Location Problems Optimization by a Self-Organizing Multiagent Approach

Sana Moujahed [*] Olivier Simonin [†] Abderrafiâa Koukam [‡]

University of Technology of Belfort-Montbéliard, France
{sana.moujahed, abder.koukam}@utbm.fr
olivier.simonin@loria.fr

Abstract

The Facility Location Problem (FLP) requires locating facilities in order to optimize some performance criteria. This problem occurs in many practical settings where facilities provide a service, such as the location of plants, bus-stops, fire stations, etc. Particularly, we deal with the continuous version of location problem where facilities have to be located in an Euclidean plane. This paper contributes to research on location problems by exploring a new approach based on reactive multiagent systems. The proposed model relies on a set of agents situated in a common environment which interact and attempt to reach a global optimization goal. The interactions between agents and their environment, which are based on the artificial potential fields approach, allow to locally optimize the agent's locations. The optimization of the whole system is the outcome of a process of agents self-organization. Then, we present how the model can be extended to the multi-level version of the location problem. Finally, the approach is evaluated to check its relevance. These evaluations concern both presented versions of the location problem.

Keywords: Environment-based Problem Solving, MultiAgent Systems, Location Problems, Optimization.

1 Introduction

The facility location[1] problems have witnessed an explosive growth. It is so rich in possibilities and perspectives that it has generated an enormous literature dating back to the seventeenth century [9]. As Krarup and Pruzan [17] point out,

[*]Corresponding author: Sana Moujahed. Address: Laboratoire Systèmes et Transport, Université de Technologie de Belfort-Montbéliard (UTBM), Rue Thierry Mieg, 90010 Belfort cedex, France. Tel: +33(0)3 84 58 38 22, Fax: +33(0)3 84 58 33 42.

[†]Researcher in the MAIA team, INRIA Lorraine (LORIA), Nancy, France.

[‡]Professor at the UTBM.

[1]Location, positioning, deployment and siting are used as synonyms.

this is not at all surprising since location policy is one of the most profitable areas of applied systems analysis. This is due to the importance of location decisions which are often made at all levels of the human organization. Thus, such decisions are strategic since they have consequential economic effects.

The term facility is used in its broadest sense. It refers to entities such as plants, bus-stops, schools, hospitals, fire stations, etc. The general problem is, then, the location of facilities to optimize some objectives such as distance, travel time or cost and demand satisfaction. However, location problems are often extremely difficult to solve, at least optimally. Even the most basic models are computationally intractable for large problem instances. Many heuristics have been proposed for these problems as well as a few exact algorithms [5]. These approaches are not easily adaptable to dynamic systems where the system constraints, or data, change online. This is a real limitation since numerous real problems involve parameters that change over the time, for instance the ambulance location problem can be quoted. To deal with this lack of flexibility and robustness, a multiagent approach is adopted, it is known to be well suited for open systems and online changes. Indeed, Open systems represent arguably the most important application of multiagent systems [32]. It will be shown through various applications that the proposed multiagent approach is able to face the environment dynamics and then to behave in the same way when the environment parameters or constraints are slightly modified. The dynamic aspects of the environment are related to online changes that may affect the environment data such as the demand number and/or the facility agent's number.

In this paper, a multiagent approach to handle the facility location problems is proposed. It is based on the self-organization of reactive agents through their interactions with the environment. The choice of a multiagent approach provides several advantages. First, multiagent systems are well suited to model distributed problems. In such systems, several entities cooperate to fulfill collective and personal goals. Second, even if the multiagent approach does not guarantee to automatically find optimal solutions, it is able to find satisfying ones without too much computational cost, besides other assets such as robustness and flexibility. In our approach, the behavior of agents has a physical inspiration, i.e., the way particles in our universe move and globally self-organize according to contextual information which is represented by potential fields. In particular, in our approach, contextual information is expressed in the form of a combination of attractive and repulsive forces. The key idea is that the behavior of reactive agents at the microscopic level leads to an emergence of solutions at the macroscopic level [24]. We, then, prove the openness, the flexibility and the robustness of our approach by tackling several examples of location problems: the location of bus-stops along already existing lines and the multi-level facility location.

The structure of this paper reflects the above reported lines of thought. Hence, the next section presents a review of the facility location problem. Then, section 3 presents the reactive and the artificial potential field approaches. Section 4 is devoted to the proposed multiagent approach. To evaluate this approach, standard test problems will be used in sub-section 5.1, a real case study is considered in sub-section 5.2. In section 6 we take a glance at the multi-level location problem and we prove the adaptation of our approach to this version. In section 7, some aspects of the model are discussed. Then, the last section gives some conclusions and perspectives.

2 Location problems

2.1 Overview

In literature, the general facility location problem is concerned with the determination of the optimal number, size and geographic configuration of facilities, in such a way that a certain criterion (or several criteria) is optimized. Three basic classes can be identified in location analysis, following the space criterion: continuous location, network location and discrete location [3]. The differences between these arise from the structure of the set of possible locations for the facilities. Hence, finding optimal facility locations on the edges or vertices of a network corresponds to a network location model while for discrete location models the facilities can be placed only at a limited number of eligible positions. Finally, continuous location models are characterized by two essential attributes: (a) the solution space is continuous, that is, it is feasible to locate facilities on every point in the space (b) distance is measured with a suitable metric. Typically, the Euclidean or the Manhattan distance metrics are employed. Each of these three classes has been actively studied, arousing intense discussions on approaches proposed to solve location problems. In this paper, we are particularly interested in continuous problems since this problem is more generic than the discrete and the network ones.

2.2 Related works

Typically, the possible approaches to location problems consist in exact methods which allow to find optimal solutions. A well-known example of methods is branch and bound [30]. However, these solutions are inefficient for very complex problems, i.e., with hundreds of constraints and variables. Moreover, they are restricted to relatively small instances. Therefore, obtaining optimal solutions for these problems requires colossal computational resources. As a consequence, heuristics are needed to quickly solve large problems and, sometimes, to provide good initial solutions for exact algorithms. These methods allow to find good solutions, but do not guarantee finding the optimal one(s), we quote: tabu search [6], genetic algorithms [16], etc. However, these approaches have several drawbacks such as the rigidity and the lack of robustness and flexibility. Particularly, they are limited in their ability to cope with dynamic problems characterized by online change of the problem constraints and optimization criteria.

Various heuristics closely related to multiagent systems have been proposed for different versions of location problems. These ones are mainly based on

Ant Systems [27]. In [28] the authors propose an ant system-based approach for a discrete problem: the Set Covering Problem (SCP), where the aim is to find a minimum cost set of facilities. In [18] Ant colony Optimization (ACO) is applied to another discrete location problem: the Single-Source Capacitated Facility Location Problem (SSCFLP). These ant-based approaches are dedicated to the discrete version of location problem. As for the purely agent approaches that deal with the problem, the work of [2] can be quoted. In this paper the authors propose a framework for situated multiagent systems and they apply their model, among others, to a discrete location problem: the shopping centers positioning. They focus on the modeling phase of a discrete problem, without seeking to optimize an objective function.

This paper explores the reactive multiagent-based heuristic for the optimization of the *continuous* version of location problems. The remainder of the paper will focus on this approach. The next section presents formally the continuous location problem that we address in this paper.

2.3 Continuous location problem statement

In the continuous version of the location problem the objective is to generate m facility sites in $\Re^2$ space to serve the demands of n customers or fixed points in such a manner to minimize the total transportation (or service) cost.

The considered uncapacitated version (i.e., no capacity constraints on the facilities), referred as the continuous p-median problem, may be formulated as follows [5]:

$$\min_{W,X} \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij} \left\| x_j - a_i \right\| \tag{1}$$

where

a_i is the known location of demand i, $i = 1, ..., n$;

$X = (x_1, ..., x_m)$ denotes the vector of location decision variables, with $x_j = (x_{j1}, x_{j2})$ being the unknown location of facility j, $j = 1, ..., m$;

w_i is the given total demand or flow required by demand i, $i = 1, ..., n$;

$W = (w_{ij})$ denotes the vector of allocation decision variables, where w_{ij} gives the flow to demand i from facility j, $i = 1..., n$, $j = 1..., m$;

$\|x_j - a_i\| = [(x_{j1} - a_{i1})^2 + (x_{j2} - a_{i2})^2]^{1/2}$ is the Euclidean norm. It represents the distance separating the demand a_i to the closest facility x_j.

The objective function above minimizes the weighted sum of distances from the demand points to their closest facility. The main difficulty in optimizing equation (1) arises from the fact that the objective function is neither convex nor concave [5] and, may have a large number of local minima. Moreover, for large sets of demands and facilities this problem is unsolvable in acceptable time [26]. To cope with this complex problem a new agent-based heuristic is presented. The next section is devoted to the description of our proposition. It is then adapted to the classic version as well as to the multi-level version of location problems.

3 A Self-Organizing approach for the continuous location problem

Our model draws from the Artificial Potential Fields (APF) which is an approach to build self-organized systems. This approach as well as the reactive one are presented in the next sub-sections, the proposed model is detailed in section 4.

3.1 The reactive approach and the artificial potential fields technique

The reactive approach arose in artificial intelligence, in the 80's with the work of M. Minsky [22]. Minsky constructed a thesis for a way in which human intelligence can be built up from the interactions of simple parts called agents. This thesis matured in the end of the 80's, when researchers where interested in the functioning of insects societies. They showed that these reactive agents are able to collectively solve complex problems. This phenomenon observable at the macro level is called emergent self-organization. Emergence in multiagent systems is a dynamic nonlinear process that leads to emergents properties, behavior, etc. at the macro-level of a system from the interaction of parts at the micro-level. Such emergent phenomena are novel since they can not be readily understood by taking the system apart and looking at the parts. The micro-macro effect of emergence implies that not one agent has to be aware of that global behavior.

Emergent self-organization exists in many natural systems and especially in insect societies. Such systems are composed of simple entities, for instance ants, which can solve complex problems without any global control [25]. Their organization results from the numerous interactions between agents and their environment. It is the environment that guides the agents' behaviors and the whole system organization according to the so called stigmergy principle [24]. Self-organization has been used to define decentralized algorithm to deal with path finding problems, as in ant algorithm, collective tasks such as box-pushing [1], navigation and foraging with robots [29], etc. Most of these works are based either on digital pheromones, as inspired by ants, or on artificial potential fields. This second one is adopted because it is well suited to deal with spatial constraints as in the location problems. Besides, APF approach promotes self-organization and self-adaptation where agents activities are automatically adapted to the environmental dynamics. The APF approach has several inspirations: physical, biological, etc. The concept was introduced by Kurt Lewin in his book “Principles of topological psychology” [19]. The basic idea is that human behavior is controlled by a force field generated by objects or situations with positive or negative values or valences. During the past decade, potential fields theory has gained popularity among researchers in the field of autonomous robots and especially in robot motion planning thanks to their capability to act in continuous domains in real-time [33]. By assigning repulsive force fields to obstacles and an attractive force field to the desired destination, a robot can follow a collision-free path via the computation of a motion vector from the superposed force fields [1].

3.2 Reactive agents-based heuristics for problems solving

Various reactive agents-based approaches have been proposed for problem solving ranging from planning to optimization. Without the ambition of being exhaustive, three classes of agent-based heuristics where the environment abstractions have a central role can be distinguished.

The first class involves the **satisfaction-based heuristics** which are mainly based on Eco-Problem-Solving (EPS) and Constraint Satisfaction. Ferber developed the Eco-Problem-Solving model [12], in which problems are composed and solved by the interactions of simple behavior-based eco-agents. These ones behave according to their specific programs of simple “tropism”, i.e. a behavior made of reactions to the environment, and are continuously questing for satisfaction state. Interaction between agents is characterized by aggression and concession. Problem solving is seen as the production of stable states in a dynamic system, where evolution is due to the behavior of simple agents. In this context, Drogoul applied EPS model to the N-puzzle problem [10].
Several other research in distributed artificial intelligence has considered the distributed Constraint Satisfaction Problem (CSP) in which variables of a CSP are distributed among agents. Each agent has an exclusive subset of the variable and has sole responsibility to instantiate their values. While satisfying its own constraints, each agent instantiates/modifies its variable values. Coordination among agents facilitates effective problem solving. Ghédira constructed a model of simple reactive agents for resource allocation problems without precedence constraint on task [15]. The model involves Task and Resource agents in interaction, each of them seeking its maximal satisfaction in terms of getting resource allocation and maximizing resource utilization.

The second class concerns the **biology inspired heuristics**. These ones utilize insects metaphor in collective problem solving [25]. Research is directed toward constructing systems composed of reactive agents that are situated in their environment and act by stimulus and response. Colorni et al. presented, for instance, a distributed optimization scheme for Traveling Salesman Problem (TSP) based on ant colonies [7].

The third class is represented by the **physics inspired heuristics**. The physical inspiration is essentially concerned by field-based approaches [21]. Techniques based on fields have proven to be valuable in various applications that involve movement of agents in a metric space [31]. The computational fields that are propagated in a distributed environment and locally sensed by agents, provide contextual information to support agent interaction. Gechter et al. proposed a problem-solving model based on a swarm approach where agents interact using physics-inspired mechanisms. This model was then applied to localization and tracking [14]. In [29], artificial potential fields are used to tackle cooperation and conflict resolution between situated reactive agents.

4 A self-organizing multiagent approach

In the proposed approach, facilities are modeled as reactive agents which are situated in the environment. The environment topology is known a priori, it corresponds to a finite and continuous space involving the demands. The proposed approach provide an interaction model for the agents in which the environment has a central role. Agent's interactions are enabled and mediated by artificial fields supported by attractive and repulsive forces. They represent a very expressive contextual information. These forces are propagated in the system by the agents (facilities) themselves and by the environment via the demands. The objective of an agent or a facility consists to:

1. Optimize its position considering the perceived demands,
2. Consider interactions with other agents in order to reach the collective problem solving.

Then, the agent's behavior corresponds to a move vector reflecting the above objectives. The computation of this vector is detailed in the following subsections.

4.1 Local demand satisfaction

The agent's objective consists in minimizing its distance from a set of perceived demands. The key idea is that a demand induces attraction forces which are applied on the agent. Considering one demand point, an attractive force is defined to pull the agent to it. It is expressed as a vector the intensity of which is proportional to the demand weight and to the distance between the agent and the demand. It is supposed that only one facility is necessary to satisfy a demand, and that a facility can satisfy (or cover) several demands. Indeed, repulsion forces are introduced to avoid that several facilities cover the same demand. The demand weight is constant. It represents for the demand the necessary service quantity to be satisfied or covered by the facility. The weight for a demand point, can be the number of passenger waiting at the bus-stop or the quantity of a product that must be served to a depot from a factory, etc. Formally, for an agent A perceiving a demand D with weight W_D:

$$\vec{F}_{D/A} = W_D \ . \ \overrightarrow{AD} \tag{2}$$

The influence of the attraction decreases when the agent moves towards the demand. Thus, if the agent attains the demand, the attraction behavior is inhibited. For a set of perceived demands, the influence on an agent is defined as the sum of all induced forces. Formally, the local attraction force undergone by an agent A is computed as follows:

$$\overrightarrow{F}_{demands/A} = \frac{\sum_{i=1}^{n} \overrightarrow{F}_{i/A}}{n} \tag{3}$$

Parameter n is the number of demands (indexed by i) perceived by the agent A through its attraction radius r_a. Figure 1 represents an agent A that is attracted by 5 perceived demands ($n = 5$), consequently the agent will move following the resultant attraction vector $\overrightarrow{F_a}$. Obviously, the radius r_a should be considered as a variable. It can range from infinity to a calculated best value (specific to the problem). But in our real experiments a fixed radius imposed by the requirements is considered. For this reason, in the following only fixed radius are considered.

The agent moves to the weighted barycenter of the demands, which is known to be the minimum average distance to several close weighted points [20, 26]. For example, if an agent is subject to two attractive forces (from two different demands), it will be more attracted towards the biggest demand. Then, it will move towards a balance point. This point is defined as the place where the two attraction forces are equilibrated. Contrary to the classical use of APF, we do not try to avoid local minima. They provide natural local solution to a facility location.

When we have several agents, attraction forces may bring the agents to the same location. In such a case the process is sub-optimal since several agents cover the same demand. To prevent this process repulsive forces are introduced to the approach.

4.2 Local coordination

In order to avoid that agents have the same locations, repulsive forces between them are introduced. The repulsion force concerns close agents, it is necessary when an agent perceive other agents through its repulsion radius (r_r in Figure 2). Indeed, the agents try to cover the demands competitively. So, an agent who is perceived by another represents an obstacle because it prevents its self-satisfaction represented by the demand covering. Thus, the agent generates a repulsive force which pushes the perceived agents away from it. Moreover, such repulsive forces are interesting to deal with constraints on minimal distances separating facilities. Such constraints are present in many facility location applications. The force intensity is defined as inversely proportional to the inter-agent distance: the less the distance is, the bigger the repulsion is. Formally the repulsive force induced by an agent B on an agent A is expressed as follow:

$$\vec{R}_{B/A} = \frac{\overrightarrow{BA}}{\left\|\overrightarrow{AB}\right\|^2} \tag{4}$$

Then, the local repulsive force undergone by an agent A is computed as follows:

$$\vec{R}_{agents/A} = \frac{\sum_{j=1}^{m} \vec{R}_{j/A}}{m} \tag{5}$$

Parameter m is the number of agents perceived by the agent A. These agents are indexed by j. Figure 2 illustrates this repulsive process between two agents.

4.3 Collective solving

The agent behavior is defined as the weighted sum of both local attraction and repulsion forces. Formally, for an agent A, it is expressed as follows:

$$\overrightarrow{Move} = \alpha \, \vec{F}_{demands/A} + (1-\alpha) \, \vec{R}_{agents/A} \tag{6}$$

The coefficient α allows to favor either the attraction or the repulsion influence. It depends on the considered application.

We now consider the whole system, where several facilities must optimize their positioning to cover numerous demands. In the self-organizing approach, no global control is used. Agents are created and distributed in the environment and act following the defined individual behavior. The agents try to satisfy their local objectives, this leads to the emergence of a global location, i.e. a sub-optimal solution. The collective solving process is presented in Algorithm 1. The agent's target move is regarded as a result of the above two tendencies i.e., attraction and repulsion. The behavior in Algorithm 1 does not prevent the main

Algorithm 1 Collective solving process

```
Initialization of Agent positions
while Fitness in progress do
    for all Agents do
        Attraction computation
        Repulsion computation
        Vector Move computation
        Move execution
    end for
    Global fitness computation
end while
```

drawback of the artificial potential fields technique: the local minima. Indeed, introducing attractive and repulsive forces leads to the emergence of areas where forces are equilibrated. Thus, an agent that is subject to these influences can be trapped in such places. In the proposed agent-based heuristic these local minima are considered as interesting places where facilities are located at the balance of different influences. They represent potential solutions globally satisfying and quickly obtained as explained in the following sections.

5 Computational study

5.1 Results on test suite

An empirical study was carried out to evaluate the proposed approach. The 50-customer problem listed in [11] and the fitness presented in sub-section 2.3 are considered. The weights w_i are specified as unitary [5]. Initial solution is obtained by a random positioning of facilities.

The number of facilities to locate was varied over a wide range (from 2 to 25 facilities). This provided a large number of problem instances ranging from small to relatively larger instances. Thus, we were able to investigate the performance of the proposed approach over an extensive range of problem difficulty.

The results which are listed in Table 1 are expressed as a percent deviation from the best solutions. These solutions which are known to be global optimal solutions are compared in [5] to several heuristics such as the Tabu Search (TS) and the projection (PROJ) ones. The performance of our agent-based solutions is also compared to these two heuristics. For more detail refer to [6] and [4] respectively for TS and PROJ. Some observations are inferred from a comparison of the results in Table 1. These are summarized below.

From 10 to 25 facilities the agent-based approach is generally better than the TS method and close to the PROJ method. Moreover, the agent approach outperforms the TS on average.

While increasing the number of facilities the three presented heuristics have relatively poor performance compared to the optimal values. This implies that random starts are not an effective solution strategy for "high" problem instances. It relates to the existence of local minima. In fact, the number of local minima increases with problem size.

5.2 Application to bus-stop location

In this section the proposed approach is applied to a real case study. The bus-stops positioning on the bus-network of the city of Belfort (France, 60,000 inhabitants) is considered. Bus-stops must be located such as the distance from the passengers to the nearest bus-stop is minimized. We dispose of the real bus-network (see lines structure in Figure 3) and the real values of demands. In this case study we have a continue demand representation. It is expressed by densities which correspond to the number of inhabitants per quarter, i.e., for each houses block we have the sum of the existing demands. In Figure 3, dark areas characterize important demands, the more the area is dark the more important the demand is. This example introduces an important constraint for facilities. While moving, bus-stop agents must remain on the lines. Each line has a predetermined number of bus-stops. Terminus agents are fixed and are not subject to attractive and repulsive influences. The integration of the new constraint does not need to update the model. Its adaptation concerns only the projection of the move vector on the bus-lines (i.e., the move vector is transformed so as the agents move along lines). The initial bus-stop positions are computed randomly, see Figure 3(a). Agents can be anywhere on the lines network. White points in Figure 3 correspond to bus-stop agents. The repartition of bus-stop agents is ensured thanks to the previous influences. Figure 3(b) shows the final state to which the system converges. The bus-stops repartition is characterized by an intensification of the agent number in areas where demand is high. To observe the convergence to a stable state a fitness index is introduced. It corresponds to the mean weighted distance separating a demand and its closest bus-stop. Figure 4 plots the fitness values which decrease until the convergence to a stable state. Convergence is attained rapidly: since the 24th iteration. The optimal number of this fitness is 175 meters. In other words, for a demand (customer), the nearest bus-stop is situated at an average distance of 175 meters.

In this case study the considered data are static: demand and bus-stop number. In our approach, this data can be changed online without disturbing the agents behavior. Here, the data changing concerns the increase or the remove of the demands and/or facilities (bus-stops) number. These modifications leads to a changing in the agents perceptions which engender an adjustment of the attraction forces, while changing the demands, and the repulsion forces, while modifying the bus-stops number. All these changes are perceived as contextual information which leads the agents to re-adapt their positions and move following their new perceived forces without any global control.

6 Adaptation to multi-level problems

This section is another illustration of the flexibility of the proposed approach. The multi-level location problem which is a variant of the location problem is tackled.

6.1 The multi-level location problem

In the classical facility location problem only one level of facilities has to be located. However, many practical situations involve more than one type of facilities and therefore multi-level models have recently an increased deal of attention [3, 8]. In literature this problem is designated as: hierarchical, multi-level, multi-echelon, multi-stage, etc. Generally, the designation of the problem indicates the maximum number of levels considered: k-hierarchical, k-level, k-echelon location problems refer to problems with, at most, k levels of facilities. The objective is to choose where to simultaneously locate facilities in each level in order to optimize a global objective function. These levels may have different characteristics (by offering different services to clients, for instance) and interact with each other. So, it is not possible to locate facilities in each level independently from the others. This problem is NP-hard, since it is a generalization of an NP-hard problem, as stated in [13]. There is several examples in our daily lives that show the importance of considering multi-level facility location problems: the hierarchical health service system, the hierarchical education system, the multi-level structure of bank and post-offices, etc. In literature, various approaches were developed to tackle the different variants of the multi-level problem. These approaches are, mostly dedicated to static version of multi-level problem where the problem parameters do not change [30]. They are also hardly useful for real-size problems. Mainly they lack robustness, scalability and adaptation to dynamic systems. As a consequence, these methods and especially exact ones have been restricted to relatively small instances.

6.2 Application to a multi-level distribution system

Minor changes were conducted to make the proposed approach able to tackle the multi-level facility location problem. The main characteristic of the multi-level problem is that a facility at a given level represents a demand for the higher level. To take into account this specific point the attraction is modified so as a facility at a level n is attracted at once by the demands of the level n-1 and the facilities of the level n+1 (see Figure 5). As for the repulsion behavior it remains unchanged. Figure 5 shows a problem with 3 levels, the lowest level presents the demands. It illustrates the attraction and the repulsion in a multi-level problem. To sum up, each agent is repulsed by the agents of the same level and attracted to the agents of the immediately inferior and superior levels.

The previous model is applied to a 2-levels distribution system. In this system the lowest level corresponds to the Demands, level 1 coincides with the Depots and the highest one with the Factories. Each demand is assumed to obtain its product from a depot or a distribution center, which is in turn supplied by a factory or a manufacturer. The distribution of products between the various levels is ensured by several vehicles. The evaluation is based on a global fitness obtained according to the fitness of each level. This one is the same fitness considered in the formula 1 (sub-section 2.3). Table 2 details the obtained results for different configurations (various number of demands, depots and factories). In this example, demands are randomly distributed over a 2D Euclidean space. Figure 6 illustrates the evolution of agents locations during the optimization process. It corresponds to the second configuration presented in Table 2. Obviously, the agents repartition after 100 iterations is better than that presented after 10 iterations. This observation is confirmed by the fitness values.

7 Discussion

The previous computational study allows to point up some observations on the proposed approach. Indeed, the obtained results are globally satisfying considering the fitness criterion. It is obvious that while adopting this field-based approach for an NP-hard problem we did not expect to rival the exact methods. But, the multiagent approach has various assets that motivate our choice, these ones are listed below.

Environmental dynamics are adaptively taken into account in that any change in the system may update influences emitted and perceived by the agent. These perturbations that tend to influence the facilities locations can be, for instance, a new facility or demand entering the system, or at the contrary removing a facility or a demand from the system. Generally, the existing solutions for facility positioning [30, 16] are not easily adaptable for the environment dynamics and the possible perturbations. They, inevitably, need to re-adapt their algorithms. At the opposite, our self-organizing approach will immediately adapt the facilities locations.

An important advantage of the proposed approach is its reusability. In section 6, it has been applied to the multi-level location problem without changing the agents' behaviors. The approach presents self-adaptation abilities facing these important changes in the environment characteristics and constraints implied by the multi-level problem [23].

The proposed approach is able to solve a wide range of location problems in a robust and flexible way (as seen in sections 5.2 and 6). Robustness and flexibility arise because even if facilities (agents) are added or removed these ones can achieve their goal without changing their behavior. Moreover, The proposed approach promotes self-organization and self-adaptation. The agents activities are automatically adapted to the environmental dynamics which is reflected in a changing force representation, without forcing the facilities to re-adapt or change their behavior. Figure 7 illustrates the robustness and the adaptability of the proposed approach. Tests were conducted on the 50-customer problem. To disturb the system the demands number is modified. Until 100 iteration 50 customers are considered (Figure 7(a)), the fitness clearly converges to a stable state (Figure 7(b)). Then from the iteration 101 the number of demands is increased to 70. This change has an immediate impact on the fitness curve. The fitness shows a peak, then it decreases and converges to a stable state. The same results are expected when the demand number is decreased, the fitness decreases and converges to a stable state.

The main limitation of the proposed approach is that it inherits the disadvantages of the potential fields techniques: the local minima. These ones represent, for us, interesting possible locations which evolve to acceptable solutions considering the fitness-time ratio. An other limit can be quoted, it is shared by most of the problem-solving heuristics: the dependence of the initial solution. Indeed, the computational study presented above showed us that the quality of the final solutions depends on the initial solution or the initial positioning of agents.

8 Conclusion

This paper has presented a self-organizing multiagent approach for the continuous location problem. The proposed model relies on a set of reactive agents with neither cognitive abilities nor a representation of the global system. The problem and its constraints are represented through the agent's environment. Facilities, which are modeled as reactive agents, move according to their local perception. They interact to reach a global optimization goal. The interactions between agents and their environment, which are based on the artificial potential fields approach, allow to locally optimize the agent's location. Further more, demands induce attractive forces and the proximity between agents generates repulsive ones which are constraints propagated between agents. The agent's behavior is then defined as a combination of these two kinds of opposite influences. The optimization of the whole system is the outcome of a process of agents self-organization. Then, the system converges to a global stable state corresponding to a set of local equilibrium in the environment. The relevance of the approach has been shown through several assets and an empirical study conducted on three case studies.

Future works will be devoted first to a deeper computational study based on larger problem instances. Second, the convergence of the proposed approach and the solutions emergence will be studied. We are also interested in the dimensioning problem, indeed, since every new facility generates a supplementary positioning cost we are trying to optimize the already considered objective function while using the minimal number of facilities. Our problem can be so formulated: how to maximize the demand covering with the minimal number of facilities? To do that, we are thinking about merging the eco-solving method with our APF-based approach. Finally, we are trying to enrich our approach by using Holonic MultiAgent Systems (HMAS) to deal with multi-level location problems. The use of HMAS will allow to exploit and control the emergence of solutions.

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Authors Biographies

Sana Moujahed is, since 2008, a Doctor of computer science at the University of Technology of Belfort-Montbéliard (UTBM), in the Systems and Transportation (SeT) Laboratory, France. Her research interests include multiagent systems, optimization and location problems.

Olivier Simonin is, since 2001, an associate professor in Computer Science at the UTBM and a member of the SeT laboratory. Since 2006 he works at INRIA Lorraine in the MAIA project (Nancy), pursuing research in multiagent systems for distributed problem solving, simulation and mobile robotics.

Abderrafiâa Koukam is a professor of computer science at the UTBM. He leads the Computer Science, Communication, Agents and Perception team in the SeT Laboratory. His research interests include software engineering, multiagent systems and optimization.

Table 1: Test values for the 50-customers problems

n=50 (50-customers benchmark)				
m	Optimal values	Agent best solutions	TS best solutions	PROJ best solutions
2	135.5222	0.58	0.00	0.00
3	105.2139	2.10	0.00	0.00
4	84.1536	3.61	0.00	0.00
5	72.2369	4.18	0.00	0.00
6	60.9713	4.11	0.00	0.00
7	54.5020	3.12	0.00	0.25
8	49.9393	2.07	0.00	0.72
9	45.6884	2.37	0.79	0.91
10	41.6851	2.96	1.77	2.40
11	38.0205	2.41	5.83	1.57
12	35.0551	2.66	7.84	0.61
13	32.3067	4.93	2.22	3.33
14	29.6559	3.73	6.35	5.65
15	27.6282	1.97	9.06	5.33
16	25.7427	2.77	8.98	5.44
17	23.9900	4.05	9.62	5.75
18	22.2851	3.97	8.73	2.97
19	20.6399	4.97	10.15	2.91
20	19.3560	3.40	6.34	3.63
21	18.0826	4.31	6.40	1.34
22	16.8220	6.21	5.18	5.34
23	15.6136	4.60	11.74	4.34
24	14.4431	8.24	9.64	0.37
25	13.3016	11.86	9.64	2.00
Av.		**3.96**	**5.01**	**2.29**

Table 2: Experimental results of 2-levels distribution system

Demand (level 0)	Depot (level 1)	Factory (level 2)	Best found solution
100	10	1	7477,72
100	20	2	5869,9
200	10	1	13839,45
200	15	2	11284,58
200	20	4	10513,04
500	10	2	35860,98
500	20	4	25468,75
500	50	6	19600,98

Captions of the figures

Fig. 1: Attractions lead the agent to the weighted barycenter of demands.
Fig. 2: Repulsions between agents A and B lead them to keep away.
Fig. 3: The evolution of the facilities positioning for the Belfort bus-network.
Fig. 4: The fitness convergence; a test with 143 bus-stops.
Fig. 5: A 3-levels problem.
Fig. 6: Agents location for iterations 10 and 100.
Fig. 7: The system adaptability facing an increased number of demands.

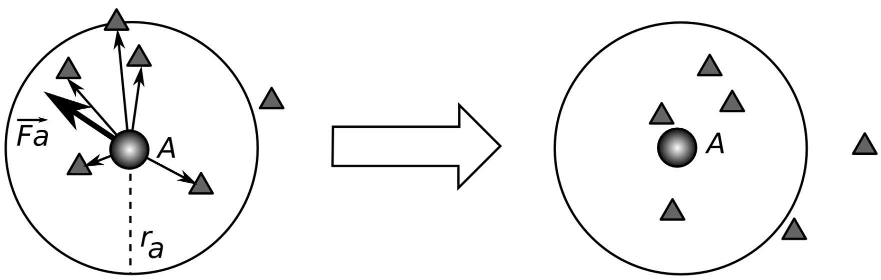


Fig. 1: Attractions lead the agent to the weighted barycenter of demands.

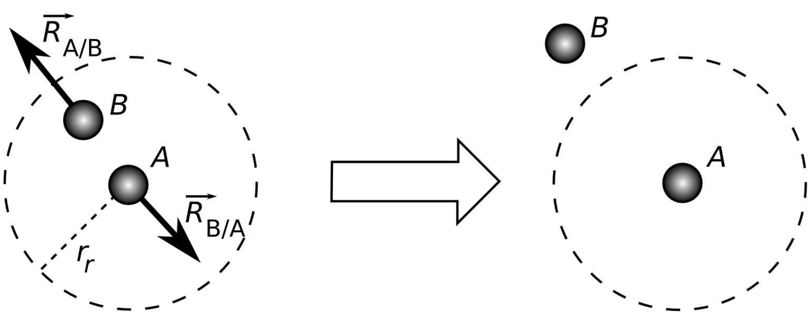
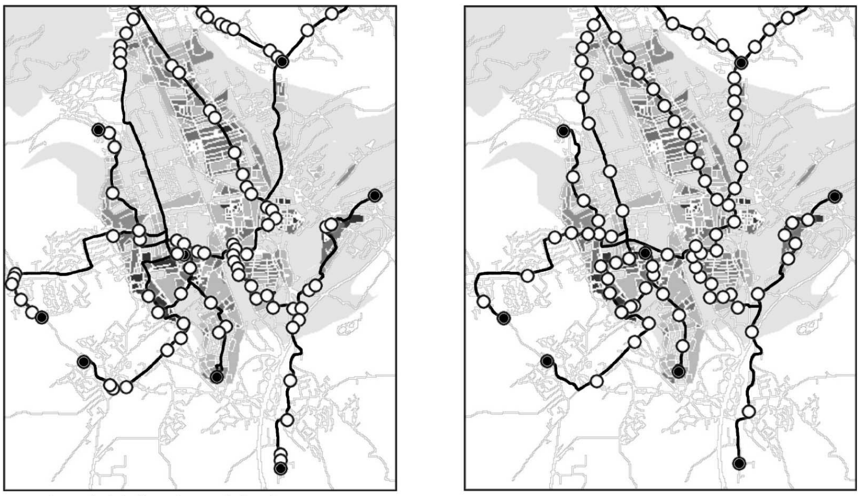


Fig. 2: Repulsions between agents A and B lead them to keep away.



(a) Random initialization of the bus-stop agents

(b) Execution final result

Fig. 3: The evolution of the facilities positioning for the Belfort bus-network.

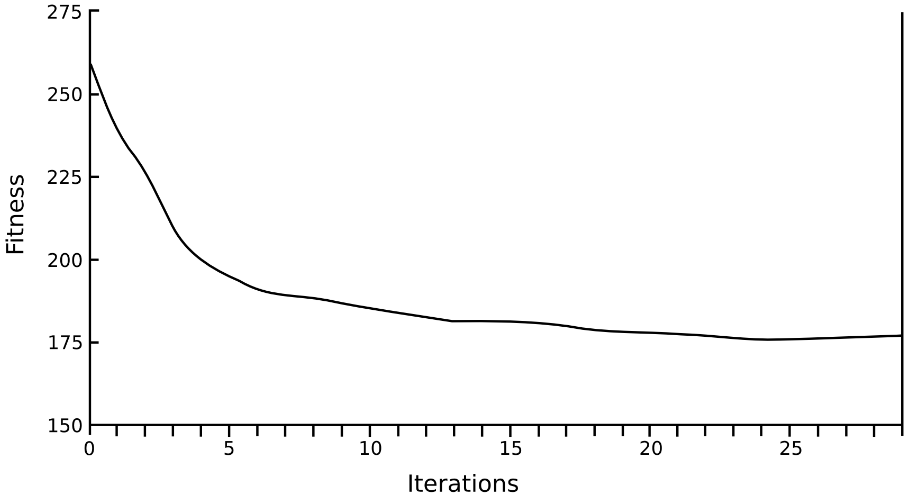


Fig. 4: The fitness convergence; a test with 143 bus-stops.

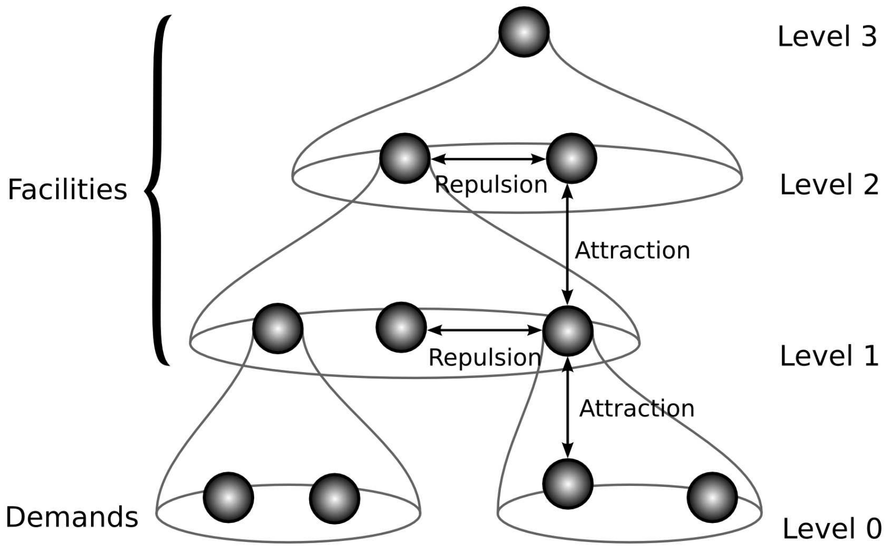


Fig. 5: A 3-levels problem.

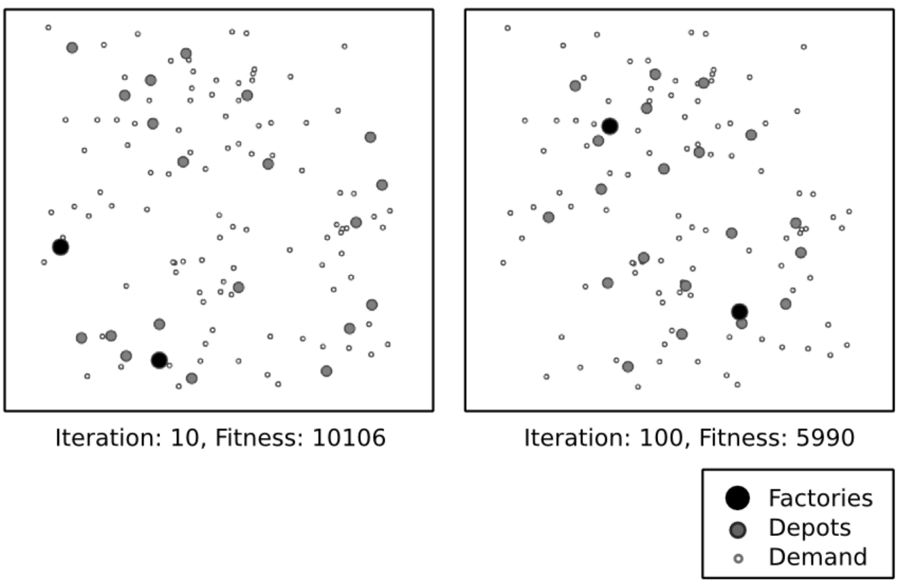


Fig. 6: Agents location for iterations 10 and 100.

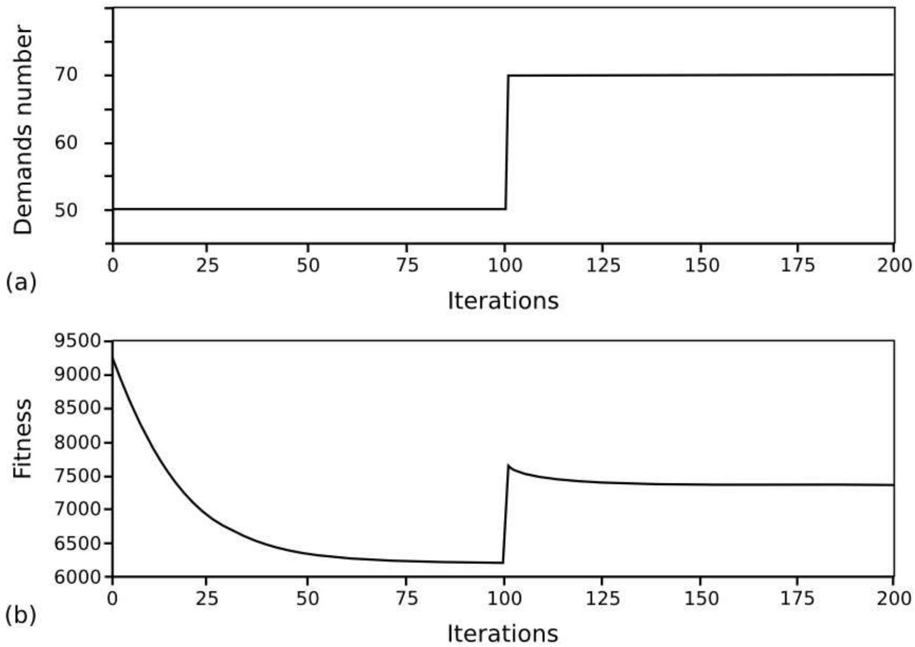


Fig. 7: The system adaptability facing an increased number of demands.