Product Intelligence in Warehouse Management: A Case Study

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Abstract. [3] The need for more flexible, adaptable and customer-oriented warehouse operations has been increasingly identified as an important issue by today's warehouse companies due to the rapidly changing preferences of the customers that use their services. Motivated by manufacturing and other logistics operations, in this paper we argue on the potential application of product intelligence in warehouse operations as an approach that can help warehouse companies address these issues. We discuss the opportunities of such an approach using a real example of a third-party-logistics warehouse company and we present the benefits it can bring in their warehouse management systems.

Keywords: product intelligence; warehouse management systems; adaptive storing; dynamic picking

1 Introduction

An approach that can treat different product instances in a special way based on their specific characteristics and needs has been argued to bring special benefits both in manufacturing and in supply chain industrial contexts [1]. Focussing on supply chain and logistics operations, the impact of such a product intelligence approach [1, 2] has been recently under consideration in a number of different areas such as road-based logistics [3], intermodal transportation [4] and production logistics [5]. In this paper, we discuss its applicability and potential benefits in another area of logistics operations, other than transportation-related ones —the operations run in warehouses.

Due to the rapidly changing preferences of customers, orders received by warehouse companies (especially third-party-logistics ones) increasingly exhibit special characteristics, such as smaller order size, higher product variety, request of shorter response time, and request for changes after the order has been initially created and placed [6]. This means that although the traditional performance targets for warehouse services (e.g. warehouse utilisation, tighter inventory control) still remain, in today's environment, they are subject to the specific, special needs of different customers. This is particularly true in third-party-logistics warehouses that manage a high variety of products and a big number of individual customers. Here, the operations are required to become more customer-oriented and more responsive to requests with different characteristics and needs in an efficient manner.

In this paper we aim to demonstrate the way the product intelligence paradigm can respond to the above challenges by studying its future application in a third-party-logistics warehouse company. After reviewing the current situation in warehouse management systems in Section 2, we discuss the opportunities for the adoption of intelligent products in warehouse operations and their potential applications in Section 3. We present our scoping case study along with two specific application examples in Section 4 before concluding with our findings.

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2 Current Issues in Warehouse Management Systems

The main operations that almost every warehouse needs to plan and control are receiving inbound items from suppliers, storing the items, receiving orders from customers, retrieving the requested items and assembling the orders for outbound shipment, and shipping the completed orders to customers [7]. In order to achieve higher performance for warehousing regarding capacity and throughput, and fulfil the service at the minimum resource cost, warehouse resources (such as space, labour, and equipment) need to be carefully chosen, operated, and coordinated. Therefore, a Warehouse Management System (WMS) becomes essential since it provides, stores, and reports the necessary information to efficiently manage the flow of products within a warehouse [8]. Currently, in order for any standard WMS to be able to overcome today's challenges and retain its competitiveness, two are the main characteristics it should possess: a) flexibility in terms of being responsive to short-term changes of customer demands in a timely manner and b) adaptability in terms of being able to maintain the service level when mid-term changes/requirements are demanded by customers.

Although a WMS should be more responsive to changes in order to enhance its flexibility and adaptability, conventional paper- or spreadsheet-based WMSs are incapable of providing timely and accurate warehouse operation information since they rely heavily on staff members to enter information manually or through a barcode system [9]. On one hand, researchers are trying to solve the issues of timeliness and accuracy on warehouse operations by capturing real-time information using Auto-ID systems (such as RFID) [9, **?**] and wireless sensor networks technologies [10]. On the other hand, even though the information technologies mentioned above can provide more accurate and real-time information regarding operations, unexpected events and disruptions, the important challenge for warehouse managers to make decisions using this information in a short response still remains [11]. On this direction, a significant amount of research has focused on developing decision support models (including heuristics and algorithms) which aim to optimally manage different warehouse operations [7]. However, due to their rigid assumptions and constraints, successful implementations of these models in current commercial WMSs are rare [12]. At the same time, most of these models use centralised, static, off-line methods, which raise significant barriers to the development of more flexible and adaptable WMSs.

Similar issues have been recently appeared in manufacturing control and supply chain management where alternative approaches such as the product intelligence one have been developed for their solution [13, 14]. We will discuss the potential application of product intelligence in warehouse management and the opportunities for its successful deployment in the systems managing them in the next section.

3 Intelligent Products in Warehouse Management Systems

Although there are numerous examples in the literature of deployments that use multi-agent approaches in warehouse management systems [15–17], the application of the product intelligence paradigm in warehouse management systems (WMS) and the benefits in the operations they manage is yet to be studied. However, the potential of a distributed intelligence approach, such as a product intelligence one, in WMSs cannot be underestimated due to reasons that might cause centralised management systems not to perform in a efficient way [18]:

- *Partial information availability*: Each possible decision-making node has only part of the information required to make the decision due to the high levels of uncertainty that many warehouse operations face. Examples of such information can be the arrival of new orders during working shifts, the arrival of new pallets/products from the supplier/client during the day, and the real-time location of the pickers in the warehouse.
- *Impracticality*: Even though there are cases where the required information is available to each decision-making node, practical constraints such as time and cost inhibit a centrally based solution. For instance, the optimal picking lists and routes for each and every picker cannot be re-calculated every time a new product or a new order arrives in the warehouse since this process will require a significant amount of time, thus making the previous solution ineffective.

– *Inadvisability*: Even if the above issues do not apply to certain systems, a centralised system might still be inadvisable due to the susceptibility of a single decision-making node to disruptions and changes. Another reason for the inadvisability of the deployment and adoption of a centralised system can be the complexity of making changes driven by new needs and requirements such as new products, capacity levels, facilities layout.

Apart from the aforementioned reasons, which can make centralised approaches in WMSs inefficient, there is also a number of opportunities for the deployment of intelligent products in the management of warehouse operations. Tables 1 and 2 aim to summarise the main areas where an intelligent product approach could be beneficial. We distinguish between opportunities for the application of Level-1 (information oriented) and Level-2 (decision oriented) Intelligent Products [1] in Table 1 and 2 respectively.

In Table 1, it is obvious that the main impact of Level-1 intelligent products refers to the automation of some time-consuming and labour-intensive tasks as well as the collection and usage of product information in static algorithms used for the determination of storage and picking policies/decisions.

Table 1. Opportunities for Level-1 Intelligent Products in warehouse operations

Operation	Opportunities
Receiving	– Better accuracy of received products when products are "checked-in" – Faster scanning of big pallets especially when wireless technologies are being used (e.g. RFID) – Improved visibility of inventory in warehouse facilities even though products are not yet stored in shelves
Storing	– Easier identification of empty shelves that meet product's physical dimensions – Determination of proper storage zones based on real historical data – Faster identification of a product's predefined storage location in a warehouse according to the storing policy – Richer information availability —such as product's turnover rate, demand, picking frequency— for storage location assignment algorithms
Picking	– Identification of products' locations in the warehouse for the determination of the fastest route – Consideration of multiple feasible locations for each product type if several product instances are available – Scheduling subject to trolley's capacity
Shipping	– Identification of proper packaging option for each order – Determination of best delivery service available – Automatic generation of shipping documents

The potential benefits from the automation of certain tasks are also depicted in Table 2 via the utilisation of products capable of deciding how they will be stored, picked and shipped. Moreover, this level of intelligence can facilitate the management of more dynamic scenarios, where unexpected events, changes and disruptions take place in the normal operations of a warehouse. Finally, the role of the customer in some of the decisions made becomes more active compared to the traditional passive role the customer normally has [1].

Table 2. Opportunities for Level-2 Intelligent Products in warehouse operations

Operation	Application areas
Receiving	– Automated proof of delivery sent to supplier – Faster checking of inbound orders' contents against product list – Notification to pickers about the availability of products requested that were previously out-of-stock
Storing	– Guidance to staff members regarding product's storage location in the warehouse – Usage of adaptive storage location assignment approaches: each product instance can be stored in a different location – Negotiation among products and/or with shelves about choosing a storage location
Picking	– Faster problem notification in out-of-stock cases – Dynamic update of picking lists after new orders arrive, orders' status change etc. – Negotiation among products and/or with pickers about updating a picking list
Shipping	– Identification of proper packaging station for each picking list – Choice of preferable delivery service by the client and/or end-customer

4 Scoping Case Studies

4.1 Company Background

The company used as a case study for this paper is a an eCommerce and mail order fulfilment warehouse. The company warehouses, picks, packs and dispatches goods to end-customers on behalf of their clients, the retailers[4]. Orders can come from a range of channels including online eCommerce stores and marketplaces such as eBay, Amazon and Play and are automatically retrieved by the company via secure cloud servers; the company also has facilities to handle mail and telephone orders. Figure 1 summarises the main operations followed every time a new order is added in the system. Although not depicted directly in Fig. 1, products are normally sent to the warehouse company from their clients before any order is placed from end-customers, that is the warehouse needs to store any products their clients ask them to store (based for example on demand forecasts).

4.2 Challenges and Opportunities for the Case Company

The specific business case offers a number of opportunities for the successful application of product intelligence in its operations:

1. *Available infrastructure*: The Company has already in place an information system capable of uniquely identifying the different products and orders in the warehouse (elements of the information system are presented in Fig. 2). At the same time, the information system in use collects and stores data related to the lifecycle of a product/order (e.g. physical dimensions of a product, demand, location in the warehouse) as well as a customer's needs and preferences associated with his orders (e.g. delivery date, priority, delivery method). In other words, the Company has already developed and used elements of Level-1 intelligence.

[4] By the "client" we refer to the warehouse's clients (the retailers) and by the "end-customer" we refer to the customers who put their orders at the retailer's website.

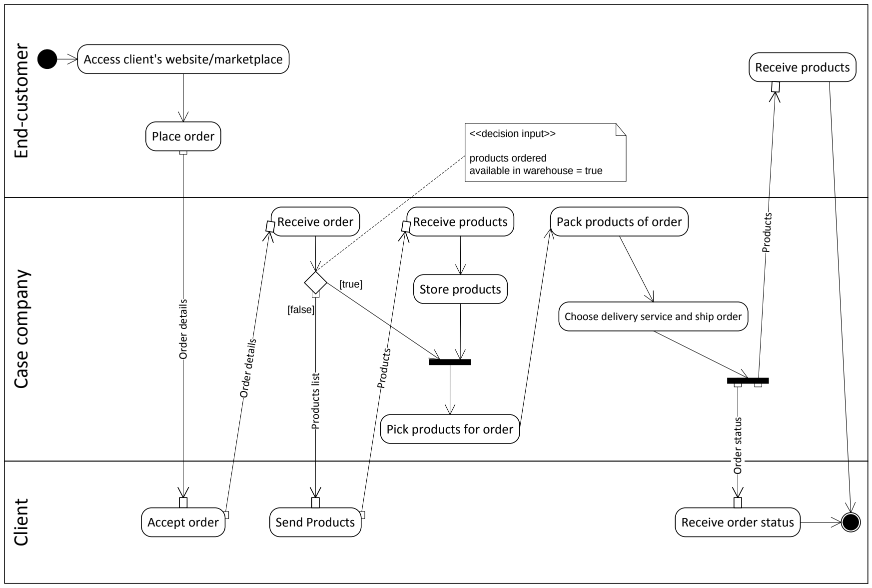

Fig. 1. Case company's main operations

2. *Quickly changing environment*: The Company is expanding quickly and unpredictably, meaning that a centralised system able to cope with the challenges faced today might not be suitable for the needs of the Company in the near future. Agreements with new clients (of different sizes) are happening in a regular base bringing new products in the warehouse with their own special information as well as bringing new end-customers that the Company has to prepare the orders for. Moreover, the capacity of the warehouse itself is growing introducing new storage locations, aisles and packing areas.
3. *High customer impact on warehouse's operations*: The specific business model that the Company is using, requires a certain level of control of their operations to be given to their clients and end-customers. For example, the Company might not know when the products from their clients will arrive during the day or what products exactly will the shipments contain. Also, each client might hold information that could be useful for the warehouse's operations like for example weekly/monthly demand, seasonality of products, new seasonal products.
4. *Need for dynamic decisions*: Many of the decisions that need to be made each day could be taken using a centralised, static system, but when multiplied up to thousands of activities and products the identification of the best one becomes a very hard to be solved problem. Static systems will also not perform very well since they are not capable of utilising real-time information during everyday operations even if this information is gathered and stored. A simple example here are end-customer orders since, in the case company, they are received continuously throughout the day.

As shown in Tables 1 and 2, there are many application areas that a product intelligence approach could be beneficial at. In the next two sections we deep into two specific examples to demonstrate how potential developments would operate in these areas, focussing on cases where the decision making properties of intelligent products could be used.

4.3 Example 1: Adaptive Storage Location Selection

The first example comes from the potential impact of product intelligence on storage policies, that is the selection of the proper storage locations for the incoming products usually aiming at minimising the picking

Fig. 2. Technology Infrastructure: Auto-ID technologies for shelves (left) and Personal tablets for staff members (right)

time of future orders. The company in our case study is currently using rule-of-thumb policies [7] choosing between the random location policy and the closest open location one based on simple zoning rules. This is happening mainly because the company cannot know in advance the specific products (and their quantities) they will receive each day from their clients as well as the point of the day they will receive them at. As a result, the usage of static algorithms that determine new storage locations for incoming product instances before the beginning of each working day is simply not practical. At the same time, the company believes that although zoning the warehouse could reduce the overall picking time, these zones will need to change very often (since the demand they are facing is volatile), thus creating confusion to the staff members.

Since the infrastructure is already in place and the staff members are used to be advised by simple interfaces regarding where to pick the products from (see Fig. 2), the company considers a similar solution for the storing process where an automated system will guide the staff members around the warehouse every time they will scan a product that needs to be stored. The location of each product can be different among product instances and throughout time. We call this policy an adaptive storage assignment policy [6], in which each product instance can be treated differently each time it has to be stored in the warehouse. In other words, each product instance (or group), represented by a product agent, will try to seek the best location in the warehouse every time it is received using information such as its turnover rate, demand, the relationships with other products, the layout of the warehouse etc. The optimality of this decision is calculated based on the expected picking time of future orders received by the company. In practice, the staff members will pick some products from the pallets received, load them on their trolleys, scan them and then receive guidelines regarding where to store each of them on the monitor attached to their trolley.

The decision regarding the storage location of the products in an intelligent product approach like the one described above can be made via a number of different ways as shown in Fig. 3. The first option (Fig. 3a) depicts a pure intelligent product approach where the products are the only decision makers. Each product will choose its preferable storage location and in case two (or more) products choose to be stored in the same location, they will negotiate with each other before they reach a decision. On the other hand, in the second option shown in Fig. 3b, the resources (here the storage locations-shelves) get a more active role by accepting or rejecting offers when products ask to be stored in them. This architecture still represents an intelligent product approach since it is up to each product to choose where and how much they will bid on, however, the resources will make the final decision.

It is obvious that both architectures can facilitate the development of an adaptive solution although there are still some open questions (which are out of the scope of this paper) such as how the products choose their preferable locations, what the negotiation mechanism between them is and how the bidding system between products and shelves operates. Another issue that comes from the practical application of such a solution refers to the common practice of storing multiple product instances of the same product type in the same storage location every time a new pallet of products is to be stored. This issue is tackled in Fig. 3c where several product instances form teams and let their "Group Leader Agent" do either the negotiation with other similar agents (Option a) or bid for specific shelves (Option b).

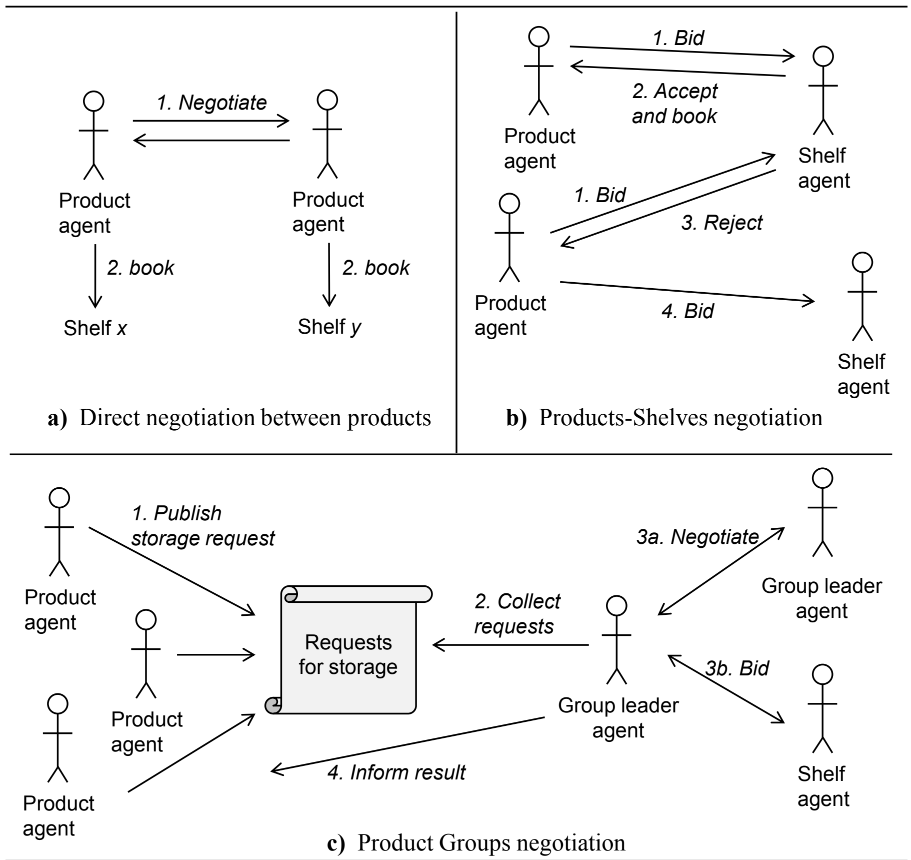

Fig. 3. Agent architectures for the adaptive storage location selection problem

4.4 Example 2: Dynamic Order-Picking Rescheduling

Order-picking operations have been identified as the most labour-intensive and costly activities for almost every warehouse [19]. In such operations, multiple pickers are assigned the task of transferring products from stationary storage locations to a common loading shed or depot, wherein the pickers begin and end the trips in the depot [16]. The case company is currently using two simple rules to operate order-picking. Orders are assigned to pickers based on the orders' priorities (higher priority orders will be picked first) and subject to the capacity of their picking trolley. Then the pickers move in the warehouse linearly, skipping any aisles where there are no picks required and trying to minimise their total walking distance while collecting the requested products. Currently, the above policy allows the company to perform in a very good level, however, they understand that it will not be sustainable for the near future. Moreover, critical decision making criteria that affect the performance of the order-picking operation —such as picking sequencing and routing, selection among multiple locations for a requested product type— have been left out from the current order assignment system.

Although there are a number of algorithms for the efficient scheduling of order-picking operations considering the critical criteria mentioned above, most of them are traditionally calculated off-line and consider the problem as being a static and deterministic one [17]. Therefore, the calculated schedule will no longer be optimal in operating environments that continuously change due, for example, to the receipt of new orders at random points during a working day. Hence, an alternative objective is the minimisation of the picking time each time an unexpected event (such as the arrivals of new orders) takes place. Although such a dynamic and automated order-picking rescheduling policy does not guarantee the calculation of a global optimum, it can lead to schedules that do take into account unexpected events and disruptions. In a WMS that uses a product intelligence approach, the products will have the opportunity to communicate with each other and perhaps make a different decision for the final picking lists when something changes in the operation.

We will demonstrate the way a product intelligence approach can operate through a simple example. Figure 4 depicts a warehouse with one depot and six pallet racks, each of them being able to store products in both sides. In this example Pickers 1 and 2 (currently located as shown in the figure) with Picker 1 scheduled to pick the products located in the shelves marked with the star sign (*) and Picker 2 scheduled to pick the products located in the shelves marked with the percent sign (%). Assuming that each picker has a capacity of 10 items, let Picker 1 have two spare spaces in his trolley after he completes his picking task. Now, let a new order, which requires two products enter the system. The available locations that contain the required product are marked with "N". With the current system (and any other off-line tool), the products for the new order will be picked after a picker is ready to start a new picking task.

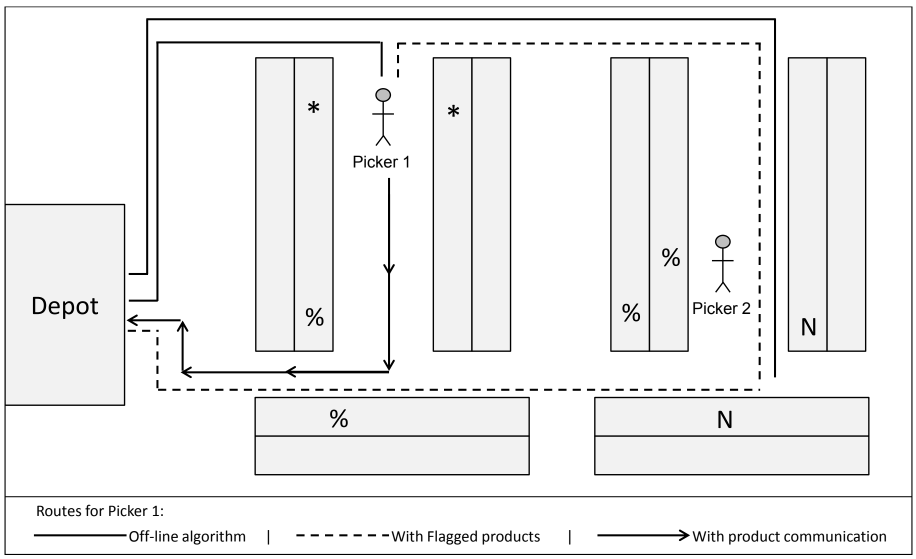

Fig. 4. Dynamic order-picking rescheduling example

In a product intelligence approach, when the new order arrives, all product instances that match the requested product type will flag themselves, indicating that they are requested for another order. According to the status of the pickers, these flagged product instances will inform Picker 1 that he should pick the "N" products before going back to the depot since he still has two spare places in his trolley. In a more intelligent solution the "N" products will identify that Picker 2 is closer to them than Picker 1. However, due to capacity limitations, the picking list needs to be modified before Picker 2 can be assigned to pick them up. At this point the products will communicate with each other and decide to re-assign the "%" products that are closer to the depot to Picker 1 and the "N" products to Picker 2. As an example, we have drawn the picking routes for Picker 1 only, in the three solutions described above. As mentioned earlier, the off-line solution requires the new order to be picked in a new picking task.

5 Conclusion and Discussion

This paper is a first attempt to identify the key areas in warehouse operations management that the product intelligence paradigm can provide some benefits at. At the same time, it aims to identify the main opportunities and challenges for its adoption in the development of warehouse management systems in real-case scenarios. More specifically, we showed how a WMS using product intelligence can be beneficial for the scheduling and control of the storage location assignment and the picking operations and we argued on the significance of these benefits using a case study of a third-party-logistics warehouse company. Although we have not managed to report quantitative results on the performance of such an approach compared to more conventional, centralised ones, we believe that its impact can be significant firstly, in cases of high uncertainty with a high numbers of unpredictable events affecting the operations and secondly, in cases where there is a need for high customer control over the warehouse's operations.

Another issue that comes out of this study regarding solutions that use the product intelligence paradigm (although not discussed in detail here) is the importance of the communication and/or the negotiation mechanism that the products and the resources participating in the operations will use among them. This element of the system, even if it might seem trivial at first sight, can have a big impact on the performance of a product intelligence approach in real operations as it can affect the final decisions that will be made and executed. Different mechanisms should be developed and tested for each specific case before the adoption of one of them in real industrial systems.

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