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A Computational Justice Model for Dynamic Resource Allocation in Ad Hoc Networks

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Abstract. Ad hoc networks are self-organizing systems that operate without a centralized controller or orchestration mechanism. As a result, it is not possible to apply allocation methods designed for centralized systems, which typically require complete information and aim to optimize overall system performance without accounting for the individual interests of network members. To address this challenge, we propose a computational justice model for dynamic resource allocation, drawing on socially inspired computing and agent-based modeling. The model integrates stochastic games, the concept of social institutions, principles of distributive justice, and adaptive strategies to design an allocation mechanism guided by fairness and cooperation. A central contribution of this work is the conceptual integration of these components into a unified framework that supports dynamic resource allocation in decentralized environments. We evaluated our proposal through simulation and compared its performance with previous works. The results show that the proposed model ensures the endurance of available resources and maintains cooperative behavior among network members, even in the presence of selfish behaviors. These findings suggest that the proposed model is a potential solution for addressing dynamic allocation problems in ad hoc networks.

Keywords: Dynamic Resource Allocation, Computational Justice, Socially Inspired Computing, Ad Hoc Networks, Self-Organization.

1 Introduction

Justice is an interdisciplinary field of research that explores methods for distributing the benefits and burdens of social cooperation. These principles have been adapted to address technical challenges in computing and communication networks, particularly in the context of dynamic resource allocation problems, where efficiency, load balancing, and Quality of Service (QoS) are critical to system performance. For instance, in computational systems, resources must be distributed equitably among processes and threads, while in computer networks, nodes expect a fair share of bandwidth to transmit and receive data. Similarly, the trend toward self-organizing networks, where users act as

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both producers and consumers of resources, introduce new challenges for allocation mechanisms, which must balance individual needs with overall system performance.

For instance, self-organizing systems such as ad hoc networks, energy grids, sensor networks, and vehicular ad hoc networks (VANETs) operate without a controller or other orchestration forms. Instead, these systems rely on cooperative mechanisms to collectively manage and use common resources [1], [2]. Since users contribute their resources, they should also be able to access others' resources for their benefit [3]. For instance, ad hoc wireless networks in disaster response must rapidly allocate communication resources; military tactical networks prioritize mission-critical communications; smart city initiatives like participatory urban sensing depend on fairness to maintain citizen trust [4]; community-driven edge computing in underserved areas relies on equitable cooperation among nodes [5]; and VANETs require efficient bandwidth and routing coordination among vehicles in real-time. This dynamic creates a scenario in which the allocation process is too fast, frequent, and complex for human operators to manage, requiring a computational approach to dynamically allocate resources in self-organizing systems [3].

To explain a scenario in which the allocation problem arises, consider ad hoc networks and mobile clouds. In these technologies, resources such as energy, storage, and computational capacity are shared opportunistically in a self-organizing manner. Mobile clouds, for instance, consist of dynamically connected nodes that cooperate to share computational resources. Energy, storage, communication interfaces, and software can be exchanged, augmented, and combined in novel ways [6]. Thus, the ability to freely share these resources enables the achievement of both individual and collective goals, but it also presents the challenge of allocating resources in a way that promotes cooperation and prevents the depletion of common resources [3].

In such scenarios, all agents (nodes, users, or services) have some conception of value that represents the resources they require to achieve their goals. Those resources can be information, CPU, memory, services, or energy, and they contribute to a value system that guides how agents make decisions and act while considering the overall system state. Under these conditions, we must consider two levels of analysis in the allocation problem. First, at the system level (or macrolevel), all agents are combined and can cooperate to achieve a successful outcome. At this level, properties such as robustness, system functionality, load balancing, and other metrics are used to analyze the system as a whole. Second, at the agent level (or microlevel), autonomous agents pursue their objectives based on a self-cost-benefit analysis. The strategies, goals, actions, and individual behaviors of the agents are examined at this level.

This dual-level analysis is critical because the rules and dynamics governing the system as a whole (the system level) often differ from those that govern individual components (the agent level). This misalignment creates a tension between cooperation and competition, where individual rationality can lead to collective irrationality, i.e., situations in which agents acting in their self-interest ultimately harm the entire system. These situations are referred to as social dilemmas [7]. Addressing these social dilemmas is critical, and a significant body of rational theory is dedicated to understanding them, which is essential for solving resource allocation challenges in self-organizing networks [3].

However, traditional allocation methods designed for centralized systems, relying on complete information and aiming at optimizing overall system performance, are not suitable for ad hoc networks. These methods often overlook the individual interests of network members, making them incompatible with decentralized environments. In ad hoc networks, where resources are dynamically distributed and nodes operate autonomously, approaches that balance collective and individual goals are required. This calls for decentralized allocation mechanisms capable of reacting to the unpredictable and self-organizing nature of such systems. Accordingly, this study seeks to answer the following research question: How can dynamic resource allocation mechanisms be designed for ad hoc networks to promote cooperation and the sustainable use of common resources, while balancing individual autonomy and collective performance?

To address this question, we propose a dynamic allocation method based on computational justice. This proposal comprises the following components: (a) Ostrom's principles for enduring institutions [8]; (b) a cooperation model based on stochastic games [9]; (c) Rescher's approach to distributive justice [10]; and (d) adaptation mechanisms implemented through voting systems and genetic algorithms [11], [12]. This research builds upon the initial computational justice model introduced in [3]. Essentially, our work shares similarities with previous studies through the adoption of Ostrom's approach to institutional analysis and the application of Rescher's theory of distributive justice. However, it differs in three key aspects. First, we employ genetic algorithms as an adaptive strategy. Second, we incorporate cooperation patterns modeled as stochastic games, which allow us to represent scenarios in which agents influence and are influenced by the state of the common resource. Third, we propose a variation of the equality canon of justice that enhances the system's robustness against cheating behaviors in demand actions, while also reducing computational overhead compared to earlier models.

This proposal formalizes normative concepts within a conceptual framework and evaluates them through simulation. Preliminary results show improved stability in cooperation levels and more efficient resource use under adversarial conditions, compared to initial models in computational justice [3]. Rather than presenting a fully deployable solution, this work should be understood as an initial step toward the development of socially inspired allocation mechanisms in ad hoc networks. It provides a foundation for the incremental deployment of such mechanisms in real-world scenarios, subject to further validation and refinement.

This article is organized as follows: Section 2 overviews the current approaches of fairness and computational justice and presents a qualitative comparison of them. We analyze models based on classical optimization techniques and socially inspired computing. Section 3 describes our proposal, where we present Ostrom's institutional approach, cooperation patterns based on stochastic games, adaptive techniques, and Rescher's distributive justice approach, and combine these elements as a set of exchangeable parameters in the internal architecture of a multi-agent system. Section 4 describes the experimental method and simulation scenarios. Section 5 presents the performance evaluation and a comparison with previous works. Section 6 concludes the article.

2 Related Work

We can define the distribution problem in self-organizing networks as follows: let R be a common and divisible resource that needs to be allocated to a set of n agents, in which each agent i has a demand $d_i \leq R$ for some portion of the resource. In other words, given a vector of demands $\langle d_1, d_2, \ldots, d_n \rangle$ and a divisible resource R, the distribution problem can be seen as the process in which a set of agents determine by themselves an allocation vector $\langle r_1, r_2, \ldots, r_n \rangle$ where r_i represents the amount of resources R allocated to the agent i [13]. This process is made in the absence of a centralized controller or other orchestration forms. There is no information about the global state of the system, and it is difficult to predict changes in the operating conditions. The system is composed of a set of heterogeneous agents with possibly conflicting goals, interacting asynchronously, in parallel, and peer-to-peer in an uncertain environment [14], [15].

To overview computational Justice models in communication networks, we analyzed two of their categories. The first category refers to those models that have been developed through classical optimization techniques. This approach takes place in distributed systems and centralized networks. The second category concerns those models that are inspired by social theories such as Distributive Justice and Social Institutions. In this approach, issues like cooperation, autonomy, and self-organization are essential aspects of the network operation. We do not aim to present a detailed description of the models but to analyze their main properties for comparison purposes.

2.1 Classical Engineering Approach

The classical engineering approach uses objective functions to optimize or evaluate the allocation of resources according to a set of parameters. This approach assumes the existence of a divisible and finite resource, denoted as R. There are N nodes sharing this resource through an allocation vector $A = \langle r_1, r_2, \ldots, r_n \rangle$, where r_i represents the amount of resource R allocated to node i and where $\sum_{i=1}^{N} r_i \leq R$. Based on their measurability, these methods can be classified as quantitative or qualitative. A common approach is to represent quantitative measures using real values through a fairness function $f : \mathbb{R}^n \to \mathbb{R}^+$, based on the allocation vector A, where n represents the number of agents involved in the process. This function is expected to satisfy the following conditions R1–R5:

R1: $f(\mathbf{A})$ should be continuous on $A \in \mathbb{R}^n$.
R2: $f(\mathbf{A})$ should be independent of the number of participants N.
R3: $f(\mathbf{A})$ should be easily mapped onto $[0, 1]$.
R4: $f(\mathbf{A})$ should be easily extendable to the multi-resources case.
R5: $f(\mathbf{A})$ should be sensitive enough to variations in A.

Qualitative approaches cannot evaluate the allocation of resources using numerical values. Instead, they assess whether the allocation method achieves fairness and offer guidance for improving the process based on specific conditions. Two of the most common approaches are max-min fairness and proportional fairness. Max-min fairness applies to scenarios where no user's allocation can be increased without reducing the resources allocated to others. This method is commonly used in flow control, bandwidth sharing, and radio channel access [13].

Table 1 presents a comparison of the most commonly used techniques in networking. We considered the following criteria: *Control* – to indicate whether the model was developed for centralized or decentralized systems. *Priority* – as the possibility of assigning individual weights during the allocation process. *Information* – to show if the model requires complete information to operate. *Measurability* – to specify whether the measure is quantitative or qualitative. *Temporality* – to show if the model considers changes in the allocation of resources over time. *Complexity* – to describe the computational cost of the fairness evaluation; and three levels, simple, medium, and complex, are used based on the analysis presented in [13]. Note that none of the mentioned measures perform properly regarding all criteria; however, it is possible to use a combination of them to evaluate a resource allocation.

Table 1. A comparison of computational justice models in the context of engineering

Model	Control	Priority	Information	Measure	Temporality	Complexity	Year
Jain's index [16]	Centralized	No	Complete	Quantitative	No	Simple	1984
Envy-based [17]	Either	No	Either	Quantitative	No	Complex	1995
Proportional [18]	Centralized	Yes	Complete	Qualitative	No	Medium	2004
Max-min [19]	Either	Yes	Either	Qualitative	No	Simple	2007
Tian Lan [20]	Centralized	No	Complete	Quantitative	No	Complex	2010
Entropy [21]	Centralized	No	Complete	Quantitative	No	Simple	2011
Altman [22]	Centralized	Yes	Complete	Qualitative	Yes	Medium	2012
Nowicki [23]	Centralized	No	Complete	Quantitative	No	Medium	2016
Nanda [24]	Centralized	Yes	Complete	Quantitative	Yes	Simple	2020
Argyris-Karsu [25]	Centralized	Yes	Complete	Quantitative	No	Complex	2022

The majority of the methods presented in Table 1 were developed for centralized systems. One of the most commonly used quantitative measures is the Jain Index, which provides a fairness perspective at the system level. However, it cannot identify unfairly treated individuals and also requires complete information to operate. Tian Lan's measure offers a more general approach to fairness analysis and can be transformed into the Jain Index, Entropy, max-min fairness, or proportional fairness. While this approach is more general, it still requires complete information to perform an evaluation. Entropy is another quantitative measure, but it cannot account for small variations in resource allocation or address system-level unfairness.

Although the max-min model can operate in self-organizing networks, it is ineffective in dynamic and uncertain environments. Additionally, it, similarly to most of these methods, requires complete information to compute the fairness measure, which cannot be guaranteed in an ad hoc network. While the model proposed by Altman accounts for time in resource allocation, it was designed for centralized operation. Similarly, although the proposals by Nanda and Argyris-Karsu use the concept of a max-min fairness measure focusing on maximizing the benefit for the least advantaged users in the system and ensuring that, under worst-case conditions, those who are worst off receive the best possible outcome, these models also require complete information to operate effectively. These approaches are unsuitable for addressing the dynamic resource allocation problem in ad hoc networks, where distributed control, incomplete information, and uncertain environments are intrinsic to the operating conditions. A detailed description of these measures and other quantitative methods can be found in [13] and [26].

2.2 Socially Inspired Computing Approach

Socially inspired computing arises as an opportunity to address dynamic resource allocation problems in self-organizing networks with endogenous resources. This approach is used when features like incomplete information, decentralized operation, and autonomous behaviors are a fundamental part of the operating conditions. They represent an alternative to classical approaches because they include a social dimension as a design principle. They combine cooperation patterns, social institutions, and Distributive Justice theories to provide an algorithm in which a set of autonomous agents can share and distribute their resources without a central controller. Table 2 presents the current approaches using the same criteria as the previous section. We added the column *Applied* to describe the application area and excluded the term *Complexity* because all methods are derived from the same initial algorithm, and there is no available information regarding a comparative analysis of the computational cost associated with these methods. Note that all proposals use *temporality*, *priority* allocation, decentralized *control*, and a *quantitative measure* to describe how fair the obtained result is. These features are required to design and develop computational algorithms for ad hoc networks [27].

Table 2. A comparison of computational justice models in the context of socially inspired computing

Model	Control	Priority	Inform.	Measure	Temp.	Applied	Year
J. Pitt [14]	Distributed	Yes	Either	Quantitative	Yes	General model	2012
J. Pitt [3]	Distributed	Yes	Either	Quantitative	Yes	Multi-agent system	2014
P. Petruzzi [28]	Distributed	Yes	Either	Quantitative	Yes	Open systems	2015
F. Torrent [29]	Distributed	Yes	Either	Quantitative	Yes	Smart grids	2016
J. Garbiso [30]	Distributed	Yes	Either	Quantitative	Yes	VANET	2017
D. Kurka [31]	Distributed	Yes	Either	Quantitative	Yes	Socio-technical systems	2019
J. Pitt [32]	Distributed	Yes	Either	Quantitative	Yes	Multi-agent system	2021

The initial computational justice model was introduced by Pitt et al. [3]. They presented a general method for allocating resources in self-organizing open systems, based on Rescher's approach to distributive justice and Ostrom's principles for designing self-organizing institutions. This work has inspired applications in smart grids, Multi-agent Systems, Vehicular Ad-Hoc Networks (VANETs), Socio-Technical systems, and the democratization of technological platforms. These applications use the principles of distributive justice and self-organization to ensure appropriate resource allocation, improved decision-making, and enhanced system adaptability to unexpected operational conditions. They use the Borda voting system to combine agent preferences and establish a priority list that allows the institution to allocate resources according to justice criteria. Although this approach presents an effective method, it is computationally expensive due to the multiple voting rounds required and is vulnerable to selfish behavior within the system.

Although there are no socially inspired computing applications for solving resource allocation problems in ad hoc networks, the current proposals provide a set of principles for developing a solution. To do so, we extended the initial work presented by Pitt et al. [3]. We explore cooperation patterns based on stochastic games and adaptative methods through genetic algorithms. We included a variation of the equality canon justice to improve the model's response to selfish agents in the system. Also, a modular perspective of the allocation method was added to describe the model as a set of exchangeable parameters. This representation maintains the structure of the algorithm, no matter if the cooperation pattern, the allocation method, or the adaptive mechanisms are changed. This modular perspective describes an initial architectural design for a real implementation in an ad hoc network.

3 A Computational Justice Model for Resources Distribution in Ad Hoc Networks

This describes our proposal, where we first present its constituents: Ostrom's institutional approach, cooperation patterns based on stochastic games, adaptive techniques, and Rescher's distributive justice approach, and then combine these constituents as a set of exchangeable parameters in the internal architecture of a multi-agent system.

3.1 Self-Organizing Institutions for Collective Actions

Based on extensive work on self-organizing institutions, Ostrom argues that a set of self-interested agents sharing common-pool resources will not always end in a social dilemma like the tragedy of the commons [8]. She noted that in human societies, these problems have often been solved through institutions combined with an understanding of which processes drive human cooperation and how norms and other feedback mechanisms can be used to reinforce positive behaviors [33]. Accordingly, Ostrom identified eight design principles as necessary and sufficient conditions for common-pool resources managed by self-organizing institutions to endure. These principles are listed in Table 3. In this work, we focus on Principles 1, 2, and 3, as they are directly related to allocation strategies and can guide the design of institutions for managing common-pool resources in ad hoc networks, particularly in scenarios where the endurance of common resources is more important than achieving an optimal allocation.

Institutions are responsible for establishing the structure and regulating the social system's behaviors; they determine who is eligible to make decisions, what actions are allowed or constrained, and contain prescriptions that forbid, permit, or require some actions or outcomes according to a specific context. Using Ostrom's approach, we can describe an institution through three different levels of nested rules: first, the *operational-choice rules*, which are concerned with the actions that affect the physical world, such as resource appropriation, provision, monitoring, and enforcement. Second, the *collective-choice rules*, which are concerned with selecting the operational rules, aggregate the agents' preferences, dispute resolution, and policy-making. Third, the *constitutional-choice rules*, which are responsible for determining who is eligible and what specific rules are to be used, to modify the *collective-choice rules*. The three levels are role-based, mutually agreed, mutable, and nested in action situations.

Note that the idea of institutions proposed by Ostrom does not say anything about the fairness of the distribution method or how it could affect the environmental state or the cooperation in the system. The notions of fairness and cooperation are highly related to the allocation method; if the agents perceive the distribution of resources as a fair process, they are likely to comply with the rules of the system and may be willing to cooperate in future interactions. We want to complement Ostrom's approach to enduring institutions with the theory of distributive justice to evaluate whether an allocation scheme can be considered a fair process. Our goal is not only to design institutions for enduring common-pool resources but also to use the idea of justice to promote cooperation among the members of the system. Applications of these principles in the context of communication systems and self-organizing systems can be found in [14] and [34].

Table 3. Ostrom's design principles

No.	Principle	Description
1	Clearly defined boundaries	Individuals who have access rights to the institution must be clearly defined, as must the boundaries of the institution itself.
2	Congruence between institutional rules and local conditions	There should be a congruence between appropriation and provision rules and the state of the prevailing environment.
3	Collective-choice arrangements	Most individuals affected by the rules of the institution must be able to participate in the selection and modification of those rules.
4	Monitoring	Monitors who actively audit the application of the institutional rules must be, or be accountable to, those affected by the institutional rules.
5	Graduated sanctions	Members who violate institutional rules are sanctioned according to the seriousness of the violation. These sanctions are given by the other members of the institution.
6	Conflict-resolution mechanisms	The members of the institution should have rapid access to fast, cheap conflict-resolution mechanisms.
7	Minimal recognition of rights to organize	Existence of and control over their institutions; they are not challenged by external authorities.
8	Systems of systems	The rules governing the institution and the application of the previous seven principles are organized in multiple levels of nested enterprises.

3.2 Cooperation in Stochastic Games

Social dilemmas such as the tragedy of the commons lead to analyzing how to manage public goods in environments composed of autonomous agents in which there is no centralized control or information [7]. Game theory suggests that iterated games based on reciprocity and trust can deal with these dilemmas. However, earlier works assume that the public good remains constant over time, no matter the outcome of previous interactions [9]. Cooperation patterns based on stochastic games allow us to model situations in which agents affect and are affected by the value of the public good [9]. The decision of whether to cooperate or to defect not only affects their payoffs but also determines the game they will play in the next round. Thus, a group of agents can find themselves in one of the multiple states in which they interact in a social dilemma with different payoffs, capturing how the current conditions of the physical and social environment affect the feasible outcomes of the agents.

Consequently, we can use the prisoner's dilemma in its stochastic versions for modeling cooperation patterns in self-organizing systems, in particular, ad hoc networks and mobile clouds. The prisoner's dilemma allows us to represent common but finite resources available in the environment owned by the members of a community that can be used without restriction. This is an example of a social dilemma [7]. In this case, cooperation entails a cost $c > 0$ and produces a benefit $b_i > c$ to the co-player, where b_i depends on the current state i.

It is important to mention that in stochastic games, cooperation evolves because defectors are affected in two different forms: first, they could receive less cooperation from other agents in the next rounds if they do not comply with the system's rules. Second, the agents move collectively towards a less profitable game when some of them are defecting. This situation can be seen as a reduction of the resources available in the environment because of the presence of free-riders. Likewise, if everyone cooperates, the environment could recover, and the original value of the public good can be restored. The different states of the environment correspond to different games that will be played according to the collective behavior of the agents: the more cooperative the agents, the more resources will be available.

We can define a stochastic game using five objects [9]:

1. The set of players N;
2. The set of possible states S;
3. The set of actions $A(s_i)$ that are available to each player in the state $s_i \in S$;
4. The transition function Q that describes how the current state and the agents' actions determine the next state; and
5. A payoff function u that describes how the payoff of the players depends on the agent's actions and the current state.

In this case, the model does not specify how much time passes between consecutive rounds, nor restricts the payoffs that are available in each round. We consider stochastic games in which agents can choose between cooperating or defecting, and their action set is defined by $\{C, D\}$. Initially, agents are in state 1, and the payoffs per round are symmetric and change according to a discounted value during all rounds in the game. In the following section, the prisoner's dilemma in its stochastic version is presented.

3.3 The Stochastic Prisoner's Dilemma

The prisoner's dilemma has been extensively used in game theory to explore situations in which autonomous agents act in pursuit of their own interests in environments in which they are not obligated to cooperate even when it seems to be best for all the members of the system. This model has usually been used to formalize the tragedy of the commons and symbolize the degeneration of the environment to be expected in situations in which many agents use a common scarce resource. The prisoner's dilemma is a non-cooperative game in which each agent has a dominant strategy (to defect no matter what the other agents choose) and represents a paradox in which the best individual strategy leads to a situation in which everyone is worse off. The game is played in consecutive rounds, and the agents make their decisions under self-interest analysis. In each round, each agent i:

- Determines its needs for resources, $q_i \in [0, 1]$;
- Makes a demand for resources, $d_i \in [0, 1]$;
- Receives an allocation of resources, $r_i \in [0, 1]$; and
- Makes an appropriation of resources, $r'_i \in [0, 1]$.

The total amount of resources owned by an agent at the end of the round is given by the resources appropriated rather than allocated. The agents freely decide the amount of resources they want to take from the public good independently of the allocation they receive. In this game, cooperation means the agent makes an appropriation lower than or equal to the allocation assigned by the institution. Also, for including a direct relationship between the number of resources and the agents' utility, the payoff function u is defined according to the matrix presented in Table 4, in which $R_t \in [0, 1]$ represents the proportion of the available resources. After each round, the resources are multiplied by a coefficient k that embodies the interdependence between the collective behaviors of the agents and the availability of resources in the system; if all the agents cooperate, the resources will increase or at least remain at the same value. Otherwise, there will be fewer resources in the next rounds. Note that the value of the coefficient k represents both the capacity of the environment to recover itself under proper conditions and a degeneration process as a result of free-riders in the system.

Table 4. Payoff matrix for the Prisoner's Dilemma

	$Cooperate$	$Defect$
$Cooperate$	$(b_1 - c)R_t$	$-cR_t$
$Defect$	$b_1 R_t$	0

Note that each interaction occurs between individual agents and the institution during the demand, allocation, and appropriation of resources. We use the institution to define a set of rules that promote cooperation and prevent social dilemmas in an environment with autonomous agents acting in a self-interested manner. Moreover, regardless of its utility, each agent i makes a subjective assessment of its satisfaction S_i, expressed as a value in $[0, 1]$, according to the relationship between its allocation and its demands. We can define the satisfaction level of agent i in round $t + 1$ as follows in Equation 1:

$$S_i(t+1) = \begin{cases} S_i(t) + \alpha\,[1 - S_i(t)] & \text{if} \quad r_i \geq d_i \\ S_i(t) - \beta(q_i - R_i) & \text{otherwise} \end{cases} \tag{1}$$

where α and β are coefficients in $\mathbb{R}$, which determine the rate of reinforcement of satisfaction and dissatisfaction of each agent. As a result, choosing different combinations of α and β allows us to model different behaviors in the agents. For instance, high values of α and low values of β enable us to model agents with a high level of tolerance to situations in which they do not get what they need. On the other hand, high values of β will make the agents dissatisfied more quickly, and therefore, they will stop following the institutional rules. This scenario is modeled through a threshold value τ and an interval value m. If for m consecutive rounds the agent i evaluates $S_i < \tau$ as true, it will stop cooperating. In the case of the prisoner's dilemma, the agents appropriate an amount of resources greater than the allocated (they turn into free-riders).

3.4 Distributive Justice

Distributive justice is related to the fair distribution of resources; it includes the available resources in the environment, the method responsible for the distribution, and the outcomes resulting from a specific allocation. The notion of justice is an essential characteristic of any social system because it is responsible for distributing the benefits and costs of social cooperation. We can explore the distributive justice theories through three main families: *equality and need*, *utilitarianism and welfare*, and *equity and desert*. The first family concerns the welfare of those least advantaged; in this case, the society is organized to give equal satisfaction of the basic needs. Egalitarianism, Rawls' theory of justice, and Marxism are examples of this approach. The second family, *utilitarianism, and welfare* focuses on an efficiency principle that tries to maximize the global welfare of the society, the greatest good for the greatest number. Utilitarian theory, Pareto principles, and Envy-freeness belong to this family. The third family, *equity, and desert* states that individuals should receive an allocation that is proportional to their contribution to society. Nozick's theory of libertarian rights belongs to this approach. A detailed description of the three families can be found in [35].

In this research, we use the idea of a pluralistic justice proposed by Konow [35] and previously applied in the methodology introduced in [3] and [14]. We aim to consider several perspectives during the process of determining what a fair distribution of resources is, and not restrict this consideration to a specific theory. This analysis coincides with the idea of distributive justice proposed by Nicolas Rescher [10], which states that individuals should be treated according to the notion of legitimate claims and canons of justice.

Table 5 summarizes these principles as the canons of equality, need, effort, supply and demand, productivity, and social utility. Rescher's idea of justice requires determining, in context, what the legitimate claims are, how they are accommodated in case of plurality, and how they are reconciled in case of conflict.

Table 5. Rescher's canons of distributive justice

Canon	Description
f_1 — *Equality*	Treatment as equals.
f_2 — *Need*	Treatment according to their needs.
f_3 — *Productivity*	Treatment according to their actual productive contribution.
f_4 — *Effort*	Treatment according to their efforts and sacrifices.
f_5 — *Social utility*	Treatment according to a valuation of their socially useful services.
f_6 — *Supply and Demand*	Treatment according to supply and demand.
f_7 — *Merits and achievements*	Treatment according to their ability, merit or achievements.

We intend to combine these canons with Ostrom's approach for institutions in order to deal with distribution problems in ad hoc networks. Thereby, we use a computational representation of each canon computing a total order over the set of agents. In this case, T denotes the number of rounds in which the agent i participates in the allocation process. Each canon is described below [3].

f_1- *The canon of equality*: we can represent this canon in two different ways: (f_{1a}) by ranking the agents in increasing order according to their average allocation (f_{1a}) (Equation 2) and (f_{1b}) (Equation 3) by ranking the agents in increasing order of the everyman satisfaction S_i.

$$f_{1a}(i,T) = \frac{\sum_{t=0}^{T} r_i(t)}{T} \tag{2}$$

$$f_{1c}(i,T) = \frac{\sum_{t=0}^{T} (r_i(t) > 0)}{T} \tag{3}$$

The first model of computational justice proposed by Pitt et al. [3] considers an additional representation for this canon in which the number of rounds in which the agents receive an allocation is used as an equality measure. However, we do not consider this representation because even if the agents do not comply with the institution's rules, it allows them to get resources from the system, promoting selfish behaviors. It would be understood as a kind of impunity for selfish agents.

f_2- *The canon of need*: This canon (Equation 4) ranks agents in increasing order according to their average demands; in this case, we suppose that similar agents demand average quantity over time, then the agent most in need is the one that so far has made the least demand.

$$f_2(i,T) = \frac{\sum_{t=0}^{T} d_i(t)}{T} \tag{4}$$

f_3- *The canon of productivity*: we can represent this claim by ranking the agents in decreasing order according to their average provision (Equation 5).

$$f_3(i,T) = \frac{\sum_{t=0}^{T} p_i(t)}{T} \tag{5}$$

It is possible to use several alternatives for representing this canon; for instance, using the total provision $(\sum_{t=0}^{T_i} p_i(t))$ or the net provision that is represented by the difference between the provision and allocation.

f_4- *The canon of effort*: Rank the agents in decreasing order according to the number of rounds spent as *prosumer*. This role is responsible for determining which agents are members of the institution. This canon is congruent with the first institutional principle proposed by Ostrom.

f_5- *The canon of social utility*: this canon is represented by ranking the agents in decreasing order according to the number of rounds spent in the *head*. This role is responsible for the allocation of resources.

f_6- *The canon of supply and demand*: This canon (Equation 6) ranks the agents in decreasing order according to this measure of compliance; in other words, those agents who follow the norms of the game, which are: first, do not withhold what is available $(p_i = g_i)$; second, only demand what is needed $(d_i = q_i)$; and third, only appropriate what is allocated $(r'_i = r_i)$:

$$f_6(i,T) = \sum_{t=0}^{T} [(p_i(t) = g_i(t)) \ \wedge \ (d_i(t) = q_i(t)) \ \wedge \ (r'_i(t) = r_i(t))] \tag{6}$$

This canon assumes that we can monitor every agent's internal state, that monitoring and reporting are perfect, and that the cost of monitoring is zero. However, in practice, we only monitor what is observable and enforceable; appropriation equals allocation.

f_7- *The canon of merits and achievements*: this canon is not appropriate in this context and is not represented.

As a final step, all canons of justice are combined using the Borda voting method to generate a priority list that guides the institution in allocating resources [9]. In this process, the agents act as candidates, and the canons serve as voters. Each canon produces a ranking of the agents based on its own criteria, and these rankings are then aggregated using the Borda count to produce a final collective ordering. The institution allocates resources by satisfying the demands of the highest-ranked agent first, followed by the next, and so on. This continues until either all resources are allocated or all demands are met. If any surplus resources remain after the allocation process, they are distributed equally among all agents.

3.5 Adaptive Behaviors in Self-Organizing Systems

The idea of adaptation in self-organizing systems is different from other disciplines like machine learning, statistics, or artificial intelligence. In general terms, these disciplines have in mind a single agent acting in an environment that could be unknown, stochastic, partially observable, and so on; it could be challenging to find an optimal strategy, but there is a well-defined notion of what an optimal strategy is. In contrast, in self-organizing communication networks, we have systems composed of multiple agents in which everyone is trying to adapt their strategy and achieve their goals at the same time. When an agent modifies its behavior, it is influenced not only by the environment but also by other agents. This condition produces a high level of interdependence in the system, increasing the complexity of the allocation process and limiting our capacity to predict the future state of the system.

Accordingly, it is possible to include adaptive strategies that allow the allocation method to adjust its parameters and react appropriately to changes in the system. To do so, a weight $w_i \in [0,1]$ where $\sum_i w_i = 1$ is attached to each canon of justice to modify their influence for future rounds of the game. We explore two different adaptive strategies: the Borda voting approach [11] and genetic algorithms [12]. Both approaches will change the values of w_i during the game and will try to find a combination of w_i that allows the allocation method to deal with changes in the behavior of the agents.

During experimentation, dynamic adjustment is applied exclusively to the weights mentioned above, while all other model parameters are kept constant. This design isolates the specific impact of the adaptation mechanism, ensuring that any observed changes in the performance of the allocation method can be directly attributed to modifications in the weights, rather than to variations in other components of the model.

3.5.1 The Borda Voting Approach

The notion of voting in the context of distribution problems can be summarized as follows: how should an institution pool the preferences of a set of individuals to best reflect the wishes of the population as a whole? We can find different approaches for dealing with this issue through voting systems based on plurality, approval, pairwise elimination, and so on [11]. Nevertheless, we use the Borda voting protocol, which is described as a consensus scheme that selects what is broadly accepted rather than what is preferred by the majority. In this method, each voter submits a ranking of the candidates and assigns them a number of points; if there are n candidates, it contributes $n-1$ points to the highest-ranked candidate, $n-2$ points to the second-highest, and so on. The winner (or winners) is who has the maximum amount of points at the end of the voting process.

We assume the agents will vote according to the canons that give them the highest utility. Each agent is treated as a voter, and the canons as the possible candidates; the Borda points of the canon f_i in a system composed of N agents are given by Equation 7:

$$Borda(f_i) = w_i . \sum_{j=1}^{N} p(j, f_i), \tag{7}$$

in which $p(j, f_i)$ represents the number of Borda points assigned by agent j to the canon f_i. In addition, the weight w_i of each f_i is updated by Equation 8:

$$w_i(t+1) = w_i(t) . \frac{Borda(f_i) - AvgBorda}{TotalBorda}. \tag{8}$$

Note that all new weights are summed and normalized to 1. This process is repeated at the end of each round and implies changes in the canons' weights based on the combined preference of all agents. Also, this method implies two voting rounds; first, a voting round is performed by the institution as part of the allocation of resources in which the canons of justices are treated as voters and the agents as the candidates. This round has the purpose of prioritizing the agents for the allocation process. In the second round, the roles are exchanged: the agents are treated as voters and the canons of justice as candidates. This round has the purpose of modifying the weight of each canon and allowing the institution to adjust its parameters to changes in the agents' behavior.

3.5.2 Genetic Algorithms

Genetic algorithms (GA) are heuristic techniques inspired by the evolution of living systems, used in complex optimization problems where the search space is too large to explore efficiently and local minima make finding the global optimum challenging. These methods work with an initial population of individuals, of which each one represents a possible solution to a specific problem. Generally, these methods perform four steps to produce a new set of solutions: *initialization*, *evaluation*, *selection*, and *reproduction*. This process is repeated until a satisfactory solution appears. We aim to use the continuous genetic algorithm approach to explore different combinations of weights during the allocation process. The four steps are described below [12]:

1. *Initialization:* To begin GA, a set of solutions is described through a genetic code or chromosome. Usually, the first population is randomly generated and represented within a data structure. In this case, the initial population is composed of N_{pop} chromosomes defined as a combination of weights for the canons of justice; $chromosome = [w_1, w_2, \dots, w_7]$ in which $w_i \in [0, 1]$ and $\sum_i w_i = 1$.
2. *Evaluation:* This mechanism uses a fitness function to assess how well each individual solves the problem. The fitness function is represented by $f(w_1, w_2, \dots, w_7)$, where $f(\cdot)$ represents the average satisfaction of all agents after n rounds of the game and is calculated using equation 1. Considering that each individual represents a combination of weights for averaging the canons

of justice, an individual with a high fitness can therefore be understood as a combination of weights that maximizes the collective satisfaction of the agents, i.e., when the relationship between the allocation and the demands of the population remains stable.
3. *Selection:* the genetic algorithm picks individuals out among the current population to produce the next generation according to the results of the *evaluation* step; the idea is to consider the ones with the best evaluation results. In this case, we select the 50% of the chromosomes with the better fitness score.
4. *Reproduction:* In this step, two individuals are recombined using genetic operators like crossover and mutation to create new individuals. Chromosomes are paired randomly, and each pair produces two offspring that inherit traits from both parents. Finally, individuals with fitness values lower than the average fitness of the population are replaced by these newly generated offspring to maintain a constant population size throughout the iterations of the algorithm.

We intend to use this method as an alternative to discover a possible combination of weights that works better during the distribution process. Although assigning equal value to each canon of justice seems to be the right choice, it is necessary to verify it with experimental analysis.

3.6 Combining the Constituents

To generate a computational executable specification that combines the principles for enduring institutions, the cooperation models based on stochastic games, Rescher's canons of distributive justice and the adaptative mechanisms presented in Section 3.5, we use the framework for institutional analysis introduced by Ostrom as the internal architecture of a multi-agent system [8]. This framework enables us to use the notion of action situations to create relationships among the set of agents, the physical attributes of the environment, and the institutional agreements related to the distribution process. The proposed architecture is presented in Figure 1.

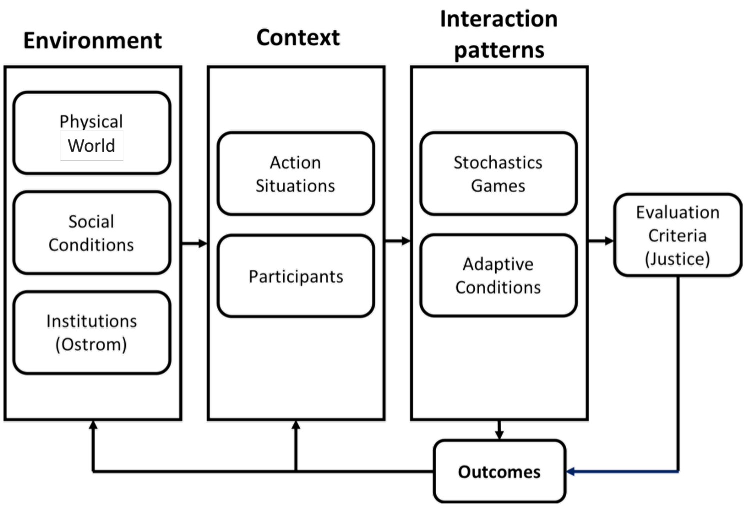

Figure 1. An institutional approach for resource distribution

In this model, an action situation represents any point in time and space in which a set of agents can cooperate to manage and share common-pool resources. Accordingly, we can define a multi-agent system as follows, with Equation 9:

$$M = \langle N, A, I, \xi \rangle \tag{9}$$

where:

- N is the set of agents;
- A is the set of action situations;
- I is the set of institutions; and

- ξ represents the physical attributes of the environment.

Each action situation has a number of roles according to the institutional rules; in this case, we use the roles of *prosumer* and *head*, where the *prosumer* determines which agents have access to institutional rights, and the *head* is responsible for performing the allocation of resources. Furthermore, each action situation $a_i \in A$ can be defined by Equation 10:

$$a_i = \langle c, \ell, g \rangle \tag{10}$$

in which:

- c represents the set of agents related to the action situation a_i, such that $c \subseteq N$;
- ℓ is a specification of I; and
- g is a game that describes a cooperation pattern in the system.

The institution specification ℓ is defined through two levels of nested rules based on Ostrom's approach. The first level, the *operational-choice rules*, is represented as a function that maps a set of demands to a set of allocations. This function is exchangeable and allows us to explore different distribution methods like legitimate claims, equality, random allocation, maximin, and so on. The second level, the *collective-choice rules*, combines the agents' preferences and computes new weights of each canon justice during the allocation process. The voting system is also exchangeable and independent of the institution's structure. The combination of all these elements enables us to do a meta-analysis of the distribution problem not only in terms of the main components involved in the process but also regarding the information flows in the system. The model includes a set of exchangeable parameters based on the idea of an action situation that allows us to maintain the structure of the multi-agent system, no matter if the cooperation pattern, the allocation method, the adaptive mechanisms, or the voting system are changed.

Algorithm 1 shows the required sequence of actions for performing the allocation process, which represents the computational implementation of the proposed model. The complexity of the algorithm is $O(|A| \cdot |c| \log |c|)$, where $|A|$ is the number of actions and $|c|$ is the number of agents. This complexity is dominated by the ranking and allocation steps, particularly the sorting of agent ranks and the Borda voting method, which contributes to the $(\log |c|)$ factor. Since the algorithm exhibits polynomial complexity concerning the number of agents and actions, it can be solved using deterministic methods, as the problem does not exhibit exponential growth. However, the adaptation strategy for adjusting the weight of each canon (line 11) is modifiable and can be implemented using different methods. This may introduce additional complexity, depending on the chosen approach.

4 Experimental Method

In this section, we evaluate the effectiveness of the proposed model by analyzing different aspects of the distribution process. For each scenario, several allocation methods and adaptive mechanisms are used to assess the model's performance. The full source code is available for download[1]. To implement and test the simulations, we use the simulator NetLogo [36], which is a multi-agent programmable modeling environment widely used in teaching and research of complex systems. Our method is tested, along with previous work, for comparison purposes. The following configuration parameters are used unless stated otherwise:

- The simulations are composed of two different types of agents: on the one hand, compliant agents who are willing to follow the institutional rules, appropriating what is allocated by the institution. On the other hand, selfish agents can cheat on the demand or appropriation actions according to a probability of 0.25; this value represents malicious repeated behaviors in the system.

[1] https://github.com/jpospinalo/Computational-Justice-Model

Algorithm 1: Resource Allocation Through Computational Justice

```
Input: I, A, N, R   // Institutions, Actions Situations, Agents, Resources
Output: Allocation vector: ⟨r_1, r_2, ..., r_n⟩
foreach a ∈ A do
    /* Step 1: Agents determine their needs and demands            */
    foreach agent j ∈ c do
        q ← j                                 // Agent j defines its needs
        d ← j                                 // Agent j defines its demand
    /* Step 2: Evaluate demands according to institutional criteria */
    foreach f_i ∈ ℓ do
        foreach agent j ∈ c do
            f_i^(j) ← f_i(j, T)               // Computing f_i for each agent j
        f_i_rank ← rank(f_i^(j))              // Ranking values of f_i
    /* Step 3: Compute weighted ranking of agents                   */
    W ← adaptation(W)
    agent_list ← borda_count(f_i_rank, W)
    /* Step 4: Allocate resources                                   */
    while R > 0 do
        /* Allocation process                                       */
        i ← head(agent_list)                  // Select highest-ranked agent
        agent_list ← tail(agent_list)         // Remove the first agent
        if R < d_i then
            r_i ← d_i                         // Allocating the demanded resource
            R ← R − d_i
        else
            r_i ← R                           // Allocate remaining resources
            R ← 0
```

- The Prisoner's Dilemma uses the following parameter values: $b_1 = 2, c = 1$ and $k = 0.4$.
- We use a population of 30 agents in the experiments; this number allows us to observe global patterns of behavior and the possible effects of the selfish agents in the system.
- An agent i is formed of a set of variables that define its behavior; in this case, q_i, d_i, g_i, r_i and r'_i represent need, demand, availability, allocation, and appropriation of resources in the current round. These variables depend on the cooperation pattern and are used according to the game presented in Section 3.3.
- S represents the agent's satisfaction and u the agent's utility; both are updated after each round.
- $\alpha = 0.1, \beta = 0.1, \tau = 0.1, m = 3, S(0) = 0.5$ are stated as the initial values for all agents in the simulations. These parameters determine if an agent keeps following the institutional rules; if for m consecutive rounds, the agent i evaluates $S_i < \tau$ as true, it will stop cooperating. These values represent a moderate behavior in which an agent will wait for several rounds without satisfactory results before it stops cooperating. Values of $\beta = 0.4$ are used to represent agents with more volatile behavior. These parameters are selected according to the results presented in [3].
- The agents' behavior is defined as follows: compliant agents will demand what they need ($d = q$) and appropriate what is allocated ($r' = r$). On the other hand, selfish agents could increase

their demand above what they need: $d = q + rand(0,1) * (1 - q)$ or increase the quantity appropriated above what has been allocated by the institution $r' = r + rand(0,1) * (1 - r)$.

- A resource is modeled by a variable $R \subseteq \xi$ that represents the available resources in the environment. To fulfill the second design principle for enduring institutions, we ensure that the expected value of the sum of all agents' needs is equal to the available resources in the system. This condition not only maintains the scarcity condition but also ensures that, in the long term, there are enough resources to keep all the agents in the system satisfied. It is important to mention that without this principle, this problem turns into a viability problem instead of a distribution problem.
- Each experiment was repeated 50 times using different random seeds to keep randomness in the simulation.

The following metrics are used to analyze the experimental results:

- *Average utility:* $\bar{u_c}$ and $\bar{u_s}$ represent the average utility of the agents during the simulations; $\bar{u_c}$ corresponds to the compliant group and $\bar{u_s}$ to the selfish group.
- *Fairness:* we evaluate the fairness of the distribution process using the Gini index over $(\sum_{i=0}^{T} r_i / \sum_{i=0}^{T} d_i)$; an index of 0 represents perfect equality, and 100 represents perfect inequality. This metric is usually used as a statistical measure of the distribution of resources in social systems.
- *Average satisfaction:* $\bar{s_c}$ and $\bar{s_s}$ represent the average satisfaction of the agents during the simulations; $\bar{s_c}$ corresponds to the compliant group and $\bar{s_s}$ to the selfish group.

Tables 5 and 6 provide a description of all variables involved in the allocation method: Table 6 lists the variables related to the cooperation process, while Table 5 includes those associated with the canons of justice.

Table 6. Summary of the variables related to the allocation method

Cooperation Pattern: Prisoner's Dilemma	
b_i	Cooperation benefits from agent i during each round of the game.
c	The cooperation cost during each round of the game.
R_t	Proportion of available resources in the environment at round t.
k	Resource regeneration coefficient during each round of the game.
q_i	Need for resources for agent i.
d_i	Demand for resources for agent i.
r_i	Allocation of resources for agent i.
r'_i	Appropriation of resources for agent i.
S_i	Satisfaction of agent i.
α	Satisfaction reinforcement coefficient.
β	Dissatisfaction reinforcement coefficient.
τ	Threshold value for stopping cooperation.

5 Experimental Results and Performance Evaluation

5.1 Scenario 1: Evaluating Different Allocation Strategies

This scenario has the purpose of verifying if this proposal achieves better results than other approaches in environments composed of complying agents. We consider the following methods for comparison purposes:

A. *Random-appropriation:* Each agent appropriates a random proportion of the available resource; this process is repeated until the resource is depleted.
B. *Random-allocation:* The institution performs a random allocation among the agents without considering their demands; the sum of all allocations is equal to the available resources in the system.
C. *Equal-allocation:* The institution allocates an equal proportion of resources to each agent.
D. *Computational-justice:* The institution performs the allocation according to the method presented in Section 3. We used an equal and fixed weight for each canon justice.

Figure 2 and Table 7 show the obtained results. They display how an equal distribution is inappropriate under a scarcity condition. This affirmation coincides with the analysis presented in [3] and controverts the idea that allocating the same amount of resources is a good alternative to face the distribution problem in self-organizing open systems. The agents' satisfaction depends on the institution's capacity to satisfy the agents' needs, not just for a particular allocation method that seems to be fair from the system level. Additionally, even though the Gini index shows a proper fairness evaluation for an equal allocation, the agents' utility is affected because the institution does not consider the agents' demands. This situation influences the endurance of the cooperation process in the long term.

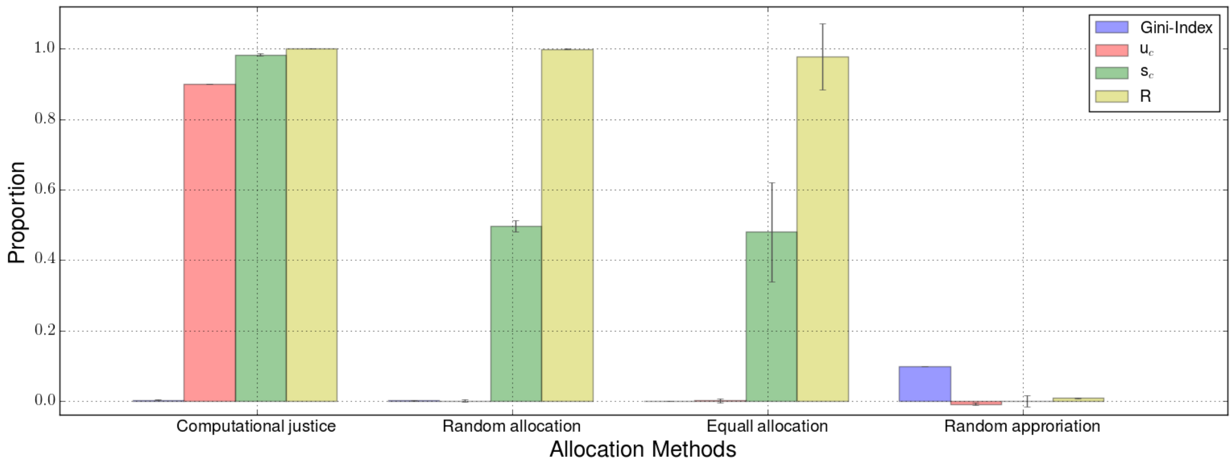

Figure 2. Comparison of allocation methods

Table 7. Comparison of allocation methods

Allocation Method	Gini-index	u_c	s_c	Round	R
Computational justice	0.0029 ± 0.0005	0.9002 ± 0.0006	0.9835 ± 0.0040	2500	1.00 ± 0.00
Random allocation	0.0013 ± 0.0002	0.0002 ± 0.0011	0.4960 ± 0.0044	2500	0.99 ± 0.01
Equal allocation	0.0000 ± 0.0000	0.0008 ± 0.0014	0.4798 ± 0.0393	2500	0.98 ± 0.03
Random appropriation	0.0980 ± 0.0002	-0.0084 ± 0.0011	0.000 ± 0.044	2500	0.01 ± 0.01

Similarly, the notion of sustainability can be defined according to the dynamics of the cooperation pattern. In the prisoner's dilemma, we represent this attribute as the availability of resources at the end of the game. Although both the random and the equal allocation methods result in a sustainable distribution process, the computational justice model shows better performance regarding the agents' satisfaction. On the other hand, the random appropriation showed the worst performance in terms of the agents' utility and the sustainability of the cooperation process. These results show how the absence of a suitable allocation method can lead the system to a social dilemma and also exhibit the high sensitivity of this proposal to cheating agents in appropriation actions.

5.2 Scenario 2: Selfish Agents

We evaluated how selfish agents affect the performance of the distribution method regarding cheating behaviors. The aim is to verify the effect of the adaptive strategies mentioned in Section 3.5. We use these methods to modify the weight of each canon of justice and allow the institution to adjust its parameters to possible changes in the agents' behavior. The behavior of the model is analyzed through two cheating strategies: demanding more than is needed and appropriating more than is allocated. The experiments were performed with a population of 30 agents (27 compliant and 3 selfish), playing a game for 500 rounds. This is the typical population used to analyze scenarios in which selfish agents can have a significant impact on the performance of the model [3]. Table 8 presents the obtained results.

Table 8. Adaptive strategies

Strategy	Cheating Method	Gini-index	u_c	u_s	s_c	s_s	R
Fixed	Demand	0.01 ± 0.02	0.71 ± 0.03	0.27 ± 0.03	0.66 ± 0.12	0.01 ± 0.02	0.83 ± 0.07
	Appropriation	0.10 ± 0.02	-0.06 ± 0.01	-0.06 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.03 ± 0.01
Voting	Demand	0.01 ± 0.01	0.58 ± 0.07	0.22 ± 0.03	0.34 ± 0.13	0.26 ± 0.09	0.70 ± 0.08
	Appropriation	0.07 ± 0.02	-0.06 ± 0.01	0.06 ± 0.01	0.0 ± 0.0	0.0 ± 0.0	0.01 ± 0.01
GA	Demand	0.01 ± 0.02	0.73 ± 0.07	0.29 ± 0.03	0.72 ± 0.11	0.52 ± 0.08	0.85 ± 0.17
	Appropriation	0.07 ± 0.02	-0.06 ± 0.01	0.06 ± 0.01	0.01 ± 0.01	0.0 ± 0.0	0.03 ± 0.01

The experiments show that computational justice can effectively manage cheating behaviors related to demand actions. Sustainability is maintained, with a significant portion of the resources remaining at the end of the game. In contrast, scenarios involving cheating through appropriation are not controlled; cooperation breaks down, and the common resource is quickly depleted, leading the system into a social dilemma. Adaptive strategies based solely on adjusting the relative importance of the canons are insufficient to address this issue. Therefore, appropriation-based cheating emerges as a critical challenge that threatens the overall stability of the system. Addressing this limitation will require the development of more sophisticated institutional mechanisms capable of detecting and responding to appropriation behavior. One possible solution is the incorporation of retributive justice mechanisms to penalize misbehaving agents, as suggested in [14].

Furthermore, the adaptation strategies do not represent a better performance in comparison with a fixed weights scenario. It showed robustness regarding demand cheating actions and allowed us to perform an allocation without the additional computational cost of including adaptive strategies. This denotes an improvement regarding the initial work in computational justice [3], in which an institution with fixed weights cannot deal effectively with this behavior, and it is a consequence of a variation in the equality canon of justice, as we explained in Section 3.4.

Although removing the additional representation of the equity canon leads to improved performance in the presence of selfish agents, it does so at the cost of weakening the social and self-organizing foundations of the model. Consequently, the decision to include or remove the equity canon depends on how participative the system is and how autonomous the agents are in a particular application. In highly centralized or mission-driven systems, equity can be relaxed in favor of performance. However, in participatory, decentralized environments, maintaining fairness is critical to ensuring cooperation and the endurance of common resources.

5.3 Scenario 3: Variations in the Number of Agents and Their Behavior

First, we analyze the performance of the model in environments composed of volatile agents. The aim is to verify how the allocation method responds to situations in which the agents' satisfaction decreases faster if the institution does not fulfill their demands. We used the adaptive strategies presented in Section 3.5. The values of $\beta \in [0.1, 0.6]$ represent agents with a lower tolerance for not getting what they need. Figure 3 a presents the result of both adaptive strategies in comparison with a fixed weights scenario. The results show how the utility of the agents decreases with high values of β and describe how the allocation method has a dependency on stable social conditions. In environments where the agents turn into free-riders faster, the institution does not have the opportunity to stabilize the allocation process, creating a dissatisfaction reinforcement that affects the system's performance. Although the use of adaptive strategies describes a better performance for some value of β, this is not a significant improvement if we consider the additional computational cost associated with introducing adaptation as part of the distribution process.

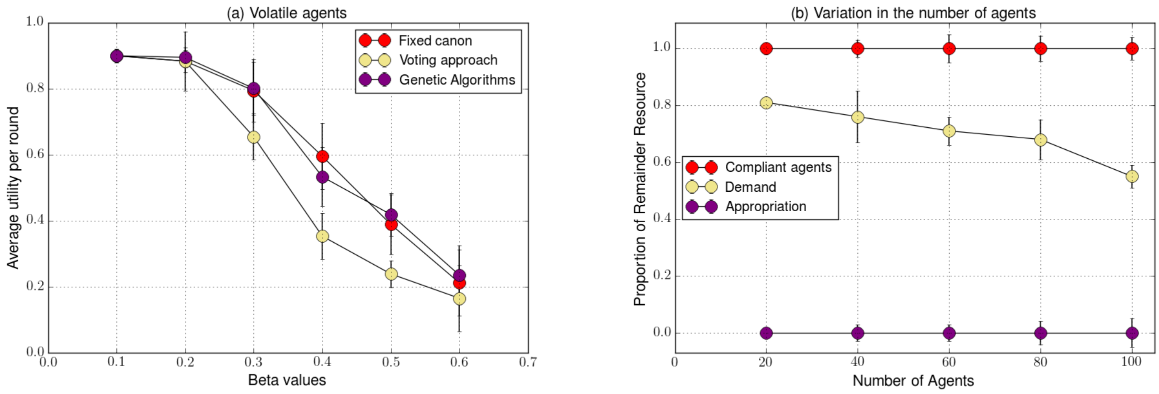

Figure 3. Variations in the number of agents and their behavior. Figure 3a represents an implementation of the genetic algorithm described, along with the voting system using the Borda count in Section 3.5. Figure 3b shows the results of the allocation process in the presence of selfish agents during appropriation and demand actions.

Second, we analyze the performance of the allocation method evaluating groups of agents of different sizes. We intend to verify how an increasing number of agents affects the stability of the distribution process. This scenario considered three types of agents: an entire group of compliant agents, a group of compliant agents with three selfish agents in demand actions, and a group of compliant agents with three selfish agents in appropriation actions. We fixed the number of selfish agents to maintain a stable social environment under the scarcity condition. The Allocation method was evaluated in groups of $20, 40, 60, 80$, and 100 agents. Figure 3b shows the obtained results. The allocation method is not affected by an increasing number of agents whenever there are no selfish behaviors. For selfish agents in demand actions, the allocation method has a performance close to the results presented in Section 5.2. However, there is a gradual loss of effectiveness when the number of agents increases. For selfish agents in appropriation actions, there is no change in the obtained results.

5.4 Scenario 4: Comparison with Related Work

In this scenario, we intend to compare the performance of our proposal with the initial computational justice model [3]. In their initial work, Pitt et al. consider an additional representation for the canon of equality in which the number of rounds in which the agents receive an allocation is used as an equality measure and then combined as a part of the agents' weight. However, we decided not to use this representation because even if the agents do not comply with the institution's rules, it allows them to get resources from the system, affecting the institution's performance and promoting selfish behaviors in the agents. Additionally, it is important to mention that we compare both methods using the stochastic version of the prisoner's dilemma and not the linear public game as the initial proposal did. We expect to evaluate the linear public good game as part of our future research.

Figure 4 and Table 9 describe obtained results. These results demonstrate that the proposed model can effectively address cheating in demand actions without requiring additional adaptive mechanisms. In contrast, the initial model presented by Pitt et al. [3] relies on a self-organizing approach based on a voting system to manage such behavior. We evaluated performance by measuring the proportion of available resources remaining at the end of the simulation. The average proportion of resources under demand cheating behaviors was 0.81 (SD = 0.10) for our model, compared to 0.63 (SD = 0.26) for Pitt et al. - SO, and 0.31 (SD = 0.16) for Pitt et al. - Fixed. To statistically validate these differences, we performed an independent sample t-test between the two most competitive methods: Pitt et al.- SO and this proposal - yielding a t-value of 6.59 and $p < 0.001$. This result provides statistical evidence supporting the observed performance of this proposal.

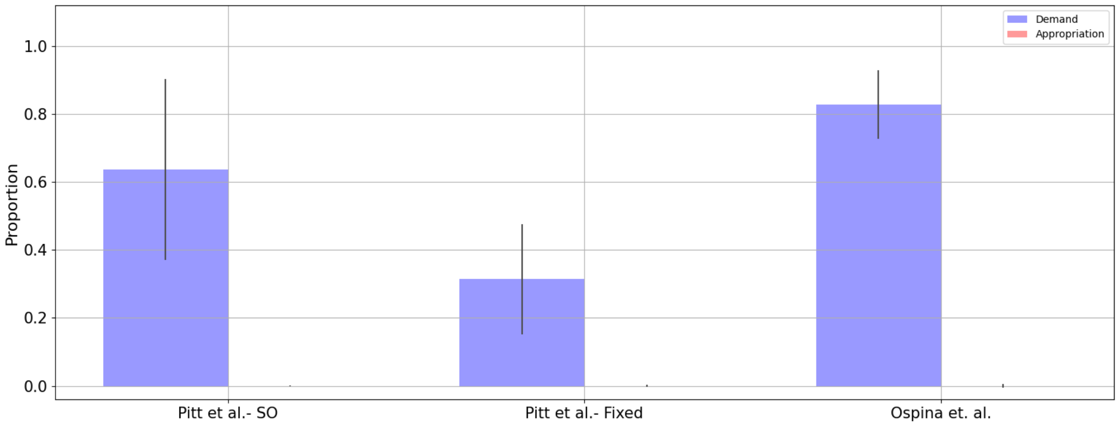

Figure 4. Comparison with related work

Table 9. Comparison with related work

Method	Cheating Method	Gini-index	u_c	u_s	s_c	s_s	R
Pitt et al. - SO	Demand	0.01 ± 0.01	0.47 ± 0.03	0.15 ± 0.02	0.42 ± 0.08	0.28 ± 0.05	0.63 ± 0.26
	Appropriation	0.01 ± 0.01	0.04 ± 0.05	0.02 ± 0.01	0.00 ± 0.00	0.00 ± 0.00	0.02 ± 0.04
Pitt et al. - Fixed	Demand	0.01 ± 0.01	0.10 ± 0.02	0.00 ± 0.00	0.01 ± 0.01	0.01 ± 0.01	0.31 ± 0.16
	Appropriation	0.06 ± 0.01	0.01 ± 0.01	0.02 ± 0.01	0.00 ± 0.00	0.00 ± 0.00	0.01 ± 0.01
Ospina et al.	Demand	0.01 ± 0.01	0.70 ± 0.03	0.27 ± 0.01	0.65 ± 0.06	0.48 ± 0.04	0.81 ± 0.10
	Appropriation	0.04 ± 0.02	0.03 ± 0.01	0.03 ± 0.01	0.01 ± 0.01	0.00 ± 0.00	0.02 ± 0.01

These results show how the proposed model reduces the computational cost associated with adaptive techniques while improving the overall robustness of the institutional framework. In contrast, for appropriation-based cheating actions, all methods exhibited similar results. This highlights the need to develop new adaptive techniques or variations in the distribution mechanism to enable the institution to effectively detect and control this form of selfish behavior.

6 Conclusion

In this work, we proved that it is possible to deal with the distribution problem in ad hoc networks using a combination of socially inspired computing and agent-based modeling. In particular, this proposal was composed of: Ostrom's approach for institutional analysis, cooperation patterns through stochastic games, Rescher's idea of distributive justice, and adaptive mechanisms through voting systems and genetic algorithms. The result showed how an allocation process based on computational justice is a potential alternative to deal with the distribution problem in environments formed by autonomous agents operating without a central controller or other orchestration forms. It is essential to mention that this work was developed on the foundation of self-organizing electronic institutions established by Pitt et al. [3], in which they showed the potential value of the distributive justice and social institutions as part of the future technological developments.

The notion of action situation allows us to maintain the structure of the multi-agent system no matter if the cooperation pattern, the allocation method, the adaptive mechanisms, or the voting system are changed. This structure enables us to do a meta-analysis of the distribution problem not only in terms of the main components involved in the model but also regarding the information flows in the system. Moreover, the inclusion of stochastic games as part of the cooperation patterns results in a suitable choice for modeling the relationship between the environment state and the agents' actions. This feature gives us a more realistic version of the distribution problem and results in better cooperation levels.

The distribution problem is perhaps as ancient as human society and presents an opportunity to use social concepts for developing new algorithms for self-organizing communication networks. Although the results provided by the allocation method may be a suboptimal solution, they ensure the sustainability of the system in the long term. This claim coincides with Ostrom's approach for designing self-organizing institutions in which, achieving the endurance of the resources and the cooperation process in the long-term is more important than finding short-term optimality. Moreover, to prove the convergence of the allocation method, it is necessary to consider: threshold conditions for the cooperation process and selfish agents; define objective functions related to the agents' satisfaction and the resource state; analyze the outcome of the whole allocation process as an emergent property related to the self-organizing nature of the system. We consider these issues as part of future research in addition to the study of agents with heterogeneous behaviors, institutions with multiple adaptive strategies, and the inclusion of new justice approaches.

We modified the equality canon introduced in the initial proposal of computational justice, resulting in a distribution method capable of handling cheating behaviors in demand without relying on adaptive strategies. This modification reduces the computational cost of the allocation process and improves performance compared to previous approaches. However, the decision to include or exclude the equality canon should be based on the application context. In highly centralized or mission-driven systems, equity can be relaxed to prioritize performance. In contrast, in participatory and decentralized environments, maintaining fairness is critical to ensuring cooperation and the endurance of common resources. Therefore, while removing the equality canon may yield efficiency gains in some scenarios, its inclusion remains crucial in systems that depend on agent autonomy and social interactions.

One limitation of this proposal is its inability to effectively address appropriation cheating, where agents take more resources than allocated. Although the model incorporates normative rules through the concept of institutions — applying canons of justice and adaptive strategies — it is not capable of fully controlling such behavior. Addressing this issue may require the integration of punitive components, such as those derived from retributive justice, along with the inclusion of Ostrom's Principles 5 and 6, to enhance the institution's ability to detect and manage appropriation cheating and prevent a tragedy of the commons. To further support coordination and learning in self-organizing environments, a possible improvement could involve integrating Multi-Agent Reinforcement Learning (MARL) with the institutional framework. MARL enables agents to learn cooperative strategies through interaction and feedback, allowing dynamic adaptation to changing conditions. When combined with normative institutional rules, MARL can improve the resource allocation process while preserving the decentralized and autonomous core of the system.

The proposed algorithm demonstrates that dynamic resource allocation in ad hoc networks can be achieved through the concept of computational justice. However, we recognize the need for a more comprehensive evaluation, particularly through comparisons with other existing approaches. However, such comparisons are currently limited by the lack of adaptable models and simulators suited to the specific requirements of ad hoc networks. Although simulators specifically designed for ad hoc networks do exist, most of these tools focus primarily on network aspects like routing, transmission medium, or network interface performance, rather than the broader self-organizing properties necessary for this problem domain. In future research, we aim to address this limitation by deploying our method a real ad hoc network, enabling a more robust, replicable, and comprehensive evaluation of this proposal.

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