, depicted in Figure 4.

Figure 5 shows a 3 h daily load curve in a power system whose primary component is industry customers. Heavy loads occur during the three time periods of 10–12 a.m., 13–15 p.m., and 16–18 p.m. It is clear that discontinuous process industries as well as continuous process industries want to work at higher PQ levels to maximize their productivity and profits. During off-peak hours, only a small amount of PQ levels are required for maintaining basic operation of the machines. Since the PQ levels vary more with different demands for loading, a coefficient λ that follows the trend of the daily load curve is introduced to realize the time-varying PQ cost [31]. The coefficient λ can be derived from the following equation:

$$\lambda = (1 + \frac{L_i - L_a}{L_a}) \times 100\% \quad (9)$$

where L_i is the load demand of the daily load curve at time slot i and L_a is the average load demand in the daily load curve, which can be derived from the following formula:

$$L_a = \frac{\sum_{i=1}^{N} L_i}{N}(N \leq 24) \quad (10)$$

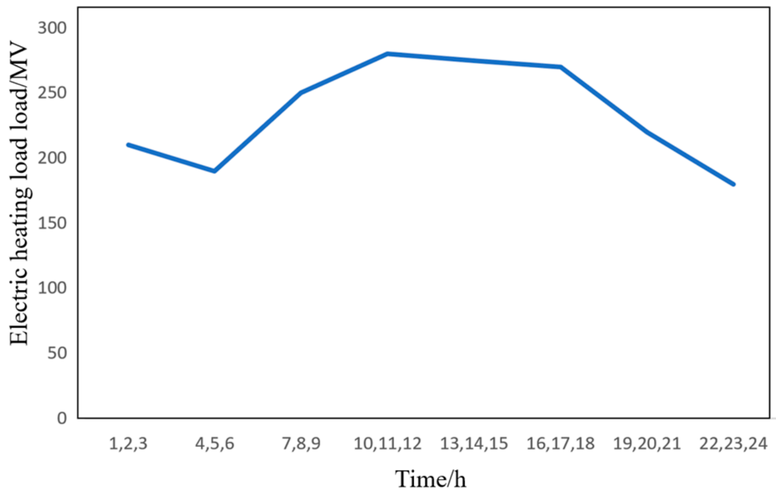

Figure 5. The three-hour segmented daily load curve.

Taking the data from Figure 5 and calculating based on Equations (9) and (10), the results are shown in Table 5.

Table 5. The values of the three-hour segmented daily load curve.

Time/h	Daily Load Cure/MVA	λ/MVA
1, 2, 3	210	0.88
4, 5, 6	190	0.77
7, 8, 9	250	1.06
10, 11, 12	280	1.16
13, 14, 15	275	1.15
16, 17, 18	270	1.13
19, 20, 21	220	0.93
22, 23, 24	180	0.70

As can be seen in Table 5, the coefficient inputs follow exactly the same trend as the daily load curve over time. The coefficient is high when load demand is high and low when load demand is low. The coefficient is slightly higher than the unity coefficient during peak hours and lower than the unity coefficient during off-peak hours. If the average PQ cost of

1 s is used as a baseline and then multiplied by this factor, it means that customers pay a little more than the average PQ cost during peak hours relative to low-peak periods.

In order to reflect the real-time variation, the daily real-time load curve at time i is used to minimize the cost, and the gradient descent strategy is used to derive the minimum value of real-time variation. Thus, the coefficient of gradient descent λ_{ri} can be derived:

$$\lambda_{ri} = (1 + \frac{L_{ri} - L_a}{L_a}) \times 100\% \times W \tag{11}$$

where L_{ri} is real-time load demand of the daily load curve at time slot i, which can be used to calculate the minimum PQ cost over time. W denotes the gradient descent equation, as follows:

$$\theta^1 = \theta^0 - \alpha \nabla J(\theta) \tag{12}$$

where θ^1 and θ^0 represent the next step location and initial location, respectively. $J(\theta)$ denotes a function at θ, and α is the learning rate. Assuming the average cost of PQ is C_{PQ}, to show the variation in PQ cost over time, C_{PQ} is adjusted into a gradient descent as follows:

$$C_{PQt} = \lambda_{ri} \times C_{PQ} \tag{13}$$

3. Validations of PQ Cost Gradient Descent Coefficient in Economic Case Studies

3.1. Case Study 1

Assuming that the main component of a customer area in the UK is a continuous process industry, the daily load curve is the same as that in Figure 4. Based on historical data and surveys, the average cost of a brief 3 s interruption is 1000 V. The economic impact weighting factors for voltage deviations are the same as those in Table 5 for these calculations. Assume that at 10:00 a.m., a nonlinear heavy load in this system is switched into the network, which causes a voltage deviation and 5 MVA energy loss due to harmonic pollution, and PQ issues are erased within 0.1 s. The real-time load at 10:00 a.m. is 285 MVA and the unit energy cost is 2000 GBP/MVA, which is converted to 18,169 CNY/MVA based on an exchange rate of GBP 1 = CNY 9.08, and the real-time purchase order costing would be illustrated as follows.

(1) Voltage deviation cost

Since the system voltage deviation affects the entire supply area, the affected loads are 285 MVA real-time loads, and according to Table 5, the weighting factor for voltage deviation is 0.1, resulting in a total voltage dip cost:

$$1000\ \text{V} \times 285\ \text{MVA} \times 0.1 = 28{,}500\ \text{V}\cdot\text{MVA}$$

$$28{,}500\ \text{V}\cdot\text{MVA} \times 1\ \text{V} \times 18{,}169\ \text{CNY/MVA} = 517{,}976{,}500\ \text{CNY}$$

(2) Harmonic cost

Where a real-time PQ cost is concerned, the aging cost is much smaller than the energy loss. Thus, the value of the real-time harmonic cost is approximately equal to the energy loss cost, and the harmonic cost is as follows:

$$18{,}169\ \text{CNY/MVA} \times 5\ \text{MVA} = 90{,}845\ \text{CNY}$$

(3) Gradient descent coefficient

According to Equation (11) and the data in Table 5, the average load demand in region L_a is 234.38 MVA. Therefore, the gradient descent factor λ_{ri} is as follows:

$$\lambda_{ri} = \left(1 + \frac{285 - 234.8}{234.8}\right) \times 100\% \times W$$

A gradient descent is applied to find the minimum value of the objective function. Suppose that the objective function is $J(\theta) = \theta^2$; then, a gradient descent is applied to reach the minimum. Assuming that the initial spot is $\theta_0 = 1$, the initial learning rate is $\alpha = 0.4$ and the gradient is updated through Equation (12), which is as follows:

$$\nabla J(\theta) = 2\theta$$

After several iterations,

$$\begin{aligned}
&\theta^0 = 1 \\
&\theta^1 = \theta^0 - \alpha \times J'(\theta^0) \\
&= 1 - 0.4 * 2 \\
&= 0.2 \\
&\theta^2 = \theta^1 - \alpha \times J'(\theta^1) \\
&= 0.04 \\
&\theta^3 = 0.008 \\
&\theta^4 = 0.0016 \\
&\ldots\ldots.
\end{aligned}$$

Assuming that the iteration is close to the minimum based on the θ_4 yields, the gradient descent coefficient λ_{ri} derived by substituting $W = 0.0016$ is as follows:

$$\left(1 + \frac{285 - 234.8}{234.8}\right) \times 100\% \times W = 0.19\%$$

(4) PQ total cost

The total average PQ cost is the sum of the voltage dip cost and the harmonic cost, which is calculated as follows:

$$517{,}976{,}500 \text{ CNY} + 90{,}845 \text{ CNY} = 518{,}067{,}345 \text{ CNY}$$

The PQ cost is calculated using Equation (13) as follows:

$$\lambda ri \times 518{,}067{,}345 \text{ CNY} = 0.19\% \times 518{,}067{,}345 \text{ CNY} = 984{,}327.956 \text{ CNY}$$

3.2. Case Study 2

The power supply and distribution system of a research institute's experimental building is currently undergoing harmonic treatment, but the building's original architectural design is not reasonable for harmonics, facing problems of power overuse and unnecessary economic costs. Firstly, the main source of harmonic capacity in the building was determined to be a variable frequency-driven air conditioning main unit, and the harmonic voltage value of this equipment was empirically estimated to be 25–50 V but may be exceeded in the actual environment. Secondly, when filtering devices are centrally located on the low-voltage busbars of the substation, harmonic technical treatment is feasible for the high-voltage supply side; take a public national grid for example. However, for the customer side—take a low-voltage national grid for example—harmonic treatment requires more consideration and the PQ does not improve, only providing a certain power-saving effect. Using exponential time-varying coefficients can derive the cost of the required treatment more quickly, and the condition for the scheme can then be determined according to the actual situation. The daily load profile is shown in Figure 6.

(1) Harmonic cost

The total 8 MVA energy loss caused by harmonic pollution is cleared within 0.1 s for both PQ problems. The real-time load measured at 20:00 is 365 MVA, and the unit energy cost is 8000 CNY/MVA. Since the aging cost is much smaller than the energy loss cost, the value of the real-time harmonic cost is approximately equal to the energy loss cost, which is given by the following:

$$D_i = D_0 \times E_t\left(G^{h_1} \ldots G^{h_{max}}\right) = 365\ \text{MVA} \times 8000\ \text{CNY/MVA} = 2{,}920{,}000\ \text{CNY}$$

(2) PQ gradient descent real-time coefficients

The daily load at 20:00 h is 100 MW, which gives an average load demand of 55 MVA in region L_a. The value of λ_{ri} from example one is also used here, so the gradient descent real-time factor λ_{ri} is as follows:

$$\lambda_{ri} = \left(1 + \frac{100 - 55}{100}\right) \times 100\% \times W = 0.19\%$$

(3) Real-time harmonic costs

When a real-time PQ cost is concerned, the aging cost is much smaller than the energy loss. Thus, the value of a real-time harmonic cost is approximately equal to the energy loss cost. Since this system is only faced with harmonic problems, the total PQ cost C_{PQt} from Equation (13):

$$C_{PQt} = \lambda_{ri} \times C_{PQ} = 0.19\% \times 2{,}920{,}000\ \text{CNY} = 5548\ \text{CNY}$$

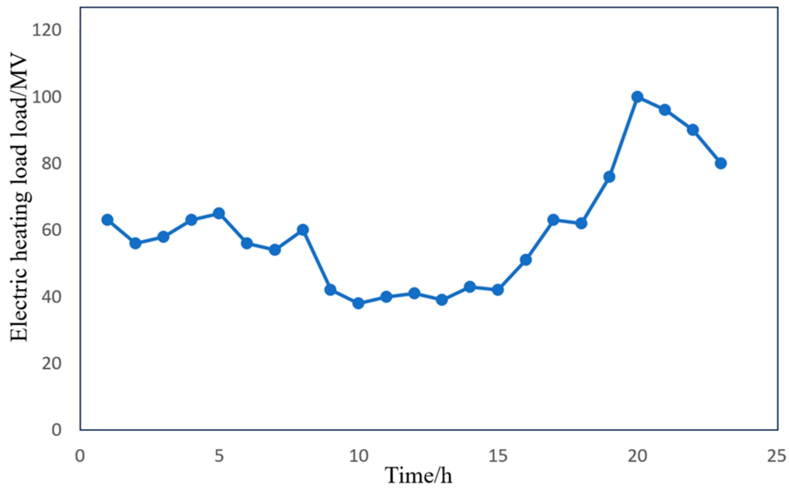

Figure 6. Daily load curve of a power supply and distribution system.

3.3. Discussion

In the economic cost analysis of continuous industrial processes in the UK region, as demonstrated in case study 1, it is found that the total PQ cost comprises a voltage deviation cost and a harmonic cost. Since the harmonic cost varies with time, the PQ total cost fluctuates in real time. To determine the minimum PQ cost, the gradient descent method is employed, iteratively minimizing the gradient descent coefficient, which is then used in the relationship to derive the optimal configuration of PQ cost under real-time changes. This method enables real-time minimization of PQ cost, maximizing economic savings.

In case study 2, analyzing the economic costs of harmonic treatment in the experimental building, it is observed that actual industrial harmonic voltages may exceed the set voltage range. While harmonic treatment is feasible for the high-voltage supply side, it only has nodal effects on the low-voltage side. Hence, real-time PQ cost estimation can quickly assess the magnitude of governance costs, aiding in decision-making for governance strategies.

By employing the gradient descent method for real-time cost estimation, economic losses are reduced, enhancing the reliability and efficiency of power systems. Both cases illustrate effective methods for calculating harmonic treatment costs and real-time load requirements, significantly contributing to the optimization management of power systems.

4. Conclusions

Due to the lack of unified theories and methods for evaluating the economic aspects of PQ, this paper proposed a gradient descent optimization algorithm based on the LASSO method to address the primary factors affecting PQ as harmonics and voltage deviations, enabling rapid computation of the minimum PQ cost. Validations of case studies demonstrated that the proposed method can swiftly calculate the minimum PQ cost based on real-time load demands, thereby reducing economic losses and stabilizing the power system. This will enhance the accuracy and applicability of the model.

This study addresses the lack of unified theories and methods for evaluating the economic aspects of PQ. A gradient descent optimization algorithm is proposed based on the LASSO method to address primary PQ factors such as harmonics and voltage deviations, enabling rapid computation of the minimum PQ cost. The results and implications of this research are summarized as follows:

- The proposed algorithm demonstrates effectiveness in swiftly calculating the minimum PQ cost based on real-time load demands, contributing to reducing economic losses and enhancing the stability of power systems.
- The case studies validate the efficiency of the algorithm and its ability to provide actionable insights for improving PQ management.

Future work will focus on algorithm optimization, explorations of additional economic analysis methods in power systems, and validations of the model through practical case studies, thereby improving its accuracy and applicability.

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