RFID-assisted Product Delivery in Sustainable Supply Chains: A Knowledge-based Approach

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Abstract. The paper proposes an integrated framework which uses knowledge representation theory and languages to annotate relevant product information in a semantically rich and unambiguous fashion so disclosing several added-value services in multiple supply chain stages, without depending on a back-end infrastructure. EPCglobal RFID protocol standard has been extended and further applied in an innovative supply chain model where production, packaging and logistics have a reduced ecological impact. Particularly, on-product information are leveraged in a more general Intelligent Transport System (ITS) framework enabling advanced delivery scheduling and product tracking.

1 Introduction

Supply chains are articulated organisms involving organizations aimed at transferring either products or services from a supplier to a customer. Nowadays, a successful supply chain should more and more rely on an extended collaboration and integration among component actors belonging to the productive and/or logistic network. Hence, information has assumed an increasing strategic role in production, logistics and marketing. From this standpoint, Radio-Frequency IDentification (RFID) is seen as a perspective key technology. RFID enables radio interconnection of *transponders* –hosting information associated to the goods to be identified– with *interrogators* able to extract carried data. EPCglobal consortium[1] is one of the most active subjects involved in the mission of a worldwide diffusion of RFID standards. Goods management during the delivery stage of a supply chain is a complex process with criticisms tied to the packaging of different and possibly incompatible products over multiple vehicles. Several systems for product tracking which also enable integrity check have been proposed to improve process quality in supply chains exploiting RFID technology [10]. Nevertheless, the original identification mechanism –exclusively providing "true/false" replies– appears as too restrictive for advanced applications. Furthermore, RFID-based technology usually relies on a stable and fixed back-end which makes every solution only partially applicable to intrinsically volatile contexts such as the transportation and delivery ones. On the contrary, given the increased storage availability (up to several kBs [1]) modern transponders provide, RFID could provide further automation of actions and processes

[1] EPCglobal, http://www.epcglobalinc.org

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related to item sorting and shipment, helping to prevent human errors and assist users in decision making.

The paper presents a framework which exploits knowledge representation theoretical studies to annotate tagged objects which can so describe themselves in several supply chain stages, without depending on a back-end infrastructure and adhering to the Ubiquitous Computing paradigm [22]. Canonical EPCglobal RFID identification has been extended [16, 7], providing semantic-based value-added services whose deployment and outcomes have been grounded in an advanced "green supply chain" setting. Semantic Web languages such as OWL[2] and DIG [3] are used for building the linguistic and semantic infrastructure underlying a networked and capillary exchange of information among chain actors aimed at overcoming restrictions imposed by existing RFID solutions. Key features are: (i) to leverage a hybrid wireless communication platform for enabling a distributed, backward compatible data management system; (ii) to provide decision support exploiting semantic-based annotations accompanying and describing goods aimed at optimizing the reliability and sustainability of the whole supply process. Case studies and simulations have evidenced usefulness and feasibility of the framework. Distinctive features of this model enabled it to support several RFID-based applications integrating Knowledge Representation techniques and technologies to improve data management and business processes. The proposed approach has been applied and tested in an innovative RFID-enabled supply chain model. On-product information have been exploited in a more general Intelligent Transport System (ITS) framework enabling advanced context-aware delivery and tracking of fruits and vegetables. Integrity checks have been also introduced for process analyses, according to the total quality management vision. Noteworthy is the capability to enable pollution-aware dynamic path calculation, fully automated goods compatibility management in delivery, truck fleet intelligent routing.

The remaining of the paper is structured as follows. In the next section relevant related work is surveyed. Section 3 outlines the framework, explaining the followed approach, Section 4 illustrates the system architecture thanks to a reference scenario and finally conclusion and future work terminate the paper.

2 Related Work

This section surveys essential related work concerning RFID technology in supply chain management and ITS for building more efficient and sustainable goods delivery.

2.1 RFID

Benefits of RFID technology in supply chain management include timeliness, accuracy and completeness [9]. In latest years, they are becoming widely acknowledged not only in distribution and warehousing, but also in the retail and post-sales domains. The largest retail groups are mandating the adoption of interoperable technology solutions

[2] OWL Web Ontology Language, version 2, W3C Recommendation 27 October 2009, http://www.w3.org/TR/owl2-overview/

to commercial partners [18]. De *et al.* [6] first introduced a system for real time tracking of items in a ubiquitous context. That work can be considered a reference for current technological architectures for supply chain management, endorsed by worldwide special interest groups such as the EPCglobal consortium [19].

Nevertheless, RFID has received relatively little attention as an information conveyor that can directly increase business process awareness and thus improve both performance analysis and support to decision processes. Most current approaches for run-time processing of RFID data in supply chains [21, 2] manage only very basic information, namely raw *(EPC, location, time)* triples produced by RFID readers, where EPC (Electronic Product Code) is the unique product identifier, while location and time mark each RFID reading event.

In order to improve decision-making capabilities and information sharing across boundaries of partner organizations, it is important to enable RFID-based run-time object/group discovery facilities in decentralized and pervasive contexts. In each supply chain node, it should be possible to process expressive requests –in terms of shared and formal domain vocabularies– without depending on a central fixed information infrastructure. In our proposal, we adapt Semantic Web techniques and formalisms to RFID-based supply chains. The basic goal is to fully characterize products equipped with RFID tags by means of annotations in semantic languages such as RDF[3], OWL and its equivalent DIG. By means of formal ontologies, knowledge about a specific domain can be modeled, shared and exploited to derive new implied information from the one stated within metadata associated to each resource.

Our proposal for semantic-enabled RFID [16] allows tags to contain a structured and detailed description of product features, endowed with unambiguous and machine-understandable semantics. Semantically annotated information is encoded in a compact way by means of an algorithm aimed at efficient compression of XML-based ontological languages [17]. Tag memory structure is extended in order to store the additional information required for semantic-based object discovery. Additional TID (Tag Identification) memory space stores a 16-bit word for optional protocol features (currently only the most significant bit is used to indicate whether the tag is semantic-enabled or not, other bits are reserved for future uses) and a 32-bit Ontology Universally Unique Identifier (OUUID) marking the ontology with respect to the description stored in the tag is expressed. The encoded product annotation and contextual parameters (depending on the specific application) are stored, instead, within the User memory bank. This is possible by adopting increasingly available models of passive EPCglobal UHF Class 1 Generation 2 RFID tags with several kilobits of available memory, such as TEGOTag[4] or Intelleflex IF602[5]. The air interface protocol for Gen 2 RFID systems is exploited but neither new commands nor modifications to existing ones are introduced, thus keeping full backward-compatibility with current RFID readers. In our simulations, we obtained a reading rate of about 10 tags/s, which is comparable with products Gen 2 standard. Further efficiency considerations in terms of data compression, response time and mem-

[3] RDF (Resource Description Framework) Primer, W3C Recommendation, 10 February 2004, http://www.w3.org/TR/rdf-primer/

[4] TEGOTag, http://www.tegoinc.com/products/products_tegotag.php

[5] Intelleflex Integrated RFID Tags, http://www.intelleflex.com/pdf/datasheet.c1g2ic.pdf

ory usage are reported in [17, 7]. In this way goods auto-expose their description to any RFID-enabled computing environment is reached. This enables decentralized approaches for context-aware application solutions, based on less expensive and more manageable mobile ad-hoc networks. Furthermore, by combining standard and non-standard inference services in Description Logics [4], several semantic-based matchmaking schemes can be designed to meet goals and requirements of specific processes and applications within a supply chain.

Few other proposals for semantic-based annotation of physical products can be found in the literature. In [20] the adoption of the Part Libraries (PLIB) standard ISO 13584 was proposed and an XML Schema for data-on-tag storage was developed. Even though the benefits of standardization are clear, the chosen standard provides only a very rudimentary taxonomy, lacking explicit semantics for product characteristics. A solution based on Semantic Web languages was proposed in [12] for ubiquitous commerce environments. In that case, however, RFID tags stored only a product code, which was used as a key to retrieve the corresponding RDF annotation from a central back-end information system. This approach, inherited from traditional RFID applications, poses major architectural and organizational challenges for information sharing in complex multi-party supply chains. Conversely, our core idea is that, as physical products flow among supply chain partners, *ipso facto* relevant high-level information about them is conveyed [16] and can be exploited for meaningful business analysis at different levels [7]. Recent studies [8, 23] highlighted factors in favor of *data-on-tag* approaches w.r.t. traditional *data-on-network* ones. Mainly, fast data access is essential when the IT infrastructure must meet real-time requirements, avoiding bottlenecks related to back-end queries. Other benefits include: avoiding single points of failure; additional security controls over information by consumer and companies; cost reductions in establishing and maintaining network infrastructures.

2.2 Supply Chain and ITS

One of the most important factors in supply chain management is efficient control of product delivery through vehicle routing. Vehicle routing problem (VRP) has always been a fundamental problem in network optimization research and it is an important objective of Intelligent Transport Systems (ITS). It was first introduced by Dantzig and Ramser [5] and it can be defined as the problem of finding the fleet route planning that serves as many jobs as possible at the least cost. Since that, many VRP types were studied and classified based on additional problem constraints required by different applications, and many algorithms and methods have been developed.

Ramachandran [15] developed an integer linear programming (ILP) model for the design of routes that satisfy the load compatibility constraints for a fleet of vehicles, transporting different types of goods. ILP and MILP (mixed integer linear programming) are –along with Markov processes and genetic algorithms– the most widespread approaches to solve this kind of optimization problems. Nevertheless, these methods require that modeling and execution are performed in off-line mode. It is hard to adapt the model to real-time applications and whenever constraints change.

In [11] an optimal solution was proposed for a VRP based on real-time environment information of perishable goods, exploiting continuous monitoring of RFID tags located in the refrigerated cargo and of road traffic flow information. The approach, however, requires large resources to compute the optimal solution. A further common shortcoming of purely mathematical and statistical methods is that they cannot provide explanation for outcomes, which is important to strengthen user trust in the system.

Mahr *et al.* [13] introduced a distributed architecture based on truck agents and order agents (containers) in a real world scenario constrained by uncertain job arrival time. The system does not need any central monitoring and delegates decision making at local level. Benefits of the distributed approach include better handling of local information and quicker adaptive reaction to unpredictable order arrivals. They apply to our current proposal as well.

Approaches at semantic-enhanced route planning have recently been attempted. Niaraki *et al.* [14] introduced a technique which uses ontologies to annotate each road segment with both user preferences and context point of view, in order to find customized routes that best match specific needs. The solution was focused on personal route planning, hence the model and the process are not easily adaptable to the requirements of supply chain VRP scenarios.

3 Framework and Approach

We propose an RFID-based delivery management system extending classic supply chain organization and shipment models using techniques and technologies for smart tagging [16] and a semantic-based decision support [4]. Due to space constraints, the reader is referred to cited works for an explanation of used Descritpion Logic languages and algorithms. Product packages (tagged with RFID transponders conforming to the EPC-global Class 1, Generation II UHF standard) and vehicles are accompanied by an OWL-DL compressed annotation [17] which include relevant object properties/purposes and vehicle features, according to a reference ontology. Product characteristics comprise relevant item properties, delivery requirements (*e.g.*, micro-climate and storage needs or possible security measures) and potential incompatibility constrains referred to other nearby products. Vehicle descriptions will contain general truck specifications along with freight equipment information and the remaining load availability.

Starting from a single logistic unit where delivery of available goods has to be planned, a semantic-based matchmaking process allows a smart allocation process aiming at maximizing vehicle carrying capability also minimizing travel distance. In order to take into account item-item and item-vehicle constraints in shipment schedule we make use of a lightweight version of non-monotonic inferences [4], which automatically detect the best load-truck associations by taking into account semantic compatibility degree of goods among them and with vehicles. Such a system aims to reduce response times in delivery decisions and improve efficiency of product allocation. Particularly, the proposed approach can be effectively integrated into existing supply chain management systems extending already supported technology. It allows to solve on-truck product allocation issues, ensuring products quality to destination (minimizing risks due to incompatibility among closely delivered goods and reducing delivery times).

A system architecture schema is shown in Figure 1. Each tag is tracked within a warehouse by either fixed RFID readers deployed in strategic locations or handheld

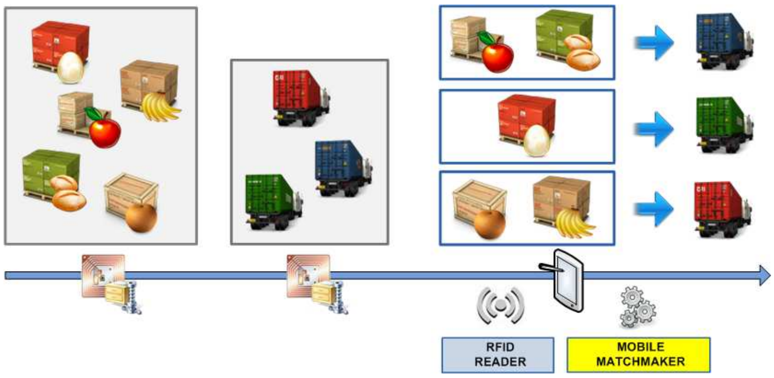

Fig. 1. System Architecture.

ones. Truck information can be read when vehicles arrive at the stocking center, whereas product tags are scanned individually before storage. Data extracted from RFID tags are decompressed and sent to a mobile matchmaker which performs inference services.

Given a shipment order, the warehouse unit can automatically build a set of products to be sent to each customer by means of a on-the-fly semantic matchmaking between product information and truck features. The matchmaking process has to satisfy the following goals.

– Products can be allocated only to trucks fulfilling their transportation requirements, in terms of needed loading/unloading equipment, containers and internal environmental conditions (*e.g.*, temperature, humidity, lighting).
– Different products cannot travel together if they have negative mutual effects. A typical case concerns *climateric* fruits (*e.g.*, apples), which can influence ripening of other fruits and vegetables.
– Product destinations must be taken into account, in order to avoid inefficient route planning.

We suppose all goods which will compose a shipment are available in a single warehouse and a delivery request has been addressed to retail endpoints, including different items to be delivered with related destination and required quantity. A semantic-based product allocation process is performed in the warehouse. Elements of the optimization problem can be formalized as follows:

– The set of stored products $P = \{p_1, p_2, \dots p_n\}$. In addition to semantically annotated description referring to an ontology $\mathcal{T}$, quantity q_i and destination location l_i are associated to each product, based on orders received from partner supply chain nodes (*e.g.*, retail stores).
– The set of available vehicles $V = \{v_1, v_2, \dots v_m\}$. Besides the semantically annotated description, the freight capacity is associated to each vehicle.
– l_0 is the warehouse location.
– A set $T = \{\theta_1, \theta_2, \dots \theta_n\}$ is derived from P. For each product $p_i \in P$, the approximated angle θ_i of the line connecting the warehouse to the destination is computed as $\theta_i = arctan(\frac{lat(l_i)-lat(l_0)}{lon(l_i)-lon(l_0)})$.

– A threshold semantic distance value $0 < s < 1$ and a threshold angle θ_{max} are defined. The latter allows to avoid grouping products that have to be delivered toward very different directions.

Algorithm 1: Greedy algorithm for product clustering.

Algorithm: $clustering\,(\langle P, T, \mathcal{L}, \mathcal{T}\,\rangle)$
Require: $\mathcal{L}$ Description Logic, acyclic $\mathcal{T}$, $p_i \in P, i = 1, 2, \ldots n$ concept expressions in $\mathcal{L}$ satisfiable in $\mathcal{T}$.
Ensure: $G = \{G_1, G_2, \ldots G_k\}$ set of product compatibility groups.

$G := \emptyset$
$k := 0$
while $P \neq \emptyset$ **do**
  $k := k + 1$
  pick $p_i \in P$
  $G_k := \{p_i\}$
  $C_k := p_i$
  for all $p_j \in P, i \neq j$ **do**
    $\delta_\theta = \min_{(p_q \in G_k)}(|\theta_j - \theta_q|)$
    if $\delta_\theta <= \theta_{max}$ AND $(p_j \sqcap C_k)$ is satisfiable in $\mathcal{T}$ AND $\frac{\textit{rankPotential}\,(\langle \mathcal{L}, p_j, C_k, \mathcal{T}\rangle)}{\textit{rankPotential}\,(\langle \mathcal{L}, p_j, \top, \mathcal{T}\rangle)} <= s$ **then**
      $G_k := G_K \cap \{p_j\}$
      $C_k := \prod_{p_q \in G_k}(p_q)$
    end if
  end for
  $P := P \setminus G_k$
  $G := G \cap \{G_k\}$
end while
return G

The optimization strategy divides the problem into the following steps.

1. Product Clustering. For all available goods, the system verifies compatibility between product descriptions to cluster items in different *compatibility groups*. All products within each group present similar storage requirements and no compatibility constraints with other items are violated. The greedy bottom-up clustering Algorithm 1 is exploited. Remarks follow.

– As a preliminary route optimization feature, a product cannot join a group if its delivery direction is too different from all the other group elements. This check is implemented by comparing the minimum angle distance δ_θ to the threshold θ_{max}.
– The algorithm exploits *rankPotential* [4] to discover semantic conflicts between product characteristics/requirements and to evaluate product similarity among members of each cluster. It is important to note that the description of a group is semantically expressed as the logical conjunction of individual item descriptions (which is satisfiable by construction). Compatibility level is calculated by normalizing the semantic distance between each new element p_j and the current product group, as returned by *rankPotential* , w.r.t. the maximum possible *rankPotential* value for p_j, which is *rankPotential* $(\langle \mathcal{L}, p_j, \top, \mathcal{T}\rangle)$ and depends only on axioms in the reference ontology. The interested reader is referred to [4] for details.
– It is easy to see that the algorithm requires $O(n^2)$ *rankPotential* calculations.

2. Cluster Allocation. Properties of product groups are subsequently matched with descriptions of the delivery trucks, in order to find the most suitable vehicles for transport: *rankPotential* inference service is exploited again to measure the semantic distance of

Table 1. Orders list.

Orders	Delivery	Distance (km)	Quantity (kg)
Golden_Delicious	Barletta	53.75	500
Altamura_Bread	Foggia	117.06	300
Ostrich_Egg	Brindisi	105.30	200
Navelina	Lecce	139.67	300
Cavendish	Taranto	79.37	300

descriptions. At most nm *rankPotential* calculations are performed at this stage. The product group with lowest score (*i.e.*, the most compatible) is selected and inserted in the suggested vehicle.

3. Storage Optimization. Now a refinement process can be performed to maximize vehicle carrying capacity. If a vehicle is overfull (*e.g.*, because the product group total volume is larger than the vehicle storage space), the system splits the group and reallocates the exceeding portions to the vehicle with second best match score. Dually, the most empty vehicles are gradually unloaded and products are reallocated to partially full trucks, according to compatibility scores. Processing ends when all goods are allocated and vehicles have minimum carrying space waste.

4. Route Planning. Detailed route planning is executed at the beginning of the delivery trip. Mobile device on board of a vehicle acts as a navigation system. Since the previous step has grouped products with destinations along the same direction, in this step the route is planned by means of a very simple algorithm: delivery point are sorted according to increasing distance from the starting point. This approach resembles the well-known SCAN algorithm for hard disk drive access scheduling: it is very quick and simple to implement and, in our case, its approximation w.r.t. the optimal static route improves when destinations span a narrower angle w.r.t. the source.

More sophisticated route planning algorithms can be plugged into the framework, in order to minimize a cost estimation function that considers the overall economic and environmental impact of route distance, trip duration, road type, traffic estimation and truck load. Inference services upon semantically annotated information can be leveraged also in this step. Using openly available and editable map data such as OpenStreetMap[6], maps can be customized with additional metadata about road segments and points of interest, in order to better suit supply chain goals.

4 Case Study: Do not Compare Apples and Oranges!

In order to better explain the proposed framework and algorithms, let us consider a practical example. *A food cooperative in Apulia has adopted semantic-based supply chain management process. Each production center ships goods to a distribution center, located in Bari. From there products have to be delivered to shopping centers located in different towns.* The orders list is showed in Table 1. Figure 2 provides a visual representation of the geographic area.

The problem is determining the most efficient method to ship the products so that they are delivered without quality loss. As described previously, our proposed framework uses mobile devices equipped with RFID reader. *Warehouse operators, endowed*

[6] OpenStreetMap project, http://www.openstreetmap.org/

Fig. 2. Map of supply chain nodes in our case study.

$\mathtt{High\_Temperature} \sqsubseteq \mathtt{Controlled\_Temperature}$
$\mathtt{Low\_Temperature} \sqsubseteq \mathtt{Controlled\_Temperature}$
$\mathtt{Room\_Temperature} \sqsubseteq \mathtt{Temperature}$
$\mathtt{Medium\_Humidity} \sqsubseteq \mathtt{Controlled\_Humidity}$
$\mathtt{Controlled\_Humidity} \sqsubseteq \mathtt{Humidity}$
$\mathtt{High\_Oxygen} \sqsubseteq \mathtt{Controlled\_Oxygen}$
$\mathtt{Low\_Oxygen} \sqsubseteq \mathtt{Controlled\_Oxygen}$
$\mathtt{Natural\_Oxygen} \sqsubseteq \mathtt{Oxygen}$
$\mathtt{Indirect\_Lighting} \sqsubseteq \mathtt{Lighting\_Source}$
$\mathtt{Pallet\_Rack} \sqsubseteq \mathtt{Stocking\_Equipment}$
$\mathtt{Shelving} \sqsubseteq \mathtt{Stocking\_Equipment}$
$\mathtt{Hydraulic\_Drill} \sqsubseteq \mathtt{Transport\_Equipment}$
$\mathtt{High\_Maturity} \sqsubseteq \mathtt{Maturity}$
$\mathtt{High\_Fragrance} \sqsubseteq \mathtt{Fragrance}$
$\mathtt{disj(High\_Oxygen, Medium\_Oxygen, Low\_Oxygen)}$
$\mathtt{disj(Controlled\_Humidity, Natural\_Humidity)}$
$\mathtt{disj(Direct\_Lighting, Indirect\_Lighting)}$
$\mathtt{disj(High\_Maturity, Low\_Maturity)}$
$\mathtt{Medium\_Temperature} \sqsubseteq \mathtt{Controlled\_Temperature}$
$\mathtt{Controlled\_Temperature} \sqsubseteq \mathtt{Temperature}$
$\mathtt{High\_Humidity} \sqsubseteq \mathtt{Controlled\_Humidity}$
$\mathtt{Low\_Humidity} \sqsubseteq \mathtt{Controlled\_Humidity}$
$\mathtt{Natural\_Humidity} \sqsubseteq \mathtt{Humidity}$
$\mathtt{Medium\_Oxygen} \sqsubseteq \mathtt{Controlled\_Oxygen}$
$\mathtt{Controlled\_Oxygen} \sqsubseteq \mathtt{Oxygen}$
$\mathtt{Direct\_Lighting} \sqsubseteq \mathtt{Lighting\_Source}$
$\mathtt{ISO\_Pallet\_Rack} \sqsubseteq \mathtt{Pallet\_Rack}$
$\mathtt{Plastic\_Shelving} \sqsubseteq \mathtt{Shelving}$
$\mathtt{Stocking\_Equipment} \sqsubseteq \mathtt{Equipment}$
$\mathtt{Transport\_Equipment} \sqsubseteq \mathtt{Equipment}$
$\mathtt{Low\_Maturity} \sqsubseteq \mathtt{Maturity}$
$\mathtt{Low\_Fragrance} \sqsubseteq \mathtt{Fragrance}$
$\mathtt{disj(Controlled\_Temperature, Room\_Temperature)}$
$\mathtt{disj(Controlled\_Oxygen, Natural\_Oxygen)}$
$\mathtt{disj(Shelving, Pallet\_Rack)}$
$\mathtt{disj(High\_Fragrance, Low\_Fragrance)}$
$\mathtt{Ripe\_Product} \sqsubseteq \exists \mathtt{Has\_Climateric\_Maturation\_Degree} \sqcap \forall \mathtt{Has\_Climateric\_Maturation\_Degree.High\_Maturity}$
$\mathtt{Unripe\_Product} \sqsubseteq \exists \mathtt{Has\_Climateric\_Maturation\_Degree} \sqcap \forall \mathtt{Has\_Climateric\_Maturation\_Degree.Low\_Maturity}$
$\mathtt{disj(High\_Temperature, Medium\_Temperature, Low\_Temperature)}$
$\mathtt{disj(High\_Humidity, Medium\_Humidity, Low\_Humidity)}$

Fig. 3. Axioms in the food transport ontology used in the case study

with RFID-enabled handheld devices, can locally manage the allocation problem and they can also monitor automated system process behavior. For each tagged product, the following information is retrieved via RFID: EPC code, unique identifier of the reference ontology [16], semantic-based annotation in compressed OWL-DL format and delivery information, expressed with geographic coordinates.

In our supply chain case study, goods and vehicles are described according to an example ontology devised for product management. Figure 3 shows a relevant excerpt of it. Each RFID tag contains a semantic description w.r.t. the reference ontology, summarizing both quality characteristics and storage and transport requirements. Descriptions corresponding to Table 1 follow:

Golden_Delicious: $Apple \sqcap \forall Has\_Colour.Yellow \sqcap \exists Has\_Colour \sqcap \forall Has\_Quality.Ordinary\_Quality \sqcap \exists Has\_Quality \sqcap \forall Storage\_Temperature.Room\_Temperature \sqcap \exists Storage\_Temperature \sqcap \forall Storage\_Humidity.Medium\_Humidity \sqcap \exists Storage\_Humidity \sqcap \forall Storage\_Oxygen.Natural\_Oxygen \sqcap \exists Storage\_Oxygen \sqcap Unripe\_Product.$

Altamura_Bread: $Bread \sqcap \forall Has\_Quality.Ordinary\_Quality \sqcap \exists Has\_Quality \sqcap \forall Storage\_Temperature.Room\_Temperature \sqcap \exists Storage\_Temperature \sqcap$

$\forall\ Storage\_Humidity.Medium\_Humidity \sqcap \exists\ Storage\_Humidity \sqcap \forall\ Storage\_Oxygen.Natural\_Oxygen \sqcap \exists\ Storage\_Oxygen \sqcap Low\_Fragrance.$

Ostrich_Egg: $Egg \sqcap \forall\ Has\_Colour.White \sqcap \exists\ Has\_Colour \sqcap \forall\ Has\_Quality.Top\_Quality \sqcap \exists\ Has\_Quality \sqcap \forall\ Storage\_Temperature.Low\_Temperature \sqcap \exists\ Storage\_Temperature \sqcap \forall\ Storage\_Humidity.Low\_Humidity \sqcap \exists\ Storage\_Humidity \sqcap \forall\ Storage\_Oxygen.Low\_Oxygen \sqcap \exists\ Storage\_Oxygen \sqcap Low\_Fragrance.$

Navelina: $Orange \sqcap \forall\ Has\_Colour.Orange \sqcap \exists\ Has\_Colour \sqcap \forall\ Storage\_Temperature.Room\_Temperature \sqcap \exists\ Storage\_Temperature \sqcap \forall\ Storage\_Humidity.Medium\_Humidity \sqcap \exists\ Storage\_Humidity \sqcap High\_Fragrance.$

Cavendish: $Banana \sqcap \forall\ Has\_Colour.Yellow \sqcap \exists\ Has\_Colour \sqcap \forall\ Has\_Quality.Ordinary\_Quality \sqcap \exists\ Has\_Quality \sqcap \forall\ Storage\_Temperature.Room\_Temperature \sqcap \exists\ Storage\_Temperature \sqcap \forall\ Storage\_Humidity.Medium\_Humidity \sqcap \exists\ Storage\_Humidity \sqcap \forall\ Storage\_Oxygen.Natural\_Oxygen \sqcap \exists\ Storage\_Oxygen \sqcap Ripe\_Product.$

Warehouse operator uses the mobile logic-based matchmaker embedded in her device to identify groups of compatible products. As previously said, each cargo should be composed of products that do not interfere with each other, causing a general quality loss. In order to accomplish this, the system adopts a greedy approach, applying the algorithm presented in the previous section. We better explain this process seeing how it is applied to our example.

1. At the beginning, **Golden_Delicious** is added to $cargo_1$ group.
2. Its semantic description is compatible with **Altamura_Bread**, because all atomic concepts, universal quantifiers and unqualified number restrictions on roles are compatible. Furthermore, products are also compatible in terms of truck direction, because the angle difference between delivery locations is about 10 degrees (with a supposed threshold of 60 degrees). For this reason it is added into $cargo_1$ group.
3. Then **Ostrich_Egg** is matched against $cargo_1$: a semantic incompatibility is returned, because some storage requirements are in conflict, *e.g.*, storage temperature is different.
4. Next, $cargo_1$ is semantically compatible with **Navelina**, but they are not compatible w.r.t. truck direction, because the angle between destinations is more than 160 degrees. Finally, it is not compatible with **Cavendish**, because both are climacteric and so they can travel in the same cargo only if they are in the same ripening stage, but in this case apples are ripe while bananas are unripe.

If needed, the system can show inconsistencies to operator by means of the Concept Contraction inference service offered by the reasoning engine [4]. Outcome explanation is a very important feature and a unique advantage of approaches based on knowledge representation.

The same process is repeated with remaining products to build other groups. The system finally returns the following groups: $cargo_1$ = {Golden_Delicious, Altamura_Bread}; $cargo_2$ = {Ostrich_Egg}; $cargo_3$ = {Navelina, Cavendish}.

Next phase consists of the allocation of each cargo on a compatible truck. The RFID reader retrieves the semantic descriptions stored on tags associated with trucks and begins a matchmaking process. For example, let us consider the following truck descriptions in the warehouse:

Table 2. Matchmaking results between cargoes and trucks.

	$cargo_1$	$cargo_2$	$cargo_3$
$truck_1$	0.132	n.c.	0.284
$truck_2$	0.154	n.c.	0.324
$truck_3$	n.c	0.432	n.c

Truck_1: $\forall$ $Storage\_Temperature.Room\_Temperature$ $\sqcap$ $\exists$ $Storage\_Temperature$ $\sqcap$ $\forall$ $Storage\_Humidity.Medium\_Humidity$ $\sqcap$ $\exists$ $Storage\_Humidity$ $\sqcap$ $\forall$ $Storage\_Oxygen.Natural\_Oxygen$ $\sqcap$ $\exists$ $Storage\_Oxygen$ $\sqcap$ $\forall$ $Storage\_Equipment.Hydraulic\_Drill$ $\sqcap$ $\exists Storage\_Equipment$ $\sqcap$ $\forall$ $Storage\_Lighting\_Source.Indirect\_Lighting$ $\sqcap$ $\exists$ $Storage\_Lighting\_Source.$
Truck_2: $\forall$ $Storage\_Temperature.Room\_Temperature$ $\sqcap$ $\exists$ $Storage\_Temperature$ $\sqcap$ $\forall$ $Storage\_Humidity.Controlled\_Humidity$ $\sqcap$ $\exists$ $Storage\_Humidity$ $\sqcap$ $\forall$ $Storage\_Equipment.Plastic\_Shelving$ $\sqcap$ $\exists Storage\_Equipment$ $\sqcap$ $\forall$ $Storage\_Lighting\_Source.Indirect\_Lighting$ $\sqcap$ $\exists$ $Storage\_Lighting\_Source.$
Truck_3: $\forall$ $Storage\_Temperature.Controlled\_Temperature$ $\sqcap$ $\exists$ $Storage\_Temperature$ $\sqcap$ $\forall$ $Storage\_Humidity.Low\_Humidity$ $\sqcap$ $\exists$ $Storage\_Humidity$ $\sqcap$ $\forall$ $Storage\_Oxygen.Controlled\_Oxygen$ $\sqcap$ $\exists$ $Storage\_Oxygen$ $\sqcap$ $\forall$ $Storage\_Equipment.ISO\_Pallet\_Rack$ $\sqcap$ $\exists Storage\_Equipment$ $\sqcap$ $\forall$ $Storage\_Lighting\_Source.Direct\_Lighting$ $\sqcap$ $\exists$ $Storage\_Lighting\_Source.$

Only if a truck is compatible, for each cargo the semantic distance is evaluated, exploiting the *rankPotential* algorithm. The results obtained are ranked using the *utility function*:

$$Rank(cargo_i, truck_i) = \frac{\textit{rankPotential}\ (cargo_i, truck_i)}{\textit{rankPotential}\ (cargo_i, \top)} \frac{residual\_space(truck_i)}{total\_space(truck_i)}$$

where: *rankPotential* $(cargo_i, truck_i)$ is the semantic distance from $cargo_i$ to $truck_i$; *rankPotential* $(cargo_i, \top)$ is the maximum semantic distance from $cargo_i$, which depends on axioms in the domain ontology; $residual\_space(truck_i)$ is the available space in the $truck_i$ after the allocation of the $cargo_i$ and $total\_space(truck_i)$ is the overall space in $truck_i$. The pair with lowest score will be selected. In this way each cargo will be allocated to the truck that better satisfies its transport requirements and that maximizes the truck load. Table 2 shows the results of the computation, in case that each truck has a maximum capacity of 1 ton. Results denote that, for example, $cargo_1$ is not compatible with $truck_3$, due to storage requirements not fulfilled by the truck. Also in this case, an explanation of the causes for incompatibility can be obtained exploiting the Concept Contraction inference service (**give up:** $\forall Storage\_Oxygen.Natural\_Oxygen$ $\sqcap$ $\forall Storage\_Temperature.Room\_Temperature$).

At the end of the matchmaking process the cargoes will be arranged on the trucks as follows: $truck_1$**:** {Golden_Delicious, Altamura_Bread}; $truck_2$**:** {Ostrich_Egg}; $truck_3$**:** {Navelina, Cavendish}.

The mobile system now performs optimization of storage space on different trucks. Referring to previous example, $truck_2$ results partially empty. In this case, the system can rearrange products moving them in other vehicle after checking compatibility with truck features and already stored product descriptions. A possible approach could exploit *rankPartial* and Concept Contraction algorithms to establish contrasting characteristics. In this way, weakly incompatible products can be delivered on the same truck to minimize unused carrying space.

Finally, products are loaded and a delivery schedule is planned for each truck. Using the simple algorithm outlined in the previous section, vehicle routes are computed as follows: $truck_1$**:** (Barletta, Foggia); $truck_2$**:** (Brindisi); $truck_3$**:** (Taranto, Lecce).

5 Conclusions

The paper presented a novel supply chain model where semantic-enhancements to RFID allows information exchange among actors involved in various stages of the good life cycle. Benefits deriving from the adoption of such an approach have been proved with reference to the environmental sustainability of products delivery in a generic fruit and vegetable market. An RFID-assisted ITS relies on tagged goods information to perform: (i) fully automated goods compatibility management in load composition, (ii) pollution-aware routing, (iii) intelligent delivery. Further work will be performed to extend and improve the proposed approach. Future developments include studying solutions to security issues specific of data-on-tag RFID approaches, whereas the current framework uses the simple security methods provided by EPCglobal standards.

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