Data Visualization Support for Complex Logistics Operations and Cyber-Physical Systems

Didem Gürdür[1], Klaus Raizer[2] and Jad El-Khoury[1]
[1]Department of Machine Design, KTH, Royal Institute of Technology, Stockholm, Sweden
[2]Ericsson Research - ARBB, Brazil

Keywords: Data Visualization, Information Visualization, Supply Chain, Automated Warehouse, Intelligent Agent, Cyber-Physical Systems, Dashboard Design, Soar.

Abstract: Today, complex logistics operations include different levels of communication and interactions. This paper explores the requirements of these operations and conceptualizes important key performance indicators, stakeholders, and different data visualizations to support the stakeholders in order to understand interactions between entities easier and faster. Three different levels were identified—supply chain, automated warehouse, and intelligent agent—to define the complex logistics operations. For each level, important stakeholders and performance indicators were determined. A case study was designed and described to exemplify the role of cyber-physical systems in complex logistics operations. Moreover, different data visualizations were developed as part of a dashboard to illustrate key performance indicators of different levels for the purpose of supporting stakeholders. This exploratory study concludes by identifying important data necessity for each performance indicator, suggesting ways to collect these data, and exemplifying how data visualization approach can be used through a dashboard design.

1 INTRODUCTION

Automated warehouses include different forms of cyber-physical systems (CPSs) (Lee and Seshia, 2016)—such as intelligent robots and autonomous vehicles, which require collaborative behavior for effective and efficient handling and distribution of goods—to manage complex logistics operations. Even though the autonomous guided vehicles have been used in warehouses to move very large and heavy objects since the 1950s (Wurman, D'Andrea and Mountz, 2008), the use of CPSs in this industry has gained speed in recent years with the help of ongoing developments in control, communication, and computation capabilities of these systems. Today, CPSs have inexpensive computational power and wireless communication and components, which are making them cheaper, smaller, and more capable.

While the adaptation of CPSs is increasing, the need to provide real-time feedback to support the design and control decisions of these systems is also arising. This research focuses on developing appropriate data visualizations to support stakeholders in their decision-making activities when architecting complex logistic operations, which includes automated warehouses and intelligent agents (IAs).

It has been decided that Soar (Laird, Newell and Rosenbloom, 1987) will be used as a cognitive architecture to explain a variety of phenomena related with IAs. Generally, cognitive architectures are producing textual data, and the data is often considered impractical by stakeholders who try to understand the behavior of the IAs. Nevertheless, both the architecture developers and subject matter experts want to learn how cognitive architectures work in detail (Avraamides and Ritter, 2002; Councill, Haynes and Ritter, 2003). One approach to help stakeholders understand the behavior of these architectures is to provide a graphical representation of the processes and behaviors of the agents.

In earlier research (Gürdür, 2016), existing data collection methods were not developed well enough to be directly useful for data analytics and data visualization development in order to improve the understanding of the CPS. Therefore, this study aims to identify important stakeholders, who are part of the decision-making activities of the automated warehouses, in order to develop necessary data

Gürdür, D., Raizer, K. and El-Khoury, J.
Data Visualization Support for Complex Logistics Operations and Cyber-Physical Systems.
DOI: 10.5220/0006569402000211
In *Proceedings of the 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2018) - Volume 3: IVAPP*, pages 200-211
ISBN: 978-989-758-289-9

collection, presentation, and interactivity methods to generate intuitive data visualizations for the purpose of increasing the understanding of important key performance indicators (KPIs). As part of this effort, this study has initiated the development of several data visualizations and a dashboard to measure KPIs and inform stakeholders about the current situation about the system.

To this end, this study aims to answer the following research questions (RQs):

- RQ1: What are the important KPIs for improving the understanding of complex logistics operations?
- RQ2: Who are the important stakeholders that can benefit from real-time data visualizations and visual analytics in order to assess the identified KPIs?
- RQ3: What are the possible data resources to be used in the development of data visualizations?
- RQ4: Which data visualization technique(s) should be used to support decision-making activities of these stakeholders?

These exploratory questions are answered by different research methods, which we will detail in Section 3. The expert opinion technique and semi-structured interviews were used to answer RQ1 and RQ2. Moreover, an example case study has been designed and described, and sample dashboard was developed to answer RQ3 and RQ4.

In Section 2, the earlier studies on automated warehouse systems will be explained, and the background information about chosen cognitive architecture will be described. Secondly, the research approach and the methodology will be explained in Section 3. Then, the case study will be described in Section 4 in order to demonstrate the data visualization needed to improve the understanding of complex logistics operations. This section identifies the KPIs and stakeholders, and presents the data visualization dashboard to accomplish better understanding of the system. Afterward, the findings of the case study will be discussed in Section 5. Section 6 summarizes related work, and finally, Section 7 will recapitulate the findings of the research to conclude the study, in addition to presenting the areas where future efforts will be devoted.

2 BACKGROUND

Logistics or supply chain management is "the process of planning, implementing, and controlling the efficient, cost-effective flow and storage of raw materials, in-process inventory, finished gods, and related information flow from point-of-origin to point-of-consumption for the purpose of conforming to customer requirements" (Management, 1986). Automated warehouses play an important role in today's supply chains, and they consist of a combination of computer-controlled systems that automatically handle, store, and retrieve products with great speed and accuracy. Some parts of these warehouses are also called automated storage and retrieval systems (AS/RSs). They offer the advantages of improved inventory control and cost-effective utilization of time, space, and equipment (Hur *et al.*, 2004; Manzini, Gamberi and Regattieri, 2006). They can be considered as CPSs since they are equipped with motors, sensors, actuators, controllers, and the ability to communicate with other systems (Basile, Chiacchio and Coppola, 2016).

It is necessary to address the design and control decisions of these systems to fully take advantage of all the opportunities they offer. For this reason, several studies are included that examine the AS/RSs from different perspectives. Roodbergen and Vis (Roodbergen and Vis, 2009) published an extensive literature review that examines the current state of the art in AS/RSs. In this study, the authors summarized the issues, such as system configuration, travel time estimation, storage assignment, dwell-point location, and request sequencing. After discussing the reviewed papers, the paper addresses the individual control policies for storage assignment, batching, parking of idle AS/RSs, and sequencing. The authors also commented that the majority of the literature addressed the design and control problems in static environments. Moreover, the authors underlined that today customer demands, order quantities, and delivery schedules are rapidly changing, and the competition is constantly increasing; hence, more flexible approach is needed.

The literature review (Roodbergen and Vis, 2009) identified that only one or two decision problems are addressed simultaneously, instead of combining different problems and developing an overall optimization solution. Certainly, it is a difficult task to include a multitude of design and control aspects of the system for an overall optimization. However, it is vital to understand the system as a whole rather than focusing on only one decision problem. Furthermore, the existing literature mainly concentrated on the relationship between AS/RSs; little effort was spent on understanding the relationship between AS/RSs and other systems in production and distribution facilities.

The literature review (Roodbergen and Vis, 2009) concluded by highlighting the need "to move towards developing models, algorithms, and heuristics that include the dynamic and stochastic aspects of current business. In this context, one can think of self-adaptive storage assignment methods, online-batching policies and dynamic dwell-point rules. Also, algorithms for physical design may need to focus more on the robustness of the design than on perfect optimality to ensure that the system will be capable of remaining efficient in yet unknown future situations." One way to fulfill the need that has been identified by the authors (Roodbergen and Vis, 2009) is to implement intelligent automated warehouses. These intelligent warehouses can examine the relationships between CPSs such as autonomous vehicles, AS/RSs, conveyor systems, cooperative robots, and humans. Moreover, it is possible to develop analytic support within intelligent automated warehouses that aids stakeholders in their decision-making activities.

One way to construct an intelligent warehouse is to use cognitive architectures that adapt the tools from computational psychology. Newell (Newell, 1987) proposed the development of cognitive architectures that provide fixed computational structures that form the building blocks for creating an intelligent system.

A cognitive architecture is a task-independent infrastructure that brings an agent's knowledge to be concerned with a problem in order to produce a behavior other than a single algorithm or method for solving a problem (Laird, 2012). Cognitive architectures are the most well-known approaches to improve the intelligence and autonomy of robots. There are different architectures that focus of modelling different aspects of cognition at different levels of abstraction (Ernst and Newell, 1969; Georgeff and Lansky, 1986; Laird, Newell and Rosenbloom, 1987; Anderson, 1996; Freed, Shafto and Remington, 1999; Just, Carpenter and Varma, 1999; Cassimatis, 2006; Franklin and Patterson, 2006).

Soar (Laird, Newell and Rosenbloom, 1987) is one of these architectures that possesses several capabilities, making it a promising candidate for use in autonomous and cooperative robots. Some of these capabilities include the following:

- simple communication between the architecture and environment through many sensors and motors;
- a mix of reactive and deliberative behaviors;
- definition of a learning mechanism; and
- the ability to collaborate with other agents or software systems (Long *et al.*, 2007).

In particular, Soar architecture provides the ability to use a wide variety of types and levels of knowledge for problem solving. It has been used to develop agents that use several methods for tasks such as reasoning, algorithm design, robotic control, simulating pilot behaviors, and so on.

3 RESEARCH DESIGN

This study has been designed to answer the three exploratory research questions mentioned in Section 1. The expert opinion technique (Clayton, 1997) was used to assist in the preliminary problem identification phase. This technique aims to gather opinions of experts in clarifying the issues relevant to a particular topic.

Several meetings have been conducted with researchers at Ericsson who extensively work on the cognitive architectures, intelligent agents, and complex logistics operations. For the purpose of identifying significant stakeholders and key factors, semi-structured interviews (SSIs) (Drever, 1995) were used as a qualitative inquiry method. SSIs are designed to collect subjective responses from interviewees regarding a particular situation or phenomenon they have experienced (Drever, 1995). They can be used when there is sufficient objective knowledge about an experience but the subjective knowledge is lacking (Richards and Morse, 2012). In this research, the subjective knowledge of the experts plays a big role in identifying relevant KPIs and stakeholders, and eventually affects the design of the data visualizations and the dashboard. The interview questions were used to collect responses of each participant and constitute the structure of the SSI. These questions aimed to understand the architecture of the system, to identify the important people and positions, and to extract the needs of each for the purpose of developing data visualizations.

Finally, an exploratory case study method (Fidel, 1984) was used to assist the development of the dashboard according to the needs that identified by expert interviews. This method is especially useful to investigate complex real-world issues, such as those involving humans and their interactions with technology. The exploratory (or pilot) case studies are condensed case studies that can be used before implementing a large-scale investigation or solution.

Their basic function is to help identify questions and select types of measurement prior to the main investigation. Hence, the case study method is an ideal methodology for this particular study, where a holistic investigation is needed (Feagin, Orum and Sjoberg, 1991; Shneiderman and Plaisant, 2006).

4 CASE STUDY

This section first describes the case study and the overall architecture/structure of an automated warehouse. Section 4.1 focuses on the identification of primary KPIs and stakeholders to answer RQ1 and RQ2. Then, the possible data visualization techniques are exemplified and discussed in Section 4.2 to answer RQ3 and RQ4.

4.1 Identifying KPIs and Stakeholders

In this case study, an automated warehouse and a supply chain were simulated to explore multi-objective computational intelligence approaches and autonomous robotics for managing complex logistics operations (Azevedo *et al.*, 2016).

The case study includes three distinct levels to describe the whole logistics operations. Level 1 describes a typical supply chain that has components such as suppliers, retailers, and an automated warehouse. Level 2 focuses on the automated warehouse component and includes different types of CPSs that work autonomously to fulfill the inventory replenishment, storage, and delivery requests, in addition to humans. Level 3 zooms in on CPSs, specifically to the intelligence of CPSs. This level illustrates intelligent agents' knowledge with Soar architecture. In the following subsections, we will describe the different KPIs, stakeholders, and the challenges for each of the three levels of this automated warehouse architecture.

4.1.1 Level 1: Supply Chain (SC) Level

The supply chain (SC) level consists of an automated warehouse, trucks, retailers, and suppliers, as shown in Figure 1. At this level, several predictive algorithms are needed to execute an optimum plan for the most profitable option. A simulation was developed to analyze how an intelligent, automated vendor-managed inventory method allows for efficient real-time integration of warehouse operations with multi-retailer inventory replenishment tasks (Azevedo *et al.*, 2016). V-REP software was used for this purpose, where a robot

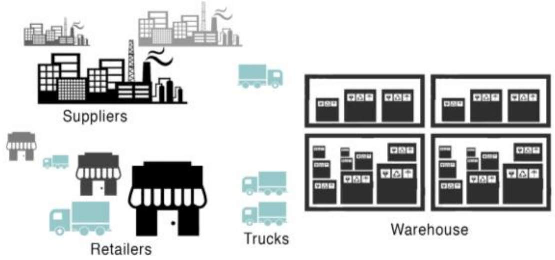

Figure 1: Overview of supply chain level.

simulator generates instructions by a multi-objective evolutionary algorithm running in real-time, aiming to simultaneously maximize profit and minimize shortage and surplus risks while deciding on-the-fly which and how many products should be delivered to which retailers and when.

The essential stakeholders of this level were identified as warehouse manager, supply chain manager, and truck driver. At this level, we identified profitability, risk, and sustainability as important KPIs by conducting SSI, as discussed in Section 3. Profitability metric refers to the degree to which a business or activity yields profit or financial gain. The risk is associated with the excess supply, a situation in which the quantity of a good or service supplied is more than the quantity demanded, and the price is above the equilibrium level determined by supply and demand (Sullivan and Sheffrin, 2003). Sustainability metric is related to the characteristics of the route that trucks take to/from suppliers, retailers such as distance, traffic congestion situation, and so on.

4.1.2 Level 2: Warehouse (W) Level

The warehouse (W) level is concerned with the interactions between IAs, where many IAs are communicating with each other and parameters such as performance, safety, and sustainability are the focus. Possible shortest path, which is doable with the current battery level, and the most efficient way to complete the task without any collision, are two relevant examples.

Figure 2 illustrates the overview of the warehouse level, where AS/RSs, robotics arms, autonomous robots, cameras, conveyor belts, and humans work together to accomplish tasks related to the warehouse. The warehouse manager, system engineer and warehouse staff are stakeholders who should be able to see KPIs to support their decision-making processes. Furthermore, knowledge reusability, safety, interoperability, performance, and sustainability are important KPIs that need to be considered.

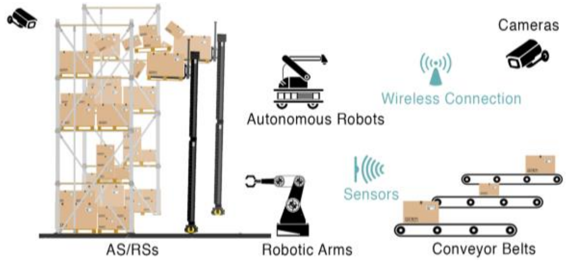

Figure 2: Overview of Warehouse Level.

4.1.3 Level 3: Intelligent Agent (IA) Level

The intelligent agent (IA) level is compliant with the Soar architecture (see Figure 3) and, therefore, consists of a framework for representing tasks and subtasks, long-term memory (LTM), working memory (WM), and related mechanism for generating goals, as well as mechanism for learning (Steinman, Lammers and Valinski, 2009). The LTM is knowledge available at the agent's inner "database." It is composed of rules, facts (semantic knowledge), and episodes the agent has experienced in the past (or had them input by a designer) and that can be retrieved when necessary. WM, on the other hand, holds only what is necessary for dealing with the current situation. It is composed of rules being used at the moment and of facts about the agent's current environment. It also contains perceptual information coming from sensors and motor instructions that are sent to actuators.

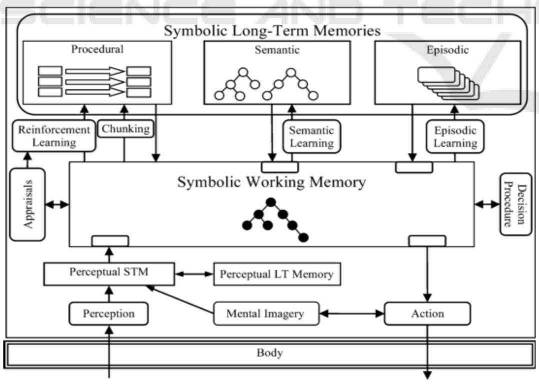

Figure 3: Overview of Soar9 (Laird, 2012).

Experts and intelligence developers are the main stakeholders who need to understand important KPIs for improving the IAs. The KPIs at this level were identified as performance and knowledge reusability.

4.2 Data Visualizations

Once we identified the stakeholders and their specific KPIs, we designed an interactive dashboard to visualize each of the KPIs for their relevant stakeholders. The dashboard is structured into three main tabs associated with each of the three levels that have been defined in earlier sections. The top panel lists these three levels.

4.2.1 Dashboard View 1: Supply Chain Level

As will be detailed in this section, KPIs (performance, knowledge reusability, interoperability, safety, profitability, and risk) are visualized in the tabs by different visualization techniques and metrics that were found to be most suitable. The dashboard design accommodates different stakeholders' needs. Each stakeholder can use one or more tabs to focus on different KPIs according to their need and can navigate through the dashboard to reach detailed analysis for specific KPIs. Moreover, all information is interactively presented on the dashboard, where stakeholders can hover or click on a visualization element and see more information about a particular KPI. KPIs can be selected to be included in the multi-objective optimization of the end-to-end supply chain process.

Figure 4 shows the dashboard design for the supply chain level. The essential information this level is summarized in the bottom part of the dashboard. The dashboard was constructed using a simple and clear design to easily represent the information. For instance, the capacity of each retailer and the warehouse is visualized as donut charts. One can see the average value of these KPIs according to week, month, or year ranges. Three trucks and their work processes are visualized below the donut charts. Stakeholders can click on the truck and can list the details about the truck on the middle panel. Important factors listed there include the name of the truck, route direction information, percentage of the completed work, sustainability metric percentage and the relationship with the average sustainability percentage, time spend to complete work, and time necessary to reach the warehouse for next shipment. On the left bottom of the dashboard, the profitability and risk metrics are shown as a density plot. This information will be updated in real time. Finally, on the right panel, all relevant stakeholders are listed, including their profile and contact information. It is also possible to provide notification mechanisms through the

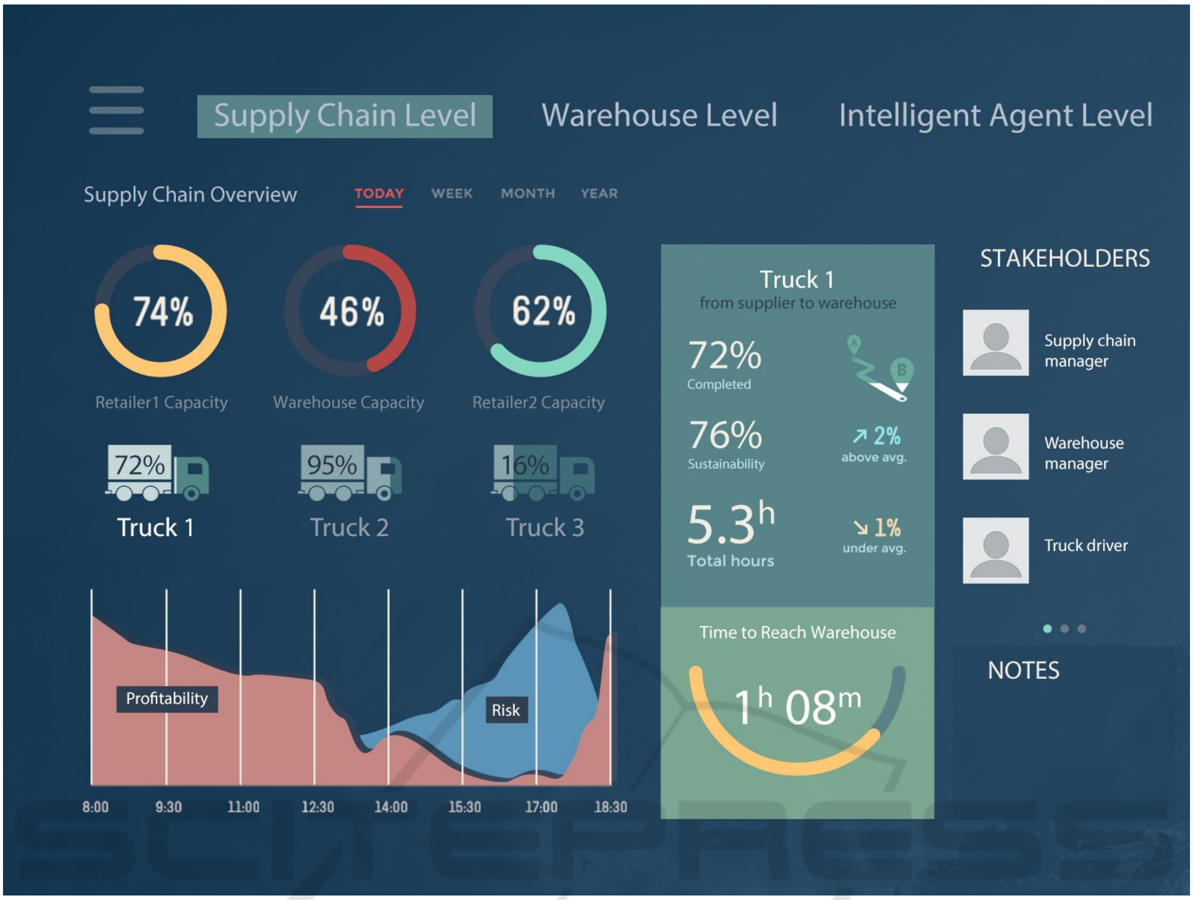

Figure 4: Dashboard design for the supply chain level, where Truck 1 is in focus for the details.

dashboard in order to inform other stakeholders for a specific situation.

4.2.2 Dashboard View 2: Warehouse Level

Figure 5 is the view of the automated warehouse dashboard. In the warehouse level, the main focus is the robots, AS/RSs, and metrics related to these systems. One of the important KPIs mentioned in the earlier section is the performance. The performance of each AS/RS is illustrated with the stacked bar chart, where each color represents different ASs/RSs over a period of working hours. It is also possible to visualize data over a week, month, or a year to see the average performance KPI of each AS/RS. The user can hover on the bar chart to learn the exact number of packages picked and placed by a particular AS/RS.

Moreover, the autonomous robot status is illustrated in real time by a dot map. The location of each robot is shown in this dot map visualization. The re-charging area and location of the conveyor belts are also included in this map in order to observe the behavior of robots. A user can learn more about a particular robot by clicking on a dot. When a robot is selected, an arrow illustrates the direction of the movement. Furthermore, the middle panel is designed to list important information related to the selected robot. For this example, this information includes the name of the robot, direction of the movement, battery status, safety status, performance and its relationship with the average performance, activity time of the robot and its relationship with the average activity, and expected time of the recharging to return back to the warehouse floor. Users can check the current situation of any other CPSs by clicking on their representation (label or element of visualization) to update the information in the middle panel. On the left bottom of the dashboard, the energy consumption status of each robotic arm is summarized. The donut chart visualization technique is used to show this information. The energy consumption metrics are important to calculate the sustainability KPI of a task or the warehouse as a bigger system.

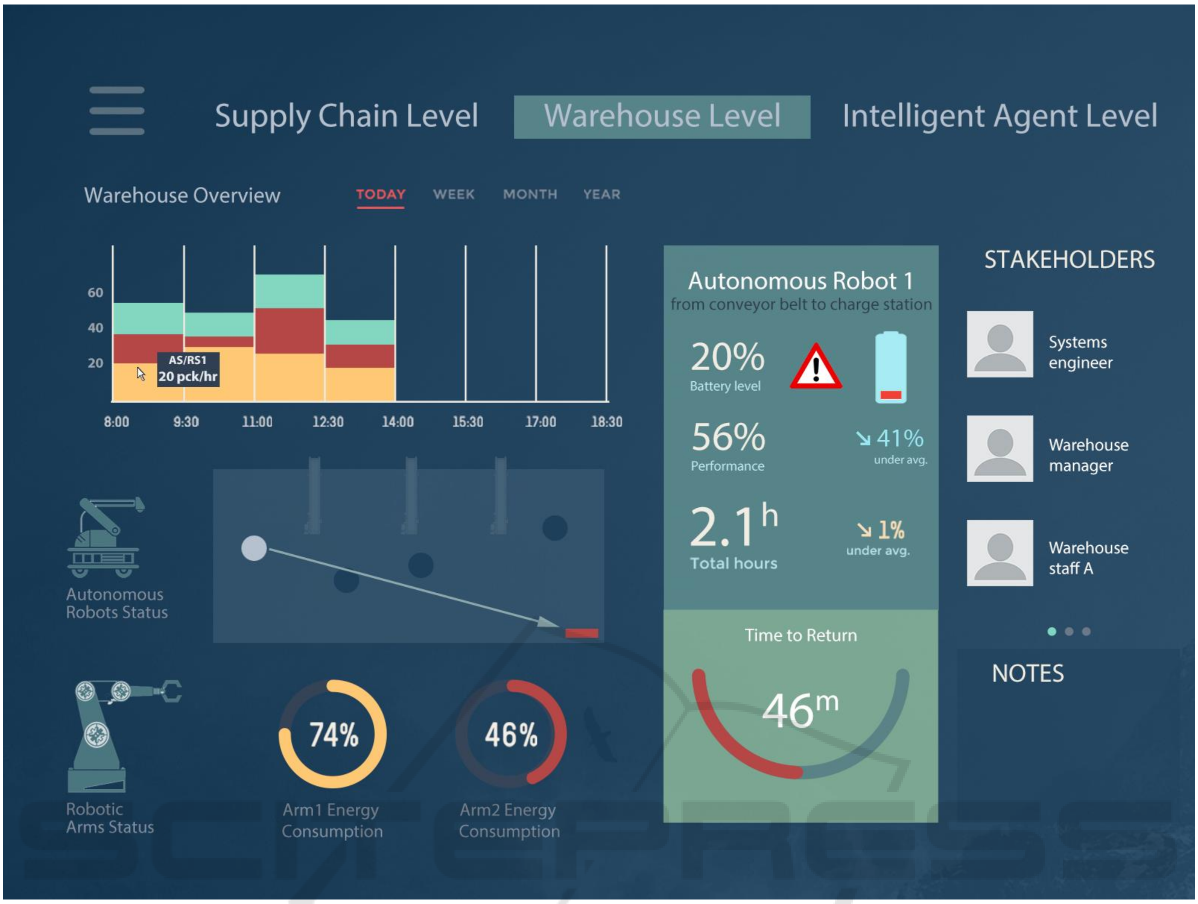

Figure 5: Dashboard design for the warehouse level, where Autonomous Robot 1 and AS/RS1 are in focus for the details.

4.2.3 Dashboard View 3: Intelligent Agent Level

The last dashboard design is illustrated in Figure 6. In this dashboard, the intelligent agent level is represented to inform stakeholders such as intelligence developer(s) and systems engineer. In this design, similar to the earlier Figures 4 and 5, the stakeholders are listed on the right panel. In the middle information panel, KPIs related to a single intelligent agent (IA 2) are summarized. This information includes the name of the agent, the task it is working on, memory usage, performance and its relationship with the average performance, and time for the task and its relationship with the average.

On the left side of the dashboard, a combination of a sunburst diagram and a chord diagram is used to visualize the active IAs and the interactions between them. The order of the sunburst diagram starts with the inner ring, where the IAs are illustrated with different colors. Then, the larger ring shows the active tasks for each IA. The last two outer rings illustrate the working memory and long-term memory, respectively. The viewer of the dashboard can get information about a specific slice or chord by hovering over it. Moreover, the viewer can view detailed information by clicking on any agent and making the middle information panel active for that specific agent.

It is important to know the amount of pre-defined or acquired knowledge for a specific agent, speed of gaining new knowledge, and amount of knowledge used between IAs. Moreover, in case an agent does not have knowledge in memory, a stakeholder needs to know the amount of time and energy needed for a search of information. Such KPIs can help identify the quantity of gained useful knowledge that should be shared between robots, or identify useless knowledge that should be forgotten. For this reason, a node link diagram illustrates the information interactions between the selected IA and other IAs. This visualization shows the useful knowledge that has been used and shared with other IAs and the relationships associated with it.

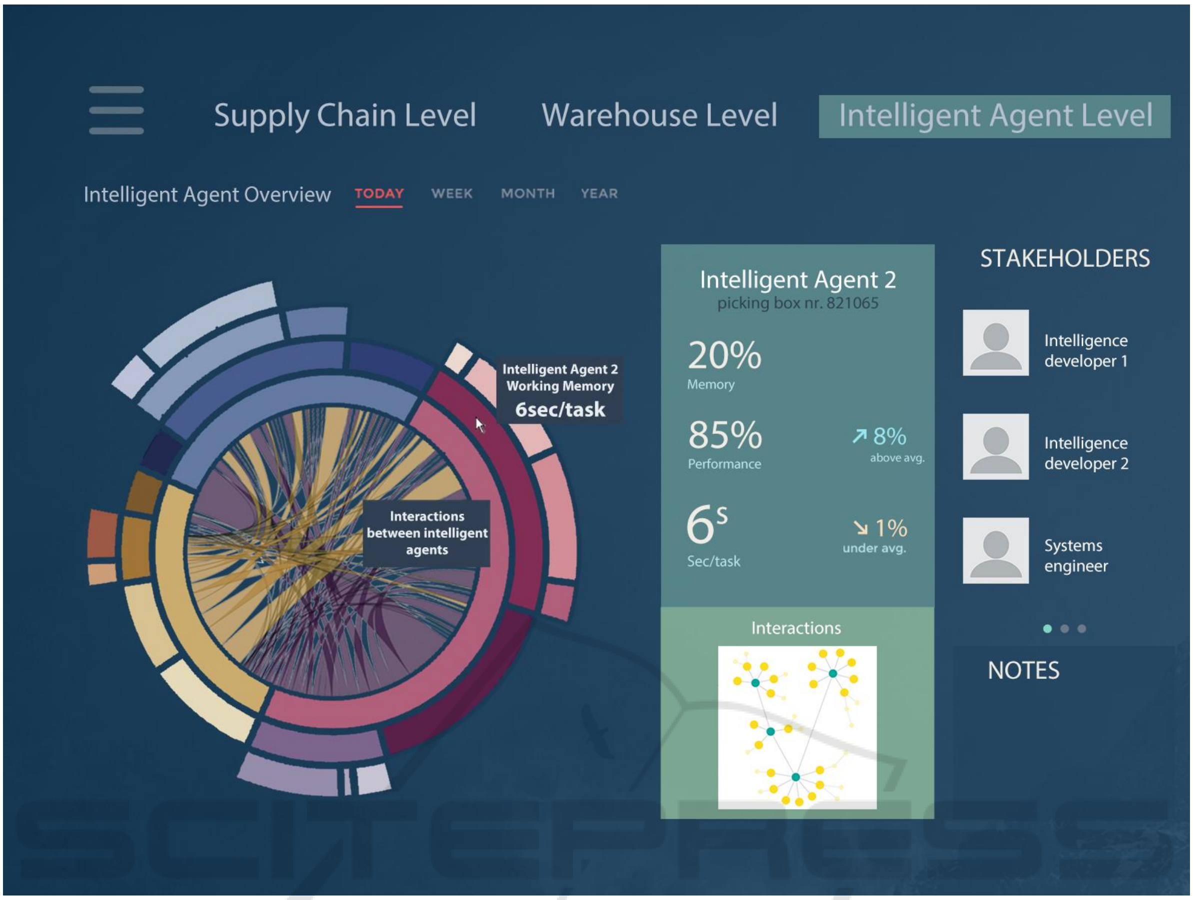

Figure 6: Dashboard design for the intelligent agent level, where Intelligent Agent 2 is in focus for the details.

4.3 Data Measurement

At the end of the case study, a dashboard was designed to visualize important KPIs about the three different levels: (1) supply chain, (2) automated warehouse, and (3) the intelligent agent. This dashboard design was developed according to expert opinions for the purpose of improving the understanding of interoperability, knowledge reusability, sustainability, profitability, risk, and safety of the system.

The input data for each KPI needs to be well-structured so that one can easily develop a dashboard that responds to a real-time stream of input data connected to an intelligent automated warehouse. One of the aims of this study was to generate necessary data collection methods. To this end, the KPIs and data needed to actualize the KPIs are listed below:

Interoperability: To visualize the interoperability KPI, one needs information about the interactions between entities. In the dashboard design, interoperability is visualized on the IA tab where the communications between intelligent agents are represented in the chord diagram. To be able to generate this visualization, data about the interactions between the robots needs to be logged. For instance, whenever a CPS encounters another CPS, the interaction should be saved by stating the names of the IAs, their actions, duration of the interaction, and so on. Moreover, this data should also include time stamps, so it can be tracked on time. Categorization of the interactions according to different actions can give information to the user about which type of actions requires better interoperability, and then the stakeholder can make prioritization decisions on these actions. To collect this useful data one can use sensors on/around the robots and other CPSs and/or network data.

Sustainability: The sustainability KPI is visualized on different levels to inform the user about the energy consumption situation of the system. Any data related to power, energy, and battery life needs to be saved for this purpose. More details about the truck, route distance, and fuel consumption can give a more holistic view about the whole supply chain sustainability.

Knowledge Reusability: The development process of knowledge is visualized on the IA level. The Soar architecture includes an epidemic memory as a record of an agent’s stream of experiences. Each chunk of knowledge inside the agent’s WM could have a “level of reusability” attached to it. The aggregation of all these values across all agents can be used to calculate/measure the knowledge reusability KPI. One can include initial set of knowledge components such as goals, milestones, self-knowledge, and other agents (Taylor *et al.*, 2002) for further analysis.

Performance: The performance KPI is very much related to time. Log files about each CPS’s task should be collected for this purpose. Time-stamped data related to the goal, process, and details about each robot’s name, position, battery situation are needed to generate the visualization(s).

Safety: Safety-level-related data could be acquired by a set of sensors located inside the warehouse. These sensors can detect human existence and change the level of safety for specific robots, distribute this information through the network, and use different notifications to inform both CPSs and humans. However, more detailed safety requirements are needed to understand the safety-related measures. For example, in case of a human-robot interaction, one should consider movements of the robots that can cause hazards to humans surrounding them. To prevent accidents, it is necessary to identify dangerous or potentially harmful movements. This is especially difficult in cases where autonomous robots are included since such robots share the warehouse space with humans instead of having dedicated spaces. During the case study, we identified safety as an important KPI to consider, but did not develop any visualizations or specific data needs for its assessment. We have listed this KPI among others since it is crucial to consider. Further work on understanding existing safety standards, such as ISO: ISO/TS 15066 (International Organization for Standardization, 2016), and on identifying cases where humans will be present in an autonomous warehouse is essential to extract the data needs for the safety KPI. Safety and necessary data to observe safety will be detailed in future studies.

Risk: This is shortage risk, or the risk of not being able to deliver the expected products in due time according to plan. To calculate the risk KPI, inventory levels and customer ordering events needs to be known. With this, expected consumption is estimated and fed into a model, which relies on a Poisson distribution to estimate shortage risk.

Profitability: In order to calculate profit, one needs the measured "revenue," "inventory cost," and "transportation costs" of the whole cycle. We also need the "missed revenue," which is calculated from the expected revenue, based on how many sales would be lost if there were shortages of specific products.

5 DISCUSSION

This study showed that it is vital to identify important KPIs and the need of data as a preliminary stage of the project to be able to assess them before designing and implementing the system. Moreover, the case study illustrated how one can use these KPIs with different data visualization techniques in order to develop dashboards.

Another aim of the study was to understand required methods for designing an intelligent complex logistics operations system. Choosing a cognitive architecture for modeling intelligent agents in our scenarios was motivated by a number of factors. Decision-making in a cognitive architecture happens similar to how it happens in the human mind, albeit at a higher abstract level. Thus, extracting an explanation from the agent for why it made a particular decision is more straightforward. This AI capability, of providing explanations for its decisions, has been gaining much importance in the design of current and future autonomous systems (Goodman and Flaxman, 2016).

In addition, cognitive architectures tend to provide a framework for developing very general agents, which ought to be applicable to many different domains. Generic software that can be applied to many domains with little extra engineering needed tend to lower time to market and reduce costs.

Despite the exploratory nature of this study, we endeavored to validate the findings by different methods. Using expert opinion at this preliminary stage of the research is a fast and comprehensive way to structure the concept and to identify the needs. In the future, we plan to employ user experience methodologies, where specialized research tools can capture the participant behaviors and attitudes when going through some scenarios. This kind of formal laboratory user studies can provide more details about the usage of the dashboard and help to draw clear conclusions. However, designing and running controlled experiments requires substantial time and resources. Formal laboratory user studies might even be inappropriate during an exploratory phase of research when clear objectives and variables might not yet be defined (Tory and Möller, 2005). Tory and Möller (Tory and Möller, 2005) summarize this as "formal laboratory user studies often focus on perceptual or simple cognitive tasks. High-level cognitive tasks (for example, thinking, deciding, and exploring ideas) are important activities, yet performance of these tasks is difficult to measure objectively and quantitatively."

6 RELATED WORK

Several graphical displays have been developed for cognitive models. Even though it is not common to have a graphical display for every model, there are models that come with graphical displays, and these displays are used to explain the models. Some relevant graphical displays are summarized below to highlight their capabilities and how this particular study differs from them:

- APEX (Freed, Shafto and Remington, 1999) modelling framework is a tool that automatically generates pictorial representations of the actions associated with the models and their dependencies. It uses pert charts for a critical path analysis for the analysis of total task time.
- The Developmental Soar Interface (DSI) was created to support model creation, debugging, and presentations for Soar architecture. It provides the ability to understand and manipulate process models built within Soar.
- The Tcl/Tk Soar Interface (TSI) (Ritter, Jones and Baxter, 1998) provides multiple views of the working memory and decision processes of a Soar agent, including a semi-graphical trace of the goal stack and the operators in a Soar model.
- The Situational Awareness Panel (SAP) (Jones, 1999) provides a number of views of a synthetic agent. These views are updated continuously during the lifetime of the agent and aim to support users to inspect the reasoning processes of the agents.
- The Visualization Toolkit for Agents (VISTA) (Taylor *et al.*, 2002) provides insight into an agent's internal reasoning processes. VISTA allows agent developers, subject-matter experts, and other stakeholders to verify the correctness of an agent's behavior without requiring technical details of the implementation. It uses Gantt and pert charts.
- The Categorical Data Display (CaDaDis) is an extension to VISTA. It offers pert charts to show tasks by category, nonstandard pert charts that show the temporal dependencies, and Gantt charts that help show occurrences of agent events along a time line

In this paper, data visualization and visual analytics techniques, rather than pictorial or graphical displays, were exercised to visualize the important KPIs in order to improve the understanding of intelligent agents and support stakeholders in their decision-making processes. Unlike in earlier graphical display aids, these KPIs do not necessarily focus only on the behavior, situational awareness, the agent's working memory, and long-term or short-term knowledge. Furthermore, this study aimed to develop data collection, mapping, selection, presentation, and interactivity methods to generate these data visualizations.

7 CONCLUSIONS

This study aimed to conceptualize the needs for complex logistics operations where cooperative robots, intelligent transportation systems, and stakeholders related with the system can work together. We have identified three different levels of this CPS: supply chain, warehouse, and intelligent agent. The important KPIs related to the system are interoperability, sustainability, knowledge reusability, performance, safety, risk, and profitability. Moreover, the supply chain manager, warehouse manager, truck driver, systems engineer, warehouse staff, and intelligence developers are also recognized as essential stakeholders who would have access to and use the dashboard to support their decisions.

Future work will be to extend the existing simulation to provide useful data identified by this study, for the use of dashboard implementation. To develop KPIs further, surveys with relevant stakeholders may be conducted. Furthermore, formal laboratory user studies will be designed and conducted as a next step to assess the success of the dashboard design.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge discussions, contributions, and helpful suggestions from Aneta Vulgarakis, Rafia Inam, Carlos Azevedo, Konstantinos Vandikas, Leonid Mokrushin, Ricardo Souza, Elena Fersman, and Martin Törngren.

The research leading to these results has received funding from the "SCOTT - Secure Connected Trustable Things." SCOTT (www.scottproject.eu) has received funding from the Electronic Component Systems for European Leadership Joint Undertaking under grant agreement No. 737422. This Joint Undertaking receives support from the European Union's Horizon 2020 research and innovation programme and Austria, Spain, Finland, Ireland, Sweden, Germany, Poland, Portugal, Netherlands, Belgium, and Norway.

REFERENCES

Anderson, J. R. (1996) 'ACT: A simple theory of complex cognition.', *American Psychologist*, 51(4), pp. 355–365. doi: 10.1037/0003-066X.51.4.355.

Avraamides, M. N. and Ritter, F. E. (2002) 'Using Multidisciplinary Expert Evaluations to Test and Improve Cognitive Model Interfaces', pp. 553–562.

Azevedo, C. R. B., Raizer, K., Souza, R. and Rohmer, E. (2016) 'Multi-Objective Autonomous Robotics for Management and Operations of Complex Logistics Systems'. Available at: https://www.researchgate.net/project/Multi-Objective-Autonomous-Robotics-for-Management-and-Operations-of-Complex-Logistics-Systems.

Basile, F., Chiacchio, P. and Coppola, J. (2016) 'A Cyber-physical view of automated warehouse systems', in *Automation Science and Engineering (CASE), 2016 IEEE International Conference on*. IEEE, pp. 407–412. doi: 10.1109/COASE.2016.7743434.

Cassimatis, N. L. (2006) 'A Cognitive Substrate for Achieving Human-Level Intelligence', *AI Magazine*, 27(2), pp. 45–56. doi: 10.1609/aimag.v27i2.1879.

Clayton, M. J. (1997) 'Delphi: a technique to harness expert opinion for critical decision-making tasks in education', *Educational Psychology*, 4(17), pp. 373–386.

Councill, I. G., Haynes, S. R. and Ritter, F. E. (2003) 'Explaining Soar: Analysis of Existing Tools and User Information Requirements', *Proceedings of the Fifth International Conference on Cognitive Modeling*, 63468, pp. 1–6.

Drever, E. (1995) *Using Semi-Structured Interviews in Small-Scale Research. A Teacher's Guide.*

Ernst, G. W. and Newell, A. (1969) *GPS: A case study in generality and problem solving*. New York, New York, USA: Academic Press.

Feagin, J. R., Orum, A. M. and Sjoberg, G. (1991) *A case for the case study*. Chapel Hill: University of North Carolina Press Books.

Fidel, R. (1984) 'The Case Study Method: A Case Study', *Library and Information Science Research*, 6(3), pp. 273–288.

Franklin, S. and Patterson, F. G. (2006) 'The LIDA architecture: Adding new modes of learning to an intelligent, autonomous, software agent', *Integrated Design and Process Technology*, pp. 1–8. Available at: http://ccrg.cs.memphis.edu/assets/papers/zo-1010-lida-060403.pdf.

Freed, M. A., Shafto, M. G. and Remington, R. W. (1999) 'Employing simulation to evaluate designs: The APEX approach', in *Engineering for Human-Computer Interaction*. Boston, MA: Springer US, pp. 207–223. doi: 10.1007/978-0-387-35349-4_12.

Georgeff, M. P. and Lansky, A. L. (1986) 'Procedural knowledge', *Proceedings of the IEEE*, 74(10), pp. 1383–1398. doi: 10.1109/PROC.1986.13639.

Goodman, B. and Flaxman, S. (2016) 'EU regulations on algorithmic decision-making and a "right to explanation"', in *2016 ICML Workshop on Human Interpretability in Machine Learning (WHI 2016)*, pp. 26–30. Available at: http://arxiv.org/abs/1606.08813.

Gürdür, D. (2016) *Making Interoperability Visible: A Novel Approach to Understand Interoperability in Cyber-Physical Systems Toolchains*. KTH Royal Institute of Technology.

Hur, S., Lee, Y. H., Lim, S. Y. and Lee, M. H. (2004) 'A performance estimation model for AS/RS by M/G/1 queuing system', *Computers and Industrial Engineering*, 46(2), pp. 233–241. doi: 10.1016/j.cie.2003.12.007.

International Organization for Standardization (2016) *ISO: ISO/TS 15066:2016: Robots and robotic devices – Collaborative robots*. Geneva, Switzerland.

Jones, R. M. (1999) 'Graphic visualization of situation awareness and mental state for intelligent computer-generated forces', *Proceedings of the Eighth Conference on Computer Generated Forces and Behavioral Representations*, (May), pp. 219–222.

Just, M. A., Carpenter, P. A. and Varma, S. (1999) 'Computational modeling of high-level cognition and brain function', *Human Brain Mapping*, 8(2–3), pp. 128–136.

Laird, J. E. (2012) *The Soar Cognitive Architecture*, *AISB Quarterly*. MIT Press. doi: http://mitpress.mit.edu/catalog/item/default.asp?ttype=2&tid=12784.

Laird, J. E., Newell, A. and Rosenbloom, P. S. (1987) 'Soar: An architecture for general intelligence.', *Artificial Intelligence*, 33(1), pp. 1–64.

Lee, E. A. and Seshia, S. A. (2016) *Introduction to Embedded Systems, A Cyber-Physical Systems Approach*. Cambridge: MIT Press. doi: 10.1007/71006.

Long, L. N., Hanford, S. D., Janrathitikarn, O., Sinsley, G. L. and Miller, J. a (2007) 'A Review of Intelligent Systems Software for Autonomous Vehicles', *2007 IEEE Symposium on Computational Intelligence in*

Security and Defense Applications, pp. 69–76. doi: 10.1109/CISDA.2007.368137.

Management, C. of logistics (1986) *What is it all about?* IL: Oak Brook.

Manzini, R., Gamberi, M. and Regattieri, A. (2006) 'Design and control of an AS/RS', *International Journal of Advanced Manufacturing Technology*, 28(7–8), pp. 766–774. doi: 10.1007/s00170-004-2427-6.

Newell, A. (1987) 'Human Cognitive Architecture', *Unified Theories of Cognition*. doi: 10.1002/wcs.1180.

Richards, L. and Morse, J. M. (2012) *Readme first for a user's guide to qualitative methods*. Sage.

Ritter, F. E., Jones, R. M. and Baxter, G. D. (1998) 'Reusable models and graphical interfaces: Realising the potential of a unified theory of cognition', *Mind modeling—A cognitive science approach to reasoning, learning and discovery*, (1998), pp. 83–109.

Roodbergen, K. J. and Vis, I. F. A. (2009) 'A survey of literature on automated storage and retrieval systems', *European Journal of Operational Research*. Elsevier B.V., 194(2), pp. 343–362. doi: 10.1016/ j.ejor.2008.01.038.

Shneiderman, B. and Plaisant, C. (2006) 'Strategies for evaluating information visualization tools: multi-dimensional in-depth long-term case studies.', in *AVI workshop on Beyond time and errors: novel evaluation methods for information visualization*. ACM, pp. 1–7.

Steinman, J. S., Lammers, C. N. and Valinski, M. E. (2009) 'A proposed open cognitive architecture framework', *Proceedings - Winter Simulation Conference*, (1), pp. 1345–1355. doi: 10.1109/WSC.2009.5429287.

Sullivan, A. and Sheffrin, S. M. (2003) *Economics: Principles in action*. New Jersey: Pearson Prentice Hall.

Taylor, G., Jones, R. M., Goldstein, M., Frederiksen, R. and Wray, R. E. I. (2002) 'VISTA : A Generic Toolkit for Visualizing Agent Behavior', *Proceedings of the 11th Conference on Computer Generated Forces and Behavioral Representation*, (January), pp. 157–167.

Tory, M. and Möller, T. (2005) 'Evaluating visualizations: Do expert reviews work?', *IEEE Computer Graphics and Applications*, 25(5), pp. 8–11. doi: 10.1109/MCG.2005.102.

Wurman, P. R., D'Andrea, R. and Mountz, M. (2008) 'Coordinating Hundreds of Cooperative, Autonomous Vehicles in Warehouses', *AI Magazine*, 29(1), p. 9. doi: 10.1609/aimag.v29i1.2082.