The Prisoner's Dilemma in the Workplace: How Cooperative Behavior of Managers Influence Organizational Performance and Stress

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Abstract

Purpose

The aim of the paper is to analyze the impact of cooperativeness of managers who occupy central positions in interaction networks on the performance and stress levels of a whole organization.

Design/methodology/approach

To explore this relationship, a multi-parameter agent-based model is proposed which implements the Prisoner's Dilemma Game approach on a scale-free network in the NetLogo environment. A description of the socio-economic aspects and the key concepts implemented in the model are provided. Stability and correctness have been tested through a series of validation experiments, including sensitivity analysis. The source code is available for further exploration and testing.

Findings

The simulations revealed that improving the stress resistance of all employees moderately increases organizational performance. Analyzing managers' roles showed that increasing only the stress resistance of managers does not account for significantly higher overall performance. However, a substantial increase in organizational performance and a decrease in stress levels are achieved when managers are unconditionally cooperative. This effect is stronger for the lowered stress resistance of employees. Therefore, the willingness of managers to cooperate under all circumstances can be a key factor in achieving better performance and building a more pleasant, stress-free working environment.

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Originality/value

This paper presents a model for analyzing cooperation, specifically in the organizational context, extending the Prisoner's Dilemma with novel concepts and mechanisms. While the results confirm the existing theories about the importance of central nodes in complex networks, they also provide further details on how the cooperative behavior of central nodes (i.e., the managers) might benefit the organization.

Keywords: *Prisoner's dilemma, cooperation, scale-free network, agent-based modeling, organizational performance, stress*
Paper type: *Research Paper*

1 Introduction

Organizational performance is the crucial parameter that companies aim to achieve high results in, in order to succeed in the marketplace. According to Afful-Dadzie et al. (2016), tracking organizational performance serves to highlight progress being made by an organization to meet an agreed sustainability target. It is vital to reach high levels of performance in a way that is sustainable in the long-term, as temporal bursts of activity that are not accompanied by a growth of underlying structure may eventually lead to collapse (Goerner, 1994).

Modern organizations usually adopt mature management systems to maintain sustainable performance. However, to analyze how the internal structure of an organization might be enhanced, it may be fruitful to adopt a systemic perspective. Given that the hierarchical nature of companies is self-organized, they can be perceived as complex systems (Banerjee, 2012, Schneider and Somers, 2006, Dominici and Levanti, 2011). Specifically, the theoretical framework used in this paper draws from three areas related to the complexity research – complex network analysis, agent-based modeling, and analysis of cooperation using the Prisoner's Dilemma Game (henceforth "PDG").

1.1 Research Gap

The evolution and maintenance of cooperation represents a fundamental problem in biology and social sciences. Over the past two decades, researchers have been extending the original concept of PDG to discover novel micromechanisms supporting the emergence of cooperation. Despite the effort invested into this area, the origin of cooperation among individuals remains an open and unsolved issue (Wu et al., 2014, Scatà et al., 2016, Lyer and Killingback, 2016, Niu et al., 2017, Bandyopadhyay and Kar, 2018). It is also unclear whether organizations should encourage either a cooperative or competitive environment between co-workers to promote performance (Livio and De Chiara, 2018). Based on a recent systematic literature review (Perc et al., 2017), human cooperation research focused specifically on organizational context is lacking.

Also, empirical research investigating the impact of employees' knowledge-based interaction on organizational performance do not provide conclusive results (Maurer et al., 2011). As a consequence, it remains unclear which mechanisms support the cooperative behavior of employees to benefit an organization, namely when their interaction topology is considered.

1.2 Research Question

To address this research gap, we focus on the investigation of the impact of central nodes on organizational performance when stress is considered. Therefore, we put emphasis on three aspects: Leadership, employees' diversity, and stress. The research question being: *How does the strategic behavior of hubs impact the performance of organizations at various levels of stress?*

Leadership: Existing research suggests that nodes with a central position in the network (hubs) may have a significant impact on organizations, both beneficial or detrimental. In this paper, an agent-based model is presented that uses a framework of complex networks with prominent nodes (hubs) that communicate more often. In the model, a node represents an employee, and a link between two nodes (employees) represents their mutual interaction. The interaction is thought to be a *channel that allows resources to flow* – be it information, knowledge, decisions, tasks, or counseling (Henttonen, 2010, Caputo, 2017). The ability of a company to support the flow of resources is traditionally perceived to be closely related to its performance (Arrow, 1974).

Diversity: Team diversity may foster the flow, as employees with different sets of skills and abilities may efficiently produce creative and innovative solutions through the mutual exchange of resources (von Hippel, 1988). The more diverse the skill sets of team members are, the higher the potential is for resources to flow through social links between them (Borgatti et al., 2013, Di Fatta et al., 2016). Skill diversity is assumed to be implicitly present among employees in our model, and it is applied when employees exchange a defined part of their tasks to produce added value – see Section 3.3 for additional details.

Stress: High team diversity in specific settings may lead to increased levels of stress that relate to miscommunication and conflicts (Guimerá et al., 2015). According to Csermely (2006), complex systems with an impaired ability to relax stress may experience a disturbance of their functions, namely their capability to distribute information or other resources. An increased risk of cascading failures or the stress overload of hubs is also attributed to be the consequence of continuously increased stress levels. Thus, stress is implemented in the model as an essential factor that affects the social interaction of employees. As a consequence, the quality of employees' interaction impacts the overall performance of the organization.

1.3 Contribution and Structure

This paper contributes to the tradition of analyzing cooperation through PDG, and it provides a deeper understanding of the role of highly central employees on organizational performance and stress. This paper presents a novel approach for modeling cooperation in organizations which reflects systemic thinking. The complexity of the model allows for the simulation of various organizational processes, e.g., processes reflecting strategies of managing human resources and organizational culture.

This paper is organized as follows: key concepts used to design and implement the model are presented in Section 3. The model was used to perform experiments addressing the research question, and the results are presented and discussed in Section 5. Managerial and theoretical implications are summarized in Section 6. Lastly, the conclusion to the paper and future direction of research is to be found in Section 7.

2 Theoretical framework and related work

Today's markets and organizations are considered to be complex systems, producing emerging properties through interdependence across multiple spatial and temporal scales (Gómez-Cruz et al., 2017). Since the early 1990s, agent-based modeling has been used in organizational studies as a platform and heuristic for theorizing about organizational responses to complexity (Miller, 2015). Henrickson and McKelvey (2002, p. 7295) argue that agent-based modeling should emerge as preferred modeling method in social sciences, since it supports *"a model-centered social science that rests on strongly legitimated connectionist, autonomous, and heterogeneous agent-based ontology and epistemology"*. Additionally, they believe that, in the future, significant *"social science contributions will emerge more quickly if science-based beliefs are based the joint results of both agent-modeling and subsequent empirical corroboration"*.

Agent-based modeling deals with a certain level of simplification or reduction of complexity, which can be justified when the analysis is focused on the system behavior instead of individual status of agents (Rhodes et al., 2016). All models simplify reality, which makes them wrong in an engineering sense. But they offer formal abstraction, which can be used to get valuable and fruitful insights into relationships that would remain hidden without such model (Epstein, 2008).

Any complex system may be represented and analyzed as a complex network, as long as the basic components of the network are discernible (Guastello et al., 2009, Bai and Wang, 2008). During the past twenty years, complex network analysis has become an increasingly popular methodology for understanding systems from a wide variety of scientific domains, from protein networks to macroeconomics (Barabási, 2016).

When representing an organization as a complex network, the employees are represented by the nodes and their interaction is represented by the links. According to Csermely (2006), many human interaction networks have a scale-free topology. A characteristic feature of a scale-free network is the existence of a low number of highly connected hubs with many sparsely connected peripheral nodes. This topology was formally described by Barabási and Albert (1999), who discovered that the scale-free property is formed by a preferential attachment whose mechanism is commonly known as the *"rich get richer"* phenomenon.

The lack of a scale refers to the fact that it is not possible to choose a representative node that would characterize the network, as differences in connectivity between hubs and peripheries might be orders of magnitude large (Barabási, 2016). As the scale-free network is a realistic approximation of a human social network, it was used as an interaction topology in the model presented in this paper.

Recent network-oriented management research aimed at the team performance has reported a variety of beneficial effects that the individuals accrue when they occupy a favorable (i.e., central) position in the network of social interaction between employees. Some of these beneficial effects include improved coordination of tasks (Tröster et al., 2014), more efficient usage of resources (Baldwin et al., 1997), high knowledge capital (Goldenberg et al., 2009, Li et al., 2009), increased knowledge flow (Tsai, 2001), more accurate decision-making (Crawford and LePine, 2013), or higher overall performance of a team when the central individual performs well (Vaz de Melo et al., 2008, Yang et al., 2009). Being central in a social network means being more influential and visible as a communication partner (Ahuja et al., 2003) or being perceived as a leader (Mehra et al., 2009). Targeting central nodes is also an efficient way of disseminating new information through the network to increase knowledge flow (Daňa, Caputo and Ráček, 2019, Fiorini, 2017). Interestingly, central nodes might be temporally stable even in the cases where the whole network is highly transitory, i.e., when numerous nodes are connecting and disconnecting from the network (Howison et al., 2006).

Conversely, central nodes may be prone to information and stress overload. When hubs are stress-flooded, it may lead to the disintegration of a network into several disconnected or sparsely connected sub-networks, significantly impairing the interaction capabilities of the network as a whole (Csermely, 2006). This effect has been observed in a case study on the online open-source SW development community (Zanetti et al., 2013), where the departure of a highly central member resulted in a significant and persistent negative effect on community performance. This observation is in accordance with a theoretical presumption that scale-free networks are quite robust against random damage or the random removal of nodes, but are highly vulnerable to attacks targeted on hubs (Albert et al., 2000, Ichinose et al., 2012, Mazzochi, 2016).

Another important aspect related to organizational performance is the quality of employee interaction in terms of cooperative behavior. The traditional approach for studying cooperation is through game theory, using the Prisoner's Dilemma Game (henceforth "PDG"). This widely-known framework illustrates that for a game with only one round, the rational choice for each player is to defect (i.e. betray) their partner. However, the situation changes when the game is played repeatedly and with more than two players.

In the late 1970s, Robert Axelrod organized a series of tournaments where scientists could propose a strategy that would overcome others when playing an iterated Prisoner's Dilemma Game (Axelrod, 1980*a*,*b*). Axelrod's tournaments had an important implication – the actual outcome of the game and profitability of individual strategies are highly dependent on the composition of the population. In other words, the best way to play the game greatly depends on how others play, which illustrates the logic of *interdependence* (Nescolarde-Selva et al., 2019). Therefore, the outcome of the game cannot be predicted, and the solution is to run simulations.

During the past few decades, many extensions to the original concept of the PDG have been introduced to simulation processes to discover new mechanisms on how cooperation can be promoted. The traditionally considered principles explaining the origin of cooperation are kin relations, reciprocal altruism, and group survival (Nowak and May, 1993). An overview of selected mechanisms that help to promote cooperation is provided in Table 1. The model presented in this paper allows agents to withdraw from the game, similar to the *voluntary participation* mechanism. Instead of a rational decision, here agents cease interaction as a result of illness – see Section 3.8 for a detailed description.

Mechanism	Source
Reputation-based recognition of partners for safe cooperation	Kim (2010), Nowak and Sigmund (1998)
Homophily – preference of agents to interact with others of the same kind	Pacheco et al. (2006), Scatà et al. (2016)
Social punishment – agents may punish defectors at own cost	Niu et al. (2017), Zimmerman and Eguíluz (2005), Wang et al. (2013)
Donations between agents with similarity in some arbitrary characteristic	Riolo et al. (2001)
Voluntary participation in the game – agents may withdraw from interaction with unfavourable outcomes	Chen et al. (2010), Jia et al. (2018), Hauert et al. (2002), Szabó and Hauert (2002)
Formation of coalitions – agents may group with others to exclude defectors	Peleteiro et al. (2011, 2012)
Historical payoff – agents remember outcomes of previous games with the same player	Geng et al. (2017)

Table 1: Selected mechanisms extending the original concept of PDG.

Analyzing interaction networks has become a useful perspective for studying cooperation, and *network science* has been successfully applied in the study of the PDG. As reported by Pacheco and Santos (2005), both evolution and maintenance of cooperation are highly sensitive to the topology of the players' interaction network. This effect is called network reciprocity (Nowak, 2006). Selected observations of network reciprocity are illustrated in Table 2, where the *scale-free topology* and *hub failure* are closely related to the research question being addressed in this paper.

Observation	Source
Scale-free topology – the emergence of cooperation is supported by the topology of network with hubs, and in other types of networks with high levels of degree heterogeneity	Kun et al. (2010), Hirihara et al. (2013), Ichinose et al. (2012), Poncela et al. (2007), Pacheco and Santos (2005), Santos and Pacheco (2005), Santos et al. (2006), Yang et al. (2009)
Hub failure – cooperation is robust against random nodes defecting, but targeting influential nodes results in quick deterioration of cooperation levels. An attack targeted at the hub may lead to the disintegration of a scale-free network	Albert et al. (2000), Kim et al. (2002), Perc (2009)
Community size – promoting cooperation increases with the size of the community. The effect of a large community cannot be replaced with a greater number of smaller communities. Larger communities of cooperators are less susceptible to invasion by defectors	Liu and Lui (2016), Wang and Perc (2008)
Cooperating supercommunity – cooperators form single giant community while several clusters of defectors might coexist	Gómez-Gardeñes et al. (2007)
Link density – in sparse networks, cooperating communities may be easily invaded by defectors as cooperating individuals have fewer alternative interaction partners	Kun et al. (2010)

Table 2: Selected observations related to network reciprocity.

The experiments presented in this paper focus on simulations of the Prisoner's Dilemma in the workplace on static scale-free networks. Two relevant reasons imply the use of a static network setup. First, it is assumed that people do not usually change their typical behavior significantly, as personality traits are relatively stable in time (Caspi et al., 2005). Second, organizations have their structure defined, and their rate of change is slower than the rate of change observed in traditional simulations of the PDG. Employees in the presented model cannot choose with whom they interact, in addition, they cannot terminate formal social links with members of their organizational unit. Hence, to simplify the situation, the simulations are performed on static Barabási-Albert networks where employees do not change their strategic behavior.

3 The Model Description

This chapter describes the fundamental properties and interactions of agents in the presented model. The methodology used in this paper is based on agent-based modeling, where the dynamics of the system emerge from attributes and behavioral rules of individual agents. Therefore, a relatively simple model can exhibit complex behavioral patterns and provide valuable information about the real-world system that it emulates (Bonabeau, 2008).

For the purposes of the model development, the NetLogo tool was used. NetLogo is an environment for agent-based modeling of complex systems, and it offers a library with existing models from a wide range of scientific disciplines. NetLogo provides high-level programming language for users to develop their own models (Tissue and Wilensky, 2004, Wilensky and Rand, 2015).

The model presented in this paper was designed and developed by the authors. Partial functionality related to network formation processes has been adopted from the existing NetLogo model library (Wilensky, 1999), yet the majority of the source code is original. The main functionality of the model was incrementally developed and tested from September 2017 to December 2018, additional modules and minor updates are subject to ongoing development. During the implementation, each functionality was evaluated through a *parameter sweep* to analyze how implemented parameters impact global behavior and the key outcomes of the model. Furthermore, the evaluation and testing allowed us to determine default values for each parameter, ensuring that the model produces reasonable outcomes, e.g., realistic employee sickness absence. The core functionality of the model has been described in a previous study, as well as results of validation experiments (Daňa, Kopeček, Ošlejšek and Plhák, 2019).

The model represents an abstract organization (e.g., a company or an academic institution) where individuals interact to create value. The activity diagram of the model is depicted in Figure 1, and it illustrates the sequence and decision-making logic during the simulation. It consists of three nested parts.

The *work activity of an employee* part captures the actions of a single employee in one workday in an organization. Diversity in individuals' skills creates the potential for knowledge flow, which results in increased performance. Hence, it is assumed that employees enter an agreement with one another to exchange part of their work for additional productivity on a daily basis. This agreement is subject to the Prisoner's Dilemma – the workers may cooperate or defect, which has an impact on interpersonal relationships, and stress levels (see the *Collaborate with a neighbor in the topology* activity in the diagram).

Employees may become ill and unable to work when they accumulate stress faster because they are unable to relax. Other essential concepts of the model

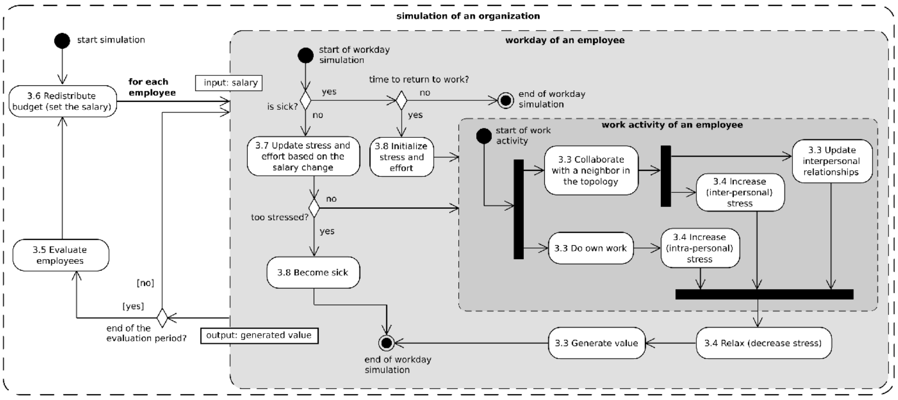

Figure 1: The activity diagram of the model. Actions inside the *workday of an employee* box represent the behavior of employees. Actions outside the box are performed by the management of the organization.

include changes in employees' stress and motivation in reaction to salary change. These mechanisms are shown in the *workday of an employee* section of the diagram. The primary input for this step is the salary of an employee. It is expected that each employee generates values comensurate with their salary. The employee's personality, other states, and the results of collaboration define to what extent this expectation is fulfilled.

The *simulation of an organization* section of the diagram shows management's strategies for rewarding employees' performance and cooperativeness. The structure of the organization affects the interaction of employees, as defined at the beginning of the simulation. Scale-free networks are used, yet the model allows simulations to be performed on other widely-known complex network topologies – i.e., regular square lattice with periodic boundaries, the Erdös-Rényi model for a randomly connected network, and the Watts-Strogatz model of small worlds. In the context of this paper, hubs with a prominent role in the scale-free network may represent a leader - i.e., an employee with a high position in the company hierarchy who is responsible for the performed tasks and who is frequently contacted by others for reporting, supervision or mentoring.

The remainder of this Section describes the model in greater detail. The numbering of actions in Figure 1 corresponds to subsections, where they are discussed.

3.1 Employee Attributes

Employee attributes reflect characteristic patterns of behavior or responses to external stimuli, as implemented in the presented model. For the sake of simplicity, it is assumed that these individual properties do not change during simulations. The values of these parameters are set as described in Table 5.

Productivity is the ability of an employee to create profit for the organization. Productivity equal to one means that the employee is able to do the work but produces no extra profit for the company. Productivity of less than one creates a loss for the company. Only those employees whose productivity value is greater than one, produce a corresponding profit.

Resistance to stress is modeled as the capacity of a virtual stress container. If the stress level is below the given capacity threshold, the employee is healthy and working. When the stress level exceeds the limit, the employee becomes ill and unable to work. The higher the capacity of the stress container, the longer it takes to exceed its threshold.

Cooperativeness is the typical behavior of an employee when interacting with co-workers. Seven strategies commonly used in the PDG context have been selected for the model, as listed in Table 3. All strategies, except for defecting, are considered as cooperative, as they always initiate the interaction with cooperation.

Strategy	Label	Description of behavior.
Defect	D	Always defects.
Cooperate	C	Always cooperates.
Tit for Tat	T	Initiates with cooperation, then repeats partner's last move.
Tit for two Tats	T2	Initiates with cooperation. Defects only if defected by the same partner in the last two rounds, otherwise cooperates.
Tit for Tat – Naïve Peacemaker	nT	Repeats partner's last move. When defected in the last round, there is a probability of cooperative response.
Pavlov	P	Initiates with cooperation. Repeats action when won last round, switches action when lost last round.
Unforgiving	U	Always defects once defected by a partner. Otherwise cooperates.

Table 3: The description of employees' collaboration strategies.

Diligence represents employees' ability to transform salary incentives into work motivation. Compared to the worker with low diligence, a highly diligent worker will be more motivated after a salary increase, and less demotivated after salary decrease. Diligence has normal statistical distribution among the population of employees. See Section 3.7 for further details related to adjustments of motivation.

3.2 Employee States

While employee attributes represent stable "personal traits" and are fixed during simulations, this subsection describes the employee's state. They are continuously changing, reflecting their actual "mood" – reactions to workplace environment and interaction with others. Sensitivity to changes in mood is affected by employee's attributes. In the model, three types of states are defined.

Effort is related to *productivity* and represents an employee's inner motivation to work. While productivity describes the employee's ability or potential to do work, effort describes to what extent the employee fulfills their potential at a particular moment — 0% can be understood as "an employee does not work at all" while 100% as "an employee does their best." The effort is adjusted as a reaction to changes in salary (see Section 3.7).

Stress is induced by solving work tasks and reduced by regeneration. It describes how much the current stress level approaches the maximum stress capacity — 0% means no stress at all while 100% means depletion of stress capacity and possible sickness. The less *resistance to stress* an employee has, the sooner the stress capacity can be reached, as discussed in Sections 3.4, 3.8, and 3.7.

Interpersonal relationships arise from interaction between co-workers. Employees remember their interaction history with particular co-workers, which is important if an employee uses a PDG strategy that reacts to past actions of other players, e.g., the "Tit for Tat," see Table 3. The interaction history would also be taken into account when selecting partners for cooperation. However, for the sake of simplicity, interaction partners are chosen randomly, as discussed in the following section.

3.3 Simulation of Work Activities

This part of the simulation algorithm can be considered as one working day during which an employee produces a certain amount of profit to the organization.

The primary input for this step is a **salary** $\beta_i \in \mathbb{N}$, which represents the amount of money that management gives the i-th employee. Management expects that the employee will produce the work at least commensurate with the value of the salary.

The primary output is a **generated value** $V_i \in \mathbb{N}$ which corresponds to the input salary increased (or decreased) as a result of the work produced during the day:

$$V_i = \beta_i((1 - w_v)V_e + w_v V_c + V_r), \tag{1}$$

where w_v represents the *cooperation weight* denoting what portion of the work will be exchanged with a co-worker. Therefore, the computation is split into three parts. A major portion of the work (V_e) is done directly by an employee. A minor portion (V_c) represent subtasks that might be exchanged with a co-worker. The mechanism of work exchange is based on a presumption that specific subtasks might be done by particular employees more efficiently. The ratio between own and exchanged work is fixed in the model during the whole simulation. The third addend V_r represents the cooperation requested by other co-workers.

Own work V_e reflects directly solved tasks. It is proportional to the *productivity* θ_i and current *effort* κ_i of individual employees:

$$V_e = \theta_i \kappa_i. \tag{2}$$

If the *effort* is 0%, then the contribution is also zero. It means that no work has been done and this part of the salary was only consumed. Another extreme arises when an employee's effort is 100%. In this case, the contribution equals to the *productivity* θ_i.

Exchanged work V_c reflects the amount of work that an individual agreed to exchange. This interaction is subject to PDG, and the outcome of the exchange is affected by the following payoff function that satisfies standard requirements put on PDG (Chong et al., 2007). From the perspective of an employee, there are four possible outcomes of the interaction:

- *Sucker's payoff:* $V_c = 0$. I did the partner's work as was agreed, but my partner did not do my work. I cannot earn anything from my exchanged work because it was not done. My cooperation part of the work is lost.
- *Cheater's payoff:* $V_c = 2.25$. I did not do the partner's work, but the partner did my work as agreed. Because they did the work more efficiently than me, I get the payoff 1.25. Moreover, I had time to do my own work, and so the final payoff is 2.25.
- *Punishment:* $V_c = 1$. We did not agree on cooperation and did the work as usual, with normal efficiency. The payoff value is 1.
- *Reward:* $V_c = 1.25$. Both of us met the agreement, and because we did the work more efficiently, both of us get a payoff 1.25.

A partner for exchanging the work is selected randomly from employee's neighbors, i.e., from co-workers that the employee is linked to with a tie on a social network. Sick employees (see Section 3.8) are excluded from the interaction as they are on sick leave.

During a single simulation round, an employee may initiate the exchange of work only once. However, one employee may interact more than once, as the interaction may be requested by other employees during that round. The more social connections an employee has, the higher is the probability of multiple exchanges of work. Results of these requested interactions are taken into the computation as **requested exchanged work** V_r:

$$V_r = \sum_j w_j \phi_j, \tag{3}$$

where j corresponds to the j-th requested cooperation, w_j is the *cooperation weight* assigned to the co-worker (co-worker's w_v in Equation 1), and ϕ_j is the employee's results of the iterated PDG played with the j-th co-worker.

3.4 Simulation of Stress

It is assumed that performing everyday work activities produces stress. The presented model incorporates two types of stress factors.

Intra-individual stress is related to *own work* V_e and the *effort* κ made by an employee to solve tasks. The more effort an employee exerts, the more stress is produced. The less resistant to stress an employee is, the faster the stress increases. The impact of intra-individual stress on simulation results can be controlled by adjusting a global variable in the model. Note that the intra-individual stress is linked to the extent of an employee's effort, not to the actual amount of work done. Consequently, two distinct employees may deliver the same amount of work at different levels of effort and stress, depending on their attributes and actual state.

Being defected by a co-worker is another source of stress. As it is induced by social interaction (through the PDG), it is referred to as **inter-individual stress** further in the text. The outcome of the PDG defines its amount. If both employees cooperate, their stress does not increase. If both defect, stress is increased proportionally to their *resistance to stress* and the amount of *exchanged work* V_e. If one cooperates while the other defects, then the cooperating employee is stressed twice as much as in the previous case, while the stress of the defecting employee does not change.

Because *intra-* and *inter-individual* stress increase continuously during the workday, the mechanism of **regeneration** has been introduced in the model. Regeneration reflects the post-work relaxation, which counterbalances stress production. The rate of continuous regeneration takes into account *resistance to stress* – the more stress-resistant an employee is, the faster the stress is regenerated. The regeneration rate may be adjusted by the model to simulate various environments or organizational cultures.

3.5 Evaluation of Employees

After a certain number of simulation steps (workdays), management evaluates the behavior of each employee. The goal of the evaluation is to achieve management objectives such as increased profit, the sustainability of production, or employees' satisfaction by evaluating employees' work results. However, in the real world, the insight of management into the behavior of employees can be restricted and inaccurate. Therefore, the model allows for incorporating the desired level of randomness by adding noise.

Evaluation $E_i \in [0, 1]$ of i-th employee is calculated as a weighted sum of real employee's contribution $F_i \in [0, 1]$ and a random number $r \in [0, 1]$:

$$E_i = w_e F_i + (1 - w_e) r. \tag{4}$$

The weight w_e is fixed during the whole simulation.

Employee contribution F_i determines how management perceives the benefit of an employee in terms of achieving the objectives of an organization. The evaluation process considers two aspects: efficiency and cooperativeness of an employee. The efficiency, expressed as the *generated value* in Equation 1, already reflects the extent of the cooperative behavior of an employee (see V_e and V_r values in the equation), whereas cheating co-workers reach better results in comparison. However, cooperativeness is profitable for the organization in the long-term perspective. Therefore, management may compensate cooperating employees by virtually "returning them" the *generated value* that they lost when interacting with defecting co-workers. If such compensation did not exist, employees would be punished for being cooperative.

The calculation is performed in two steps. First, an added value W_i is computed as the difference between the *generated values* that an employee accumulated during the evaluation period ($\sum V_i$) and the *salary* earned during that period ($\sum \beta_i$). ΔV_i is the value that given employee lost when exchanging work with defecting co-workers:

$$W_i = \sum V_i - \sum \beta_i + \Delta V_i. \tag{5}$$

The *employee contribution* is then calculated relative to other employees:

$$F_i = (W_i - W_{min})/(W_{max} - W_{min}), \tag{6}$$

where W_{max} and W_{min} are the maximal and minimal W_i observed in the current evaluation period.

3.6 Budget Redistribution

At the beginning of the simulation, the company earmarks a certain **budget** $\alpha \in \mathbb{N}$ for all employees. This budget is evenly distributed among them as their input *salary* β_i.

During the simulation, employees usually produce a profit ($\sum V_i > \sum \beta_i$) through which the overall value of the organization increases. Management may decide to use part of the profit to increase the budget that employees receive. If the company produces a loss, then the *budget* α remains the same as in the previous evaluation period. It is assumed that this strategy reflects a socially responsible organization that keeps the profit when productivity is high to support employees to overcome the temporary period when productivity is low. This strategy should also act as a prevention to a downward spiral of performance through decreased motivation, poor evaluation leading to further loss of motivation.

The redistribution of budget is driven by **relative performance** $\rho_i \in [\rho_{min}, \rho_{max}]$, which is continuously updated during the whole simulation. It represents a relative long-term efficiency of individual employees as, potentially imprecisely, perceived by the management. Initially, it is set to 1 for all employees (100% performance), but then it is re-calculated after every evaluation:

$$\rho_i = \rho_i + \rho_i\left(\frac{E_i}{E_{avg}} - 1\right)w_p, \tag{7}$$

where $w_p \in [0,1]$ defines the intensity of the impact of the evaluation process. The result is replaced with predefined limits ρ_{min} or ρ_{max} whenever the value is out of this range so that the *relative performance* remains in reasonable limits around 100%.

The *budget* α is then redistributed taking ρ_i into the account:

$$\beta_i = \alpha \frac{\rho_i}{\sum \rho_i}, \tag{8}$$

where $\sum \rho_i$ is the relative performances of all employees.

3.7 Impact of the Salary Change on Employees

Changes in salary have an impact on employees and their future behavior.

Impact on *stress*: An increase in salary decreases the employee's *stress* and vice versa. Sensitivity to salary change is affected by the *relative performance* of the employee. Stress-wise, employees with lower salaries are more sensitive to salary changes. Compared to high earners, employees with lower salaries will be more stressed when given less money and more motivated when given more money. This behavior reflects the so-called Easterlin paradox, which states that increased income correlates with increased happiness, but the increments of happiness diminish after reaching a certain threshold (Clark et al., 2008).

Impact on *effort*: Changes in salary may be motivating or demotivating, depending on how difficult it was for the employee to make money. The subjective difficulty δ_i is calculated as a ratio between a new *salary* β_i and the amount of work done in the current evaluation period:

$$\delta_i = \frac{\beta_i}{\rho_i(1-w_e)M + \rho_i w_e \chi_i}, \tag{9}$$

where ρ_i is the relative performance, w_e represents the cooperation weight, M is the length of the evaluation period, and χ_i is the total number of interactions that employee participated in during given evaluation period.

To determine whether it was easier or harder for the employee to make money, the coefficient δ_i is compared with its value $\delta_i^{'}$ from the previous evaluation period. The difficulty of earning money versus the salary change defines four situations captured in Table 4. Motivating conditions lead to increased effort and vice versa. The shift in the effort is proportional to the extent of how much *added value* an employee brought to the organization:

$$\xi = \beta_i - \beta_i^{'}, \tag{10}$$

where β_i is a new salary, while $\beta_i^{'}$ is the salary from the previous evaluation period.

The motivational factor is also affected by employees' *diligence*, and the effect is positive linear.

	difficulty to earn money	
	easier	**harder**
salary decrease	motivating	demotivating
salary increase	demotivating	motivating

Table 4: Impact of the salary change and the difficulty to make money on the effort adjustment.

The effort change of sick employees is re-calculated in the same manner as working employees. Nevertheless, the effect of effort change on their performance is applied after they return to work and start to produce the *generated value* again.

Impact on *interpersonal relationships*: In the current model, *interpersonal relationships* of employees are affected only by the PDG strategy and the history of interactions with a particular co-worker. Therefore, changes in salary do not modify the collaborative behavior of employees.

3.8 Sickness

A metaphor of **sickness** is used in the model to simulate the impact of high stress on the work activities of employees. If the income of stress is higher than an employee's regeneration rate for a particular time such that the stress level exceeds their stress capacity, then the employee becomes ill.

These employees are on sick leave; thus, they do not work. The organization still supports them, so they receive normal *salary* β_i, but they produce zero *generated value* V_i. Since they do not work, their stress and interpersonal relationships remain unchanged.

The stress level is checked at the end of each simulation step. The length of sick leave is fixed in the model to seven days (simulation steps). After that period, the employee returns to work relieved, having stress level reset to zero. If the current *effort* κ_i is higher than the initial effort, then the value is decreased slightly to reflect the fact that people usually do not work at their best after an extended period of inactivity. In the same way and for the same reason, also, the *relative performance* ρ_i (see Section 3.6) is decreased towards 100% whenever it is above this threshold.

4 Simulations Setup

The previous Section describes selected fundamental concepts and mechanisms that define the behavior of the model. Interested readers may refer to online repository (Daňa et al., 2018) where description, documentation, and source code with the model to be run in the NetLogo environment is available to download.

Simulations presented in this study include 3,600 simulation steps where each step may be perceived as one day. Therefore, a single simulation can be seen as approximately ten years of organization lifespan. As discussed earlier, in real-world institutions, individuals usually do not structurally change their work habits and typically cannot voluntarily decide who their co-workers are. For the sake of simplification, the network used in the experiments is assumed to be static – the employees cannot create or terminate links, and they also cannot change their strategy while playing PDG.

The size of the company is set to $n = 100$ employees. The number of hubs representing managers or leaders depends on the network formation process, which is probabilistic. Most commonly, there are 5 ± 2 hubs. Evaluation of employees by management is performed once per 30 steps, i.e., monthly. The values of key parameters used for the simulations are summarized in Table 5.

Fixed attributes of employees		
cooperativeness	4:1	Proportion of cooperative vs. defecting employees
productivity	3.8 ± 1	Mean value and SD
stress capacity	300 ± 5	Mean value and SD
regeneration	1.125	Implicit value of stress relaxation
diligence	0.5 ± 0.175	Mean value and SD
Initial employees' states		
effort	75%	Employees use 75% of their productivity
stress	0	Employees are relaxed
interpersonal relationships	none	No cooperation history
Other features of employees		
cooperation weight	20%	Fixed part of work exchanged with a co–worker when playing PDG
Features of management		
evaluation period	30 steps	Frequency of management intervention

Table 5: Selected parameters of performed simulations (SD = standard deviation.

The simulation process is stochastic, i.e., identical parameter settings yield different global outcomes as a result of random processes in the model. In order to obtain unbiased results, 500 runs were executed for each setup to eliminate the effects of stochasticity. Validation experiments showed that 500 repetitions are sufficient to accurately represent the results in terms of obtained mean value and data dispersion.

During the model development, we intensively tested the stability of the obtained complex system concerning various parameter settings. The validation experiments included sensitivity analyses to set up default values of parameters to produce reasonable outcomes. One of the analyses aimed at identifying implicit value for the regeneration rate of employees, i.e., to what extent they will be able to cope with stress. Based on this analysis (see Figure 2), the implicit value for regeneration was set to 1.125.

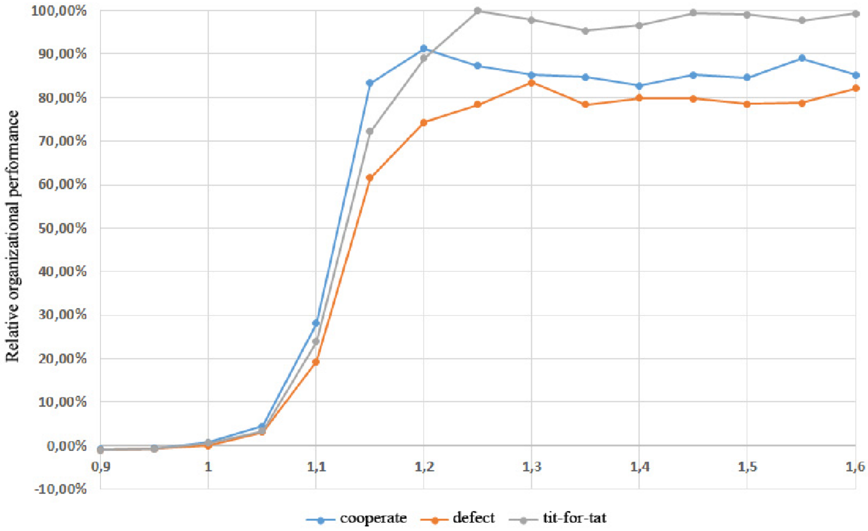

Figure 2: A sensitivity analysis of employees' regeneration rate and its impact on organizational performance for selected PDG strategies of hubs. A sigmoid progression is observed, with sharp increases in organizational performance for small increments of regeneration in region $r \approx 1.05$ and $r \approx 1.2$. For values $r \geq 1.2$, the number of ill employees converges to zero, and there are no ill employees for regeneration rate $r \geq 1.6$ and for any hub strategy setup. Observed fluctuations in organizational performance are caused by other mechanisms implemented in the model.

The aim of this study is to analyze the impact of a highly central node behavior in a social network (i.e., a manager) on the overall organizational performance. To generate a network with a few highly connected nodes (the *hubs*), the Barabási-Albert network model was used. For an illustrative network visualization, see Figure 3 below. Strategy of the *hubs* was predefined to particular strategy (e.g. *Cooperate*, *Defect* ...) for each set of 500 simulations per 3,600 days.

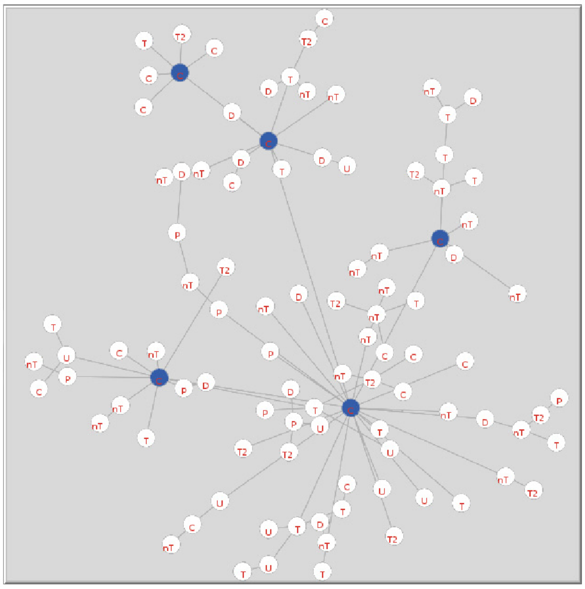

Figure 3: An example of a scale-free network with $n = 100$ nodes, average degree $k \approx 2$. Labels on the nodes denote employees PDG strategy (see Table 3). A few highly connected hubs are highlighted.

5 Results

As described in Section 3 of this paper, organizational performance is not only dependent on the productivity of employees, but also on the quality of their interaction and management evaluation. These mechanisms impact motivation and stress levels of individuals, which might significantly influence the overall organizational performance. The results of performed simulations reveal that a specific behavior of a manager (conceptualized as a hub in the social network) might substantially impact the key parameters of the organization. Note that the results presented in this section are normalized against the maximum value obtained for a given set of simulations.

The organization achieves the highest levels of performance (Figure 4) and

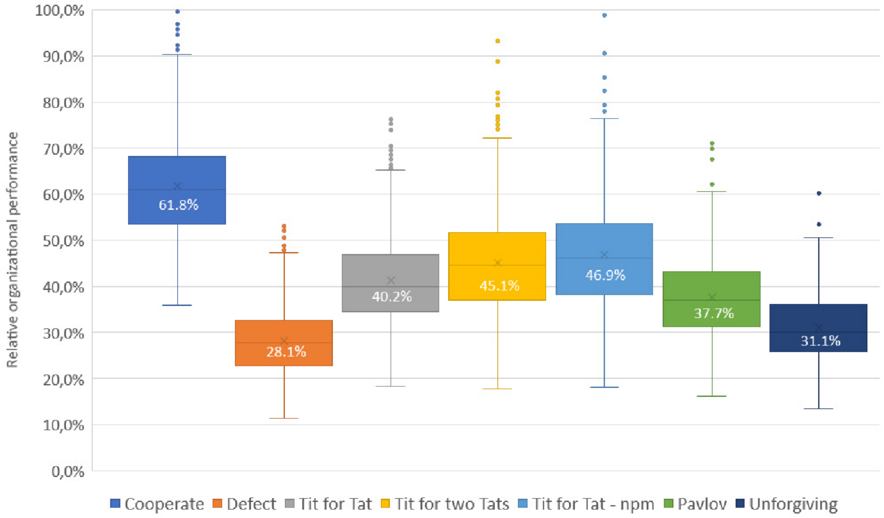

Figure 4: The impact of hubs' strategy on organizational performance. The highest organizational performance is achieved when hubs remain unconditionally cooperative. Values inside boxplots represent average performance for the given setting when compared to the highest result obtained from the experiment.

the lowest rates of illness (Figure 5) when the highly central employees in the interaction network i.e., the managers, are unconditionally cooperative. The sickness rate is calculated as a cumulative sum of employees who become ill as a result of high levels of stress during the simulation.

It is widely accepted that the topology of the scale-free network, and the degree heterogeneity in general, is a contributing factor that facilitates the emergence of cooperation on dynamic complex networks. In such a setting, the cooperation propagates through the network as individual agents copy the strategy of successful cooperating hubs. However, the results presented in this paper were obtained from static networks, where agents can neither change their strategy, nor create or terminate social ties. When interpreting the data, it is essential to focus on the effect of stress, as it may significantly influence the total economic outcome of the organization. At high levels of stress, employees frequently become ill and therefore produce no value.

When a manager who occupies a highly central position in the network defects, their uncooperative behavior has an *area effect* of stress because of the many social connections with other colleagues. Moreover, many employees at the network periphery may be connected only with the nearest hub, as a consequence of the scale-free network topology. These peripheral employees cannot substitute the malfunctioning interaction with the manager because they do not have any other social connections. Depending on their strategy, peripheral

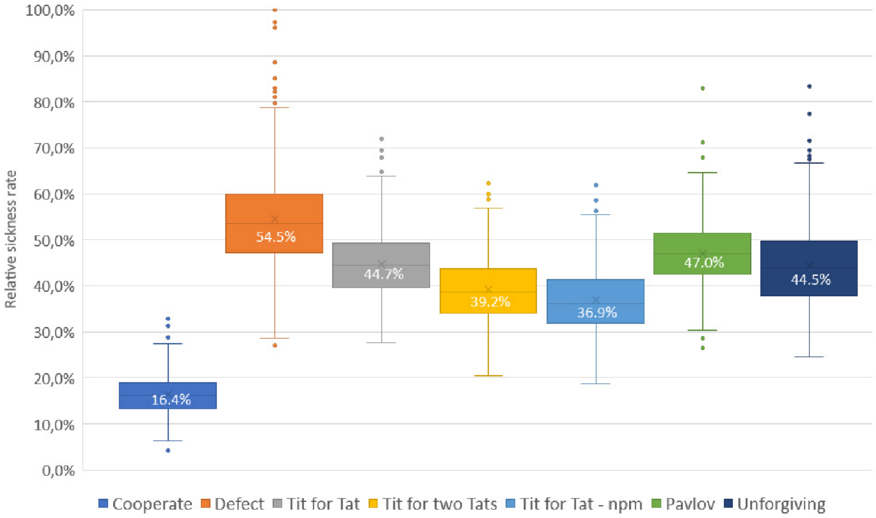

Figure 5: The impact of hubs' strategy on the sickness rate of the employees for implicit regeneration level $r = 1.125$. The highest level of stress is observed when hubs do not cooperate. Values inside boxplots illustrate the average sickness rate of all employees compared to the highest obtained result.

nodes either cooperate with the manager and receive stress, or they do not interact at all. Consequently, their stress is not increased, but there is also no generated value resulting from the part of the work exchanged between manager and employee.

It is important to note that highly central nodes are susceptible to stress overload, as discussed in Section 2. Figure 6 illustrates that hubs are up to three times more likely to get sick when their resistance to stress is the same as the resistance of peripheral nodes. With increasing stress resistance, the likelihood of hubs becoming ill is substantially reduced. However, the results suggest that adjusting the capacity of hubs to resist stress does not produce significant differences in the overall performance of the organization.

To further analyze the effects of stress, additional experimental setups were considered. Since increasing the stress resistance solely for hubs does not account for significant improvement of organizational performance, increasing the regeneration for all nodes was considered. As the global regeneration rate increases, the beneficial effect of hubs cooperating unconditionally diminishes, the difference between cooperative and defecting hubs becomes less significant, and hubs with *Tit for Tat* strategy account for the highest organizational performance (Figure 7). For the sake of illustrative visualization, only three hub strategies are included – variants of Tit for Tat and Pavlov strategies scored similarly to pure Tit for Tat, and Unforgiving strategy scored similarly to Defecting

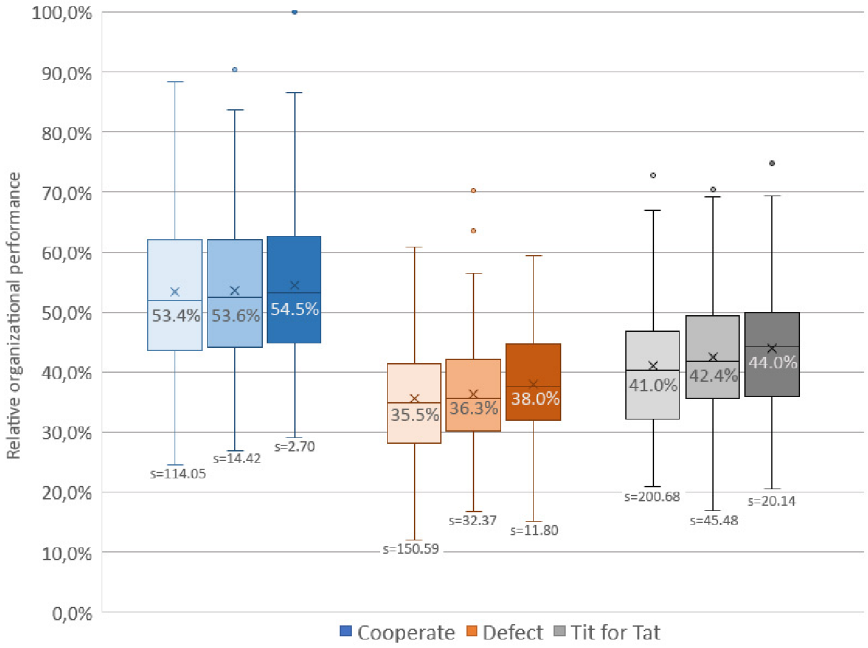

Figure 6: The impact of increased stress resistance of hubs on organizational performance. For any strategy, darker hue of the same color illustrates increased hubs' resistance to stress – 100% (left), 130% (middle), and 150% (right), while stress resistance of peripheral nodes remains unchanged. Values of s refer to an average number of hubs becoming sick during the simulation for given setup ($s = 60.9$ for peripheral nodes). An implicit regeneration level $r = 1.125$ was used for all setups.

strategy.

An additional experiment was considered to compare the results of all implemented hub strategies while eliminating stress. To control the effects of stress, all parameters were set to their implicit values (see Table 5), and regeneration r was set to $r = 100$ (note that the implicit value is $r = 1.125$). This setting prevented any stress build-up among employees that could result in their becoming ill. The results of this experiment illustrate that there are no significant differences in organizational performance when changing the strategy of central employees (Figure 8). Eliminating stress reduces the beneficial effect of unconditionally cooperative hubs on organizational performance. Except for defecting and unforgiving strategies, all strategies scored close to 60% of the highest observed value.

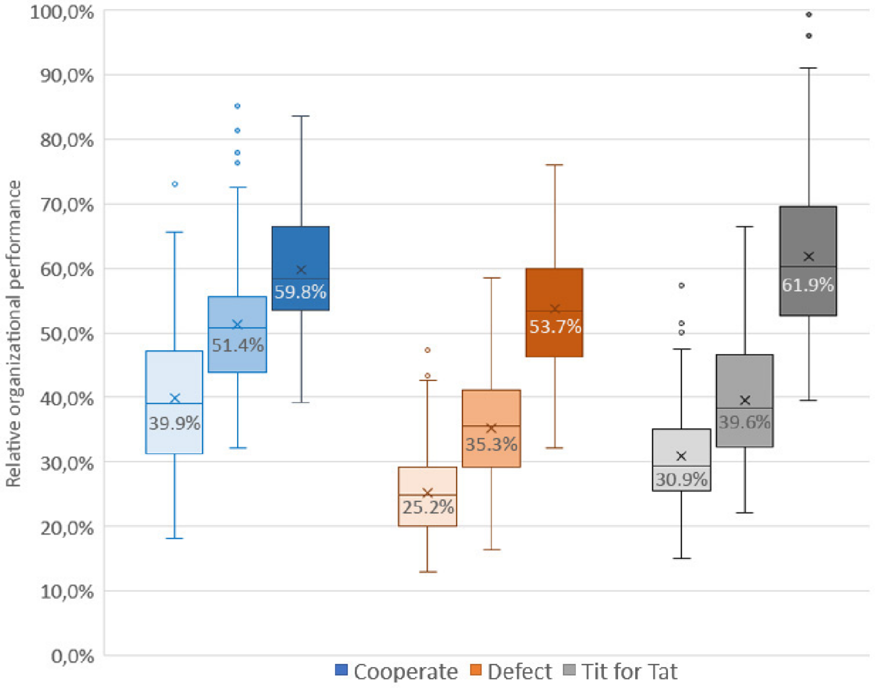

Figure 7: The effect of increased regeneration level on organizational performance for selected strategies of hubs. For each strategy, the darker hue of boxplot color illustrates increased regeneration r with values $r = 1.125$ (left), $r = 1.135$ (middle), $r = 1.500$ (right). As stress resistance increases, the beneficial effect of being a cooperative hub diminishes, and *Tit for Tat* becomes an optimal strategy for a hub to achieve the highest organizational performance.

6 Implications

The results of the performed experiments suggest the following managerial implications.

A stressful work environment requires cooperative leaders. Organizations experiencing increased levels of stress should carefully evaluate the cooperative behavior of managers, team leaders and other employees in central positions within the organizational hierarchy. The increased level of stress may be observed indirectly through an increased employee turnover or increased rate of employees' sick leave – in these situations, the cooperative behavior of hubs has a significant beneficial effect for an organization.

Employees' stress resistance has a positive effect on performance. The ability of employees to resist stress was shown to be an important mechanism which contributes to organizational performance under a wide range of

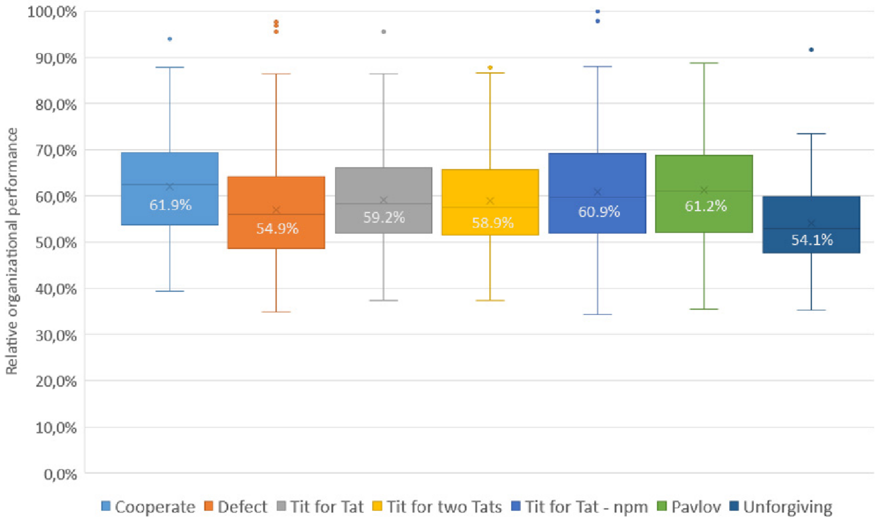

Figure 8: The impact of hubs' strategy on organizational performance when controlling the stress level to zero. Values inside boxplots illustrate an average relative performance compared to the highest observed value. The significant advantage of unconditionally cooperative hubs has been reduced.

conditions. As the employees' relaxation rate stems from organizational culture, the results presented in this paper are in accordance with the traditionally perceived link between organizational culture and performance.

Stress-resistant work teams perform steadily. Organizations whose employees are highly resistant to stress can be also more tolerant to the behavior of managers. In other words, managers may experiment with acting cooperatively or competitively towards employees, as the potential detrimental effect on organizational performance is low. Conversely, the cooperative behavior of managers is extremely important when employees' resistance to stress is low, as previously mentioned.

Aside from the specific managerial implications related to the findings, the research has also brought important theoretical and technical implications to light.

A contextual perspective is important for the evaluation of an organization. From the theoretical point of view, the results underline the general importance of contextual perspective when evaluating organizational ecosystems. Following the logic offered by Henrickson and McKelvey (2002), the behavior of individual employees at lower scales provides an important context for the organization at a higher scale. In particular, our research shows that such a higher-scale structural effect emerges through the mechanisms of stress and its relaxation by employees. As parameters modifying stress change, the importance of hubs in social networks of organization are affected significantly. Our simulations reveal how specific stress-related conditions may cause the hubs to have a less significant role than is traditionally perceived.

A simulation framework is now available to allow for further experimentation and extension. The generic model that we are making publicly available was developed with the aim of simulating the aforementioned contextual perspectives. Agent-based modeling used in the model is inherently associated with simplification and abstraction of complex reality. The presented model simplifies human behavior to focus on the global, emergent, organizational level. Moreover, the performed experiments aim to analyze how strategic decision-making related to human resources may impact both organizational performance (the *macro* level), and the quality of employees' lives (the *micro* level). We are aware that the inherent simplification and abstraction related to agent-based modeling complicate the validation of every included parameter. However, the model was continuously tested and validated during the development to be robust, reliable, and to produce reasonable results.

7 Conclusions and Future Research

The presented paper contributes to the tradition of research aimed at modeling and simulations of the Prisoner's Dilemma Game. Over the decades, many extensions of the original concept of the game have been introduced, illustrating more detailed aspects of cooperation emergence. While some of the studies focused on discovering new mechanisms that help to promote cooperation, others researched the effects of interaction topology, i.e., how the structure of the social network between agents influences the outcome of the game.

The model described in Section 3 of this paper addresses both of the approaches mentioned above. It is a multi-parameter model developed in the NetLogo environment for the modeling and simulation of complex systems. The model extends the PDG by setting it in an organizational context where agents represent employees who interact to create added value for the company. The model also presents novel concepts that influence the outcome of the simulations. Specifically, the key novel concept is stress, which is functionally connected with other mechanisms implemented in the model – i.e. the interaction between agents, motivation level, or illness. Through their joint effects, stress has a significant impact on overall organizational performance, as presented and discussed in Section 5.

The goal of this paper is to investigate whether the specific behavior of a manager may have a significant influence on organizational performance. To obtain a network with a few highly central nodes and many peripheral nodes, a Barabási-Albert model of the scale-free network was used. A set of simulations was designed to allow manipulation with the cooperative behavior of hubs while controlling for all other parameters. Simulations were performed on static networks, where agents do not change their strategy or social ties.

The experiments aimed at the verification of the stability and the expected behavior of our model in defined scenarios confirmed its correctness and usefulness for complex simulations. The subsequent experiments evaluating the impact of stress and cooperative behavior of the key employees on the organizational performance provided results based on which several managerial implications were formulated. We believe that further experiment with the presented model might yield interesting outcomes in the future.

As for the future direction of research, several possible extensions to the existing model are being considered. Currently, the model performs the simulations with a fixed number of agents for the whole experiment. To bring the model closer to reality, an algorithm that would adapt the number of employees depending on the actual economic situation of the organization could be implemented. When employees are 'hired', their PDG strategy could be either: random, the most successful strategy, or the strategy of the nearest hub. Additionally, the network formation rules may be updated such that the newcomers would link to existing employees based on their similarity (e.g., to employees with the same PDG strategy) – in existing literature, this process is called *assortativity*.

When people are under pressure, they might inaccurately evaluate other people's intentions or behavior. Therefore, another concept considered for implementation is the introduction of noise whose level will be proportional to the actual stress of an employee. The level of noise would represent the probability that an act of co-worker's cooperative behavior will be perceived as defection.

Finally, the extension of an algorithm that rewards employees for their above-average performance is currently being implemented. The goal of this functionality is to find a suitable approach that would balance employees' motivation and righteousness of rewarding, beneficial for the organization as a whole.

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