Towards Better Coordination of Rescue Teams in Crisis Situations: a Promising ACO Algorithm

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Abstract. Crisis management challenges decision support systems designers. One problem in the decision marking is developing systems able to help the coordination of the different involved teams. Another challenge is to make the system work with a degraded communication infrastructure. Each workstation or embedded application must be designed such as potential decisions made trought other workstations are treated as eventualities. We propose in this article a multi-agent model, based on an ant colony optimization algorithm, and designed to manage the inherent complexity in the deployment of resources used to solve a crisis. This model manages data uncertainty. Its global goal is to optimize in a stable way fitness functions, like saving lives. Moreover, thanks to a reflexive process, the model manages the effects of its decisions into the environment to take more appropriate decisions. Thanks to our transactional model, the system takes into account a large data amount and finds global optimums without exploring all potential solutions. In perspective, users will have to define rules database thanks to an adapted graphical interface. Then, if the nature of the crisis is deeply unchanged, users should be able to change rules' databases.

1 Introduction

Today, crisis management is an important domain throughout the world. Crisis can be earthquakes, industrial accidents, nuclear crises, etc [1]. Moreover, crises can appear as an imbrication of several emergencies, which can produce more complex crises. One issue is to manage and minimize the effects of this complexity. Our work is centered on tasks planning and resources deployment, through an embedded application distributed into an asynchronous network.

This study refers to the project AidCrisis, financed by the French Region Champagne-Ardenne and the European Regional Development Fund. The project aims to produce solutions for the decision making, in order to prevent mainly from nuclear, radiological, bacteriologic and chemical risks. Three kinds of aspects have been discriminated [2]. The first one consists of preparing or anticipating potential crises, through classification of circumstances, identification of critical sites, training, scripting events [3], simulation, etc. The second aspect consists of treating an ongoing crisis, by identifying it, deploying resources and managing the logistic, dealing with localized events, and exposing results. The third aspect consists of analyzing the crisis after its progression, into order to deduce lessons.

During the treatment step, several groups, like first aid agents, police, Doctors, government delegates must collaborate into the working site. Each group has to follow its own organization, and its own goals, according to a categorized event. Three kinds of groups have been segmented [1], which are the management centers, the hospital centers, and the agents working on the accident area.

We present into this article a model that enables the constitution of a strategy to apply considering a crisis and the deployment optimization of the human and material resources. Let see one possible scenario. One person, which can be a professional or a civil person, declares a fire. It specifies the type of fire, like house fire, factory fire, nuclear power station fire, etc. If we consider a pessimistic senario where the user does not have time to specify which kind of fire appeared, the system considers all possibilities as valid, with the respect to their probabilities of occurences. For each possible event, the system deliberates which tasks it had to plan thanks to a graph of possible actions. In our fire example, tasks can be ground-to-ground intervention, or air-to-ground intervention. The tasks choice depends on their efficiency, but also on the availability of the needed resources. Moreover, the system considers events which are likely to appear and manage conflicts of resources deployed at the same time for several goals. We propose in this article a data structure and an algorithm of combinatorial optimization adapted to the introduced problematic.

In the section 2, we relate the different algorithms of optimization and we justify our choice. According to a particular data structure articulating events, goals, tasks, and resources, we propose an adaptation of the chosen algorithm into the section 3. This model is adapted for large scale applications, manages uncertainty, and by a reflexive process, adapts its decision process according to the effect of its decisions over the time. We end with a conclusion and perspectives into the section 4.

2 Related studies

2.1 Critical of statistical approaches

Statistical approaches have this default that although their predictions seem in average good, they can seriously induce the human and computer deliberation to severe faults. For example, Parunak et al. [4] have demonstrated how a colony of agents, typically a prey/predator ecosystem, can prove wrong a statistical approach. Others objections have been done about more complex statistical approaches, for example in the finance domain [5, 6]. [6] proposes to prefer more stable laws like those of Pareto to deal with random variables which does not follow a normal distribution.

The interpretation of a model is often developed according to the model itself, and the only way to develop the criticism and to avoid a kind of fatalism would be to construct new models. By opposition or competition with statistical based models, our way is to develop a simulation based model designed for coordination and assignment of human and material resources. Simulation based model have the advantage to make appear empirically unlikely phenomena, where statistical approaches can consider some potentially important events as insignificant. However, both simulation and statistical based model can accumulate approximations, which should make the system producing incoherent data, then incoherent decisions. To avoid, or at least to limit this phenomena, we suppose that the introduction of the data uncertainty should force the system to have a stable reaction.

Simulation, optimizations, and finally decision making are done according to several goals which can be independent or correlated. We will describe now the related approaches that deal with multi-goal optimization.

2.2 Combinatorial optimization

A problem of combinatorial optimization can be defined as follow: considering a set of combinations S and a fitness function $f : S \rightarrow IR$, the combinatorial optimization consists of find the combination $s \in S$ minimizing f such as: $f(s) \leq f(s_i), \forall s_i \in S$.

According the related works exposed in [7], two main types of optimization algorithms exists: complete approaches and heuristic approaches.

Complete approaches, like branch and bound solutions, or dynamic programming solutions, have to explore every combination contained into S. They do not permit to resolve problems whose complexity class is NP.

Heuristic approaches can be decomposed into two kinds of approaches: local search approaches and constructive approaches.

Local search approaches [8] consist of make solutions progressing into their neighborhood. The main difficulty of these approaches is to avoid local optimum. Simulated annealing method [9] was inspired from annealing in metallurgy. It is a statistical method which consist of virtually control the temperature of the material, i.e. the set of solutions. If the temperature is hot (or cold), particles are free (or not) and then solutions are free to move from one to another (or not). Then, the method consist of progressively decreasing the temperature, to make the system converging to the better optimums. Inspired from observations of the nature, genetic approaches [10] consist of generating competition between individuals of a population, thanks to reproducing, genetic mutations, and fitness functions. Several strategies have been developed in the genetic algorithms domain, to avoid local optimums, but global optimums cannot be insured. Particle swarm optimization [11] is also an evolutionary approach, but based on a stochastic approach. The method is inspired from the observation of the movement of organisms in a bird flock or fish school. Particles adapt their speed and their directions according to the current optimal solutions, to discover new potential solutions.

Constructive approaches start with empty solutions, and construct them progressively. With dreedy algorithms, the choice of each element can be made randomly, or according to a heuristic, called gradient criterion. The performance of theses approaches depend highly on the gradient criterion. So it is not adapted for all applications. Estimation of distribution algorithms [12] are evolutionary models based on the progressive construction of probabilities defining the quality of each choice. Initially proposed in [13], optimizations by ant colony consist of taking advantage in the use of intelligence emerging from a collective work of an ant colony. The ant colony optimization (ACO) consist for ants in founding the shortest path between the anthill and the nearest located food. Ant colony algorithms are well adapted for problems whose complexity class is NP. We will see how this algorithm is mathematically formalized for multi-goal optimization problems.

In most time, our application should coordinate local resources to manage a crisis. Moreover, every combination of task and every strategy do not have to use all human and material resources. But sometimes, in a severe crisis context, the system could take into account a large set of resources. For example, in a forest fire context, the system could have to call firemen which come from other regions, and sometimes from other countries. Taking account of every resource of every region could become a very complex problem. But the ant colony algorithm let show us that ants do not really explore all their environment and become near from their anthill. Moreover it is possible to limit the exploration of the ants according to the best current obtained path. Then, even if a workstation does not have the entire data of the entire regions, the ants can move from a workstation to another to look for their goal. And because, they don't have to explore all their environment, the system can resolve a goal without making all workstations contributing to the problem. For this reason, ant colony algorithm appears for us well adapted.

3 The proposed approach

3.1 Goals

Thanks to a rules database defined by competent actors, the system has to generate a plan of actions and a plan of deployment of the different resources, this to manage the crisis ongoing, its uncertainty, and its dynamical reaction to human intervention. Another challenge is to work with different workstations represented by actors located on different regions. The reason for this distribution is justified by the necessity to, 1) enable the system working with a deteriorated network, and 2) involve actors coming from other regions in some cases. We present an optimization algorithm which does not explore all the space of solutions.

3.2 Data structure

Structurally, the input data is organized as follow. From a graphical interface to define, and before a crisis appears, different actors into the management center can enter into the system different kind of possible events. These events correspond to possible real events like fire, health problem, aggression, etc. Each of these events/problems can be specialized into sub-events. For example, fire can be specified as a house fire, a public building fire or a nuclear power station fire. Moreover, a set of events can be a superposed state. Moreover, each event can trigger other events according specific functions, which can depend from time and more generally from the evolution of the parent event parameters. For each event, the system has to solve a goal. A goal can have several fitness functions to minimize. To reach this goal, the user has to enter a graph of possible tasks to apply. For each task, a list of resources can be used. Moreover, each task can be localized or not. If it is the case, the system generates tasks of transportation of resources.

3.3 Algorithm

The first step of our method is to decompose according to a discrete grid, events which have superposed time positions and superposed space positions, into superposed events which have unique positions.

Then the system deduces the list of goals it has to solve. For each goal, the system will have to plan the allocation of resources according to time and space, and without conflict with other goals. One solution to solve these goals is to consider them as a global multi-goal optimization problem. However, this solution will force the system to process a global optimization centralized into one server, and making the entire network dependent from this server. Instead of this solution, we propose a transactional model. Our solution consists of optimizing each individual goal as bubble of realities. Then, if two bubbles have conflicts of resources, a parent bubble will be generated to solve these conflicts by generating sets of constraints adapted for each possible alternative solution. Thanks to this transactional model, resources data which can be located only into other servers, workstations, or smart-phones, are explored during the goal optimization step only when no close free resource has been detected. As for the transactional memory programming [14], this method should give in most cases, better performances. The figure 1 shows how node bubbles are optimized. When all bubbles have been optimized, and when all bubbles have no conflict with any bubbles, than the system goes to the dynamical projection step.

When a task is applied into the environment, the state of the system is likely of changing. With our data structure, the application of a task, or the application of another task will change the evolution of the events, and those of the triggered events. So deliberation of the system can alter the variables responsible of this deliberation, and then alter this deliberation. Since we do not consider global

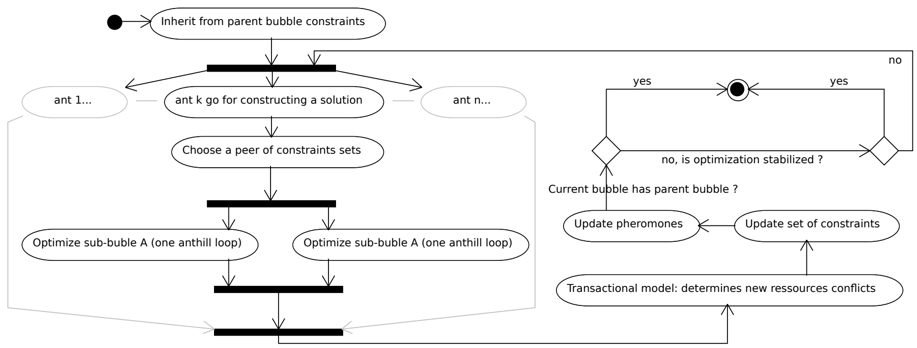

Fig. 1. Node bubble optimization process (diagram of activities).

exploration, we have developed the next strategy. When all bubbles have been optimized, the system projects for each bubble their related decisions over time, and deduces new future events. These last are merged with equivalent events which have been deduced in the previous loops. The fusion process consists of considering a same deduced event as an event which has superposed states. From this set of deduced events, is deduced a new set of bubbles. If changes have been detected, the system goes back to the bubble optimization step. Else, it proposes its plan of resources deployment and its plan of tasks to apply.

3.4 Ant colony optimization (ACO) for multi-goal optimization problems

Our system must be able to solve problems which are formalized according to several goals, i.e. several fitness functions. [15] discussed several ACO approaches adapted to multi-goal problems. Experimentations have been done in [7] and it appears that the best of these approaches (m-ACO$_6$) is also a Pareto based approach. m-ACO$_6$ appears also better than several evolutionary algorithms [7]. We will present in this subsection the mathematical formalism of the m-ACO$_6$ approach [7], that will enable us to develop our model.

Considering that ants construct solutions through a graph $G = (V, E)$ whose definition depends on the problem to solve, pheromones are associated to each node of the graph. The algorithm 1 show how an anthill loop is repeated until optimization has found a stable state, or has reached a maximum number of loops.

4 Conclusion and perspectives

We have proposed a model able to plan a set of tasks and able to deploy a set of resources according to declared events during a crisis, but also according

Algorithm 1 Generic ACO algorithm for multi-goal optimization problems

initialize pheromones marks to τ_{max}
repeat
  processing an anthill loop...
  for all ant $k \in$ colony **do**
    construct a solution
    simulates the application of this solution into the environment through $Influence(P(O_{AE}), S^i, O_R)$
    chooses randomly a fitness function to optimize $f_{Ci,AE_0}(x)_c$
    evaluates the results of this simulation thanks to the chosen fitness function
    forgives the effects of the simulation
  end for
  for all $c \in$pheromones structures **do**
    update the c^{th} structure of pheromones
    if one mark is lower than τ_{min}, set it to τ_{min}
    if one mark is higher than τ_{max}, set it to τ_{max}
  end for
until A maximum number of cycles is reached **or** the optimization process is stable

to a set of simulated events over the future. The system processes a reflexive deliberation by applying a projection of its decisions over time, and by deducing related issues to deal with. Moreover, it manages data uncertainty, according to a formalism based on the Pareto law that produces stable results, in the context of a stochastic environment. Finally, the model produces a global optimum by exploring solutions locally in a first step, and globally if necessary. This solution is then adapted to large scale systems, that should be a huge distributed network of workstations. This work can then be introduced into a more global project, i.e. the conception of an asynchronous and distributed embedded application able to manage the deployment of human and material resources in the context of a crisis.

Future works should be centered into: the introduction of a user avatar taking into account the preferences of the user; the management of uncertainty related to avatars when workstations are disconnected from the network; the simplification of data managed by users through a participative solution and through an ergonomic interface [16, 17]; the process of experimentations and evaluations.

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