

Optimized Data Presentation Strategies for Efficient Retrieval and Analysis: A Semantic and Structured Approach

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ABSTRACT

In the majority of domains such as public health, industrial safety, and weather forecasting, monitoring of the environment is essential. The legacy monitoring systems do not have real-time data capture and cannot provide structured, queryable data. Sensors, cloud storage, and semantic web technologies are all employed in IoT-based solutions to address these issues. A system for environmental monitoring based on IoT for capturing, processing, and semantically representing real-time temperature and humidity information is suggested in this research. Semantic technologies drive the transformation of IoT sensor data into an even more valuable and useful form to support smart applications in different domains. Raw sensor data is augmented with context-dependent meaning through ontologies and RDF-based representation, improving machine comprehension and interoperability. It improves data exchange, analysis, and reasoning and is particularly useful for smart cities, industrial control, healthcare, and environmental monitoring. In smart cities, semantic IoT data supports efficient resource management, in industrial automation, process control and predictive maintenance are maximized and Context-aware technologies can provide individualized patient monitoring in the medical field. Semantic web technologies simplify IoT information, making it more structured, accessible, and actionable, paving the way for complex, intelligent systems.

Keywords: Ontology, Semantic Web, RDF Triple, SPARQL, Protege, Sensor, Internet of Things.

INTRODUCTION

By connecting different gadgets and sensors to the Internet, the Internet of Things (IoT) allows them to gather and exchange data. In contrast, the Semantic Web is an extension of the World Wide Web that aims to represent information semantically so that computers can comprehend and process it more efficiently. Nowadays, the majority of industries that give people a convenient and adaptable lifestyle are centered around the IoT. Numerous services in fields including home automation, transportation, medical, and agriculture are provided by the IoT. We may use IoT to remotely manage our equipment and obtain real-time data for precise business decision-making [1]. Many smart household appliances, such as cellphones, refrigerators, washing machines, smart TVs, and many more, are made possible via the IoT. IoT applications in agriculture have completely changed how farms are operated and managed. Soil conditions, weather, pest infestations, livestock, and crop conditions could all be monitored by IoT devices to optimize harvests while minimizing expenses. By using real-time data and automation, IoT helps farmers make appropriate decisions and optimize resources [2]. Additionally, these gadgets are helpful for communicating and interacting with each other. Semantic web technologies can be used to manage, query, integrate, and observe data. By engaging with domain concepts and quality constraints rather than technological specifics, users can function at abstraction layers above format and integration.

The emergence of the semantic web, which makes it possible to describe and distribute knowledge and information across the web, has led to the widespread use of ontologies. Semantic technologies are required to convert IoT sensor

data into an even more useful and valuable form, facilitating smart applications across domains [3]. Sensor raw data is contextualized using ontologies and RDF-based representation for the purpose of adding meaning, optimizing machine understanding as well as interoperability. Using ontology concept definitions to supplement raw sensor data with semantic annotations allows for more expressive data representation that facilitates knowledge discovery [4]. Semantic IoT data offers efficient resource management in the event of smart city implementation. In industrial automation, it improves predictive maintenance and process control. In healthcare, context-aware systems can offer personalized patient monitoring. In environmental monitoring, semantic models support real-time decision-making for sustainability.

This paper attempts to bring out the advantages of representing IoT sensor data using Ontology for easy retrieval of relevant information through queries formed using natural language. As part of this study, an IoT node has been developed using NodeMCU ESP8266 microcontroller board enabled with internet connectivity via a WiFi module and interfaced with a DHT11 sensor to capture temperature and humidity values real-time and posts the same to ThingSpeak cloud platform. This paper also describes how to use an ontology to present and interpret the data that is stored on the cloud, create an RDF graph, and use SPARQL queries in protege tools for a Smart Climate Monitoring System.

RELATED WORK

In 2025, Gajendrasinh et. al. used a sensor for measuring the temperature and humidity and NodeMCU for getting real-time data of temperature and humidity on the cloud platform. They used an ontology for presenting and processing the collected data. The ontology was represented using RDF (Resource Description Framework) and OWL (Web Ontology Language) to ensure semantic consistency and interoperability. Applied SPARQL query to retrieve the data for Home Automation System [5]. In 2024, Anitha et. al, proposed a novel Heterogeneous INTERoperable sensors (HintSense) technique which improves semantic interoperability between data and end-user applications by enabling deep knowledge in the IoT link layer. Two service domains, namely weather and healthcare, were used in the experiments. The proposed model provides scalable and effective solutions for IoT ecosystems, particularly in weather monitoring and healthcare applications [6]. In 2024, Gomez-Cabrera, A., et al. presented ViLanIoT, a new visual language for representing IoT systems that are thought of as cyber-physical systems. ViLanIoT makes IoT system representations easier to comprehend, more straightforward, and simpler by giving each component a visual characteristic that carries semantic significance. It has precision issues when applied to complex IoT systems [7]. In their 2022 study, Amara et al. addressed how different IoT devices and sensors produce data, and since they all follow different formats, it might be difficult to manage in an IoT context in order to share and utilize raw data for reuse. This leads to a major issue known as lack of interoperability. It is necessary to use data modeling and knowledge representation to address these issues. This will be accomplished by leveraging RDF triple concepts to transform raw IoT data into an enriched representation using semantic web technologies [8]. In 2022, Bhgat et al. presented a model that gathers environmental information with the help of various sensors and transmits it through Wi-Fi to a cloud server. This data can be used by scientists, nature analysts, and environmentalists who have to monitor particular areas such as volcanoes or rainforests. Furthermore, the system can be extended to monitor pollution in urban and industrial areas, ensuring public health safeguarding through round-the-clock environmental monitoring. [9]. In 2022, Pavlopoulou et al. proposed a system to solve IoT issues of data integration, heterogeneity, redundancy, and usability. It presents DBVARC, an incremental and parameter-free clustering algorithm, for summarization, reasoning rules, and Triple2Rank scoring for top-k filtering. [10]. In 2021, Phua et al., proposed a system that included two sensing units such as a heart pulse sensor and a temperature and humidity sensor using Arduino. The data is then examined to find the parameter in various circumstances. When the heart rate falls below the condition set before, the system interprets the individual as neither active nor awake and thus switches off the fan and light. This system remains active in home monitoring and will help those in need who can operate household appliances depending on the elderly's health [11]. In 2020, Naidu et al. monitored temperature and gas sensors using an Arduino and a NodeMCU ESP8266 microprocessor. The NodeMCU ESP8266 Wi-Fi module is coupled to gas and temperature sensors, which collects data and stores it in the cloud via the Adafruit IO platform. It is a cloud service that enables us to access and show data from any location by creating gauges, charts, and graphs [12]. In 2020, Wu et al. proposed a system that discusses RDF and SPARQL standards for climate studies which use knowledge graph data modeled by

the climate analysis ontology. Depending on the kind of data, this study covers two types of weather analyses, namely categorical analysis of the meteorological records and quantitative analysis of the temperature. A basic grasp of the weather in the respective cities is given by both analyses. In the future, semantic technologies will be added to climate knowledge graphs, increasing their usefulness to climate researchers. It is reasonable to draw the conclusion that semantic web technology will be helpful in this situation for giving weather forecasting data context and prediction [13]. Usman et al. in 2019 discussed the construction and utilization of an ontology to foster harmonious understanding of information or knowledge among humans and machines. This ontology confirms the principles of the Semantic Web and establishes interoperability based on cloud computing abilities. By allowing machines to understand and concur on particular knowledge, this ontology helps people to achieve precise and fulfilling results [14]. The IoT-based deployment of a temperature and humidity monitoring system with NodeMCU was proposed by Khaing et al. in 2019. This device regulates the humidity and temperature of the room and makes predictions about the parameters based on past data. The sensor is connected to a NodeMCU ESP8266 and sends data to ThingSpeak Cloud through an Internet-connected gateway. The cloud receives the signal of the sensor through variables. A heating or cooling signal will then be received by the system through the controller [15]. In 2019, Prasanna et al. presented a system that makes use of ThingSpeak, an analytics platform for Internet of Things devices that is offered by MathWorks, the company that makes Simulink and MATLAB. It enables real-time data visualization, aggregation, storage, and analysis in the cloud. ThingSpeak's architecture allows graphical data uploaded by our sensors or devices to be visualized instantly. [16]. In their study, Pandey et al. in 2019 emphasized the importance of the Semantic Web in improving the value and interoperability of IoT sensor data. Semantic technologies can be employed to supplement IoT sensor data with contextual information, relationships, and relevant metadata. This augmentation makes it easier to integrate, find, and analyze data that will be useful for machine interpretation [17]. In 2018, Faroom et al. proposed an Android app-based home automation system. In order to send a signal to an Arduino board, the system uses an Android application. A wireless module attached to the Arduino board then receives the signal. The relay board employs the Arduino to automate smart appliances. The Arduino device is the central command station of the system. To carry out the "ON" and "OFF" operations, relays are used. For people who can't move around much to use domestic appliances, this method is helpful [18].

METHODOLOGY

Working Principle

DHT11 is connected to the NodeMCU via a Digital IO pin. The software module runs in the NodeMCU pulls temperature and humidity data from the DHT11 sensor with the help of 1-wire protocol and then transmits the data to the ThingSpeak cloud via WiFi interface connected to the internet gateway. The data is analyzed, visualized, and exported into a CSV file in ThingSpeak cloud. An ontology is created from the CSV data, knowledge is represented using the RDF triple format in the PROTEGE tool. Apache Jena Fuseki server facilitates data storage in triple format so that queries submitted to SPARQL endpoint can be used to retrieve meaningful insights in our suggested system. Regarding the link between ThingSpeak and PROTEGE, one is for the storage, visualization, and analysis of data, and the other is for the RDF triple representation of knowledge. Figure 1 describes the design of the suggested system.

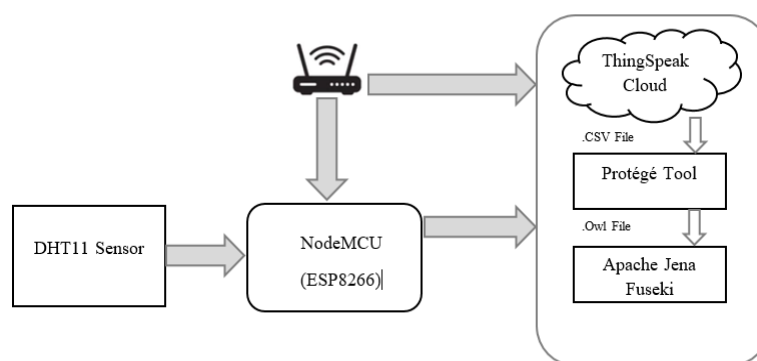


Fig.1. Suggested system architecture [5]

Hardware Description

NodeMCU ESP8266 Wi-Fi Module

NodeMCU ESP8266 microcontroller board has been manufactured by Espressif Systems. It has integrated Wi-Fi capabilities and is made to work with Arduino IDE. Figure 2 illustrates that this module is compatible with several Wi-Fi frequencies, including 802.11n and 802.11b. Because of this, it can be utilized as a Wi-Fi system and an Access Point (AP) simultaneously [19].

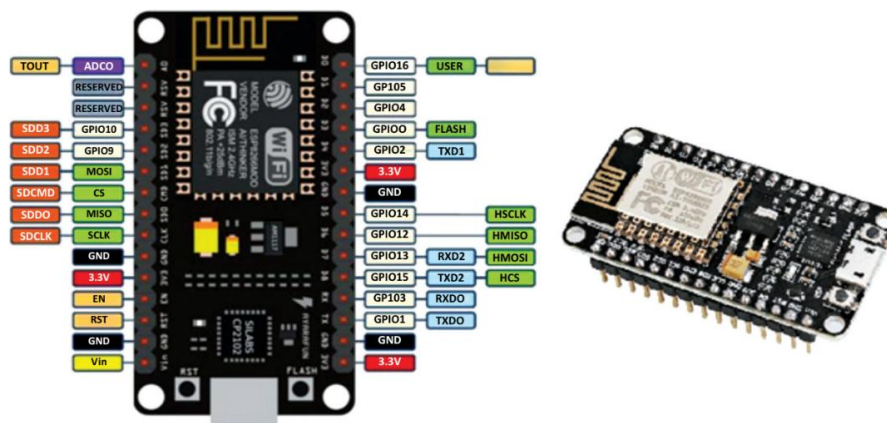


Fig.2. Depiction of the pins connecting the ESP8266 to the node MCU [20]

DHT11 Temperature & Humidity Sensor

The DHT11 sensor makes it simple to measure temperature and humidity. It measures humidity (H) and temperature (T) via optical signals. It uses the Negative Temperature Coefficient (NTC) idea to monitor temperature and humidity values as serial data. Humidity ranges from 20% to 90%, while temperatures range from 0°C to 50°C. It is inexpensive, has anti-interference capabilities, is easy to install, and has dependable quality and fast reaction times [21]. The DHT11 sensor pinout is displayed in figure 3.

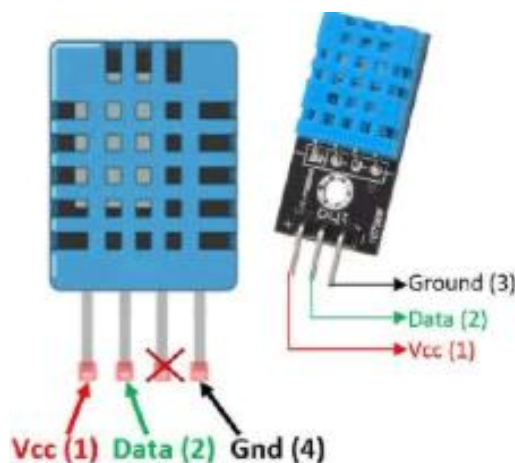


Fig 3. DHT11 sensor pinout [21].

Software Description

Arduino IDE - It is an open source software which makes microcontroller programming accessible. It is a simple interface with intuitive controls for programming Arduino compatible devices [22].

ThingSpeak Cloud Platform- Building IoT apps is made possible by the ThingSpeak platform's numerous services. It allows users to collect data in real-time, visualize it as charts, and develop apps and plug-ins to integrate with social networks, web services, and other APIs. This allows us to design a channel using various widgets that offer rich data

visualization and publish it in either the public or private domain. A crucial component of this platform is the API key, which aids the import and export of data features and read and write data into the channel [23].

PROTEGE Tool - A popular tool among developers and consumers, PROTEGE is free and open-source. Ontologies and RDF graphs can be created and developed with it, and SPARQL queries can be applied to them. In addition to a library of components and extensions that give extra helpful functionalities, PROTEGE provides comprehensive plugin support. The PROTEGE tool allows us to construct many kinds of attributes for entities, including annotation properties, entity properties, and object data properties [24].

SPARQL - Data saved in Resource Description Framework (RDF) format can be retrieved and altered using SPARQL, the Semantic Web query language. SPARQL is capable of extracting values from semi-structured and structured data. It can perform intricate joins of various databases in a single straightforward query and explore data by querying unknown relationships. It can also convert RDF data across different vocabularies [25].

Apache Jena Fuseki- It is an open-source RDF triple storage and SPARQL endpoint from the Apache Software Foundation, is a popular tool for developing Semantic Web applications. It functions as a strong tool for RDF data management and inquiry. Because it provides effective semantic data storage and retrieval, it is a popular option for these types of applications [26]. Neo4J and RDF are fierce rivals in this regard, but RDF has the advantage of supporting a higher level of semantics than Neo4J, specifically OWL.

System Architecture

The system follows a three-layer architecture as exhibited in figure 4.

Perception Layer: Collects temperature and humidity information using the DHT11 sensor.

Network Layer: Uses NodeMCU ESP8266 to transmit data over WiFi to the ThingSpeak cloud.

Application Layer: Performs semantic data modeling and retrieval using Protégé and SPARQL.

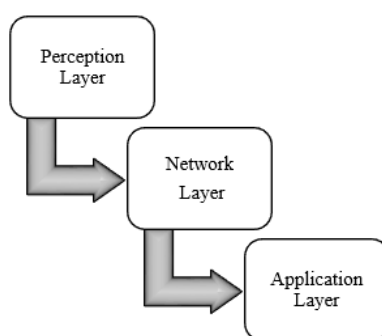


Fig 4. Three-layer architecture.

PROPOSED SYSTEM

The DHT11 sensor is dependable, less costly, and simple to install for measuring humidity and temperature. The NodeMCU ESP8266 Wi-Fi Module has built-in Wi-Fi, hence the Ethernet and Wi-Fi connections don't need to be separated. The Arduino IDE shows the serial monitor data which is collected using the DHT11 sensor. After the NodeMCU ESP8266 is linked to the Internet, it may be remotely controlled from any location by using its IP address. The ThingSpeak cloud platform, which is accessible from any location, provides the most recent temperature and humidity data. In this system, the data is exported from the cloud platform and used to create a semantic data model using the Protégé tool's Ontology or RDF graph. An Apache Jena Fuseki server is then used to store the resultant triples for future SPARQL queries and for effective storage. This system helps the users to query the real time information from the historical climate data stored to make actionable insights.

The DHT11 Sensor is connected to the NodeMCU ESP8266 Wi-Fi Module via GPIO-2 configured as a digital input pin as shown in Table 1.

NodeMCU is powered through a USB port connected to the workstation as shown in the figure 5.

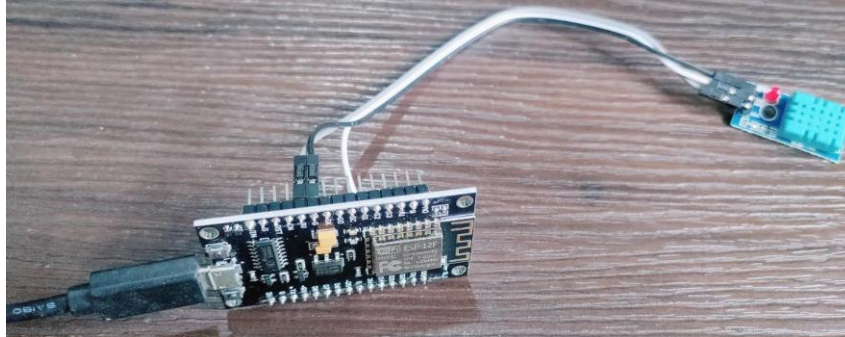


Fig 5. Connection Layout

TABLE 1. Pin Mapping

Jumper wire	DHT11 Pin	NodeMCU Pin
White	VCC	3V
Grey	Data	D4(GPIO2)
Black	GND	GND

The code is written in Arduino IDE, which uses libraries such as ESP8266WiFi, ESPAsyncTCP, ESPAsyncWebServer, and Adafruit_Sensor. Following that, the Wi-Fi credentials are set. The temperature and humidity values are displayed on the serial monitor and data are sent to the ThingSpeak cloud platform.

After establishing the connection, log in on ThingSpeak cloud to create a channel and obtain data. The channel is created and it displays two charts - one for temperature and the other for humidity. Figure 6 depicts the display of data on ThingSpeak Cloud.

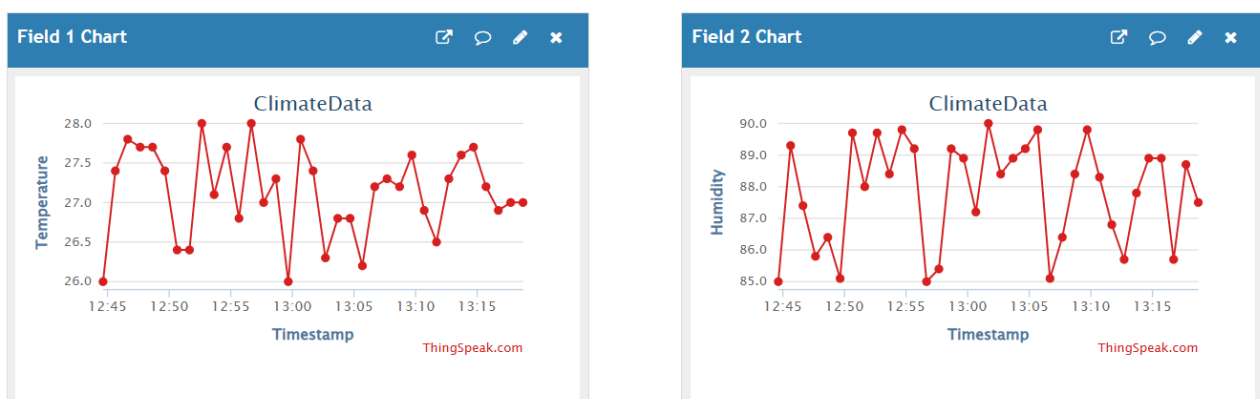


Fig. 6 Data representation on ThingSpeak Cloud

A step-by-step pseudocode for the transformation from CSV/XLSX data into RDF triples and subsequent ontology construction is given below.

Algorithm: *Transform_CSV_to_RDF_Triples*

Input:

- *weathersensordata.xlsx* // XLSX file exported from ThingSpeak
- *ontoRules.owl* // Base ontology in Protégé

Output:

- *weather_rdftriples.ttl* // RDF triples ready to load into Fuseki

1: Load XLSX file using a data reader library

data ← read_excel ("weathersensordata.xlsx")

2: Initialize RDF Graph

3: for each row in data:

a. Extract fields:

timestamp ← row["created_at"]

temp ← row["field1"] // Temperature

humidity ← row["field2"] // Humidity

id ← row["entry_id"]

b. Create a new individual URI, say '*weathersensingURI*'

c. Create triples:

(*weathersensingURI*, rdf: type, :Feed)

(*weathersensingURI*, :entry_id, Literal(id))

(*weathersensingURI*, :temperature, Literal(temp, datatype=xsd:float))

(*weathersensingURI*, :humidity, Literal(humidity, datatype=xsd:float))

(*weathersensingURI*, :created_at, Literal(timestamp, datatype=xsd:dateTime))

d. Add all triples to RDF Graph

4: Export RDF Graph to TTL/OWL file:

write_to_file (rdf_graph, "*weather_rdftriples.ttl*")

5: Load *weather_rdftriples.ttl* into Protégé for visualization and validation

6: Load *weather_rdftriples.ttl* into Apache Jena Fuseki for SPARQL querying

RESULTS AND DISCUSSION

After displaying data on ThingSpeak cloud, the next stage is to export that data into a CSV file and then convert it into an XLSX file for generating an RDF graph. Following this, data Property is added as a feed along with an instance of it like feed1, feed2 and so on which is depicted in figure 7. Then the Protege tool is opened and the Internationalized Resource Identifier (IRI) is set. The actions such as Feed class creation under Thing entity, Data Property creation, and setting of domain and range etc are performed.

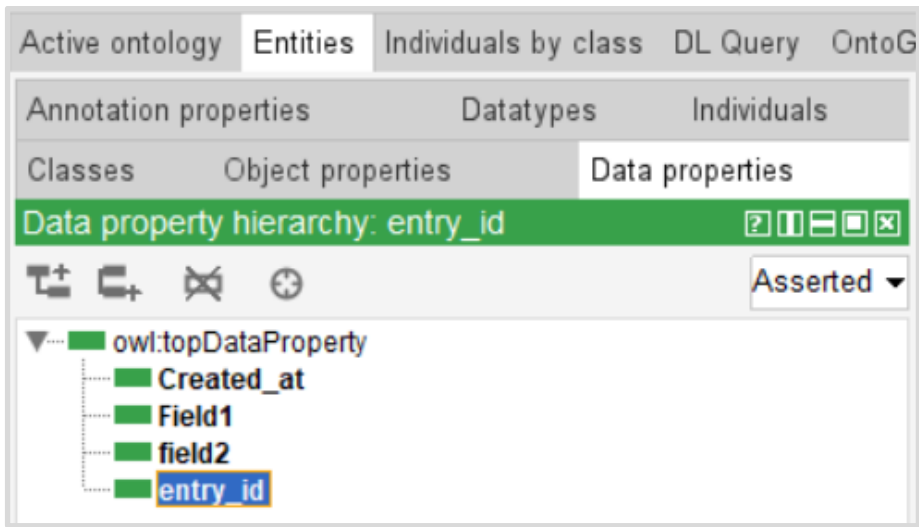


Fig 7. Data property of entity field

Using *create axioms*, transformation rules are developed. Using the code below which is shown in figure 8, transformation rules are introduced once the XLSX file is opened in Protege Tools. A sample entry after applying Transformation Rules in Protege is shown in figure 9. After obtaining data successfully, a SPARQL query is run to get data as RDF triple. Figure 10 depicts the SPARQL query used.

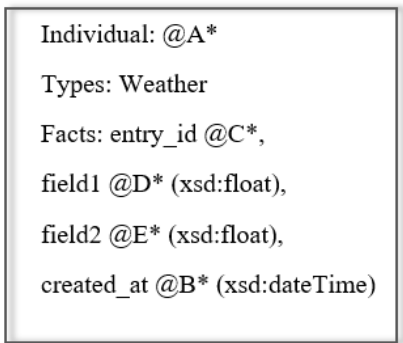


Fig. 8. Transformation Rules

Individual works as a reference, *Weather* is a class, *Facts* will be *entry_id*, *field1* and *field2* for temperature and humidity data respectively, *created_at* for the timestamp.

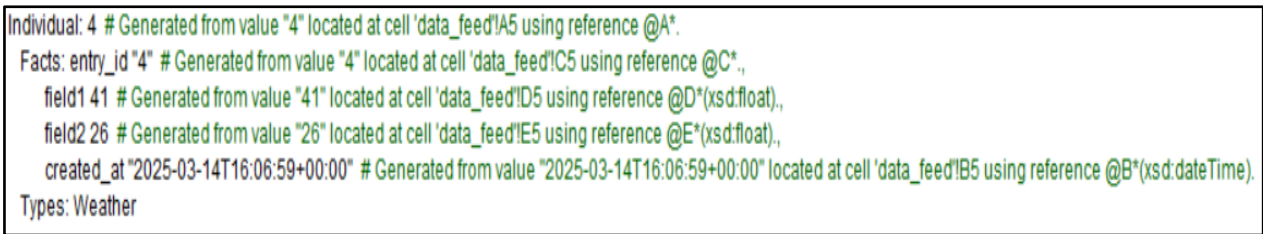
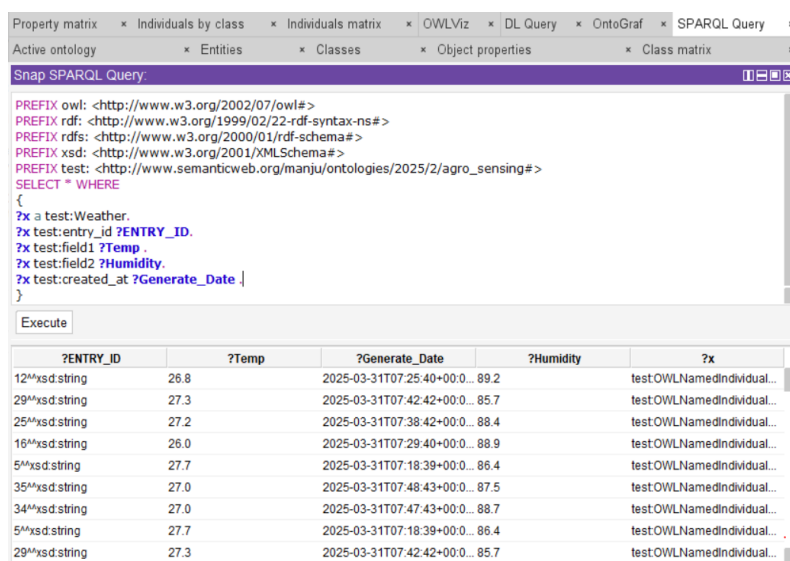


Fig 9. A sample entry after applying Transformation Rules.



The screenshot shows a SPARQL query interface with a query editor and a results table. The query is as follows:

```

PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX test: <http://www.semanticweb.org/manju/ontologies/2025/2/agro_sensing#>
SELECT * WHERE
{
  ?x a test:Weather.
  ?x test:entry_id ?ENTRY_ID.
  ?x test:field1 ?Temp.
  ?x test:field2 ?Humidity.
  ?x test:created_at ?Generate_Date.
}

```

The results table displays the following data:

?ENTRY_ID	?Temp	?Generate_Date	?Humidity	?x
12^xsd:string	26.8	2025-03-31T07:25:40+00:00...	89.2	test:OWLObjectPropertyDomainIndividual...
29^xsd:string	27.3	2025-03-31T07:42:42+00:00...	85.7	test:OWLObjectPropertyDomainIndividual...
25^xsd:string	27.2	2025-03-31T07:38:42+00:00...	88.4	test:OWLObjectPropertyDomainIndividual...
16^xsd:string	26.0	2025-03-31T07:29:40+00:00...	88.9	test:OWLObjectPropertyDomainIndividual...
5^xsd:string	27.7	2025-03-31T07:18:39+00:00...	86.4	test:OWLObjectPropertyDomainIndividual...
35^xsd:string	27.0	2025-03-31T07:48:43+00:00...	87.5	test:OWLObjectPropertyDomainIndividual...
34^xsd:string	27.0	2025-03-31T07:47:43+00:00...	88.7	test:OWLObjectPropertyDomainIndividual...
5^xsd:string	27.7	2025-03-31T07:18:39+00:00...	86.4	test:OWLObjectPropertyDomainIndividual...
29^xsd:string	27.3	2025-03-31T07:42:42+00:00...	85.7	test:OWLObjectPropertyDomainIndividual...

Fig 10. SPARQL to retrieve data as RDF triple.

PROTEGE lacks the capacity to store large volumes of data, such as Big Data, and is primarily a modeling tool. For storing huge data sets, researchers have a number of other options, including Amazon Neptune, OntoText's GraphDB, Apache Jena Fuseki, the Cellfie plug-in for uploading Excel/CSV files, and Neo4j for uploading OWL files. According to prior research work carried out, the Apache Jena Fuseki is one of the proven platforms for storing huge data in ontology representation using RDF triple format since the server is open source and free. In the suggested system, it is thought to be a dependable option for a triple store and SPARQL endpoint.

The suggested semantic web model is depicted in Figure 11. The PROTEGE tool is used to generate a semantic model. This will produce an.owl file that Apache Jena Fuseki can utilize as input. After that, SPARQL searches are run in accordance with the specifications. By adding a SPARQL endpoint using the Python language, results similar to those illustrated in figure 12 can be retrieved.

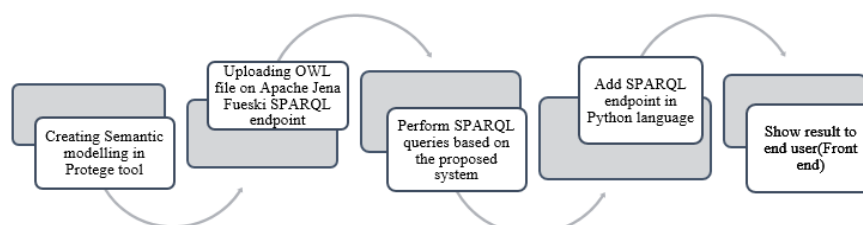
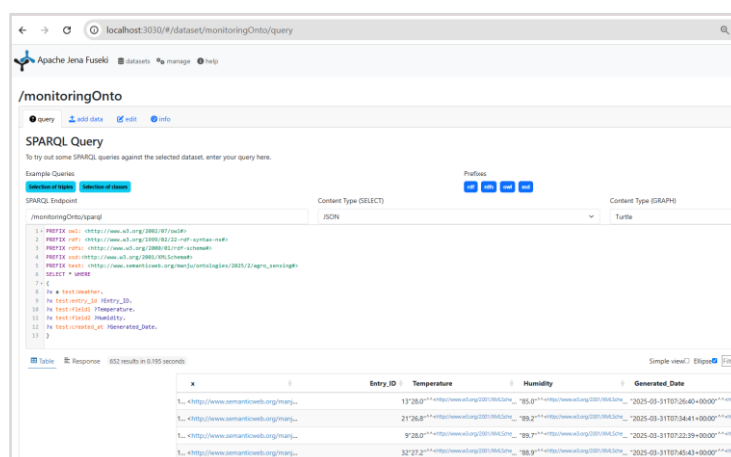


Fig 11. An IoT system based on semantic web technology



The screenshot shows the Apache Jena Fuseki web interface. The SPARQL query is the same as in Figure 10. The results are displayed in a table with the following columns: Entry_ID, Temperature, Humidity, and Generated_Date. The results are as follows:

Entry_ID	Temperature	Humidity	Generated_Date
12	26.8	89.2	2025-03-31T07:25:40+00:00...
29	27.3	85.7	2025-03-31T07:42:42+00:00...
25	27.2	88.4	2025-03-31T07:38:42+00:00...
16	26.0	88.9	2025-03-31T07:29:40+00:00...
5	27.7	86.4	2025-03-31T07:18:39+00:00...
35	27.0	87.5	2025-03-31T07:48:43+00:00...
34	27.0	88.7	2025-03-31T07:47:43+00:00...
5	27.7	86.4	2025-03-31T07:18:39+00:00...
29	27.3	85.7	2025-03-31T07:42:42+00:00...

Fig 12. Apache Jena Fuseki with SPARQL query for IoT sensors.

LIMITATIONS OF THE PROPOSED SEMANTIC IOT SYSTEM

Although the integration of semantic web technologies and IoT for sensor data management offers increased interoperability and smart querying, there are a number of practical constraints that need to be addressed for large-scale deployment and reliable real-time usage. Table 2 provides an overview of the limitation, its effects, and the solution.

TABLE 2. Overview of the limitation, its effects, and the solution.

Limitation Area	Problem	Impact	Solution
Data Privacy	Unsecured data sharing, inference risk	Legal risk, exposure of sensitive info	Secure endpoints, access control
Annotation Quality	Manual, error-prone annotation	Poor interoperability and query reliability	Auto-annotation tools, standard ontologies
Real-Time Bottlenecks	Latency in RDF and SPARQL operations	Not suitable for real-time applications	Stream processing, caching, indexing

COMPARISON BETWEEN TRADITIONAL AND SEMANTIC WEB APPROACH

Table 3 below provides an overview of the distinctions between the semantic web approach and conventional IoT data management based on various features like representation of data, query type, scalability, reasoning support, latency and extensibility.

TABLE 3. Summary of comparative evaluation

Feature	Semantic Web Approach	Traditional IoT Data Handling
Data Representation	RDF Triples, Ontology (meaningful)	Flat tables/fields (structural only)
Query Type	Context-aware, Semantic (SPARQL)	Basic filtering (SQL/API-based)
Scalability	Medium to High (needs tuning)	High (via distributed DBs)
Reasoning Support	Inference possible	No reasoning layer
Latency	Moderate (depends on triple store)	Low (fast filtering)
Extensibility	High (plug in new ontologies)	Limited

MATHEMATICAL MODEL

For ensuring the strength, efficiency, and scalability of the suggested semantic IoT framework, various mathematical models and quantitative analyses are utilized here. The metrics provide indications of system performance, semantic accuracy, and real-time feasibility.

Query Latency - The average query latency across several SPARQL executions is computed in order to evaluate reasoning efficiency over the semantic knowledge base.

$$\text{Latency}_{\text{avg}} = \frac{1}{n} \sum_{i=1}^n t_i \quad (1)$$

Where t_i is the execution time of the i^{th} query.

Rule inference - Logical implications are used to express domain-specific knowledge norms. To add inferred facts to semantic knowledge bases, these rules are encoded using SPARQL CONSTRUCT, SWRL, or rule engines.

$$A \wedge B \Rightarrow C \quad (2)$$

Storage Overhead - When compared to flat CSV data, it measures the amount of additional space that RDF triples and ontologies take up.

$$\text{Overhead (\%)} = \left(\frac{\text{Size}_{RDF} - \text{Size}_{CSV}}{\text{Size}_{CSV}} \right) \times 100 \quad (3)$$

PERFORMANCE EVALUATION

Query Latency: Time taken to execute a SPARQL query over RDF triples.

Ontology Reasoning Time: Time required to infer new facts using OWL reasoners (e.g., Pellet, Hermit).

Storage Overhead: Size and complexity added by RDF serialization and ontology metadata.

Interoperability: Ability to integrate with other semantic systems and ontologies.

Scalability: Capacity to handle growth in sensor data and ontology expansion.

Table 4 represents the comparative analysis.

Table. 4. Performance Measure Indices

Metric	Current System (Protege + Fuseki)	Comparison (Traditional DB or Cloud-only)
Query Latency	220ms for simple queries; higher for nested queries	SQL queries usually faster for simple filters (<100ms)
Ontology Reasoning Time	~2–5s for moderate datasets (~1k individuals)	Not applicable in flat data models (no reasoning possible)
Storage Overhead	37% higher than CSV or SQL due to verbose RDF structure	More compact in NoSQL/CSV formats
Interoperability	Excellent (RDF/OWL/SPARQL are W3C standards)	Limited in traditional relational/IoT cloud systems
Scalability	Scalable with effort (requires optimized triple stores)	Easier horizontal scaling in SQL/NoSQL or BigQuery

The performance evaluation of semantic technologies demonstrates remarkable strengths across key criteria. A comprehensive assessment of performance of the system based on various aspects such as accuracy, query flexibility, semantic reasoning and data integrity is given in table 5.

Table 5. Performance Indicators

Criteria	Description
Accuracy	High accuracy achieved through semantic modeling, ensuring precise and context-aware data representation.
Query Flexibility	SPARQL enables expressive and complex queries over RDF triples for efficient and versatile data retrieval.
Semantic Reasoning	Protégé with OWL supports reasoning to infer new knowledge, such as deducing humidity ranges.
Data Integrity	Maintained via strict RDF schema definitions and ontology constraints, ensuring consistency and reliability.

FUTURE WORK

To improve performance, future deployments should utilize optimized triple stores like Blazegraph, GraphDB, or Virtuoso, which are optimized to enhance SPARQL query execution performance. Indexing RDF triples can greatly speed up query lookup, allowing for quicker data retrieval. Incremental reasoning can be implemented to decrease the time needed for full ontology reloads, making updates more efficient and reducing computational overhead. Furthermore, using modular ontologies can reduce memory usage while increasing reasoning speed, hence making systems scalable and efficient. Finally, caching of regular queries can greatly help in real-time applications by reducing redundant computations and providing response at a quicker pace, eventually boosting overall system performance.

By mapping the application domain ontology and references ontologies, the system applies the annotation process to tag these data by concepts. Developers no longer have to worry about integrating data from many sources because the annotation process makes it possible for software agents to easily consume data in an intelligible fashion [27].

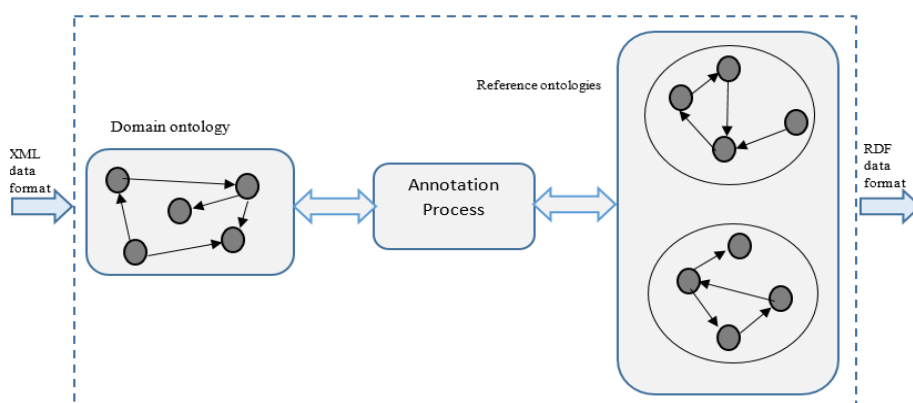


Fig 13. Data annotation

CONCLUSION

The Internet of Things (IoT) has made its way to almost all aspects of human life including Smart Home, Agriculture, Manufacturing, Logistics, Transportation, Food, Education, Space, Entertainment etc. As a result, increasing numbers of mobile devices, sensors and actuators have been incorporated into our everyday lives. Consequently, enormous amounts of data are produced, and it is very important to reveal the knowledge hidden within these huge quantities of data. But the structures, scopes, and forms of the IoT data produced by multi-modal sensors or devices are vastly different, posing the challenge of interpretation and understanding by machines. This study proposes a method to transform sensor data captured from a sample IoT use case of "basic Climate monitoring" system to an interoperable semantic representation using ontology framework to facilitate improved real-time data acquisition, structured representation of data, and effective querying. The system efficiently collects and uploads sensor data on ThingSpeak, where it is displayed via live graphs to allow for real-time monitoring. With ontology-based modeling, the system ensures effective interpretation of meaningful and structured data, allowing for effective integration with other IoT frameworks. Moreover, SPARQL queries enable accurate retrieval of particular sensor data, improving data usability and accessibility. Interoperability of the system also guarantees compatibility with future IoT reasoning engines, making it an efficient and scalable solution for environmental monitoring applications. Future developments will prioritize real-time streaming of data, intelligent decision-making, and accessibility to the user. Data transmission will be streamlined using MQTT, and advanced ontology reasoning will provide for greater wisdom. Furthermore, a mobile app will serve as an accessible front end to enable real-time monitoring and control and to promote usability and scalability in the system.

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