Research and Analysis of Quantitative Methods for the Feasibility Study and Evaluation of Power Grid Digital Projects Based on Floating Impact Factors

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Abstract: In view of the current problem that the impact factor approval relies on expert experience to achieve strong subjectivity and insufficient accuracy, and the manual review mode is difficult to adapt to the surging demand of power grid digital projects, this paper proposes a quantitative method for impact factors that integrate multiple technologies and constructs a digital auxiliary review system.
Firstly, the method uses natural language understanding technology to automatically process the historical WBS workload evaluation form, feasibility study report and other project data, and extract key features. Based on expert experience, discriminant strategies and conflict resolution mechanisms (such as hierarchical judgment method and weighted voting method) are formulated, and a fixed impact factor prediction model is constructed to achieve the regularization and objectivity of basic quantification. Secondly, a machine learning model (including stacked integration, gradient lifting tree and other optimization methods) is constructed based on the preprocessed historical data to calculate the first floating influence factor. The second floating influence factor is obtained by using the semantic similarity weighted sum historical influence factor of the large language model. The workload is adjusted by automatic code generation of the generative large model, and the evaluation model is constructed in combination with artificially set factors, and the third floating impact factor is output. Finally, the fixed impact factor is used as the benchmark to set the judgment interval to eliminate the outliers, the weight is determined according to the characteristic correlation degree, and the three floating impact factors are fused to form a digital auxiliary review system.
Practice shows that the proposed method can effectively reduce manual intervention and subjective bias, fully mine the value of historical data, improve the evaluation efficiency and quantitative accuracy of impact factors, optimize project resource allocation, and adapt to the review needs of the rapid development of power grid digital projects.
Keywords: Power grid digitization project; Feasibility study; Floating impact factor

1. Background Technology

Under the WBS system of State Grid Corporation of China, the entire project can be divided into smaller and more manageable parts in the project feasibility study, and the approved project workload can be quantified in the form of "impact factor × workload", so as to evaluate the resources, cost and time required for the project relatively reasonably. However, the approval of impact factors mainly depends on the experience of project review experts, and it is difficult to be objective and accurate. In many cases, this empirical assessment can lead to overestimation or underestimation of workload, which can affect the allocation of project resources, subject to subjective factors and external circumstances. Overestimation can lead to wasted resources, while underestimation can lead to project delays and risks in project quality.

In addition, the current working mode completely relies on manual project review, and the review experts need to read through the feasibility study report and understand it to finally determine whether the project complexity assessment is reasonable. However, with the expansion of power grid construction and the increase of digital projects, the work pressure on review experts has surged, which requires the construction of a digital auxiliary review system to assist review experts in auxiliary review.

At present, the review system based on WBS of State Grid Corporation plays an important role in the feasibility study of projects. The WBS serves as a work breakdown structure that divides the entire project into smaller, more manageable parts, making it easier to assess the resources, cost, and time required for the project. By quantifying the approved project workload in the form of impact factor* workload, the resources, cost, and time required for the project can be evaluated relatively reasonably, and provide an important basis for project decision-making. However, there are also some problems with the current review system. The approval of impact factors mainly depends on the experience of project review experts, and it is difficult to be objective and accurate. In many cases, this empirical assessment can lead to overestimation or underestimation of workload, which can affect the allocation of project resources, subject to subjective factors and external circumstances.

2. Construction Content

The quantitative method for reviewing project impact factors, comprising the following steps: obtaining project data and automatically processing it, and the project data includes a historical WBS workload evaluation table; construct a fixed impact factor prediction model, and determine the fixed impact factor in combination with the automatically processed project data; the historical WBS workload evaluation table is preprocessed, and a machine learning model is constructed, and the first floating influence factor is calculated according to the machine learning model; According to the project data, the second floating influence factor is calculated in combination with the semantic similarity of the large language model; According to the preprocessed historical WBS workload evaluation table, the evaluation model is constructed through the automatic code generation of the generative large model, and the third floating impact factor is calculated; The first floating impact factor, the first floating impact factor and the first floating impact factor are fused to generate a floating impact factor, and the floating impact factor is combined with the fixed impact factor to design a digital auxiliary review system.

2.1 Optimal Scheme for Quantifying the Impact Factor of the Review Project

2.1.1 Obtain Project Data and Automate Processing

Including: obtaining project data, analyzing and processing the project data through natural language understanding technology, and identifying the features in the text description.

2.1.2 Determine the Fixed Impact Factor

Including: determining fixed impact factors, including: formulating discriminant strategies and constructing fixed impact factor models; Based on the fixed impact factor prediction model, combined with the characteristics in the text description, the fixed impact factor is determined. The beneficial effect of this preferred technical scheme is to formulate a discrimination strategy based on expert experience and construct a fixed impact factor model, combined with natural language understanding technology to analyze the characteristics in the project text description, to realize the systematic determination of fixed impact factors, which reduces the dependence on individual expert experience, avoids the bias caused by subjective factors and external environment, improves the objectivity of impact factors, provides a reliable basis for project workload evaluation, and reduces the risk caused by evaluation bias.

2.1.3 The Historical Wbs Workload Evaluation Table is Preprocessed, and A Machine Learning Model Is Constructed to Output the First Impact Factor

comprises: screening the historical item characteristics in the historical WBS workload evaluation table, and preprocessing; the preprocessed historical item features are screened, and the machine learning model is constructed; Based on the machine learning model, the first floating impact factor is output in combination with the characteristics of the new project. The beneficial effect of this preferred technical scheme is to provide high-quality input for the machine learning model by screening the project features in the historical WBS workload evaluation table and preprocessing, combined with expert experience, further screening key features, and providing high-quality input for the machine learning model, which can accurately extract effective information from historical data, reduce noise interference, improve model learning efficiency and prediction accuracy, and optimize the model based on real project data and expert experience, which can more reliably predict the impact factors of new projects, enhance the objectivity of evaluation, and provide a scientific basis for project resource allocation.

2.1.4 Calculate the Floating Influence Factor by the Semantic Similarity of the Large Language Model

comprising: calculating the project data through the large language model and obtaining the impact factor of historical projects; The beneficial effect of this preferred technical scheme is to capture the similarity between the functional description of the new project and the historical item with the help of the semantic understanding ability of the pre-trained large language model, and then use the similarity as the weight to weighted the historical impact factor, and the method makes full use of the value of historical data, reduces the dependence on subjective experience, and improves the objectivity of prediction. At the same time, it adapts to the diversity of projects, enhances the quantitative accuracy in complex scenarios through semantic matching, and helps rational resource allocation.

2.2 Optimal Scheme for Quantifying the Impact Factor of the Evaluation Project

2.2.1 Construct an Evaluation Model and Calculate the Third Floating Impact Factor

Comprising: based on the generative large model, using the semantic similarity of the large language model, adjusting the workload through the characteristics of the historical project, and combining the factors set by the hand, constructing an evaluation model and outputting the third floating influence factor.

2.3 Optimal Scheme for Quantifying the Impact Factor of the Evaluation Project

2.3.1 Construct Floating Influence Factors

comprising: according to the numerical distribution characteristics of the fixed impact factor, the judgment interval with the fixed influencing factor as the reference value is set; the values of the first floating impact factor, the second floating impact factor and the third floating impact factor exceeding the judgment interval are determined as outliers and eliminated; the correlation degree of the first floating impact factor, the second floating impact factor, the third floating impact factor and the new project characteristics is calculated by the feature correlation degree algorithm; the weight coefficients of the first floating influence factor, the second floating influence factor and the third floating impact factor are determined based on the correlation degree value, and the sum of the weight coefficients is 1; The first floating influence factor, the second floating impact factor and the third floating influence factor after removing the outlier value are multiplied by the corresponding weight coefficient and summed to obtain the floating impact factor.

3. Construction Effect

Through multi-dimensional technology integration and systematic design, it effectively solves the problems of relying on expert experience, strong subjectivity and low efficiency in traditional project evaluation. Automate the processing of project data through natural language understanding technology, accurately identify key features, and reduce manual processing errors. Combined with expert experience, a fixed impact factor model is constructed to achieve regular quantification and improve the stability of basic evaluation. The machine learning model is constructed using historical WBS data, and the floating influence factor is calculated with the semantic similarity weighting of large language model to fully mine the value of historical data and enhance the objectivity and adaptability of dynamic evaluation. Automatically generate and adjust the workload through generative large models to further optimize quantitative accuracy; Finally, multiple models and fixed impact factors are integrated to form a digital auxiliary review system, which reduces the burden on experts, improves the efficiency and accuracy of review, optimizes resource allocation, and adapts to the increasing development needs of digital projects in the power grid.

4. Construction Specific Plan

In view of the above problems of subjective impact factor approval, low review efficiency and insufficient standard adaptation, the regular and objective quantification of impact factor basis is realized by automatically processing project data and constructing a fixed impact factor prediction model based on expert experience. At the same time, the machine learning model is trained using historical WBS data, and the semantic similarity weighting of large language models and the automatic code generation and correction workload of generative large models are avoided, avoiding the limitations of traditional empirical evaluation. Finally, the digital auxiliary review system was designed by integrating multiple models and fixed impact factors, which realized the accurate quantification of impact factors with less manual intervention and adapted to the needs of the rapid development of power grid digital projects.

Obtain project data, including historical WBS workload evaluation form, project feasibility study report text, expert review records, and historical project impact factor approval results.

4.1 Automated Processing is Specifically Data Cleaning and Structured Transformation.

It should be noted that structured transformation includes converting the unstructured feasibility study report text into identifiable project feature information, which needs to focus on extracting key information related to impact factors, such as decomposing the description of the system function development part in the feasibility study report into features that can match technical complexity and business complexity rules, so as to provide a basis for subsequent model calculations.

If there is a conflict between factor elements in the establishment of fixed impact factors, the discriminant strategy is implemented.

Specifically, when the degree of association exceeds the set threshold, the conflict features exceeding the set threshold and the conflicting features that do not exceed the threshold can be assigned conflict weights in a ratio of 9:1.

The fixed factor abstract model is mainly divided into consulting design impact factor score, system function development impact factor score, system implementation impact factor score, system performance optimization impact factor score, and data product development and implementation impact factor score.

It should be noted that the weights in the formula are artificially modified through historical items and natural language understanding technology is used to analyze the feasibility study report text in the preprocessed project data, identify the key features in the text, determine the corresponding types of each part of the project, match the corresponding weight parameters in the above rules, and calculate and determine the fixed impact factor through the multi-rule conflict discrimination strategy and combined with the structured project feature information.

In one implementable approach, the multi-rule conflict discrimination strategy can also be implemented by the hierarchical determination method based on rule priority. Based on the impact factor rules of different types of projects, the rules are prioritized in advance based on business importance. When multiple rules are matched, the high-priority rule is triggered first. If the priority is the same, the rule with the highest accuracy in the historical case is selected based on the frequency of application of the rules of similar items in the historical WBS evaluation table to ensure that the conflict determination is in line with both business logic and actual project scenarios.

In another implementable method, the multi-rule conflict discriminant strategy can also be implemented by the weighted voting method. Based on the impact factor verification results of historical items, dynamic weight rules are assigned to each rule, and the higher the accuracy when applied in historical items, the greater the weight. When multiple rules conflict, the weighted score of each rule is calculated, and the rule result with the highest score is selected as the final judgment basis, and the weight is regularly updated in combination with the annotation data of experts on historical conflict cases, so that the discrimination strategy is continuously optimized with the accumulation of project data and the adaptability of conflict handling is improved.

The historical WBS workload assessment table is preprocessed and a machine learning model is built to calculate the first floating impact factor, including steps A1 and A2:

A1: Preprocess the historical WBS workload evaluation table to form a training dataset.

A2: Build a machine learning model and calculate the first floating impact factor.

Specifically, in step A1, the historical WBS workload evaluation table is preprocessed, and the characteristic information of the historical project is extracted, including the project scale, team member level and number of people, development cycle, technology stack, associated modules and data flow, and this characteristic information is associated with the corresponding historical impact factors to form a training dataset.

Specifically, in step A2, the traditional machine learning prediction model is trained using the training dataset, with the item features as the input and the historical impact factor as the output, and the model that can be used to predict the impact factor of the new project is constructed by learning the correlation between the characteristics of the historical project and the impact factor.

In another implementable way, the machine learning model construction in step A2 can also be implemented through stacking in ensemble learning. Based on the need to learn the correlation between historical features and impact factors, multiple basic models, such as linear regression, decision tree and support vector machine, are used as the first-layer model to output the prediction results. Then, using these results as new features, the second-layer metamodel is trained, such as logistic regression, to perform result fusion, which can integrate the advantages of different models and better capture the complex nonlinear relationship of project features.

The digital auxiliary review system inputs the fixed impact factor prediction model to obtain the fixed impact factor by receiving the project feasibility study report and other data, and inputs the machine learning model, semantic similarity model and automatic code generation evaluation model to obtain the floating impact factor after automatic processing in step S100. According to the adjustment of the floating impact factor according to the fixed impact factor, it provides visual auxiliary decision support for the review experts.

5. Conclusion

In summary, the present invention effectively solves the problems of relying on expert experience, strong subjectivity and low efficiency in traditional project evaluation through multi-dimensional technology integration and systematic design. Automate the processing of project data through natural language understanding technology, accurately identify key features, and reduce manual processing errors. Combined with expert experience, a fixed impact factor model is constructed to achieve regular quantification and improve the stability of basic evaluation. The machine learning model is constructed using historical WBS data, and the floating influence factor is calculated with the semantic similarity weighting of large language model to fully mine the value of historical data and enhance the objectivity and adaptability of dynamic evaluation. Automatically generate and adjust the workload through generative large models to further optimize quantitative accuracy; Finally, multiple models and fixed impact factors are integrated to form a digital auxiliary review system, which reduces the burden on experts, improves the efficiency and accuracy of review, optimizes resource allocation, and adapts to the increasing development needs of digital projects in the power grid.

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