Semantic Networks for Engineering Design: State of the Art and Future Directions

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ABSTRACT

In the past two decades, there has been increasing use of semantic networks in engineering design for supporting various activities, such as knowledge extraction, prior art search, idea generation and evaluation. Leveraging large-scale pre-trained graph knowledge databases to support engineering design-related natural language processing (NLP) tasks has attracted a growing interest in the engineering design research community. Therefore, this paper aims to provide a survey of the state-of-the-art semantic networks for engineering design and propositions of future research to build and utilize large-scale semantic networks as knowledge bases to support engineering design research and practice. The survey shows that WordNet, ConceptNet and other semantic networks, which contain common-sense knowledge or are trained on non-engineering data sources, are primarily used by engineering design researchers to develop methods and tools. Meanwhile, there are emerging efforts in constructing engineering and technical-contextualized semantic network databases, such as B-Link and TechNet, through retrieving data from technical data sources and employing unsupervised machine learning approaches. On this basis, we recommend six strategic future research directions to advance the development and uses of large-scale semantic networks for artificial intelligence applications in engineering design.

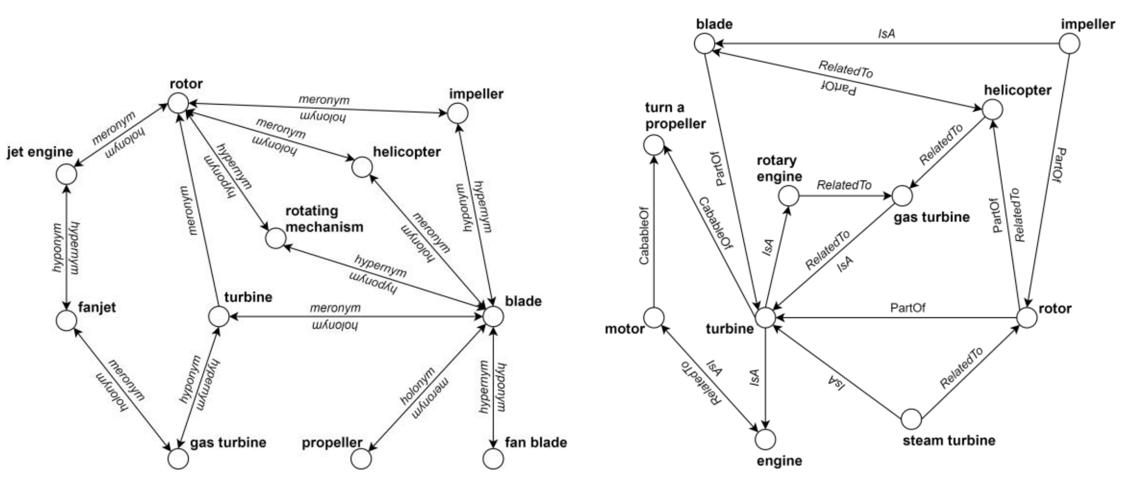
Keywords: *Artificial Intelligence, Data-Driven Design, Machine Learning, Semantic Network, Engineering Design, Knowledge Base*

1. Introduction

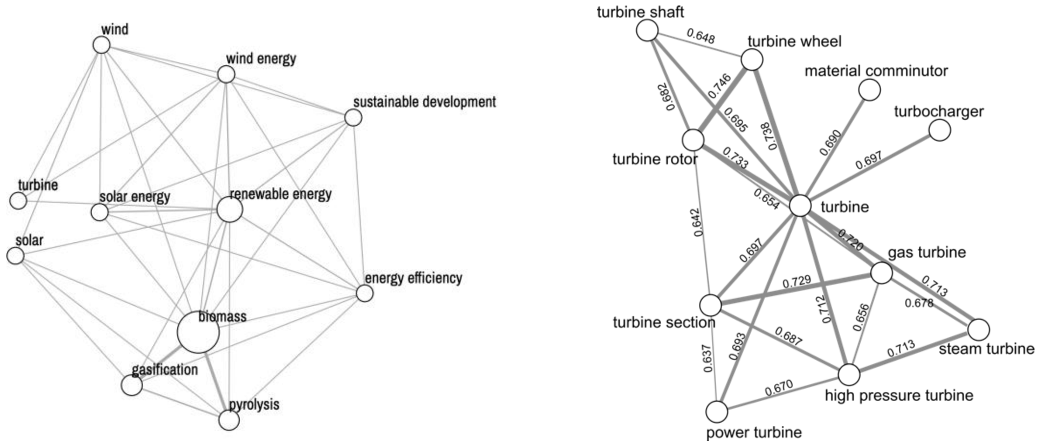
Engineering design is a knowledge-intensive process, where knowledge retrieval, representation and management play an essential role [1, 2]. Digital knowledge bases, which are often in the form of semantic networks, are used increasingly in the design process to support engineering designers in various activities. Semantic networks are artificial associative networks that represent knowledge using graph structures in relation patterns containing interconnected nodes [3]. Nodes in semantic networks represent specific knowledge pieces, ideas, or concepts, which are known as semantic entities. The nodes are connected to one another via links that represent mental connections, demonstrating how knowledge can be accessed from one another, which are known as semantic relations [4]. Employing semantic networks to represent engineering design knowledge has several advantages, such as supporting the reasoning, analysis, and operation of the knowledge contained in design documents [5] by enhancing design information retrieval [6].

In the engineering design literature, WordNet [7], ConceptNet [8-10], YAGO (Yet Another Great Ontology) [11], and NELL (Never-Ending Language Learning) [12, 13] are the most often used open-source, public semantic networks. Such semantic networks are often employed as knowledge bases and digital infrastructures for supporting computational concept inferences to represent, discover, learn, synthesize, and evaluate knowledge for engineering design. However, these open-source, public semantic networks only contain general or common-sense knowledge and relations, and were not created for engineering design in particular. In recent years, there is an emerging interest in designing and developing new semantic networks using engineering data sources and applying them as engineering knowledge bases to support engineering design knowledge representation, discovery, analysis, synthesis, and learning [14, 15].

Figure 1 illustrates several exemplary semantic networks extracted from either common-sense or engineering knowledge bases. WordNet links its common-sense entities through semantic and lexical relations, such as synonym, hyponymy and meronymy. ConceptNet connects its entities through several specific semantic relations, such as 'IsA', 'RelatedTo' and 'PartOf'. The engineering and technical terms in B-Link are related to one another by employing normalized network distance, while TechNet utilizes cosine similarity of word embedding vectors to associate technical terms.



a) WordNet b) ConceptNet



c) B-Link d) TechNet

Figure 1. Exemplar semantic networks of entities and relations centered around the concept 'turbine' from a) WordNet, b) ConceptNet, c) B-Link and d) TechNet

The aim of this paper is to elucidate the state of the art of semantic networks for engineering design and illuminate promising future directions for the research and implementation of large-scale semantic networks as knowledge bases to support engineering design research and practice. The remaining of the paper is structured as follows. Section 2 provides an overview of how semantic networks serve as knowledge bases for engineering design to offer computational design aids and how engineering semantic networks are constructed, focusing on data sources and development methods. On this basis, Section 3 presents several promising directions for future research and applications of engineering design semantic networks. The paper is then concluded in Section 4.

2. State of the art

For nearly two decades, engineering design researchers have developed many methods to represent design information in a structured and reusable way and utilize readily available knowledge bases to inform various engineering design tasks. In this section, we first review the engineering design studies that utilize a great amount of information in available knowledge bases such as large-scale semantic networks, ontologies, and knowledge graphs. Secondly, we focus on constructs specifically built on engineering and technology-related knowledge to serve the engineering design community.

Search phrases, such as 'semantic network', 'semantic', 'network', 'ontology', 'knowledge graph', 'knowledge base', 'data-driven design', 'WordNet', 'ConceptNet', 'natural language processing', 'text mining' are used to run an exhaustive search in Web of Science for indexed top engineering design journals, including 'Journal of Mechanical Design', 'Artificial Intelligence in Engineering Design, Analysis and Manufacturing', 'Journal of Computing and Information Science in Engineering', 'Design Studies', 'Research in Engineering Design', 'Computer-Aided Design', and 'Design Science'. The authors of this paper read the titles and abstracts (and full text of the paper if necessary) of the query results to determine related papers.

In addition to this exhaustive search in Web of Science, the authors added the articles that they have already accumulated in their paper repositories from their prior researches in this field, including articles published in leading engineering design conferences such as 'International Design Engineering Technical Conferences and

Computers and Information in Engineering Conference', 'International Conference on Engineering Design', and other AI and engineering-oriented journals such as 'Expert Systems with Applications', 'Knowledge-Based Systems' and so forth, in order to yield a comprehensive state of the art review result.

2.1. Semantic Networks: Knowledge Bases

Domain-specific and detailed knowledge bases, which are not necessarily semantic networks, have been used and/or curated extensively by engineering design researchers. One important aspect of these knowledge bases is that they are targeted at specific tasks or domains directly. Such specialized knowledge representations were aimed for detailed and specific relations between the entities in a specialized design domain. For example, the Concept Generator [16] is an automated design tool based on an algorithm using the Functional Basis [17, 18]. It employs a small online design knowledge repository as its knowledge base to generate feasible design concept variants. However, the design knowledge repository is not a semantic network and only contains domain-specific knowledge. Song et al. [19] created a 'function network' according to the co-occurrences of functional terms in prior patents related to spherical rolling robots. This semantic network represents the function space of spherical rolling robot designs. Based on the optimal core-periphery partition of the network, the functions in the network core are recommended for inclusion in a product platform and combination with other functions in the network periphery to generate new product variants into the product family. Mukherjea et al. [20] came up with a BioMedical Patent

Semantic Web by annotating patents from the biomedical domain. The semantic entities and relations were retrieved from biomedical ontologies based on a set of predefined patterns.

Some of these domain-specific knowledge bases are also used to support studies on Design-by-Analogy. DANE (Design-by-Analogy to Nature Engine) [21, 22] is a computational design support tool for bio-inspired idea generation, which contains a hand-built semantic network as the knowledge base. The semantic network is based on the SBF (Structure-Behaviour-Function) [23, 24] modelling framework and involves a limited amount of domain-specific knowledge with regards to biological and technological systems. Analogy Finder [25] is another Design-by-Analogy tool that employs the US patent database as the knowledge base for retrieving adaptable analogues to support problem-solving. The knowledge base involves technical knowledge from patents, but not in the form of a semantic network. Idea Inspire 4.0 [26] is a computational tool for supporting idea generation based on Design-by-Analogy, which provides access to biological information by employing a human-curated knowledge base. The SAPPhIRE (State-Action-Part-Phenomenon-Input-oRgan-Effect) [27] ontology is utilized as the backbone of the knowledge base to represent natural and artificial systems. WordNet is employed to enhance the tool's capability in searching for related words of the provided keyword. One common aspect of these knowledge bases is that they require manual encoding of semantic relations between the entities. While this aspect makes them grounded resources for specific tasks and specialized domains, it also limits their scalability to cover many different design domains or extensibility for different tasks.

In addition, Li et al. [28] introduced a design rationale retrieval method that retrieves rationale information from design ontologies supported by WordNet for synonym extension tasks. The study suggested the need to replace WordNet with an engineering design knowledge base for improving the accuracy of synonym expansion. Hu et al. [29] came up with the Intelligent Creative Conceptual Design System (ICCDS) for supporting conceptual design. The system employs a domain-specific Function-Behaviour-Structure (FBS) knowledge cell library as its knowledge base for design knowledge retrieval. Besides, it utilizes WordNet's ontology to calculate semantic similarity for providing semantic understandings to extend the design space. Georgiev et al. [30] proposed a computational approach to synthesize existing scenes via thematic relations for generating ideas of new scenes. The approach employs a hand-built knowledge base which involves thematic relations for storing scenes and a semantic network, a hierarchically structured dictionary, to measure similarity between words for thematic relation synthesis.

Luo et al. [31-33] developed a computer-aided design tool for supporting idea generation, named InnoGPS, which provides rapid concept retrieval as inspirational design ideation stimuli and real-time evaluation of ideas generated. The tool employs a technology space map, constructed by using the complete cross-domain patent database and organised as a network map of technology domains according to statistically estimated knowledge distance between them, as its knowledge base. In turn, the knowledge distance acts as a guide for knowledge exploration and retrieval across far and near fields. He et al. [34] created a semantic network of concepts associated according to their co-occurrences in a large set of idea descriptions from an online crowdsourcing campaign via Mechanical Turk. The semantic network is presented in a core-periphery network structure and as a visual aid to guide designers in exploring concept recombination into new ideas. Acharya and Chakrabarti [35] developed a decision-making support tool, named concepTe, to support designers in their familiar domains at the conceptual design stage. The tool employs a knowledge base which is grounded in the domain-agnostic SAPPhIRE model ontology [27], for semantically translating design elements to solution definitions.

In recent years, open-source large-scale semantic networks are utilized increasingly in the engineering design domain. These large-scale semantic networks, in general, cover enormous knowledge in many domains. Therefore, they are often employed as the backend knowledge base for developing computational approaches and tools to support design idea generation and analysis. Among these semantic networks, WordNet [7], which was collectively built via human efforts, has been the most popular one. For example, Word graphs [36, 37], which contain annotations and semantic associations between words, are used for enhancing the fluency of 'architects' design. A prototype design system was developed to capture the semantic associations using WordNet relations between single annotations or words and for intermediary words during design sessions. Chiu and Shu [38] introduced an algorithmic approach to identify biologically meaningful verbs from a biology-related corpus. They leveraged

WordNet's troponym/hypernym structure to populate their search for keywords in biological texts. Linsey et al. [39] proposed the WordTree method that supports brainstorming sessions by leveraging the hierarchical structure of the WordNet to populate a tree structure, where the functional features of the design problem are represented and redefined with additional verbs to explore analogical solutions. Taura et al. [40] conducted a computer simulation for generating creative design ideas by capturing patterns or characteristics in the concept generation process. The simulation employed WordNet as a semantic network to trace the relationships among concepts. Sosa et al. [41] introduced a semantic-based approach to explore design documents for reconfigurable or transformable robotics. They used WordNet to form a lexically hierarchical structure with abstracted functional verbs. Yoon et al. [42] came up with a computational approach to discover patents based on their function similarity evaluated by leveraging WordNet's hierarchical structure. Their results suggested WordNet lacks a highly specialized collection of terms to support the application. Geum and Park [43] utilized WordNet's hierarchical structure to further populate morphological matrices to facilitate creative idea generation in the early product development phase. Lee et al. [44] presented a methodology to organize morphology-based solutions from biology-related texts utilizing WordNet to semantically extract information. However, they indicated that WordNet has a low recall value, as it cannot recognize terms which are rarely used in general English.

Cheong et al. [45] used WordNet for high-level concept classification and word2vec for low-level concept classification to extract function knowledge from natural language texts. Kan and Gero [46] employed WordNet to connect segments by exploring synset IDs for constructing linkographs to characterize innovative processes in design spaces. Georgiev and Georgiev [47] measured divergence, polysemy, and creativity of new ideas by using a set of curated WordNet-based metrics. Narsale et al. [48] integrated WordNet to their ideation aid tool, the Ideator, and utilized it in the process of reframing design problems based on semantic relations. Goucher-Lambert and Cagan [49] categorized crowdsourced ideas as stimuli for supporting design idea generation according to their semantic measure of similarity calculated based on WordNet. Nomaguchi et al. [50] introduced a method to assess the novelty of functional combinations in conceptual ideas using the semantic similarity measures derived by WordNet and a word embeddings model trained by word2vec on Wikipedia. Their result suggested a negative correlation between semantic similarity and novelty. Liu et al. [51] developed a concept network by retrieving concepts from the design problem related technical documents and associating them via the world-embedding vectors and synset relations in WordNet. Gilon et al. [52] introduced a system to enable targeted analogical search. Their system enables a user to select a specific design aspect of a product and then allows the user to make desired abstractions that focus on the specific needs of the product by employing Cyc [53] knowledge base and WordNet in the backend. The system then employs the necessary abstractions to the whole corpus and utilizes an RNN-based approach to vectorize abstracted representations and sorts the products with respect to their similarities to the queried product.

In addition to WordNet, a few other publicly available semantic networks have also been employed as knowledge bases in engineering design research and methodologies. For instance, ConceptNet [8, 9] is a large-scale open-source semantic network automatically extracted from Wikipedia, WordNet and other crowdsourced resources and expert-created resources, built and maintained at the MIT Media Lab. Yuan and Hsieh [54] developed a tool for supporting designers to frame the creation process for exploring insights by employing the knowledge from ConceptNet. However, the knowledge used is not domain-specific and may contain some noise to mislead users. Han et al. [55] came up with a computational idea generation support tool, named the Combinator, for inspiring designers by combinational textual and pictorial stimuli. The tool employed a knowledge base containing design knowledge extracted from design websites associated with one another via the semantic relations in ConceptNet. Han et al. [56] developed another creative idea generation support tool embracing aspects of analogical reasoning, employing only ConceptNet as the knowledge base for expanding queries and constructing new design ontologies. Chen and Krishnamurthy [57] introduced an interactive procedure for words and terms retrieval by employing ConceptNet to add ideas to a mind-map for stimulating designers. Nevertheless, it is indicated that ConceptNet is not particularly suitable for solution space exploration, as it does not contain the necessary specific technical terms. Han et al. [58] used ConceptNet to assess new design ideas based on the semantic distance between the elemental concepts, of which suggesting far-related concepts could prompt more creative outcomes. Bae et al. [59] employed ConceptNet as the knowledge graph to support mind-mapping by employing a biased random walk to simulate the process of generating non-obvious associations. Camburn et al. [60] introduced a set of metrics to automatically assess the natural language descriptions of crowdsourced design ideas by employing the semantic similarity information in Freebase [61], a large-scale knowledge base acquired by Google and then partly supported Google Knowledge Graph.

As shown in the preceding, large-scale semantic networks containing general knowledge, such as WordNet and ConceptNet, as well as other language models that are not specifically trained for engineering applications, are often used in engineering design studies. However, the common-sense knowledge that they are built on does not cover technical domains sufficiently and their semantic relations are limited to enable engineering-related retrieval, representation, and reasoning. In addition, engineers' perception of terms, especially technical terms, is biased. Thus, knowledge bases curated by focusing on technological knowledge may reflect the same bias [14]. The emerging uses of such open-source semantic networks as knowledge bases in the engineering design research field have motivated the development of semantic networks based on engineering and technological data. For example, Shi et al. [15] retrieved and analysed nearly one million engineering papers in a span of 20 years from the Elsevier database to construct a large-scale semantic network, known as the B-Link, containing engineering and technical knowledge. This semantic network has been used as the knowledge base by Chen et al. [62] for producing a variety of semantic level cross-domain knowledge associations, synthesized together with images, to prompt creative design idea generation.

Sarica et al. [14] developed a technology semantic network, named TechNet, which contains more than 4 million technology-related entities and their relations (semantic distances) by exploring the complete digitalized USPTO patent database from 1976 to 2017. The utilization of the complete patent database has ensured the comprehensiveness and balanced coverage of technical knowledge in all technology domains. Furthermore, benchmark tests were performed to compare TechNet with other existing semantic networks, such as B-Link, ConceptNet, and WordNet, of which the result showed TechNet outperformed the others regarding entity retrieval and semantic similarity tasks in the specific context of engineering and technology [14]. Thereafter, TechNet has been employed by researchers to represent the knowledge structure of a product as a semantic network [63], augment patent search by query expansion [64], forecast the evolution of a technology domain by identifying new technologies around the existing designs of the domain [65], generate [66] and evaluate new ideas [58] based on semantic distance.

A summary of the engineering design studies using semantic networks is presented in Table 1, with highlights of the semantic network used, the application of the method or tool, the role of the semantic network, and the type of knowledge involved. Please note that the studies listed in the first column follow a chronological order.

Table 1. Semantic networks in engineering design studies

Prior Studies	Semantic Networks	Applications	Roles of the Semantic Networks	Knowledge Type		
				Domain-specific	General	Engineering and Technical
[38]	WordNet	Knowledge extraction	Knowledge retrieval		X	
[21, 22]	Hand-built based on SBF modelling framework	Idea generation	Knowledge retrieval	X		
[39]	WordNet	Idea generation	Knowledge retrieval		X	
[40]	WordNet	Idea generation	Knowledge association		X	
[41]	WordNet	Design representation	Reasoning		X	
[42]	WordNet	Patent discovery	Reasoning		X	
[54]	ConceptNet	Idea generation	Knowledge retrieval and reasoning		X	
[43]	WordNet	Idea generation	Reasoning		X	
[30]	Hand-built extracting thematic relations, Concept Dictionary	Idea generation	Knowledge retrieval and reasoning	X	X	
[29]	FBS knowledge cell library; WordNet	Idea generation	Knowledge retrieval and reasoning	X	X	
[45]	WordNet and word2vec	Knowledge extraction	Reasoning		X	
[47]	WordNet	Idea evaluation	Reasoning		X	
[52]	Cyc and WordNet	Design representation	Knowledge retrieval		X	
[55]	Hand-built extracting design keywords; ConceptNet	Idea generation	Knowledge retrieval and association	X	X	
[46]	WordNet	Characterise innovative processes	Knowledge association		X	

[26]	Idea Inspire 4.0 database; WordNet	Idea generation	Knowledge retrieval	X	X	
[56]	ConceptNet	Idea generation	Knowledge retrieval and reasoning		X	
[60]	Freebase	Idea evaluation	Reasoning		X	
[62]	B-Link	Idea generation	Reasoning			X
[49]	WordNet	Idea generation	Reasoning		X	
[34]	Extraction of idea descriptions	Idea generation	Knowledge retrieval and reasoning	X		
[31-33]	Technology space map	Idea generation and evaluation	Knowledge retrieval and reasoning			X
[50]	WordNet and word2vec	Idea evaluation	Reasoning		X	
[35]	SAPPhIRE model ontology	Conceptual design	Reasoning		X	
[57]	ConceptNet	Idea generation	Knowledge retrieval and reasoning		X	
[51]	WordNet	Idea generation	Reasoning		X	
[64-66]	TechNet	Idea generation, evaluation, prior art search	Knowledge retrieval and reasoning			X
[63]	TechNet, WordNet, ConceptNet	Design representation	Knowledge association		X	X

As shown in Table 1, domain-specific, cross-domain general or common-sense, and cross-domain engineering and technical knowledge are the main types of knowledge employed in engineering design studies. Domain-specific knowledge belongs to a specific or specialised target domain, which is often contained in those hand-built semantic networks or ontologies. For example, the biological and technological systems knowledge contained in the SBF based semantic network employed by DANE. Domain-specific semantic networks capture and extend the implicit knowledge of human experts. However, these domain-specific networks can only be applied to solve specific tasks and employed in specialised tools.

Cross-domain general knowledge is the common-sense knowledge that all humans have, such as 'a tyre is a part of a car', which are often involved in large-scale semantic networks, such as ConceptNet. These large-scale cross-domain general knowledge semantic networks are often used as knowledge bases for supporting query expansion, semantic similarity measurement and reasoning tasks, but are limited regarding the depth of the knowledge contained. Due to their lack of coverage of technical and engineering domains, it is challenging to apply these common-sense knowledge bases to make design inferences in the engineering and technical context.

Large-scale cross-domain engineering and technical semantic networks, such as B-Link and TechNet, are thereby developed and used in recent years to tackle this issue. These networks involve cross-domain engineering and technical knowledge from various disciplines, such as physics, chemistry, material science, solid and fluid mechanics. However, there might be difficulties for non-experts to perceive the knowledge provided.

Whether the exclusive use of a certain type of semantic network (domain-specific, common-sense, or particularly engineering-technical) is beneficial or harmful for the design process in a specific domain remains an open question in most existing works. Thereby, the relationship between the specific design domain and the type of semantic network being used needs further investigation. Nevertheless, several researchers, such as Li et al. [28], Yoon et al. [42] and Chen and Krishnamurthy [57], demonstrate that common-sense semantic networks can be limiting for engineering design tasks that are solution-oriented, require more domain details, or require a better clarity on fine-grained product functionality. Sarica et al. [14] showed that TechNet (an engineering-technical semantic network) outperforms WordNet and ConceptNet (common-sense semantic networks) for knowledge retrieval and inference tasks in the engineering design domain.

With regards to design phases, the majority of the studies reviewed have employed semantic networks for early stages, such as idea generation and evaluation, and problem clarification, while few investigate later design stages. However, there seem to be no direct relations between the specific design stage and the type of semantic network being used to support the design task. For example, WordNet, as a common-sense semantic network, has been used for opportunity identification [41, 42], idea generation [26, 29, 39, 43] and evaluation [50]. Therefore, we have analysed the roles of semantic networks in the engineering design studies reviewed to provide further insights.

As shown in Table 1, the main roles of semantic networks in engineering design studies include facilitating knowledge retrieval, association, and reasoning. Knowledge retrieval refers to tasks that retrieve entities and relations from semantic networks in an automated and structured manner to augment knowledge-based intelligence for engineering design applications. For example, query expansion, which involves retrieving relational knowledge based on semantic relations, either semantic distance or specific relations, to populate the existing keywords in the search query [26, 38, 56, 64]; and knowledge discovery and representation, which involves the use of a semantic network or part of the network for knowledge exploration [21, 22, 26, 29, 34, 39, 43, 57, 65]. Knowledge association indicates connecting unlinked entities in an existing database or knowledge base utilizing the semantic relationships from semantic networks [40, 46, 55]. Reasoning involves tasks that utilize the structure and knowledge associations of semantic networks to support various applications, such as providing semantic understandings or measures [29, 35, 41-44, 47, 48, 50, 51, 57, 60], classifying knowledge [45, 49, 54], and producing new knowledge [30-34, 56, 62, 65, 66].

Thereby, a semantic network even plays different roles in different studies to support the same specific design stage or application. Using ideation as an instance, Han et al. [55] employed ConceptNet to associate existing design knowledge to construct the design space for combining prior ideas into new ones; Chen and Krishnamurthy [57] utilized ConceptNet for semantic measures to guide the retrieval of ConceptNet knowledge for populating a mind-map to prompt designers; Han et al. [56] used the semantic distance from ConceptNet to expand queries and the specific semantic relations to generate new design ontologies.

2.2. Semantic Networks: Constructions

Different approaches, such as hand-built, supervised and unsupervised, and different data sources, such as Wikipedia, Elsevier paper publication database and

USPTO patent database, have been employed to construct semantic networks for general purposes or engineering design. Table 2 presents a summary of the construction approaches, data sources, semantic relations involved, and the relevance to engineering and technology, of primary semantic networks that have been used in engineering design studies.

Table 2. A summary of primary semantic networks for engineering design

Semantic Networks	Construction Approaches			Data Sources	Semantic Relations	Engineering and Technology-Related
	Hand-built	Supervised	Unsupervised			
WordNet [7]	X			Human lexicographers	Synonymy, hyponymy, meronymy, troponymy, antonymy	
ConceptNet [8-10]			X	Open Mind Common Sense, DBPedia, Wiktionary, Open Multilingual WordNet, OpenCyc, GWAP Project	34 types of relations: e.g. RelatedTo, FormOf, IsA, PartOf, HasA, UsedFor	
YAGO [11]	Partial hand-build		X	Wikipedia, WordNet	76 predefined relations	
NELL [12, 13]		Semi-supervised		Web content	461 different types of relations	
Knowledge Vault [67]		X		Web content	4469 different types of relations	

Pre-trained word2vec [68]			X	Google News	Cosine similarity	
Pre-trained GloVe [69]			X	Wikipedia, Gigaword, Common Crawl	Cosine similarity	
Function Network [70]		Semi-supervised		WordNet, Functional Basis	Action-Object	X
B-Link [15]			X	Academic papers, design blogs	Normalized network distance	X
TechNet [14]			X	Patents	Cosine similarity	X

Most of the semantic networks and ontological structures that are utilized in engineering design studies are based on common-sense knowledge, as observed from Table 1 and Table 2. WordNet [7] is a large-scale lexical database of English manually developed by experts through retrieving synsets, which are interlinked by semantic and lexical relations (such as hyponymy and meronymy), to express distinct concepts. ConceptNet [8-10] is a freely available semantic network containing common-sense knowledge. It is built by employing unsupervised learning through retrieving entities from crowdsourced and expert-created resources, such as Wikipedia, Wiktionary and WordNet, and games with a purpose, and connecting them via common-sense relations, such as 'IsA', 'UsedFor', and 'RelatedTo'. YAGO [11] is another large-scale general knowledge semantic network, which automatically retrieves entities from WordNet and Wikipedia via an unsupervised approach to fit a set of hand-built relations. NELL [12, 13] uses an infinite loop analogous to an Expectation-Maximization algorithm for semi-supervised learning of information in web pages. Knowledge Vault [67] employs a supervised learning approach to fit probabilistic binary classifiers to fuse distinct data retrieved from web pages. Word2vec [68] is a popular pre-trained word embedding vector database. It employs a neural network to derive the vector representations of words from Google News. GloVe [69] is another popular pre-trained word embedding database, which derives relations based on global statistics of co-occurrence counts of words from Wikipedia, Gigaword, and Common Crawl.

Only a few studies focused on constructing semantic networks specifically for engineering design. For instance, Kim and Kim [70] mined the causal and effect functions as well as the objects related to these functions from patent texts to form action-object tuples and construct a function network to enable the search for analogical inventions, objects and actions. B-Link [15] is a large-scale semantic network contacting engineering and technical knowledge. It employs unsupervised learning to correlate concepts retrieved from the Elsevier database and design blogs by applying probability and velocity network analysis. TechNet [14] is another engineering and technical semantic network developed using unsupervised learning. It employs natural-language-processing (NLP) techniques to extract entities from massive technical patent texts and uses up-to-date word embedding algorithms, such as word2vec and GloVe, to vectorise the entities and construct the semantic relations in the vector space.

Among these primary semantic networks utilized in engineering design studies, only WordNet is constructed by employing a hand-build approach, despite that YAGO has employed a set of manually defined relations. The construction of hand-built semantic networks and ontologies is usually time-consuming and labour-intensive, and thereby often resulted in domain-specific semantic networks containing a limited amount of knowledge [71, 72], such as the SBF-based semantic network used in DANE [21, 22], the thematic semantic network used by Georgiev et al. [30], and the FBS knowledge cell library employed in ICCDS [29]. Knowledge Vault is constructed via a semi-automatic approach employing supervised learning, which often requires human efforts. Supervised models need to be trained manually on large scale corpora prior to automatically recognising semantic entities and extracting semantic relations. Moreover, these models could only recognise the types of relations predefined in the training sets. The domain-specific knowledge graphs constructed by Li et al. [73] still requires predefined pattern matching and a domain-focused FBS ontology structure and lexicon. Therefore, it is challenging to use supervised learning and predefined rules and structures to construct semantic networks for engineering design involving diverse engineering relations. By contrast, ConceptNet, YAGO, pre-trained word2vec and GloVe, B-Link, and TechNet have all employed unsupervised learning to automatically extract semantic relations from data sources.

Among the large semantic networks covering a wide range of knowledge domains, only B-Link and TechNet are developed via employing engineering and technology-related data sources, such as academic technical papers and patents. In contrast, the others use general knowledge data sources, such as Wikipedia and Google News, as shown in Table 2. In addition to B-Link and TechNet, Ishii [74] proposed a semantic network structure with predefined node and link types to represent designs. Glier et al. [75] presented an unsupervised method for identifying text passages, which uses a text-mining algorithm trained on survey data to support designers. Munoz and Tucker [76] developed an unsupervised semantic network of lecture content. The semantic relation between two words is constructed according to their sequential appearance within a given context window.

Other than semantic networks, many studies focus on the construction and utilization of domain-specific ontologies. Li et al. [77] came up with a partial-unsupervised approach for constructing an engineering design domain-specific ontology. It employs basic NLP techniques and semantic analysis to retrieve knowledge from design documents and map them to a pre-structured ontology model. Li et al. [78] proposed a partial-unsupervised approach to create engineering ontologies with the support of a semi-automatic acquisition tool, of which pre-processed engineering documents, including technical reports, catalogue descriptions, and engineers' notebooks, are used as the data source. Chang et al. [79] introduced an ontology generation process and demonstrated its usefulness for Design for Manufacturing. Lim et al. [80, 81] and Liu et al. [82] demonstrated an unsupervised faceted information search and retrieval framework for constructing product family ontologies. However, neither of these studies were aimed at constructing large-scale comprehensive semantic networks for engineering design. Therefore, these semantic networks and ontologies could not be used as knowledge bases or infrastructures to actively support prospective and diverse engineering design projects and studies.

3. Propositions: Future Research Opportunities and Directions

In engineering design literature, the most widely used knowledge bases are two large-scale public semantic networks - WordNet and ConceptNet. These two semantic networks contain large amounts of cross-domain common-sense knowledge. Additionally, ConceptNet consists of explicit semantic relations between entities, which could be used to expand queries, measure semantic similarities, and make inferences for simple engineering design tasks. However, they are trained on non-engineering and non-technical data sources, containing general knowledge and lexical data. These general knowledge semantic networks could not sufficiently support engineering design activities, due to the lack of necessary engineering and technical knowledge with contextual relations.

Meanwhile, there are increasing efforts in constructing large-scale comprehensive engineering and technical-contextualised semantic networks to support engineering design applications by training the networks on technical publication [15] and patent databases [14], which contain engineering design knowledge. These semantic networks have been used to support idea generation and evaluation, design information retrieval, augmenting prior art search, and technology forecasting [14, 15, 58, 62-66]. Thus, it is feasible to use these semantic networks as infrastructures or knowledge bases for supporting an extensive and diverse range of engineering design activities. This leads to our first proposition for the future research, design, development and use of semantic networks to advance engineering and technical language processing for engineering design.

Research Direction 1: Extend the use of comprehensive large-scale semantic networks containing engineering and technical knowledge, such as B-Link [15] and TechNet [14], perhaps blending their uses with common-sense semantic networks, such as WordNet [7] and ConceptNet [8-10], for supporting engineering design activities.

Design as a process has a wide coverage of tasks and activities, such as requirement elicitation, conceptual design, and embodiment design and detailed design [83]. The type of semantic networks that is most useful in supporting very early design phases, such as needs discovery and design problem definition, may be different from those most useful for the later phases, such as idea generation or embodiment and detailed design. Such associations have not been clarified in the prior literature, whereas this present paper does not focus on a specific design phase or task but explores semantic networks in the whole engineering design process.

Also, the effectiveness and usefulness of a semantic network might be closely associated with the person who is designing and the computer support tool which is used. For experienced design engineers, much of what semantic networks capture is likely internalized, while for novice designers, some aid from a broader network could be helpful. However, it can be challenging for a specialized or inexperienced designer to comprehend information-heavy engineering and technical terms from distant domains in a broad cross-domain semantic network based on engineering and technical knowledge. In contrast, comprehending terms and associations from large scale common-sense semantic networks, such as WordNet and ConceptNet, could be relatively easier. Therefore, combining engineering and technology-focused semantic networks, such as TechNet and B-Link, with generic ones, such as WordNet and ConceptNet, has the potential to better support engineering design.

In general, our understanding of the utilities and limitations of different types of semantic networks for uses in different design tasks, different design phases and by different designers is still limited. To advance such understanding would require standard benchmark tests for the uses of semantic networks in various design tasks and design phases, such as design knowledge discovery [64] and representation [63], and design concept generation [55, 62, 66]. In the field of natural language processing and computer vision, various gold-standard tasks are available and commonly used for comparing and testing new and alternative algorithms. However, such standard tests are not yet available for benchmarking and evaluating different semantic networks in terms of their utilities in engineering design. This leads to our second proposition for future research.

Research Direction 2: Create canonical gold-standard benchmarking tasks for benchmarking, testing and evaluating the utilities of new and alternative semantic networks for various specific design tasks (e.g., design retrieval, representation, association, reasoning) across different design phases (e.g., requirement elicitation, concept generation, embodiment, and detailed design).

The rapid advancements in the field of NLP based on deep learning have provided new and better means to retrieve engineering data and learn engineering knowledge to construct semantic networks for engineering design. Recently, there is a surge of language models that employs deep neural network architectures, unlike word2vec and GloVe, for generating unfixed but context-aware word embeddings, such as ELMo [84] by AllenNLP, ULMFiT [85] by fast.ai, Generative Pretrained Transformer (GPT, GPT-2, GPT-3) [86-88] by OpenAI, and BERT [89], XLNet [90], ALBERT [91] by Google. These models are pre-trained on very large corpora, allowing researchers and practitioners to fine-tune them with considerably small datasets to achieve downstream tasks, such as domain-specific text classification, named-entity detection, and sentiment detection.

Models such as BERT, GPT, and XLNet introduced complex transformer architectures to solve sequence-to-sequence problems such as language translation better. These models have resulted in record-breaking performances in various common NLP tasks, such as natural language inference, question answering, sentence similarity, and classification. For example, BERT, a pre-trained unsupervised NLP model for better discerning the context of words by using masked language modelling, can represent each word based on the other words in a sentence. These new data science and NLP techniques could be adopted to construct semantic networks and tackle challenging NLP tasks for engineering design by enhancing document and design exploration, enabling derivation of higher quality vectoral representations, detecting engineering entities with a higher accuracy, training models that can derive engineering-focused relations, developing context-based intelligent collaborative design agents, supporting automatic textual design summarization, design synthesis and evaluation. This leads to our third proposition for future research and development of semantic networks for engineering design.

> **Research Direction 3:** Apply up-to-date deep-learning and NLP techniques, such as transformer-based language modelling architectures (ELMO, BERT, GPT, and so on), to better capture semantic relations in the context of engineering design.

One of the main limitations of those large-scale comprehensive semantic networks, such as B-Link and TechNet, is that the relations contained are one-dimensional. The entities are interconnected to one another with weighted links representing their semantic similarities. In contrast, domain-specific ontological databases allow drawing specialized and domain-specific qualitative semantic relations among entities [92], but lack generalizability.

Knowledge graphs generally pose a trade-off between coverage and specificity [93]. It is aimed at creating a model of the real world by covering knowledge from a wide range of areas, with continuous expansions of online data and constructions of relatively generalizable links between the entities stored [94]. These advantages of knowledge graphs provide relational information that could be understood easily by both computers and humans. In addition, with the support of language models and graph embeddings, the structure of knowledge graphs powers AI tasks, such as knowledge search and discovery, reasoning, summarization, and question answering. Google, Microsoft, Facebook, IBM, Netflix, Amazon, and many other companies alike have all developed knowledge graphs to support their machine learning and artificial intelligence engines. Similarly, comprehensive knowledge graphs trained using engineering and technical data are also expected to inform and augment engineering design tasks. Here comes our fourth proposition of future research direction.

> **Research Direction 4:** Develop a comprehensive knowledge graph based on engineering knowledge data, which can evolve naturally, by constructing necessary pipelines to manage (process, train, verify) continuous data flow.

As shown in Table 2, academic papers and patent documents have been employed as the main data sources to create large-scale engineering and technical semantic networks via unsupervised learning approaches. Academic papers contain inclusive and balanced representations of knowledge from various domains, while patent documents provide technical descriptions of processes and products [14]. These data sources are readily available and have been validated externally through peer-review or examinations. However, not all inventions are patented and not all engineering design knowledge is published. Furthermore, the knowledge contained in academic papers and patents is usually not up-to-the-minute, as it is time-consuming to publish papers and file patents.

In recent years, there is an emerging interest in applying crowdsourcing approaches to create databases for supporting engineering design activities. For example, Goucher-Lambert and Cagan [49] and He et al. [34] used crowdsourced idea descriptions as sources of design stimulation for supporting idea generation; Forbes et al. [95] introduced a crowdsourcing approach to construct a knowledge base for product innovation; and Camburn et al. [96] employed crowdsourcing to gather actual industry design concepts. Crowdsourcing produces massive, diverse and up-to-the-minute knowledge in a cost-effective manner, which presents a promising choice for constructing semantic networks for engineering design. However, crowdsourced knowledge is often more suitable for supporting concept generation and evaluation activities rather than an embodiment and detailed design where higher levels of contributions from the crowd are needed [97].

Crowdfunding platforms (such as Kickstarter and Indiegogo) could be potentially considered a useful data source. A large number of technical designs, with abundant design information, are deposited on crowdfunding platforms, which could be mined and utilized to support various design activities. For instance, Song et al. [98] utilized the historical data from crowdfunding platforms to train a prediction model for guiding future design innovation projects. Besides, engineering textbooks, such as 'Engineering Design: A Systematic Approach' [99] and 'Mechanical Design Engineering Handbook' [100], cover the full spectrum of engineering principles, components, calculations, and design skills. These textbooks containing fundamental engineering design knowledge could be employed as the data source for constructing semantic networks. Here comes our fifth proposition regarding new data sources for constructing semantic networks for engineering design uses.

> **Research Direction 5:** Employ additional and promising data sources such as crowdsourcing databases, crowdfunding websites, and engineering textbooks to construct large-scale engineering and technical semantic networks for supporting engineering design.

The value of semantic networks for design is also conditioned by the process of designers interacting with the computer to mine, view, perceive and utilize the information in the semantic networks to inform design tasks and decisions. In the literature, little attention has been given to morphing semantic networks into computer-based tools that can really support design. Although the researchers that trained B-Link [15] (http://www.b-link.uk/) and TechNet [14] (https://www.tech-net.org) also created public web interfaces as tools for others to retrieve the terms from terms according to their associations and small subgraphs from their large semantic network base, it is unclear if these interfaces result in the interaction workflows that are most effective for simultaneous information retrieval and human cognition.

Kerne et al. [101, 102] and Makri et al. [103] have explored Information-based ideation that involves the generation of new ideas by finding and exploring the use of information. Information-based ideation employs information composition to promote the creative cognition of the relationships between information, which constructs a holistic representation of a curated set of sensory feeds as a visual semantic connected whole. Song et al. [104] studied general AI-human interactions and suggested high-level strategies for designing such interaction processes. Han et al. [56], Chen et al. [62], and Chen and Krishnamurthy [57] have proposed specific human-computer interfaces and interaction workflows for concept generation and evaluation, as well as design problem exploration using semantic networks. These preliminary efforts call for more research on the design principles and guidelines with regards to the interface and the process of interactions between human designers and AI design tools/systems based on semantic networks as the backend knowledge base. This leads to our sixth proposition of future research.

> **Research Direction 6:** Develop principles and guidelines for the design of cognitively effective human-computer interface and interaction workflows between human designers and AI tools/systems, by employing semantic networks as the backend knowledge base, to better support engineering design.

To summarize, we recommend six future research directions for the design, development and use of semantic networks to advance the support towards artificial intelligence applications for engineering design. These propositions are grounded on and suggested by our key findings of the state of the art of the field, as depicted in Figure 2.

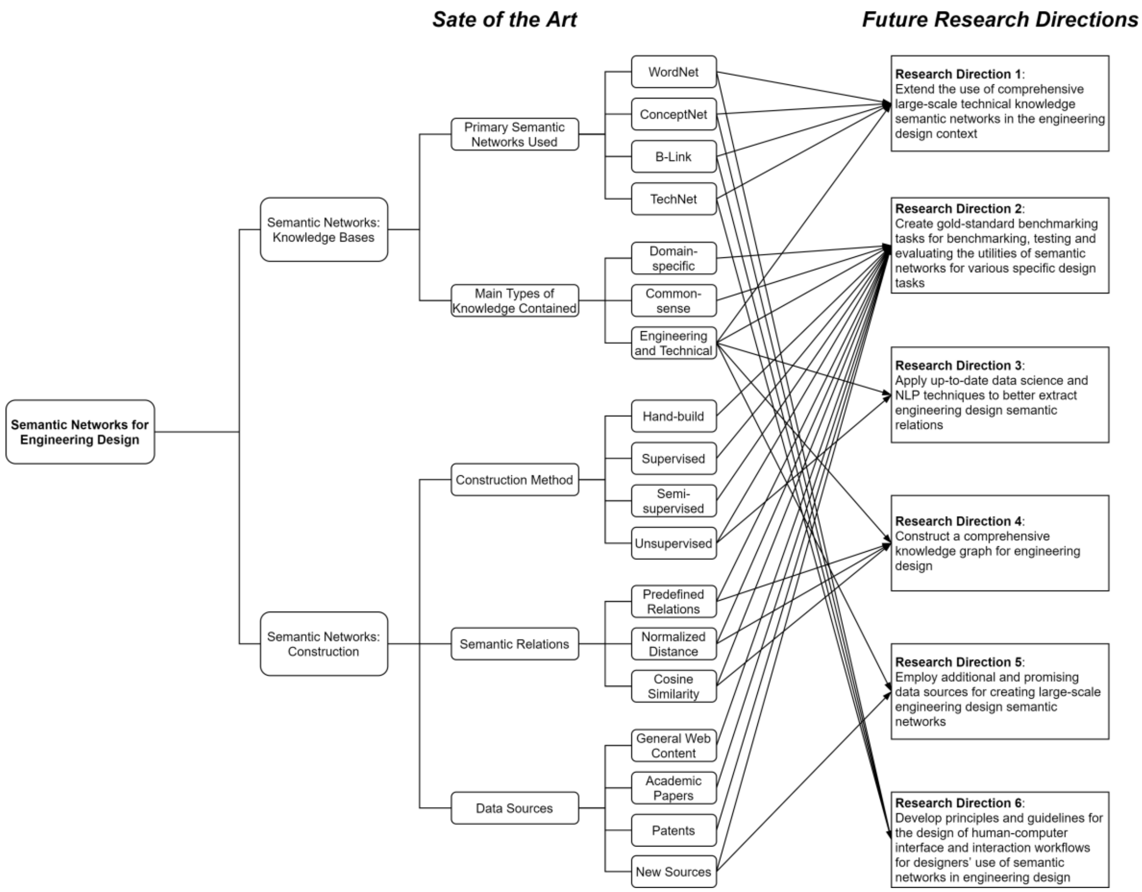


Figure 2. Summary of the state of the art and future research directions of semantic networks for engineering design

4. Conclusions

Semantic networks are often used as knowledge bases and infrastructures, especially in computational design tools, for supporting a variety of engineering design tasks. However, most of the current publicly available semantic networks do not establish relations between knowledge from an engineering design perspective and are thereby incapable of supporting relevant applications. This paper provides an overview of the state of the art of semantic networks for engineering design by reviewing the use of semantic networks as knowledge bases in engineering design studies and the construction approaches of primary semantic networks for engineering design.

Our study suggests six promising future directions of research of semantic networks for engineering design: 1) to extend the use of comprehensive large-scale technical knowledge semantic networks in the engineering design context; 2) to create gold-standard benchmarking tasks for benchmarking, testing and evaluating the utilities of semantic networks for various specific design tasks; 3) to apply up-to-date data science and NLP techniques to better extract engineering design semantic relations; 4) to construct a comprehensive knowledge graph for engineering design; 5) to employ additional and promising data sources for creating large-scale engineering design semantic networks; and 6) to develop principles and guidelines for the design of human-computer interface and interaction workflows for designers' use of semantic networks in engineering design.

This study contributes to the growing literature on data-driven design [20, 27, 105, 106] and NLP based design analytics [15, 20, 105, 107]. We hope the present paper can serve as a systematic guide for the future research, development, and applications of semantic networks in engineering design, analysis, informatics, and knowledge-based artificial intelligence.

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