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An ontology-based CBR approach for personalized itinerary search systems for sustainable urban freight transport

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This paper presents a novel information retrieval approach for personalized itinerary search in urban freight transport systems. The proposed approach is based on the integration of three techniques: Case Base Reasoning, Choquet integral and ontology. It has the following advanced features: (1) user-oriented ontology is used as source of knowledge to extract pertinent information about stakeholder's preferences and needs; (2) semantic web rule language is considered to provide the system with enhanced semantic capabilities and support personalized case representation; (3) a CBR-personalized retrieval mechanism is designed to provide a user with an optimum itinerary that meets his personal needs and preferences. The above features lead to a personalized and optimum itinerary search that meets the user's needs as specified in their queries such as fuel consumption, environmental impact, optimum route, time management etc. This has the potential to effectively manage fright movement according to stakeholder's needs and alleviate congestion problems in urban areas. The proposed intelligent decision support system (Onto-CBR) is implemented to an itinerary search problem for freight transportation users in urban areas. Its performance is further compared to an itineraries search system that was proposed by the authors in an earlier publication. Both approaches are compared in terms of their ability to meet user's personal preferences and achieve accuracy in case retrieval. The experimental results showed the ability of the proposed system to improve the accuracy of case retrieval and reduce retrieval time prominently. The ability of the proposed system tailor the search to stakeholders needs, improve the accuracy of case retrieval and facilitate the search process are among the main positive features of the proposed intelligent decision support system.

1. Introduction

The last decades have witnessed tremendous efforts aiming at creating and developing intelligent transportation systems that can potentially reduce congestion, minimize fuel consumption, lower environmental impacts and increase the safety of passengers and goods in urban areas. However, urban freight transport has often received much less attention from the research community than its passenger counterpart despite its significance in urban traffic management and logistics. This is probably due to the fact that urban freight management is a complicated task that involves many actors such as shippers, public authorities, citizens and requires a significantly large and robust information system to insure its efficient operation. Further, the increase of freight movements in urban areas, especially during peak hours, contributes to high levels of congestion. The latter leads to reduction in accessibility increase in fuel consumption, pollution and increased travel costs. These effects contribute to the progressive degradation of the environment and urban infrastructure (Millsa & Price, 1984). Thus, a better organization of urban freight traffic movement can reduce urban congestion and its negative externalities and improve security for people and goods, leading to sustainable urban freight transport systems.

To mitigate the problem of congestion in transportation networks, several route planning and traffic management systems have been proposed and investigated recently. Among these applications, we can mention real-time path recommendation protocols (Bani Younes & Boukerche, 2015), intelligent traffic light systems (Keyarsalan & Montazer, 2011), route planning system (Zolfpour-Arokhlo, Selamat, & Zaiton Mohd Hashim, 2013). Those systems were designed to either offer routes that solve traffic

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congestion problems (Ji, Yu, Yong, Nan, & Yu, 2012) or provide the shortest paths using a model of the transportation network (Geisberger, 2011; Kosicek, Tesar, Darena, Malo, & Motycka, 2012). A major drawback of the above route management systems is the fact that decision maker provides the optimum solution based on traveler's behavior (Shi, Na, & Chun-bin, 2008) and according to the manager's willingness (An, Na, & Chun-bin Hu, 2008) without taking into consideration user's input. However users' preferences and needs are scalable and rapidly changing and users with similar demographic information and similar search criteria might have completely different preferences about the criteria. These preferences might even vary for the same person depending on his circumstances. Hence, personalization should be an integral part of the algorithm in order to provide itineraries that satisfy the most user's needs and preferences. Further, personalization can increase the user satisfaction by reducing the information overload problem (Liang, Lai, & Ku, 2007).

Among the recent research activity on various aspects of personalized information systems in the field of transportation, especially for passengers, we might list: (Akasaka & Onisawa, 2008; Bouhana, Fekih, Abed, & Chabchoub, 2013; Bouhana, Soui, & Abed, 2010; Letchner, Krumm, & Horvitz, 2006; Nadi & Delavar, 2011). The aim of those works was to provide users with high quality personalized information that satisfies their preferences in the field of public transport. However, those studies did not consider the problem of urban freight transportation despite the increased number of fright transportation means and the diversity of users. Indeed, urban freight transport involves a great number of users and stakeholders with various preferences, perceptions and criteria of selection alternatives. Further, while the multiplicity of fright transportation means and their operators as well as the diversity of users profiles make the task of designing a homogeneous information system for urban freight transport a challenging one, the problem is no longer the availability of information but rather the ability to select the relevant information that meets the precise needs and interests of various stakeholders (residents, retailers–authorities, supplier, carrier).

Another drawback for the above listed systems of personalization is the fact that they rely on classical methods of personalization in their retrieval process such as content-based or collaborative-based methods, which complicate the search and are slow to respond. This is due to the fact that content-based methods suffer from is the cold start issues, while collaborative-based methods can be inconsistent in personalization as they rely on a complete model of the user. Another weakness detected in the above approaches is the fact that all of them do not, or only occasionally, use external knowledge, which limits their use in personalization retrieval. Further, none of the above personalization of itinerary systems was implemented to urban freight transport.

In order to overcome the above listed shortcoming, we propose in this paper a new method of personalization based on the integration of the ontology concept, the Case Base Reasoning (CBR) tool and a multi-criteria technique to satisfy the preferences of all city logistics' actors and optimize freight movement. The benefit of using the CBR approach is to provide a more convenient retrieving process in order to reach conclusions and give recommendations based on knowledge from previous experiences. In fact, CBR solves a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation (Aamodt & Plaza, 1994). However, relying on CBR alone in distributed and complex applications can lead to systems that suffer too much in knowledge acquisition and indexing (Akmal, Shih, & Rafael Batres, 2014; Amailef & Lu, 2013). Hence, we propose in this paper to integrate the ontology concept with the CBR tool in our system of personalization. In this context, the ontology would support CBR approach in the following ways: it is a user friendly tool where case representation and queries are defined using every day terminology. Further, ontology facilitates similarity assessment by making a connection between the query and the case base respective terminologies. Furthermore, the combination of ontology and case-based reasoning reduces the effect of 'cold-start' issue and increases the performance of the system.

The main contributions of this paper are as follows:

- The design of a novel personalized information retrieval system which combines the properties of Case Base Reasoning, Choquet integral and ontology for improved performance.
- The suggestion of a new method of personalization that exploits the inference power of the SWRL rules.
- The suggestion of a new similarity measures method in the retrieval step of the CBR that take into consideration textual and numerical instances.
- This approach is the first to develop and apply ontology for real-time knowledge management in freight transport systems.

The rest of this paper is organized as follows. Section 2, provides a brief state of the art review about personalization. The proposed approach is illustrated in Section 3. Details about our framework of personalization in city logistics are provided in that section. The proposed approach is validated using a freight transport movement problem. Results of the implementation and are illustrated in Section 4. Discussion section in Section 5. Finally, Section 6 concludes this paper and lists some possible future research directions.

2. State of the art in personalization

Personalized information systems are designed to provide users with relevant information that is adapted to their unique needs, preferences and profiles. Personalization in public transport aims at specifically improving the quality of transport 'before' 'during' and even after transit in order to avoid perturbation, delays, congestion, etc.

2.1. Personalization: definition and its application to the transportation filed

In the literature, there are many definitions attributed to the concept of personalization. In our work, we present two relevant definitions that match exactly the context of our work. In Hagen, Manning, and Souza (1999), personalization is defined as "the ability to provide content and services that are tailored to individuals based on knowledge about their preferences and behavior" and in Ho and Y. (2012) personalization is defined as "the process of generating and presenting the right content in the right format to an individual at the right time in the right location." Hence, personalization takes into account several features such as: personalization of the presentation (Anli, 2006), personalization of the structure, personalization of functionalities, and personalization of the content (Bouhana et al., 2013; Oliveira, Becha, Mnasser, & Abed, 2013). The latter will be the focus of our work.

Some recent approaches dealing with personalization of the content in the field of transportation, especially for passengers, have been proposed. Among those works we can mention (Bacha, Oliveira, & Abed, 2011; Oliveira et al., 2013) who proposed three systems of personalization for public transit combining various means of transport. However, those methods focused on the personalization of the user interfaces and neglected the problems of personalization of itineraries search. Hence, approaches dealing with personalization of content based on the user's preferences and using a set of criteria were proposed (Bouhana et al., 2010; Bouhana et al., 2013; Nadi & Delavar, 2011; Niaraki & Kim, 2009;

Zipf & Jost, 2006). The above mentioned approaches focused on the personalization of information without the use of any information retrieval technique for the task of personalization. Only user preferences in navigation systems were taken into consideration (Jozefowiez et al., 2008; Niaraki & Kim, 2009; Zipf & Jost, 2006). Further, those works also neglected the user decision strategy in their proposed approaches. Furthermore, existing itineraries research algorithms suffer from a number of major difficulties, mainly due to the insufficiency of criteria modeling for personalization. Nadi and Delavar (2011) proposed a new method of personalization that takes into consideration the user navigation preferences and decision strategy at the same time. A decision strategy defines whether a user insists on satisfying all of his/her preferences regarding the selection of one itinerary from a set of itineraries or not. This is crucial when designing a decision support system with a strong emphasis on personalization. Nadi and Delavar (2011) presented a generic model based on multi-criteria decision strategies for personalized route planning. The proposed model integrated a pair wise comparison method with a quantifier-guided ordered weighted averaging (OWA) aggregation operators to form a personalized route planning method that incorporates different decision strategies. The model can be used to calculate the impedance of each link regarding the user preferences in terms of route criteria, criteria importance and decision strategies.

In order to overcome the above mentioned limitations, the authors proposed in earlier works two multi-criteria approach for suggesting personalized itinerary in which user preferences were integral part of the search process (Bouhana, Abed, & Chabchoub, 2011; Bouhana et al., 2013). Those approaches made use of strong information retrieval techniques to yield better itinerary search. For instance, the approach in Bouhana et al. (2013), integrated case-based reasoning with Choquet integral and personalized information retrieval was processed based on criteria which weights are determined using the two-additive Choquet integral and by the retrieval steps in the CBR cycle. The performance of the proposed algorithm was assessed by solving a real-life itinerary planning problem defined in the Tunisian urban public transit network. Though the approach provided the best solutions for applications requiring personalization based user's preferences in a multi-criteria setting, it could further be improved by including the ontology concept.

2.2. Ontology: definition and its application in the transportation domain

The term ontology is widely used for different purposes and in different fields within Artificial Intelligent (AI) systems .In AI, there are a number of definitions of ontology. The most quoted definition of ontology in the literature, by Gruber (1993) states that an 'ontology is an explicit specification of a conceptualization'. However, other relevant definitions suggest important contributions such as: sharing, modeling, logics... etc. Ontology has been exploited in many domains and studies such as in industry (Guo, Jie, & Peng, 2012), energy (Yang, 2013), the medical domain (Bulu, Alpkocak, & Balci, 2012), logistics (Anand et al., 2012), information science (Bastinos & Krisper, 2013) and transport (Verstichel et al., 2011).

For instance, Riano et al. (2012) suggested ontology for the care of chronically ill patients and implemented two personalization processes and a decision support tool. The first personalization process adapted the contents of the ontology to the particularities observed in the health-care record of a given concrete patient, automatically providing a personalized ontology containing only the clinical information that is relevant for health-care professionals to manage that patient. The second personalization process uses the personalized ontology of a patient to automatically transform intervention plans describing health-care general treatments into individual intervention plans. Shi and Setchi (2013) integrated ontology-based personalized retrieval and reminiscence support to assist people in recalling, browsing and re-discovering events from their lives by considering their profiles and background knowledge and providing them with customized information retrieval. Users with identical queries are provided with different results according to their profile and background knowledge. To facilitate cross-domain retrieval, multiple user-oriented ontologies are applied to construct user profile spaces. Using ontology/user profile space graphs, the semantic feature- selection algorithm selects relevant semantic features to enhance a query's representation, which improves the retrieval performance. The quality of the ontology is important, which directly affects the query-expansion accuracy and retrieval performance. The main drawback of this system: the building and maintaining processes of user-oriented ontology rely on users which should increase human error and work load and difficulty during these processes which influencing on the relevance of personalized results. A major drawback of the systems presented in Riano et al. (2012) and Shi and Setchi (2013) is the fact that they used a user profile ontology model for the task of personalization. However, user profile is constantly in perpetual evolution which further complicates the task. Further, as the user ontology base grows, handling the complex ontology became very difficult. As a result, the personalization system performance decreases exponentially with the increased complexity of user profiles. Furthermore, those systems are intelligent personalized information retrieval systems but not expert systems because they lack a reasoning engine to support the OWL language and SWRL rules in the inference and reasoning process to enhance the quality and the process of personalization.

Only a handful of studies dealing with the application of ontology to the transport system can be found in the literature. The first authors to use the ontology concept in transportation filed were Becker and Smith in 1997. In Becker (1997) the authors defined ontology for multi-modal military transportation planning and scheduling systems. Their ontology focused on concepts about transportation services, activities, resources and constraints, which dictate how, when, by whom and where transportation activities can be executed. This ontology considered different means of transport, but was not complete enough to support the development of travel planning systems because it was limited to military transportation activities. Another system was developed by Timpf (2002) in the field of multi-modal public transport in urban areas. The author designed two Ontologies, the first one based on the traveler, and the second one based on public transportation systems. His work identified the concepts to define ontology from the description of directions given verbally by five people. Timpf (2002) obtained a list of concepts of both perspectives and showed that one is a subset of the other. However, the list of concepts obtained is only a part of the ontology definition, since proprieties, relationships and axioms were not defined. In the same field of public urban transportation Yang and Wang (2012) introduced urban traffic ontology. They looked for ways to rapidly build ontology with massive real time traffic information and effectively analyze required information with the ontology. The aim of the developed ontology was to improve the process of information integration, describing the semantic rules and relationships, as well as the regulations of semantic mergence and the selection and verification of semantic fusion. They showed that the semantic fusion based on ontology, increased the efficiency of the urban traffic information integration, reduced the storage quantity and improved query efficiency and information completeness. Application of ontology to the railway domain can be found in Verstichel et al. (2011), where the authors suggested an efficient data integration system through an ontology-based methodology.

2.3. Ontology-CBR for information retrieval systems

Ontologies can be combined with CBR in various ways to overcome classic information retrieval problems. Advantages of integrating ontology with CBR are as follows: (1) ontology has the power to gather and represent exhaustively the knowledge of a particular domain by an intelligent manner. Indeed, ontology has the power to represent a group of various data sources in order to generate the initial knowledge base (KB). Combined with automated reasoning applications, ontologies can be used for several purposes such as knowledge extraction and information retrieval; (2) although in CBR the main source of knowledge is represented by the set of previous experiences, its integration with ontology allows the creation of complex knowledge structures to support the CBR process; (3) the integration of ontology concept and the CBR tools which is a reasoning support can be used in the function of an expert system. Besides the SWRL rules can be used for additional expressivity; (4) integrating CBR in an ontology-based IR system may improve query reformulation in a question–answering context, and precision of search.

Ontologies can be used by a CBR system to represent the input problem (Lau, Tsui, & Lee, 2009), or enhance similarity assessment (Bulu et al., 2012), represent cases (Alexopoulos, Wallace, Kafentzis, & Askounis, 2010; AssaBen Mustapha, Baazaoui Zghal, Aufaure, & Ben Ghezala, 2010; Li, Sun, & Sun 2009), reformulate Query (Besbes and Baazaoui-Zghal, 2014), or abstract and adapt cases (Amailef & Lu, 2013). Assali, Lenne, and Debray (2009) presented a knowledge-intensive Case-Based Reasoning platform for Diagnosis (COBRA). It integrated domain knowledge along with cases in an ontological structure. COBRA enables users to describe cases using any concept or instance of a domain ontology, leading to a heterogeneous case base. The proposed ontology-based CBR platform allows the capitalization and reuse of past failure experiences based on ontological models that describe the domain and case representation. Another interesting feature of COBRA is that it allows dynamic representation of cases; i.e., users can define their cases' attributes at run time, which leads to a heterogeneous case base. However, this heterogeneity complicates the case retrieval phase. Further, this system was dedicated to information retrieval not to the personalization of the information search.

Ben Mustapha et al. (2010) presented a semantic search approach based on CBR and a modular ontology learning. The CBR was used for ontology learning and for contextualizing the search process. Modular ontology is designed to be used for case representation and indexing. In this system the case representation is structured in three parts: problem, solution and rating evaluation. For the problem representation (Ben Mustapha et al., 2010) described the context of the query from the ontology module an instantiated graph of concepts related to a particular ontology module representing the common structure of a set of similar queries. For case indexing, the authors used a multi-layer ontology warehouse to index cases by the means of ontology modules. This system is an intelligent information retrieval system but this kind of system cannot capture all users' preferences. For example, users with the same demographic information may not necessarily have the same preferences, and not taking that in consideration will negatively influence the relevance of the search.

Alexopoulos et al. (2010) suggested a new approach for utilizing imprecise knowledge in ontology-based CBR systems by Means of Fuzzy Algebra. The integration of Fuzzy Logic in ontology-based CBR is performed in this framework in two levels, the first having to do with the representation of imprecise knowledge itself: a new method for Fuzzy Case Representation and the second with the latter's exploitation for case retrieval by the development of a Fuzzy Semantic Similarity Framework for case retrieval in the environment of imprecise knowledge.

Bulu et al. (2012) presented an ontology-based annotation of mammography and a Case-based Retrieval approach for breast masses from digital mammography archive. First, the authors present their Mammography Annotation Ontology focusing on its main concepts and relationships, as well as the annotation tool. Then, they propose a model for similarity calculation between breast masses based on their high, mid and low-level features. They use Semantic Query-enhanced Web Rule Language (SQWRL) to process retrieval of similar masses from annotated mammography collection in OWL. SQWRL is built on the semantic web rule language (SWRL), which is an expressive OWL-based rule language. However, the time performance of this tool is quite large to be used in a large mass collection. As the number of instances increases, so does the execution time of SQWRL rules processing in the Protégé environment, slowing down the system tremendously.

In Besbes et al. (2014), the authors proposed a hybrid system combining automatic modular ontology building with CBR (CBR Mod-Onto) for information retrieval. This hybridization resulted in an improvement of query reformulation, predicted ranking score and user's satisfactions. For the query reformulation: the modular ontology is used to enrich the user's query by the "closest" concepts to the terms of the query. For that, semantic similarity was calculated between concepts of the ontology and terms of the query. Then, the concepts with highest weight are used to enrich the query. The advantage of enriching the query with modular ontology could further enhance IR relevance than enrichment based on queries formed by a user whose knowledge in the field is limited.

In Amailef and Lu (2013), the authors present new approach the OS-CBR (Onto-CBR) approach based on the CBR method, combined with ontology technology that is capable of improving the efficiency of decision makers in an emergency situation. This new OS-CBR system has the ability to learn from past situations and to generate solutions for new problems based on past solutions provided for earlier problems.

All the above mentioned systems were dedicated to the field of information retrieval for various kinds of applications. Further, no existing systems of information retrieval took into consideration the problem of overloaded information in urban freight transport.

Though, the integration of the ontology concept and the CBR technique can improve the quality of the retrieval process, the approach may not easily detect user preferences or interests in the retrieving process which might negatively impact the relevance of the results. Few researchers tackled this challenging issue due to the lack of learning techniques. Further, the re-ranking process for search results requires more explicit interaction with the users in the above approach.

A major challenge of providing personalized information retrieval services is the ability to capture user's interests in the working domain in order to enhance the retrieval results.

The information retrieval system responds to the query using a given algorithm and a similarity measure. For the similarities measures used in all the mentioned information retrieval research (Alexopoulos et al., 2010; Amailef & Lu, 2013; AssaBen Mustapha et al., 2010; Besbes and Baazaoui-Zghal, 2014; Bulu et al., 2012; Lau et al., 2009; Li et al., 2009) most similarity measures used evaluate differences between values of numeric properties such as in the numerical difference between two given diameter values. However, many applications also require non-numeric similarities (for example for systems that need textual research and numerical measure at the same time).

3. Proposed approach

In order to overcome the above mentioned disadvantages and enables an improvement of query reformulation, predicted ranking score and user's satisfactions, we propose in this paper a new personalized retrieval system for itinerary search in urban area. The proposed system is aimed at further improving the approach proposed by the authors in Bouhana et al. (2013) by adding a new source of external knowledge which is the ontology to our previous system, improving the process of personalization by suggesting a new method based on SWRL rules to overcome the drawbacks encountered in the traditional problem and improve the similarity measures for case retrieval by combining two forma of attributes: numerical similarities and textual similarities. We also propose to further extend the implementation to a freight transport problem, an issue rarely tackled by research community due to its complexity.

In the logistics domain, we encountered several problems when gathering and selecting the right data, so we used the ontology concept as a source of knowledge to extract the pertinent information. Hence, ontology can share a large group of information sources knowledge organization, and interoperability among systems and the CBR can improve the user's interaction with the knowledge base. The combination of the CBR technique and the ontology concept in our proposed approach leads to the enhancement of the interactivity and the efficiency of the information search operation. A modified version of the city logistics ontology 'GenCLOn' (Anand, Mengchang, van Duin, & Tavasszy, 2012) was considered to build the domain model for a knowledge rich CBR application. We have exploited the city logistics ontology that provides the vocabulary for describing the elements involved in the CBR knowledge base and we use after that the CBR technique as an automatic learning tool to update the Knowledge Base based on the previous

The proposed approach includes the following particular features:

(1) It builds a new case retrieving process to provide a more convenient decision support system based on knowledge from, and solutions provided for past similar itinerary searches;
(2) It develops a new method for case representation by using the new generated SWRL rules extracted from the city logistics ontology to define a personalized structure for the case representation.
(3) It suggests new methods of personalization based on SWRL rules. The personalization tasks are carried out solely by the inference power of these rules. This allows the system to overcome the cold start problem encountered in content-based methods (Bouhana et al., 2013).
(4) It develops a new formula for similarities measure in the step of case retrieval in order to enhance the efficiency of the retrieval technology for the CBR technique. Both textual and numerical similarities measures are considered.
(5) It develops and applies ontology for real-time knowledge management in urban freight transport.

Further, the proposed intelligent personalized information retrieval system is an expert system. This is due to the fact that it is based on the combination of two strong techniques of reasoning, the ontology concept and the CBR tool to supports the OWL language and SWRL rules in the inference and reasoning process for enhancing the quality and the process of personalization.

The proposed framework of personalization is illustrated in Fig. 1.

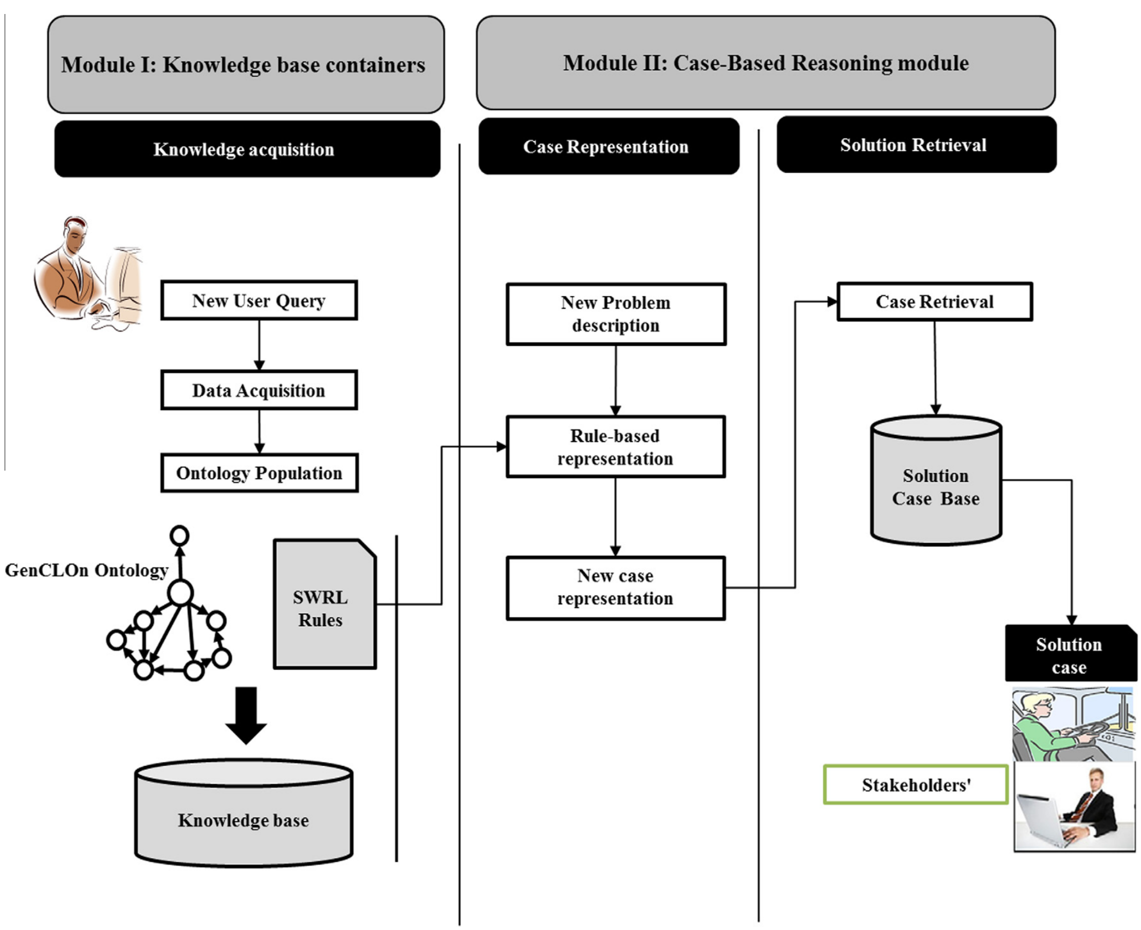

Fig. 1. Architecture of the CBR-based ontology system for personalized itineraries search.

The proposed approach operates as follows. The user submits a new request to the system. The user interface can guide the new user to record all necessary information for his research such as specifying: his function (carrier, shipper or retailer…), interest and preferences in building the new case or the target case. Based on the information given by the formulated request, the SWRL rules are used to capture and facilitate the detection of user preferences in a specific and personalized way. These SWRL rules enable first of all the selection of the list of cases that match exactly the specific user from the case base for example select all the cases stored in the case base that correspond to the shipper. Another type of filtering is then considered to further refine the search. That is, after selecting the list of cases for the particular user, the system will make a second selection from the specified list of cases according to the requested user Origin–destination itinerary based on the new formula the textual similarity measures. Afterwards, based on the numerical similarity measures defined by Bouhana et al. (2013) and the final list of cases already selected from the base case, the proposed approach provides the best solution that has the highest degree of similarity with the target case (user query).

3.1. Knowledge containers module

The knowledge containers module involves two components:

- The GenCLOn ontology;
- The knowledge base.

3.1.1. Scope of GenCLOn ontology

City logistics deals with the study of the dynamic management and operations of urban freight transport and distribution systems. The aim is to ensure optimum productivity, reliability and customer service whilst reducing environmental impacts, air pollution emissions, energy consumption and traffic congestion. City logistics is classified as a discipline which can cope with sustainable problems encountered in urban logistics freight transportation. One of its key characteristics is its ability to take into consideration the heterogeneity of the stakeholders in the decision process (heterogeneity of information and interest exchanged between different stakeholders (residents–retailers–authorities–supplier–carrier) (see Table 1).

In Anand et al. (2012), the authors proposed an ontology based city logistics tool (GenCLOn). The aim of this ontology is to formalize the domain knowledge of the city logistics in order to facilitate communication and share different knowledge with several terminologies and types of decisions making made by the different actors in the city logistics such as residents–retailers–authorities–supplier–carrier. From the semantic point of view, Anand et al. (2012) used the concept of ontology to develop a sort of glossary or a common language in order to facilitate communication and coordination among the different actors involved in city logistics. The objective of this ontology is to capture the maximum knowledge about the city logistics domain. In our work, this ontology will be exploited by every aspect of the system, especially in the information extraction, inference and SWRL rules. City logistics ontology would support CBR approach in the following ways: (1) vocabulary, ontology enables us to define case representation; (2) terminology, to define the SWRL for personalized case representation ontology allows us to define the query vocabulary. Further, ontology facilitates similarity assessment by establishing a connection between the query terminology and the case base terminology.

Table 1
Objectives of stakeholders involved in city logistics.

Stakeholders	Objectives
Residents	Receive goods fast and with minimum cost
	Less environmental impact
Retailers	Profitability and competitiveness
Authorities	Accessibility
	Respect the legislation and restriction
	Reduce environmental impact and fuel consumption
	Ensure safety of goods and residents
Supplier	Market growth and profitability
Carrier	Avoid congestion
	Reduce of transportation cost and fuel consumption
	Ensure safety of goods
	Reduce time distribution
	Reduce the pickup and delivery time

3.1.2. Knowledge base

The knowledge base (KB) stores information which may define new problems with ontological concepts and their instances extracted from users' queries. The knowledge base may include facts about instances (OWL (Ontology Web Language) individuals) that are members of concepts (OWL classes), as well as various derived facts, facts not literally present in the original textual representation of the ontology, but entailed (logically implied) by the semantics of OWL. The structure of KB is illustrated in Table 2.

3.2. CBR cycle module

In this section, we describe the different steps involved in the CBR cycle or our approach. Four components are considered as follows:

- Case representation;
- Case indexing;
- Case retrieval;
- Cases retain.

The representation of a case plays a major role in a given CBR cycle. In the following sub-section, we provide the details of our proposed new method of case representation.

3.2.1. Case representation

The case representation process is one of the major steps in case base construction, where each decision could condition the rest of the system, but also each technique used could affect the final design of the case. Hence, the performance of the CBR system depends on case representation. However, when designing a CBR system for a multidisciplinary and complex filed such as the urban freight transport, the question of which components must be presented in the case and which ones should not, can only be answered by an expert system. In our situation the use of the city logistics ontology can provide a top level formal description of case representation and endow the system with capability of reasoning.

Case representation incorporates three major components: problem description, solution and outcome (Zhang, Li, & Tan, 2010). In the CBR technique, a case is formed by a set of attributes or criteria that identify the instance of the problem, the suggested solution and its outcome. In our work, we adapt the definition proposed by McGinty and Wilson (2009). Hence, we define a case using a 2-tuple:

$C_a = (P, S)$ where P and S are refer respectively to a set of features that describe the problem and a set of attributes that describe possible solutions to the given problem (P).

Table 2
Knowledge base structure.

Instance characteristics	Content
Type	Concepts that I belongs to
SubjOf	All properties that (I, P, ?) exists
ObjOf	All properties that (?, P, I) exists
Text	Keywords of instance I

The set of cases form the case base, $C_a \in CB$, C_a is a case identification number used to distinguish a case from another with $a = 1, \ldots, n$.

Based on this representation the personalized itineraries search process can be described as a pair of attribute value that represent the problems and solutions features:

- Problem definitions

A problem consists of the description of user's needs in the information search. It is defined by a vector of attributes which correspond to the user's request.

In our approach, we describe the context of the new problem (query) by the following elements which represent the context of user needs:

– An ontological representation O^C (Table 3): a domain ontology which contains a set of concepts with its common properties strongly related by semantic relations used to identify the context of search.
– A rules-based case representation: a set of SWRL rules is used to represent the new query and to personalize the search.

User query is analyzed based on textual and numerical instances which belong to different concepts and properties in O^C (see section: solutions definition).

The table below describes some of the most important concepts for an itinerary search (attributes) and their corresponding ontological representations O^C (GenCLOn). Note that the attributes have been conducted based on the consultation of a number of experts in the associated literature.

In the proposed, the information relating to itineraries details and users personal information (such as age, address, preferences, etc.) represents the problem features of a case, while the itinerary suggested to the user is considered as a solution to the case.

- Solution definitions

The solution describes the derived outcome for a personalized itineraries search process. The solution contains output features which correspond to the best solution (itinerary) which satisfies exactly the needs and preferences of the stockholders (users).

A solution is a set of answers which refer to a set of cases retrieved from the case base. The answer may be a concept or instances of concept strongly related by semantic relations. In our approach, it refers to the best solution (itinerary) which satisfies exactly and at the same time the needs and preferences of the user request. For each case, two vectors of weighted concepts (Textual_vector and Numerical_vector) are constructed in order to obtain the most relevant solutions as specified in Section 3.3.1. Textual concepts represent information about a given itinerary namely; the address of origin and destination, stockholders, directions, vehicle type, customers.... etc. However, numerical concepts represent the search criteria which are mainly stockholders objectives (fuel consumption, transportation cost, emission reduction...). The next step in our case representation consists on the integration of the SWRL rules in order to provide a personalized presentation of each new case and facilitate the retrieval process.

3.2.1.1. Rules based representation. A set of rules defined using SWRL[1] and adopted from GenCLOn (Anand et al., 2012) are considered in our approach. The objective of these rules is to select the rel-

[1] http://www.w3.org/Submission/SWRL/

Table 3
Ontological representation of some features pertaining to itinerary search.

Keyword query	Ontology concepts	Ontology properties	Type
Origin/destination	OWLClass_00000046661641579586 Annotations: rdfs:label "Shipper" OWLClass_00000046661637366480 Annotations: rdfs:label "Carrier" OWLClass_0000004666164059677 Annotations: rdfs:label "Receiver"	OWLObjectProperty_0000003714219380954 Annotations:rdfs:label "connect" OWLObjectProperty_00000043948583785090 Annotations: rdfs:label "origin" OWLObjectProperty_00000044016042214862 Annotations: rdfs:label "destination" OWLObjectProperty_00000045309184500823 Annotations: rdfs:label "ship_address	Textual
Vehicle type	OWLClass_00000048681345885021 Annotations: rdfs:label" Road_freight_vehicle"	OWLObjectProperty_000000485818 Annotations: rdfs:label "has_resource"	Textual
Fuel consumption	OWLClass_00000017260945781935 Annotations: rdfs:label "Fossil_fuel_consumption_reduction"	OWLClass_00000022452118786605 Annotations: rdfs:label "Logistics_cost_reduction" OWLObjectProperty_00000049659148982342 Annotations: rdfs:label "has_objective"	Numerical
Transportation cost	OWLClass_00000017260940625694 Annotations: rdfs:label "Transport_cost_reduction"	OWLClass_00000022452118786605 Annotations: rdfs:label "Logistics_cost_reduction" OWLObjectProperty_00000049659148982342 Annotations: rdfs:label "has_objective"	Numerical
Emission CO_2	OWLClass_00000017260944876793 Annotations: rdfs:label "Emission_reduction"	OWLClass_00000022452118786605 Annotations: rdfs:label "Logistics_cost_reduction" OWLObjectProperty_00000049659148982342 Annotations: rdfs:label "has_objective"	Numerical

Table 4
Feature selection techniques considered in CBR models.

CBR model	Features selection methods
Hybrid CBR an genetic algorithm (Ahn & Kim, 2009a; Ahn & Kim, 2009b)	Sequential forward selection with GA
Evolutionary fuzzy CBR (Li & Ho, 2009)	From expert analysis
TOPSIS with CBR (Li & Sun, 2011a)	From expert analysis
Decision trees and CBR (Cho, Hong, & Ha, 2010)	Decision trees
Multiple case representations (Li & Sun, 2011b)	Commonly used ratios
Outranking relations CBR (Li & Sun, 2009a; Li & Sun, 2009b)	Stepwise discriminant analysis (grid search technique for optimizing)
Majority voting combination of MCBR (Li & Sun, 2009b)	Grid search and leave one out cross validation (no feature reduction technique)
Forward Ranking CBR (Li & Sun, 2011a)	Forward feature selection using Wrapper approach
CBR ensemble (Li & Sun, 2011b)	All features, stepwise multivariant discriminant analysis, *t*-test, stepwise logit
Ranking CBR (Li & Sun, 2008)	Hold-out method and cross-validation
CBR with support vector machine (Li & Sun, 2009a; Li & Sun, 2009b)	ANOVA: analysis of variance
CBR with Choquet integral (Bouhana et al., 2013)	PCA : principle components analysis
Hart (1968)	Nearest neighbors
Ahn and Kim (2009a), Ahn and Kim (2009b)	Genetic algorithm

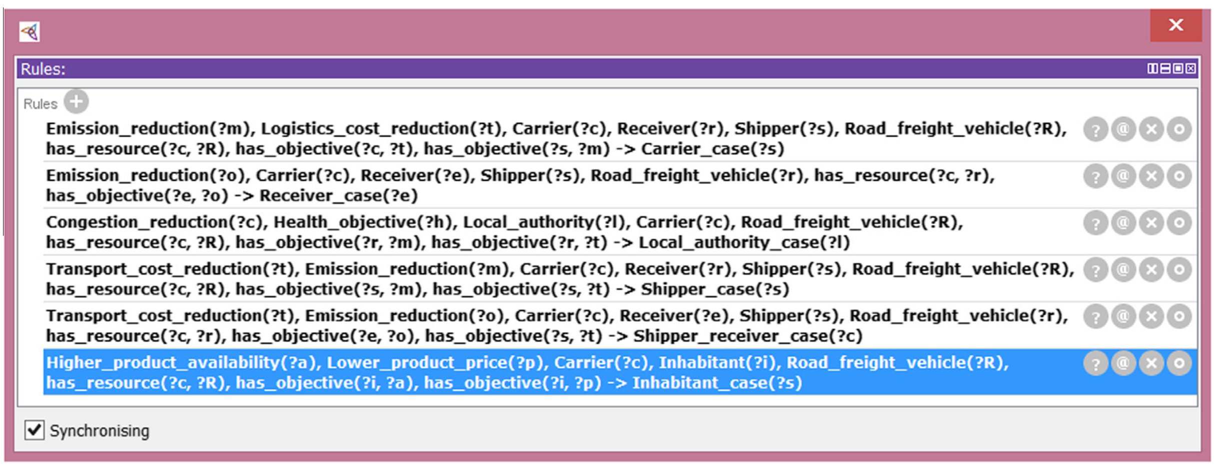

Fig. 2. SWRL rules generated automatically by the system.

evant concepts (features) for a given user (stakeholders). For this reason, a set of DL-safe rules R^C was written, using SWRL (see Fig. 2).

Here, the SWRL is used to select only the subset of features that are relevant to the target case (new problem) thus removing or avoiding possible irrelevant or redundant ones. Indeed, some features may be very important for the case reasoning but others may not and will only dramatically increase the case memory and further complicate the case retrieval task.

Various research projects aiming at optimizing the task of case representation were proposed in the literature. Some of the most widely used methods are summarized in the table below (see Table 4).

In our framework, we proposed a novel method of selection that permits the election of the most relevant features in a personalized manner. Its objective is to find significant features and delete redundant ones to enhance the efficiency of retrieval algorithm. SWRL plays a key role in the selection. The aim of this technique is to reduce the whole case-base into small subsets that include only the representative cases which positively affect the CBR system. The proposed system can be used by different stakeholders in urban freight transportation such as carrier, receiver, shipper, retailer, etc. It can also be used by private transporter managers. In the ontology GenCLOn, we have an exhaustive list of actors with different objectives (see Table 1). Depending on the chosen objectives by users, the system can determine the category of cases where these users will be affected. To do this, our system generates a set of SWRL rules (see Fig. 2). A rule can be defined as the conjunction of triples of semantic entities (see equation. (1)). As an example, if the stakeholder in the query is a "Receiver" and the selected objectives are economic and environmental objectives (fuel consumption, transportation cost, Emission reduction, ... etc), we get the triples (<receiver(x), hasObjective, fuel_Consumption(y)), (<receiver(x), hasObjective, Emision_reduction) . The rule consists on classifying this query as a case dedicated to actors of type "receiver_case". This last represents what we call "topic concept". Note that if a user cannot find the appropriate actor in the list, he can add a new one. The addition of a new actor implies the creation of a new class in the GenCLOn Ontology (sub-class of the class «stakeholders»).

An SWRL rule is defined as follow:

$$C_t(x) \leftarrow \wedge_1^n \exists y_i, \exists R\theta_i(x, y_i) \text{ avec } \; i \in \{1, \ldots, n\} \tag{1}$$

where, C_t is topic concept, $\wedge$ is a conjunction function of triples of semantic entities. This triple contains entities which refer to stakeholders and their objectives. y_i represents instances of objectives classes, x represents instance of stakeholders classes (actual user), θ_i depicts entities triples which have x as domain an y_i as range, and R represents the relation between the stakeholders and their respective objectives.

As mentioned above the generation of new topic concepts implies the creation of new taxonomy. As illustrated in Fig. 3. However, this requires dealing with the ontology enrichment process. According to Petasis, Karkaletsis, Paliouras, Krithara, and Zavitsanos (2011), only semi-automatic approaches require the intervention of domain experts to validate the addition of new elements and to check the consistency of the enriched ontology. Our approach is able to detect new topical concepts through the

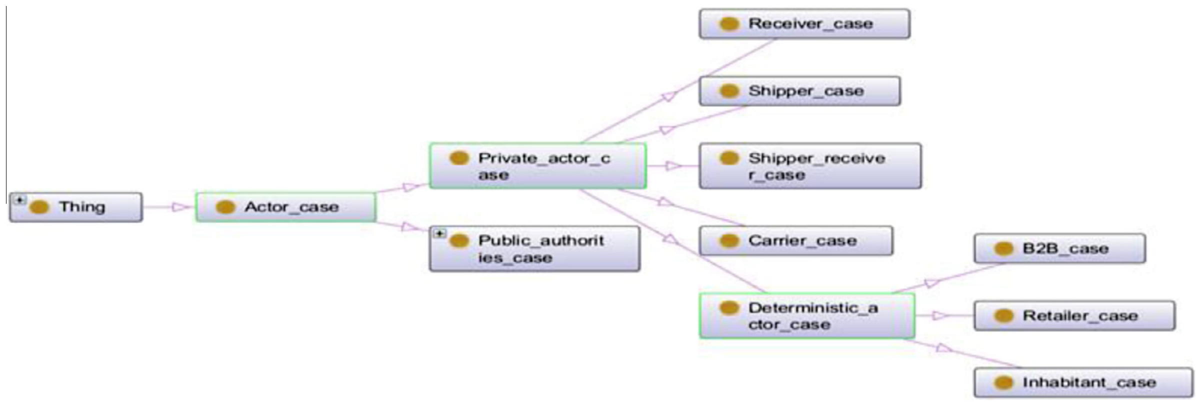

Fig. 3. Taxonoy of topic concepts generated from SWRL.

semantic rules as explained above. Further, the user can introduce new concepts via the interface as detailed in Section 4.1.

In order to add new concepts into the existing ontology, we adopt the following two techniques:

- Topic concepts: they are automatically placed by the system in the form of a new taxonomy that does not necessarily relationships with old classes.
- Other concepts (new actors): are also automatically placed by the system. This is mainly done to add a sub-assumption relation (is-a) with the selected classes in the interface. Indeed, other relationships are inherited from selected classes; add a similar relationship with the sub-class (new concept) and existing classes makes no sense because it leads to an information redundancy.

Consequently, a SWRL rule was defined in order to associate the user with all the cases that meet exactly the structure defined to him before finding the right case that satisfy exactly his needs and preferences. The main advantage of this method is the fact that it avoids human involvement in deciding the number of features thus increasing the robustness of the objective-based results and decreases the human errors.

Example of personalized case representation:

The representation of case in our system corresponds to the concept defined in GenCLOn ontology (Anand et al., 2012). The data structure of the case is the same as the concept in the ontology. In our approach, information pertaining to itineraries details and user's particular information (such as categories of users (shipper; carrier; receiver, etc...), address, preferences, etc.) represents the problem features of case, while the itinerary suggested to the user is considered as a solution to the case.

In our paper we consider the following representation for each case (see Fig. 4).

3.2.2. Case indexing

In the CBR cycle, case indexing and retrieval are the most important steps and the performance of CBR systems usually depends on them. Indeed, if the retrieved case is not the most relevant, the rest of the process will not provide any useful results or information (Ahn & Kim, 2009a).

In our approach, we propose a new case indexing approach. Our case indexing schema is based on the analogy between searching a case base for a given case and searching text database for documents. The underlying structure of our indexing is based on the inverted index that has been widely used for text-query evaluation. Inverted index allows the optimization of scalability while providing high performance retrieval (Culpepper & Moffat, 2010). Our inverted index works by maintaining a list of textual instances in the case base, called a vocabulary. For each instance I_i in the vocabulary, the index contains an inverted list, which records an identifier for all cases C_{ai} in which the Instance I_i exists. For the weighting procedure (see Section 3.3).

3.2.3. Case retrieval

The retrieval step is the most important one in the CBR process. Once case representation and indexing are completed, a retrieval structure can be organized. Case retrieval is one of the most important issues for CBR (Jiang & Tan, 2006). Usually, it calls to a similarity function.

In our work, we propose a two-stage retrieval model in which similar case retrieval is released based on concept equivalence in the first stage and instance matching or similarities measures in the second stage.

3.2.3.1. Concept equivalence

This stage consists on checking the existence of the same features in both the case in memory Ca_{mem} and the new case Ca_{new}. We start with a simple technique which only considers the equivalent concepts between the current and the new cases. The case in memory Ca_{mem} and the new case Ca_{new} are respectively represented as the following sets:

$V_{c\_mem} = \{C_1^{mem}, C_w^{mem}, C_3^{mem}, \ldots, C_p^{mem}\}$, where C_p^{mem} $(p = 1, \ldots, \mathrm{m}) \in \mathrm{O}^{\mathrm{C}}$

$V_{c\_new} = \{C_1^{new}, C_{21}^{new}, C_3^{new}, \ldots, C_q^{new}\}$, where C_q^{new} $(q = 1, \ldots, n) \in \mathrm{O}^{\mathrm{C}}$

This is a purely Boolean process that is based on exact match between concepts. Consequently, the similarity between the new case and the case in memory is then computed using the binary cosine similarity coefficient:

$$B(V_{c_{new}}, V_{c_{mem}}) = \frac{|V_{c_{new}} \cap V_{c_{mem}}|}{|V_{c_{mem}}| \times |V_{c_{new}}|} \tag{2}$$

where $|V_{c\_new} \cap V_{c\_mem}|$ represents the number of concepts in the intersection of V_{c_new} and V_{c_mem}, and $|V_{c\_new}|$ and $|V_{c\_mem}|$ are respectively the number concepts in V_{c_new} and V_{c_mem}.

3.2.3.2. Instances matching

Instance matching is the process of evaluating the degree of similarity of pairs of instances across case in memory and the new case. For each specific instance type (textual and numerical), appropriate matching techniques are provided to calculate the similarity of instances values. For textual instances, we focused on string values due to the fact that string data are the most frequently used type in database and knowledge repositories for real-world entity descriptions (Castano, Ferrara, Montanelli, & Varese, 2011). We adopted as similarities functions, the cosine

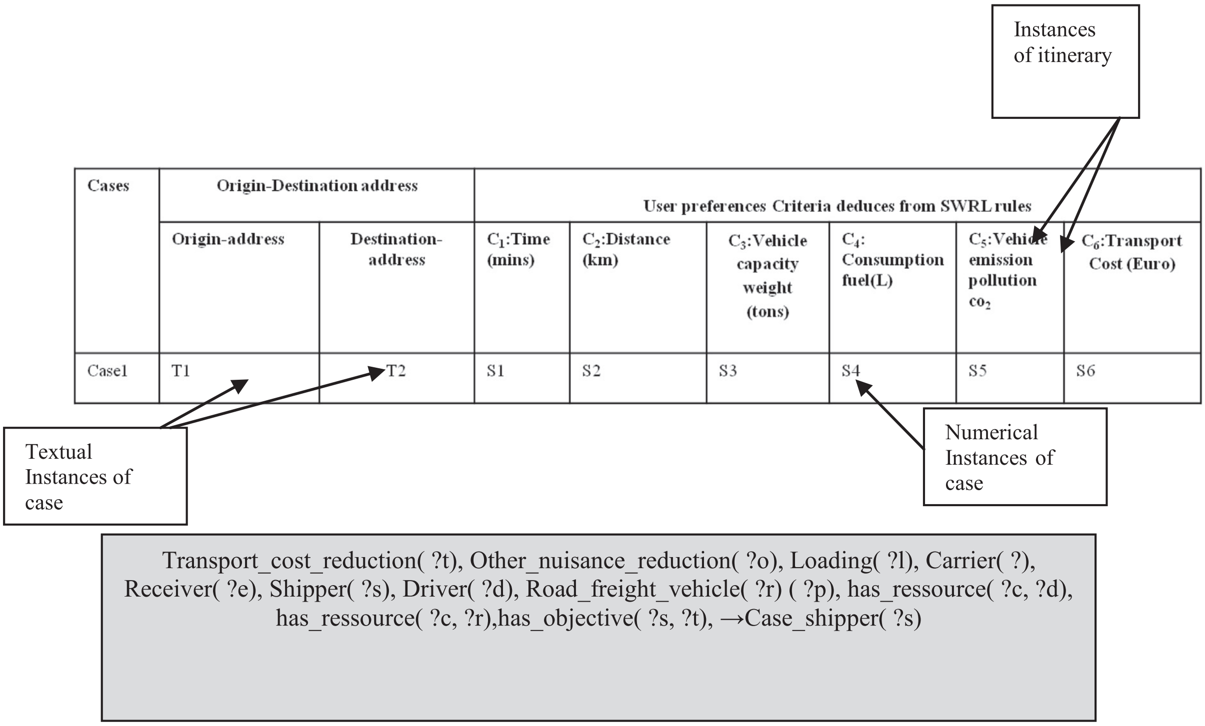

Fig. 4. Example of case representation architecture in the case base.

distance with TF/IDF, for textual instances matching and global similarities (Bouhana et al., 2013) for numerical instances matching (see Section 3.3).

3.3. Case retrieval and similarities measures

Similar case retrievals depend on case representations, their indexing and their organization in the case base. It leans from similarity measures that measure the similarity between the posed problem and cases candidates.

As mentioned previously, two vectors of weighted instances (Textual_vector and Numerical_vector) are constructed and associated with each case in order to obtain the most relevant cases.

- **Textual_vector**: (T) This vector is used to represent concepts with textual instances. This vector is the n-tuple $((w_1\ I_1^t)(w_2\ I_2^t)\ldots(w_n I_n^t))$ where $I_i^t \in O^C$. w_i represents the weight of all terms referring the instances of concepts in case Ca_i which belongs the ontological representation O^C.
- **Numerical_vector**: (N) This vector is used to represent concepts with numerical instances. This vector is the n-tuple $((f_1\ I_1)(f_2\ I_2)\ldots(f_m\ I_m))$ where $I_j^n \in O^C$. f_j represents the weight of all terms referring instances of concepts in Ca_i which belongs the ontological representation O^C.

The above two vectors are used to represent the case features and are respectively used in the step of case retrieval.

Given two cases Ca_{mem} and Ca_{new} as input, instance matching is defined as the process of comparing set of instances I_p $(p = 1,\ldots,m)$ which belong respectively to concepts C_p^{mem} $(p = 1,\ldots,m)$ and an instance I_q which belong respectively to concept C_q^{new} $(q = 1,\ldots,n)$, with a mapping between their matching assertions. In each case, we represent the set of textual instances

where w_p and w_q are weights assigned to concept C_p^{mem} $(p = 1,\ldots,m)$ and concept C_q^{new} $(q = 1,\ldots,\mathrm{n})$ during the indexing process and calculated according to the Choquet integral 2-additive (see Section 3.3.1.3).

3.3.1. Similarities measures

The similarities calculations are based on two steps: textual similarities and numerical similarities for qualitative and quantitative criteria. To retrieve similar events from historical cases, similarity measurement is commonly used in case retrieval. The value of similarity is between 0 (not similar) and 1 (most similar).

3.3.1.1. Textual similarities

In each case, textual instance weight is computed automatically by an adaptation of the TF-IDF algorithm (Sunchez et al., 2011), which is based on the frequency of occurrence of the textual instances in each case. More specifically, the weight w_i of an instance I for a case Ca is computed as:

$$w_I = \frac{freq_{I,Ca}}{\max_J freq_{J,Ca}} * \log\frac{N_C}{n_I} \tag{3}$$

where $freq_{I,Ca}$ is the number of occurrences in Ca of the keywords attached to I, $max_J\ freq_{J,Ca}$ is the frequency of the most repeated instance in Ca, n_I is the number of cases which contain I, and N_C is the set of all case in the case base. The similarity between the new case and the case in memory is then computed using the Cosine similarity coefficient between the two vectors (Text-features) for each case.

$$sim(T_{mem}, T_{new}) = \frac{T_{mem}\cdot T_{new}}{|T_{mem}|\cdot|T_{new}|} \tag{4}$$

3.3.1.2. Numerical similarities

In the proposed model, we opt for the following local similarity metric (Bouhana et al., 2013):

$$sim_j(N_i, N_{new}) = 1 - \frac{|N_i - N_{new}|}{range} \tag{5}$$

where j is a criterion in k with $j = 1,\ldots,m$, N_i is the value of case i under the criterion j with $i = 1,\ldots,n$, N_{new} is the value of the new case under the criterion j and range is the absolute value of the difference between the superior boundary-mark and the lower boundary-mark of the set of values of all cases under a criterion j.

Then, global numerical similarities will be calculated by aggregating the local similarities using the Choquet integral formula:

$$sim_{gnum}(Ca_{mem}, Ca_{new}) = \sum_{j=1}^{m}[sim_{\sigma(j)}(Ca_{mem}, Ca_{new}) - sim_{\sigma(j-1)}(Ca_{mem}, Ca_{new})]\mu(A_j)$$

$$\text{where} \quad A_j = \{\sigma(j), \ldots, \sigma(m)\} \qquad (6)$$

$$sim_{\sigma(0)}(Ca_{mem}, Ca_{new}) = 0$$

σ is a permutation on N such that :

$$\text{sim}_{\sigma(1)} \leqslant sim_{\sigma(2)} \leqslant sim_{\sigma(m)}$$

Weights of criteria W_i groups are defined by the capacities μ or fuzzy measures (see Bouhana et al. (2013)). In fact, in order to determine the unknown parameters of the Choquet integral 2-additive that's mean μ capacities of the different groups of criteria, the following quadratic program is constructed:

$$\text{Minimize} \sum_{a \in CB}[Ca_{mem_\mu}(a) - Ca_{new_\mu}(a)]^2 \qquad (7)$$

Under the following constraints:

$$\mu(C_i) \leq \mu(C_j) \forall C_a \subset CB$$

$$\mu(i,j) \leq \text{or} \geq \mu(i) + \mu(j) \quad \forall\ i,j \subset a$$

$$Ca_{mem_\mu}(a) - Ca_{new_\mu}(a') \geq \delta \forall a, a' \in CB$$

With CB: the set of base cases, Ca_{new_μ}: The global score for the new case, C_i, C_j: criteria groups in k, i, j: criteria in N, δ: the indifference fixed degree, a, a': cases in CB.

3.3.1.3. Global similarities measures

The proposed approach consists in combining textual similarity measures with numerical similarity measures.

$$Sim\ glob(Ca_{mem}, Ca_{new}) = sim(average\ textual + sim_{gnum} Average\ num) * \alpha$$

$$With\ \alpha a\ coefficient\ of\ normalization\ \alpha \in [0.1]$$

$$\begin{aligned} Sim\ glob(Ca_{mem}, Ca_{new}) &= \{sim(T_{mem}, T_{new}) \\ &= \frac{T_{mem} \cdot T_{new}}{|T_{mem}| \cdot |T_{new}|} + sim_{gnum}(Ca_{mem}, Ca_{new}) \\ &= \sum_{j=1}^{m}[sim_{\sigma(j)}(Ca_{mem}, Ca_{new}) \\ &\quad - sim_{\sigma(j-1)}(Ca_{mem}, Ca_{new})]\mu(A_j)\} * \alpha \end{aligned} \qquad (8)$$

These elements have a value ranging from 0 (not similar) to 1 (maximum similar). Finally, the case having the biggest global similarity with the new case will be selected. The case retrieval algorithm works as follows (see Fig. 5).

Input:
A new case Ca_{new} is described as follows:
m concepts: $C^{new} = \{C^{new}_1, C^{new}_2, C^{new}_3 \ldots C^{new}_p\}$,
where C^{new}_p (p=1… m) ∈ O^C

Output:
Similarity degree of a new case within the case base
Local variables:
Old case Ca_{mem} is described as follows:
n concepts: $C^{mem} = \{C^{mem}_1, C^{mem}_2, C^{mem}_3 \ldots C^{mem}_q\}$,
where C^{mem}_p (q=1… n) ∈ O^C
Instance-type = {Numeric, String}
Weight (w) is the weight factor of the textual features (TF-IDF) Eq.(2)
Weight (f) is the weight factor of numerical features (Choquet integral)

Begin
Compare concepts of C_{new} and C^{mem}
do Eq (1).
For each C^{new}_p of Ca_{mem} do (0≤q≤n).
Begin
Compare instances value of C^{new}_p and C^{mem}_q:
if (instance-type)='Numeric' then do Eq. (3)
if (instance-type)='String' then do Eq. (4)
End
Calculate the degree of similarity of retrieved case to Eq. (5)
End

Fig. 5. Case retrieval algorithm.

3.4. Case retain

When a new case occurs, it is compared to a set of itineraries solutions that are already known. The most similar and significant itineraries (solutions) are retrieved. The solution of the retrieved case is then adapted using our proposed algorithm. The revised solutions are then retained temporarily and then when the suggested solutions are actually applied, the outcomes for the current solution can be evaluated. Finally the new problem description (new case) and its solution is retained as a new case in the case base in order to assist the user in finding the right solution for future searches in a more personal way.

4. System implementation

The interface and the functionality of the application are implemented in JEE (Jsp and Servlet). For the ontology extension and development, we used OWL in order to ensure the maximum possible expressiveness and the efficient support of reasoning. The definition of rules is implemented in SWRL. Protégé 4 has been selected as the appropriate ontology environment for the ontology and rules complete OWL reasoning. Also, the system uses OWL API to manage the ontology visualization. In addition, we made use of Pellet, an open-source Java based OWL reasoned, which guarantees automatically without acceding to Protégé. The special feature of Pellet is its support for reasoning with DL-safe rules which makes it particularly suitable for our needs.

In the proposed system, we adopted a keyword-based interface as it provides a convenient and user friendly way to submit a query (Fig. 6). The queries are formulated using semantic entities which can be classes, properties (relation or attribute) or instances. The objective is to assist the user in his queries formulation. As indicated in Fig. 6, using the form (user information), the first step consists on selecting one or more actor which are presents in GenCLOn (private or public) using a scrolling menu and then filling the selected actor's name. The next step consists on selecting the type of objectives in the desired itinerary. If the selected objective is economic objective, an automatic display of the corresponding criteria is done in the research form. The text field "add new actor" allow the addition of a new actor which represents a new concept in GenCLOn (see Section 3). The second form (search) allows to select the origin and the destination in the itinerary and to enter the criteria of itinerary search which were generated automatically while selecting the type of the objective in the first form. To determine the weight of the search criteria, the user must enter a number between [1 and 5] after each filled criteria. This number is used in the similarities measures in order to aggregate the search criteria (see Section 3.3.1.2). The user interface is depicted in Fig. 6.

Our objective is to search for a solution to a new case (user request) arising in the base of case while exploiting the last cases.

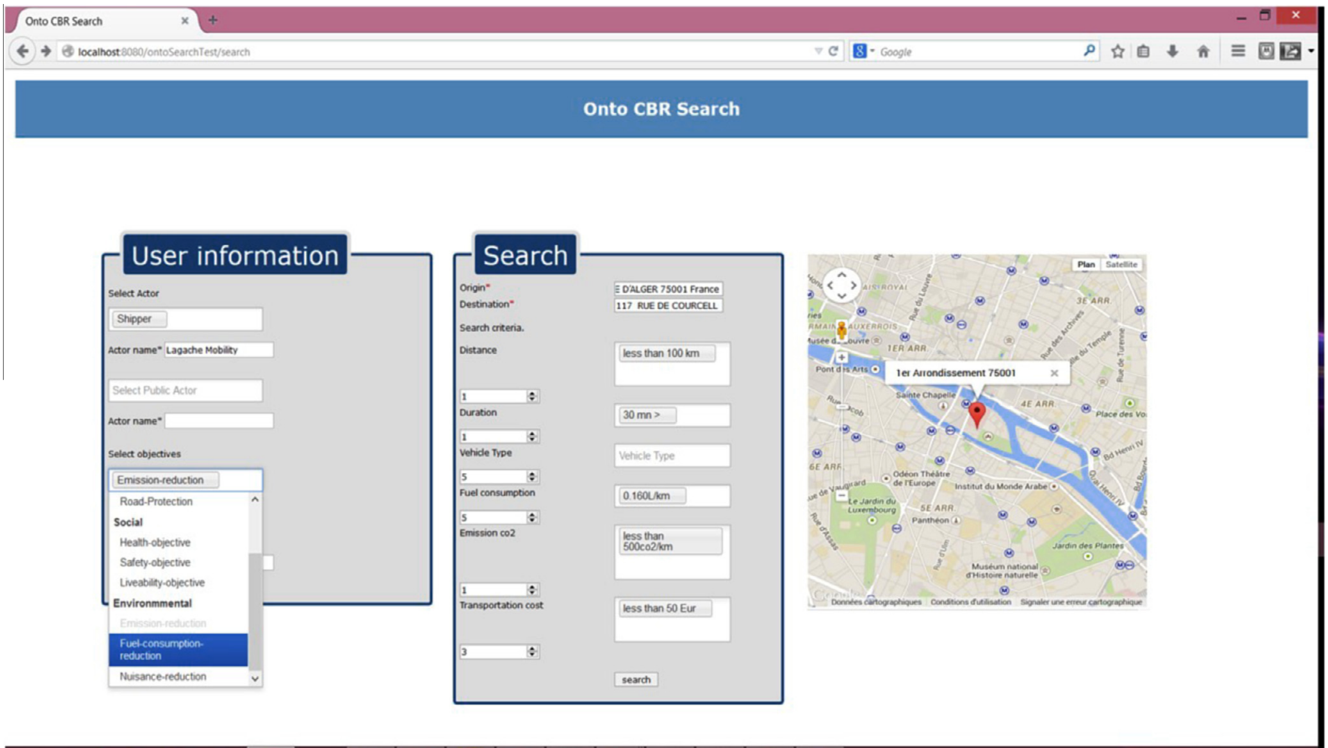

Fig. 6. Onto-CBR user interface.

This case is described by the same attributes as those of the cases of the base (see Appendix A).This new case is a user whose preferences are described in Appendix A. We need to help him find the best itinerary which closely satisfies his needs and preferences and optimize a set of criteria to avoid congestion and his consequences in urban area.

Fig. 7, illustrates an advanced interface for the query results. The first part of the interface represents a set of personalized results (cases) depicted from real world applications. These results show the 4 similar cases to our target case. The second part of the interface illustrates the resulting explanations which are generated automatically when the user selects a given itinerary.

The diagram, which is automatically generated based on the user query, represents the used SWRL rule. The ontological representation table summarizes the concepts and their instances. The smaller table shows the resulting scores of numerical concept similarities (score1), textual concept similarities (score2) and global score of the selected itinerary, respectively. In the selected result, the stakeholders like shipper (BHL) and receiver (LAVRAGE) have respectively an economic (Transportation cost) and environmental (Gaz emission) objectives and the type of vehicle chosen is a vehicle with a capacity less than 3.5 tones.

From the results highlighted in Fig. 7, we can conclude that the most similar case (or itinerary) to the new case (requested itinerary) is mentioned on the Fig. 4. The pertinent information included in this selected case is deducted from the case base for use in the remainder of the CBR cycle.

Fig. 7, shows that the search resulted in fulfilling the requested Origin –Destination with the preferences that match exactly the user's needs.

4.1. Experimental analysis

This section illustrates the major results of the experiments conducted to examine the performance of our approach. To evaluate the proposed approach, we distinguish tow main Criteria. In the first step and due to the lack or inexistence itinerary search method based on the integration of the ontology and CBR tool, or based separately on the ontology or the CBR, we chose to evaluate our approach with the classic CBR methods developed by Bouhana et al. (2013). To show the important role of the CBR-ontology integration and the role of the SWRL rules to enhance the personalization retrieval process and reasoning features compared to traditional retrieval system based only on the CBR tool. For this set of experimental analysis, the knowledge base was created using City logistic ontology (Anand et al., 2012) with real data from Paris Open Data[2]. The mapped data represent instances which will rely to cases. Then, we started our experiments with a set of 100 users' queries (see example in Fig. 8).

Two main experiments were conducted. The main steps of the first experiment are:

- Running first query set in our system;
- Representing each query by semantic entities and generate an appropriate rule if possible. A new case is therefore created;
- For every new case, look for solutions from similar cases in the case base;
- Return results.

After running the query set, our system was able to create new cases based on three rules automatically generated (Table 5).

The case base includes 95 cases, 40 cases represented by Rule # 1, 35 represented by # Rule2, 20 cases represented by # Rule3 and other cases represented only by triplets of semantic entities. In, Table 5, SWRL Rules column shows the used rule for each case set. Textual concepts and Numerical concepts columns shows the number of instances in each rule. The properties column shows the number of properties (e.g. relations) in each rule. The Case

[2] http://opendata.paris.fr/page/home/

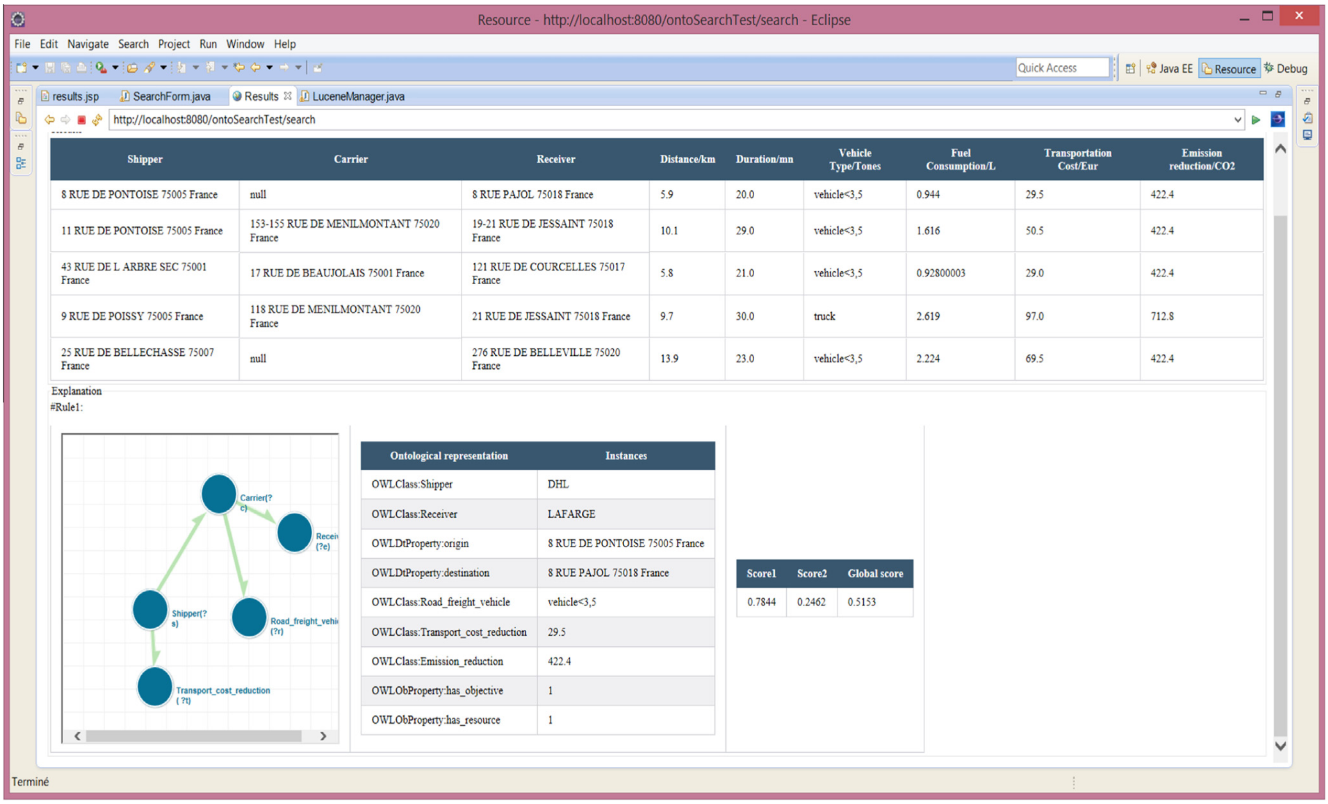

Fig. 7. Query results.

<query>
<num>3</num>
<content>
Actor name: Lagache Mobility
Origin: 4 RUE D'ALGER 75001 France
Destination: 117 RUE DE COURCELLES 75017 France
Distance: Less Than 100 weight: 1
Duration: 22. Less Than 60 weight: 2
Fuel Cosumption:0.180/km weight: 3
Transportation Cost: Less than 50 weight: 1
Emission reduction: Less than 0.180/km weight: 4
</content>
</query>

Fig. 8. Example of a given query from query-set used for tests.

count column provides the number of cases for each rule (see Table 6).

The second experiment consists on the following steps:

- Identifying query sub-sets from the first query set. This new sub-sets rely to queries represented by our system using generated rules as mentioned above.
- Running the new query sub-sets in the system proposed in Bouhana et al. (2013).

Evaluation was performed using the standard information retrieval measure: precision and recall. The recall score measures the ratio of the relevant retrieved cases against all available relevant cases present in the case base (equation (9)). The precision score measures the ratio of relevant cases that was retrieved against all the cases that was retrieved (equation (10)). Let N be a collection of cases, n represents relevant cases and r relevant cases retrieved from N. our approach recognizes a collection of cases, in which k represents all results retrieved (see Table 7).

Table 5
Rule-based case representation.

Topic concepts	SWRL Rules	Explanation
Receiver_case	Emission_reduction(?o), Carrier(?c), Receiver(?e), Shipper(?s), Road_freight_vehicle(?r),has_ressource(?c,?r), has_objective(?e,?o)->Receiver_case(?e)	The SWRL described for this rule show that the receiver has a emission reduction as an objective
Shipper_case	Transport_cost_reduction(?t), Carrier(?), Receiver(?e), Shipper(?s), Road_freight_vehicle(?r), has_ressource(?c, ?r), has_objective(?s, ?t)->Shipper_case(?e)	The SWRL described for this rule show that the shipper has a transport cost reduction as an objective
Shipper_receiver_case	Transport_cost_reduction(?t), Emission_reduction(?o) Carrier(?), Receiver(?e), Shipper(?s), Road_freight_vehicle(?r),Itinerary_pattern(?p), has_ressource(?c, ?r), ,has_objective(?s, ?t), has_objective(?e, ?o)->Shipper_receiver_case(?p)	For the case where the shipper and the receiver have objectives in the same itinerary to reduce a set of criteria

Table 6
Distribution of cases according to their rules.

SWRL rules	Textual concepts	Numerical concepts	Properties	Case count
#Rule1	7	3	2	40
#Rule2	7	3	2	35
#Rule3	7	5	4	20

Table 7
Analysis of precision and recall (Amailef & Lu, 2013).

	Relevant	Not-relevant	Total
Retrieved	a	b	a + b = k
Not-retrieved	c	d	c + d = n − k
Total	a + c = r	b + d = n − r	a + b + c + d = N

$$Recall = \frac{\text{Relavant and Retrieved}}{\text{Relevant}} = \frac{a}{a+c} \tag{9}$$

$$Precision = \frac{\text{Relavant and Retrieved}}{\text{Retrieved}} = \frac{a}{a+b} \tag{10}$$

Since our system was able generate three rules in the first experiment, the evaluation was performed for three query sub-sets, with the classic CBR proposed in Bouhana et al. (2013) and our system which combines CBR and ontology. Comparing the performance of the two approaches in our experiments, which are shown in Fig. we found that Onto-CBR approach exhibits a significantly better performance than the CBR approach. These experiments refer to three query sub-sets which are based respectively on #Rule1 (Fig. 9), #Rule2 (Fig. 10), and #Rule3 (Fig. 11). The three Figures illustrate the precision-recall curves obtained for the three query sets. This experiment aims at assessing the performance of the personal information retrieval process using the proposed approach. The precision improvements of the ontology-based approach are +3, 4% (Rule#1), +13, 8% (Rule #2) and +14, 3% (Rule #3). Moreover, the proposed approach has the strong advantage of retrieving information on a semantic basis, which is not possible with the classic CBR approach. It addresses the short query problem and applies external knowledge (Rules) to solve the semantic knowledge gap. The selected semantic features are highly correlated with the query, which further increases the level of personalization in the retrieval process.

Based on the above experiments, we can conclude that the proposed approach (Onto-CBR) results, show better performance than the CBR approach alone:

- Accuracy was significantly improved by using the new integration with the CBR tool and the GenCLOn ontology.
- The new similarities measures improve the step of retrieving process in the CBR cycle and have a positive impact on the relevance of itinerary search results.

Further, our previous system (Bouhana et al., 2013) provided low efficiency results (low precision measures) compared to the current system. This is due to the absence of semantic relationship between the keywords used in the query and features in the previous approach.

5. Comparison analysis

To further illustrate the performance of the proposed approach, we present in this section a qualitative comparison analysis with the following methods (Bouhana et al., 2013; Jiang & Tan, 2009). This comparison involves two levels; a comparison of our approach with other personalization of information systems and a comparison with systems specifically design for itinerary search.

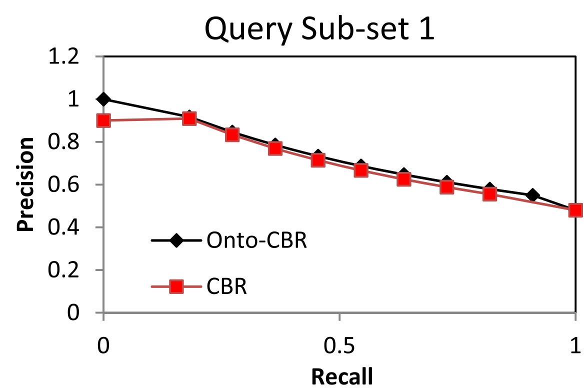

Fig. 9. Precision-recall results for the query based #Rule1.

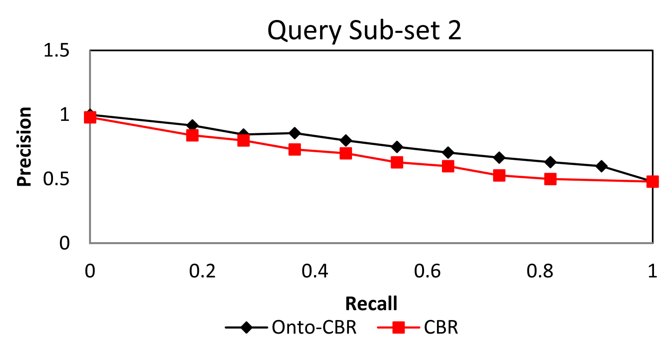

Fig. 10. Precision-recall results for the query based #Rule2.

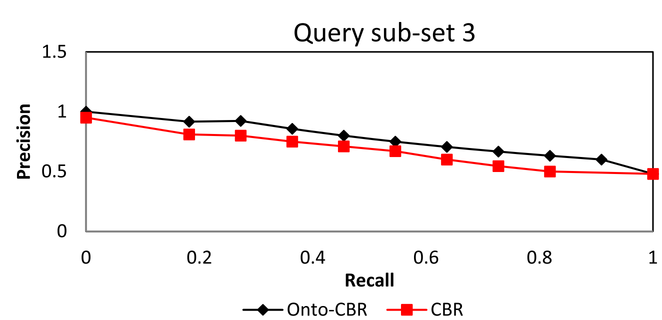

Fig. 11. Precision-recall results for the query based #Rule3.

5.1. Comparison with other personalization of information systems

The results of the comparison are illustrated in Table 8.

Compared to the above approaches, the advantages of our method are summarized as follows:

- Using the SWRL rules, our method can capture all the information about the user and propose a personalized solution without constructing a user model. The defined rules have the power to suggest to the user personalized services based on this rules.

Table 8
Comparison with other personalization of information systems.

Approach	Features					
	Domain of applications	Methods of personalization	Technique of reasoning or inference	Similarities measures	Tool of criteria aggregation	Source of knowledge
CBR and the Choquet integral (Bouhana et al., 2013)	Public transport	Content method	CBR	Numerical measure based on the Choquet intergral	Choquet integral	Case Base
User Ontology (Jiang & Tan, 2009)	Documentary Web Research	Ontology and user profile	Spreading activation theory	Cosine and position based measure	Coefficient of normalization	Ontology
Oliveira et al. (2013)	Personalization of user interface in transport	Ontology and model-driven architecture (MDA)	Ontology	Edge Distance	–	Ontology
CBR-Ontology and Choquet integral (new approach)	Urban freight transport	SWRL	Ontology + CBR + SWRL	Textual and numerical measure	Choquet integral	Ontology and case base

Table 9
Comparison between various approaches used for personalization itinerary search in the literature.

Approach	Features					
	Domain of applications	Methods of personalization	Technique of reasoning	Source of knowledge	Similarities measures	Tool of criteria aggregation
Niaraki and Kim (2009)	Public transport	Content method	–	Ontology	Not mentioned	AHP
Nadi and Delavar (2011)	Public transport	Content method	–	–	Not mentioned	OWA
CBR and the AHP (Bouhana et al., 2011)	Public transport: multi-modal	Content method	CBR	CBR	Euclidian measure	AHP
CBR and the Choquet integral (Bouhana et al., 2013)	Public transport: multi-modal	Content method	CBR	CBR	Numerical measure	Choquet integral
CBR-Ontology and Choquet integral (new approach)	Urban freight transport	SWRL	Ontology + CBR + SWRL	Ontology and Case base	Textual and numerical measure	Choquet integral

– In Jiang and Tan (2009) work, the authors developed an ontology-based user model, called user ontology, its aim is to capture the user interest and preferences for providing a personalized document retrieval services. One of the main disadvantages of their method is their system's inability to handle increased complexity due to the growth of user ontology. However, for an information retrieval system the user profile is constantly in perpetual evolution which further complicates the task. For this reason our proposed method of personalization performs better in this kind of situation.
– In the approach proposed by Oliveira et al. (2013), the authors used the Ontology as source of knowledge to provide vocabulary and facilitate the information exchange and generate a personalized user interface (UI) for transportation interactive systems domain. The authors used Model-Driven Architecture (MDA) to personalize in the integrative system. The model of user profile considered in that approach is very generic is not pertinent because two users having the same demographic information do not necessarily have the same preferences. For generating a better personalized interactive user interfaces SWRL rules can perform better in personalizing the content than MDA. Also, the ontology defined and used in this proposition was limited and could not deal with the problem of travel planning generically.
– Comparing our new system to the previous one (Bouhana et al., 2013), the system describe herein suggests a new method of personalization by using the SWRL rules and solving the cold start issue encountered in the traditional method of personalization used in Bouhana et al. (2013). Indeed, the efficiency of this system decreases due to the problem of cold start: the system suffers too much in knowledge acquisition in the field of transport and especially in city logistics. It is inconvenient and inefficient for users to retrieve cases from heterogeneous sources in such a way. The process of inference results in Case base Knowledge systems those are not fully trusted since this affects the relevance and efficiency of the system results. For this raison, we added to our previous system a new external source of knowledge the GenCLOn ontology to extract all the relevant information and criteria of preferences about the user in order to build a strong knowledge base to overcome this problem and to further enhance the system's performance.

For the technique of reasoning or inference in our new approach, we use the ontology concept and the CBR tool to supports the OWL language and SWRL rules in the inference and reasoning process for enhancing the quality and the process of personalization. This cooperation allows our system to function as an expert system. The combination of two types of reasoning make our system stronger than those systems which use only one reasoning support (Bouhana et al., 2013; Jiang & Tan, 2009; Oliveira et al., 2013).

5.2. Comparison with other itinerary search systems

Only a relatively small amount of research covering the problem of personalization of itinerary search can be found in the literature. We found in the literature only few papers dedicated to the personalization of route planning for passenger (Nadi & Delavar, 2011; Niaraki & Kim, 2009). Also, there is no system for itinerary search dedicated to resolve the problem of traffic congestion for urban freight transport; all existing systems are dedicated to passengers (Bouhana et al., 2010; Bouhana et al., 2011; Bouhana et al., 2013; Letchner et al., 2006. A comparison study between our new approach and the existing ones in the field of personalization itinerary search is illustrated in Table 9.

Table A
Example of case base generated from the GenCLOn ontology and Paris open data.

Case	Origin–destination address			User preferences criteria deduces from SWRL rules					
	Shipper address	Carrier address	Receiver address	C_1:Time (mins)	C_2: Distance (km)	C_3:Vehicle capacity weight (tons)	C_4: Consumption fuel (L)	C_5:Vehicle emission pollution CO_2	C_6:Transport Cost (Euro)
1	4 RUE D ALGER 75001 France	1 RUE DE L ARBRE SEC 75001 France	117 RUE DE COURCELLES 75017 France	16	4.7	Vehicle < 3, 5	1.992	422.4	31.0
2	2 RUE DE L AMIRAL DE COLIGNY 75001 France	15 RUE DE L ARBRE SEC 75001 France	120 BOULEVARD DE COURCELLES 75017 France	17	5.7	Vehicle > 3, 5	3.188	475.2	46.2
3	9 RUE DE VALOIS 75001 France	18 RUE MONSIEUR LE PRINCE 75006 France	2 RUE GUSTAVE CHARPENTIER 75017 France	22	14.7	Truck	6.968	712.8	184.0
4	40 RUE DE VIARMES 75001 France	38 RUE MONSIEUR LE PRINCE 75006 France	14 RUE GUSTAVE CHARPENTIER 75017 France	21	14.6	Vehicle < 3, 5	4.752	422.4	86.0
5	3 PLACE DES VICTOIRES 75001 France	1 RUE DE MONTFAUCON 75006 France	11 RUE GUSTAVE DORE 75017 France	21	6.2	Vehicle > 3,5	2.53	475.2	59.5
6	5 RUE MONTMARTRE 75001 France	18 RUE D ARTOIS 75008 France	79 RUE JOUFFROY D ABBANS 75017 France	7	1.9	Truck	2.809	712.8	67.0
7	14 RUE MONTMARTRE 75001 France	39 RUE DE BERRI 75008 France	85 RUE JOUFFROY D ABBANS 75017 France	5	1.5	Truck	2.701	712.8	63.0
8	24 RUE MONTMARTRE 75001 France	3 RUE BERRYER 75008 France	97 RUE JOUFFROY D ABBANS 75017 France	5	1.5	Vehicle < 3, 5	2.056	422.4	33.0
9	30 RUE MONTMARTRE 75001 France	6 RUE DE LA BIENFAISANCE 75008 France	98 RUE JOUFFROY D ABBANS 75017 France	5	1.9	Vehicle > 3, 5	1.954	475.2	37.1
10	2 RUE D ALEXANDRIE 75002 France	24 RUE DE LA CHAUSSEE D ANTIN 75009 France	52 RUE LAUGIER 75017 France	14	4.4	Vehicle < 3, 5	1.992	422.4	31.0
11	6 RUE D ALEXANDRIE 75002 France	40 RUE DE CLICHY 75009 France	58 RUE LAUGIER 75017 France	11	3.5	Vehicle < 3, 5	2.152	422.4	36.0
12	9 RUE D ALEXANDRIE 75002 France	25 RUE DROUOT 75009 France	92 RUE LAUGIER 75017 France	16	4.8	Vehicle < 3, 5	2.056	422.4	33.0
13	12 RUE D ALEXANDRIE 75002 France	4 RUE DU FAUBOURG MONTMARTRE 75009 France	1 RUE LE CHATELIER 75017 France	17	5.5	Vehicle > 3, 5	2.368	475.2	53.2
14	11–13 RUE D ALEXANDRIE 75002 France	2 RUE FLECHIER 75009 France	9 RUE LE CHATELIER 75017 France	14	4.8	Vehicle < 3, 5	2.232	422.4	38.5
15	43 RUE DE L ARBRE SEC 75001 France	17 RUE DE BEAUJOLAIS 75001 France	121 RUE DE COURCELLES 75017 France	14	4.1	Vehicle < 3, 5	1.928	422.4	29.0
16	6 RUE DE CASTIGLIONE 75001 France	27 RUE D ARGENTEUIL 75001 France	98 RUE DES DAMES 75017 France	13	2.8	Vehicle < 3, 5	1.591	422.4	18.5
17	20 RUE DAUNOU 75002 France	29 RUE VICTOR MASSE 75009 France	83 RUE LEMERCIER 75017 France	8	2.2	Vehicle < 3, 5	1.704	422.4	22.0
18	39 RUE DUSSOUBS 75002 France	15 RUE D ALSACE 75010 France	88 RUE LEMERCIER 75017 France	15	4	Vehicle > 3, 5	2.17	475.2	45.5
19	18 RUE ETIENNE MARCEL 75002 France	8 RUE DU BUISSON SAINT LOUIS 75010 France	89 RUE LEMERCIER 75017 France	19	5.9	Vehicle < 3, 5	2.36	422.4	42.5
20	26 RUE ETIENNE MARCEL 75002 France	3 RUE DU CHATEAU D EAU 75010 France	95 RUE LEMERCIER 75017 France	19	5.2	Vehicle > 3, 5	2.206	475.2	46.89
21	2 RUE CATINAT 75001 France	25 RUE COQUILLIERE 75001 France	104 RUE DES DAMES 75017 France	15	3.5	Vehicle > 3, 5	1.702	475.2	27.3
22	50 RUE ETIENNE MARCEL 75002 France	42 AVENUE CLAUDE VELLEFAUX 75010 France	97 RUE LEMERCIER 75017 France	18	5.4	Truck	3.349	712.8	87.0
23	5 RUE COQ HERON 75001 France	12 RUE DES HALLES 75001 France	106 RUE DES DAMES 75017 France	17	4.4	Vehicle < 3, 5	1.864	422.4	27.0
24	27 RUE COQUILLIERE 75001 France	1 RUE ROUGET DE LISLE 75001 France	116 RUE DES DAMES 75017 France	11	2.8	Vehicle > 3, 5	1.792	475.2	30.8
25	19 RUE DE LA PAIX 75002 France	17 RUE MARTEL 75010 France	1 RUE MARCEL RENAULT 75017 France	19	5.4	Truck	3.16	712.8	80.0
26	4 RUE DE PALESTRO 75002 France	27 RUE DE ROCROY 75010 France	9 PLACE DU MARECHAL JUIN 75017 France	14	4.9	Vehicle > 3, 5	2.296	475.2	50.39
27	10 RUE CROIX DES PETITS CHAMPS 75001 France	2 RUE D ABOUKIR 75002 France	1 RUE DAUBIGNY 75017 France	15	4.2	Vehicle > 3, 5	1.918	475.2	35.7
28	6 RUE DE PALESTRO 75002 France	199 QUAI DE VALMY 75010 France	6 RUE MARGUERITE LONG 75017 France	16	6.8	Truck	3.646	712.8	98.0
29	16 RUE DE PALESTRO 75002 France	24 RUE ALEXANDRE DUMAS 75011 France	3 RUE MARIOTTE 75017 France	24	7.5	Vehicle > 3, 5	3.16	475.2	84.0

Note that our previously developed systems of personalization (Bouhana et al., 2011; Bouhana et al., 2013) suffer from the problem of cold start and knowledge acquisition. To overcome this problem we integrated in the system proposed in this paper an external source of knowledge, the city logistic ontology, which is also the first ontology specifically designed for the field of urban freight transport. It endows the system with the ability to capture the dynamic behaviors of individual stakeholders and their interconnection. Further, the integration of the GenCLOn ontology (Anand et al., 2012) with the CBR tool resulted in an expert system that is more powerful than the previously proposed one (Bouhana et al., 2011; Bouhana et al., 2013; Nadi & Delavar, 2011; Niaraki & Kim, 2009) Further, it has the ability to handle a big amount of heterogeneous data thanks to the inference power the SWRL rules and strong reasoning ability of the CBR tool.

Comparing our similarities measures concept to the one designed by Nadi and Delavar (2011), Niaraki and Kim (2009), we should note that the authors did not use a similarities measures rather a multi-criteria technique like the AHP and Ordered Weighted Averaging (OWA) to integrate assessment of the decision maker to assist the user. The major disadvantage of the AHP method is the limitation of the use of the nine-point scale. Sometimes, the decision-maker might find it difficult to distinguish alternatives and tell for example whether one alternative is 6 or 7 times more important than the other. Another limitation for these two methods the AHP and OWA are often noted for their inability to sufficiently handle the inherent uncertainty associated with the mapping of the decision maker perception. For Ordered Weighted Averaging (OWA) (Nadi & Delavar, 2011) this method is inefficient when using same criteria that are time dependent, such as traffic congestion. For this reason we used the Choquet integral as a method of aggregation to improve the step of similarities measures because this latter is a powerful method of aggregation. The main advantages of this approach are its ability to quantify qualitative and quantitative criteria while taking into account the interaction between criteria. Further, it can handle any kind of uncertain or time depend criteria such as traffic congestion because in the Choquet integral model, where criteria can be dependent, a fuzzy measure (Sugeno, 1974) is used to define a weight on each combination of criteria. Further, this tool can provide the user with results that can optimize simultaneously various qualitative and quantitative criteria at the same time hence improving the similarity measure in the CBR cycle and providing better performance.

Though, some methods for similarity measures can be found in practical CBR applications, in-depth study when faced with an information retrieval system which involves numerical values of attributes and textual documents in the research process is still lacking. In our proposed approach we tried to develop new hybrid similarity measures for case retrieval that combines two formats of attributes, numerical and textual. For the numerical values of attributes, we use the formula developed by Bouhana et al. (2013) and for the textual formula we use the Cosine similarity coefficient between the two vectors (Text-features) for each case.

6. Conclusion

This paper presents a novel approach for personalization in itinerary search that has the potential to effectively manage urban freight movement and alleviate congestion in transport systems. The approach is based on the integration of ontology supported Case Base Reasoning and a Multi-Criteria Decision Making approach with the Choquet integral. The proposed framework improves the quality of personalization by suggesting a new search method based on the semantic web rule language (SWRL). This latter improves the step of case representation and enhances the quality of the retrieving process. Further, the integration of the semantic web rule language into the new method of personalization plays a key role in capturing and satisfying the needs and preferences of each stakeholder in a given context. The proposed approach was illustrated using an application in the field of urban freight transport urban freight transport. The ability of the proposed system tailor the search to stakeholders needs, improve the accuracy of case retrieval and facilitate the search process are among the main positive features of the proposed intelligent decision support system.

In our future work, we propose to consider the following research directions: (1) improve the steps of case adaption by creating additional knowledge to ensure a solution is provided even when the case base does not have enough historical cases stored in the case base, (2) improve the user interface in order to support natural language query processing, (3) use machine learning techniques for the ontology enrichment process in order to deal with ontology growth, (4) find ways to enable our system to deal with massive real time traffic information and effectively analyze required information with ontology.(5) expand the applications of the proposed approach to other complex systems such as e-commerce, medical prescription, warehouse automation.

Appendix A

See Table A.

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