B-009

Establishment and Maintenance of Knowledge Base Utilizing Industrial Internet of Things (IIoT)

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Abstract: Industrial Internet of Things (IIoT) systems collect equipment and production data from industrial sites. Analysis yields insights into equipment performance, site execution, and product production. Statistical analysis of these events, combined with on-site production conditions, facilitates the creation and maintenance of a knowledge base based on IIoT data to aid decision-making.

Keywords — Knowledge Base, IIoT, Decision-Making

1. Introduction

A knowledge base (KB) is a set of sentences, each sentence given in a knowledge representation language, with interfaces to tell new sentences and to ask questions about what is known, where either of these interfaces might use inference.[1]

Knowledge bases have a broad spectrum of applications in the industrial sector. Firstly, by modeling production processes and products, they can aid decision-making on the production floor, such as selecting the most suitable equipment parameters.[2] Secondly, with the widespread adoption of industrial IoT systems, digital twins that utilize field data can uncover deeper insights from this data, extracting detailed production information and thereby constructing a more precise knowledge base.[3]

To leverage industrial IoT data for knowledge base construction, we begin by extracting events from the vast amount of field data. These events can include product completions on the production line, equipment anomalies, and more. Next, we utilize these events to construct a causal diagram. This diagram is then validated with subsequent data to identify potential causal pathways. Finally, we leverage the extracted events and the derived reasoning rules from the causal paths to construct a monitoring system. This system facilitates on-site, production-assisted decision making.

This paper is organized as follows: First, we will outline the fundamental methodological steps for building a knowledge base using industrial IoT data. Next, we will present a case study demonstrating the construction of a knowledge base in a real production scenario, utilizing data from a previously implemented industrial IoT project. Following this, we will discuss the case study and highlight key considerations for building an effective knowledge base. Finally, we will explore future research directions in response to the challenges and deficiencies encountered during the implementation.

2. Methodology

2.1 Definitions

In this paper, we use the following definitions:

- Entity:
  the object that can either send data to the system or receive data from it.
- Event:
  a major status change of an entity within the system.
- Causal Diagram:
  a causal diagram is a crucial tool in causal inference, used to represent the relationships between variables. Typically presented as a Directed Acyclic Graph (DAG), these diagrams feature nodes that represent variables and arrows that indicate the direction of causality.
- Causal Pathway:
  a reachable path between two nodes in a causal diagram.
- Reasoning Rule:
  scheme for constructing valid inferences.

2.2 System

As shown in the figure 1, the system comprises the following components:

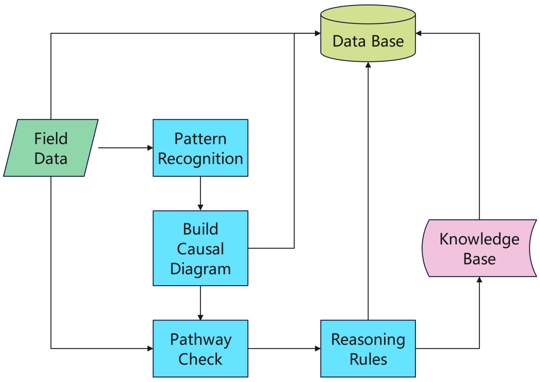

Fig. 1 System Topology Diagram

- An external IoT data source.
- A pattern recognition module that extracts events from the IoT data.
- A causal diagram construction module that generates the causal diagram.
- A causal path checking module that verifies the validity of the causal diagram using data from the external IoT data source.
- A reasoning rules module that encodes the validated causal paths into reasoning rules.
- A knowledge base module that stores the reasoning rules and the built-in events.
- A database where the above modules share data storage.

2.3 System Execution Process

Before deploying the system, it is essential to have an industrial IoT system already in place at the industrial site and to ensure access to on-site sensor data through a predefined HTTP interface.

The pattern recognition module can be initiated in two ways:

- Without predefined events:
  In this case, the module continuously checks the data using

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the built-in KS (Kolmogorov-Smirnov) algorithm, counting the frequency of each data type. The most frequently occurring data is recognized as normal data.

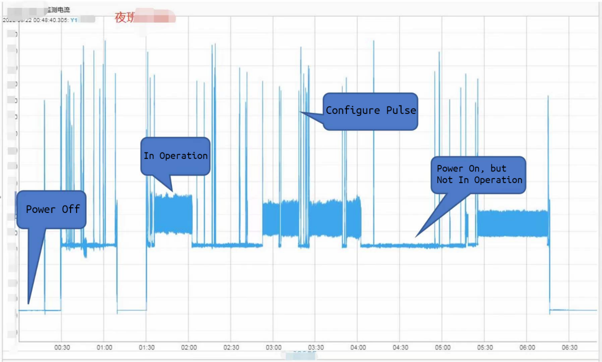
- With predefined events:
  Here, the module starts with predefined normal data and provided samples of abnormal behavioral data.

To construct a causal diagram, we begin by organizing events into sequences. These events are chronologically ordered, starting from the production start event and concluding with the production completion event. Subsequently, sequences of events demonstrating no less than 90% confidence in the occurrence of each step are retained as causal diagrams.

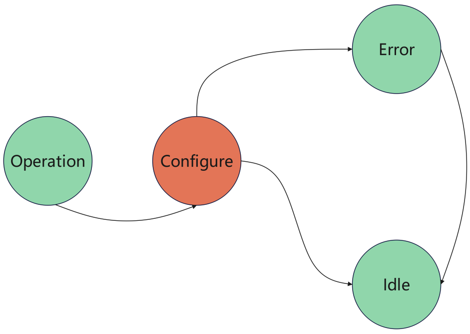
After processing the causal diagram based on the backdoor criterion, we utilize real-time IoT data to validate the paths. Causal paths with more than 90% confidence are then filtered and recorded as reasoning rules to be incorporated into the knowledge base.

3. Case Study

We have deployed an Industrial IoT system within a manufacturing plant[4] and are now presenting a case study based on the data gathered from this project.



(a) IoT Data Sample



(b) Causal Diagram Sample

Fig. 2 Field Data Analysis

In Figure 2(a), we display the current production equipment data obtained from the field, which serves as the basis for modeling equipment behavior. To conserve computational resources in the field, we attempted to model the device using only a single parameter: current. This parameter, also utilized for power tuning of the device, is deemed valid by the manufacturer, further justifying our choice. Following discussions with the consultant, we have pre-modeled equipment behavior considering event characteristics such as shutdown, operation, standby, and idle states.

For the described scenario, we developed a straightforward example of a causal diagram (Figure 2(b)). Upon completion of its operation, if the device's parameters are adjusted, it undergoes a self-test. If the self-test is successful, the device transitions to the Idle state. Conversely, if the self-test fails, it enters the Error state. In the latter case, the parameters automatically revert to the last available settings, and the device returns to the Idle state.

After multiple runs, the knowledge base system can conduct pre-checks on setting modifications and suggest more appropriate parameters accordingly.

4. Conclusion and Discussion

We've devised and executed a system for constructing and upholding a knowledge base tailored to industrial IoT data, utilizing conventional statistical models. This system has been deployed in actual production environments, aiding in equipment parameter adjustments and optimizing processes on-site.

Data serves as the cornerstone for all applications. Hence, the fundamental requirement for initiating the knowledge base project is the installation and deployment of an industrial IoT system at the industrial site, ensuring the acquisition of dependable field data. In our instance, we initially established the industrial IoT system. Through an operational period, we amassed on-site production equipment operational data, which served as the foundation for modeling equipment behavior, laying the groundwork for subsequent knowledge base construction.

If we can furnish predefined event information during the implementation phase, the efficiency of knowledge base creation will be significantly boosted. Simultaneously, given the computational requirements for field data analysis, traditional statistical models are better suited for edge servers than machine learning. Predefined events can further economize computational resources on this basis.

In this paper, we opt for a 90% confidence interval instead of the more stringent 95%, as we have observed in our practical usage and testing that it strikes a better balance, accounting for factors such as the frequency of IoT data collection, computational resources in the field, and computation latency.

In the future, we aim to incorporate multiple types of sensor data into unified modeling to capture a broader range of dimensional information. This approach is expected to enhance the prediction accuracy of the system.

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