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Bio-inspired multi-agent systems for reconfigurable manufacturing systems ☆

Paulo Leitão [a,b], José Barbosa [a,c,d,*], Damien Trentesaux [c,d]

[a] Polytechnic Institute of Bragança, Campus Sta Apolónia, Apartado 1134, 5301-857 Bragança, Portugal
[b] LIACC – Artificial Intelligence and Computer Science Laboratory, R. Campo Alegre 102, 4169-007 Porto, Portugal
[c] Univ. Lille Nord de France, F-59000 Lille, France
[d] UVHC, TEMPO Research Center, F-59313 Valenciennes, France

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ABSTRACT

The current market's demand for customization and responsiveness is a major challenge for producing intelligent, adaptive manufacturing systems. The Multi-Agent System (MAS) paradigm offers an alternative way to design this kind of system based on decentralized control using distributed, autonomous agents, thus replacing the traditional centralized control approach. The MAS solutions provide modularity, flexibility and robustness, thus addressing the responsiveness property, but usually do not consider true adaptation and re-configuration. Understanding how, in nature, complex things are performed in a simple and effective way allows us to mimic nature's insights and develop powerful adaptive systems that able to evolve, thus dealing with the current challenges imposed on manufacturing systems. The paper provides an overview of some of the principles found in nature and biology and analyses the effectiveness of bio-inspired methods, which are used to enhance multi-agent systems to solve complex engineering problems, especially in the manufacturing field. An industrial automation case study is used to illustrate a bio-inspired method based on potential fields to dynamically route pallets.

1. Introduction

The current global economy imposes new challenges for manufacturing companies, with cost, quality and responsiveness being the three critical foundations on which every manufacturing company stands to remain competitive (ElMaraghy, 2006). Under these circumstances, manufacturing systems are required to be more flexible, robust and reconfigurable, supporting the agile response to the changing conditions through their dynamic re-configuration on the fly (i.e., without stopping, re-programming or re-starting the processes or the other system components). Since the systems are more complex, distributed and reconfigurable, the probability of the system malfunction also increases (Trentesaux, 2009).

Since the traditional approaches, based on centralized, rigid structures, do not have enough flexibility to cope with modularity, flexibility, robustness and re-configuration, several paradigms have been introduced over the last few years: Multi-Agent Systems (MAS) (Wooldridge, 2002), Holonic Manufacturing Systems (HMS) (Deen, 2003; Leitão and Restivo, 2006) and Bionic Manufacturing Systems (BMS) (Okino, 1993). In spite of their natural differences, these paradigms propose distributed, autonomous and adaptive manufacturing systems, which can respond promptly and correctly to external changes. These paradigms differ from the conventional approaches due to their inherent ability to adapt to changes without external interventions. In addition, the HMS and BMS paradigms indicate that hierarchy is needed to guarantee the inter-entity conflict resolution and to maintain overall system coherence and objectivity in the face of the individual, autonomous attitude of the entities (Sousa et al., 1999).

The work on MAS, HMS and BMS provides a good framework to rise to the challenge of developing a new class of adaptive and reconfigurable manufacturing systems that will support robustness and re-configurability quite naturally (see the surveys of Leitão (2009a) and Pechoucek and Marik (2008)). However, the current application of such paradigms usually does not consider self-adaptation and self-organization, which results in the systems becoming increasingly reconfigurable, adaptive, organized and efficient.

In biology and nature, complex systems behave simply because of the cooperation of individuals, who are very simple, with very

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* Corresponding author at: Polytechnic Institute of Bragança, Campus Sta Apolónia, Apartado 1134, 5301-857 Bragança, Portugal.
E-mail addresses: pleitao@ipb.pt (P. Leitão), jbarbosa@ipb.pt (J. Barbosa), damien.trentesaux@univ-valenciennes.fr (D. Trentesaux).

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limited cognitive skills (e.g., the colonies of ants and bees). Biological insights have been the source of inspiration for the development of several techniques and methods to solve complex engineering problems, such as logistics and traffic optimization, telecommunications networks, economic markets and production systems (Leitão, 2009b). Multi-Agent Systems have already inherited certain ideas derived from biology and nature, but they can be enhanced with other biological insights, notably the swarm intelligence and self-organization, to obtain more responsive, adaptive systems that address the current requirements imposed on manufacturing systems. In particular, bio-inspired techniques can contribute to obtaining manufacturing systems with the desired characteristics of flexibility, robustness, re-configuration and responsiveness.

The motivation of this paper is to understand how bio-inspired techniques can be used to solve complex engineering problems. Thus, some biological phenomena are studied, some of the existing bio-inspired applications are analyzed, and then the real benefits of bio-inspired MAS for solving the current manufacturing control problems are examined. A real implementation of a bio-inspired solution for routing pallets in a flexible manufacturing system is described to illustrate its suitability.

The remainder of this paper is organized as follows. Section 2 provides an overview of biological phenomena, and Section 3 introduces some bio-inspired techniques and methods used to solve complex problems, especially manufacturing problems. Section 4 discusses the suitability of bio-inspired multi-agent systems solutions for the manufacturing field, and Section 5 describes a bio-inspired solution based on potential fields for an industrial automation case study. Finally, Section 6 presents our conclusions and our prospects for future research.

2. Basic concepts found in biology

Nature offers plenty of powerful mechanisms, refined by millions of years of evolution, to handle emergent and evolvable environments (Leitão, 2009b). This section tries to show how complex things behave simply in nature and biology, introducing the concepts of swarm intelligence (Section 2.1) and evolution and self-organization (Section 2.2).

2.1. Swarm intelligence

In biology, complex systems are based on entities that exhibit simple behaviors, made of a small set of simple rules, with reduced cognitive abilities. The global system behavior emerges from a multiplicity of non-linear interactions among the individual entities. In such systems, the emergent behavior occurs without a pre-defined plan, is not driven by a central entity, and occurs only when the resultant behavior of the whole is greater and much more complex than the sum of the behaviors of its parts (Holland, 1998). Some illustrative examples of this kind of emergent behavior can be found in the ant and bee societies. In fact, everybody knows that "*a single ant or bee isn't smart, but their colonies are*" (Miller, 2007); they are capable of displaying surprisingly complex behaviors.

Swarm intelligence, found in colonies of insects, can be defined as "*the emergent collective intelligence of groups of simple and single entities*" (Bonabeau et al., 1999), thus reflecting the emergent phenomenon. Swarm intelligence offers an alternative way of designing intelligent, complex systems, in which the traditional centralized control is replaced by a distributed operations where the interactions between individuals lead to the emergence of "intelligent" global behavior, previously unknown (Bonabeau et al., 1999). Examples of swarm intelligence include ant colonies, bird flocking, fish shoaling and bacterial growth (Miller, 2007).

In such colonies, individuals possess a partial view of the world and require some way of communicating with others to achieve global objectives. However, the individuals in these colonies usually do not have the ability to communicate directly each other (e.g., like humans) and thus have recourse to an indirect form of communication that establishes a "channel" of information sharing. For example, ants communicate by using an indirect coordination mechanism known as stigmergy, derived from the Greek words *stigma*, which means mark or sign, and *ergon*, which means work or action (Grassé, 1959). In stigmergy, the trace left in the environment stimulates the execution of a subsequent action, by the same or different entity. In this mechanism, ants use a chemical substance known as pheromone, which acts like a trigger that individuals from the same species can sense and/or use in favor of the swarm (e.g., guidance when foraging for food) (Bonabeau et al., 1997) (Fig. 1a).

After finding a food site, ants walk back to the nest and lay down a pheromone trail to share information. Other ants foraging for food can sense the odor diffused by pheromones, and may lay a trail reinforcing the existing pheromones. The pheromones deposited in the nature suffer a natural process of evaporation, resulting in a reduction of the intensity of the odor; the reduction is directly proportional to the time elapsed from the nest to the food source (i.e., the more intense, the shorter distance traveled). If several ants make different trips to the same source of food,

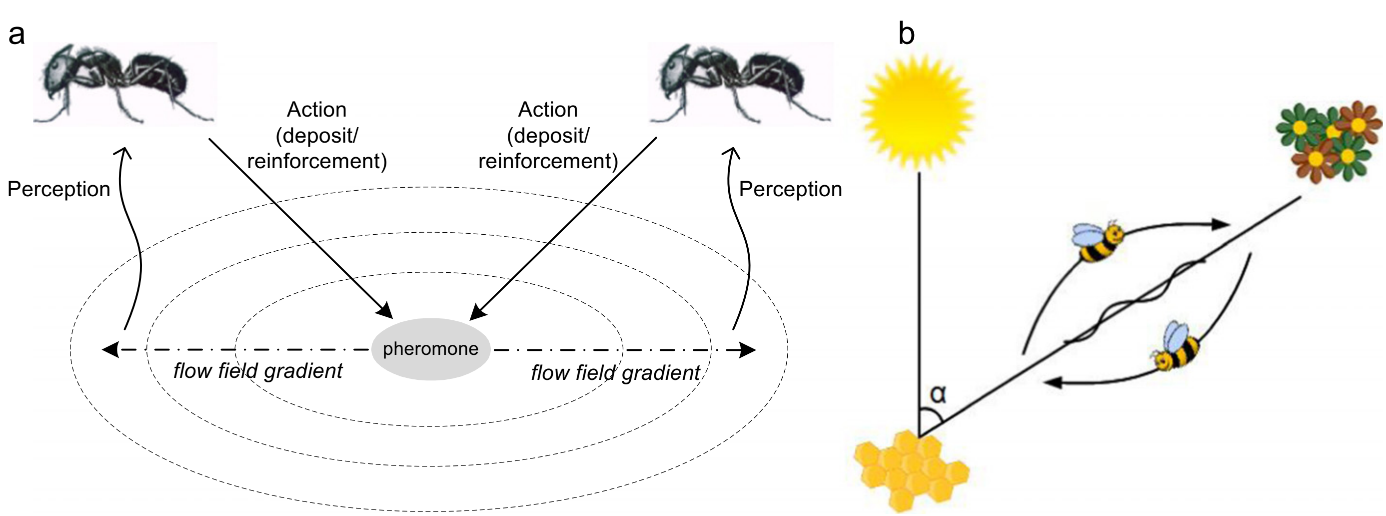

Fig. 1. Indirect communication in insect swarms: (a) ant pheromone deposition (adapted from Parunak and Brueckner, 2001); (b) the waggle dance used by bees.

there will be several trips to the same source. The optimal solution (i.e., the shortest one) will be the trail that has more intense pheromones. After a while, gradually, the trails that have less intense pheromones are abandoned by the ants because the pheromones are not reinforced. Naturally, these trails are no longer considered as options. Sometimes, ants can walk randomly instead of choosing a pheromone trail, which is a good way to find new paths that have appeared in the mean time (Bonabeau et al., 1997).

The double-bridge experiment conducted by Deneubourg et al. (1990) reinforces the idea that ants can indeed find the shortest paths to goals. In their experiments, if two equal paths from the nest to a food source, each path is chosen 50% of the time; in each experiment, the ants tend to choose only one path. On the other hand, if one path is significantly longer than the other, the ants chose the shortest one (Goss et al., 1989).

Another illustrative example of indirect communication supporting swarm intelligence is related to the waggle dance used by honey bees to share information about the direction and distance to patches of flowers yielding nectar and pollen. After scouting an area for a food source, honey bees return to the hive and inform other bees about the food source, performing a dance known as the "waggle dance", as shown in Fig. 1b. This dance provides the following information to the other bees: (1) the rotation angle of the dance, in relation to the sun, states the direction in which the food source can be found and (2) the duration of the dance represents the travel distance to the food source (Bonabeau et al., 1999; Frisch, 1967). Other researchers suggest that this dance also provides a third kind of information related to the quality and quantity of the food source. This last information is shared by releasing a pheromone-type odor (Dornhaus et al., 2003).

Swarm intelligence can be achieved more from coordinating activities of individuals and less from using decision-making mechanisms. A well-known example is the movement of flock of birds (e.g., the typical V formation), where individuals coordinate their movements in relation to the movement of the others (Reynolds, 1987). For this purpose, simple mechanisms are used to coordinate the individual behavior: feedback mechanisms, which use positive and negative feedback to regulate the system's behavior (Camazine et al., 2002):

(i) in positive feedback, the system responds to the perturbation in the same direction as the change (i.e., towards the amplification of the perturbation); and
(ii) in negative feedback, the system responds to the perturbation in the opposite direction (i.e., towards the stabilization of the perturbation).

By combining both positive and negative feedback, the system can be maintained under control but pushed to its limits (Camazine et al., 2002). For example, the simple rule "*I nest where other similar individuals nest unless there are too many fishes*" (Camazine et al., 2002), used to describe fish nesting, combines positive and negative feedback: the first part uses positive feedback, allowing the aggregation of fishes in the same place to be increased, and the second part uses negative feedback, thus avoiding a high concentration of fishes in the same place. Other similar coordination mechanisms are found in other areas of science and nature, namely market laws (Markus et al., 1996) and potential fields (Vaario and Ueda, 1996), based on regulating the expectations of individuals with conflicts of interest.

2.2. Evolution and self-organization

The Darwinian theory of evolution is a form of adaptation to dynamic environmental evolution. Darwin stated that nature is in a permanent transformative state in which the species would change from generation to generation, evolving to better suit their environment. Basically, Darwin saw the evolution as a result of environmental selection acting on a population of organisms competing for resources. In this evolutionary process, the selection is natural in the sense that it is purely spontaneous without a pre-defined plan. In other words, species tend to evolve to overcome their limitations and to adapt to external natural conditions. For example, a species can perform small spontaneous changes within their chromosomes, which provokes some physiological changes after a few generations.

Self-organization is another form of adaptation to dynamic environmental evolution. Several distinct, not necessarily contradictory, definitions can be found in the literature (Massotte, 1995; Bousbia and Trentesaux, 2002; Tharumarajah, 1998). However, the definition used in this paper is: "*The ability of an entity/system to adapt dynamically its behavior to external changing conditions without external intervention*" (Leitão, 2008b). Self-organizing systems do not follow an approximate, rigid organization, but instead evolve through a dynamic, non-linear process with a constant optimization of the individuals' behavior.

Examples of self-organization can be found in several domains:

- *Physics*—In thermodynamics, the 2nd law states that everything in the universe tends to move from a state of order towards a state of chaos (introducing the concept of entropy), which explains that hot bodies tend to get colder with an external cold source (e.g., a refrigerator). Another example is found on the Bénard rolls phenomenon in which the hot and cold molecules self-organize themselves in order to create a flow.
- *Chemistry*—For example, molecules exhibit self-assembly properties, which drive the molecular structure to self-organization (Whitesides et al., 1991). Another example is the Belousov–Zhabotinsky chemical oscillator, which is composed of a reaction sequence that forms a loop (Shanks, 2001).
- *Nature*—The stigmergy phenomenon is used to achieve self-organization in ant colonies.

The coordination mechanisms found in colonies of ants and bees, besides allowing members of these species to communicate, allow the whole community to achieve and display self-organization behavior. Bonabeau et al. (1997) suggest that the basic ingredients to achieve a self-organized system are positive feedback, negative feedback and fluctuations (e.g., random walks and errors). They also suggest that self-organization relies on the multiple interactions between the individuals.

3. Survey of bio-inspired applications for solving complex problems

Several researchers used biological behavior (e.g., colonies of insects) to solve complex mathematical engineering problems. In this section, bio-inspired techniques and methods in engineering are briefly reviewed, with special attention to their applicability in manufacturing.

3.1. Applied to mathematical engineering problems

The insights inherited from the swarm intelligence principles led researchers to design optimization evolutionary algorithms: Ant Colony Optimization (ACO), the Artificial Bee Colony (ABC) Algorithm and Particle Swarm Optimization (PSO).

Dorigo (1992) introduced the Ant Colony Optimization (ACO) technique, inspired by the food foraging behavior of ants, to solve problems that need to find optimal paths to some goal. In ACO, acting as ants, agents travel over a weighted graph randomly, leaving marks (i.e., pheromones) wherever they go. After an initial phase, the "ants" make their decisions according to the pheromone level, instead of making decisions randomly. Over time, the pheromone trail becomes weaker in the less used paths, making the most used path (i.e., the most optimized path) prevail.

The ACO algorithm has been used to solve diverse engineering problems from different application domains. In fact, in the financial domain, the ACO algorithm has been used to classify firms as to the different levels of credit risk (Marinakis et al., 2008b) and, in the medical field, to distinguish cancer from non-cancerous diseases, by helping with the evaluation of proteomic patterns (Meng, 2006). In engineering world, the ACO algorithm has been used to determine the optimal values for the components in an electronics power circuit (Zhang et al., 2008b), to achieve an optimal image threshold by separating the object from its background (Malisia and Tizhoosh, 2006), and to update the telecommunications routing tables dynamically and adaptively (Di Caro and Dorigo, 1998). In the army, this algorithm has been applied for the dynamic re-planning of Uninhabited Aerial Vehicles (UAV) (Duan et al., 2009) and for the cooperation among swarm robots to accomplish a complex task (Nouyan et al., 2009). In the real world, *Air Liquide* has used an ant-based strategy to manage the truck routes for delivering industrial and medical gases (Miller, 2007), and Bell and McMullen (2004) has used a similar algorithm to optimize vehicle routing logistics. Southwest Airlines has used an ant-based behavioral model to improve its aircraft scheduling at the gates of the Sky Harbor International Airport in Phoenix (Arizona, USA) (Miller, 2007).

The behavior of bees is the source of inspiration for the development of the Artificial Bee Colony (ABC) algorithm. This algorithm uses employed bees, onlooker bees and scout bees (Karaboga and Basturk, 2007). Employed bees are those that have found a food source and are responsible for recruiting onlooker bees, which are waiting in the dance area. After being recruited by employed bees, onlooker bees, become employed bees and are responsible for recruiting. Scout bees are responsible to perform random searches in order to discover new food sources. Briefly, after recruiting onlooker bees, employed bees move to the food source (i.e., possible solution) and search for a new nearby solution, which is then transmitted to onlooker bees. When an employed bee food source becomes exhausted, this bee becomes a scout, and this process is repeated until a good solution is found. Applications using the ABC algorithm can be found on the parameter optimization of a hybrid power system model (Chatterjee et al., 2010) or the dynamic path planning of mobile robots in uncertain environments (Ma and Lei, 2010).

Particle Swarm Optimization (PSO) was inspired by the social behavior of bird flocks and fish schools. Initially, Kenedy and Eberhart (1995) introduced PSO, which is a population-based stochastic optimization technique. Briefly, the system is initialized with a population of random solutions, and the algorithm searches for optimal solutions by updating generations. The potential solutions, called particles, fly through the problem space, following the current optimum particles. As the swarm iterates, the fitness of the overall best solution improves (i.e., decreases for minimization problem). The PSO algorithm has been applied to solve problems ranging from the social to the engineering fields. For example, it has been used to optimize the parameters for PID controller design (Gaing, 2004), to assess credit risks (Li and Pi, 2009), to design evolvable hardware (Peña et al., 2006), to route vehicles with simultaneous pickup and delivery (Ai and Kachitvichyanukul, 2009) and to optimize the parameters for spatiotemporal retina models (Niu et al., 2007).

The swarm intelligence principles have been used to forecast Turkish energy demands (Miller, 2007) and to solve traffic and transportation problems (Teodorovic, 2008). A more widespread example of the application of the swarm intelligence principles is Wikipedia (Leitão, 2009b), in which a huge number of people contribute to the constant evolution of the encyclopedia with their individual knowledge. No single person knows everything; however, collectively, it is possible to know far more than was expected.

Genetic Algorithms (GA), derived from natural evolution, are based on a population of abstract representations of candidate solutions to an optimization problem that evolves toward better solutions. GA use evolutionary operators (i.e., inheritance, mutation, selection and crossover), and they have been successfully applied in various application domains: power distribution (Ramirez-Rosado and Bernal-Agustin, 1998), image segmentation (Peng et al., 2000) and scheduling and route selection for military land moves (Montana et al., 1999).

Table 1 provides some applications that use insights from biology and nature to solve complex engineering and mathematical problems.

Table 1
Bio-inspired applications to solve engineering and mathematical problems.

Problem domain	Existing ACO-inspired solutions	Existing PSO-inspired solutions	Existing GA-inspired solutions
Communication networks	Di Caro and Dorigo (1998), Zhao et al. (2009), Sim and Sun (2002)	Dongming et al. (2008), Li et al. (2008)	Lima et al. (2007), Lee et al. (1997)
Control	Van Ast et al. (2009), Boubertakh et al. (2009), Zhang and Wang (2008)	Gaing (2004), Jalilvand et al. (2008), Hu et al. (2005)	Wai and Su (2006), Toderici et al. (2010), Bae et al. (2001)
Finance	Fang and Bai (2009), Yuan and Zou (2009), Hong et al. (2007), Marinakis et al. (2008b), Kumar et al. (2009)	Li and Pi (2009), Majhi et al. (2008), Chen et al. (2009a)	Badawy et al. (2005)
Hardware design	Zhang et al. (2008b), Abd-El-Barr et al. (2003), Sethuram and Parashar (2006)	Peña et al. (2006), Goudos et al. (2008), Ren and Cheng (2009)	Tsai and Chou (2006), Regue et al. (2001)
Image processing	Malisia and Tizhoosh (2006), Tian et al. (2008), Wang et al. (2005)	Chen et al. (2009b), Chandramouli and Izquierdo (2006), Ma et al. (2008)	Peng et al. (2000), Katayama et al. (2006)
Medicine	Meng (2006), Lee et al. (2009), Logeswari and Karnan (2010), Yu et al. (2009)	Niu et al. (2007), Meng (2006), Marinakis et al. (2008a)	Maulik (2009), Das and Bhattacharya (2009), Tohka et al. (2007)
Military	Duan et al. (2009), Cheng et al. (2009), Munirajan et al. (2004)	Matlock et al. (2009), Cui and Potok (2007), Thangaraj et al. (2009)	Moore and Sinclair (1999), Montana et al. (1999), Liu et al. (2005)
Power energy	Lee and Vlachogiannis (2005), Liu et al. (2009), Colson et al. (2009)	Liu and Ge (2008), Zhang et al. (2008a), Leeton et al. (2010)	Ramirez-Rosado and Bernal-Agustin (1998)
Robotics	Nouyan et al. (2009)	Zhengxiong and Xinsheng (2010)	Tohka et al. (2007) Karlra and Prakash (2003), Pessin et al. (2009), Albert et al. (2009)
Sensor networks	Camilo et al. (2006), Muraleedharan and Osadciw (2009)	Aziz et al. (2007), Tewolde et al. (2008), Li and Lei (2009)	Jiang et al. (2009), Brown and McShane (2004), Khanna et al. (2006)
Vehicle routing/ traffic control	Miller (2007), Bell and McMullen (2004)	Ai and Kachitvichyanukul (2009), Wu and Tan (2009)	Tong et al. (2004), Jun (2009), Tunjongsirigul and Pongchairerks (2010)

In this table, the problem domain can range from finance to energy. This table does not intend to be exhaustive but instead to demonstrate the many domains that are already using bio-inspired solutions.

3.2. Applied to manufacturing problems

A similar analysis of the applicability of bio-inspired techniques can be performed for manufacturing. In the manufacturing domain, algorithms based on the ant behavior have been used to optimize machine layouts (Corry and Kozan, 2004), schedule continuous casting aluminum in a Quebec factory (Gravel et al., 2002) and coordinate adaptive manufacturing control systems (Hadeli et al., 2004). The food-foraging behavior of honey bees is the source of inspiration for solving job scheduling problems (Pham et al., 2007b) and optimizing the manufacturing layout formation (Pham et al., 2007a). The behavior of wasps has been used for task allocation (Cicirello and Smith, 2001a) and factory routing and scheduling (Cicirello and Smith, 2001b).

In addition, the PSO technique has been applied to machinery fault detection (Samanta and Nataraj, 2009), job shop scheduling (Xia and Wu, 2005), machine load balance as part of a job shop manufacturing system (Zhao et al., 2006) and manufacturing cells layout and robot transport allocation optimization (Yamada et al., 2003). GA have been used to generate and evaluate assembly plans (Lazzerini et al., 1999), to design optimized layouts (Wang et al., 2008), and to generate schedules for flexible job-shop production systems (Qiu et al., 2009).

Self-organization principals have been used to solve complex adaptive problems: in holonic manufacturing control (Leitão and Restivo, 2006), in dynamic resource allocation of a Daimler Chrysler plant (Bussmann et al., 2004), in the development of self-organized and self-assembled bio-inspired robots (Moudada et al., 2004) and in manufacturing scheduling (Tharumarajah, 1998). A stigmergic approach has also been used as the routing mechanism in a flexible manufacturing system (Sallez et al., 2009).

The potential fields have been used to solve some manufacturing problems. Although this is a concept usually found in physics, in this paper, it is included in the bio-inspired world. This concept has been used to allocate products within a group of resources (Vaario and Ueda, 1998) and to guide Automated Guided Vehicle (AGV) in a manufacturing site (Weyns et al., 2008). In addition, Zbib et al. (in press) has used a potential fields approach for dynamic task allocation and product routing. Table 2 provides some of the existing bio-inspired applications in the manufacturing field.

4. Applicability of bio-inspired systems in manufacturing

The analysis in the previous section shows the tremendous potential of using of bio-inspired systems to solve complex engineering problems. This section discusses the applicability and benefits of combining bio-inspired techniques with multi-agent systems in the manufacturing domain in order to address the current challenges.

The MAS paradigm has already inherited biological insights (Barbosa and Leitão, 2010):

- *Distributed nature*—multi-agent systems are based on a set of distributed, autonomous and cooperative agents, and the functioning of the whole system is determined by the interaction among these individuals.
- *Division of labor*—multi-agent systems define different types of agents with distinct roles, objectives, behaviors and skills; in insect colonies, ''division of labor'' means that an individual usually does not perform all tasks but rather specializes in one set of tasks (Bonabeau et al., 1999).
- *Emergence from collective simple behavior*—the obtained behavior of the whole system is greater and much more complex than the simple sum of the behaviors of its parts (Holland, 1998).

A MAS application that fulfils these insights offers an alternative way of designing intelligent, robust and adaptive systems that replace traditional centralized control. These systems provide *robustness*, since the system is not dependent on a centralized entity and has the ability to continue working even if some entities fail when performing their tasks, and *flexibility*, since the society of the entities can dynamically be plugged in, plugged out or modified to face changing environments on the fly. Detecting new entities may remind readers of fluctuation amplifications found in the ant food foraging behavior (e.g., the random walks).

As illustrated in Fig. 2, the simple application of multi-agent system principles usually allows the behavior to emerge, thus guaranteeing the fulfilment of flexible and robustness requirements. However, these systems lack the capacity to evolve. This capacity is related to how the system can adapt quickly and efficiently to environmental volatility, thus addressing the responsiveness property.

To face this challenge, biology and nature can provide useful insights, especially the self-organization phenomenon.

Table 2
Bio-inspired Applications to Solve Manufacturing Problems.

Problem domain	Existing solutions inspired by ant and bee behavior	Existing solutions inspired by self-organization or GA	Other existing bio-inspired solutions
Assembly/disassembly	Shan et al. (2007), Sharma et al. (2009), Lu et al. (2008)	Lazzerini et al. (1999), Gao and Chen (2008)	Lv and Lu (2009), Dong et al. (2007)
Layout optimization	Jain and Sharma (2005), Sun and Teng (2002), Chen and Rogers (2009), Corry and Kozan (2004)	Wang et al. (2008), Kulkarni and Shanker (2007)	Ning et al. (2004), Ohmori et al. (2010), Lei et al. (2003), Pham et al. (2007a), Yamada et al. (2003)
Manufacturing scheduling	Arnaout et al. (2008), Chen et al. (2008), Xu et al. (2009), Blum and Sampels (2004), Gravel et al. (2002)	Qiu et al. (2009), Aggoune et al. (2001), Tharumarajah (1998)	Shi et al. (2009), Zhang and Wu (2008), Pham et al. (2007b), Cicirello and Smith (2001a), Cicirello and Smith (2001b), Xia and Wu (2005), Zhao et al. (2006)
Production control	Hadeli et al. (2004)	Leitão and Restivo (2006), Bussmann et al. (2004), Sallez et al. (2009)	Vaario and Ueda (1998), Ueda et al. (2001) Weyns et al. (2008), Zbib et al. (in press)
Supply chain	Suva et al. (2004), Sun et al. (2008), Caldeira et al. (2007)	Elmahi et al. (2004), Kaijun et al. (2010), Jianhua and Xianfeng (2010)	Sinha et al. (2009), Qi et al. (2008)

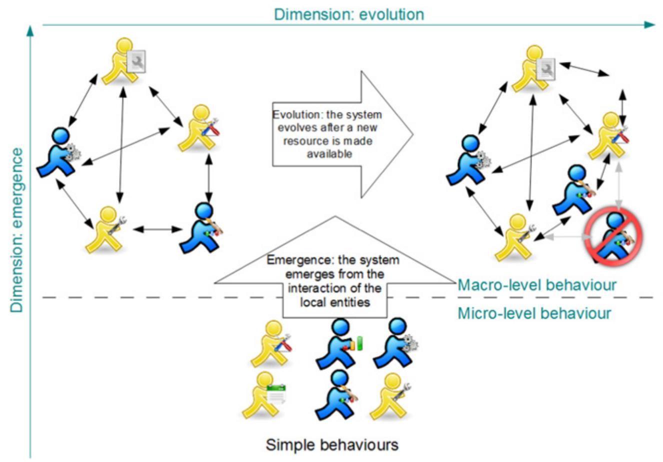

Fig. 2. Emergence and evolution in the manufacturing system design.

Self-organization applied to multi-agent systems allows several self-⁎ properties to be achieved (Leitão, 2008a):

- *Self-configuration*—the capacity to dynamically adapt to changing conditions by modifying the system's own configuration, thus permitting the addition/removal/modification of entities on the fly, without disrupting the service.
- *Self-optimization*—the system's capacity to adjust itself proactively to respond to environmental stimuli.
- *Self-healing*—the capacity to diagnose deviations due to unexpected conditions and act proactively to normalize these deviations, thus avoiding service disruptions.

The self-⁎ properties are crucial for developing highly adaptive, evolvable systems, addressing the current requirements, and supporting re-configurability in a quite natural manner.

Despite the enormous potential of the bio-inspired insights, special care must be taken when translating these insights into the real-world problem-solving. If the biological behaviors are simply copied, the system will not work as expected. Mimicking behaviors can drive the system into danger (e.g., the circular mill in army ants) (Anderson and Bartholdi, 2000). Based on this observation, we do not advise to copy the entire behavioral aspect of the biological mechanism, but instead translate and adapt the insights in order to match the system's objectives. This translation/adaptation requires collaboration between experts in biology and experts in engineering, which may lead to new insights from a different point of view.

This observation may provoke a question related to the fact that, in manufacturing, there is little space to send physical entities (e.g., products or trucks) on a random walk to explore alternative routes. It is important to remember that a multi-agent manufacturing system is composed of two components: the agents and the physical resources (i.e., products and machines). Naturally, the product cannot be sent on a test trip, but agents, running bio-inspired algorithms, can use virtual ants (i.e., agents) to explore the best solutions in order to route products.

However, bio-inspired techniques to enhance multi-agent systems can be analyzed from another perspective. Manufacturing and automation cover a wide range of application domains, presenting different requirements and constraints. Sometimes, the manufacturing areas can benefit more from using such bio-inspired techniques. Based on the authors experience, using bio-inspired techniques combined with multi-agent systems can help to design more intelligent, modular, flexible and adaptive systems, especially in the following manufacturing domains:

- *Supply chains and virtual organizations*, which require the frequent re-organization of partners to achieve optimization and responsiveness.
- *Shop floor layout*, which requires optimizing the shop floor layout in order to minimize transport time and to minimize transport distances, in situations where shop floor resources move physically.
- *Product demand*, in which the manufacturing system re-organizes itself to adapt to the changes in the product demand (i.e., faced with the mass customization trend), increasing/reducing the number of resources or modifying their capabilities, based on the forecast production demands.
- *Planning and scheduling*, in which the goal is to find the most current optimized plans and schedules, while taking the product demands and the capabilities of the shop floor resources into consideration.
- *Adaptive control*, in which the goal is to identify an adaptive, dynamic production control strategy based on the dynamic on-line schedule, which is adapted in cases of unexpected disturbances.
- *Predictive maintenance*, in which predicting machinery failures is essential for tolerating disturbances and malfunctions, which helps to develop an adaptive production system.
- *Diagnosis*, in which distributed entities are able to cooperate to achieve a dynamic, reliable and clear diagnosis of the detected symptoms.
- *Adaptive processes and equipment*, in which developing new sensors, actuators and controllers will help to design and implement more adaptive manufacturing equipment.

These bio-inspired solutions can be more useful when the environment in which they operate is unpredictable. The other issue that must be taken into account is applying these mechanisms may not be advantageous in cases where strong real-time constraints are needed. Special care must be taken, and the right mechanisms applied, in order to not affect the system performance.

In spite of the promising prospects that bio-inspired principles can bring to engineering systems, especially in the manufacturing domain, these principles have been adopted less than expected in industrial situations. The major problem is that industry demands proven technology, without wanting to be the first ones to try it in their production processes. The maturity of the technology and the proofs of its real applicability and merits will solve this problem. Furthermore, industry is usually afraid of using emergent terminology associated to these new technologies, such as ontologies, self-organization, emergence, distributed thinking and learning.

The challenge for engineers developing bio-inspired solutions for manufacturing is to convince people from industry of the real advantages of using distributed systems based on the behavior of simple, effective and adaptive entities regulated by simple coordination mechanisms, such as those occurring in nature. For this purpose, it is important to develop demonstrators and real case studies to be used as a proof of concept. Simulation platforms simplify the design, testing and debugging of these bio-inspired applications, ensuring a framework to simulate/validate strategies to support decision-making. This is a crucial issue. Several computational platforms are currently available for the simulation/validation of bio-inspired models (e.g., SWARM, RePastS and NetLogo), in which the behaviors of biological entities (e.g., ants and bees) are usually implemented using software agents. (More information can be found in Railsback et al. (2006) and Arunachalam et al. (2008)).

An interesting example is using the NetLogo platform to simulate the dynamic determination of the best path to route the products in situations with disturbances (Sallez et al., 2009). The idea here is to simulate the manufacturing system taking into account the real conditions (e.g., the equipment status). In this way, the model gets real information, performs the simulation, and sends the commands to the real environment. The system operates in a bidirectional manner: the real environment provides fault inputs to the modeling system, and the modeling system gives scheduling orders to the real environment.

5. An automation case study: a bio-inspired approach

An experimental case study was used to demonstrate the applicability of bio-inspired multi-agent systems in manufacturing. For this purpose, the full-size flexible manufacturing system (FMS), located at the AIP-PRIMECA production center (*Université de Valenciennes et Hainaut-Cambrésis*, France), was used. The FMS is composed of seven work stations (i.e., assembly robots, quality control units and load/unload units), interconnected by a flexible conveyor system that uses shuttles to move pallets with the products (Fig. 3).

The bio-inspired control system, with the goal of dynamic task allocation and dynamic pallet routing, based on the concept of potential fields, which generate attractive and repulsive fields to govern the system behavior (Vaario and Ueda, 1998). In this system, the resources emit attractive fields according to the services they provide and their availability. The potential fields are usually emitted in all directions (3D), but in this production context, the fields are only emitted in 1D because of the typology of the conveying system. Since a resource can perform more than one service, or operation, it emits a vector of potential fields. The potential fields are hosted in the decisional nodes of the conveyor system. The fields are propagated among decisional nodes, while taking the reduction of their intensity according to the distance into account. In each decisional node, the representation of the potential fields uses a matrix correlating resources and services:

$$\begin{array}{c} \\ R_1 \\ R_2 \\ R_3 \end{array} \begin{array}{c} \begin{array}{cc} S_1 & S_2 \end{array} \\ \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \\ \lambda_{31} & \lambda_{32} \end{bmatrix} \end{array}$$

where λ_{ij} represents the potential field emitted by the resource R_i to perform the service S_j.

A shuttle is used to transport the product, and, for experimental purposes, a notebook is used to host the product intelligence. A product moving in the conveyor system senses the potential fields in the decisional nodes. Taking into consideration its service list that indicates the next service to be executed, the product decides dynamically to allocate the service to the resource that emits the highest potential field. (More details about the potential-field control architecture can be found in Zbib et al. (in press)).

Described in detail by Zbib et al. (in press), the experimental results obtained shows an average production time gain of 10% when compared with a contract-net approach, which is typically used in multi-agent control solutions to implement the resource allocation. In fact, the control system based on potential fields results in the following advantages:

- Simpler and easier engineering process—the programming effort to develop the potential fields approach is significantly smaller than to develop the contract-net approach. In the potential fields approach, the algorithm embedded in the product has only to choose the maximal value of potential fields for a specific service. On the other hand, in the contract-net approach, the algorithms embedded in the product need to handle the resource allocation process (implemented by using the contract-net protocol) and then to select the best path to convey the shuttle to the target resource, which has been implemented in the experimentation by using the well-known Dijkstra's algorithm (Sallez et al., 2010). Please note that the routing process is naturally included in the potential fields approach.
- Better reactive behavior—the system perturbations (e.g., resource or conveyor breakdown) are easily managed by decreasing the strength of the potential fields. The products can easily react to the change in the potential fields and dynamically re-allocate the service and the route towards new resource.

This case study illustrates that bio-inspired applications are promising, adaptive and reactive when faced with dynamic complex environments, often found in manufacturing systems. However, the potential fields approach, and generally the bio-inspired methods, presents some drawbacks related to the local perspective of the individuals, which leads to myopia and the lack of future predictions. In fact, ants and bees act in a purely reactive way and do not have any explicit knowledge about the actions and goals of the other entities. In other words, they do not consider the global aspects in their decision-making. This feature is logically projected in bio-inspired control methods and should be addressed in future research by combining different methods that also introduce the global perspective.

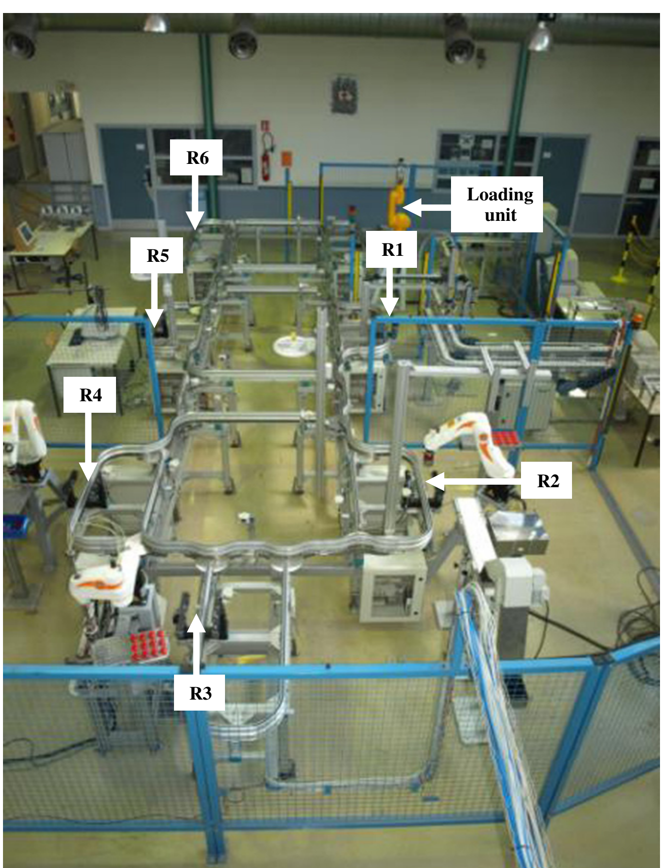

Fig. 3. The AIP-PRIMECA FMS.

6. Conclusions

This paper analyzed some mechanisms found in biology and nature, especially swarm intelligence and self-organization, and tried to understand their potential benefits to solve complex engineering problems. Special attention was devoted to the existing bio-inspired applications, particularly in manufacturing. This paper also discussed the application of bio-inspired techniques to enhance multi-agent systems in the different manufacturing areas and considered how to achieve a greater adoption in industry.

The conclusions drawn from this analysis are the real applicability of bio-inspired techniques for developing new control solutions for manufacturing systems. These systems must exhibit flexibility, robustness, re-configurability and responsiveness, based on the decentralization of the control over distributed, simple and autonomous entities, which cooperate to achieve the system's objectives. The main biological insight is to use simple and effective mechanisms to obtain complex and adaptive systems. A bio-inspired solution, based on potential fields, for controlling a flexible manufacturing system was used to illustrate the applicability of these insights in manufacturing. The results obtained show that these insights can really help to develop more flexible and adaptive manufacturing systems. Future work should study how bio-inspired solutions that have self-$*$ properties will ensure robustness, scalability, flexibility and re-configurability in adaptive manufacturing systems, and then combine different bio-inspired methods with the objective of obtaining adaptation without degrading performance optimization.

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