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Knowledge management of eco-industrial park for efficient energy utilization through ontology-based approach

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HIGHLIGHTS

- An intelligent energy management system for Eco-Industrial Park (EIP) is proposed.
- An explicit domain ontology for EIP energy management is designed.
- Ontology-based approach can increase knowledge interoperability within EIP.
- Ontology-based approach can allow self-optimization without human intervention in EIP.
- The proposed system harbours huge potential in the future scenario of Internet of Things.

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ABSTRACT

An ontology-based approach for Eco-Industrial Park (EIP) knowledge management is proposed in this paper. The designed ontology in this study is formalized conceptualization of EIP. Based on such an ontological representation, a Knowledge-Based System (KBS) for EIP energy management named J-Park Simulator (JPS) is developed. By applying JPS to the solution of EIP waste heat utilization problem, the results of this study show that ontology is a powerful tool for knowledge management of complex systems such as EIP. The ontology-based approach can increase knowledge interoperability between different companies in EIP. The ontology-based approach can also allow intelligent decision making by using disparate data from remote databases, which implies the possibility of self-optimization without human intervention scenario of Internet of Things (IoT). It is shown through this study that KBS can bridge the communication gaps between different companies in EIP, sequentially more potential Industrial Symbiosis (IS) links can be established to improve the overall energy efficiency of the whole EIP.
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1. Introduction

Based on synergy through cooperation between physically proximate businesses within a certain region, Eco-Industrial Park (EIP) is becoming a popular form of industry cluster. According to US Environmental Protection Agency (EPA), EIP is defined as "a community of manufacturing and service businesses seeking enhanced environmental and economic performance through collaboration in managing environmental and resource issues including energy, water, and materials. By working together, the community of businesses seeks a collective benefit that is greater than the sum of the individual benefits each company would realize if it optimized its individual performance only" [1]. The key concept behind EIP is Industrial Symbiosis (IS), which requires an industrial system to be viewed not in isolation, but in concert with it surrounding systems [2]. In EIP, resources, including but not limited to materials, energy, water and information, can be reused at different levels through networks, both *intra-company* and *inter-company*, such that collective benefits can be achieved. These networks, and the processes through which they are generated, display a complexity and variety that is still poorly understood. Particularly for the energy networks in EIP, they are quite different from traditional urban or industrial energy systems [3]; because many companies in EIP produce and consume energy at the same

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time, this shift from consumer to prosumer blurs the distinction between supply side and demand side in energy systems, which brings additional complexity to the design and optimization of EIP energy systems [4,5]. The typical schematic of EIP energy system is shown in Fig. 1. As shown in Fig. 1, in EIP there are usually multiple companies serving as part of the energy network; sequentially, knowledge management becomes a main barrier for efficient energy utilization in EIP. Knowledge management refers to the process of creating, sharing and using knowledge; in the context of EIP, since there are various companies participating in the IS, thus there is possibility that one company is not aware that its waste energy can be utilized by other companies and viceversa. To overcome such heterogeneity, there must be a bridge linking all the companies together in terms of knowledge sharing; usually Knowledge-Based System (KBS) plays such a role.

A Knowledge-Based System (KBS) is defined as "a computer program that reasons and uses a knowledge base to solve complex problems" [6], the complex problem in this paper turns out to be energy utilization in EIP. In a broader sense, KBS belongs to the so-called Information and Communication Technologies (ICT). In fact, in 2008 the European Union (EU) pointed out that "addressing the challenge of energy efficiency through information and communication technologies" could significantly improve the energy efficiency across the whole society [7]. Unsurprisingly, application of KBS in energy sector has become an active area of research for the past two decades. James et al. [8] developed KBS for integrated modelling of urban energy system, the database of this tool contains models of different energy conversion and transportation technologies; the tool was applied to a case study of a UK ecotown and it showed its capability to screen the most proper energy conversion technologies and transport network for the town. Kontopoulos et al. [9] presented a KBS approach for optimizing domestic solar hot water system. The main function of the delivered approach is decision making support. In their research, the KBS was able to select the optimum system configuration according to different criteria through a user-friendly online interface. Ramakumar et al. [10] presented a KBS approach for the design of integrated renewable energy system. This approach can find the optimal combination of renewable energy sources and end-use technologies based on lowest capital cost criteria. The usefulness of the proposed approach is proved through an application case of renewable energy system design. Abbey et al. [11] proposed a KBS for control of two-level energy storage for wind energy system. The knowledge-based management algorithm can better schedule the power from two levels compared to an alternative scheduling approach. In such a context, the proposed study aims to demonstrate the possibility of using KBS to increase energy efficiency of EIP.

The necessity and benefits of applying KBS in EIP energy management are also closely related to the emerging trend of Industry 4.0 and Internet of Things (IoT). Industry 4.0 is a newly emerging conception of industrialization, it creates what has been called a "smart factory" [12]. Within the modular structured smart factories, cyber-physical systems monitor physical processes, create a virtual copy of the physical world and make decentralized decisions. In the future scenario of Industry 4.0, networking and integration of different companies through consistent integration of information and communication technology is allowed. IoT is a key enabler for Industry 4.0. IoT allows to collect and exchange data through network. However it is expected that during the data fusion process, great difficulties will emerge: for instance, two databases from different sources may use different identifiers for the same concept; or the statistics from one agent can serve as feed stream for another software agent while the format heterogeneity between them will hinder the possibility of autonomous communication. In all these cases, an ontology intermediary to enhance the performance of linked data which means that the capability of KBS to deal with complex and unstructured data, makes it indispensable in knowledge management of complex systems such as EIP.

In the future scenario of Industry 4.0 and IoT, knowledge management in EIP could be totally different from what it is now. The current design and optimization approaches that need large-scale human intervention will not be suitable in such application contexts. Considering the complexity and heterogeneity of processes and operations occurring in EIP, traditional human-based approaches may need to deal with large amount of information every day, which would result in huge human resources to be consumed. Hence developing KBS that can properly handle the complex and unstructured big data from EIP seems to be a promising trend in the future scenario of Industry 4.0. At least two requisites must be fulfilled in order to develop such a KBS: firstly, an explicit knowledge base that contains core concepts as well as the relationships between the concepts within the domain of discourse should be designed; secondly, the syntax and semantics of knowledge representation must be both human-readable and machine-interpretable to enable effective communication not only between people, but also between machines. In this context, ontology-based approach becomes a perfect candidate due to its abilities in tackling these problems.

Based on these background introductions, an ontology-based approach for knowledge management of EIP is proposed in this paper. Specifically, firstly a systematic ontology data framework that can serve as an overall knowledge repository for EIP energy system is established; secondly, a KBS based on such an ontology, namely J-Park Simulator (JPS), is described in the paper; finally, the advantages of KBS based EIP energy management are demonstrated through a case study. Under such an arrangement, the reminder of this paper is structured as follows: Section 2 gives a brief introduction about the fundamentals of ontology, the development of EIP energy system domain ontology is also described in this section; Section 3 describes the ontology-based KBS named JPS; Section 4 presents the results and discussion of a case study which demonstrates the system capabilities in reconciling semantic heterogeneity and intelligent decision making; Section 5 summarizes the accomplishments and indicates the roadmap for future work.

2. State of the art: why ontology?

A key concept in the proposed KBS is ontology. Ontology, philosophically representing "theory of existence", is defined as explicit description of domain conceptions and their relationships in engineering science. While ontology has been an active tool in the community of artificial intelligence for several years, only recently is gaining popularity in many other disciplines, such as gene informatics, medicine and energy [13–15]. Three basic components of ontology are: *classes* which correspond to concepts in natural language, *slots* which correspond to attributes of concepts, *instances* which correspond to examples of certain concepts. More complex ontology may also have object properties which describe the relationship between different classes as well as rules and axioms [16]. Since ontology is formalized conceptualization, it needs to be populated with instances. A simple example of ontology is given here to facilitate the understanding of it. In this example, the knowledge "water has boiling point of 100 °C" is meant to be shared. So, firstly *classes* (i.e. material, property and value) need to be defined; for then *slots* (i.e. magnitude and unit) are defined; also, the relationship between *slots* and *classes* needs to be defined (i.e. "material has property, property has value"); and finally, "water", "boiling point" and "100 °C" are assigned as *instances* of material, property

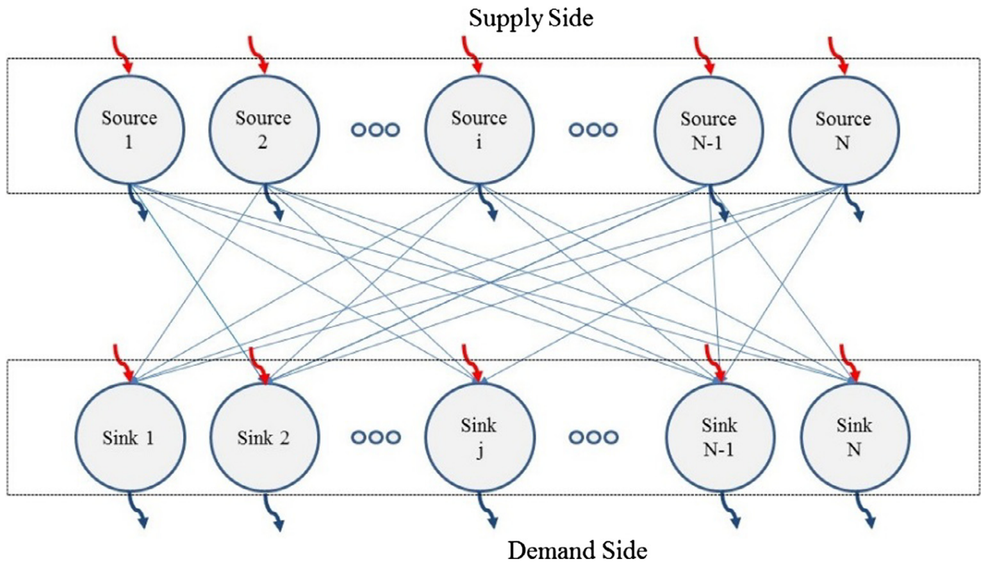

Fig. 1. Schematic of EIP energy network.

and value respectively. The visualization of such an ontology in human readable format is shown in Fig. 2.

However, a machine-readable format of ontology is also needed to make it accessible to computers, the most common modelling language in such forms is Web Ontology Language (OWL) [17]. In this case an OWL ontology is a Resource Description Framework (RDF) graph. RDF is a metadata model in the form of subject–predicate–object expressions, which is usually referred to as a "triple". So essentially an ontology defined with OWL is no more than a collection of triples. More in particular the machine-readable format of the example ontology scheme complying with RDF/XML syntax is shown in Fig. 3: *headers* specify an ontology about water boiling point as well as Uniform Resource Identifiers (URI) for different concepts; *object properties and data properties* specify the knowledge "material has property, property has value"; *classes and individuals* specify the knowledge "water is an example of material which has property of boiling point".

Back to the specific area of EIP energy management, the task is to develop an ontology framework that contains the codification of tacit knowledge in this domain so that the developer's understanding of this domain can be reused [18]. Regarding ontology development, several rules have been specified but it can be stated that there is no single correct way to design ontology, as long as an ontology can satisfy the application's requirements. In development of ontology, it is always favourable to consider reusing existing ontologies. Some ontologies can always be reused in all knowledge bases, such ontologies are usually called *upper ontology* (e.g. the ontology defining very general concepts such as things, actions etc). The next level of detail is classified as *domain ontology*, for example EIP energy system ontology can be treated as a domain ontology [19]. The last level of detail is *application ontology* which is specifically oriented for certain tasks, for example the ontology of waste heat utilization through Organic Rankine Cycle (ORC) can be treated as an application ontology under domain ontology of EIP energy system.

By our investigation, there are several existing ontologies that can be referred to during the development of EIP energy system ontology. The first one is OntoCAPE, which is a large-scale ontology for the domain of Computer Aided Process Engineering (CAPE), it aims to "represent all concepts that are related to materials processing and the corresponding operating devices" [18]. There are five different layers in OntoCAPE, namely *meta layer*, *upper layer*, *conceptual layer*, *application-oriented layer* and *application-specific layer*. Generally, the reusability of these layers become lower as they go more specific, so ideally the classes and relationships defined in meta layer and upper layer can be reused in other domains, conceptual layer is specifically for chemical engineering community, the application-oriented layer and the application-specific layer (collectively referred to as 'application layers') extend the ontology towards concrete applications. Another important ontology that would be helpful for EIP thermal energy system ontology development is the e-symbiosis ontology [20]. E-symbiosis ontology aims to describe the main conception related to IS , which is the pillar of EIP. This ontology treats all things in EIP belonging to three classes, namely *resource*, *technology* and *role*. Each class is further divided into different subclasses by their type, input and characteristics. The relationships between each one of them are defined in this ontology; for instance technology can process resource, solution provider can provide resource, solution consumer can provide resource, etc. A web platform has been developed based on this ontology; this platform enables processing technologies participation in IS due to the benefits of information sharing and technology provided by the ontology and it is claimed that this platform has helped to save 4.4 million tons of CO2 emission, 9.22 million tons of water waste and 0.22 million tons of hazardous gases emission [21]. Based on these references, the domain ontology for EIP energy system is developed as shown in Fig. 4.

In this study we only focus on the case of process integration of ORCs as an illustrative example of how the proposed KBS works. So, a detailed application ontology for process integration of ORCs is further developed in this study as shown in Fig. 5. In this application ontology, waste steam is described as *resource* whereas ORCs are described as *technology*. The relationships between them are defined through object properties (e.g. technology can process resource). In Section 4, this application ontology would be used to facilitate the screening of proper ORCs from ORCs products database so that the proper ORCs can be screened to integrate to certain processes in EIP. Finally, it has to be pointed out that the application ontology for process integration of ORCs is just a small portion of the EIP energy system domain ontology (refer to Fig. 6). Literally various application ontologies can be developed based on the domain ontology with moderate efforts in the future so that the proposed approach can be applied to more problems. The proposed ontology is realized in Protégé which is an open-source ontology

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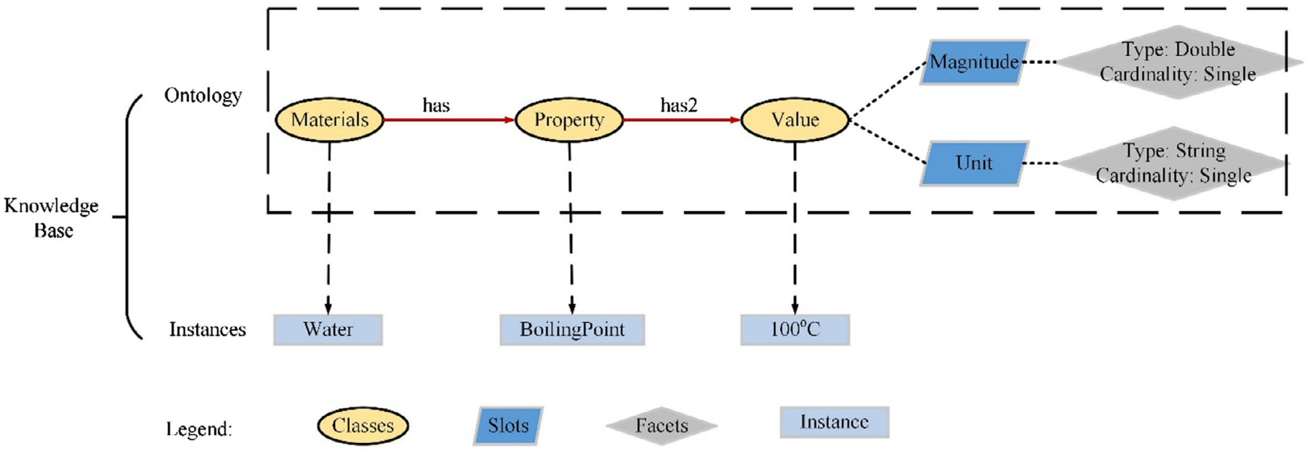

Fig. 2. An example of ontology in human-readable format.

```
<rdf:RDF xmlns="http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint#"
xml:base="http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint"
xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
xmlns:owl="http://www.w3.org/2002/07/owl#"
xmlns:WaterBoilingPoint="http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint#"
xmlns:xsd="http://www.w3.org/2001/XMLSchema#"
xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#">
<owl:Ontology rdf:about="http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint"/>

<!-- http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint#has -->
<owl:ObjectProperty rdf:about="&WaterBoilingPoint;has">
<rdfs:domain rdf:resource="&WaterBoilingPoint;Materials"/>
<rdfs:range rdf:resource="&WaterBoilingPoint;Property"/>

<!-- http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint#Magnitude -->
<owl:DatatypeProperty rdf:about="&WaterBoilingPoint;Magnitude"/>

<!-- http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint#Materials -->
<owl:Class rdf:about="&WaterBoilingPoint;Materials"/>

<!-- http://www.semanticweb.org/administrator/ontologies/2016/2/WaterBoilingPoint#BoilingPoint -->
<owl:NamedIndividual rdf:about="&WaterBoilingPoint;BoilingPoint">
<rdf:type rdf:resource="&WaterBoilingPoint;Property"/>
<Name rdf:datatype="&xsd;string">Boiling Point</Name>
</owl:NamedIndividual>

</rdf:RDF>
```

Headers

Object Properties

Data Properties

Classes

Individuals

Fig. 3. The example ontology schema in RDF/XML format.

editor together with the embedded Hermit reasoner, which can conduct reasonability inference based on ontology definition.

3. J-Park Simulator: an ontology-based EIP knowledge management system

In Section 2, the domain ontology of EIP energy system and the application ontology for process integration of ORCs are successfully established. However, ontology is not equal to KBS although it is the core part of a typical KBS. The process of how a typical KBS works is shown in Fig. 7, through the analogy between the proposed KBS and human decision making process; ontology is the counterpart of brain in human decision making process which serves the role of knowledge base in the system. Ideally all domain human expert's knowledge should be covered in the KBS so that relevant information can be called when it is needed. Semantic query plays the role of communication in the proposed KBS as opposed to the role of nerve system in human being; semantic query can facilitate the communication between ontology-based knowledge and sensor network. Finally, the sensor and actuators in the sensor network layer can implement the signals sent

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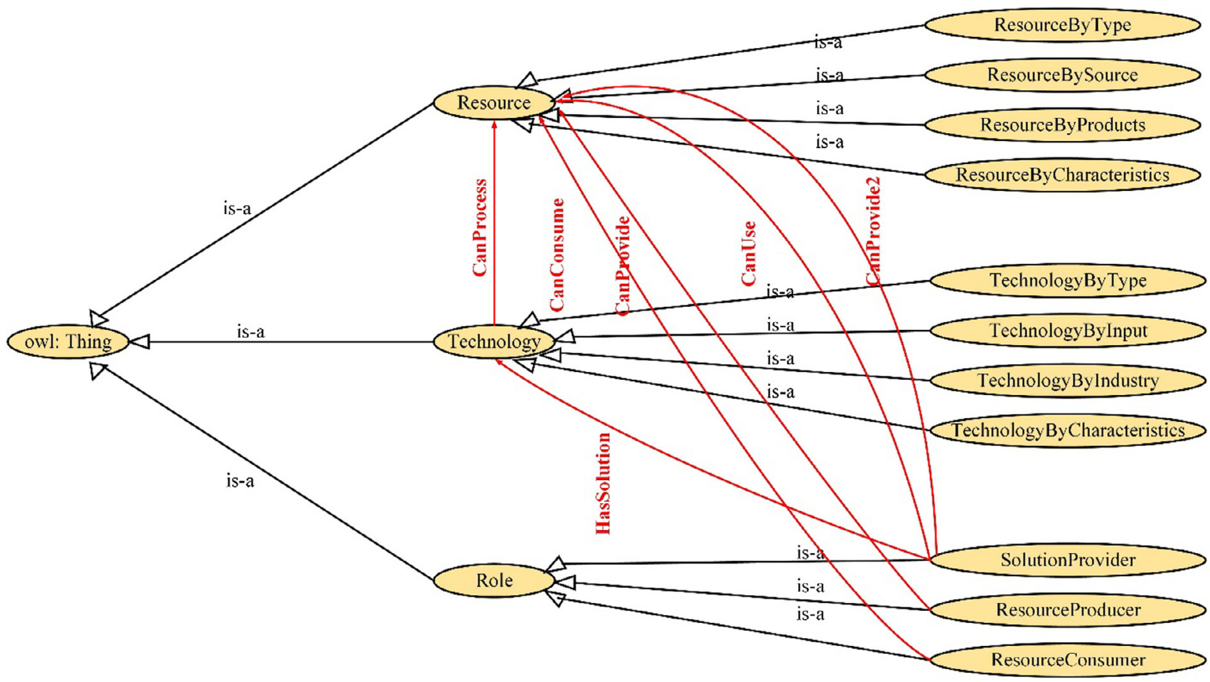

Fig. 4. Domain ontology for EIP energy system.

through query, then control and optimize the corresponding physical entities in EIP energy system. In summary, the developed ontology should be integrated with corresponding user interfaces to make a systematic KBS. In this study, the KBS we developed for EIP energy system knowledge management is named J-Park Simulator (JPS); a further detailed discussion of the functionality of the JPS can be found in the official website [22].

The system architecture of JPS is also shown in Fig. 8. It can be seen from Fig. 8 that in JPS, ontology plays the role of database. Various kinds of raw data from EIP is stored into the ontology. There is a simulator applet which can help users to query data from the ontology as a user interface. Once the ontology receives orders from the user, it can manipulate the embedded solvers to solve the problem. Then the solution of the problem can be updated into the ontology, sequentially communicated to the user through the simulator applet. In such a manner, the proposed KBS is able to interact with users.

4. Results and discussions

In this section, the capabilities of the proposed KBS through two case studies will be demonstrated. It is worth noting that these two case studies are not exhaustive of what the proposed KBS could handle, indeed it can do much more in various aspects such as optimal synthesis, predictive control which have been proved in literature [23]. However, understanding how the proposed KBS works in these two cases can facilitate the understanding of how the system works in more complicated cases.

4.1. Ontology-based information integration

Overcoming data heterogeneity both structurally and semantically is a feature of ontology which is illustrated in Fig. 9. In this scenario, data from different sources, namely A to E in Fig. 9, will enter the data processing layers through different gateways; then these datasets will be reorganized in the ontology-based data warehouse, this is described as ontology based data fusion in Fig. 9; sequentially the data quality will be enhanced, then the fused data can be communicated to either software agents or human interface for further usage as shown in application layer in Fig. 9.

In order to better understand how ontology can overcome data heterogeneity, the following example is given: there are two different resources, namely *WasteSteam* and *Exhaust* defined in Table 1, as well as some objective properties and data properties related to them. In other words, *WasteSteam* is a resource that has five objective properties and three data properties; *Exhaust* is another resource that has two objective properties and three data properties. In the proposed ontology, it is also defined that *WasteSteam* belongs to the category of *heating utility*, *gas state* and *waste heat* as shown in Fig. 10(a); whereas *Exhaust* is a resource of which we do not know the category it belongs to, as shown in Fig. 10 (a). The coming question is: could the ontology-based KBS tell us which kind of resource *Exhaust* exactly is? Is *Exhaust* cooling utility or heating utility? Does *Exhaust* belongs to power or thermal energy? The engineering problem behind this could be: there are two entities in an EIP, they are using different terminologies for describing the same object. If they want to share information between them totally through computers without human participation, can the computers be smart enough to figure out the different terminologies refer to same object? In our case, can computers be smart enough to figure out *WasteSteam* and *Exhaust* are indeed the same thing?

In this case, the reasoning ability of ontology works like this: since *Exhaust* has data property of *Temperature* as shown in Table 1, while *Information* and *Materials* do not have such properties, so it cannot belong to the category of *Information* or *Materials*; since *Power* has data property of *Voltage*, while *Exhaust* does not have such property, so it cannot belong to the category of *Power*. It means *Exhaust* must belong to the category of *ThermalEnergy* because there are only four mutually exclusive classes under the category of *ResourseByType*, if *Exhaust* belongs to none of the above-mentioned three categories (e.g. *Information*, *Materials*, *Power*), it must belong to the fourth category (e.g. *ThermalEnergy*) as shown in Fig. 10(b). In similar ways, the reasoner of ontology is smart enough to finally figure out that *Exhaust* and *WasteSteam* are equivalent as shown in Fig. 10(b). In practice, it means the KBS

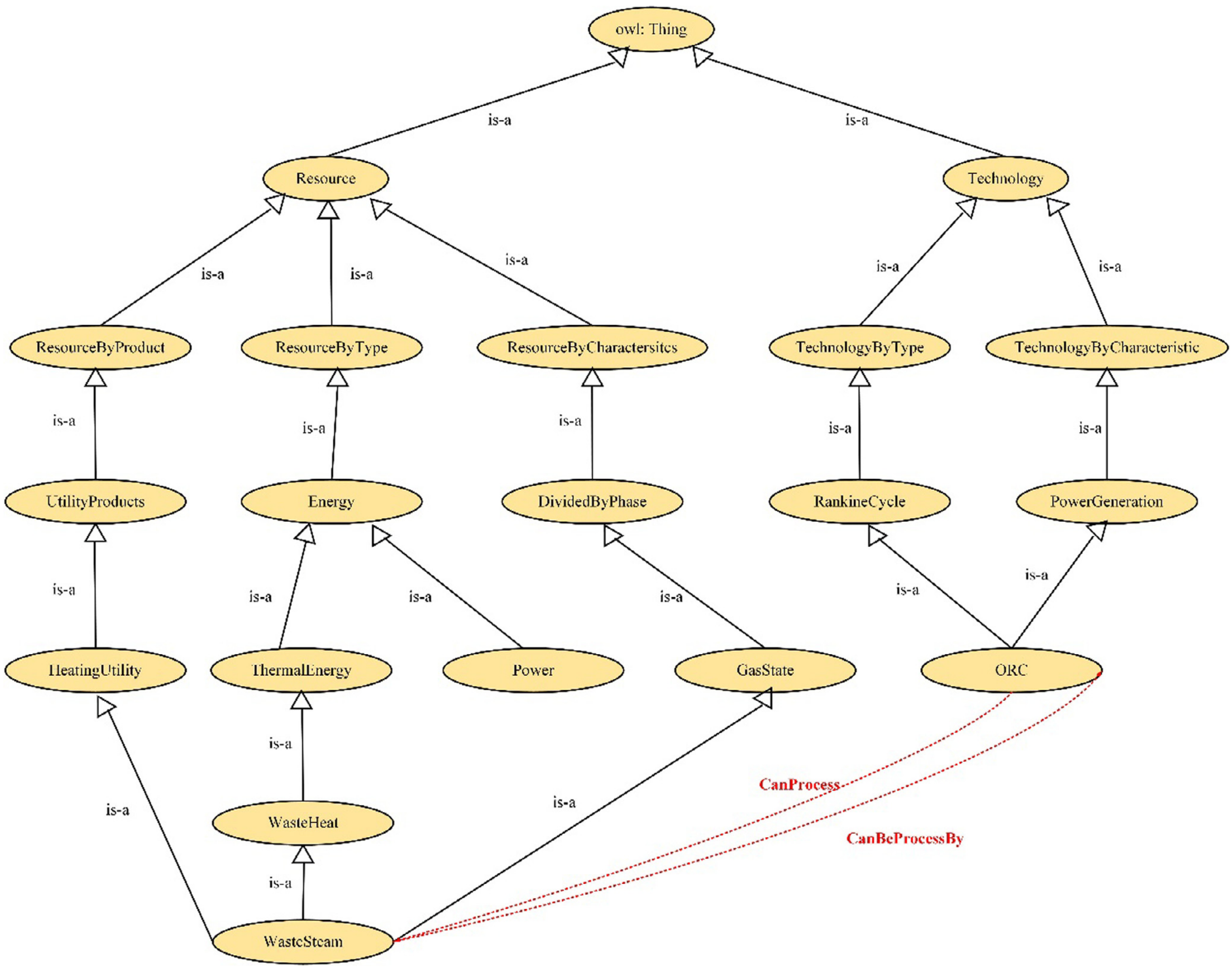

Fig. 5. Ontology for process integration of ORCs.

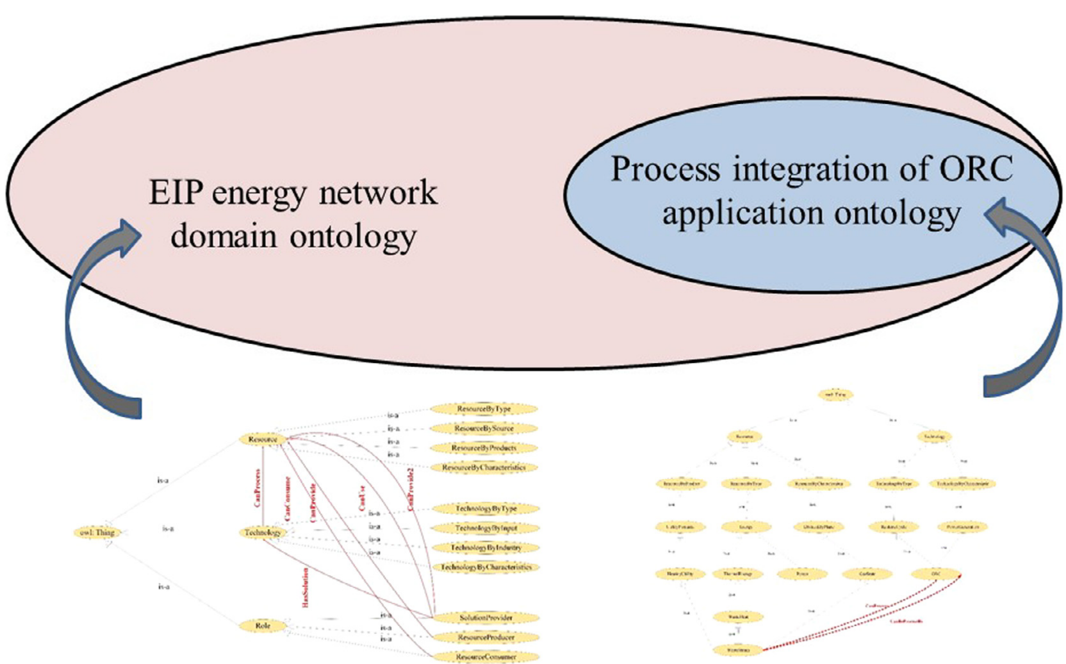

Fig. 6. Application ontology (i.e. process integration of ORCs) and domain ontology (i.e. EIP energy system).

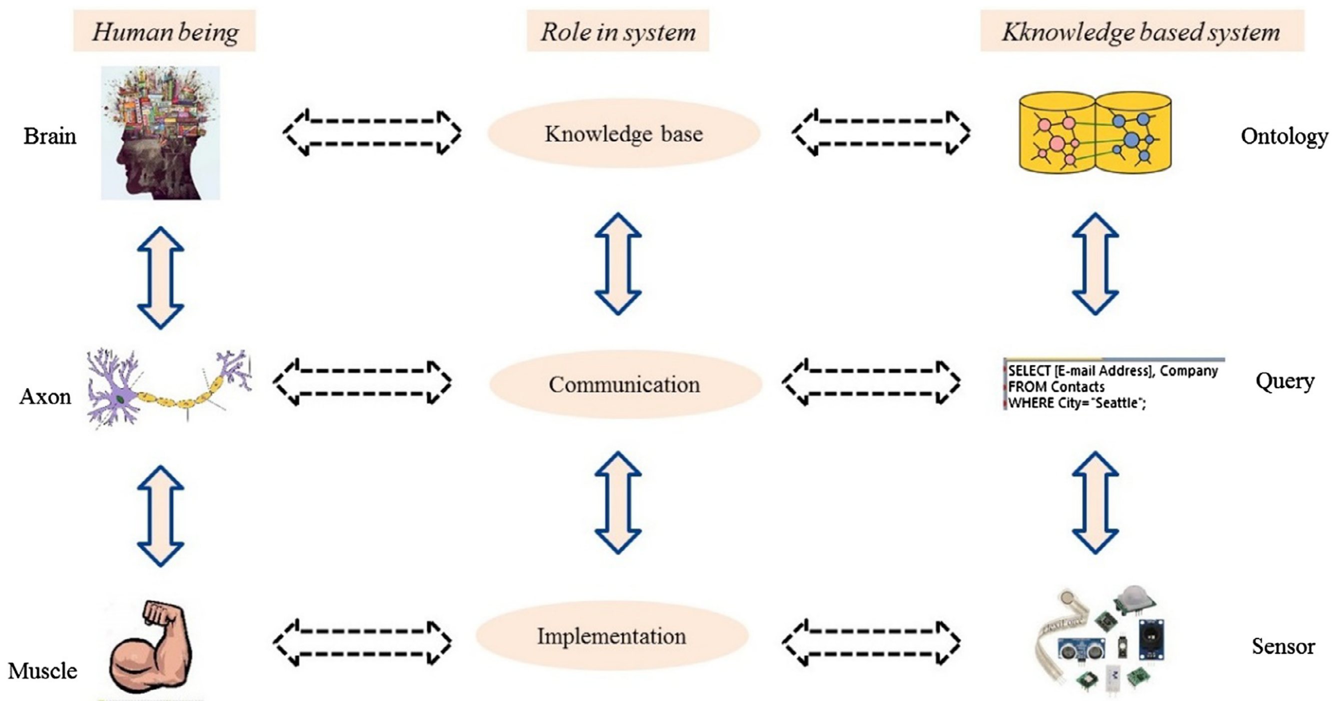

Fig. 7. Analogy between human being and knowledge-based system.

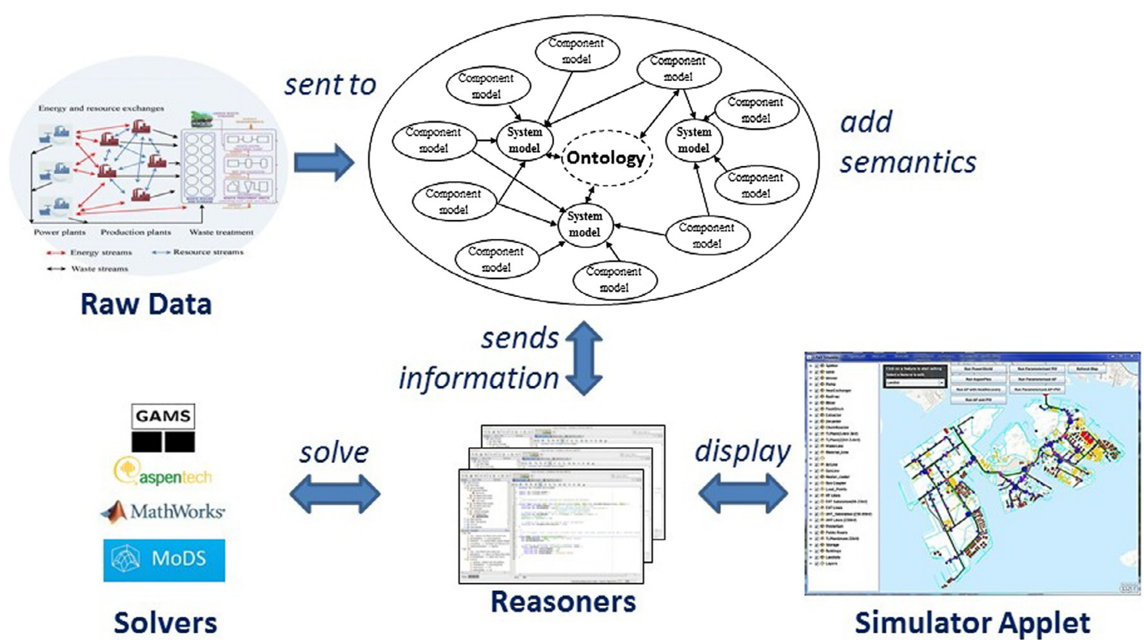

Fig. 8. System architecture of J-Park Simulator.

can successfully figure out synonyms through its own reasoning ability, which is critical for increasing knowledge interoperability between different businesses in EIP.

4.2. Ontology-based intelligent decision making

The second feature of ontology-based approach is its ability in intelligent decision making. In particular, it is assumed a case in which there are five different plants in an EIP that has waste heat with different available temperatures; meanwhile there are five different ORCs with different evaporation temperature requirements as listed in Table 2 [24]. In such a context, the ontology-based approach will provide the options for different plants to match different ORCs based on temperature comparison[1]. The task of matching ORCs and plants in Table 2 is very easy for

[1] It needs to be noted here that the integration of ORC and plants is purely based on temperature comparison in this paper, this is an oversimplification which serves well to explain the decision-making process because much more conditions need to be satisfied to integrate them together in real application. Yet ideally the proposed intelligent system can tackle all these issues in a similar way that it does temperature comparison.

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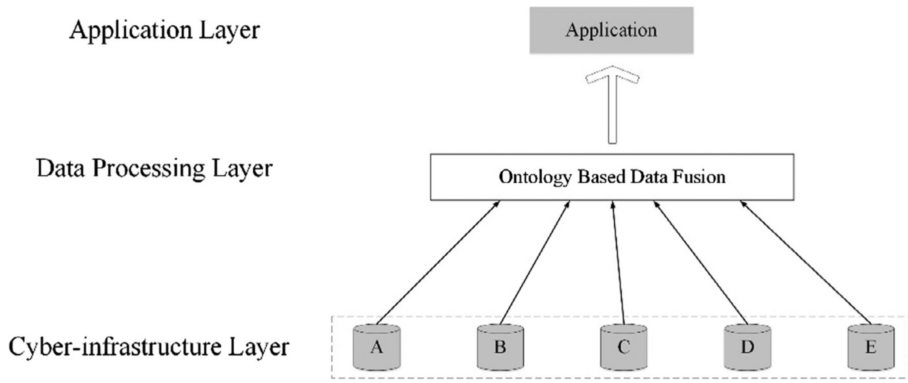

Fig. 9. Ontology-based data integration in the proposed KBS.

Table 1
Properties of *WasteSteam* and *Exhaust* defined in ontology.

	WasteSteam	*Exhaust*
Objective properties	*CanBeConsumedBy* *CanBeProcessedBy* *CanBeProvidedBy* *CanBeUsedBy* *CanBeProvidedBy2*	*CanBeUsedBy* *CanBeConsumedBy*
Data properties	*Temperature* *Pressure* *Enthalpy*	*Temperature* *Pressure* *Enthalpy*

humans but not necessarily for machines, because: firstly, the machine should be aware that ORCs can recover waste heat; in this way, the connection between ORCs and plants can be built. Secondly the information about ORCs and plants may be stored in two separate databases; thus, the ontology-based approach should be able to retrieve information from both sources, make use of the retrieved data, and then facilitate the decision-making process.

In order to facilitate the ontology-based decision making, an application ontology for process integration of ORCs needs to be specified (refer to Fig. 5). In this ontology, ORC is defined as subclass of *PowerGeneration* and *RankineCycle*, while *WasteSteam* is defined as subclass of *HeatingUtility*, *WasteHeat* and *GasState*. The objective property *CanProcess* gives the relationship between *ORC* and *WasteSteam*. Another objective property *CanBeProcessedBy* is defined as the reverse of *CanProcess*, which is shown in Fig. 5 as well.

The ontology of Fig. 5 can then be published in the web and choose a Uniform Resource Identifier (URI) so that people can always find it when they want to reuse it. In this paper, a domain name for putting the URI is currently not available, so the URI is stored locally. For the server side, *Apache Jena Fuseki* is used as a local host. The query language is SPARQL Protocol and RDF Query Language, which can retrieve data from RDF format database. Three queries are designed to demonstrate the decision-making ability of ontology as shown in Table 3, the compact URI definition is shown in Table 3 as well. In Table 3, the different problems these queries are targeting are:

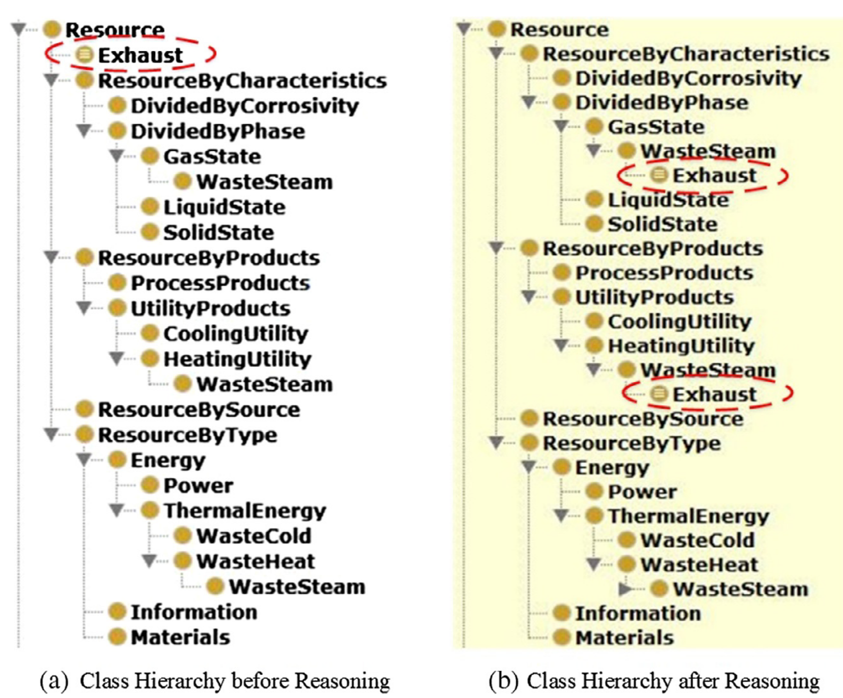

Fig. 10. Class hierarchy of resource (a) before reasoning; (b) after reasoning.

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Table 2
Information of ORCs and plant for process integration.

ORC evaporation temperature/°C	Plant waste heat temperature/°C
ORC 1: 120	Plant 1: 130
ORC 2: 90	Plant 2: 110
ORC 3: 140	Plant 3: 100
ORC 4: 80	Plant 4: 90
ORC 5: 180	Plant 5: 170

Table 3
Semantic query in the proposed intelligent system (PREFIX whr: <http://www.semanticweb.org/administrator/ontologies/organicrankinecycle#>PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>).

Query	Result
*select *{?OrganicRankineCycle whr: CanProcess whr: WasteSteamFromPlant5}*	*whr: ORC1 whr: ORC2whr: ORC3 whr: ORC4*
*select *{?WasteSteam whr: CanBeProcessedBy whr:ORC1}*	*whr: WasteSteamFromPlant1whr: WasteSteamFromPlant5*

- The first query aims to find out all ORCs that can process waste steam from plant 5. URIs for plants and ORCs are used in this semantic query to accurately refer to the corresponding entities. The result of this query is ORCs 1, 2, 3, 4, which means theoretically integration of plant 5 and ORCs 1, 2, 3, 4 is possible.
- Similarly, the second query successfully finds out the waste steam that can be processed by ORC 1 coming from Plant 1 and Plant 5.

The query results themselves might not be exciting, yet given the condition that all these queries are based on machine-readable language, it will enable completely contemporary communication between machines without human intervention if proper cyber-infrastructure is set up as shown in Fig. 11. Ideally what would happen in the scenario described by Fig. 11 is: the sensors embedded in chemical plants can monitor the temperature of waste steam, then the sensor output flows into the ontological representation of plants; meanwhile the ontological representation of ORCs is stored at another remote database. By using the semantic queries designed in Table 3, the information from both databases can be retrieved. Based on the query results, some decision-making can be made and sent to some intelligent agents. The intelligent agents can further implement the queries by communicating with the actuators. In such a manner, the intelligent process integration of ORC can be fulfilled. It also has to be underlined that since there are only five ORCs in the ORC databases in the given example, the power of the proposed KBS is not fully unleashed. If more ORCs (i.e. serval thousands) are included in the database, the advantages of KBS overall human becomes then clear because literally human based approach would not even find the most approximate matches between ORC and waste heat, let alone allow the possibility of contemporary communication.

Finally, it should be noted that the success of such a contemporary automation also depends on well-designed cyberinfrastructure as well as complex sensor network, yet as the digitalization development for modern industrial processes [25,26], it is not something impossible, on the contrary, the authors see it as a great opportunity in the future scenario of Industry 4.0.

5. Conclusion

A Knowledge-Based System (KBS) for Eco-Industrial Park (EIP) knowledge management was proposed in this study. Knowledge management, which means the process of creating, sharing and using knowledge, is important in EIP because it can increase knowledge interoperability within different companies in EIP. Ontology is the core conception of the proposed KBS, ontology is

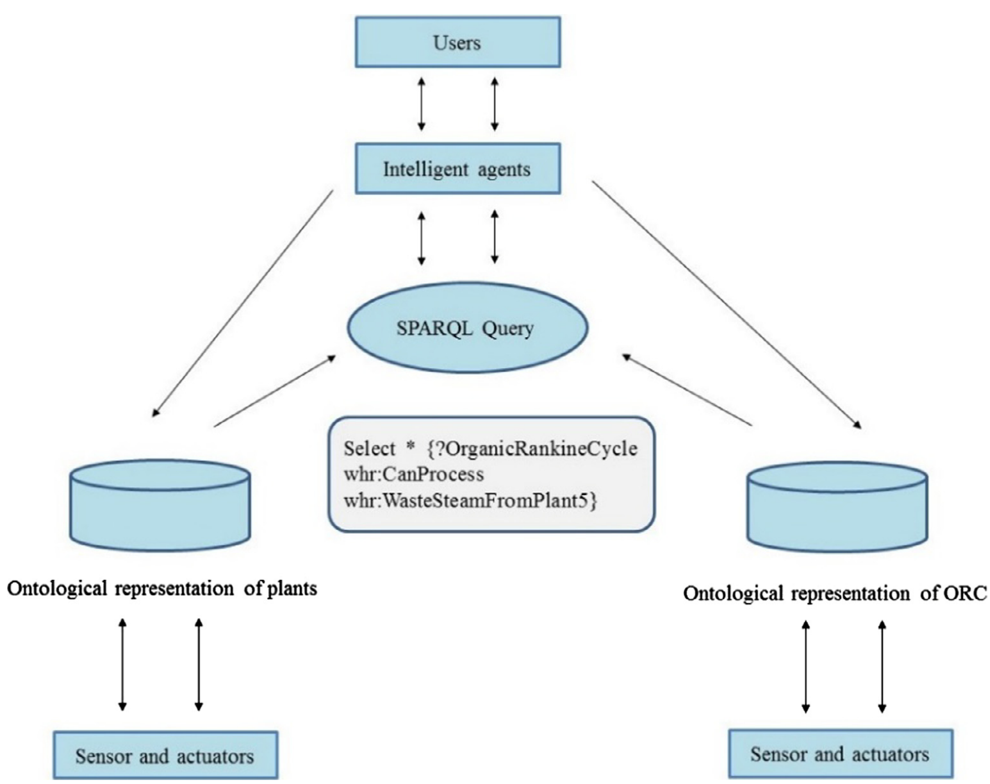

Fig. 11. Intelligent process integration of ORC in the future scenario of Internet of Things (IoT).

the formalized conceptualization of related entities in EIP. By deploying ontological representation of EIP, a virtual EIP can be constructed in the cyber space as counterpart of real EIP in physical world. Since there are so many conceptions related with EIP, thus it is neither possible nor desirable to cover all EIP related conceptions in one study; for this reason, the paper only focusses on the energy systems in EIP as ontology modelling object in this paper. The domain ontology for EIP energy system is established in this study. More specifically, the application ontology for EIP waste heat utilization through ORC is also detailed in the paper. The relationship between these two ontologies are: domain ontology includes application ontology; application ontology is part of domain ontology.

Based on the developed domain ontology and application ontology, a KBS for EIP energy system, namely J-Park Simulator (JPS), is proposed in this study. In the system architecture of JPS, there are three key components: ontology, query and sensor. Interaction of JPS with users is realized through a Java-based Applet. In order to demonstrate the capabilities of the ontology-based approach, two case studies are discussed in the paper. In the first case study, two different resources (e.g. Waste Steam and Exhaust) together with their related properties are defined. Then ontology can successfully understand synonyms through its own reasoning ability, which is critical for increasing knowledge interoperability between different companies in EIP. This functionality of overcoming data heterogeneity is of vital importance in EIP knowledge management because typically data from different companies in EIP are heterogeneous either structurally or semantically. In the second case study, two databases about ORCs and process waste heats are given, the ontology is expected to select appropriate ORCs from the ORCs database to match the process waste heat profile. Through the designed SPARQL query, the ontology-based decision-making is done by using two disparate databases from different sources (e.g. one from ORCs, the other from process waste heat profiles). The query results can be further sent to intelligent agents to be implemented. In such a manner, intelligent control of process integration can be fulfilled.

Through the case studies covered in the paper, it can be concluded that ontology is an effective tool for knowledge management of complex systems such as EIP. By applying KBS such as JPS to EIPs, more efficient energy utilization can be achieved because KBS can bridge the communication gaps between different companies in EIP, sequentially more potential links can be established to improve the overall energy efficiency of the whole EIP. Further work will be done in expanding the domain ontology, validating the usefulness of this ontology-based approach through more applications, or even breaking out of the realm of virtual world by using properly designed sensors and actuators to see how ontology can allow the possibility of artificial intelligence in EIP energy management.

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References

[1] Chertow MR. Industrial symbiosis: literature and taxonomy. Annu Rev Energy Env 2000;25:313–37.
[2] Pan M, Sikorski J, Akroyd J, Mosbach S, Lau R, Kraft M. Design technologies for eco-industrial parks: from unit operations to processes, plants and industrial networks. Appl Energy 2016;175:305–23.
[3] Kastner CA, Lau R, Kraft M. Quantitative tools for cultivating symbiosis in industrial parks; a literature review. Appl Energy 2015;155:599–612.
[4] Zhang C, Zhou L, Chhabra P, Garud SS, Aditya K, Romagnoli A, et al. A novel methodology for the design of waste heat recovery network in eco-industrial park using techno-economic analysis and multi-objective optimization. Appl Energy 2016;184:88–102.
[5] Sikorski JJ, Brownbridge G, Garud SS, Mosbach S, Karimi IA, Kraft M. Parameterisation of a biodiesel plant process flow sheet model. Comput Chem Eng 2016;95:108–22.
[6] Akerkar R, Sajja P. Knowledge-based systems. Jones & Bartlett Publishers; 2010.
[7] Palensky P, Dietrich D. Demand side management: demand response, intelligent energy systems, and smart loads. IEEE Trans Industr Inf 2011;7:381–8.
[8] Keirstead J, Samsatli N, Shah N. SynCity: an integrated tool kit for urban energy systems modelling. Energy efficient cities: assessment tools and benchmarking practices; 2010. p. 21–42.
[9] Kontopoulos E, Martinopoulos G, Lazarou D, Bassiliades N. An ontology-based decision support tool for optimizing domestic solar hot water system selection. J Cleaner Prod 2016;112(Part 5):4636–46.
[10] Ramakumar R, Abouzahr I, Ashenayi K. A knowledge-based approach to the design of integrated renewable energy systems. IEEE Trans Energy Convers 1992;7:648–59.
[11] Abbey C, Strunz K, Joós G. A knowledge-based approach for control of two-level energy storage for wind energy systems. IEEE Trans Energy Convers 2009;24:539–47.
[12] Pan M, Sikorski J, Kastner CA, Akroyd J, Mosbach S, Lau R, et al. Applying industry 4.0 to the Jurong Island eco-industrial park. Energy Proc 2015;75:1536–41.
[13] Ashburner M, Ball CA, Blake JA, Botstein D, Butler H, Cherry JM, et al. Gene ontology: tool for the unification of biology. Nat Genet 2000;25:25–9.
[14] Barnaghi P, Wang W, Henson C, Taylor K. Semantics for the Internet of things: early progress and back to the future. Int J Semantic Web Inform Syst (IJSWIS) 2012;8:1–21.
[15] Hailemariam L, Venkatasubramanian V. Purdue ontology for pharmaceutical engineering: part I. Conceptual framework. J Pharmaceut Innovat 2010;5:88–99.
[16] Noy NF, McGuinness DL. Ontology development 101: a guide to creating your first ontology. Stanford knowledge systems laboratory technical report KSL-01-05 and Stanford medical informatics technical report SMI-2001-0880, Stanford, CA; 2001.
[17] Bechhofer S. OWL: Web ontology language. Springer Encyclopedia of Database Systems; 2009. p. 2008–9.
[18] Marquardt W, Morbach J, Wiesner A, Yang A. OntoCAPE: A re-usable ontology for chemical process engineering. Springer Science & Business Media; 2009.
[19] Marquardt W, Morbach J, Wiesner A, Yang A. Design principles of OntoCAPE. OntoCAPE: Springer; 2010. p. 353–68.
[20] Cecelja F, Raafat T, Trokanas N, Innes S, Smith M, Yang A, et al. E-Symbiosis: technology-enabled support for industrial symbiosis targeting small and medium enterprises and innovation. J Cleaner Prod 2015;98:336–52.
[21] Raafat T, Trokanas N, Cecelja F, Bimi X. An ontological approach towards enabling processing technologies participation in industrial symbiosis. Comput Chem Eng 2013;59:33–46.
[22] JParkSimulator. <http://www.jparksimulator.com/>.
[23] Wiesner A, Morbach J, Marquardt W. Information integration in chemical process engineering based on semantic technologies. Comput Chem Eng 2011;35:692–708.
[24] Desai NB, Bandyopadhyay S. Process integration of organic Rankine cycle. Energy 2009;34:1674–86.
[25] Kagermann H, Helbig J, Hellinger A, Wahlster W. Recommendations for implementing the strategic initiative INDUSTRIE 4.0: securing the future of German manufacturing industry; final report of the industrie 4.0 working group. Forschungsunion; 2013.
[26] Hermann M, Pentek T, Otto B. design principles for industrie 4.0 scenarios. 2016 49th Hawaii international conference on system sciences (HICSS). IEEE; 2016. p. 3928–37.

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