Article

Robust Simulation of Cyber-Physical Systems for Environmental Monitoring on Construction Sites

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Abstract: Environmental monitoring is a crucial part of environmental management on construction sites. With the increasing integration of environmental-monitoring systems and cyber-physical systems (CPS), the environmental-monitoring cyber-physical system (E-CPS) has been developed, but it still suffers from uncertainty problems and a lack of robustness. In this study, ontology is utilized to establish an E-CPS model that can realize the integration and interaction of physical space, cyberspace, and social space, and the E-CPS model contains perception, transportation, fusion, and decision-making layers. Three uncertainty scenarios are then identified in four layers of the E-CPS to address the current E-CPS shortcomings. The proposed E-CPS model is applied in a construction project, and simulation experiments are then conducted on construction sites. The results show that the abnormal-data-recognition algorithm based on spatiotemporal correlation, whose detection rate is stable around 96%, improves the system's anti-interference ability against anomalous data entering the perception layer and the transportation layer. This algorithm ensures the accuracy of environmental monitoring for early warning. The sensory data-fusion results based on the belief function method vary from 52.16 to 52.50, with a decrease rate reduced to 0.65%. Finally, the decision-fusion algorithm based on the improved Dempster–Shafer (D-S) evidence theory achieves robust performance. This study could enhance the robustness of the E-CPS in uncertainty conditions and aid the project managers to make decisions and take targeted measures according to the environmental monitoring results and experts' decisions.

Keywords: cyber-physical systems; ontology; system robustness; uncertainty scenarios; environmental monitoring

1. Introduction

The construction industry consumes several raw materials and energy resources, concentrating on pollutant emissions with a wide range of impacts on society [1]. For instance, dust pollution and noise pollution are generated during the construction process, causing disputes between builders and nearby residents, while more attention is paid to this issue by the environmental supervision department. These disorders are often associated with environmental monitoring systems, and a failure to provide reliable and accurate visual observations or inspections for decision-makers [2]. Hence, environmental-monitoring systems for construction sites play an important role in government environmental supervision. Currently, wireless sensor network (WSN)-based environmental-monitoring systems have been widely used to achieve the real-time monitoring of dust and noise on construction sites [3,4]. However, they have some limitations, such as the lack of several system functions, unbalanced coordination between information space and physical space, and low levels of integration [5,6].

Cyber-physical systems (CPS) can integrate computation, communication, and control systems in order to achieve the interaction between information space and physical space. Considering that CPS can solve these problems and bring great value to society, it

has become a significant direction of studies and a growing concern for the construction industry. Based on previous studies on CPS and environmental monitoring [7–9], the environmental-monitoring cyber-physical system (E-CPS) can be applied on construction sites using multi-source sensors to gain real-time environmental information, and dynamically perceive the environmental changes on construction sites. An E-CPS framework has four main layers: perception, transportation, fusion, and decision-making layers. The existing studies on E-CPS mainly focus on the improvements of the perception layer and the transportation layer, in order to quickly and accurately obtain monitoring data. However, they ignore the environmental changes' impact on the decision-making layer of the E-CPS. Therefore, the decision-making model and controller can be performed to accurately achieve integrated construction management. Due to the complexity of the construction sites, the limited accuracy of sensor measurement, and the interference of environmental changes, E-CPS faces several uncertainty challenges from the perception layer to the decision-making layer. These challenges mainly derive from three aspects: the imprecision and incompleteness of monitoring data, the non-conventionality of environmental assessment, and the inconsistency of human irrational behavior and understanding [10,11].

Robustness, as an extension of the uncertainty theory, emphasizes the measurement and control of data. It also improves the reliability of systems [12]. The robustness of the E-CPS has two characteristics (reliability and adaptability). It is crucial to consider the interaction between CPS and the environment on construction sites [13]. More precisely, a robust E-CPS can stably achieve decision-making when monitoring noisy or damaged data. In addition, it can automatically detect unexpected events and make advanced adjustments to adapt to the environmental changes. Several studies on the influencing factors in robustness, robustness design, and robustness measurement [14–17] exist. Some researchers consider CPS as technical systems, and they explored the robustness of software and operating systems [18,19]. However, they ignore the important fact that CPS are technology-social systems, and their robustness characterizes the joint action of technology, management, and personnel elements. It is important to mention that the influencing factors and mechanisms of the E-CPS robustness are crucial. However, uncertainty is a critical issue that should be paid attention to regarding E-CPS, and there is a lack of studies on the robustness design, simulation, and evaluation of the E-CPS. This cannot address the environmental monitoring issues on construction sites.

Within this context, this study aims to build up a comprehensive E-CPS model characterizing the joint action of technology, management, and personnel elements, to handle the aforementioned environmental monitoring problems. This study aims to handle the environmental monitoring problems. Ontology can be regarded as a formal description that can be represented, understood, and utilized by computers. It is characterized by conceptual clarity, machine readability, and formal representation. Currently, ontology and semantic web technologies have been widely employed to realize the integration and sharing of domain knowledge through creating domain ontology [20]. The ontology-based model can build a unified semantic model and realize the integration and interaction of physical space, cyberspace, and social space, handling heterogeneous information issues to conduct semantic collaboration [21]. Furthermore, the formal language of ontology can describe the logical relationship among ontologies and realize the sharing and reuse of knowledge, so that the system can still make effective decisions in face of unanticipated events. Considering that low reliability exists when E-CPS interacts with construction sites, ontology is used to construct an E-CPS model to conduct environmental monitoring and evaluation, which characterizes three main functions: early warning, remote control, and the auxiliary evaluation of construction sites. The E-CPS robustness simulation is also performed on construction sites. This offers guidance for the robustness design of the E-CPS and the accurate environmental management of construction sites, which can deepen one's understanding of the E-CPS robustness. Moreover, the proposed model can further expand the understanding of information management and aid project managers to conduct information management on construction sites.

The rest of the paper is organized as follows. To proceed, Section 2 reviews the literature on the application of the E-CPS and system robustness. Section 3 demonstrates the methodology, including the establishment of evolution models of stakeholders involved in the ecological compensation of rail transit projects, as well as the replicator dynamic analysis of multi-stakeholders, and the evolutionary stable strategy (ESS) of tripartite mainstay. After that, Section 4 conducts E-CPS modeling and uncertainty-factor identification, and then Section 5 carries out uncertainty detection and processing. Finally, Section 6 discusses the results of three uncertainty detection algorithms. Section 7 draws the conclusions in this study.

2. Literature Review

2.1. Applicability of CPS

According to the previously mentioned characteristics, CPS can enhance the information processing and address human–machine-environment coupling problems by achieving bidirectional coordination between the virtual world and physical structures [9]. Hence, CPS are used in several fields, including manufacturing, transportation, and the construction industry. When CPS are used on construction sites during the construction process, their data are first collected by the sensors on construction sites. Consequently, the decision support system (DSS) makes decisions, and the actuator network then takes necessary actions in response to the dynamic environmental changes on construction sites and maintains interaction with project managers. Therefore, some researchers endeavor to conduct the building monitoring and visualization of construction sites using CPS. For instance, Yuan et al. proposed temporary-structure monitoring (TSM) based on CPS. The latter integrates the virtual model and physical structure on construction sites [22]. Akanmu et al. created a cyber-physical postural training environment using wearable sensors [23]. During the operation period of projects, CPS can also be used to monitor the real-time performance of buildings, in order to offer insurance for project managers in decision-making. This can be achieved by combining building information-modeling (BIM) and CPS, after they are tested by a customized simulator [24]. As for E-CPS, important studies try to combine the environmental monitoring with CPS in order to handle environmental issues, and the system architecture of the E-CPS has been developed and enriched (cf. Table 1).

Table 1. The main existing methods and themes in E-CPS.

Author	Research Methods	Theme
Liu et al. [9]	CPS + WSN + GPS + BIM	Monitoring greenhouses gas emissions of prefabricated buildings
Nazerdeylami et al. [8]	CPS + deep learning	Monitoring litter surveying and prediction of human littering activities in the coastal area
Amuthadevi et al. [25]	CPS + WSN	Monitoring risk of air pollutant in urban areas
Ding et al. [26]	CPS + IoT + cloud-edge orchestration	Monitoring production-status service and energy consumption in the shopfloor
Zografopoulos et al. [27]	CPS + simulation modeling	Evaluating the system's performance under adverse scenarios

In summary, previous studies have confirmed the applicability of CPS in the construction and operation period; it plays a crucial role in the management of the building life-cycle. Although significant efforts have been made toward CPS-based environmental monitoring and visualization, studies on the applicability in the construction industry are still at the initial stage. There are few studies on combining environmental monitoring and construction process by developing a system suitable for environmental management on construction sites. Moreover, the existing studies focus on enhancing the remote control of the environmental monitoring in the E-CPS while ignoring the impact of the environmental changes on decision-making. The functions of the E-CPS, such as early warning and auxiliary evaluation, are rarely performed to assess environmental management using E-CPS.

Hence, this study addresses the necessity and benefits of the E-CPS in environmental monitoring for construction sites.

2.2. System Robustness

Researchers in several fields defined robustness with different connotations, while the entry points for previous studies correlated with robustness also vary [28,29]. Robustness is a crucial attribute in systems' handling of uncertainty problems [30]. Some studies focus on the influencing factors in system robustness and achieving system robustness [31,32]. Other studies focus on system robustness design. This ensures that the system can achieve robustness by creating control structures or schemes. There are mainly two ways for achieving system robustness in order to respond to environmental changes. Firstly, reaction capabilities can be used to passively respond to environmental changes. Secondly, preemptive capabilities can be used to respond actively. Consequently, some researchers conducted studies from different perspectives. Security defense is a crucial issue in achieving system robustness [33]. In this complicated system, fault tolerance also characterizes a system's robustness under uncertainty conditions such as modeling uncertainty, parametric uncertainty, and unpredictable events. According to the connotation of CPS, individuals such as implementers and decision-makers are also constituent elements since their irrational behaviors are associated with making inappropriate decisions. Some researchers mention that constructing a general fault-tolerance framework for error detection and error handling can enhance the capacity of fault tolerance [34,35]. Consequently, McPhail established a generic guidance framework in order to identify the most robust decision choices and applied a software package to gain intelligent decisions [36].

In terms of resource failure, an isolation strategy is developed to promote the power system's robustness. In this approach, some typical clusters are separated from the main network, and independent alternative energy sources are used as a power supply [37]. Another method to improve the system's robustness consists in building autonomous nodes that have stripped off the interaction among networks, in order to cope with the damage caused by buffer failures [38]. Although the current studies yield some benefits, the system's robustness still suffers from several limitations. In fact, most of the existing robustness methods are based on specific application scenarios, and they are difficult to migrate to different types of application scenarios. On the other hand, several researchers consider CPS as a technical system while ignoring the fact that E-CPS is a technology-social system, whose robustness results from the interaction of technology, management, and personnel elements.

The literature review demonstrates that uncertainty is a critical issue that should be paid attention to regarding E-CPS. The existing studies focus on the security defense, resource failure, and fault tolerance of system robustness, while a lack of studies on E-CPS robustness exists. However, E-CPS suffers from more severe problems such as maintaining satisfactory performance when facing uncertain data quality and model specifications. Therefore, it is necessary to extend E-CPS robust design and simulation scenarios according to the actual needs of construction sites, as well as conduct targeted operations within corresponding scenarios.

3. Research Framework

According to the characteristics of robustness, the inputs–processes–outputs (I–P–O) paradigm is used to develop a robust simulation I–P–O framework for the construction of site monitoring and decision-making. With the deepening of ontology theory and construction technology, ontology has been utilized in the construction field to realize the integration and sharing of knowledge information on construction sites. The existing studies attempted to identify construction safety risks by developing domain ontology during the construction period [39,40]. Based on these studies, Li et al. considered more issues on health and well-being to promote safety and information management on construction sites [41]. Moreover, Petnga and Austin combined ontology with CPS to conduct

information modeling and decision support on construction sites [42]. This study focuses on environmental issues on construction sites and constructs an environmental monitoring and evaluation model through ontology and CPS. Therefore, this study creates a workflow (Figure 1) that illustrates the prototypical framework to measure the robustness of the E-CPS.
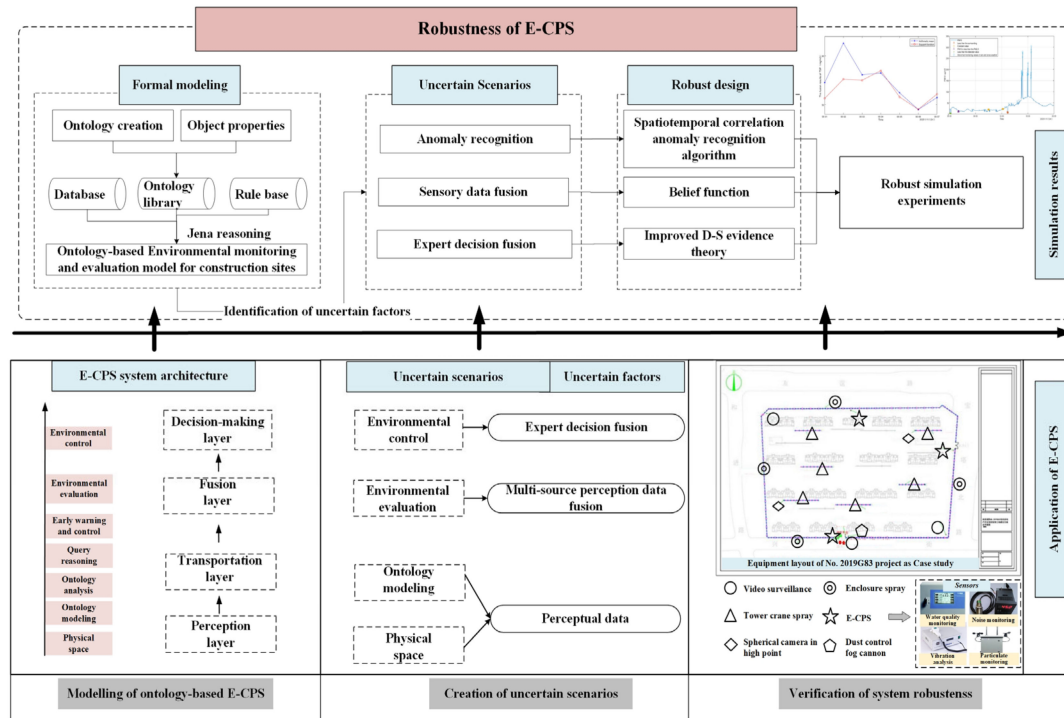

Figure 1. Overall research framework.

Considering that the E-CPS framework has four main layers (perception, transportation fusion, and decision-making layers), the ontology is first used to develop an E-CPS model since the ontology-based model can perform the integration of physical space, cyber space, and social space, as well as assess the semantic collaboration. This can describe the relationships among ontologies and perform the sharing and reuse of data, so that the system can make efficient decisions when facing uncertainty [43]. More precisely, the ontology objects, including projects, equipment, and sensors in the perception layer and the object properties, are created and saved in the ontology library. After the database and rule base are established, the Jena inference engine is used for ontology reasoning. In addition, the inference results are obtained accordingly in Eclipse, in order to perform the early warning and control of TSP, PM2.5, PM10, and noise on construction sites. The data from the environmental monitoring and evaluation indicators are then fused in the fusion layer. Finally, they enter the decision-making layer for project managers, in order to conduct data processing and make decisions based on experts' evaluation and stakeholder interaction.

The E-CPS model contains three environmental-monitoring systems with PM10, PM2.5, TSP, and other sensors, as well as five video monitoring sites with three dust reduction controllers: fog cannon, enclosure spray, and tower crane spray. Afterward, the proposed ontology-based E-CPS model faces different uncertainties on construction sites: (1) uncertainties of anomalous data from the ontology objects such as sensors and equipment in the perception layer and the transportation layer; (2) uncertainties of multi-source perception data fusion of rule reasoning and expert scoring in the fusion layer; (3) uncertainties of experts' decision fusion results for project managers in the decision-making layer. Therefore, three categories of uncertainty scenarios of the E-CPS are created according to the uncertainty factors of the four layers in the E-CPS.

As for the anomalous data in the perception layer and the transportation layer, uncertainty detection and processing are conducted in the ontology-based E-CPS model using a spatio-temporal correlation anomaly-recognition algorithm. This improves the E-CPS robustness since the algorithm can use the temporal and spatial correlation of the monitoring data to identify anomalous data [44]. Previous studies have explored some algorithms, including belief functions, as well as D-S evidence theory to conduct uncertainty detection and processing [45–47]. Considering that belief functions can determine the confidence level of the monitoring data to improve the accuracy and stability of the fusion results, this study integrates the belief function and the fuzzy-index belief function, in order to develop a sensor data-fusion belief function that improves the accuracy and stability of the fusion results. The Dempster–Shafer (D-S) evidence theory is a method of uncertainty inference, proposed by Dempster and developed by Shafer [47]. It can fuse uncertain information. However, it sometimes displays poor robustness [48]. Therefore, this study combines the fuzzy theory and the D-S evidence theory, according to the combination approach of conflict evidence, in order to conduct conflict detection and the processing of experts' decisions on evaluating environmental monitoring results [49]. Finally, the proposed ontology-based E-CPS model is applied in a construction project in Nanjing, Jiangsu Province, China. The environmental monitoring indicators in this model are determined using the literature review, the questionnaire survey, and the expert consultant. In this context, the simulation experiments are performed to examine the improvements of the system robustness using the recognition algorithm based on spatio-temporal correlation, the data-level fusion algorithm based on belief functions, and the decision-fusion algorithm based on the improved D-S evidence theory.

4. E-CPS Modeling and Uncertainty-Factor Identification

4.1. Development of the E-CPS Model Based on Ontology

The ontology-based E-CPS model can provide a platform for querying and analyzing the environmental information on construction sites, including the main features such as the sensing elements and control elements. Based on the studies of Zhong et al. [50] and Wang [43], the process of ontology modeling is presented in Table 2, and the ontology-based environmental monitoring and evaluation model is illustrated in Figure 2.

Table 2. The process of ontology modelling in the E-CPS.

Step	Task Definition	Primary Content
1	To establish the ontology model	The ontology model contains five basic elements—human, machine, matter, events, and time—as well as the interaction between the elements.
2	To establish the rule base	According to the actual needs of construction site environmental management, a number of rule statements can be created in the rule base to analyze the physical space based on industrial standards and expert experiences.
3	To establish the database	The database is utilized to store historical data and real-time data. The data are derived from sensors and video surveillance in physical space, which reflect the environmental information.
4	To establish the inference engine	The established inference rules, ontology models, and databases can be connected to the inference engine.

(1) Development of the ontology model

E-CPS model needs to build a universal ontology. The construction site arranges the environmental monitoring CPS system by project, and the various devices, sensors and monitoring data in environmental-monitoring systems depend on the construction project in question, so the construction project can be used as a generic ontology on which the sensors, monitoring devices, and other entities can be extended. The attributes of construction site project in the model established in this paper are: Project_name, Project_ID, and Project_address. Considering that the ontology model reflects all the important system characteristics, the main features of the E-CPS are the monitoring equipment, sensors,

information centers, and controllers. According to the actual needs on construction sites, ten categories of sensors, including PM10, PM2.5, and TSP; three categories of controllers, including Envelop-Sprayement, Towercrane-Sprayement, and Workers; and two categories of alarm (PM10_alarm and Noise_alarm) are developed. The proposed E-CPS model can obtain real-time information from environmental monitoring indicators such as PM10, sewage discharge, and noise, for example.
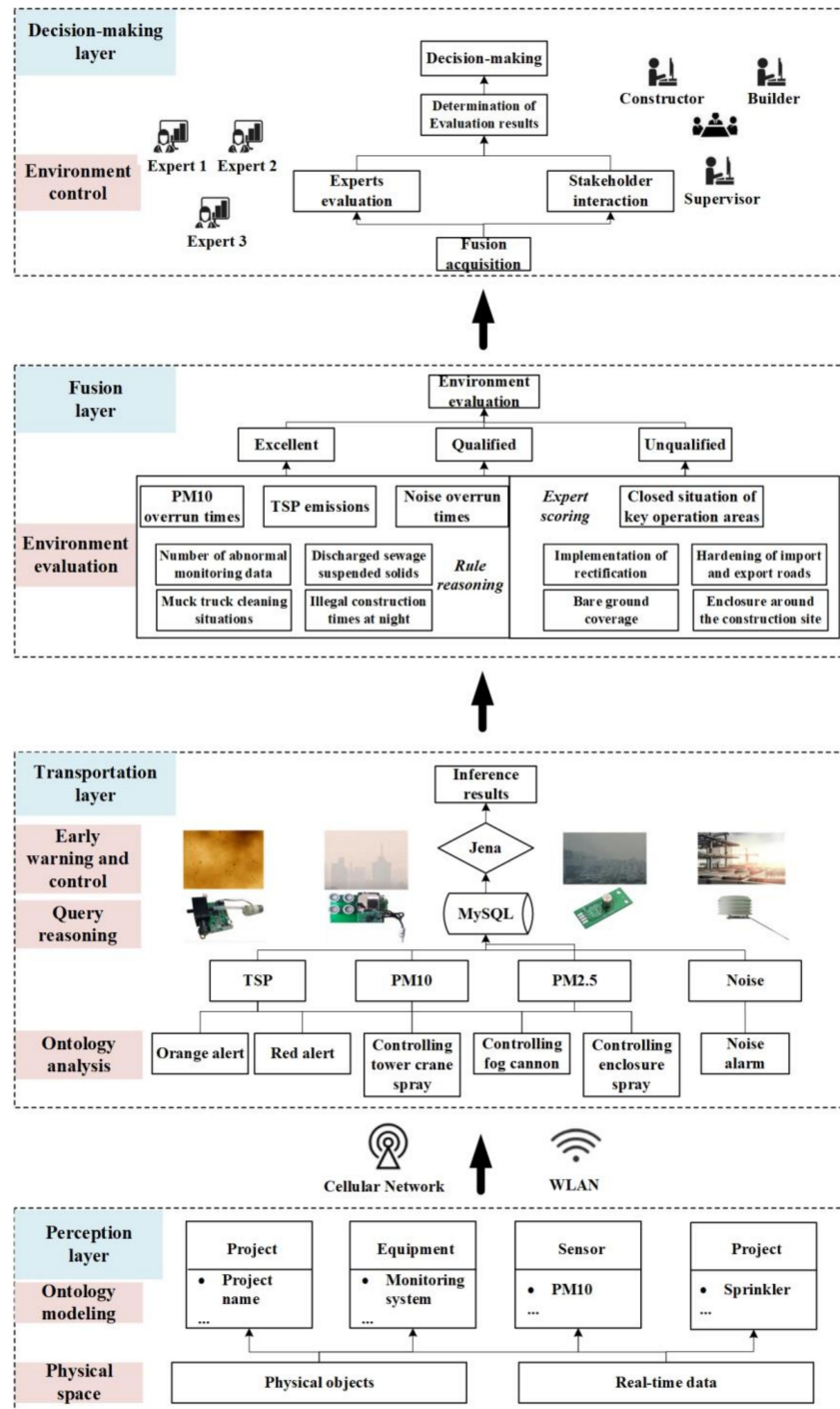

Figure 2. The ontology-based environmental monitoring and evaluation model.

The ontology-based E-CPS model needs to realize the main function of environmental monitoring and evaluation. Hence, the environmental monitoring and evaluation indicator system in the E-CPS model contains real-time environmental monitoring indicators, which

can reflect the level of environmental management of the project. By on-site investigation and previous studies on environmental monitoring on construction sites [5,50], the environmental monitoring and evaluation indicator system was developed and applied in the construction project in Nanjing, China (Table 3). This project involves 5 video monitoring points and 3 E-CPSs. Each system contains PM10, PM2.5, TSP, and other sensors, as well as three kinds of dust-reduction controllers: fog cannons, enclosure sprays, and tower crane sprays.

Table 3. The environmental monitoring and evaluation indicator system.

No.	Indicator	Description	Source
1	PM10 overrun times	Times of PM10 exceed the limit per month	PM10 sensor
2	TSP emissions	Difference between the monthly average concentration of TSP and the urban background value (mg/m^3)	TSP sensor
3	Noise overrun times	Times of the monthly noise exceed the limit	Noise sensor
4	Illegal construction times at night	Times of night construction violations without approval	Noise sensor
5	Discharged sewage suspended solids content	The content of suspended solids in the sewage discharged from the construction site	Water quality monitoring sensor
6	Muck truck cleaning situations	Whether departing vehicles are flushed as required	Vehicle flushing capture system
7	Number of abnormal monitoring data	The number of abnormal monitoring data per month	Information platform
8	Hardening of import and export roads	The main roads and sites on the construction site are hardened as required	Video Surveillance
9	Enclosure around the construction site	Enclosure measures shall be taken around the construction site, and the front door and the vicinity of the enclosure shall be cleaned in time	Video Surveillance
10	Bare ground coverage	The bare ground and mounds of the construction site shall be covered, solidified, or greened, as required	Video Surveillance
11	Closed situation of key operation areas	The outer scaffolding is enclosed by dense mesh nets, metal safety nets	Video Surveillance
12	Implementation of rectification	Whether to deal with warning information promptly; after heavy air pollution and extreme weather warning information, stop production and limit production and response measures according to the corresponding warning level	Information platform

According to Table 2, the process of environmental monitoring and evaluation on construction sites is as follows. A "project" is first determined. It has a monitoring "equipment" arranged in different "regions". The "equipment" contains several "sensors", and the "sensors" collect "environmental monitoring data". When the "environmental monitoring data" exceed the limit, an "alarm" message is issued, and relevant instructions are then sent to the "controller" in order to take relevant measures. Finally, the "evaluation of green construction" is performed based on the "environmental monitoring data" collected by the monitoring "equipment". From the perspective of the environmental monitoring and evaluation, the object properties are hasarea, hasmonitorfacility, hassensor, hascontroller, conductalarm, and conductevaluation [50], thereby establishing the data relationship between ontology concepts and defining object properties, as shown in Figure 3.

The data property establishes the relationship between classes and data and is simpler than the object properties. Data are associated with a class through a data property, and data properties depend on the class for their existence. This study entered the data properties in the data property hierarchy of the Protégé software. Firstly, the data property was created, then all classes with the data property were added to "domains". Finally, the data form "string" in "ranges" was selected to complete the process of creating the data attribute.
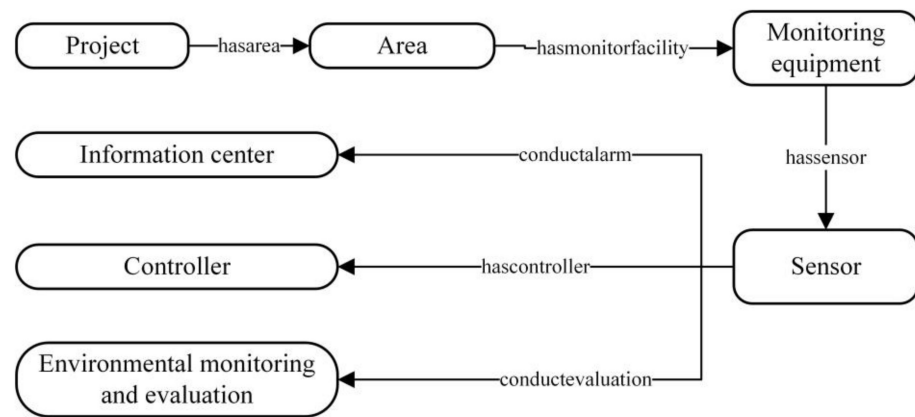
Figure 3. The relationship between the ontology objects of the E-CPS.

After creating the above ontology, object attributes, and data attributes, the E-CPS ontologies can be constructed as Figure 4.
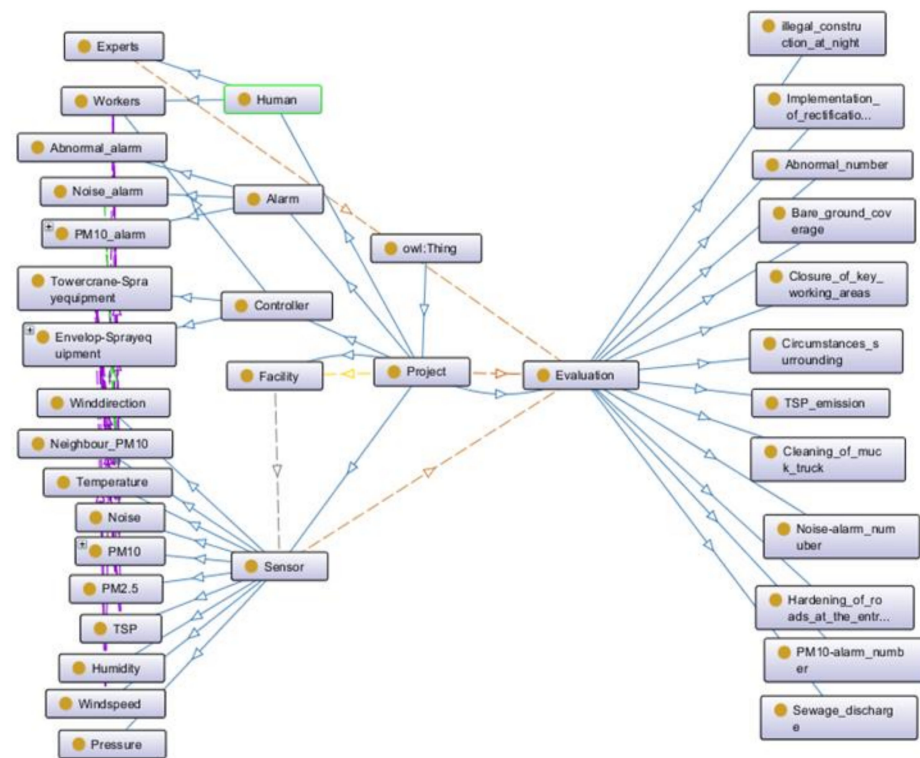

Figure 4. The ontologies in the E-CPS model.

(2) Ontology reasoning

The inference engine is the core of the ontology-based E-CPS model for construction sites. Considering that the inference engine should support the rule extension, the Jena inference engine is used for ontology reasoning in order to enhance the precision of ontology reasoning in the E-CPS [51]. Taking the PM10 over-limit early warning in the E-CPS as an example, the "Nanjing Construction Site Intelligent Monitoring of Dust Monitoring Guide (Trial)" stipulates that the value of early warning for PM10 is 100 μg/m^3. When the monitoring data of PM10 reaches the limit, E-CPS issues an early warning signal. This rule aims to issue an orange warning when the monitoring value of PM10 is between 100 and 150. Similarly, other rules can be formulated. After the rules are defined (Table 4), they are saved in a ".rules" file format to build an extended rule library.

Table 4. Jena inference rules of early warning.

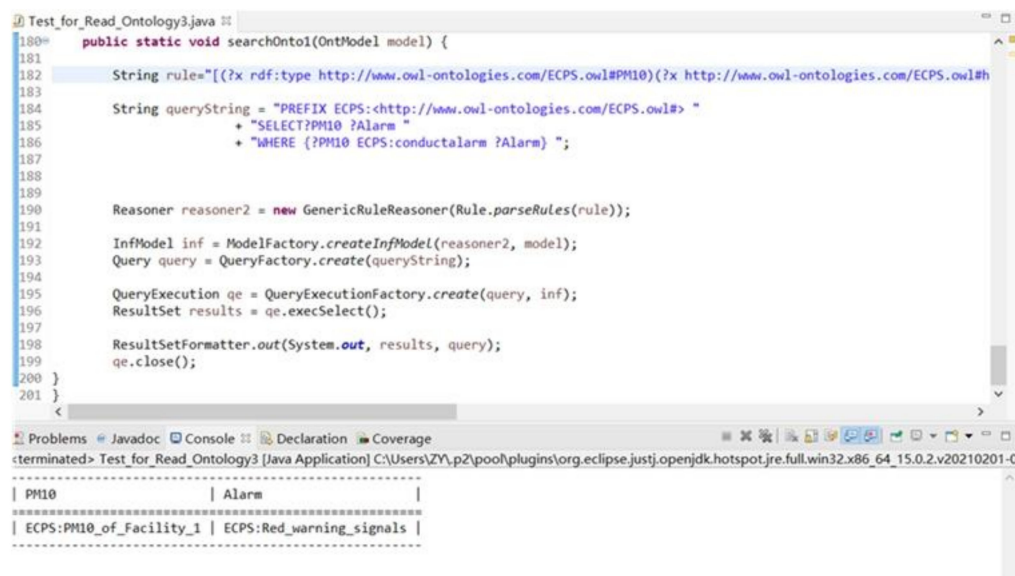| Rule	Jena Rules	Early Warning
Rule 1	[(?x rdf:type http://www.owl-ontologies.com/E-CPS.owl#PM10 (accessed on 24 August 2022))(?x http://www.owl-ontologies.com/E-CPS.owl#hasvalue (accessed on 24 August 2022) ?y) + "greaterThan(?y,150)" + "->(?x http://www.owl-ontologies.com/E-CPS.owl#conductalarm http://www.owl-ontologies.com/E-CPS.owl#Red_warning_signals) (accessed on 24 August 2022)]	A red alert is issued when the PM10 monitoring value is greater than 150 ug/m^3.
Rule 2	[(?x rdf:type http://www.owl-ontologies.com/E-CPS.owl#Noise (accessed on 24 August 2022))(?x http://www.owl-ontologies.com/E-CPS.owl#hasvalue (accessed on 24 August 2022) ?y)" + "greaterThan(?y,70)" + "->(?x http://www.owl-ontologies.com/E-CPS.owl#conductalarm http://www.owl-ontologies.com/E-CPS.owl#Noise_alarm) (accessed on 24 August 2022)]	Noise warning is issued when the noise value is greater than 70 dB.
Rule 3	[(?x rdf:type http://www.owl-ontologies.com/E-CPS.owl#PM10 (accessed on 24 August 2022))(?x http://www.owl-ontologies.com/E-CPS.owl#hasvalue (accessed on 24 August 2022) ?y) + "greaterThan(?y,150)" + "->(?x http://www.owl-ontologies.com/E-CPS.owl#hascontroller http://www.owl-ontologies.com/E-CPS.owl#Open-Envelop-Sprayequipment) (accessed on 24 August 2022)]	The enclosure spraying is open and dust reduction measures are taken when PM10 monitoring value is greater than 150 ug/m^3.
Rule 4	[(?x rdf:type http://www.owl-ontologies.com/E-CPS.owl#PM10_alarm_number (accessed on 24 August 2022))(?x http://www.owl-ontologies.com/E-CPS.owl#Performance_of_indicators (accessed on 24 August 2022) ?y) + "greaterThan(?y,1)" + "->(?x http://www.owl-ontologies.com/E-CPS.owl#Evaluation http://www.owl-ontologies.com/E-CPS.owl#unqualified) (accessed on 24 August 2022)]	The evaluation result of this indicator is unqualified when the number of PM10 warnings is greater than 1.

(3) Ontology and data storage

In this study, the MySQL database is developed to store ontology/data due to the simplicity and convenience of storage of ontology/data operation, and assistance of reasoning. After customizing the rule library, the Jena inference engine is used in Eclipse in order to obtain the ontology model. Persistent storage is then performed in MySQL. Afterward, the rule acquisition and the inference results are obtained. Finally, the functions such as over-limit early warning, remote control, and the evaluation of green construction can be performed. An example is when the monitoring value from the PM10 sensor in the protégé ontology model is 160 ug/m^3. The corresponding output results are presented in Figure 5.

4.2. Creation of Uncertain Scenarios

The E-CPS model integrates man–machine materials, reasoning, control, and evaluation [52]. It has a series of reasoning calculation processes, and the calculation results could be affected by personal experience and subjective judgment. The E-CPS model integrates reasoning, control, and evaluation and confronts uncertainties in different layers of the E-CPS model. The perception layer is composed of controllers and network nodes responsible for collecting the construction site environmental data such as PM10, PM2.5, noise, temperature, and wind speed, using sensor components and video monitoring. The middle layer in the E-CPS system architecture is the transportation layer, which connects the perception

layer and the fusion layer. It is responsible for information transmission using wired networks, wireless sensor networks, and WLAN. The upper layer is the fusion layer, in which data fusion of multiple different point sensors is performed for a consistent description of the same object. The top layer is the decision-making layer, which is responsible for data processing and computing decisions, as well as performing user interaction. Based on the E-CPS framework and the on-site investigation on construction sites, this study identifies the uncertainty factors in the proposed model and then constructs typical uncertainty scenarios, which make contributions to performing robust design and simulation.


```java
public static void searchOnto1(OntModel model) {

    String rule="[(?x rdf:type http://www.owl-ontologies.com/ECPS.owl#PM10)(?x http://www.owl-ontologies.com/ECPS.owl#h

    String queryString = "PREFIX ECPS:<http://www.owl-ontologies.com/ECPS.owl#> "
                + "SELECT?PM10 ?Alarm "
                + "WHERE {?PM10 ECPS:conductalarm ?Alarm} ";



    Reasoner reasoner2 = new GenericRuleReasoner(Rule.parseRules(rule));

    InfModel inf = ModelFactory.createInfModel(reasoner2, model);
    Query query = QueryFactory.create(queryString);

    QueryExecution qe = QueryExecutionFactory.create(query, inf);
    ResultSet results = qe.execSelect();

    ResultSetFormatter.out(System.out, results, query);
    qe.close();
}
}
```

```
| PM10                 | Alarm                |
================================================
| ECPS:PM10_of_Facility_1 | ECPS:Red_warning_signals |
```

Figure 5. PM10 warning inference program run.

Uncertain scenario 1: The perception layer data of the E-CPS has some shortcomings such as low data quality, and poor stability and timeliness. Considering that wrong data will directly lead to wrong decision-making, four categories of errors that occur in the sensor exist: (1) large value, i.e., the monitoring data deviates from the average value and swiftly returns to the normal value. In general, the oversized data are generated under severe circumstances such as rainy and snowy days, instrument failures, unstable gateways, and interference with transmission signals. (2) Constant value. It is revealed that the data remain unchanged in a certain period. This is because the constant value of the monitoring data is the crash of the sensor processing device. (3) Zero value. This is revealed in the fact that the platform data continue to be zero for a certain period. (4) The dust/noise monitoring data are clearly lower than those of the surrounding environment.

Uncertain scenario 2: The construction site is equipped with more than two monitoring points. The values of similar sensors at each monitoring point differ because of the large area of the construction sites. When the green construction helps the evaluation of the difference between the monthly average concentration of the TSP and the urban background value, and the environmental noise at night, the project with multiple monitoring points requires multiple TSP sensor data fusions, and therefore the sensor data fusion is measured. Due to insufficient sensor accuracy, network noise, and other influencing factors, the monitoring data are under uncertainty conditions.

Uncertain scenario 3: The environmental monitoring and evaluation indicators also include qualitative indicators, which require experts scoring based on on-site surveillance videos. However, the evaluation value provided by experts has certain uncertainty, leading to inconsistent evaluation results among the experts. It is universally approved that the average of the scores of multiple experts is computed as the final score of the evaluated index. However, this cannot eliminate the subjective factors. In view of the conflicts in the fusion of expert scores and decision-making, a decision-making fusion model is constructed

to ensure the desired quality of evaluation and decision-making. In this study, the identified uncertainty factors are summarized into three uncertainty scenarios (Figure 6).
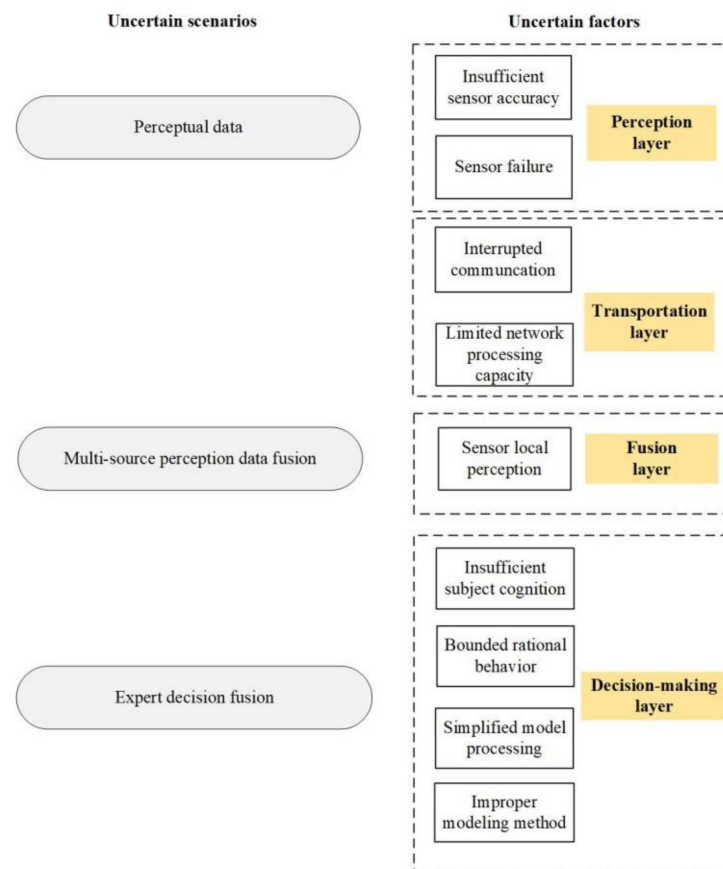

Figure 6. Identification of uncertainty factors and scenarios.

5. Uncertainty Detection and Processing

According to the I–P–O paradigm within the identified three uncertainty scenarios, unanticipated problems of detection and processing are performed to improve the system's robustness.

In Scenario 1, the system robustness is assumed so that the perception layer and the transportation layer in the E-CPS cannot be interfered with when facing uncertainty in data quality, which indicates that the abnormal data can be identified and processed, the environmental early warning can be issued, and the decisions that have been made are reliable.

In Scenario 2, the system robustness is assumed so that the interfering data can be identified by the data-fusion algorithm within the uncertainty context regarding multi-source data fusion, so that the fusion results can keep a steady state due to the changes in the individual data. The stability and robustness are associated with the uncertainty when facing multi-source data fusion.

In Scenario 3, the system robustness is assumed so that the decision-making model can efficiently handle the conflicting evidence when group decision evidence conflicts are produced. When the basic trust assignment of the evidence focal element slightly changes, the results remain qualitatively unchanged.

5.1. Abnormality Detection and Processing of Monitoring Data

The spatio-temporal correlation method can more accurately identify the anomalous data in the E-CPS system. An anomalous-data-identification model is then developed

based on the principle of spatio-temporal correlation. During the uncertainty detection, the probability of abnormal data is a crucial indicator for identifying abnormal data [53].

$$P_j(t_i) = P_j(t_{i-1}) + c \tag{1}$$

where $P_j(t_i)$ is an accumulated value that represents the probability of an abnormality at sampling time t_i, and c is a variable representing the increase in the probability of anomalies at the sampling moment t_i over the sampling moment t_{i-1}.

If sensor reading $r_j(t_i)$ is continuously judged as the abnormal data at several sampling moments, $P_j(t_i)$ is accumulated. If sensor reading $r_j(t_i)$ fails to meet the judgment condition, it is cleared until it meets the standard. When $P_j(t_i)$ reaches threshold R, the anomaly is detected in the node and fed back to the platform in order to prevent the abnormal data from entering the E-CPS [54]. Considering the differences of several sensors and the method robustness, R can be determined according to the sampling period of each sensor and the statistical characteristics of the dataset [55]. According to the definition of anomalous data provided by Hawkins [56] and the construction practice, this study considers PM10 as an example in order to detect and process the anomalous data regarding the environmental monitoring in Uncertain Scenario 1. This can be categorized into the following: the monitoring data are less than the detected value; constant value; the measured data inside the field is much less than that outside the field; the monitoring value of PM10 is less than the value of PM2.5; and the PM10 monitoring value is abnormal on rainy and snowy days.

(1) The monitoring data are less than the detected value

This category of conflict data is a monitored data value that is not within the set range of the detected value. The monitoring data are manifested as 0 or lower than the detection limit (the detection limit of the PM10 and PM2.5 monitoring data is 5 ug/m^3), which fails to conform to the laws of nature. In this study, the monitoring data are less than the detected value. If $r_j(t_i) < 5$, the monitoring data are judged as abnormal data. If $r_j(t_i) \geq 5$, the monitoring data are maintained.

(2) Constant value

Since PM10 is continuously monitored in the E-CPS, a fluctuation in the monitoring data exists within a certain range. When encountering circumstances such as equipment failure, poor network transmission environment, data acquisition and processing device crash, energy exhaustion, or damage, the same data can be continuously produced at different sampling moments. Hence, the constant-value detection is defined as follows. If $r_j(t_i) = r_j(t_{i-1})$ and the monitored value remains unchanged for a long time, they should be judged as abnormal data.

(3) The measured data inside the field is much less than that outside the field

According to the law of dust propagation, the value of the dust within the boundary of the construction site should be greater than that of the dust outside the boundary of the site. The actual measurement data within the field boundary is much smaller than the abnormal event detection concept outside the field boundary. There is no processing when the absorbable particulate matter concentration $r_j(t_i)$ within the construction site's boundary is not lower than the surrounding absorbable particulate matter concentration $r_{nearby}(t_i)$ far away from the construction site. If $r_j(t_i) < r_{nearby}(t_i)$, the probability value of abnormal data is accumulated. When the probability of conflict reaches the robust threshold, it is determined as abnormal data, and an abnormal event report is then sent to the construction party.

(4) The monitoring value of PM10 is less than the value of PM2.5

PM10 is the inhalable particulate matter with an aerodynamic equivalent diameter less than or equal to 10 microns. On the other hand, PM2.5 refers to the particulate matter in the ambient air with an aerodynamic equivalent diameter less than or equal to 2.5 microns [57]. Hence, the monitoring value of PM10 should be greater than that of PM2.5. If $r_{PM10}(t_i) < r_{PM2.5}(t_i)$, the probability value of abnormal data is accumulated. When the probability value of abnormal data reaches the robust threshold, it is judged as abnormal data.

(5) PM10 monitoring value is abnormal on rainy and snowy days

The laser backscatter method is performed to measure PM10. The built-in high-stability laser signal source irradiates the dust particles. The irradiated dust particles will then reflect the laser signal, and the reflected signal intensity is positively associated with the dust concentration. Therefore, the dust concentration can be calculated using a specific algorithm. Due to the fact that there is no dust pretreatment device, liquid substances can also be theoretically measured as fugitive dust. On rainy days, rainwater enters the sensor and meets the laser signal, which increases the laser-reflection signal. Therefore, the dust indicator value is too high, which results in increasing the PM10 monitoring value to exceed the standard. Under this circumstance, if $r_{PM10}(t_i)$ is less than the limited value, with the rain and snow sensors revealing the precipitation at this time, it is judged as abnormal data. Figure 7 presents the identification of abnormal data in the perception layer, according to the previously mentioned abnormal detection.
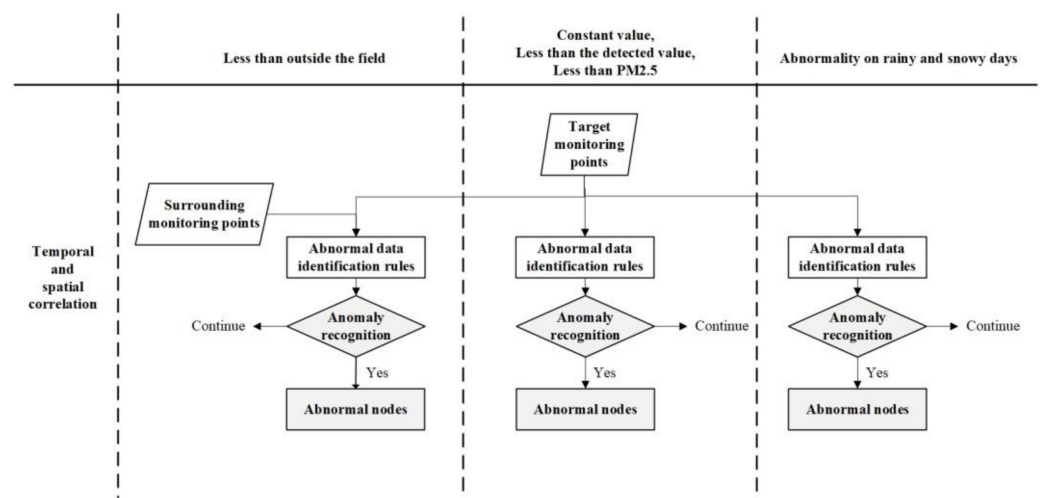

Figure 7. Identification process of abnormal data.

5.2. Conflict Detection and Processing of Monitoring Data

The reliability of the data collected by the sensors is first determined using belief functions. When the level of reliability is low, the data from these sensors cannot participate in the data fusion. When the reliability is within the threshold range, the fusion weight is calculated by the belief function proposed in Yager [45] in order to perform multi-sensor data fusion and therefore improve the stability of the fusion results. This study integrates the Yager [45] belief function and the fuzzy-index belief function (Jiao et al. [46]), in order to develop a sensor data-fusion belief function to deal with uncertain data in Scenario 2.

Step 1: Development of the belief function

Considering the large-scale of construction sites, there are large value differences in terms of TSP sensors at different points. If the difference between x_i and x_j is larger than the fusion upper limit of the belief function, the belief degree will turn to 0, making the result too absolute. In order to avoid the loss of information, the sensor data-fusion belief function is established.

$$b(x_i, x_j) = K \times e^{-|x_i - x_j| \cdots}, K \in [0, 1] \tag{2}$$

Among them, *K* represents the magnitude of belief, denoted as 1 for the purpose of simplicity of calculation. When $|x_i - x_j| < 20$, $b(x_i, x_j)$ is approximately 0, which is consistent with actual situations on construction sites.

Step 2: Establishment of the belief matrix

n represents the number of sensors, and the belief matrix is established according to the proposed belief function.

$$B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix}$$

Step 3: Fusion of the weighted sensor data

The degree to which the i-th sensor is supported by other functions is in Equation (3).

$$\sup(x_i) = \sum_{j=1}^{n} b_{ij}, i \neq j \tag{3}$$

After normalizing the belief function, the weight of the sensors can be obtained in Equation (4).

$$w_i = \frac{\sup(x_i)}{\sum_{i=1}^{n} \sup(x_i)} \tag{4}$$

According to the weights of n sensors, the reading value of fused sensor can be obtained in Equation (5).

$$x = w_1 x_1 + w_2 x_2 + \cdots w_n x_n \tag{5}$$

5.3. Conflict Detection and Processing of Evaluation Decision

In order to accurately measure the conflict between pieces of evidence in Scenario 3, this study combines the fuzzy set theory and D-S evidence theory according to the combination approach of conflict evidence proposed by Ma and An [49]. The similarity *Sim* is defined by combining the two features of fuzzy closeness F_n and correlation coefficient *Coc*, as well as adjusting the evidence credibility. The high-conflict data fusion based on the improved evidence theory is presented in the sequel.

Step 1: Calculation of transition probability

Assuming that $\Theta = \{\theta_1, \theta_2, \cdots, \theta_n\}$, there are k bodies of evidence, and the probability distribution of evidence is $m_i (i = 1, 2, \cdots, k)$, which can be obtained by the probability transition formula k probability vectors, where the transition probability formula is in Equation (6). In Equation (6), $BEL = \sum Bel(\theta_i)$, where Bel represents the value of the belief function, and BEL represents the total value of belief functions.

$$P(\theta_i) = Bel(\theta_i) + \frac{BEL \cdot Bel(\theta_i) + (1 - BEL)pl(\theta_i)}{\sum_{\theta_i \in \Theta} BEL \cdot Bel(\theta_i) + (1 - BEL)pl(\theta_i)} (1 - BEL) \tag{6}$$

Step 2: Combination of the fuzzy closeness and correlation coefficient

Then, the fuzzy closeness of k probability vectors is shown in Equation (7). In Equation (7), $\wedge$ and $\vee$ are the minimum and maximum operators separately. $F_n(m_i, m_j) \in [0, 1]$, when P_i and P_j are more similar, the fuzzy closeness $F_n(m_i, m_j)$ is closer to 1.

$$F_n(m_i, m_j) = \frac{\sum_{s=1}^{n} (P_i(\theta_s) \wedge P_j(\theta_s))}{\sum_{s=1}^{n} (P_i(\theta_s) \vee P_j(\theta_s))} \quad i, j = 1, 2, 3 \cdots, k \tag{7}$$

However, it is unreliable to measure the similarity between the types of evidence based on the fuzzy closeness F_n, and the robustness stands at an undesirable level [58]. Hence, the correlation coefficient *Coc* can be analyzed to measure the similarity between the types of evidence. In this study, the definition of the correlation coefficient is shown in Equation (8).

$$Coc(m_i, m_j) = \begin{cases} \frac{m_i\left(\theta_{\max}^{m_i}\right) + m_j\left(\theta_{\max}^{m_j}\right)}{2}, if\theta_{\max}^{m_i} = \theta_{\max}^{m_j} \\ \frac{m_i\left(\theta_{\min}^{m_i}\right) + m_j\left(\theta_{\min}^{m_j}\right)}{2}, if\theta_{\min}^{m_i} \neq \theta_{\min}^{m_j} \end{cases} \tag{8}$$

In Equation (8), *Coc* is used to measure the similarity of the propositions supported by the maximum trust of two pieces of evidence. If the propositions of two pieces of evidence are the same, the two pieces of evidence are considered to be similar, and *Coc* is equal to the average of the maximum trust values of the two pieces of evidence. On the contrary, if the propositions are different, the two pieces of evidence are considered to be in conflict, and *Coc* is equal to the average of the minimum trust values of the two pieces of evidence.

Fn measures the similarity from the basic probability distribution structure of evidence, while *Coc* measures the similarity of the evidence from the perspective of evidence reliability. In order to comprehensively measure the similarity between the types of evidence, *Fn* and *Coc* are combined through *Sim* in Equation (9). This shows that the degree of belief of evidence is associated with the degree of similarity. The greater the degree of similarity between the types of evidence, the higher the credibility is.

$$Sim(m_i, m_j) = \frac{Fn(m_i, m_j) + Coc(m_i, m_j)}{1 + F_n(m_i, m_j) \times Coc(m_i, m_j)} \tag{9}$$

Step 3: Fusion of the weighted average evidence

The calculation formula for the credibility degree *Sd* is as follows:

$$Sd(m_i) = \sum_{j=1, j \neq i}^{k} Sim(m_i, m_j) \tag{10}$$

After normalizing *Sd*, the credibility *Cd* of the evidence is obtained in Equation (11) as the weight of the evidence.

$$W(m_i) = Cd(m_i) = \frac{Sd(m_i)}{\sum_{s=1}^{k} Sd(m_i)} (1 \leq i \leq k) \tag{11}$$

After obtaining the weight of the evidence, the average evidence *WAE* is obtained in Equation (12). Finally, the average evidence *WAE* is fused to produce the result according to the Dempster combination rule.

$$WAE(m) = \sum_{i=1}^{k} W(m_i) \times m_i \tag{12}$$

6. Results and Discussion

6.1. Anomaly Recognition

In order to verify the feasibility and accuracy of the proposed anomaly identification algorithm, simulation experiments are performed using MATLAB. The monitoring point is sampled every 1 min, with a total of 1429 data. The abnormal data are then infused, including 11 "data less than the detected value", 27 "constant value", 9 "abnormal data PM10 less than PM2.5", 8 "data far below the out-of-site monitoring value", and 29 "abnormal data on rainy and snowy days". The fault injection rate is 5.8%, which is mainly consistent with the probability of abnormal data in practice. The objective of developing an abnormal-data-monitoring algorithm is to accurately identify the abnormal data and avoid false alarms. Therefore, the detection rate *R* and false alarm rate *N* are selected as evaluation indicators in order to measure the E-CPS robustness.

$$R = \frac{TP}{TP + FN} \tag{13}$$

In Equation (13), *TP* represents the number of samples that are abnormal data, and *FN* denotes the number of samples that are abnormal data but are incorrectly classified as normal data.

$$N = \frac{TN}{TP + TN} \tag{14}$$

In Equation (14), TN represents the number of samples that are normal data but identified as abnormal data, and TP denotes the number of samples that are abnormal data and identified as abnormal data. In this study, 8 "far below the monitoring value outside the field", 35 "constant value", 9 "abnormal PM10 less than PM2.5", 11 "less than the detected value", and 29 "abnormal data on rainy and snowy days" are detected by the simulation experiments. The simulation results are presented in Figure 8.
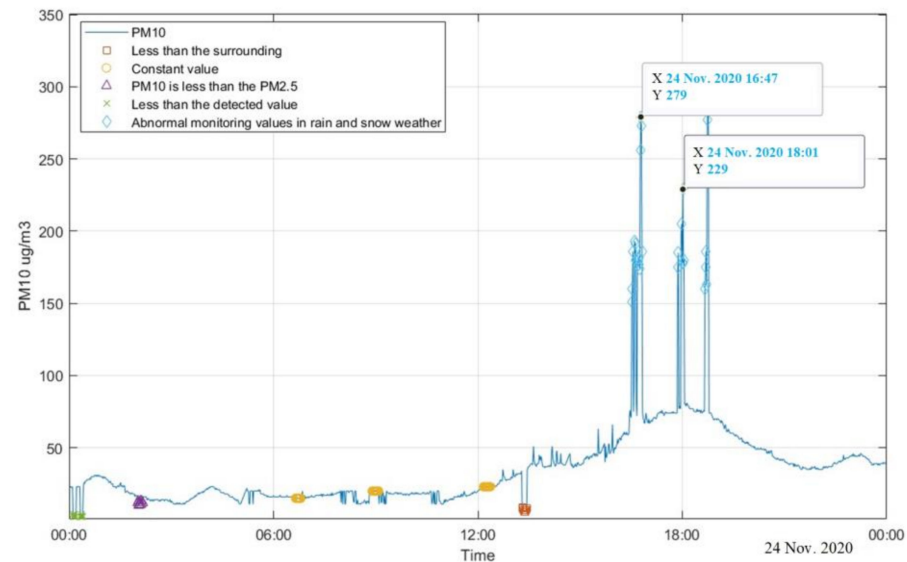

Figure 8. Identification of the PM10 monitoring value abnormal data.

The abnormal data are added at 16:36 on 24 November 2020 and 18:46 on 24 November 2020. The PM10 monitoring value at these two moments exceeds 100 ug/m^3. If E-CPS fails to perform abnormal data detection, the platform sends two early warning messages to inform the construction enterprises of the dust control. After abnormal data identification, the two moments are judged as abnormal points, and no early warning processing is performed. It is deduced that the identification of abnormal data can improve the anti-interference ability, which avoids affecting the decision-making due to the input of abnormal data and ensures the efficiency of the decision-making and the stable output. Therefore, the robust performance of the E-CPS is improved.

In this study, the detection rate of abnormal data obtained using the detection algorithm is approximately 96%, slightly fluctuating with the changes of the sample size. This is due to the fact that the abnormal data discriminating rules are based on dust propagation laws and mathematical models, rather than relying on learning samples. Hence, the detection rate can remain stable, and the detection rate of "PM10 is less than PM2.5" and "less than the detection value" can reach 100%.

The "constant value" is a reason of false alarms. In this experiment, the robust threshold of "constant value" is set to 10, which indicates that the data are judged as abnormal data when the value of PM10 remains unchanged within 10 min. However, it is deduced that, when the wind speed at night is slow, the PM10 value remains unchanged for 10 min, which results in a higher false alarm rate of 9.3%. If the robust threshold of "constant value" is set to 12, the false positives of the constant value can be highly reduced, as shown in Figure 9. In the constant-value detection, the detection rate and false alarm rate should be taken into consideration according to the actual situations on construction sites, and the abnormal probability threshold should meet the site conditions. In addition, the data "far below the monitoring value outside the field" may also result in false alarms during work stoppages.
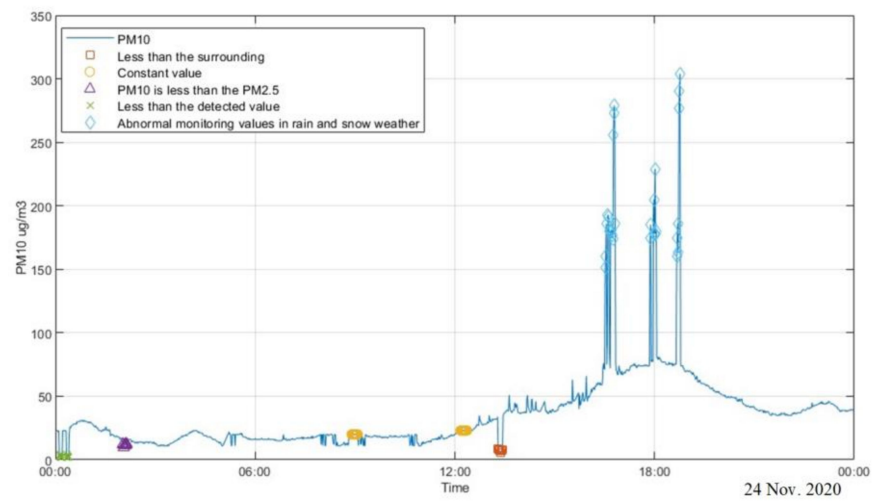
Figure 9. Anomaly recognition effect after adjusting the constant-value detection threshold.

6.2. Sensory Data Fusion

The experimental data of the robustness of sensor data fusion comes from the TSP values of three monitoring points at seven times (0:01, 0:02, . . . , –0:07), on 24 November 2020.

The seven sets of data are processed according to the arithmetic mean and belief function method. Figure 10 shows the fluctuation of the monitoring data after the belief function fusion is reduced, which is also verified by the sample standard deviation. The sample standard deviation of the data fusion of the arithmetic mean is 3.49, while the sample standard deviation of the belief function method fusion is 2.78, which is 20.34% lower than that of the arithmetic mean method. This indicates that the input stability of the monitoring data should be improved.
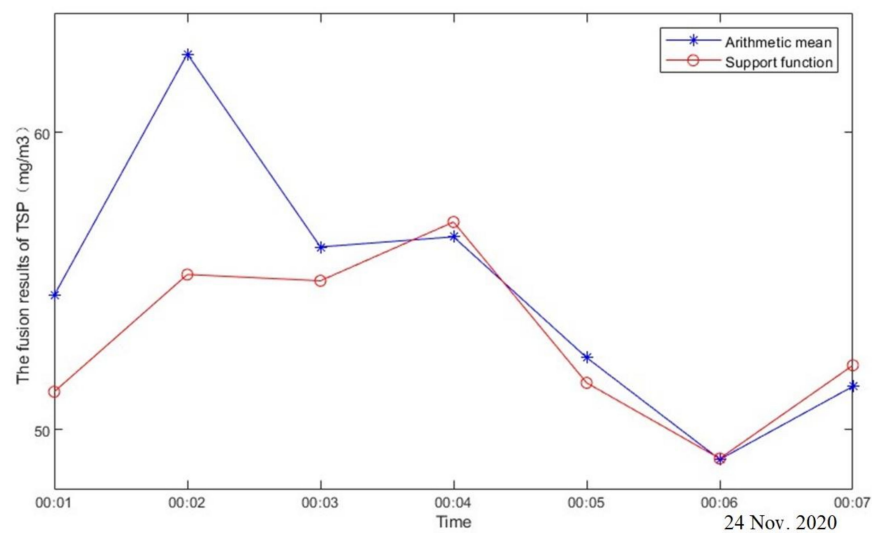

Figure 10. Data-fusion results obtained in two ways.

In addition, a comparative analysis of the anti-interference performance of the two fusion algorithms is conducted. The first data in the 7th group of measured data is changed to 47.12, while the other data remain unchanged. The fusion results obtained using the arithmetic mean method vary from 51.45 to 50.78, with a decrease rate of 1.29%. Consequently, the fusion results based on the belief function method vary from 52.16 to 52.50, with a decrease rate reduced to 0.65%. The random experiments using the seven sets of data demonstrate that, when large interfering data exist in a set of data, the belief function can identify the interfering data at a desirable level, which improves the robustness of the output data.

6.3. Expert Score Fusion

In Example 1, the classic data fusion based on the D-S evidence theory cannot produce accurate results. Hence, the efficiency of the improved D-S evidence theory is evaluated.

The average evidence *WAE* can be obtained according to Equations (6)–(12) (cf. Table 5), where $m(Excellent) = 0.45$, $m(Qualified) = 0.1$, and $m(Unqualified) = 0.45$. The evidence-fusion results are presented in Table 6.

Table 5. The calculation process of the weighted average evidence.

Equation	Parameter	Results
Equation (6)	Transition probability P_j	$P = \begin{bmatrix} 0.9 & 0.1 & 0 \\ 0 & 0.1 & 0.9 \end{bmatrix}$
Equation (7)	Fuzzy closeness F_n	$F_n = \begin{bmatrix} 1 & 0.0526 \\ 0.0526 & 1 \end{bmatrix}$
Equation (8)	Correlation coefficient Coc	$Coc = \begin{bmatrix} 0.9 & 0 \\ 0 & 0.9 \end{bmatrix}$
Equation (9)	Combination of Fn and Coc through Sim	$Sim = \begin{bmatrix} 1 & 0.0526 \\ 0.0526 & 1 \end{bmatrix}$
Equation (10)	Degree of belief Sd	$Sup(m_1) = Sup(m_2) = 0.0526$
Equation (11)	Credibility Cd	$Cd = \begin{bmatrix} 0.5 & 0.5 \end{bmatrix}$
Equation (12)	Average evidence WAE	$m(Excellent) = 0.45$, $m(Qualified) = 0.1$, $m(Unqualified) = 0.45$.

Table 6. Evidence fusion results in Example 1.

	Excellent	Qualified	Unqualified
D-S evidence theory	0	1	0
Improved D-S evidence theory (Expert 1, Expert 2)	0.4880	0.0241	0.4880
Expert 3	0.9	0.1	0
Improved D-S evidence theory (Expert 1, Expert 2, and Expert 3)	0.9983	0.0016	0.001

It can be seen from Table 6 that the result of the classic evidence combination rule is "qualified", which is in contrast to intuition. Based on the credibility method, the conflict between the evidence can be reduced by weighting the high-conflict evidence. Although the fusion result is $m(Excellent) = m(Unqualified)$, the evaluation result cannot be obtained, and therefore the judgment result relying on the two negative pieces of evidence of Expert 1 and Expert 2 cannot be obtained. When the new evidence from expert 3 is added, the result points to "excellent", with a maximum trust degree of 0.9983. The results after the fusion of credibility evidence are presented in Table 7. These results are consistent with the conditions on construction sites, which indicates that the proposed method can reasonably and effectively handle the conflict problems.

Table 7. Basic probability distribution.

	Excellent	Qualified	Unqualified
Expert 1	0	0.9	0.1
Expert 2	0.6	0.4	0
Expert 3	0.75	0.25	0
Expert 3′	0.8	0.2	0
Improved D-S evidence theory	0.9983	0.0016	0.001

Due to the insufficient cognition and subjective judgment of experts, expert scoring is often unreliable, and the mass function changes within a certain range. The slight changes in mass function can result in high changes, which indicates that the robustness of the method is at an undesirable level. The robustness of the credibility algorithm is verified by slightly changing the mass function of the evidence. Assuming that three independent

elements in the framework Θ are excellent, qualified, and unqualified, the mass functions of the four pieces of evidence are determined (cf. Table 7).

It can be seen from Table 7 that the mass functions of Expert 3 and Expert 3′ undergo minor changes. The classical evidence theory, Murphy, and improved D-S evidence theory based on the credibility method for decision-making fusion are respectively used.

Expert 2, Expert 3, and Expert 3′ are considered "excellent" with the greatest trust value. However, expert 1 is the most likely to become "qualified". The credibility of expert 1 is lower than that of expert 2 and expert 3, and the fusion result tends to be "excellent".

It can also be seen from Table 8 that the results obtained using the classical evidence theory method, before and after, are both "qualified". This is inconsistent with the subjective judgment, which is consistent with Zhao's findings [59]. Murphy [60] indicates that using actual belief functions in the combining rule confirms Bayesian theory and convergence. The result based on the Murphy's method has the largest "qualified" trust value among the three results. In this study, the fusion result should be "excellent", which demonstrates the poor robustness of Murphy's method utilized in conflicts in experts scores, although it is calculated simply when making decisions with incremental evidence. In this context, Ma and An [49] handled conflict evidence with different weighting factors through a new probabilistic dissimilarity to handle the issues due to unreliable evidence instead of Dempster rules. Based on this study, this study combined the fuzzy theory and D-S evidence theory to improve the credibility of evidence and better system robustness and effectiveness performance. The two fusion results based on the proposed method point to "excellent", and the trust degree remains mainly unchanged. This indicates that the output results maintain a satisfactory performance when the evidence is highly conflicting, and the evidence focal element slightly changes, which can be utilized in expert score fusion of evaluating green construction on construction sites.

Table 8. Fusion results of three evidence-fusion methods.

		Excellent	Qualified	Unqualified
D-S evidence theory	m_{123}	0	1	0
	$m_{123}{}'$	0	1	0
Murphy	m_{123}	0.397	0.602	0.01
	$m_{123}{}'$	0.551	0.449	0
Improved D-S evidence theory	m_{123}	0.8544	0.1456	0
	$m_{123}{}'$	0.8837	0.1152	0

In summary, the abnormal-data-recognition algorithm based on the spatio-temporal correlation improves the system's anti-interference ability to prevent anomalous data entering the perception and transportation layer of the E-CPS and enhances the quality of the environmental monitoring data on construction sites. This can be used to identify and process the anomaly monitoring data on construction sites and lay a foundation for the stable and accurate output of early warning. The developed belief functions can detect the interfering data and improve the fusion of the monitoring data from different sensors on construction sites in the fusion layer of the E-CPS. This enhances the system robustness of the output data when witnessing the changes of individual data and helps the project managers deal with the problems of sensory data conflicts during the process of environmental management. Finally, the decision-fusion algorithm based on the improved D-S evidence theory can resolve the highly conflicting data and achieve stable results of the experts' decisions in the decision-making layer of the E-CPS. This indicates that the E-CPS model can maintain a robust performance during the construction period. In practice, different experts' decisions on the environmental monitoring results are collected on construction sites. The decision-fusion algorithm can be used to assess the project managers to better fuse the experts' decisions and efficiently evaluate the environmental performance and remote control of the environment on construction sites according to the experts' decisions.

6.4. Limitations of the Study

E-CPS is a complex system, and the formation of robustness requires multi-link and multi-factor synergy, as well as both technical and management guarantees, but the research on E-CPS is still in the initial stage. This study identified three typical scenarios, including inaccuracies and inconsistencies in perception data, multi-source perception data fusion, and experts' decision fusion during the process of environmental monitoring and evaluation. There may be a lack of theoretical support in the identification of impact factors and the creation of uncertainty scenarios. E-CPS uncertainty scenarios and concepts will be further combined to drive theoretical analysis, and theoretical system development and platform applications will be improved in the future. Moreover, the uncertainty scenarios were considered mainly in technical space in this study. In the future, uncertainty factors regarding organization and management on construction sites in different scenarios can be more considered and optimized to create more comprehensive uncertainty scenarios in the E-CPS. Since the quantification of system robustness for organization and management is still a challenging issue, it deserves further study in the future.

7. Conclusions

This study proposed developing an ontology-based E-CPS model for construction sites. The study also conducted a robustness design and simulation of the E-CPS within three scenarios, including uncertain perceptual data, sensory data conflicts, and expert score conflicts, using the spatio-temporal correlation, belief functions, and improved D-S evidence theory. The simulation results demonstrate that the three methods allow the system to have anomaly recognition, conflict resolution, and fault-tolerant reasoning capacities, thus improving system robustness.

The main findings are summarized as follows. (1) The established ontology-based E-CPS model can achieve early warning, remote control, and green construction evaluation functions under uncertainty through Jena reasoning, which can be applied on construction sites. (2) The abnormal-data-recognition algorithm based on the spatio-temporal correlation can significantly improve system robustness against erroneous data, which ensures the validity of the decision-making of project managers on construction sites. (3) The data-level fusion algorithm based on the belief function can effectively identify interfering data, thus improving the stability of the output data when E-CPS witnesses individual data changes; (4) the proposed algorithm based on the improved D-S evidence theory can improve system robustness regarding experts score conflicts. Hence, the aforementioned methods can be utilized to perform the uncertainty-detection process in different scenarios, and they can prevent uncertain monitoring data, such as PM10 and noise entering the decision-making layer of the E-CPS and interfering with the environmental control on construction sites. This helps project managers to make more reliable and efficient decisions, in order to better control noise and dust on construction sites, when the uncertain data are detected and processed.

This study can deepen the understanding of the E-CPS robustness, and the proposed model can further expand the understanding of information management on construction sites, which will provide a reference for E-CPS design on construction sites. In addition, this study can aid project managers to better conduct environmental management on construction sites. This can make contributions to promoting green construction management on construction sites. Although a significant amount of time was required to analyze E-CPS robustness, it is challenging to measure the robustness of organization and management. Like any other new feature, there is room for optimizing environmental-monitoring indicators in the ontology-based E-CPS model, in order to comprehensively evaluate the environmental performance on construction sites. In future work, more effort will be dedicated to ensuring the system robustness within uncertain situations such as organization and management in the operation period of the projects.

Abbreviations

CPS	Cyber-physical system
E-CPS	Environmental-monitoring cyber-physical system
WSN	Wireless sensor network
GPS	Global positioning system
BIM	Building information-modeling
I–P–O	Inputs–processes–outputs
TSP	Total suspended particulate
PM2.5	Fine particles with a diameter of 2.5 µm or less
PM10	Inhalable coarse particles with a diameter of 10 µm or less
D-S evidence theory	Dempster–Shafer evidence theory

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