University of Camerino
School of Sciences and Technology
Master of Science in
Computer Science (LM-18)

University of Applied Sciences and Arts Northwestern Switzerland
School of Business
Master of Science in
Business Information Systems

HAI-BEMS: A Hybrid Artificial Intelligent Approach for Building Energy Management Systems

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A thesis presented to the School of Sciences and Technology of the University of Camerino and School of Business of the University of Applied Sciences and Arts Northwestern Switzerland in partial fulfillment of the requirements for the degree of Master of Science in Computer Science

A.Y. 2023/2024

Abstract

The Thesis Abstract is written here (and usually kept to just this page)...

Statement of Authenticity

I, Piermichele Rosati, hereby confirm that this report was performed autonomously using only the sources, aids and assistance stated in the report, and that quotes are readily identifiable as such.

Signed: 

Date: 20th June 2024

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2.1 Knowledge Graphs

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Knowledge Graphs (KGs) have came up as a key technology in the field of data management and Artifical Intelligence (AI), enabling sophisticated data integration, retrieval and analysis, and analysis. This literature review provides an in-depth examination of KGs, their theoretical foundations, practical applications and recent advances.

Theoretical Foundations of Knowledge Graphs

Definition and Structure

KGs are directed graph-based data structures that represent real-world entities and their interrelations, providing a way to model complex domains and their underlying semantics. A KG consists of nodes (also called entities) and edges (also called relationships), forming a network of interconnected information. This structure allows KGs to capture rich contextual information and provide a semantic framework for data (Hogan et al., 2021).

A KG refers to a semantic network graph which is consisted of diverse entities, concepts, and relationships in the real world. It is used to formally describe various things and their associations in the real world. KGs are generally represented in triples $KG = \{E, R, F\}$.

- E represents the entity set $\{e_1, e_2, ..., e_E\}$, and the entity e is the most basic element in the KG, referring to the items that exist objectively and can be distinguished from each other.
- R represents the relation set $\{r_1, r_2, ..., r_R\}$, and the relation r is an edge in the KG, representing a specific connection between different entities.
- F represents the fact set $\{f_1, f_2, ..., f_F\}$, and each f is defined as a triple $(h, r, t) \in f$, in which h denotes the head entity, r stands for the relationship, and t indicates the tail entity.

Ontologies and Semantic Web Technologies

An ontology is a formal representation of knowledge in a domain, specifying the concepts, relationships, and constraints that exist within that domain. The term "ontology" can be used to the shared understanding of some domain of interest (Uschold and Gruninger, 1996). Ontologies play a critical role in defining the schema and semantics of KGs. They specify the types of entities, relationships, and constraints, thereby providing a formalized structure for the data. The Semantic Web technologies, particularly the Resource Description Framework (RDF) and the Web Ontology Language (OWL), are fundamental to the development and functioning of KGs (G. (Grigoris) Antoniou and Frank. Van Harmelen, 2008).
RDF is a standard model for data interchange on the web. It uses triples (subject-predicate-object) to represent information, providing a flexible and extensible framework for creating and managing KGs (Cyganiak et al., 2014). The RDF standard is a framework for representing information about resources on the web. RDF is a part of the W3C's Semantic Web activity and provides a model for data interchange on the Web. RDF data is structured as triples, each consisting of a subject, predicate, and object. The subject is the resource being described, the predicate is the property or characteristic of the subject, and the object is the value of the property, which can be a literal or another resource. RDF uses Uniform Resource Identifiers (URIs) to uniquely identify subjects and predicates, ensuring that resources are globally identifiable. Objects can be literals, which are concrete data values such as strings, numbers, or dates. RDF can be serialized in various syntaxes, including RDF/XML, Turtle, N-Triples, and JSON-LD. RDF/XML is the original RDF syntax using XML to represent RDF triples. Turtle is a more human-readable syntax for RDF data, concise and easier to write and read compared to RDF/XML. N-Triples is a plain text format for encoding RDF triples, useful for streaming data or simple data exchange. JSON-LD is a JSON-based format to serialize Linked Data, designed to be easy to use and integrate with existing JSON-based systems. RDF Schema (RDFS) is a semantic extension of RDF that provides

mechanisms to describe groups of related resources and the relationships between these resources. It allows for defining classes, which are categories of resources; properties, which are relationships between resources; and hierarchies, enabling inheritance. RDF is widely used in various domains, including the Semantic Web, where it enables the creation of a web of data with meaning, allowing machines to understand and process web content; KGs, powering large-scale graph-based data structures used by organizations like Google and Amazon (Kejriwal, 2022); data integration, integrating data from disparate sources by providing a common data model; and ontology engineering, defining and using ontologies to model domain knowledge. RDF provides a robust and flexible framework for representing structured information, enabling interoperability and integration of data across different systems and domains.
OWL is used to explicitly represent the meaning of terms in vocabularies and the relationships between those terms. It enables more complex and expressive representations compared to RDFS (Deborah and van Harmelen Frank, 2004). The OWL standard is a W3C technology for defining and using web ontologies, enhancing RDF by offering greater expressiveness for complex information. OWL ontologies consist of classes, properties, and individuals, enabling detailed descriptions of relationships and characteristics. It supports complex class expressions, including logical operators and restrictions like cardinality and property constraints. OWL has three sublanguages: OWL Lite (simple feature set), OWL DL (maximum expressiveness with computational guarantees), and OWL Full (greatest expressiveness without computational guarantees). Reasoning capabilities in OWL allow for inferring implicit knowledge, consistency checking, and classification. OWL is used in knowledge management, information integration, and semantic search, providing a common framework for understanding and integrating data. It promotes interoperability and the creation of semantically rich, interconnected web data.

Query Languages

SPARQL Protocol and RDF Query Language (SPARQL) is the standard query language for retrieving and manipulating data stored in RDF format. It allows users to write complex queries to extract specific information from a KG, making it a powerful tool for data analysis and knowledge discovery (Pérez et al., 2009). It allows users to query RDF data by specifying patterns of triples and to update RDF data by inserting, deleting, and modifying RDF triples. RDF is a foundation for Linked Data, which involves interlinking data across the web using URIs and RDF. This enables the creation of a web of data that can be easily connected and queried.

Cypher is another query language for graph databases, such as Neo4j, that allows users to interact with graph data using a pattern-matching syntax. Cypher queries are used to traverse the graph, retrieve specific patterns, and perform operations on the data (Francis et al., 2018). Cypher supports complex queries involving multiple nodes and relationships, aggregation, sorting, and limiting results. It also provides functions for working with strings, numbers, dates, and collections, as well as support for subqueries and variable-length paths. Cypher is widely used for graph analytics, network analysis, and data exploration, enabling users to easily express complex graph traversals and operations. It leverages Neo4j's indexing and optimization capabilities to ensure efficient execution of queries, making it a powerful tool for working with connected data.

Applications of Knowledge Graphs

General Applications

KGs have been adopted across various domains due to their ability to integrate heterogeneous data sources, provide semantic context, and enable advanced querying and reasoning. According to Kapanipathi et al., 2020, in healthcare KGs are used to integrate patient records, clinical trials, research data, and medical ontologies, enabling personalized medicine and decision support systems. They help in identifying relationships between diseases, treatments, and patient outcomes.
Financial institutions leverage KGs to connect data from various sources, such as market data, regulatory information, and customer transactions. This integration facilitates risk management, fraud detection, and compliance monitoring (Tchechmedjiev et al., 2019).
In e-commerce, KGs enhance product recommendation systems by linking customer preferences, purchase history, and product information. They enable more personalized and relevant recommendations, improving customer satisfaction and sales (Zhang et al., 2021).

In compliance with Zou, 2020, Fig. 2.1 shows a mind map illustrating the main applications of knowledge graphs. It divides the applications into five main categories: question answering, recommendation systems, information retrieval, domain-specific applications and other applications. With regard to question answering, methods based on semantic parsing, methods based on information retrieval, methods based on embedding, methods based on Deep Learning (DL) and more complex tasks are included. KGs significantly enhance search engines by providing semantic search capabilities. They enable the understanding of user queries in context, allowing for more accurate and relevant search results. Google's Knowledge Graph is a prominent example, enhancing search

results with information about entities and their relationships (Singhal et al., 2012). Recommender systems are classified into embedding-based methods, path-based methods and other methods. Information retrieval includes query representation, document representation, ranking and DL. Domain-specific applications include medicine, computer security, finance, news and education. Within enterprises, KGs are used to manage and utilize internal knowledge effectively. They integrate data from different departments, such as human resources, finance, and operations, providing a unified view of the organization's information. This integration supports decision-making, collaboration, and innovation (Pujara et al., 2013). Other applications include social networks, classification, geosciences and various other applications.

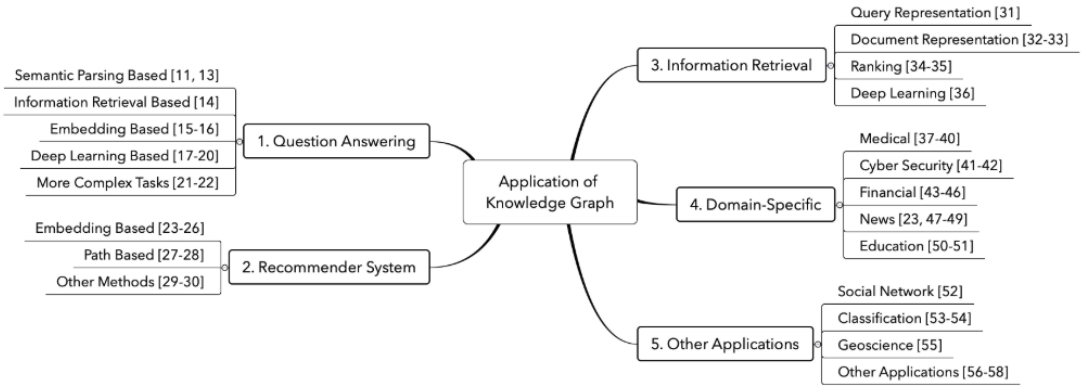

FIGURE 2.1: Application Fields of Knowledge Graphs (Zou, 2020)

Recent Advancements in Knowledge Graphs

Integration with Machine Learning

Recent research has focused on integrating KGs with Machine Learning (ML) and DL techniques to enhance their capabilities and applications. These integrations have led to significant advancements in various areas, including Natural Language Processing (NLP), recommendation systems, and predictive analytics.

- **Knowledge Graph Embeddings (KGEs)**: KGE techniques represent entities and relationships in a continuous vector space, enabling the use of ML algorithms for tasks such as link prediction, entity classification, and clustering. Popular methods include TransE (Bordes et al., 2013), TransH (Z. Wang et al., 2014), and TransR (Lin et al., 2015), each providing different ways to model relationships in the embedding space (Q. Wang et al., 2017).

- **Graph Neural Networks (GNNs)**: GNNs are DL models designed to operate on graph-structured data. They leverage the relational nature of graphs to perform tasks such as node classification, link prediction, and graph classification. GNNs have been successfully applied to enhance the capabilities of KGs in various domains (Wu et al., 2021).

  Section 2.2 provides a comprehensive and in-depth description of GNNs.

Natural Language Processing and Question Answering

KGs have been instrumental in advancing NLP applications, particularly in question answering systems. By providing structured and semantically rich information, KGs enable systems to understand and generate human language more effectively. Question Answering Systems: KGs support question answering systems by enabling them to retrieve and reason over structured data. These systems can answer complex queries by traversing the graph and applying logical inferences based on the relationships between entities (Yasunaga et al., 2021). Semantic Search and Text Analysis: KGs enhance text analysis and semantic search by providing contextual information about entities mentioned in the text. This contextual understanding improves the accuracy of information retrieval and the relevance of search results (Fernández et al., 2011).

Challenges and Future Directions

Scalability and Performance

As KGs grow in size and complexity, scalability and performance become critical challenges. Efficient storage, querying, and updating of large KGs require advanced techniques and architectures. Research in distributed computing, graph databases, and parallel processing is ongoing to address these issues (Chaudhri et al., 2022).

Data Quality and Integration

Ensuring the accuracy and consistency of data in KGs is essential for their reliability. Data quality issues, such as inconsistencies, duplications, and inaccuracies, can significantly impact the performance of applications relying on KGs. Developing methods for automatic data cleaning, validation, and integration is an active area of research (Paulheim, 2017).

Privacy and Security

The integration of sensitive data into KGs raises concerns about privacy and security. Protecting personal and confidential information while allowing for meaningful data analysis is a significant challenge. Research is focusing on developing techniques for secure data sharing, access control, and anonymization within KGs (Bonatti et al., 2017).

Interoperability and Standardization

Interoperability and standardization are crucial for the widespread adoption of KGs. Ensuring that different KGs can work together seamlessly and that their data can be easily integrated requires the development of common standards and protocols. Efforts such as the Linked Open Data (LOD) initiative and W3C standards aim to address these challenges (Bizer et al., 2023).

Conclusion

KGs represent a transformative technology for data integration, retrieval, and analysis, offering significant benefits across various domains. Their ability to provide semantic context and capture complex relationships makes them invaluable for applications in healthcare, finance, e-commerce, and enterprise knowledge management. Recent advancements in ML, particularly in the integration with GNNs, have further enhanced the capabilities of KGs, opening new avenues for research and application. However, challenges related to scalability, data quality, privacy, and interoperability remain and must be addressed to fully realize the potential of KGs. Continued research and development in these areas will be crucial for the future evolution and adoption of KGs.

2.2 Graph Neural Networks

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Graph Neural Networks have become fundamental to Deep Learning field, particularly for tasks involving non-Euclidean data structures. These models have had a significant impact on several domains, such as social network analysis, bioinformatics, recommender systems and NLP. This literature review explores the development, key architectures, methodologies, applications and methodologies, applications, challenges and future directions of GNNs.

Historical Context and Evolution

Early Work and Foundations

Graphs have received success because the achievements of Neural Networks, for ML tasks such as object detection and speech recognition. Graphs are used to represent real-world datasets like protein-protein interaction networks, social networks, traffic forecasting, e-commerce, geographical maps, KGs and so on. In Deep Learning, if we think of images, they are represented as a grid in Euclidean space. At this point, a Convolutional Neural Network (CNN) takes the image as input and is able to extract features for achieving the task in question. DL has achieved much success due mainly to the advancement of computational resources and the availability of data made available. Nowadays, however there is a continuous increase in applications and domains that use complex structures such as graphs (Wu et al., 2021). The complexity of graphs implied not insignificant problems on existing ML algorithms because a graph may have a variable number of nodes or edges; or it might have nodes that may have a different number of neighbours. This last point is very important in some operation like convolution, that is easy for image but difficult for graphs. Another motivation comes from graph representation learning, which aims to learn to represent graph nodes, edges or subgraphs by low-dimensional vectors (Zhou et al., 2020). Existing word embedding methods like DeepWalk, node2vec, LINE, TADW have achieved very good results but they have 2 important drawbacks. The first one is that there are no shared parameters in the encoder, which implies computationally inefficency (n. of parameters grows linearly with the n. of nodes); The second drawback is that there's a lack of generalization because they cannot deal with dynamic graphs or generalize to new graphs.

Inspired by CNNs and Recurrent Neural Networks (RNNs), GNNs have developed in order to operate on non-Euclidian space.

Spectral Approaches

The breakthrough in spectral approaches marked a significant evolution in GNNs. Bruna et al., 2013 introduced a method leveraging spectral graph theory to define convolution operations on graphs. This approach was refined by Defferrard et al., 2016, leading to more efficient models. Kipf and Welling, 2017 simplified this concept further, making it more accessible and practical, thus popularizing the Graph Convolutional Network (GCN).

Key Architectures and Methodologies

Graph Convolutional Networks (GCNs)

GCNs represent one of the most influential architectures in the GNN landscape. They generalize the convolution operation to graph data, enabling the aggregation of feature information from a node's neighbors.

Mathematical Formulation:

A GCN layer can be represented as:

$$H^{(l+1)} = \sigma\left(\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}H^{(l)}W^{(l)}\right)$$

where:

- $\tilde{A} = A + I$ is the adjacency matrix with added self-loops.
- $\tilde{D}$ is the degree matrix of $\tilde{A}$.
- $H^{(l)}$ and $H^{(l+1)}$ are the input and output feature matrices for layer l.
- $W^{(l)}$ is the trainable weight matrix.
- σ is an activation function like ReLU.

Advantages:

- Simplicity and effectiveness for semi-supervised learning tasks.
- Captures local neighborhood structures well.

Limitations:

- Limited expressiveness due to fixed aggregation scheme.
- Struggles with capturing long-range dependencies.

Graph Attention Networks (GATs)

Veličković et al., 2017 introduced GATs, which incorporate attention mechanisms to dynamically weigh the importance of neighboring nodes.

Attention Mechanism:

$$e_{ij} = \text{LeakyReLU}\left(a^T[Wh_i \| Wh_j]\right)$$

where e_{ij} is the attention score, a is the learnable attention vector, and $\|$ denotes concatenation.

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in \mathcal{N}(i)} \exp(e_{ik})}$$

The node features are updated as:

$$h'_i = \sigma\left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij} W h_j\right)$$

Advantages:

- Handles heterogeneous graphs by assigning different importances to neighbors.
- Enhanced interpretability through attention weights.

Limitations:

- Computationally expensive due to the attention mechanism.
- Can become inefficient for very large graphs.

GraphSAGE

GraphSAGE (Hamilton et al., 2017) introduced an inductive approach that can generalize to unseen nodes by sampling and aggregating features from a node's local neighborhood.

Sampling and Aggregation:

GraphSAGE samples a fixed-size set of neighbors and uses aggregation functions such as mean, LSTM, or pooling to update node embeddings:

$$h_i' = \sigma\left(W \cdot \mathrm{AGG}\left(\{h_j, \forall j \in \mathcal{N}(i)\}\right)\right)$$

Advantages:

- Scalable to large graphs.
- Supports inductive learning.

Limitations:

- Information loss due to fixed-size sampling.
- Requires carefully designed aggregation functions.

Message Passing Neural Networks (MPNNs)

MPNNs (Gilmer et al., 2017) formalized the message-passing framework for GNNs. In each layer, nodes exchange messages with their neighbors and update their states.

General Framework:

1. Message Function: $m_{ij}^{(l)} = M(h_i^{(l)}, h_j^{(l)}, e_{ij})$
2. Update Function: $h_i^{(l+1)} = U\left(h_i^{(l)}, \sum_{j \in \mathcal{N}(i)} m_{ij}^{(l)}\right)$

where h_i and h_j are node features, and e_{ij} are edge features.

Advantages:

- General and flexible framework.
- Can model complex dependencies and interactions.

Limitations:

- High computational cost for dense graphs.
- Complexity in designing effective message and update functions.

Training Techniques and Challenges

Mini-Batch Training

To manage large graphs, mini-batch training techniques are employed. Subgraphs or neighborhoods are sampled in each training iteration to reduce memory consumption and improve efficiency.

Graph Partitioning

Graph partitioning techniques like METIS and Louvain divide large graphs into smaller subgraphs that can be processed independently. This helps in parallelizing computations and managing memory usage.

Challenges:

- Maintaining the integrity of graph structure during partitioning.
- Ensuring balanced computational load across partitions.

Optimization Algorithms

Specialized optimizers, such as Adam and RMSprop, are used to stabilize training. Regularization techniques like dropout and weight decay help prevent overfitting.

Applications of GNNs

Social Network Analysis

GNNs are extensively used in social network analysis for tasks such as community detection, link prediction, and influence maximization. They model complex interactions and dependencies among users, providing insights into social dynamics.

Examples:

- Community Detection: Using GNNs to identify overlapping communities in social networks (Chen et al., 2017).
- Link Prediction: Predicting future connections by learning node embeddings (Zeng et al., 2019).

Biological Networks

In bioinformatics, GNNs are used to analyze molecular structures, predict protein functions, and understand biological processes. They model intricate interactions between biological entities, aiding in drug discovery and genomics.

Examples:

- Protein-Protein Interaction: Predicting interactions between proteins by modeling their structural properties (Fout et al., 2017).
- Drug Discovery: Identifying potential drug compounds by analyzing molecular graphs (Jin et al., 2018).

Recommendation Systems

GNNs enhance recommendation systems by modeling user-item interactions. They improve the accuracy and relevance of recommendations by capturing complex relationships.

Examples:

- Collaborative Filtering: Enhancing collaborative filtering with GNNs to model user-item interactions (X. Wang et al., 2019).
- Content-Based Recommendations: Using GNNs to model item features and user preferences for personalized recommendations (Ying et al., 2018).

Natural Language Processing

GNNs are applied in NLPs for tasks like semantic parsing, machine translation, and text classification. By representing sentences or documents as graphs, GNNs capture relationships between words or entities.

Examples:

- Semantic Parsing: Modeling the syntactic structure of sentences for accurate semantic parsing (Zeng et al., 2019).
- Relation Extraction: Extracting relationships between entities in text using GNNs to model dependency trees (Sahu et al., 2019).

Recent Advances and Future Directions

Scalability

Scalability remains a critical challenge for GNNs. Recent advancements focus on models and techniques that handle large-scale graphs efficiently. Methods like GraphSAINT (Zeng et al., 2019) and Cluster-GCN (Chiang et al., 2019) emphasize sampling and partitioning strategies to enable scalable training.

Future Directions:

- Distributed GNNs: Developing distributed frameworks for training GNNs on large-scale graphs.
- Efficient Sampling Techniques: Improving sampling methods to balance efficiency and information retention.

Expressiveness

Enhancing the expressiveness of GNNs involves designing architectures that capture more complex patterns and dependencies. Higher-order GNNs and graph transformers are being explored to address this need.

Future Directions:

- Higher-Order GNNs: Extending GNN architectures to capture higher-order interactions between nodes. Graph Transformers: Leveraging transformer models for graph data to enhance representational power.

Interpretability

Understanding the decision-making process of GNNs is crucial for their adoption in critical applications. Techniques like attention visualization, gradient-based methods, and node importance scores are being developed to interpret GNN predictions.

Future Directions:

- Explainable GNNs: Designing GNN models with built-in interpretability features.
- Interpretable Training Methods: Developing training techniques that enhance model transparency and explainability.

Challenges and Limitations

Despite the significant advancements and applications, GNNs face several challenges and limitations:

- Computational Complexity: GNNs can be computationally intensive, especially for large and dense graphs, limiting their practical applicability.
- Scalability Issues: Handling extremely large-scale graphs remains challenging, requiring efficient algorithms and distributed computing frameworks.
- Over-smoothing: Deep GNNs can suffer from over-smoothing, where node representations become indistinguishable after several layers, reducing model performance.
- Lack of Interpretability: The black-box nature of GNNs poses challenges in understanding their decision-making process, which is crucial for sensitive applications.
- Limited Expressiveness: Some GNN architectures struggle to capture long-range dependencies and complex interactions, necessitating further research into more expressive models.

Conclusion

Graph Neural Network have revolutionized the field of Deep Learning by providing powerful tools for modeling graph-structured data. They have demonstrated remarkable success across various domains, including social network analysis, bioinformatics, recommendation systems, and NLP. Despite their advantages, GNNs face challenges related to scalability, interpretability, and computational complexity. Ongoing research aims to address these challenges, exploring new architectures, efficient training techniques, and methods to enhance expressiveness and interpretability. The future of GNNs looks promising, with potential breakthroughs that could further expand their applications and impact.

2.3 Building Energy Management Systems

Building Energy Management System (BEMS) are critical in the effort to reduce energy consumption and enhance sustainability in residential, commercial, and industrial buildings. BEMS integrate various technologies to monitor, control, and optimize the energy usage within buildings, ensuring efficient operation and reduced environmental impact.

This literature review examines the evolution, methodologies, technologies, applications, challenges, and future directions of BEMS. insert somewhere Manic et al., 2016

Historical Context and Evolution

Early Developments

The concept of managing building energy consumption dates back to the 1970s, spurred by the oil crises that highlighted the need for energy conservation. Initial efforts focused on manual control systems and basic automation to manage heating, ventilation, and air conditioning (HVAC) systems. These early systems were often limited in scope and functionality, primarily due to technological constraints.

Advancements in Automation and Control

The 1980s and 1990s saw significant advancements in automation and control technologies, enabling more sophisticated BEMS. The integration of microprocessors and the development of control algorithms allowed for more precise control of building systems. During this period, building automation systems (BAS) began to emerge, providing centralized control over HVAC, lighting, and other building systems.

The Digital Age and Smart Buildings

The turn of the 21st century brought about the digital age, which revolutionized BEMS. The advent of the Internet of Things (IoT), advanced sensors, and big data analytics enabled real-time monitoring and control of building energy systems. Smart buildings, equipped with intelligent BEMS, became capable of autonomously adjusting energy usage based on occupancy, weather conditions, and other factors.

Key Components and Methodologies

Sensors and Data Acquisition

Sensors are fundamental to BEMS, providing the necessary data for monitoring and control. These include temperature sensors, humidity sensors, occupancy sensors, and energy meters. Data acquisition systems collect and transmit sensor data to the BEMS for processing.

Advantages:

- Real-time monitoring of various parameters.
- Enhanced data accuracy and reliability.

Challenges:

- Integration of heterogeneous sensor types.
- Managing and processing large volumes of data.

Control Systems

Control systems are the core of BEMS, responsible for regulating building systems based on sensor inputs and predefined algorithms. These systems use various control strategies, including:

- Proportional-Integral-Derivative (PID) Control: A feedback control loop mechanism widely used in industrial control systems.
- Model Predictive Control (MPC): An advanced control strategy that uses a model of the system to predict future states and optimize control actions.

Advantages:

- Improved energy efficiency through precise control.
- Ability to adapt to changing conditions.

Challenges:

- Complexity in modeling and implementing control algorithms.
- Ensuring robustness and reliability in real-world conditions.

Communication Networks

Effective communication networks are essential for the seamless operation of BEMS. These networks facilitate data exchange between sensors, control systems, and management platforms. Common communication protocols include BACnet, Modbus, and LonWorks.

Advantages:

- Enhanced interoperability between different systems and devices.
- Real-time data transmission and control.

Challenges:

- Ensuring cybersecurity and data privacy.
- Integrating legacy systems with modern communication protocols.

Data Analytics and Machine Learning

Data analytics and machine learning play a crucial role in modern BEMS, enabling predictive maintenance, anomaly detection, and optimization of energy usage. Techniques such as regression analysis, clustering, and neural networks are commonly used.

Advantages:

- Enhanced predictive capabilities and decision-making.
- Continuous improvement through learning and adaptation.

Challenges:

- Handling large datasets and ensuring data quality.
- Developing accurate and generalizable models.

Applications of BEMS

Energy Optimization

BEMS are primarily used to optimize energy consumption in buildings, reducing operational costs and environmental impact. Techniques such as demand response, load shifting, and peak load management are employed to achieve these goals.

Examples:

- Demand Response: Adjusting energy usage based on real-time electricity prices or grid demand.
- Load Shifting: Moving energy-intensive tasks to off-peak hours to reduce demand charges.

HVAC Control

HVAC systems are significant energy consumers in buildings. BEMS optimize HVAC operations by adjusting temperature settings, controlling airflow, and managing equipment schedules based on occupancy and weather forecasts.

Examples:

- Temperature Control: Maintaining optimal indoor temperatures while minimizing energy use.
- Ventilation Management: Regulating airflow to ensure indoor air quality and energy efficiency.

Lighting Control

BEMS improve lighting efficiency by using occupancy sensors, daylight harvesting, and automated scheduling. These systems ensure that lights are used only when needed, reducing energy waste.

Examples:

- Occupancy Sensors: Automatically turning off lights in unoccupied areas.
- Daylight Harvesting: Adjusting artificial lighting based on the availability of natural light.

Renewable Energy Integration

BEMS facilitate the integration of renewable energy sources, such as solar panels and wind turbines, into building energy systems. They manage the generation, storage, and consumption of renewable energy, maximizing its use and reducing reliance on the grid.

Examples:

- Solar Energy Management: Optimizing the use of solar power through real-time monitoring and control.
- Energy Storage: Managing battery storage systems to balance supply and demand.

Building Performance Monitoring

BEMS continuously monitor building performance, providing insights into energy consumption patterns, equipment performance, and potential areas for improvement. This data is used to identify inefficiencies and implement corrective actions.

Examples:

- Energy Audits: Conducting regular audits to assess energy performance and identify savings opportunities.
- Fault Detection: Identifying and diagnosing equipment faults to ensure optimal operation.

Challenges in BEMS

Integration of Diverse Systems

One of the primary challenges in BEMS is integrating diverse systems and devices, often from different manufacturers, into a cohesive management platform. This requires standardized communication protocols and interoperability.

Solutions:

- Developing and adopting open standards for communication and data exchange.
- Using middleware solutions to bridge compatibility gaps.

Cybersecurity and Data Privacy

As BEMS become more connected and data-driven, ensuring cybersecurity and data privacy becomes critical. Unauthorized access to BEMS can lead to operational disruptions, data breaches, and even physical damage.

Solutions:

- Implementing robust encryption and authentication mechanisms.
- Regularly updating and patching software to address vulnerabilities.

Scalability and Flexibility

BEMS must be scalable and flexible to accommodate changing building requirements and technological advancements. This involves designing systems that can easily integrate new devices and functionalities.

Solutions:

- Using modular architectures that allow for incremental upgrades.
- Leveraging cloud-based platforms for scalable data storage and processing.

Cost and Return on Investment

The initial cost of implementing BEMS can be high, posing a barrier for adoption. Demonstrating a clear return on investment (ROI) is essential to justify the costs.

Solutions:

- Conducting detailed cost-benefit analyses to highlight long-term savings.
- Providing financing options and incentives for energy-efficient upgrades.

Future Directions

Advanced Analytics and Machine Learning

The future of BEMS lies in the continued development and application of advanced analytics and machine learning techniques. These technologies will enable more accurate predictions, adaptive control strategies, and automated fault detection.

Examples:

- Predictive Maintenance: Using machine learning to predict equipment failures and schedule maintenance proactively.
- Energy Forecasting: Leveraging advanced analytics to predict energy consumption and optimize operations.

Internet of Things (IoT) and Edge Computing

The proliferation of IoT devices and the advent of edge computing will transform BEMS by enabling real-time data processing and control at the edge of the network. This will enhance responsiveness and reduce latency.

Examples:

- Edge Analytics: Performing data analysis and decision-making at the edge, closer to the source of data.
- IoT Integration: Connecting a wide range of sensors and devices to create a more interconnected and responsive BEMS.

Blockchain for Energy Management

Blockchain technology holds potential for enhancing transparency, security, and efficiency in energy management. It can facilitate peer-to-peer energy trading, secure data sharing, and decentralized control.

Examples:

- Peer-to-Peer Energy Trading: Enabling buildings to trade excess energy directly with each other using blockchain.
- Secure Data Sharing: Using blockchain to ensure the integrity and security of energy data.

Human-Centric Building Management

Future BEMS will increasingly focus on human-centric building management, prioritizing occupant comfort and well-being. This involves integrating indoor environmental quality (IEQ) metrics and user preferences into energy management strategies.

Examples:

- Occupant Feedback Systems: Using feedback from occupants to adjust building systems for optimal comfort.
- Personalized Climate Control: Implementing systems that tailor the indoor environment to individual preferences.

Conclusion

Building Energy Management System are essential for achieving energy efficiency and sustainability in modern buildings. They integrate various technologies to monitor, control, and optimize energy usage, providing significant benefits in terms of cost savings and environmental impact. Despite the challenges, advancements in analytics, IoT, blockchain, and human-centric design offer promising directions for the future of BEMS. Continued research and innovation will drive the evolution of these systems, making them more intelligent, responsive, and sustainable.

2.4 Research Gap

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Chapter 3

Conclusion

Bibliography

Bizer, C., Heath, T., & Berners-Lee, T. (2023). Linked data - the story so far. In *Linking the world's information: Essays on tim berners-lee's invention of the world wide web* (1st ed., pp. 115–143). Association for Computing Machinery. https://doi.org/10.1145/3591366.3591378

Bonatti, P., Kirrane, S., Polleres, A., & Wenning, R. (2017). Transparent personal data processing: The road ahead. In S. Tonetta, E. Schoitsch & F. Bitsch (Eds.), *Computer safety, reliability, and security* (pp. 337–349). Springer International Publishing.

Bordes, A., Usunier, N., Garcia-Durán, A., Weston, J., & Yakhnenko, O. (2013). Translating embeddings for modeling multi-relational data.

Bruna, J., Zaremba, W., Szlam, A., & LeCun, Y. (2013). Spectral networks and locally connected networks on graphs. http://arxiv.org/abs/1312.6203

Chaudhri, V. K., Baru, C., Chittar, N., Dong, X. L., Genesereth, M., Hendler, J., Kalyanpur, A., Lenat, D. B., Sequeda, J., Vrandečić, D., & Wang, K. (2022). Knowledge graphs: Introduction, history, and perspectives. *AI Magazine*, *43*, 17–29. https://doi.org/10.1002/aaai.12033

Chen, J., Zhu, J., & Song, L. (2017). Stochastic training of graph convolutional networks with variance reduction. http://arxiv.org/abs/1710.10568

Chiang, W. L., Li, Y., Liu, X., Bengio, S., Si, S., & Hsieh, C. J. (2019). Cluster-gcn: An efficient algorithm for training deep and large graph convolutional networks. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 257–266. https://doi.org/10.1145/3292500.3330925

Cyganiak, R., Lanthaler, M., & Wood, D. (2014). *RDF 1.1 concepts and abstract syntax* (W3C Recommendation). W3C. https://www.w3.org/TR/2014/REC-rdf11-concepts-20140225/

Deborah, L. M., & van Harmelen Frank. (2004). Owl web ontology language overview. http://www.w3.org/TR/2003/PR-owl-features-20031215/

Defferrard, M., Bresson, X., & Vandergheynst, P. (2016). Convolutional neural networks on graphs with fast localized spectral filtering. https://github.com/mdeff/cnn_graph

Fernández, M., Cantador, I., López, V., Vallet, D., Castells, P., & Motta, E. (2011). Semantically enhanced information retrieval: An ontology-based approach. *Journal of Web Semantics*, *9*, 434–452. https://doi.org/10.1016/j.websem.2010.11.003

Fout, A., Byrd, J., Shariat, B., & Ben-Hur, A. (2017). Protein interface prediction using graph convolutional networks.

Francis, N., Green, A., Guagliardo, P., Libkin, L., Lindaaker, T., Marsault, V., Plantikow, S., Rydberg, M., Selmer, P., & Taylor, A. (2018). Cypher: An evolving query language for property graphs. *Proceedings of the ACM SIGMOD International Conference on Management of Data*, 1433–1445. https://doi.org/10.1145/3183713.3190657

G. (Grigoris) Antoniou and Frank. Van Harmelen. (2008). *A semantic web primer*. MIT Press.

Gilmer, J., Schoenholz, S. S., Riley, P. F., Vinyals, O., & Dahl, G. E. (2017). Neural message passing for quantum chemistry.

Hamilton, W. L., Ying, R., & Leskovec, J. (2017). Inductive representation learning on large graphs.

Hogan, A., Blomqvist, E., Cochez, M., D'Amato, C., Melo, G. D., Gutierrez, C., Kirrane, S., Gayo, J. E. L., Navigli, R., Neumaier, S., Ngomo, A. C. N., Polleres, A., Rashid, S. M., Rula, A., Schmelzeisen, L., Sequeda, J., Staab, S., & Zimmermann, A. (2021). Knowledge graphs. *ACM Computing Surveys*, *54*. https://doi.org/10.1145/3447772

Jin, W., Barzilay, R., & Jaakkola, T. (2018). Junction tree variational autoencoder for molecular graph generation.

Kapanipathi, P., Abdelaziz, I., Ravishankar, S., Roukos, S., Gray, A., Astudillo, R., Chang, M., Cornelio, C., Dana, S., Fokoue, A., Garg, D., Gliozzo, A., Gurajada, S., Karanam, H., Khan, N., Khandelwal, D., Lee, Y.-S., Li, Y., Luus, F., ... Yu, M. (2020). Leveraging abstract meaning representation for knowledge base question answering. http://arxiv.org/abs/2012.01707

Kejriwal, M. (2022). Knowledge graphs: A practical review of the research landscape. https://doi.org/10.3390/info13040161

Kipf, T. N., & Welling, M. (2017). Semi-supervised classification with graph convolutional networks. http://arxiv.org/abs/1609.02907

Lin, Y., Liu, Z., Sun, M., Liu, Y., & Zhu, X. (2015). Learning entity and relation embeddings for knowledge graph completion. www.aaai.org

Manic, M., Wijayasekara, D., Amarasinghe, K., & Rodriguez-Andina, J. J. (2016). Building energy management systems: The age of intelligent and adaptive buildings. *IEEE Industrial Electronics Magazine*, *10*(1), 25–39.

Paulheim, H. (2017). Knowledge graph refinement: A survey of approaches and evaluation methods. *Semantic Web*, *8*, 489–508. https://doi.org/10.3233/SW-160218

Pérez, J., Arenas, M., & Gutierrez, C. (2009). Semantics and complexity of sparql. *ACM Transactions on Database Systems*, *34*. https://doi.org/10.1145/1567274.1567278

Pujara, J., Miao, H., Getoor, L., & Cohen, W. (2013). Knowledge graph identification. *The Semantic Web–ISWC 2013: 12th International Semantic Web Conference, Sydney, NSW, Australia, October 21-25, 2013, Proceedings, Part I 12*, 542–557.

Sahu, S. K., Christopoulou, F., Miwa, M., & Ananiadou, S. (2019). Inter-sentence relation extraction with document-level graph convolutional neural network. http://arxiv.org/abs/1906.04684

Scarselli, F., Gori, M., Tsoi, A. C., Hagenbuchner, M., & Monfardini, G. (2009). The graph neural network model. *IEEE Transactions on Neural Networks*, *20*, 61–80. https://doi.org/10.1109/TNN.2008.2005605

Singhal, A., et al. (2012). Introducing the knowledge graph: Things, not strings. *Official google blog*, *5*(16), 3.

Tchechmedjiev, A., Fafalios, P., Boland, K., Gasquet, M., Zloch, M., Zapilko, B., Dietze, S., Todorov, K., & Zloch, M. (2019). Claimskg: A knowledge graph of fact-checked claims, 309–324. https://doi.org/10.1007/978-3-030-30796-7_20

Uschold, M., & Gruninger, M. (1996). Ontologies: Principles, methods and applications.

Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., & Bengio, Y. (2017). Graph attention networks. http://arxiv.org/abs/1710.10903

Wang, Q., Mao, Z., Wang, B., & Guo, L. (2017). Knowledge graph embedding: A survey of approaches and applications. *IEEE Transactions on Knowledge and Data Engineering*, *29*, 2724–2743. https://doi.org/10.1109/TKDE.2017.2754499

Wang, X., He, X., Wang, M., Feng, F., & Chua, T. S. (2019). Neural graph collaborative filtering. *SIGIR 2019 - Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 165–174. https://doi.org/10.1145/3331184.3331267

Wang, Z., Zhang, J., Feng, J., & Chen, Z. (2014). Knowledge graph embedding by translating on hyperplanes. www.aaai.org

Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., & Yu, P. S. (2021). A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, *32*, 4–24. https://doi.org/10.1109/TNNLS.2020.2978386

Yasunaga, M., Ren, H., Bosselut, A., Liang, P., & Leskovec, J. (2021). Qa-gnn: Reasoning with language models and knowledge graphs for question answering. http://arxiv.org/abs/2104.06378

Ying, R., He, R., Chen, K., Eksombatchai, P., Hamilton, W. L., & Leskovec, J. (2018). Graph convolutional neural networks for web-scale recommender systems. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 974–983. https://doi.org/10.1145/3219819.3219890

Zeng, H., Zhou, H., Srivastava, A., Kannan, R., & Prasanna, V. (2019). Graphsaint: Graph sampling based inductive learning method. http://arxiv.org/abs/1907.04931

Zhang, W., Deng, S., Chen, M., Wang, L., Chen, Q., Xiong, F., Liu, X., & Chen, H. (2021). Knowledge graph embedding in e-commerce applications: Attentive reasoning, explanations, and transferable rules. *ACM International Conference Proceeding Series*, 71–79. https://doi.org/10.1145/3502223.3502232

Zhou, J., Cui, G., Hu, S., Zhang, Z., Yang, C., Liu, Z., Wang, L., Li, C., & Sun, M. (2020). Graph neural networks: A review of methods and applications. https://doi.org/10.1016/j.aiopen.2021.01.001

Zou, X. (2020). A survey on application of knowledge graph. *Journal of Physics: Conference Series*, *1487*. https://doi.org/10.1088/1742-6596/1487/1/012016

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Acknowledgements

The acknowledgements and the people to thank go here, don't forget to include your project advisor...