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NATURAL LANGUAGE PROCESSING FOR CONSTRUCTION SITES MANAGEMENT

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Abstract

Information flow management has historically been a problem in the construction industry. Fragmentation of processes within the sector, interdisciplinarity, and lack of unambiguous methods for passing information are some of the obstacles that make it difficult to have a non-splintered flow of data. BIM approach is, if well adopted, a valuable support for optimal information flow management. Studies suggest that the use of Natural Language Processing (NLP) with vocal assistants can facilitate the access and understanding of the information to non-technical users. This research proposes the development of a system for querying BIM models through natural language and without the use of specific keywords. Input is provided by spoken language, while output can be either spoken or visual, provided a graphic device is connected to the virtual assistant. This eases information retrieval in environments where it is difficult to use hand-held computing devices such as a construction site.

Introduction

Architecture, Engineering, Construction and Operation (AECO) industry is well known for its fragmentation which dramatically affects two characteristic aspects of the sector: the intensive use of information in decision making and the limited access to, and consequently the insufficient use of, pertinent information that is potentially available (Kovačević et al., 2008). It has been shown, indeed, that the lack of effective access to information is the primary cause of loss of productivity in the building design and construction process (Abanda et al., 2022; Yaser and Rahman, 2018). Facing these issues, BIM methodology is expected to support information flow management within the building life cycle more efficiently. BIM is in fact focused on managing the information flow related to the built environment through the integration of data open format and standards following an agreed approach among project stakeholders. The main pathway to achieve a well-organized data collection in a BIM-aided project is to have a Common Data Environment (CDE); a virtual platform managed by the project team for assembling, handling, and distributing digital information among themselves (Siebelink et al., 2018). Anyway, since the information from diverse disciplines continues to integrate during the whole life cycle of an AECO project, the BIM becomes increasingly large (Lin et al., 2016) with the risk of causing users difficulty in acquiring the information they truly desire (Wu et al., 2019). This then becomes even more evident in situations such as the construction site where consulting a BIM CDE on a mobile device, with limited space for interaction, can be an obstacle to the implementation of digitization. The situation will be even worse for personnel without extensive knowledge of Industry Foundation Classes (IFC) or for non-experts of BIM softwares. Supported information extraction would avoid the tediousness and fallibility of manual works for Request for Information (RFI) (Boukamp and Akinci, 2007). However, over 80% data in construction projects is unstructured, most of which are texts. Hence, it is important and cost-effective to extract and understand text data automatically and intelligently. It is becoming increasingly clear that exploitation of NLP can fulfill the above purpose. Furthermore, the wide adoption through smartphones and home devices of voice assistants such as Siri, Google, Alexa and Cortana have represented a new way of human-machine interaction for RFI that is increasingly becoming part of our daily use. NLP assistants for CDEs can enable project participants to easily access project information and perform tasks such as searching for documents, creating, and updating schedules, and managing issues and RFIs. One of the most significant benefits of NLP assistant is the ability to understand and respond to natural language queries. This means that project participants can simply ask questions in natural language rather than having to navigate through the system using traditional means (such as clicking through menus or typing in keywords) and receive accurate and relevant information without the necessity of deep knowledge of IFC or other standards (Dar et al., 2019). This research proposes the development of a system for supporting intelligent data retrieval in BIM CDE. The CDE where BIM models are uploaded and managed is built on a graph database namely Arango DB. The paper describes the development of a “question-and-answer” system (named Virtual Assistant) that provide immediate responses, both in natural language and via visual results displayed on the CDE user interface, to questions posed in natural language by participants in the construction process.

Literature review

Many industries, and even the AECO industry, have attempted to study and apply speech recognition systems in their operations to improve work efficiency and productivity (Shin et al., 2021). It is not until 2015 that NLP is increasingly adopted for various engineering applications, because of two reasons, i.e., data availability and algorithm capacity. NLP is a discipline that integrates linguistics, computer science, and mathematics. It studies theories and method for realizing human-computer interaction based on natural language (Chowdhury, 2003). NLP applications in construction have mostly invested the following processes: document management (Caldas et al., 2003; Fan et al., 2014; Wu et al., 2020), safety management (Cheng et al., 2020; Fan and Li 2013; Tixier et al., 2017), compliance checking (Salama and El-Gohary, 2013; Xue and Zhang, 2020), risk management (Lee et al., 2020) and BIM management (Lin et al., 2016; Xie et al., 2019; Zhou et al., 2020). As far as the latter is concerned NLP has been adopted to solve a well-known problem of AECO sector: information retrieval. Wu et al., 2019 presented a natural-language-based intelligent retrieval engine for the BIM object database and Revit modeling. They developed first and IFC-based BIM object database and then a search engine that speed up the process of retrieving building components for modelling.

Anyway, in recent years, there has been also a growing interest in using NLP to simplify and accelerate the querying of graph based CDEs. A CDE according to ISO 19650 is an agreed source of information for any given project or asset, for collecting, managing, and disseminating each information container through a managed process. It can be defined also as a digital platform where project participants can access and share project information such as design models, drawings, and documents. Anyway, information retrieval in CDE that should contain IFC models can be tough so the development of tool that admits query using natural language can be beneficial. Lin et al., 2016 presents a cloud-based framework for intelligent BIM data retrieval and representation using natural language queries. Their process laid the basis for retrieving information in an IFC-structured BIM data model. The retrieved data results were analyzed and represented in the form of charts, tables, animations, or a combination of forms based on the expectations of users.

There are also studies that speech focus on spoken natural language, which is more in line with the purpose of the research work presented here. Shi et al., 2021 developed a building information modeling automatic speech recognition (BIMASR) framework that requires no knowledge of BIM commands, which allows for the input of natural language-based questions into BIM software using human voice to search and manipulate data. They developed a system for BIM information retrieval inside a BIM authoring software (Revit) with the specific aim of being able to modify data when needed. Also, (Wang et al.,2021) developed a framework for intelligent Building Information Spoken Dialogue System (iBISDS) to achieve speech-based information extraction from building information models. This study is focused on extracting attribute information of building components. The automatic speech recognition module implemented the Google speech recognition service from the Python package speech_recognition to convert a speech query into textual one.

The proposed research aims to apply natural language processing (NLP) to a graph based CDE in order to retrieve valuable information during AECO operations. The system developed in this study uses spoken natural language as the query input, without requiring the definition of fixed keywords. Unlike other research, the output of the retrieval task is presented in natural language, spoken by the machine. Additionally, the results are reported in written form, with highlighted objects if involved in the query. The CDE platform proposed here uses building information models in IFC format in order to be fully interoperable with existing BIM software and considering that open formats are usually required by public administrations.

Methodology

From IFC to graph databases

IFC is a comprehensive representation of building models and the rules and protocols that define building data, proposed by the International Alliance of Interoperability (IAI, also known as BuildingSMART), to solve the problem of inadequate interoperability. Each IFC model consists of IFC entities built in hierarchical order, where each IFC entity includes a fixed number of IFC attributes, plus any number of additional IFC properties. The IFC data model is hierarchically structured, with entities grouped into different levels of abstraction, connected by relationships that are also entities (Ismail et al., 2017). The IFC data schema has three basic entity types: IfcPropertyDefinition describes all the characteristics that can be associated with objects; IfcObjectDefinition denotes all objects or processes that are manipulated; IfcRelationship summarizes all relationships between objects.

Since cloud computing platforms using distributed, non-relational databases are now widespread, it is useful and feasible to explore how IFC models can be stored and shared based on these NoSQL databases.

Translating IFC data into a graph database is convenient for working with construction and building projects, as it enables more efficient queries, visualizations, and integrations with other systems. The advantages can be summarized as follows (Pradeep et al., 2019):

- Flexibility: A graph database enables flexible data modeling, which can be especially useful when working with IFC data. IFC data are hierarchical and can have complex relationships between entities, which can be easily represented as nodes and edges in a graph.

- Scalability: Graph-based databases can handle large amounts of data.
- Query efficiency: Graph databases can be queried using graph traversal algorithms, which can be more efficient than traditional SQL-based queries when working with hierarchical, interconnected data.
- Visualization: a graph database can accommodate and link together 3D models from more than just IFC datasets.
- Integration with other systems: IFC data can be easily integrated with existing BIM creation systems that can also store data in graph format.

In this research, we followed a method for translating IFC data into a graph structure that involves grouping IFC entities into a collection of nodes, where each node represents a unique IFC entity. The relationships, both direct and inverse, between these entities were then represented as edges in an additional collection. The tool used to perform this transposition was IFC Engine Toolbox and part of the methodology expressed in (Ismail et al., 2017). By organizing the IFC data in this way, we were able to effectively capture the hierarchical and interconnected nature of the data, while enabling efficient querying and manipulation of the data.

Natural language graph querying

The use of a graph-based database to represent the IFC structure enables the ability to perform ad-hoc queries, which are typically difficult or even impossible to execute using traditional databases. For example, it allows for the retrieval of information such as identifying all the doors that are fire-rated within the building model.

Despite the advantages of No-SQL databases in terms of querying performance, the ability to effectively query such databases is typically limited to IT specialists who possess a deep understanding of the specific query language and data structure used by the database. This limitation can be a significant challenge for stakeholders in the AECO sector, who may not have the necessary technical expertise to effectively query the data and extract valuable insights.

Therefore, it is essential to have a robust and flexible data retrieval strategy that can accommodate both technical and non-technical stakeholders, allowing them to query the models in an efficient and user-friendly manner.

An intelligent data retrieval approach based on NLP would provide a flexible way to retrieve BIM data for a wide range of stakeholders. By utilizing NLP techniques, it is possible to develop a virtual assistant that can understand natural language queries from users and translate them into the appropriate query language for a No-SQL database. This can be accomplished with algorithms and techniques that are designed to understand and interpret human speech, enabling the system to understand the intent behind a user's query and convert it into a structured query that can be executed against a No-SQL database.

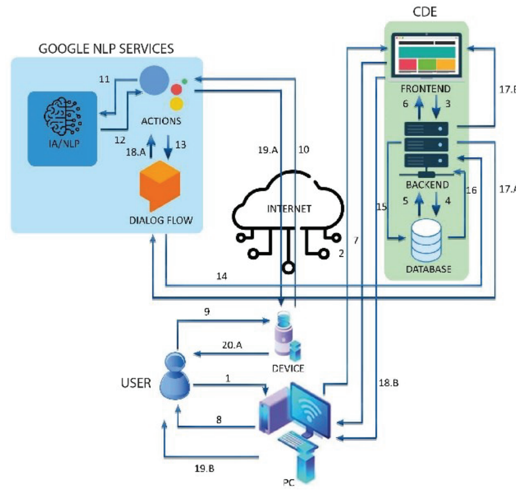

Figure 1. Figure 1. System Architecture. The numbers indicate the sequential order in which data is exchanged among the various components of the framework.

The NLP process involves multiple steps. It starts with a Speech-to-Text (STT) procedure that converts the user speech into text. Then, it usually follows the tokenization, which is the process of breaking down text into individual words or phrases. The tokens are therefore analyzed using various techniques such as part-of-speech tagging, syntactic parsing, and semantic role labeling (Mondal et al., 2019). Finally, the processed data is used to generate a response or perform a specific task by means of a Text-to-Speech (TTS) process. There are several NLP services available, such as Google Cloud Natural Language, Amazon Comprehend, and Microsoft Azure Text Analytics, that can be integrated into applications to add natural language capabilities.

System architecture

The proposed methodology involves the development of a virtual assistant that enables seamless access to BIM data stored within a web-based platform, built on a graph database, making it accessible to all stakeholders regardless of their technical expertise. Figure 1 shows the proposed framework architecture. The numbering of the arrows reflects the order of data exchange between the various components.

The architecture of our system is divided into three environments: the user environment (hosting the virtual assistant but also other devices such as computers, tablets, mobile smartphones, etc.), the on-premises server hosting the web-based platform and GUI as well as the graph database where project information are stored, and the Google cloud servers hosting the NLP services. These environments communicate with each other through internet, exchanging various types of data, each with clearly defined levels of abstraction.

The interface presented to the user is referred to as the workstation. It includes any kind of device on which the virtual assistant is available (Google and Android systems). It is the interface for voice and visual interaction with the model. It is worth noting that voice requests made by the user will not only elicit a natural language response from the system but may also update the BIM model displayed to the user through the web GUI in real time.

As previously mentioned, the on-premises server plays a crucial role in the proposed system architecture by hosting both the web-based platform and the graph database on which it relies. The graph database is used to make the project data persistent, and information can be retrieved using the native query language (AQL in our implementation based on ArangoDB). The web platform services are divided into two main categories: frontend and backend services. The frontend services are those that are directly available to the users through a web-GUI and respond to their input, while the backend services automate and process this input, allowing for direct communication with the database. Furthermore, the backend service enables information retrieval by the vocal assistant even when there is no frontend service running, i.e., even if no user is currently interacting with the web-GUI.

On the other hand, the Google environment is responsible for the computation regarding the NLP services. Among the various existing NLP engines, in this work we chose to use Google Actions. Such framework is based on the DialogFlow language for structuring the interaction with a vocal assistant. The latter allows to specify the user intents understood by the vocal assistant. Each such intent is characterized by a set of key sentences allowing to discriminate between intents and is connected to a backend service to be invoked when the intent is recognized. The virtual assistant is responsible for invoking the DialogFlow agent forwarding to it the vocal registration of the user speech. The agent itself transcribes the user's vocal command into text and then identifies keywords and parameters provided by the user in the context of the sentence. The interactions between the three environments can be classified into three types:

- Traditional interactions between the user and the web application. In this case, the user, through a device capable of connecting to the server with a browser, interacts with the application that responds on the same browser to his or her requests. This is the typical way in which web applications interact, without the use of natural language.
- Vocal natural language interactions, in this case, the user sends natural language inputs to a device capable of receiving it. The device, through the virtual assistant, processes the request and obtains a response for the user through the same device used for input. This is the use of a tool that is spreading in recent years, that of the construction site assistants, which have a similar architecture to that of "home assistants" used in the domestic environments.
- Multisensory natural language interactions, where the interaction can be made through a device capable of receiving a natural language input and emits a response that is both verbal and visual, with the aid of displays on the user environment that are connected to the frontend services provided by the web-based platform. Such interaction enables also real-time collaboration and co-design tasks in future research developments.

System Implementation

As a starting point for the implementation of the proposed system, it is important to note that in this paper we make use of an already existing web based CDE that relies on a graph database engine (ArangoDB) coming from the development of a PRIN project “A Distributed Digital Collaboration Framework for Small and Medium-Sized Engineering and Construction Enterprises”. This CDE can store IFC models as collections of nodes and edges and gives the possibility to query them through AQL. Both the CDE platform and the database are hold by the on-premises server of the DICEA Department of the Polytechnic University of Marche.

Thus, the implementation of the system involves configuring the Google Actions NLP service and integrating it with our backend services to formalize the vocal assistant. This integration allows users to make natural language requests to the system, which will then be translated into the Arango Query Language (AQL), providing a more intuitive and user-friendly way of interacting with the BIM models.

To build an interface that transforms the typical human intents from natural language into an AQL query we proceeded first by categorizing a series of possible basic intents into the Dialogflow. The intents configured in the system for testing were: 1. Count objects, 2. List objects, 3. Give objects measures. Figure 3 shows the “List Object in Space” intent. For each intent, a list of possible phrases was provided to the Dialogflow service so that the user did not have to make the request in a standard way (Fig.2). After the intents are defined Part-of-Speech (POS) tagging starts. For the purposes of our test, we defined three tags: 1. “Object type”, highlighted in yellow in Fig.2; 2. “Space code”, in pink in Fig. 2 and 3. “Space type”, in violet in Fig. 2. For tags 1 and 3 a set of possible word were given to the system. Dialogflow also gives the possibilities to set accepted synonyms so as the user has the possibility to choose among different word to say the same thing. As far as the “Space code” tag is concerned through regular expression the system is told the characters from which the codes are made up. Simultaneously, we structured a set of AQL queries in the CDE platform, each

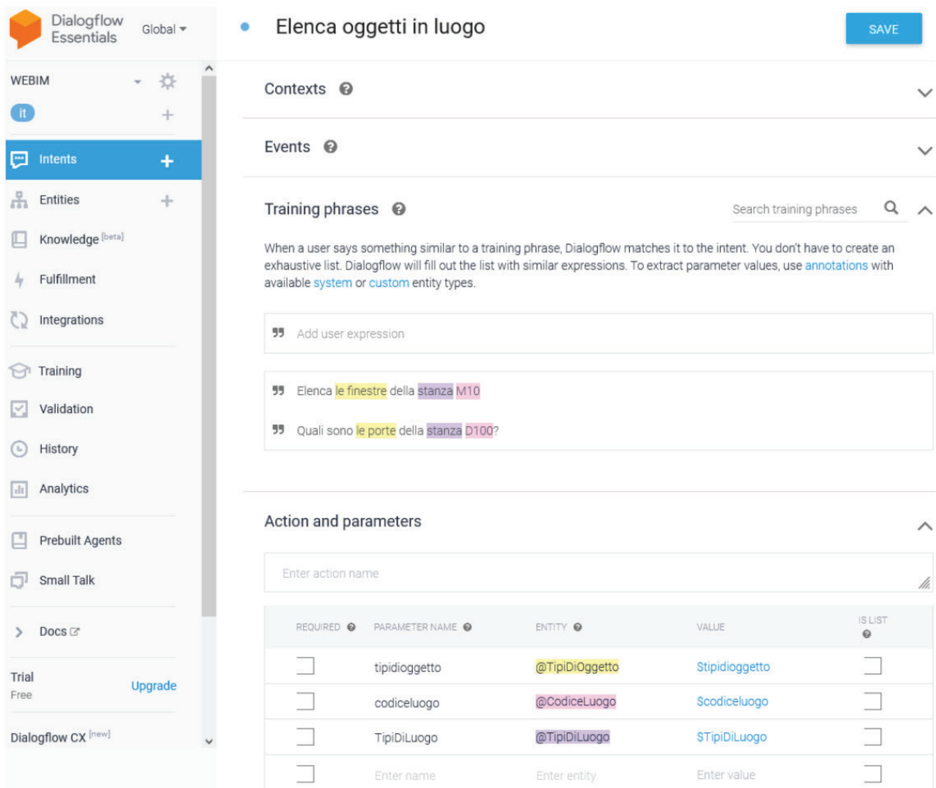

Figure 3. "List Object in Space" intent. In this case, two training phrases are given to the system (e.g., "List the windows of the room M10" and "What are the doors of the room D100?"). The yellow, pink, and purple highlighted words respectively refer to: Type of Object entity, Space Index entity, and Type of Space entity.

corresponding to one of the aforementioned user intents. These queries serve as starting patterns with undefined parameters and can also be accessed by selecting them through the web-GUI of the CDE. The AQL queries are targeted by the keywords identified within the user vocal request by the Dialogflow system.

Specifically, the Dialogflow recognizes the intent and the keywords in the sentence (i.e., location, objects, and indexes), then it automatically triggers the corresponding AQL query into the CDE platform through a backend service (called a webhook by GoogleAction) and updates the undefined parameters with the specific values provided by the user in the context of the sentence. At that point the system automatically queries the graph representation of the IFC model retrieving the desired data. The backend service is responsible for linking the retrieved information with the NLP service that performs the text-to-speech (TTS) conversion service. Hence, the virtual assistant can answer vocally in natural language to the user. Figure 3 shows the query patterns formalized into the web platform and the preview of the "Object Count in Space" query pattern.

Results

To evaluate the effectiveness of the proposed system, the Duplex IFC model was imported into the CDE, and two types of tests were conducted. The first test aimed

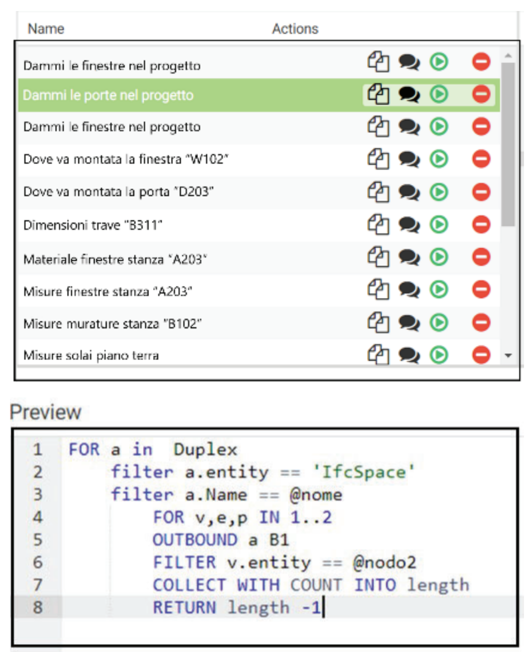

Figure 2. (Top) Archive of AQL query patterns within ArangoDB; (Down) Example query pattern: preview of the Object Count in Space query where @nome and @nodo2 are the undefined parameters that will be replaced with the requested 'IfcSpace' and 'IfcBuildingElement' respectively.

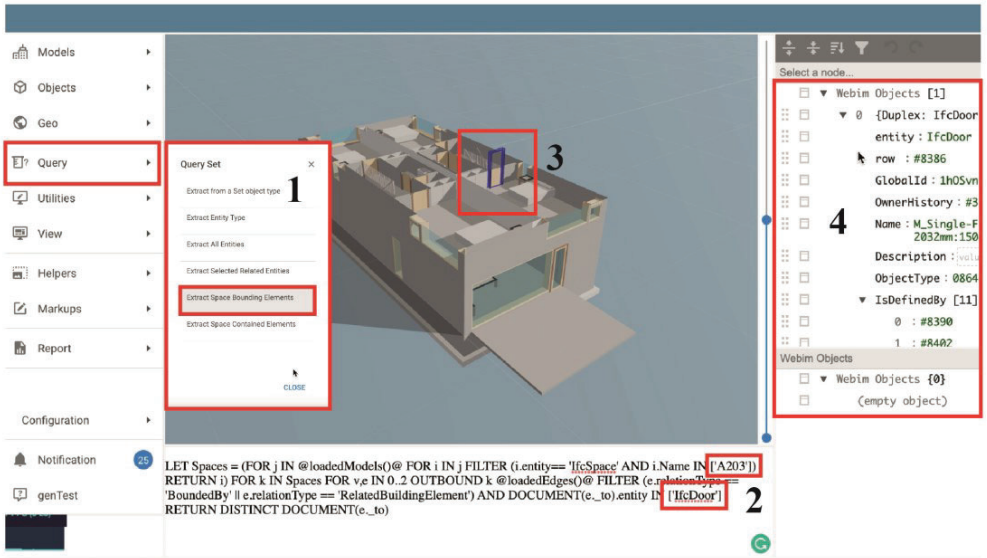

Figure 4. Querying the system through the CDE Query Set. The required query pattern can be found in the Query Set list to the left (1). The predefined parameters of the query can be updated in the text box to the down (2). Once the query is performed, the result is shown on the model. In this case the IfcDoor that bounds the IfcSpace 'A203' was found and highlighted on the model by the system (3), that also retrieved the IFC information related to that particular door (4).

to verify that the set of queries within the CDE could be accessed manually through the web-based GUI of the CDE. The second test aimed to assess if the system can provide the correct data querying them with spoken commands.

For what concerns the former, Figure 4 shows the result of the use of one of the available query patterns contained in the Query Set accessible on the webpage of the CDE. In this case the process consisted in choosing the required query pattern from the list (e.g., in the example the query for the extraction of space boundary elements was selected), and the default parameters were replaced with the desired entities (e.g., the IfcDoor that bounds the IfcSpace 'A203'). Upon execution, the system correctly retrieved the requested information for the user. All query patterns included in the Query Set were thoroughly tested and found to work.

The second test was designed to evaluate if querying the system through the virtual assistant gave the same correct results as the manual selection of queries in the CDE (Figure 5). The user's vocal interaction with the virtual assistant is presented here in the form of a transcription within the Dialogflow chat. The virtual assistant, using the Google's NLP algorithms, was able to extract the relevant parameters from the user's spoken phrase and automatically insert them into the appropriate query, replacing the default parameters. The system's response was provided both vocally, as transcribed in the Dialogflow chat, and graphically, with the relevant entities being highlighted on the web platform's graphical interface. The entire process was carried out without the need for manual input, further emphasizing the system's ease of use and accessibility.

The results of our tests demonstrate the effectiveness of the proposed virtual assistant in facilitating the querying of IFC models within our CDE using natural language. At present, the system works only with parameters defined in the IFC model. In fact, a test was performed asking for the measurements of the furniture in room 203, and in this case the system gave the response "Sorry I can't answer that question.".

Conclusions

In conclusion, this paper presents a novel framework for querying BIM models in graph based CDE using natural language through a virtual assistant. The proposed system is composed of three main environments: the user's workstation, the on-premises server, and the Google server for the implementation of NLP services. These environments interact with each other through the network, exchanging different types of data, each with specific levels of abstraction. The proposed methodology was implemented and tested using an IFC model, and the results show that the proposed virtual assistant allows easy and fast querying of the IFC model within the CDE using natural language. On the one hand this allows to overcome the barriers currently encountered in querying complex data structures.

On the other hand, it automates the manual process of selecting queries. Moreover, this kind of man-machine interaction is of high value for all that context where devices, such as tablet or laptop, can be difficult to use (e.g. construction sites where sunlight, dust, etc can make difficult to look at a screen, on-site operation that requires hand free technician).

However, it should be noted that there are still some limitations and challenges that need to be addressed. For example, the accuracy of the NLP technology in

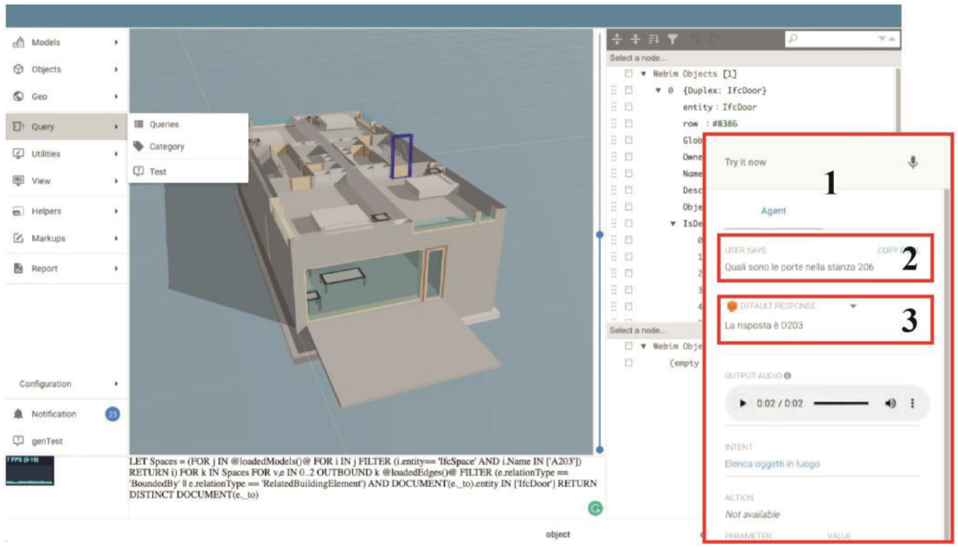

Figure 5. Testing the virtual assistant. The figure shows how the same query used in the previous test was automated by using natural language. The Dialogflow chat box shows the vocal interaction (1). In this test, the user posed the query "What are the doors within the room '203'?" (2). The system retrieved the information from the IFC model providing the response "The answer is 'D203'" (3), which corresponds to the unique door bounding room 'A203' in the model. Additionally, the system concurrently updated the GUI of the CDE by highlighting the relevant IfcDoor entity and displaying its corresponding IFC information, as previously demonstrated in manual testing. This greatly improves accessibility for all stakeholders in the AECO industry, overcoming the barriers previously faced by those without specialized knowledge in both complex data structures and query languages. Our system proves to be a valuable tool for efficient and streamlined querying of BIM models.

understanding natural language queries may be affected by the complexity and specificity of the technical terms and jargons used in the industry, or by the accent and voice of the users. Additionally, the integration of NLP with vocal assistants may also raise concerns regarding data privacy and security that must be taken into consideration.

Next developments of the proposed system might involve the possibility of writing queries in natural language (without the need for speech) so as to avoid the need to use AQL and allow each user to work not only with pre-set queries.

Furthermore, future work in this research may address methods for updating information in the CDE using NLP-based commands and pre-set possible operations so as to facilitate information entry when keyboards cannot be used.

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