Research on Constructing a Knowledge Graph for Risk-Aware Electricity Marketing Events

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Abstract. Considering the diverse evolution of electricity marketing business requirements alongside the advancement of socioeconomic development and deepening market reforms, the effective utilization of extensive and dynamically changing data in electricity marketing has presented both opportunities and challenges for marketing risk management. Thus, this paper, commencing from the needs of risk perception in electricity marketing events, proposes an innovative approach using a novel method of integrating marketing data – the Event Knowledge Graph. Building on this, the paper explores the model and construction process of the electricity marketing event knowledge graph, as well as the methodological pathway for conducting risk perception based on this knowledge graph. The objective is to facilitate knowledge-based management of electricity marketing events and offer support for risk awareness and regulatory decision-making in this context.

Keywords: Electricity Marketing, Risk Perception, Event Knowledge Graph

1 Introduction

Currently, with the development of the socio-economy and the deepening of market-oriented reforms, there has been a substantial increase in the demand for electricity usage by consumers. This growth has resulted in a diversified landscape of electricity marketing requirements[1]. In addition to the traditional services such as business expansion installations, electricity metering, and fee collection, new emerging services such as demand response, integrated energy, and energy substitution have been introduced. While these diversified business models and increased business volumes have brought convenience and efficiency to people's lives, they have also elevated the probability of marketing risks occurring, leading to a surge in marketing risk events.

Risk perception in electricity marketing events is fundamentally about extracting valuable event elements from relevant information and deepening the understanding of the current event through the analysis and perception of existing risk events. Combining risk perception, utilizing historical data for risk prediction and deduction, forms the basis for providing support to risk alerting in electricity marketing events. For risk management in the context of electricity marketing events, addressing how to

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effectively harness the massive, diverse, and dynamically changing data in the electricity marketing field[2], conducting in-depth analysis of the relationships between event entities, and constructing event descriptions for electricity marketing risks have become pressing and pivotal issues.

Knowledge Graph (KG) is an organizational structure that has its roots in the development of semantic web technology. It provides a deep-level representation of knowledge based on semantic understanding, offering structured descriptions of concepts, entities, and their relationships within the objective world[3]. Events represent a special type of knowledge [4], and an Event Knowledge Graph (EKG) is a complex knowledge graph constructed around events. It can be seen as a complex combination of observed empirical facts and fact relationships, revealing the evolutionary logic between events from a dynamic perspective[5][6]. The development of event knowledge graphs provides new insights into solving event risk perception problems.

Addressing the unique attributes of extensive data in power marketing events, event knowledge graph technology is leveraged. This technology enables a profound examination of event data, which encompasses diverse dimensions and intricate details. Employing a multi-tiered, multidimensional approach, a comprehensive analysis of power marketing event data is conducted. This approach is conducive to the interconnection of marketing event data and the systematic disclosure of event structure. Furthermore, a deep dive into the comprehensive perception and analysis of risks associated with power marketing events is undertaken, utilizing this knowledge to support management decisions regarding power marketing risk events.

Therefore, this paper focuses on risk perception in electricity marketing events. It constructs an event knowledge graph representation model based on event knowledge theory to organize and apply event data effectively. This model depicts events, entities, and their relationships. The paper also proposes a method for constructing an event knowledge graph in the context of electricity marketing events, enabling the structured organization and application of big data. Additionally, it explores risk perception methods based on event knowledge graphs to support management decision-making regarding electricity marketing event risks, providing valuable information and knowledge support for improving electricity marketing management capabilities.

2 Research on Event Knowledge Graphs

2.1 Theoretical Research on Event Knowledge Graphs

Knowledge graphs commonly feature entities represented as words, emphasizing the static characteristics of entities or concepts, making it challenging to represent rich event information. Any entity can be a constituent element of an event, which is a specific fact that evolves over time[7]. Researchers both domestically and internationally have conducted relevant studies around event evolution, such as statistical script learning and the identification of causal temporal relationships in events[8][9][10]. In 2017, a concept called "Causality Graph" was introduced by the team led by Ting Liu at Harbin Institute of Technology. It involves constructing a logical knowledge base of causality to uncover the evolutionary patterns and rules among events[11]. In 2018, Gottschalk S. and Demidova E. pointed out the limitations of existing knowledge bases, which mainly focus on entity-centric information, and the insufficient coverage and completeness in terms of event and temporal relationships. They proposed an event-centric knowledge graph called EKG (Event Knowledge Graph), which integrates information narrated around events and their temporal relationships[12].

2.2 Research on Event Knowledge Graph Construction and Application

Event knowledge graph construction involves three primary steps: event extraction, event relation inference, and event information completion[13]. Event extraction is mainly concerned with automatically extracting event information of interest from unstructured natural language texts and presenting it in a structured format[14]. Event relation inference entails identifying objective logical relationships that exist between events, including temporal, causal, comparative, and co-reference relationships[15]. Event information completion utilizes existing knowledge within the event knowledge graph and employs rules to supplement missing elements in event arguments[16]. As event knowledge graph technology continues to advance, it has progressively found applications across various industry domains, encompassing sudden events[17][18], monitoring online public sentiment[19][20], and predicting financial events[21], among others.

3 Construction method of power marketing event graph

As Marketing 2.0 advances, the significant role of big data in power marketing for event risk perception becomes increasingly evident. When risk events occur, it provides comprehensive and real-time event element information to marketing managers. Addressing the risk perception needs in power marketing events, this paper proposes a method to construct a power marketing event map that combines event entity relationships and event evolution logic, enabling multi-dimensional and multi-level analysis of events.

3.1 Power marketing event graph construction ideas

This paper described power marketing event graph primarily consists of three layers: the data layer, the entity layer, and the event representation layer. The data layer is composed of power marketing system data relevant to events. The entity layer is formed through the parsing of power marketing event information, yielding instances of entities, specific events, and their associated relationships. The event representation layer constitutes the knowledge representation model of the power marketing event graph. The model description corresponding to the structure of the power marketing event graph is denoted as $EMES = \{EMEs,\ Es,\ Rs,\ Is\}$. Here, $EMEs$ represents the set of power marketing event classes, Es represents the set of relevant entity classes in power marketing events, Rs denotes the set of relationships and Is represents the set of instances.

Definition 1: Electricity Marketing Event (EME). Drawing on prior research in the field of events[22][23], this paper defines an Electricity Marketing Event as a quintuple, represented as $EME = (A, O, T, V,\ P)$, where A denotes a series of action elements related to the electricity marketing event; O encompasses object elements associated with the electricity marketing event, including participating entities, objects, and relevant object matters; T signifies the specific temporal elements of the event occurrence; V represents environmental elements relevant to the event; and P constitutes assertion elements, encompassing the event's antecedent conditions, intermediate assertions, and consequent conditions.

Definition 2: Classes in the Electricity Marketing Event Graph. The event class, denoted as $EMEs$, represents the set of all sub-events related to a particular electricity marketing event EME, inheriting from the event base class EME. It is defined as $EMEs = (eme_1, eme_2,\ \ldots, eme_n)$. The entity class, denoted as Es, represents the set of all entities related to the base event EME. In the context of electricity marketing events, this typically includes entities such as customers and electricity marketing personnel. It is defined as $Es = (e_1, e_2,\ \ldots, e_n)$.

Definition 3: Relationships in the Electricity Marketing Event Graph. The relationship class, denoted as Rs, represents the set of relationships among events and entities related to a specific electricity marketing base event EME. It is defined as $Rs = (r_1, r_2,\ \ldots, e_n)$. In theory, this includes relationships between events, relationships between entities, and relationships between events and entities.

Definition 4: Electricity Marketing Event Graph (EMEG). The Electricity Marketing Event Graph is represented as a directed labeled graph, denoted as $EMEG = (N, L)$, where N represents the vertices in the graph, including entities and event values, and L represents the edges in the graph. The edge is defined as $(n1, n2, label)$, signifying a relationship between two vertices, n1 and n2, with a specific label. These labels encompass causal relationships, compositional relationships, temporal relationships, and associative relationships, among others.

Therefore, based on the fundamental definition and hierarchical structure of the electricity marketing event graph, we first provide the relevant data from the electricity marketing system and deconstruct the data associated with electricity marketing events. Secondly, on this basis, we parse events, entity classes, and their associative relationships to construct a unified representation model for electricity marketing events. Finally, we explore mechanisms for graph completion and updates, iteratively optimizing the initially constructed electricity marketing graph representation model to enhance the graph's comprehensiveness.

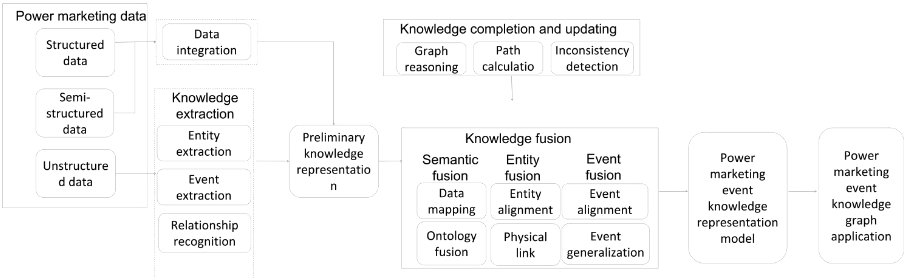

Fig. 1. Power marketing event graph construction flow chart.

3.2 Power marketing event graph data collection and knowledge extraction

Constructing the data layer of the event graph focuses on achieving comprehensive integration of multi-source data in power marketing and knowledge extraction. The big data environment in the power system mainly consists of multimodal data sensed by the power IoT and digital grid, as well as data from external systems such as the transportation system, satellite remote sensing system, weather system, and social systems, among others[24]. Firstly, data collection involves building a model that links events with data information. Through feature extraction and human-machine interaction, data sources are selected and analyzed to identify information relevant to power marketing events. Secondly, knowledge extraction is performed on the collected power marketing event information. For structured and semi-structured data, knowledge extraction involves mapping data patterns to event semantic expressions using data model semantic mapping techniques. For unstructured data, the core lies in high-quality training corpora. Due to the absence of a universal power marketing corpus, a combination of techniques such as entity extraction, relationship extraction, and event extraction[25], employing deep learning models and algorithms for text preprocessing and event annotation, including event elements such as events, trigger words, time, context, participants, and objects. In practical applications, specialized terminology in the field of power marketing is constructed. Relevant text data, including industry reports, regulations, and operating manuals, are collected, preprocessed, deduplicated, and segmented based on specialization, topic, and region to construct a corpus, thereby extracting specialized vocabulary in the field of power marketing. Natural language processing techniques are employed to assist in corpus construction.

3.3 Power marketing event graph knowledge representation model

Based on the knowledge extraction of power marketing events, the research investigates various units of event knowledge and their inherent logical connections to form a knowledge representation model for power marketing events. The knowledge representation of the power marketing event graph mainly consists of two layers of logic: Firstly, through a directed graph, it reveals various entities associated with events, event classes, and their mutual relationships, achieving a unified knowledge representation of event entities. Secondly, it describes the dynamic evolution process of power marketing events oriented towards risk perception, realizing the dynamic presentation of event risks

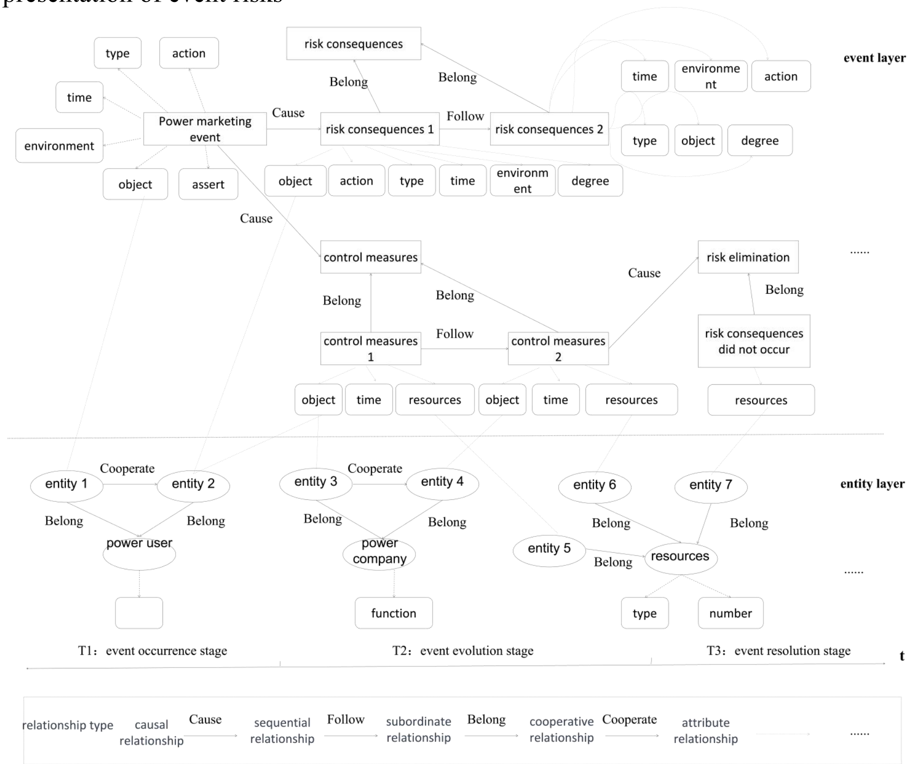

Fig. 2. The knowledge representation model of the electricity marketing event graph.

Building the knowledge representation model of power marketing event graph requires first analyzing the main event types of power marketing events, examining the dynamic and static relationships between different types of events, and dividing power marketing risk events into occurrence, impact, and control categories based on the status and evolution of risk events, corresponding to the occurrence, evolution, and control phases of power marketing events. Each event category may generate many sub-events, with each event inheriting the base class of power marketing events and containing corresponding temporal, environmental, object, action, and assertion elements. On this basis, the study focuses on the entity types involved in power marketing events, the description of the relationship graph, and the logic graph of event evolution, achieving the fusion of knowledge across the three levels: the data layer, the entity layer, and the event layer. Subsequently, mapping from the data layer to the entity layer and the event layer is carried out to achieve semantic integration from data to entity and event, establish semantic connections among various event knowledge subjects, and form a unified knowledge base of power marketing events.

Finally, for event-related entities, techniques such as entity alignment and entity linking[26][27] are employed to normalize different expressions of the same entity. Additionally, to enhance the consistency between data sources and real-world entity references, techniques like event generalization and event alignment[28][29] are applied for event disambiguation and unified representation. Through the effective fusion of these three levels, a unified representation of event knowledge can be achieved.

3.4 Power marketing event graph represents model completion and update mechanism

The information content related to electricity marketing events will undergo iterative updates as the electricity market evolves. Simultaneously, the early prototype construction of the electricity marketing event graph representation model heavily relied on the expert judgment of marketing business professionals. Significant differences still exist in the specific event categories and entity classes of electricity marketing events. Therefore, this paper borrows from the methods found in the literature[30] and proposes a knowledge supplementation and updating mechanism for the electricity marketing event knowledge graph representation model.

Utilizing the constructed marketing event representation model, starting from specific instance data and knowledge elements, patterns are induced for entities, events, and their associative relationships. Gradually, missing concepts and relationship patterns in electricity marketing knowledge are extracted from the bottom up. Furthermore, through a semantic data mapping model, the missing parts are supplemented within the entity and event layers, continuously enhancing the representation model of the electricity marketing event graph.

Furthermore, the completion and updating of the electricity marketing event graph representation model should be based on the evolving patterns of events, facilitating the iterative updates of entities and events. Firstly, a comparison analysis should be conducted between the extracted entities and the existing knowledge base and corpus, allowing for the supplementation of entity information. Secondly, given the complex associative relationships between events and entities, different events and information may lead to diverse associative relationships. As it is impossible for the event graph representation model to enumerate them comprehensively, knowledge computation methods such as graph reasoning, path calculation, and inconsistency detection should be employed to update and complement implicit knowledge. Finally, considering the dynamic evolution of events, the development of events may result in dynamic changes in the relationships between events and entities. Therefore, incorporating spatiotemporal features is essential for dynamic model exploration, ensuring ongoing completion and updating of the event graph.

4 Implementation Approach for Event Risk Perception Based on Event Knowledge Graph

4.1 Construction of a Multidimensional Risk Description Framework

Leveraging the electricity marketing event graph to support risk perception, this establishes a "knowledge-service" pathway for risk awareness. Utilizing the hierarchical structure of the electricity marketing event graph, it enables the observation and comprehension of marketing risk scenarios. Catering to the diverse risk perception needs of electricity users, marketing professionals, and decision-makers, it utilizes historical marketing event data and risk rule analysis to implement risk alert functionality, thereby identifying risks during the event's development process.

This paper considers electricity marketing event risk perception as a systematic process. From a system construction perspective, it proposes a pathway for electricity marketing event risk perception based on event graphs, as depicted in Figure 3. Firstly, electricity marketing event risk management involves multiple stages and stakeholders. Different stakeholders have varying responsibilities in risk management decisions, and their information needs are not identical. It is essential to analyze the risk management requirements of different stakeholders, such as electricity users' needs for event risk status perception, which includes event risk types, occurrence times, and consequences. In addition to event risk status perception needs, electricity marketing personnel require risk prevention and control information corresponding to specific statuses, including control processes and necessary resources. Depending on the stage of the risk, collaboration among different specialized parties may be necessary. Decision-makers need to consider the development trends of events and provide warnings about unknown risks. It's crucial to define the dimensions of stakeholders and risk stages that the risk perception events are oriented towards and complete the requirement modeling. Secondly, by combining the electricity marketing event risk perception requirement models for different stakeholders, a multi-dimensional risk perception system functional structure is constructed. This structure transforms risk requirement description dimensions into system functionalities by defining relevant data analysis tasks to achieve the system's functions. Lastly, the paper explores methods for extracting risk states based on event graphs to support the implementation of system functionalities.

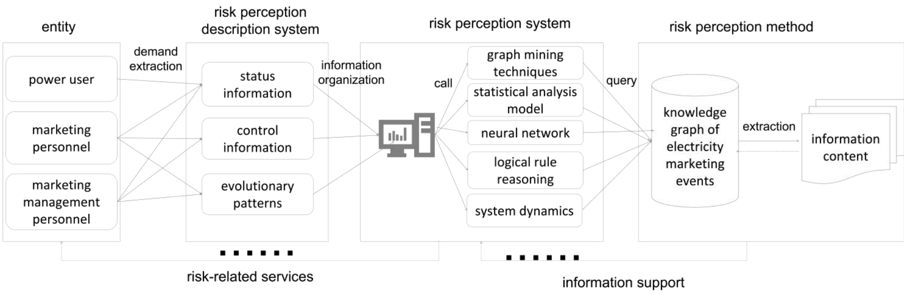

Fig. 3. The implementation path of electricity marketing event risk perception based on event knowledge graph.

4.2 Risk State Perception Method

Electricity marketing event risks involve complex elements, and risk states may be related to various factors, multiple entities, and more. It is challenging to accurately and comprehensively extract the elements of event risk states due to the characteristics of multi-source, heterogeneous, and dynamic electricity marketing big data. Therefore, this paper proposes a risk state perception method based on the event knowledge graph. First, regarding the information content of electricity marketing events obtained from various sources, event classes, entity classes, and their mutual relationships are constructed using the event graph representation model. Machine learning algorithms are applied to extract events, event elements, and entities from relevant information content, identify their relationships, and achieve semantic fusion and fusion at the entity and event levels. Graph mining techniques and semantic matching methods are used to find all node elements related to the current event risk in the event graph. Secondly, for the perceived risk elements, statistical analysis models and rule matching methods are used to form an understanding of the current risk, including risk assessment and risk warning, and to create control measures for the corresponding risk based on historical experience rules. Finally, historical events similar to the current event are found in the event graph, and relationships are mined based on the evolution rules in the event graph. Methods such as neural networks, logical rule inference, and system dynamics are used to build risk prediction and simulation deduction, predict the possible trends of events, supplement risk knowledge elements, and present the results of risk analysis to different users, achieving automatic perception of risk events, timely alerts, and assisting in decision-making.

5 Conclusion

This paper addresses the diverse needs of different stakeholders for electricity marketing risk perception. It proposes an event knowledge graph representation model and an event knowledge graph construction process. These facilitate the systematic organization of electricity marketing events, entities, and their relationships. By leveraging the foundation of electricity marketing data and innovating in the expression of electricity marketing knowledge graphs, this approach effectively enhances the organization and management of electricity marketing information. Building upon this foundation, it presents a methodological path to achieving electricity risk perception based on event knowledge graphs, effectively serving the risk status perception, monitoring, and early warning needs of various stakeholders. This, in turn, promotes the enhancement of electricity marketing management capabilities.

However, this paper primarily conducts research on the theoretical and methodological aspects of electricity marketing event graphs. The next steps involve integrating various technological methods to realize the construction and application of concrete prototypes of electricity marketing event graphs. This will enable the practical implementation and validation of event knowledge graphs within electricity marketing risk prevention and control systems. Subsequent validation and summarization of results are also essential to complete the research cycle.

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