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Augmenting the distribution of goods from warehouses in dynamic demand environments using intelligent agents

Full Paper

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Abstract

Warehouses are being impacted by increasing e-commerce and omni-channel commerce. Future innovation may predominantly involve automation but many warehouses remain manually operated. The golden rule of material handling is smooth product flow, but there are day-to-day operational issues that occur in the warehouse that can impact this and order fulfilment. Standard operational process is paramount to warehouse operational control but inflexible processes don't allow for a dynamic response to real-time operational constraints. The growth of IoT sensor and data analytics technology provide new opportunities for designing warehouse management systems that detect and reorganise around real-time constraints to mitigate the impact of day-to-day warehouse operational issues. This paper presents an intelligent agent framework for basic warehouse management systems that is distributed, is structured around operational constraints and includes the human operator at operational and decision support levels. An agent based simulation was built to demonstrate the viability of the framework.

Keywords: warehouse management systems, distributed intelligence, software agents, decision support.

1   INTRODUCTION

Changes in product make up and e-commerce orders present new issues for warehouses and distribution centres. The impact of expanding e-commerce and omni-channel business models (Michel 2016) create a new way of working that is characterised by increasingly changing customer demands, higher product variety, smaller order size, the expectation of reliably shorter response times (Lu et al. 2014) and irregular order arrival (Leung et al. 2018). Storing a wider variety of products in a warehouse in smaller quantities can mean that the way the warehouse and its systems work is different (Davarzani and Norrman 2015). In fact, only 10% of distribution centres exclusively handle pallets now, while 66% handle a mixture of pallets, cases, split cases, and pieces (Michel 2018a). Many warehouse management systems (WMS) are not designed for small orders picked in piece units.   In the 2018 Warehouse/Distribution Center (DC) Equipment Survey(Michel 2018b), 29% of respondents indicated that the most common process for e-commerce fulfilment in their operation was "buy online and ship to customer from DC" although there was growth in "buy online and ship to customer from vendor". This suggests that the DC might be struggling with the processing of e-commerce orders. This pressure may see the default of members of the supply chain and this can alter the behaviour and the exposure to risk of other members of the supply chain (Gibilaro and Mattarocci 2019).

Warehouse design including operational processes are predominantly based on current and projected future demand (De Koster et al. 2007) and changes to design after construction are costly (Gu et al. 2007). The warehouse control systems and software that operate them are costly to implement and change and require considerable training and support (Min 2006). Warehouses are designed to be well-defined process-driven product flow machines (Bartholdi and Hackman 2008). Their aim is to achieve maximum throughput with minimum investment and operational costs (Bartholdi and Hackman 2008; Rouwenhorst et al. 2000; van den Berg and Zijm 1999). However, their inability to flexibly respond to dynamic changes in demand leads to common issues such as aisle congestion, mistimed replenishments of the pick face, short-picks and double handling (Gong & De Koster 2011, Bartholdi & Hackman 2008; Gu, Goetschalckx & McGinnis 2009). Dynamic responses are needed when the fixed constraints of the environment have been impacted.

In dynamic environments, a small number of constraints can lead to operational issues that have a large impact on the warehouse throughput as a whole. These can impact warehouse performance if not detected and corrected in a timely manner. These include:

- The operator is unable to complete order selection or replenishment of a selection location.
    - o   Potential causes:
        - ▪ Congestion (for selector or forklift operator) (Zhang et al. 2009)
        - ▪ Inventory system inaccuracies (inventory record does not match reality). Many factors can cause inventory inaccuracies including visual complexity (Barratt et al. 2018).
        - ▪ Inaccurate product and packaging dimension data
- Slow replenishments
    - o   A replenishment that is triggered too early or too late has flow-on effects to picking (Richards 2014; Rushton et al. 2014) such as overfull location (too early) or short-pick (too late). Short picks require extra order selection trips and delay order completion.
- Slow receiving/checking processes.
    - o   A failure to prioritises stock that will be required sooner based on order demand
- Picking from incorrect location, Incorrect stock in location, Over-picking, Under-picking
    - o   Identification of this issue (occurring even with bar-coding, RF scanning & voice picking technology) can highlight incorrect case or inner case barcoding or operator error. Picking inaccuracies that are not discovered prior to shipping can result in returns, repeat deliveries and loss of goodwill (García et al. 2007). Pick error rates were reported at between 0.02% and 0.05% by companies participating in a qualitative analysis of work schedule deviances (Glock et al. 2017).
- Staging dock congestion
    - o   Badly managed staging areas can lead to congestion and scattered staging of picked orders causing issues when loading trucks for delivery. Picked goods for dispatch should not be

ready too early as this causes congestion and should also not be late as this holds up the loading process and the despatch door (Walker 2018)

As with most errors that occur with flow-on effects in a system, prevention or detection and correction in a real-time or near real-time manner is desirable. This is especially important in the order fulfilment space, where truck scheduling and delivery time windows need to be met and returns are costly or become losses (especially with high value stock).

Current warehouse management systems (WMS) are generally top-down, centralised systems and their decision support functions are the same. The disadvantages of central control include a single point of failure, inconsistent speed of response and a high dependency in the structure (Haneyah et al. 2013). Most of these software packages deal with producing tasks to completely pick and despatch a batch of customer orders in a given time period. Inventory management and interfaces to transport and billing (ERP) systems are managed as part of order fulfilment. The dynamic operational control is mainly done by humans via summary reports and screens that require human intervention and that are highly customised (Haneyah et al. 2013). This study sought to find a better way to design warehouse management systems, utilizing intelligent agents. It sought to answer the following research question:

> *How can distributed intelligent agents augment warehouse operations to mitigate the impact of dynamic day-to-day issues?*

The purpose of this paper is to propose a distributed model for designing warehouse management systems that detects and reorganises around real-time constraints to mitigate the impact of day to day warehouse operational issues. The model is depicted in Figure 1.
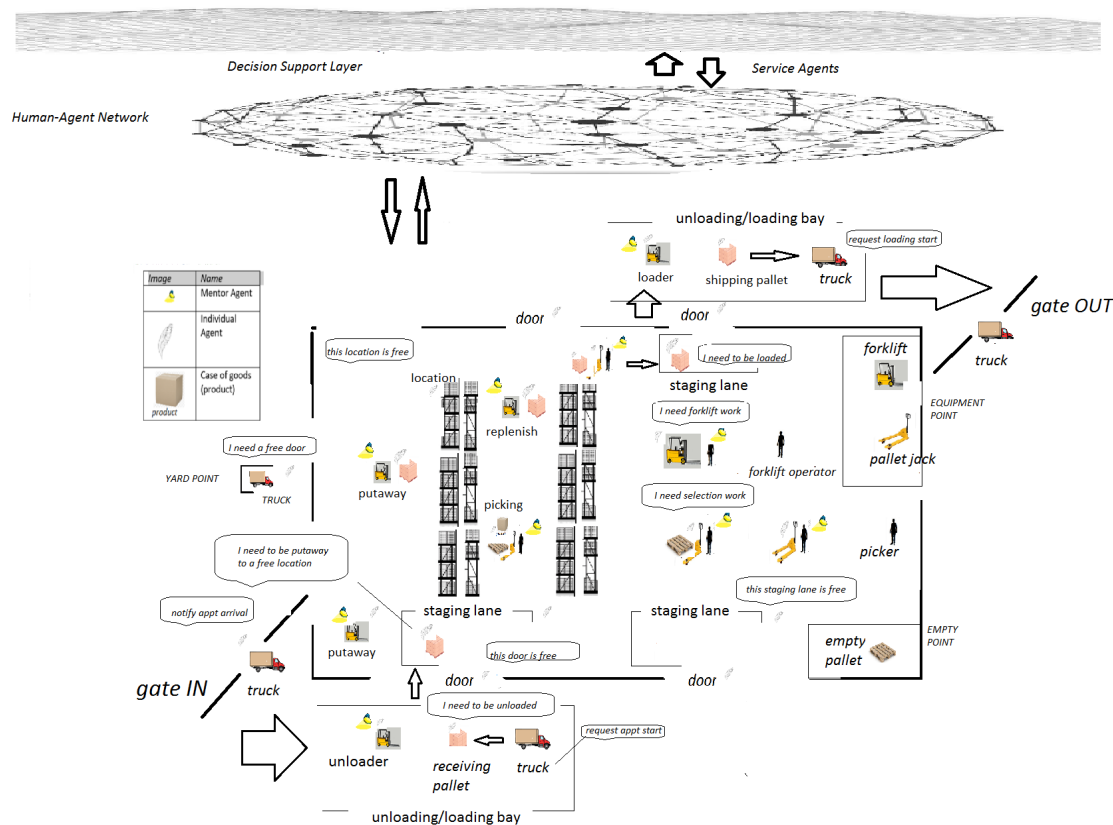
Figure 1 Conceptual Model of proposed WMS design framework

The elements of this model include:

- Distributed intelligence via cooperative agents
- Real time feedback/detection mechanisms
- Incorporate real-time constraints in the framework
- Embed the human operator as an actor in the framework with consideration of:
  - Physical, mental and social real-time constraints

- o The information required at different levels for decision support

- o Adaptive learning based on trends for decision support

- o Allow for AI algorithms to be plugged in where applicable and appropriate based on the temporal environment.

2 LITERATURE REVIEW

The challenges faced in decision support for complex systems such as warehouses are: infeasibility (all the information is not available in one place), impracticality (it would not be practical to come up with a centrally determined optimal solution), inadvisability (even if you had such a solution it would not be advisable) (Marik and McFarlane 2005). Distributed intelligence (DI) as a bottom-up approach to solving these issues has been proposed to enhance flexibility and agility (García et al. 2007). DI is a system of elements that have a degree of autonomy of operation, can reason solely or jointly and can interpret the state of the environment and the intentions of other elements (McFarlane et al. 2012). Distributed intelligence can be implemented using an intelligent agent framework (Shukla and Frank Chen 1996).

Decision making within distributed intelligence can be determined by the data visibility at each point or node of a system. Technologies such as RFID, Internet of Things (IoT), GPS and other tracking systems are making this easier (Ding 2013; Karagiannaki et al. 2011; Liu et al. 2013).

One can imagine a warehouse environment in which information from sensors is used to form a picture of the environment and make a decision in real-time. (Estanjini et al. 2011) developed such a system to determine the next task to be allocated to forklift drivers in a grocery warehouse. The system used a sensor network, an information collection system, a localisation algorithm and dynamic programming to determine the next task to allocate to an available forklift. A dynamic programming technique – actor critic algorithms was used to determine the optimal average cost in simulation and this value was used in the implementation in a case study. Dynamic programming is used in multi-dimensional problem spaces such as this one where finding an exact optimum solution is almost impossible.

One approach using product intelligence (Giannikas et al. 2013) uses a product and a shelf agent to select an appropriate storage location. This introduces the concept of non-human agency in the warehouse giving agency to products and shelves and is an important aspect of actor-network theory (Latour 2005). This "intelligent product" concept has been extended into concepts such as "communicating objects"(Trab et al. 2017) and "smart warehouses" (Ding 2013). A new model using multi-agent systems (MAS) and IoT is proposed by (Reaidy et al. 2015), responding to the growing norm of uncertainty in supply chains. This model uses a bottom-up approach in which simple functions with local objectives are distributed. Ambient intelligence is achieved through sensors, control science (expert systems) and telecommunications. Agent communication strategies may be cooperation, competition, coo-petition or comp-eration (Reaidy et al. 2015). Trab et al. (2017) use the "communicating object" concept and IoT to deal with the safe handling of hazardous products in a warehouse. All actors in the warehouse are modelled including human operators. The proposed hybrid intelligent system (central and distributed elements) has three levels of interaction O2O (object to object), O2H (object to human) and O2E (object to environment). Liu et al. (2013) discusses full electronic and GPS tracking of all goods coming in and out of the warehouse using RFID, GPRS (GPS) and Zigbee WSN for tracking within the warehouse. A model for the safe handling of hazardous good in warehouses is also proposed using RFID and IoT to track materials and notify of incorrect placement and to support storage decisions (Zhang et al. 2016). An artificial neural network (ANN) is used for environment detection. What emerges from the above research is a model where information about the environment is pieced together from sensors and made sense of through algorithms and AI.

Multi-agent systems (MAS) have been studied in warehouse management systems (García et al. 2007; Kim et al. 2002; Rubrico et al. 2006). A MAS system was proposed to control stock levels using information from input and outputs of a bedding company warehouse captured via RFID (García et al. 2007). The stock level control was done at the ERP level while the enhanced RFID/IMS system was used to improve warehouse inventory management and picking accuracy. This was a bottom up approach feeding decision support systems. Multi-agent systems that communicate have been used to optimise the assignment of a pick route to an available picker based on proximity to the first location to be picked (Gharbi et al. 2013). The location of the pickers is determined via RFID.

In one agent-based model presented for the movement of products from the main warehouse to storage in the production warehouse for use on the production line four agents are used: production, storage,

forklift and main warehouse (Maka et al. 2011). The products are moved between the storage and production warehouses by forklift. As well as communication, there is some complex logic in scheduling which products should be moved, in what priority and in what sequence they should be loaded and unloaded from the forklift. The authors make an interesting point about the value of following global rules in storage decisions compared to the intelligence gained from analysing historical data such as product trends. Instead of the rule that all products must be stored in the closest empty location for instance, it is more efficient for products that are usually retrieved together for the production line to be stored together. However this information is dynamic and based on recent historical data.

Of the indirect measures of warehouse performance, labour is especially important since any inefficiency on the part of a human operator can impact shipping and delivery time. The importance of the human element (from operators to supervisors and management) as the actor whose "service failure or inefficient performance directly increases customer-order cycle time and negatively impacts the level of service as perceived by the customers" (Staudt et al. 2015) cannot be overlooked.

A different way of thinking of work environments is that of a cooperative partnership rather than a differentiation between the "computer system" and the "human" as entities that enhance the fulfilment of goals. The desired precepts of a system in which human and non-human agents interact in a "team" are that: 1) agents agree to collaborate to achieve a joint state and goal, 2) agents are predictable, able to be directed, observant and transparent in intentions and behaviour and 3) agents coordinate, negotiate and communicate (Klien et al. 2004).

Increasingly, the future of warehouses is considered to be completely automated and human-less. Not all warehouses can feasibly be automated, however. The expense of automation can preclude this solution in many smaller warehouses. Products that are odd shapes and bulky can also be difficult to handle robotically. This study proposes that advances in IoT and AI can bridge the gap between existing largely manual warehouses and full automation. In the model presented in this paper, new technologies and algorithms are used to augment the natural decision-making and learning capacity of people to create more flexible and productive work environments.

3 METHODOLOGY

Design Science research methodology was used for this study because of its iterative approach to developing and improving the system. Design science research involves six activities as defined by (Peffers et al. 2007): Identify Problem and Motivate, Define Objectives of a Solution, Design and Development, Demonstration, Evaluation and Communication. Three distinct design iterations are described:

1. Development of the conceptual model (depicted in Figure 1). This involved defining the industry problem and reviewing the literature. The conceptual model was developed via a synthesis of research literature and industry experience.

2. Design of the multi-agent system. This involved defining and specifying the types of agents required, their specifications, goals and behaviours. This is elaborated in section 4.

3. Simulation. This involved developing a warehouse simulation environment and coding the behaviour of the agents, using JadeX. The simulation was used to validate the design of the conceptual model. Real-world scenarios and constraints were used to test and evaluate the model. This is elaborated in section 5.

4 CONCEPTUAL DESIGN OVERVIEW

The design development of a distributed framework for a warehouse management system involved: Requirements Modelling and Agent Modelling. Requirements analysis was used to determine the required agents and their interactions. Agent modelling determined the agent states, goals, plans and modes of interaction.

4.1 Requirements Analysis

ANEMONA (A Multi-agent Methodology for Holonic Manufacturing Systems) (Botti and Giret 2008) was used to develop a basic requirements analysis of the agent and agent responsibilities for a warehouse. ANEMONA was chosen because of the structured and iterative approach to analysing and defining agents from the organisational diagram to abstract agents, goals, tasks and interactions into agents. Figure 2 shows a version of the abstract agents representing various warehouse roles.
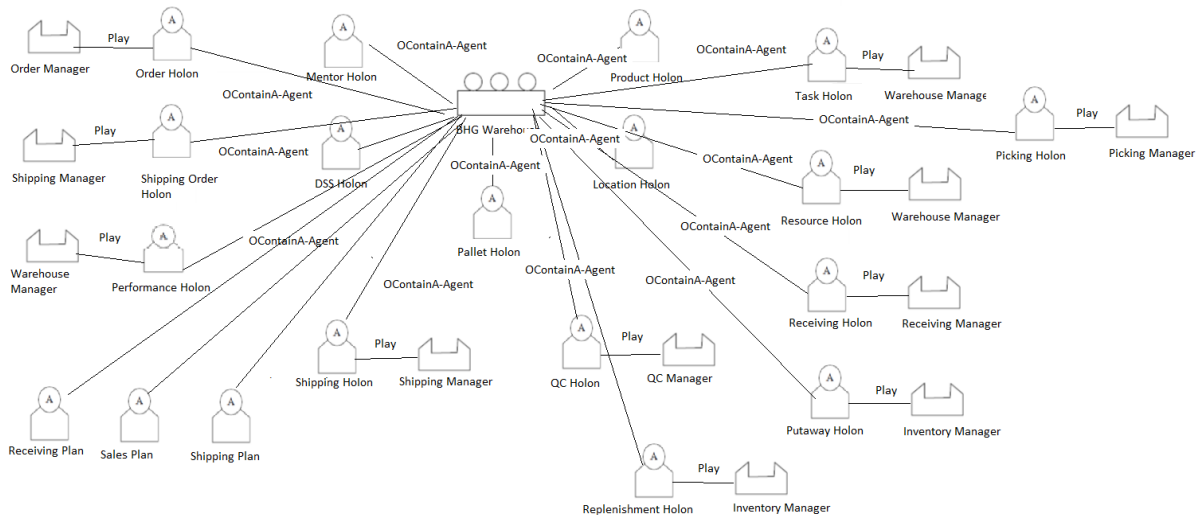
Figure 2 Abstract agents and the organisational diagram

4.2 The Agent Model

Three types of agents were modelled: entity agents that were connected to a physical entity (location, inventory pallet, human, forklift, shipping pallet), mentor agents (forklift operator and selector operator mentors) and service agents. Entity agents could be associated with sensors and other direct feedback mechanisms. Mentor agents were associated with a human operator and were in control of communicating with other agents to obtain available tasks and communicating task instructions to the human operator. Service agents were either providers of a function or information or fulfilled a role (generally a manager role). The design of these agents involved goals and plans that were either triggered by a request from another agent via a communication protocol or a change in the state of the agent due to a change in the environment. As such the design of the agents involved state diagrams and an inter-agent communication protocol. Each agent had a defined communication interface through which they receive a request for information or action. Each communication protocol involved the exchange (incoming and outgoing) of a message (request or response) and an object of data. Figure 3 shows some of the agent interactions in a mostly non-hierarchical configuration.
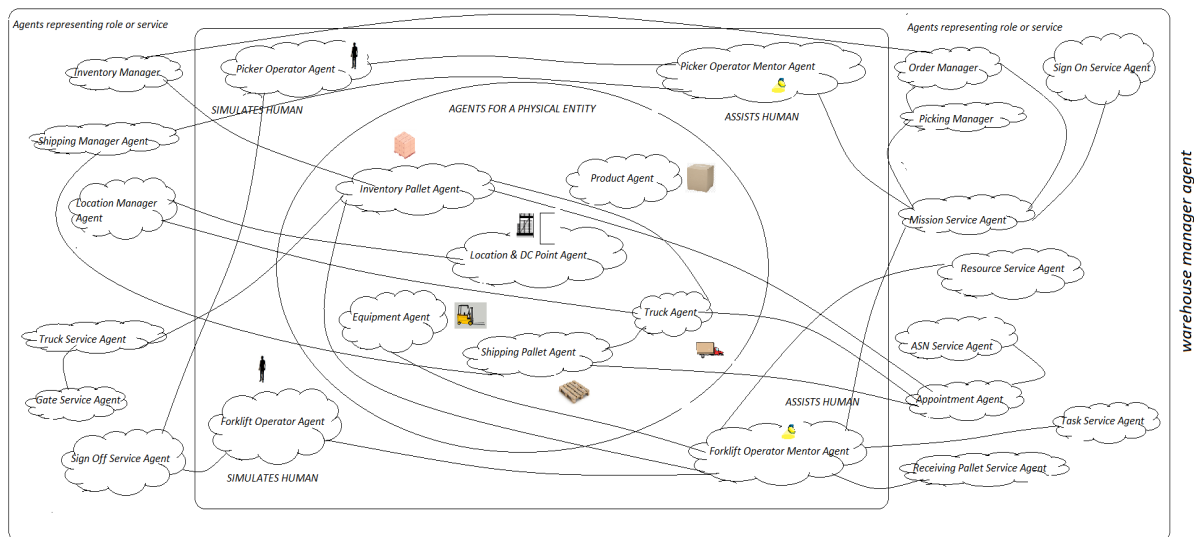

Figure 3 Agent Interactions

4.2.1 State Diagrams

The agent goals were either triggered by a change of agent state or by a request from another agent. A change in state indicated a change in the environment and hence a change in the actions required from the agent. In the example of a receiving pallet in Figure 4, a change of state to "Arrived" triggers a goal to unload the pallet from the truck, creating the task required to unload it. This task is prioritised by the

Work Priorities agent and allocated to a forklift operator through the task service agent. Once the pallet has been unloaded from the truck its state changes to "Unloaded" triggering a goal to find a suitable warehouse location for it. The goals that are initiated by a change of state in an agent are predictable. Entity agents maintain a state (status) and a position within the warehouse so that this can be maintained when the simulation is restarted.
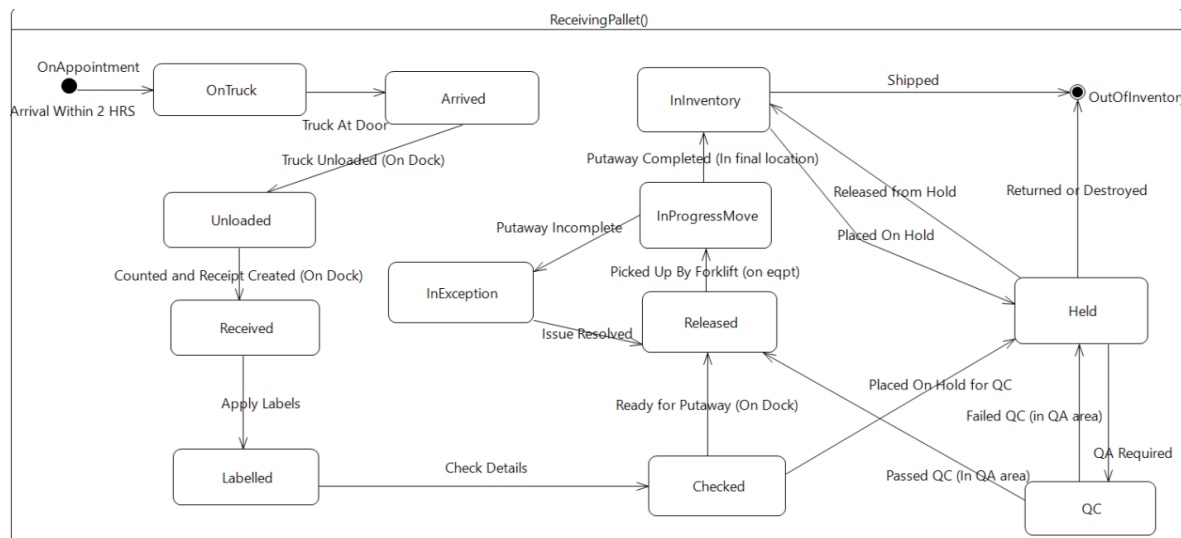

Figure 4 State Diagram for a pallet received into the warehouse

5   SIMULATION DEVELOPMENT

This research examined various tools for the simulation development. JADEX (Pokahr et al. 2005) was chosen and used to develop the agent simulation with associated database tables using MySql (Widenius et al. 2002). JADEX agents are based on the traditional BDI (Belief, Desire, Intentions) agent model and its active components features facilitate the interactions between agents. The BDI agent model was most suitable for simulating this conceptual model.

5.1   Simulation Scenario - Generating a Replenishment

A replenishment is the refill of a primary selection location with product from another location. It involves identifying that there is a shortage in the primary selection location and triggering the move required to fill it in enough time to prevent shortages during order selection. The scenario is as follows:

- A customer order for 4 of product 108081 arrives into the system. The selection location for product 108081 is "01-01-1-1" and only has a quantity of 3. A pallet of 40 cases for product 108081 is on a receiving truck that has arrived with 10 other pallets but has not been unloaded yet. Table 1 shows the sequence of events in the distributed model in simulation.

6   DISCUSSION

Warehouses and warehouse management systems are complex and dynamic systems traditionally controlled by strict adherence to process and sequence. The problem with this is that when an unexpected exception occurs, the process cannot be followed and something else has to be done in its place and this causes delays and flow-on effects. Adaptive mechatronic systems with societies of autonomous adaptive agents can exhibit self-organising behaviours that can overcome these small bottlenecks in operational processing. As in the scenario in section 5, the pallet yet to be unloaded can be prioritised and the task destination changed dynamically by the real-time detection of a deficit in selection. Adaptation can occur by recording predicted estimates of task completion against actual task completion outcome and incorporating the error (difference) into future estimates. Adaptation can also occur in storage by connecting patterns of inventory inaccuracies with product characteristics such as similarity contributing to operator error.

Agents can communicate a real-time status. This means that dynamic tasks can be generated closer to the time that they will be actioned. As a result, more appropriate locations will be available for inventory to be put away, the resources to complete the tasks will be available (potentially) and time and

productivity is not spent actioning tasks that are not ready to be completed and that may potentially not be able to be completed.
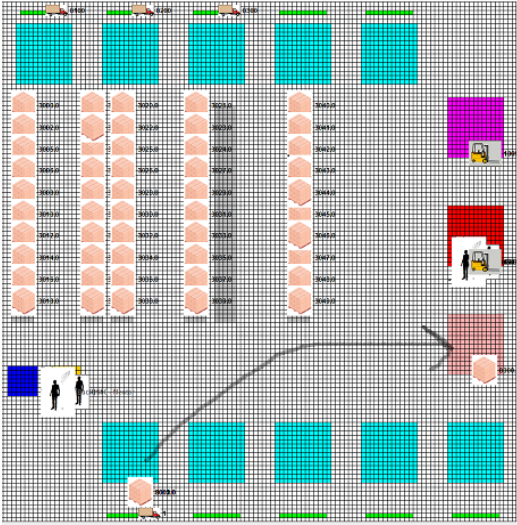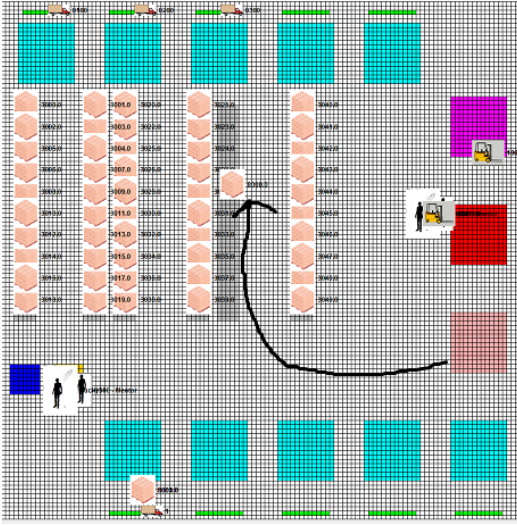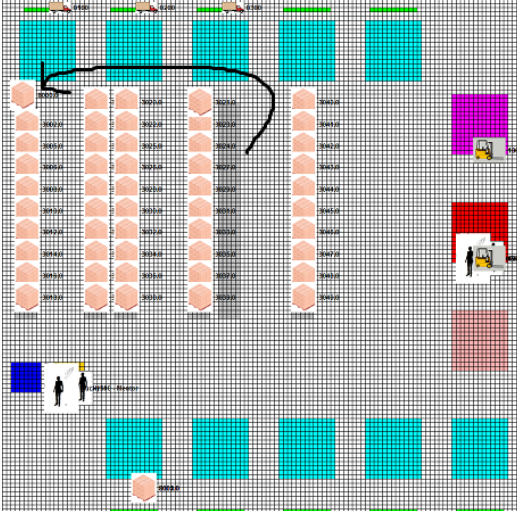
Description	Screenshot
Order Manager Agent: ☐ Receives a request to release customer orders for picking and initiates plan to release order. ☐ Detects that there is only a quantity of 3 in active (in a warehouse location) inventory. ☐ Creates a selection assignment for 3 and backorders 1. ☐ Requests Work Priorities Manager review priorities of "Receiving" for this product. **Work Priorities Manager Agent:** ☐ Increases the priority of all unload work on the receiving appointment truck. The pallet with 108081 has a higher priority. **Task Manager Agent:** ☐ Changes the destination of the pallet with product 108081 to the priority lane. Other pallets go to the staging lane ☐ Forklift driver is allocated the unload task and completes it.	
Inventory Pallet Agent: ☐ Generates a put-away task when the 108081 pallet is placed in the priority lane. This put-away task is of high priority because the unload task was high priority. ☐ Forklift driver is allocated the put-away task and completes it. ☐ With Augmented Reality wearable glasses connected to the mentor agent, put-away pickup could be allocated to a specific operator and directed with colour coding. ☐ Completing a high priority put-away task triggers a request by the forklift mentor agent on the primary selection location to review its replenishment requirements.	
Inventory Pallet agent: ☐ Requests the Pick Manager for an estimate of time before location is empty. ☐ Requests the Inventory Manager for an estimate of time to complete the "best" replenishment. ☐ Requests Task Service to generate a replenishment. ☐ Requests Work Priorities Manager review priorities of "Replenishment" for this product. The priority manager can do this in cooperation with the resource agent. ☐ Selector visits location and picks 3. ☐ Forklift driver is allocated the replenishment task and completes it. ☐ Order manager releases the backorder quantity.	

Table 1 Distributed Model for Replenishment Scenario

Agents have goals and goals can persist. Agents continue to be execute plans until the goal is fulfilled so an exception does not need to be handled manually all the time. For instance, a replenishment that failed to be physically completed will trigger a replacement task (until the selection location is refilled). A pallet that failed to be physically put away in its designated location will be taken to the resolution zone and if appropriate will self-generate another put away task for itself. Tracking the reason for task failure (exceptions) in real-time allows more information to be given to the inventory manager to resolve issues that could not be self-resolved, aiding the decision-making process. Human intervention, where needed, can correct the system data to the point where the agents can continue their normal processing.

The purpose of the mentor agent is to provide a real-time ability to react to real-time changes in the environment. Human operators are generally just following instructions and encountering a real-time constraint issue such as congestion. The mentor agent, communicating agent-agent, agent-human or human-agent, can provide the advantage of a smarter view of the warehouse environment for the operator. With sensors detecting changes in the warehouse environment, different algorithms can be deployed to determine selector travel path or to re-evaluate the sequence of available tasks.

7   CONCLUSION

Warehouses are real-time environments that involve a work schedule, available resources, and time and space constraints. Increasingly, the outlook to solving this problem is to fully automate. This research aims at innovation by augmenting people rather than replacing them. This paper presents a framework for designing warehouse management systems that uses distributed intelligence to react to real-time events and constraints, in order to mitigate the impact of small operational issues on product flow and order fulfilment. A simulation based on intelligent agents was designed and constructed in order to validate the viability of the framework.

This paper contributes to industry by proposing a new way of designing warehouse management systems that augments and enhances the operations of manual warehouses instead of replacing them with automation. With advances in IoT and sensor technologies this approach may be more suitable to the challenges posed by demand being driven by changing consumer behaviour.

Future research iterations of this project may take several paths. Firstly, various AI methods and algorithms can be tested as plug-ins within the intelligent agents, in the simulation, to improve operational functionality and the ability of the model to forecast and resolve problems. Secondly, the simulation can be run against historical real life WMS data, to more accurately assess the improvements the proposed model can provide to warehouse operations.

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