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Abstract. The durability of an automobile factory depends on its flexibility and its evolution capacity to meet market expectations. These expectations tend increasingly to the vehicles' customization. Therefore, automobile factories may be able to manufacture several vehicle models on the same assembly line. It makes automobile manufacturers face big logistic challenges in their production sites. They must be capable of simplifying, synchronizing and proposing intelligent and flexible logistic flow. Thus, digital tools for decision support are needed. This paper aims to propose an architecture to model the logistic process of supplying materials to the assembly line as a multiagent system. Thus, multiagent learning and collective intelligence techniques can be applied to guarantee a good performance of the process. The case study focuses on a kitting picking zone from a Renault production site which manufactures six different vehicle models, each one with its variants.

Keywords: Artificial Intelligence, Collective Intelligence, Multiagent Systems, Kitting Picking; Automotive Industry.

1 Introduction

Internal logistics in the automotive industry must ensure that for each vehicle, the right piece will be available at the right place at the right time to avoid assembling a piece on the wrong vehicle. With the ongoing trend of mass-customization and the increasing product variety, almost every vehicle that is being assembled is unique. So that, logistics becomes one of the greatest challenges in the automotive industry.

The delivery of pieces to the assembly process can be divided in two types: line-side supply and kitting. Line-side supply consists in storing all the pieces to be assembled next to the assembly line and the operator must choose the right pieces from all the available ones. This method needs large areas next to the assembly line, quality errors may be common when there is high variety of products and it lacks flexibility to production changes. This is why many of the biggest automobile manufacturers implement kitting [1]. It means that the assembly process is supplied with collections of components and/or subassemblies in different places, in order to support one or more assembly operations for a given product. It allows to have more flexibility in the assembly lines, parallelize different assembly tasks, build product structures with many part numbers and ensure a high assembly's quality.

Kitting requires order picking to be performed somewhere in the system. This process might follow a predefined product structure and a production schedule known at a previous stage. In addition, it involves several technological bricks such as bin picking robots, Automated Guided Vehicle (AGV), warehouse management systems, quality control systems and automated kitting processes. When several systems or entities are inside the same environment, if they have their own objectives and beliefs, their relationship may be either of conflict or of cooperation.

In order to warrant a good performance of the whole logistic process of delivering the right kit, to the right place at the right time to the assembly process, all the bricks mentioned above need to interact and communicate between them and with the humans, also involved in the process. Managing all these system interactions is an important question to keep and improve the global performance of whole process.

Moreover, the artificial intelligence arrival to the society and to the industry has had big impacts. These impacts have been boosted by the deep learning development and its increasing number of applications in our current life. Regarding the kitting topic, exploring the use of the artificial intelligence and the collective intelligence for dealing with the interactions of all the agents implicated in the process is worth.

The purpose of this paper is to propose an architecture to model the logistic process of supplying materials to the assembly line of an automotive industry as a multiagent system. Thus, multiagent learning and collective intelligence techniques can be applied to guarantee a good performance of the process as well as deal with the perturbation that can take place during the process.

We present in Section 2 a general description of the industrial use case and a review of the related work. We describe the current situation in Section 3. We display a proposal for the application of multiagent systems and collective intelligence techniques in a kitting picking zone of an automotive production site in Section 4. Finally, we conclude the article and make suggestions for further work in Section 5.

2 Problem description

2.1 Use case, problematic and objective

The industrial use case is an assembly line supplied with the kitting method in an automotive production site. The objective is to warrant a good performance of the whole logistic process of supplying materials from a kitting picking zone to the assembly line. Kitting performance is defined as a function of the kit conformity (kits composed by the right pieces) and the delivery timeliness (to avoid the assembly line stops).

The assembly process follows a fixed sequence in different workshops dedicated to a specific zone of the vehicle such as the underbody, the chassis, the power train, the wheels, the doors and the vehicle's body. At the beginning the underbody and the body are assembled with their components on separated lines. Then, both lines merge and other elements are assembled to the product in the principal assembly line.

During the assembly stage, a vehicle can be equipped up to 2000 components. Most of these components are delivered to the production site by internal or external suppliers. Internal suppliers are other production sites from the same automotive group that are dedicated to the manufacture of vehicle pieces for the assembly sites. External suppliers are companies which do not belong to the automotive group.

In order to reduce the size of the line-side delivery areas, to relieve operators' mental load and to ensure product quality, kitting picking areas are installed in the production plant. Each workshop on the assembly line has a dedicated kitting picking zone with the purpose of dealing with product diversity. Kitting zones are supplied with packages of pieces by operators, then other operators prepare kits for the vehicles present in the assembly line and finally these kits are delivered to the line by AGV. The number of references managed may vary highly from one kitting zone to another one. Some zones manage around 100 references whereas others manage around 1000.

Currently, the considered production site manufactures 6 different vehicle models with a production rate in the range of 30 to 60 vehicles per hour. Each model has several versions and can be customized depending on the vehicle finishing and on the equipment chosen by the client. In addition, these models change constantly. One of the models is in the beginning of the production phase whereas for three of them the production will be stopped during the next two years. However, in 2024 a new vehicle project will arrive to the same plant.

The high number variety, the high production volume, the high number of vehicles components, the changeable number of products manufactured and the high number of means involved in the supplying process, make internal logistics vastly challenging and prone to perturbations. In this context, the application of collective intelligence and multiagent techniques are suitable to model and support this logistic process.

2.2 State of the art

Research in the field of the Artificial Intelligence (AI) has its beginning in the decade of 1950. Since then, the field of AI has experienced several periods of interest and disappointment. However, enthusiasm and funding have revived recently. Most of the early applications of the AI concerns what is known as Symbolic AI. It mainly focused on areas such as: Problem solving, Pattern recognition and Reasoning. However, this approach was then complemented by a cognitive modeling approach. It was interested in theories of intelligence related with Neural Networks. It had success in Pattern recognition and Learning task problems [2].

Later, the concept of Intelligent agent brings with it the notion of interaction and adaptation with the environment. An intelligent entity should be able to sense the environment around it, process the information making decision depending on its goals and carry out actions that affect it [3].

Multiagent systems are distributed systems of the independent actors defined above, that cooperate or compete to achieve a certain objective [4]. Current challenges as automated driving, distributed traffic light control and coordination of large swarms of robot, as well as web applications like Wikipedia, Amazon and YouTube have a distributed nature and involve high degrees of uncertainty [5]. Thus, agents need to consider dynamic and changing environments. In order to solve this kind of problems, they have to learn autonomously from the experience [6]. Through the work on these applications, the AI focus changed gradually from trying to replicate human intelligence to augment human capabilities [2].

The ability of a group of agents cooperating together to solve big and complex problems, where each one makes independent contributions is defined as Collective intelligence [7]. In this kind of groups, the quality of a group's performance does not depend on the intelligence of the individual members of the group [8].

Multiagent learning is the field that integrates machine-learning techniques in Multiagent systems. Reinforcement learning algorithms are the most studied in this field. The purpose is to create adaptive agents since each agent faces a moving-target problem: "what needs to be learned by an agent depends on and changes with what has been learned by the other agents" [4].

The most advanced and sophisticated algorithms in the field can be found in videogames. Popular games as hide and seek [9], and capture the flag, developed by Open AI and Deepmind [10] respectively, are examples of these. In both games, there are two teams composed by several agents which need to cooperate to win the game against the opposing team. A similar application can be found in [11] where reinforcement learning algorithms are implemented in a Polo game context.

Regarding applications on the industrial field, we can find two different branches: homogeneous multiagent systems and heterogeneous multiagent systems. The first one concerns systems composed by several agents with the same characteristics and similar goals. Here, we can find applications like mobile robotic control [12] and contextualization in cooperative robotics [13].

On the other hand, the second one is about systems composed by agents, where each one has different characteristics from the others. Using multiagent systems in this context help to deal with problems like online scheduling in smart factories [14] and the organization of reconfigurable production systems [15],[16]. Likewise, we can find the use of multiagent systems to detect anomalies in several process in the industry, as it is presented in [17].

In conclusion, we can see that the problematic addressed in this paper belongs to the heterogeneous multiagent system area. More specifically, considering the attributes of the systems involved in the process and based on the agent classification proposed by Nwana in [18], this paper deals with intelligent agents: the factory operators and with collaborative agents: physical machines.

No studies considering the application of multiagent system techniques in a picking kitting zone of an industrial process have been found. Consequently, we propose in this article an architecture to apply multiagent learning and collective intelligence techniques to warrant a good performance of the whole logistic process of supplying materials to the assembly process in a Renault plant. The topics covered by the papers [15],[16] and [17] are a source of inspiration for the proposal presented in the following section.

3 Current process description

The wide customization possibilities for the customers requires a high variety for pieces of the same type. As it has been mentioned before, a vehicle can have around 2000 components that are assembled in the assembly line. Most of those components are delivered to the factory by external or internal suppliers.

On the overall flow of pieces, from the reception at the warehouse or at the unloading area to the point of consumption on the production line, the flows are classified in three types: rank 0, rank 1 and rank 2 (**Fig. 1**).

- The rank 0 flow consists in unloading the delivery truck and storing the products in the warehouse or on temporary areas. These flows are operated by forklift drivers.
- The rank 1 flow consists in moving the pieces from the warehouse or temporary areas to the Picking/Kitting areas. These flows can be performed either using forklifts or using mobile bases driven by operators.
- The rank 2 flow moves kits of several pieces from the Picking/Kitting areas to the production line. These flows are mainly performed by AGV.

Moreover, depending on several factors such as its number of diversities, its dimensions and weight and its consumption rate, a piece can be delivered to the assembly line by different logistic solutions.

There are mainly six logistic solutions that are detailed hereinafter.

Programmed Logistic 1 (PL1). The goal of this solution is to transport the goods from the storage zone to the kitting areas. The pallets of these goods must then have been already labelled with the corresponding kitting zone label. Operators will be affected to a particular kitting area. They are in charge of preparing and supplying the pieces needed in the area. The frequency of the distributions is determined according to the autonomy of the kitting area and from one distribution to the next, only the quantities to deliver change, but the distributor will still work in the same area. The quantities are determined by the observation of the operators.

Programmed Logistic 1' (PL1'). The goal of the PL1' solution is the same as for the PL1, it is to transport the goods from the storage zone to the kitting areas. However, with this method, the planification of deliveries is performed based on the sequence of production, which does not exist in the PL1.

Needs on the assembly line for day D+2 are determined on day D, according to the production sequence. Thus, the deliveries from the storage area to the kitting areas are planned in periods of 2 hours or more, depending on the autonomy of the kitting zone. So that, the pallets with the needed pieces are prepared and placed in determined areas for their distribution at the right time.

Programmed Logistic 2 (PL2). The logistical solution PL2 can be applied only to the small packages. As well as for PL1', this solution plans deliveries in time periods of 2 hours generally, according to the needs on the assembly line. The needs are also determined thanks to the final production sequence. The main difference between PL1' and PL2 is that for PL2 solutions, the pallets of pieces are prepared and labelled by the supplier and not by operators. In this case, operators are in charge only of the distribution of the pieces. This makes it possible to avoid the storage of the pieces, because the delivered packages will be consumed on the same day as the delivery or next one.

Direct flow solutions. These solutions are based on the Just-In-Time principle, the goods are not stored in the factory, but they are placed briefly in waiting area before being sent to the picking/kitting areas. These solutions do not require the goods to be handled by forklift drivers, nor do they require large storage surfaces. It is generally used for pieces assembled in 100% of vehicles.

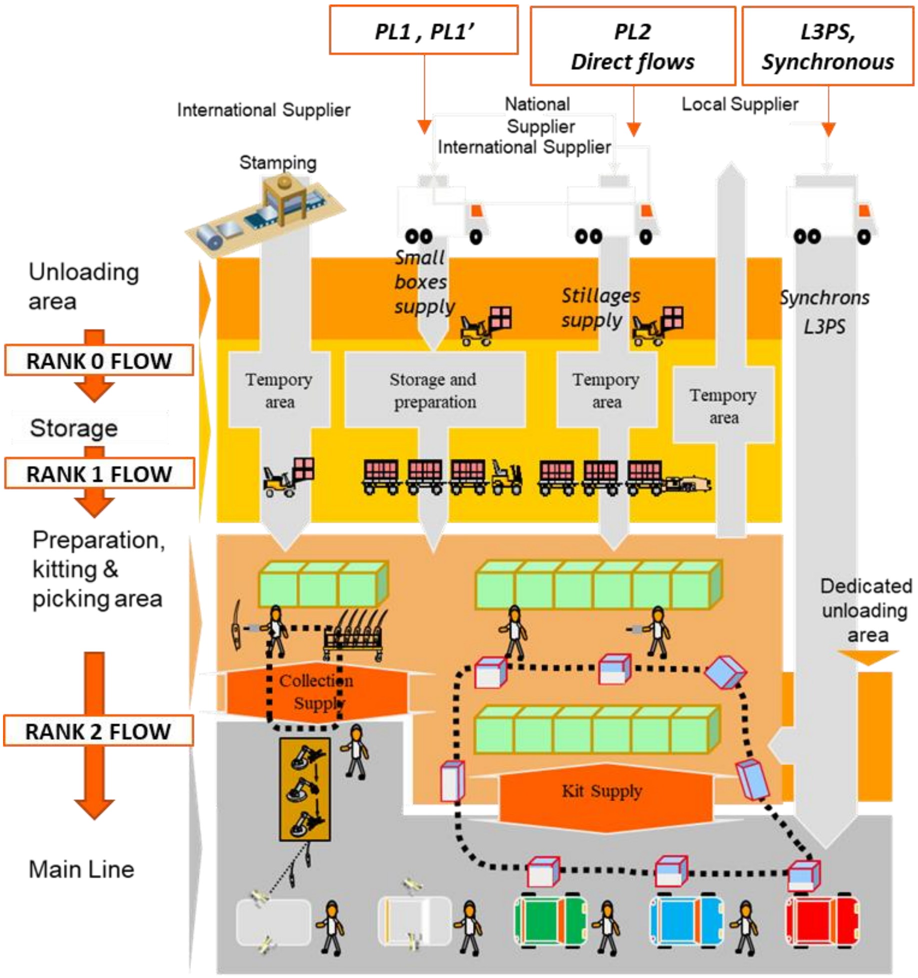

Fig. 1. Types of flows and logistic solutions illustrated on a factory layout

L3PS. The objective of this solution is to deliver the pieces in the order of the production sequence on the assembly line. The pieces are produced and delivered sequentially by the supplier, based on the order of the vehicles on the assembly line. As it can be seen on the **Fig. 1** the packages containing the sequenced pieces are stored only for few hours and then sent to the assembly line or to a kitting or picking area, depending on the chosen alternative of deployment. This solution is suitable for piece with high variety or number of diversities and for high dimension pieces that can be handled manually by an operator.

Just in Time (Synchronous). The pieces that are delivered using this solution are perfectly ordered with the production sequence. The delivery order is sent to the supplier when the associated vehicle is entering the assembly line. So that, the vehicle sequence can not be modified. The supplier has only few hours to produce the pieces in sequence and deliver them directly to the assembly line. The pieces are assembled almost immediately so they do not need to be stored in the factory.

The supplier can also receive the production forecast and the initial sequence of production in order to be able to plan its own production and avoid having any shortage. To implement this solution, the supplier must be located very close to the factory so that it can keep up with the production throughput. This solution is applied to pieces with a high variety and with massive dimensions because they are difficult to handle manually by an operator.

Regarding the kitting process, it consists in regrouping pieces of different families that will be assembled on the same vehicle. For creating a kit, operators are placed in organized zone with tens of packages around them, each one containing pieces of a particular product. An information system connected with the production system indicates which pieces to collect and put into the kit. It is done through a lighting system installed on the piece packages. When a piece needs to be taken, the associated light enlightens to inform operators.

Then, when kits are prepared, they are transported to the assembly line by AGV.

4 System Modeling Proposal

4.1 Identified target

In this paper, we want to focus on the problems and perturbations that can come up during the delivery process of pieces from the kitting picking zones to the assembly line. In this context, we focus on rank 1 and rank 2 flows, and on the internal process of the kitting picking zones. Since just in sequence logistic solution does not supply kitting picking zones, this method is not taken into account in this study.

The principal perturbations that have been identified and that we want to address with the architecture proposal can be classified in three categories:

- Kit conformity:
  - The assembly line operator is not able to assemble the piece on the vehicle because the piece is missing in the kit or it is not the right piece.
- Kitting zone supply conformity:
  - The pieces supplied to the kitting zone are wrong. It can be due to the delivery of an incorrect package of pieces by operators to the kitting zone or because the pieces inside the right package do not correspond to the package label.
  - The supplier is not able to deliver the pieces at the right time.
- AGV availability:
  - The AGV are stopped by some obstacles in their path or they need to stop to recharge their batteries. If it is not expected, it may delay the delivery process and stop the assembly line.
  - In the kit preparation, some diversities take more time than others. AGVs need to wait, it generates delays in the kit delivery process, and it may produce the stop of the assembly line.

4.2 Architecture proposal

The delivery of pieces from the kitting picking zones to the assembly line involves several actors and systems.

Remembering that an intelligent agent is an entity capable of sensing its environment, making decisions and carrying out actions depending on its goals [3], among the variety of agents involved in the logistic process studied, only operators i.e., human beings respect this definition. Other entities as the AGV, robots, automated forklifts or the informative system, have a fixed program that they must respect. If something not expected in their program pops up, they are not able of making decisions or propose solutions to face the unexpected event. Humans, by contrast, are able to.

Based on the architecture mentioned in [17], on previous experiences of installing systems involving Artificial Intelligence on the industrial field and knowing the distrust towards this kind of systems, we propose the following architecture with the purpose of implementing collective intelligence and multiagent learning techniques to address the perturbations.

The architecture is presented in **Fig. 2**. It is composed by three levels. The first level, at the bottom of the figure, represents the production process level, the agents of the industrial field. The second level is called the solution proposal level. It is the digital representation of the first level. Every agent of the first level has its digital agent in the second level. Finally, the third level is the decision-making level. Here, an agent is in charge of centralizing all the information sent by every agent from the second level and communicating the decision made to face the perturbation to the operators.

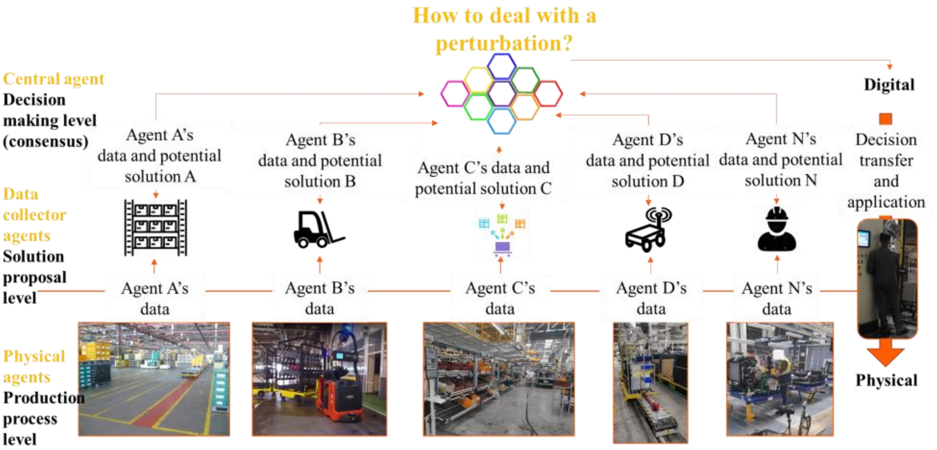

Fig. 2. Multiagent architecture proposal

Production process level. This level is composed by the physical elements involved in the delivery of one kitbox to the assembly line. They can be classified into two groups:

- *Non intelligent agents*: stock status, semi-autonomous forklifts, forklifts, trolleys, kitting robots, AGV.
- *Intelligent agents:* stock operator, forklift drivers, kitting picking operators.

Solution proposal level. This level is composed by virtual intelligent agents, where each agent represents a physical agent. Its functions are:

- Data collection: each virtual agent processes and monitors the data generated by each physical agent in the production process. The data is also transmitted to the central agent. Thus, these agents are called data collector agents.
- Reaction to face perturbation: when a perturbation arrives or is predicted, each agent can propose a solution based on its own knowledge. The solution is then sent to the central agent.

Decision making level. The virtual central agent receives all the data collected by the collector agents. Its function is to detect if there is any abnormal behavior in the data.

If an anomaly is detected, the central agent must identify the cause, consider all solution proposals and select the most adequate one. Then, the decision is communicated to the physical operators.

To implement the decision made through the three previous levels a next activity is needed: **decision transfer and application** (**Fig. 2** on the right). A key point in this architecture is the relevance of the industrial field operators. They are the intelligent agents of our industrial context, they can perceive their environment, make decisions and carry out actions. In addition, thanks to their experience, they have a great knowledge of the industrial field.

Thus, in our proposal, the operators are the agents that will receive the proposals made by the central agent and evaluate them based on their experience. Once the proposals are validated, the operators will carry out the actions needed over one or more agents, to adjust the behavior of the physical system.

So that, we ensure that the implemented proposal should be beneficial for the industrial process and progressively we gain the trust of the industrial field operators on the system.

Beyond the application addressed in this paper, the proposed architecture could be used to model other processes where several physical systems are involved, exchange information between them and share a general goal. Most of manufacturing processes might be modeled as so. Nevertheless, as presented in [19] centralized architectures allow also to deal with the planning definition of assembly lines, the coordination of several agents to exchange information and analyze the factors that affect the manufacturing, costs and assembly of the products and with the optimization of the design of the manufactured products.

5 Conclusions and Future Work

In this paper, we presented a kitting process used by an automotive company to supply materials to the assembly line. Taking into account all the involved entities, the size of the case study and the variety of anomalies or perturbations that can come up in this process, we proposed an architecture to model it as a heterogenous multiagent system. For the architecture design, we also considered a collective intelligence approach in order to centralize and take advantage of the intelligence of each virtual agent. Operators from the industrial field play an important role in the proposal. This is why the proposed methodology aims to gain progressively their trust towards the system.

The proposed architecture will allow to develop an accurate simulation model of the real system. It will be enriched with more and more constrains from the industrial field. Perturbations and anomalies from the real system will be considered in the simulation model. Then, using collective intelligence and multiagent learning techniques, the model will propose solutions that will be transmitted to the real system. This digital twin will help the real agents to deal with hazards that can take place during the kitting and supplying process. For this, three main axes need to be developed: (1) use Discrete Event Simulation frameworks to model the logistic process, (2) determine the behavior model of the system with the purpose of detecting anomalies during the process and (3) make the digital agents involved in the process intelligent in order for them to be able to propose solutions for a given perturbation.

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