Centralization *Vs* Distribution decision-making organizations during crisis situations

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Abstract*— The centralization or the distribution of decision support systems depends on various factors, such as the organization type, the nature of the decisions to be made, and the intensity of the situation. Critical and uncertain environments, such as crises, impose significant constraints and necessitate prompt resource management decisions to correctly allocate objects. In this context, it is particularly important to choose between (i) a centralized organization, where a single central authority decides everything for everyone, or (ii) a distributed organization, where everyone talks to each other to try to coordinate local decisions. To resolve this problem, this article compares these two organizations of decision-making, while the distributed organization is represented by the *Contract Net Protocol* (CNP), which is a distributed auction where one hospital acts as the host/auctioneer while the others participate as guests. Our contribution is that *we investigate the integration of Altruism Percentage (AP) as a key factor within a decision-making framework supported by a multi-agent system (MAS) to illustrate the ability of each agent to have its own objectives and constraints. We explore various configurations of AP among autonomous collaborative agents using the "Agent" library in the AnyLogic simulator, coupled with the CPLEX solver.* Our work demonstrates that one can represent the centralized organization through the distributed organization (CNP) with an extreme AP value ($AP = 100\%$). We examine in this article how to improve patient distribution in a hospital group during a crisis. The problem is formulated as a Multiple Knapsacks Problem (MKP) with finite resources that are allocated to multiple demands with constraints and optimization objectives. The results show that a hybrid combination of the two organizations makes it possible to approach the efficiency of centralization, with the advantages related to the autonomy of distribution. The numerical experiments show that with the addition of a controlled AP it is possible to strike a balance between local adaptability and global coordination. Our results also show that *taking into account the autonomy of agents by adding the altruism factor AP in our version of the distributed organization $CNP + AP$ could provide a balance between distributed autonomy and centralized control, allowing more efficient and flexible decision-making processes.

I. Introduction

Knowing the impact of the level of (i) the centralization of decision-making, where a single central authority decides everything for everyone, or (ii) the distribution of decision-making, without anyone above where everyone discusses with everyone to try to coordinate local decisions, can be translated into the scientific challenge of knowing how to allow a distributed system to approach the efficiency of a centralized model, while exploiting the benefits (responsiveness, autonomy and resilience) of decision distribution.

This article therefore deals with the scientific challenge of the best centralization or distribution of decision-making utilizing advanced digital technologies. In our case, we rely on (i) agent-based simulation and (ii) optimization of MILP (Mixed-Integer Linear Programming). In order to study the (de)centralization of decision-making, we compare (i) the centralized organization (CO) modeled by a unique solver of MILP (software for optimizing Integer Linear Programs) and (ii) the distributed organization (CNP for *Contract Net Protocol*) modeled as a multi-agent system (MAS) in which each agent "thinks" thanks to a MILP solver. An MAS involves autonomous entities named "agents" who can each pursue their own objectives. By giving agents a certain autonomy to promote their own interests, while regulating this autonomy through appropriate coordination mechanisms, the distributed organization can better meet the requirements of a dynamic environment. This approach not only improves local agility and responsiveness but also the overall robustness of the system by minimizing risks associated with errors or delays in decision-making. Success in such contexts therefore relies on agile decision governance, capable of calibrating this altruism factor to take advantage of the benefits of distributed decision-making while avoiding overall disorganization or under-optimization.

We aim to ensure the optimal efficiency of the centralized organization while preserving the autonomy of the distributed organization to achieve this goal. *Our contribution is the modification of a famous multi-agent protocol, the CNP* (for *Contract Net Protocol*) introduced by [1], by *adding a parameter modeling the altruism* of agents, denoted as AP (for *Altruism Percentage*). We name *CNP+AP* our variant of the CNP.

Our work addresses the issue of centralizing or distributing decision-making through its application to the management of hospitals within a "Territorial Hospital Group" (GHT). It is a concept implemented by several countries around the world with the aim of (i) grouping purchases, (ii) sharing patient data, and (iii) improving their healthcare systems. COVID-19 illustrates the challenges of crisis management and the importance of knowing when, where, and how to make quick and effective decisions within a GHT. In other

*This work *uses interchangeably the terms "decentralization" and "distribution" of decisions*, the first to use the shortcut of "(de-)centralization" when a sentence is true both for "decentralization" and "centralization", while the second term is the one that seems most common in literature.

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words, coordination and communication problems during epidemic outbreaks illustrate how the situation of a GHT can quickly worsen during an already critical situation, putting public health and social stability at risk.

II. Summary of the results found in the literature

Zielinski [2] defines centralization as: "The purely centralized model implies (a) that there is more than one level of organization and (b) that decisions are only taken by the higher level (central authority). No decisions are made at lower levels."

On the other hand, Zielinski [2] defines decentralization by: Decentralization is a one-tier model – it works without any central authority and implies the existence of more than one decision-making centre. The perfectly competitive market is a classic example of a fully decentralized market.

These two organizations have been compared in several aspects. In this study, however, we narrow our focus on works that investigate the centralization–decentralization paradigm based on investigations using MAS. The MAS is often explored in multiple bibliographic searches, such as the one from [3] where they compared centralized and decentralized approaches to solving cooperative coverage problems with limited energy agents. They find that *the centralized approach in general leads to an improved average hedging performance compared to the decentralized approach*. More recently, [4] used multi-agent simulation to study the (de)centralization of information. Their results underline the *compromise between security and efficiency in decentralized architectures*. The concept of an agent has also been used to analyze (de)centralization via the principal-agent theory. [5] address the problem in a governance context and show that decentralized political structures could be optimal, even if all localities have the same preferences. On their side, to optimize dynamic carpooling, [6] compared (i) a centralized method based on an integer linear programming model with (ii) a decentralized approach based on MAS. They have demonstrated *the efficiency of their distributed system because it allows for better responsiveness to local requests while maintaining global coordination*. These systems are built on the concept of an agent, which is both autonomous and interdependent, and can operate independently or as part of a larger system [7]. Coordinating activities and decisions among various parts of the organization is a characteristic of MAS. Process synchronization is made possible and conflicts are minimized [8] and [9]. The flexibility of MASs allows for managing different resources, whether they are material, human, or informational [10]. Each agent has the ability to make autonomous decisions based on its local context, which can lead to increased agility and adaptability to change [11] and [12]. Being able to adapt is crucial in dynamic and complex environments [13] and [14]. The effectiveness of distributed decisions in a crisis situation depends heavily on the behavior of the agents, including their selfishness or altruism. Through the analysis of various research articles, we have discovered that the selfish behavior of agents in distributed systems leads them to approximate the optimality of centralized organization, even when sharing less information [15] and [16]. Local decision-making and limited information can be leveraged by distributed systems to achieve near-centralized efficiency, as highlighted by [12].

III. Modeling problem

A. Centralized organization (CO)

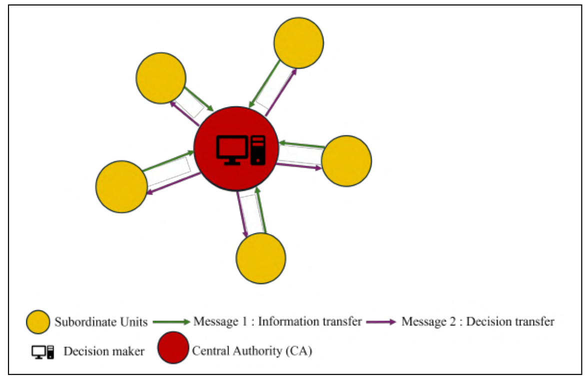

Fig. 1. Centralized organization (CO).

The principle of centralized organization (CO) is that the allocation of all objects is managed solely by the central authority, which must therefore know everything in relation to the whole. CO requires that the central authority (CA) knows not only its own capacities and its objects, but also the capacities and objects of other subordinate units. More precisely, Figure 1 indicates that the subordinate units send all their information in the message 1 (Information transfer).

B. Our distributed organization (CNP)

CNP starts when a unit, no matter its hierarchical position, becomes a Host. *A Host is the first unit to notice that it has more objects than resources available.* The Host is in charge of making decisions by recommending object moves between units and broadcasting the availability of resources to other units. All other units are called guests, formulating local decisions on resources based on individual constraints and communicating them back to the Host. CNP distributes the calculations among the guests in parallel. Ultimately, the Host consolidates these inputs to make the final decision for all involved units. To incorporate the heterogeneity of agents' behaviors in the CNP (Contract Net Protocol), we add the behavioral hospital factor presented by an *Altruism Percentage* (AP). Due to our modeling of the problem by an MKP (Multiple Knapsack Problem), we present below the agents (units) by knapsacks. Each knapsack has its own capacities and categories of items to keep. We define AP as *the minimum proportion of objects that a unit (guest) deliberately chooses to delegate to the host, not due to capacity constraints, but as a strategy to increase its own occupancy rate.* This parameter captures the degree of autonomy and self-interest exhibited by each unit. Hence, AP allows for a realistic representation of the behavior of all the units as a result of distributed decision-making processes, which

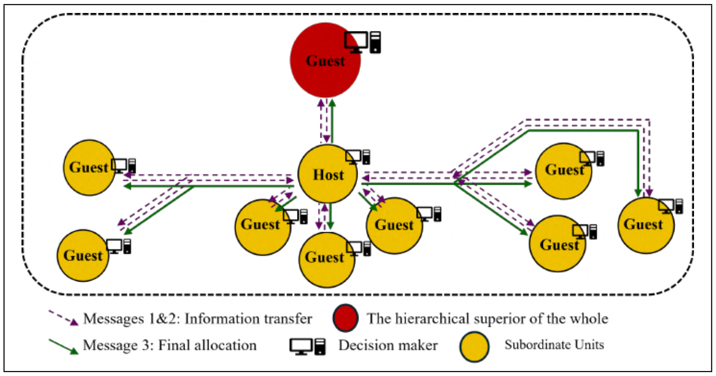

Fig. 2. Distributed organization named Contract Net Protocol (CNP).

can be used to evaluate their impact on the overall system performance. We now detail the technical aspects of adding

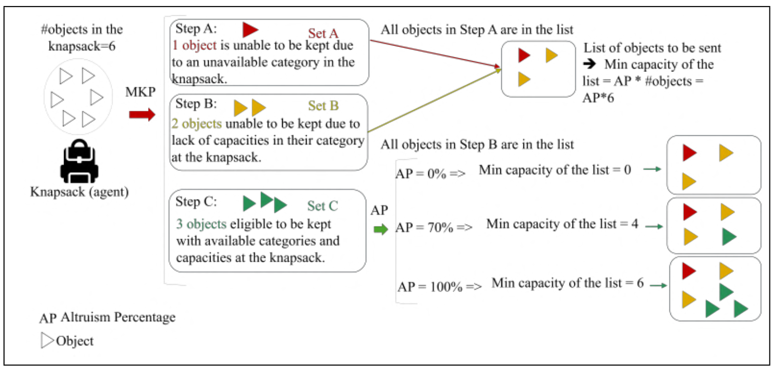

Fig. 3. Our addition of a Altruism Percentage AP to CNP.

AP to the CNP. To this end, Figure 3 explains how AP controls the number of objects included to be sent to the host of the CNP. The list of objects to be sent is obtained in three successive steps:

A. *Addition of all objects whose categories are not present in this knapsack (agent)* (cf. red object in Figure 3): the guest begins by including in the list to be sent to the host the objects he is unable to keep because he does not have the required category. Therefore, this guest will include all objects of this type (shown in red in Figure 3) regardless of the value of their AP. We name together A (with $|A| = 1$ in our example), represented in the figure by "Set A", these objects added at step A.
B. *Addition of all objects whose categories are present in the knapsack but for which there is a lack of capacity* (cf. two yellow objects in Figure 3): The guest then adds to the list all the objects that he cannot keep due to lack of available capacity in the requested category. So the guest will include all objects of this type (shown in yellow in Figure 3) regardless of their value of AP. We name together B (here, $|B| = 2$), represented in the figure by "Set B", the objects added in step B.
C. *Addition of locally keepable objects up to AP per knapsack capacity* (cf. three green objects in Figure 3): The guest is able to keep these objects, but he still offers them for a possible transfer to another knapsack (agent). We refer to these objects by the set C, represented in the figure by "Set C". Some of them can be added to the list sent to the host. For a guest g_i, the capacity of this list is $AP \times |O_{g_i}|$ where $|O_{g_i}|$ is the number of objects initially present at that guest; in our example, the total number of objects of this knapsack (agent) is $|O_{\text{knapsack}}| = 6$ in Figure 3. This figure shows three different cases depending on the value of AP:
   - $AP = 0\%$: In this case, the guest is totally selfish in the sense that he will not collaborate with the other knapsacks (agents). By keeping all the objects which can be kept, he does not share these resources with the other knapsacks. With the goal of maximizing their own occupancy rate, the client seeks to retain as many items as possible. He keeps his objects, that is to say, all the objects indicated in green in Figure 3, individually without considering the exchanges that could be beneficial for the set. Thus, the knapsack (agent) retains for keeping all objects defined in the figure indicated above by $Step\, C$, therefore all objects of the set C: $|C| = 3$ objects.
   - $AP = 70\%$: In this case, the knapsack is partially altruistic. It must keep a list of objects whose number is greater than or equal to $(|O_{\text{knapsack}}| \times AP)$, with
   $$|O_{\text{knapsack}}| = |A| + |B| + |C|$$
   For $AP = 70\%$, the knapsack must keep at least $6 \times 70\% = 4$ objects, so it must add all C objects until satisfying the equation above. The list to be sent, presented in Figure 3, already contains 3 objects filled with $|A| + |B| = 3$; the knapsack therefore adds only one green object, that is to say, an object that it could nevertheless keep for itself.
   - $AP = 100\%$: In this case, the guest is totally altruistic. The knapsack wants to collaborate to maximize the total number of objects kept by the GHT as a whole. Thus, it proposes all its objects, including those which can be kept locally (cf. objects in green in Figure 3). It adds to the list of objects to be sent all green objects from set C, that is $|C| = 3$ objects, and thus sends:
   $$|A| + |B| + |C| = 6 = |O_{\text{knapsack (agent)}}|.$$
   which represents the total number of objects initially present at the knapsack.

In the case of $AP = 100\%$, each knapsack sends all its objects to the host for reassignment; in this case, they will solve the same problem as the central authority (CA) in the centralized organization (CO). We, therefore, model the CO by the distributed organization in the case where $AP = 100\%$, which presents our second contribution.

C. MKP problem modeling and application case

GHT[1] are groupings of hospitals which have been created by many countries in order to mutualize purchases, share patient data, and improve the efficiency of their healthcare systems. Our study is applied to GHT “Loire” in the department of “Loire” in France. This GHT is a collaborative network of 15 hospitals designed to ensure comprehensive and equitable healthcare access across the department. These 15 hospitals are (i) the support hospital (SH) “CHU Saint-Étienne” (in French, “*Centre Hospitalier Universitaire*”, *i.e.*, University Hospital named after its city), (ii) 5 mediator hospitals (MHs), and (iii) 9 local hospitals (LHs). GHT “Loire” supports approximately 15,300 professionals with 7,700 beds and ensures coordinated and innovative healthcare for the department of “Loire”. In order to take into account the context of shortages caused by a crisis, this section recalls the MKP (Multiple Knapsack Problem) and explains how we adapt it to the assignment, between hospitals, of patients requiring care in various specialties. To do this, each of the knapsacks models a specialty in a hospital.

More precisely, each knapsack represents a distinct medical service (named specialty in the following) in a given hospital with bed capacity. We model the allocation of patients in a GHT with MKP as follows. Each of the knapsacks models

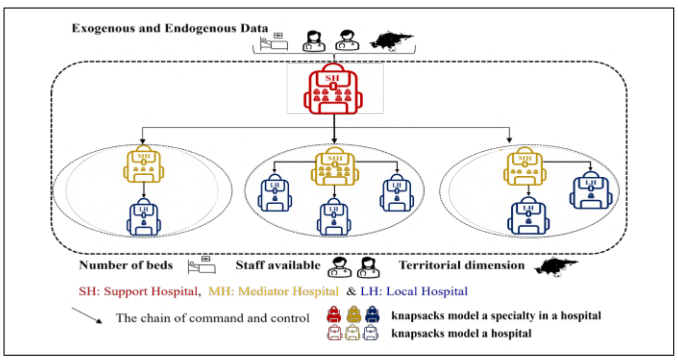

Fig. 4. Modeling the structure of GHT using the MKP

a specialty in a hospital. That is, every knapsack represents a distinct medical department in a given hospital with a bed capacity. Our two organizations use the same formulation of MKP but with various numbers of patients. That is, either the Central Authority (CA) in the centralized organization (CO) solves the global MKP with all the patients in the GHT, or the guests and host in CNP solve this same problem with fewer patients. Table I defines the parameters modeling MKP. The following equations describe MKP when it is solved by CA in CO (with explanations between parentheses about its use in CNP by the host or a guest):

$$minimize \quad \sum_{h \in H} \sum_{p \in P'} Cost_{hp} x_{hp} \tag{1}$$

$$\sum_{h \in H} x_{hp} = 1 \qquad \forall p \in P' \tag{2}$$

$$I(s_p, S_h) = 1 \Rightarrow x_{hp} \geq 0 \forall s_p \in S_h \tag{3}$$

$$\sum_{p \in P'_h} x_{hp} \leq b_{hs} \qquad \forall h \in H, \forall s \in S_h \tag{4}$$

$$x_{hp} \in \{0, 1\} \qquad \forall h \in H, \forall p \in P' \tag{5}$$

[1]GHT means “*Groupement Hospitalier de Territoire*” in French.

Eq. 1 is the objective function that minimizes the total cost of allocating patients from either P' when CO solves the global MKP, or P'_h when CNP makes every hospital h solve local MKPs. The next part will explain that $Cost_{hp}$ will be replaced by either $Cost^+_{hp}$ in Eq. 6 or $Cost^*_{hp}$ in Eq. 7. Eq. 2 ensures that each patient must be allocated to a specific hospital. (When MKP is solved in CNP, P' is either restricted to the patients initially at the considered guest, or, when solved by the host, this set contains all the patients submitted by the guests to the host.) Eq. 3 checks that a patient may be allocated to a hospital only if this hospital offers the specialty corresponding to this patient's disease. Eq. 4 constrains the number of patients for each specialty in each hospital to be less than or equal to the number of free beds in that hospital for that specialty. Eq. 5 defines decision variable x_{hp} as a binary variable which equals 1 if and only if patient p is allocated to hospital h. When used in CNP by a guest, set H in Eqs. 3, 4, and 5 only contains one hospital, namely the guest which is solving the MKP. We now detail parameter

TABLE I
PARAMETERS OF MKP.

Notation	Description
H	Set of all *h*ospitals in the GHT
P'_h	Set of *p*atients ordered by severity in Hospital h
S_h	Set of *s*pecialties available at Hospital h
s_p	*S*pecialty required for Patient p's disease
d_p	Patient p's *d*egree of severity (5 for Extreme... and 1 for Low)
t_{hp}	*T*ansportation time required to move a Patient p to Hospital h
$I(s_p, S_h)$	Indicator function that equals 1 if s_p belongs to S_h, and 0 otherwise
b_{hs}	Number of *b*eds available in Hospital h for Specialty s

$Cost_{hp}$ in Eq. 1, which we define as either of two variants. Both aggregate parameters t_{hp} and d_p differently. Let us recall that t_{hp} is the time (in minutes) taken to transport a patient p from their initial location to Hospital h. Please notice that, for a given hospital, all patients have the same values for t_{hp}. The other parameter, d_p, is the severity of patient p's disease. The idea of both variants of cost is that the higher the considered cost, the less likely a patient will be transferred to another hospital. Therefore, both variants need to be high when d_p is high, that is, when a patient's state is more severe, such that MKP will transfer another patient with a lower severity. $Cost^+_{hp}$ is defined in Eq. 6 as the sum of t_{hp} and 10^{d_p}, while $Cost^*_{hp}$ in Eq. 7 is the product of t_{hp} and d_p. Hence, d_p has a larger impact on $Cost^+$ than on $Cost^*$ in order to have very few severe patients transferred.

$$Cost^+_{hp} = t_{hp} + 10^{d_p} \qquad \forall p \in P, \forall h \in H \tag{6}$$

$$Cost^*_{hp} = t_{hp} * d_p \qquad \forall p \in P, \forall h \in H \tag{7}$$

Our two cost functions are designed such that they increase with both (i) patient p's transfer time t_{hp} from their current location to hospital h and (ii) the severity of p's condition d_p. More precisely, both cost functions evaluate a long transportation in an ambulance as more expensive than a shorter one, as the objective function should penalize long transfers. Similarly, patients with a lower severity should be transported rather than more serious ones; hence, the cost of patients in severe condition needs to be higher in order to avoid their transportation. *A patient allocated to an available bed has the same cost as a patient on the waiting list—that is, a patient waiting for a bed in a corridor.*

IV. Simulation and analysis of results

We now detail our experiments comparing centralized organization (CO) and distributed organization (CNP). We do not simulate CO itself but CNP with $AP = 100\%$, even if the text below uses CO in order to be shorter. We perform all our simulations with AnyLogic 8.5.2 and CPLEX 22.1.1 on a PC running Windows 11 with an 11^{th} Gen Intel(R) Core i7-11370H@3.30GHz CPU. The input data are based on "GHT Loire" in France and are as follows:

- *Hospital data* are the name, specialties, location, type (SH, MH, or LH), and capacity/number of beds of each of the 15 hospitals.
- *Patients* are identified by an ID and characterized by a name, a type of disease (corresponding to the possible specialties of hospitals), severity, and initial hospital.
- *Transportation times* are the durations in minutes to move patients from one hospital to another.

We compare centralized organization (CO) and distributed organization (CNP) based on the following indicators:

- *Total cost* is the sum of the cost (either $Cost^*$ or $Cost^+$) of every patient allocated to an available bed and the cost of patients on the waiting lists for all hospitals. In other words, this indicator is used as the objective function in Eq. 1 of the global (not local) MKP.
- *Patient distribution* represents the spread of patients both (i) allocated to available beds in a hospital and (ii) placed on the waiting list of a hospital. This metric evaluates which organization is the most effective in maximizing the number of patients treated, providing insights into the efficiency and capacity utilization of centralized and distributed healthcare systems.

We consider an approach to generate the population of patients in order to assess hospital capacities under extreme conditions to study stress-test scenarios. In other words, we use an approach to generate more patients than beds available ($i.e.$, saturation level over 100%) in order to take the context of crisis into account. The approach randomly (i) creates patients and (ii) assigns them a severity level between 0 and 4 with the same probability (20%). The rest may be described as follows:

- *Specialty-centered population:* This generation of patients is closer to reality. Conversely to the previous bullet point, this one focuses on medical specialties rather than individual hospitals. The number of patients for each specialty is determined based on the total saturation of beds available across all hospitals with that specialty. Once the total number of patients for each specialty is established for the entire GHT, the patients are randomly assigned to hospitals that offer the corresponding specialty.

A. Impact of the altruism factor AP on the total cost

In order to study the influence of AP (Altruism Percentage), we simulate each of 1,000 instances of patient populations for AP varying between 0% and 100%. The simulations were made with experimental parameters for the GHT "Loire" healthcare network (15 hospitals with 7,700 beds), at a 200% saturation level per specialty, which was translated into 15,400 simulated patients. Hospital specialties were allocated according to the real data of the GHT Loire (`www.ghtloire.fr`).

It is important to note that the cost function used in both versions does not correspond to a specifically defined physical unit. Consequently,the horizontal axis in Figures 5 and 6 is presented without any associated unit.

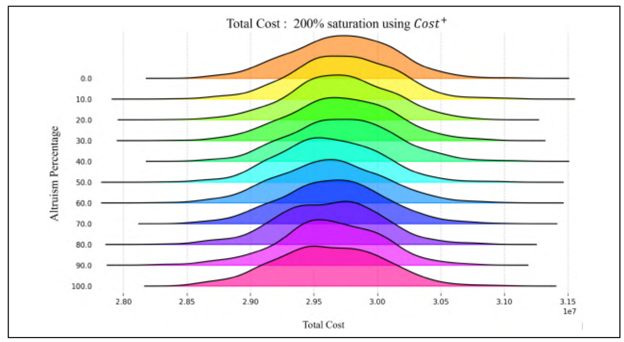

Fig. 5. Total cost with $Cost^+$ in Equation 6.

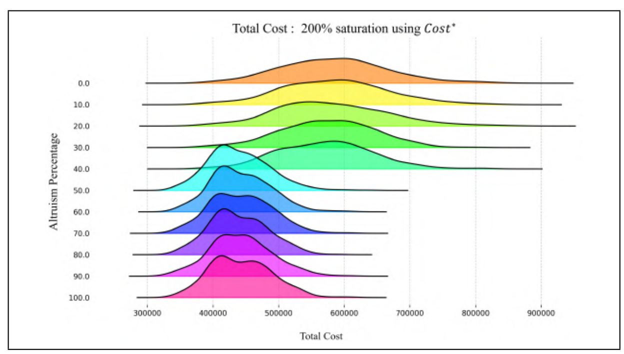

Fig. 6. Total cost with $Cost^*$ in Equation 7.

The distribution of total costs is somewhat impacted by AP when $Cost^+$ is considered, while AP has a significant impact when $Cost^+$ is used. The following subsection presents the distribution of patients for the same experiments.

B. Impact of AP on patient distribution

We now turn our attention to the number of patients who are assigned to a bed – which we also call "treated" - or placed on a waiting list. *As a result, although the centralized organization obtains the lowest possible total costs, it may not handle as many patients as the distributed organization, which tends to prioritize the capacity and accessibility of local hospitals.* Furthermore, the figures all show that $AP \approx 50\%$ results in the highest number of patients treated. We just said that the average number of patients treated increases

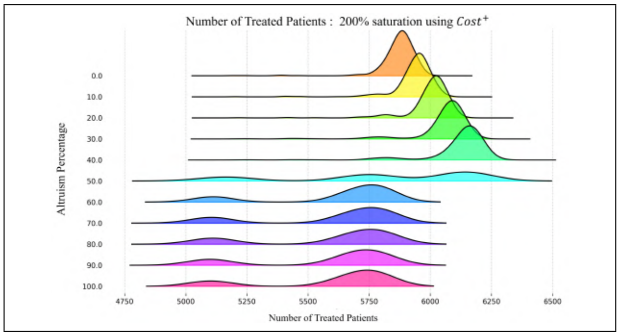

Fig. 7. Patients treated with $Cost^{+}$ in Equation 6.

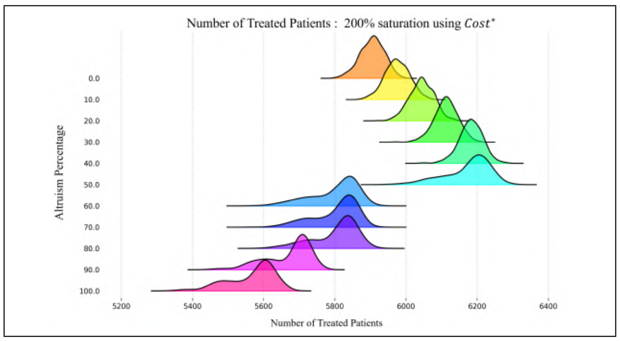

Fig. 8. Patients treated with $Cost^{*}$ in Equation 7.

when AP falls to 50%. However, this is done at the cost of increased variability in the number of patients treated (the average decreases but the standard deviation increases). The values of AP (60% to 80%) seem to balance the situation, which allows for a large number of patients treated while maintaining a manageable variability in the number of patients. These results demonstrate the presence of a threshold effect, where the intermediate values of AP ($\approx$ 40%) are a transition from stable but suboptimal distributed behavior to a constant linear improvement phase, finally achieving performances close to the optimum, similar to the centralized organization (CO). This supports the hypothesis that incorporating a controlled level of altruism into our CNP (Contract Net Protocol) can bridge the gap with CO while reducing the need for information sharing.

V. Conclusion

Previous works have mainly considered the selfish behavior of agents in MAS models through game-theoretic, learning-based, and distributed optimization approaches [11], [12], [17], [16]. In contrast, our approach integrates the AP mechanism directly into the CNP to illustrate the ability of each agent to have its own objectives and constraints. Our results highlight the potential trade-offs between efficiency and equity in distributed decision-making. They suggest that introducing limited cooperation or dynamic adjustments to AP may improve the performance of a GHT (Territorial Hospital Group). These adjustments could provide a balance between distributed autonomy and centralized control, allowing for more efficient and flexible decision-making processes. This analysis underscores the inherent trade-offs between cost efficiency and patient treatment capacity in the design of a healthcare system. [2] [3]

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[2] This study is well detailed in our article [18] submitted to the journal "Decision Support System".

[3] A multi-period version is presented in the article[19] submitted to the journal "Expert Systems with Applications".