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Neighbourhood communication model for enhancing trust and promoting players' cooperative behavior: a case of iterated n-players prisoner's dilemma

Khaled Suwais

Faculty of Computer Studies, Arab Open University, Riyadh, Saudi Arabia

ABSTRACT
Human beings collaborate when organized in an unchanging network of social relationships and if the advantage of collaboration surpasses the entire cost of collaboration with all neighbours. Cooperation may be seen in community and natural systems when selfless action is rewarded despite the risk of exclusion. Trust between neighbours is crucial since cooperative behaviour spreads more rapidly and efficiently in environments with a high trust rating. In this paper, we introduce an alternative neighbourhood communication topology to enhance the level of trust between *n* prisoner's dilemma players and promote cooperative behaviour. The proposed topology allows players to communicate with their local neighbours and share their experiences within the universe of other players that are not locally connected. To understand the overall players' behaviour locally and globally, the topology is supported by a knowledge base accessible by all players. Our topology was tested against five other communication topologies over four 1000-game tournaments. The results show that our model outperforms other strategies in promoting cooperative behaviour among participating players in small and large populations.

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Neighborhood topology; cooperative behaviour; prisoner's dilemma; game theory

1. Introduction

Game theory is a mathematical tool used to evaluate the interactions between interdependent individuals or competitors. The theory allows players to make appropriate decisions in various strategic settings. The main factors affecting these individuals' interactions include the participant's payoff and strategies implemented by both parties. A player can utilize game theory to develop frameworks that mimic real-world interactions. The models consist of individual interactive frameworks, such as the different choices for the indices that the researchers obtain through abstraction. The other framework is the payoff function which helps to provide a numerical value for each combination of choices.

Since game theory is strategic, it is essential for players to use it through different applications [1–5]. The consequences of the interactions rely on the individual player and on the decisions made by the players in the corresponding game.

The prisoner's dilemma, a symmetric matrix game where the players seek to achieve the highest score against each other, is one of game theory's most valuable applications. The game involves using a transparent payoff matrix; thus, the players have no prior knowledge about the opponent's choices before the game. Game theory can help the players achieve the highest score since it involves striving for the best path [6].

A one-time version of the prisoner's dilemma occurs when a rational player plays a single game. With limited real-life applications, the one-shot version of the game is not interesting for real-life scenarios. Moreover, the game has a mutual defection strategy that depends on the lack of future of the one-shot version. If two players meet and play several games together, it becomes an Iterated Prisoner's Dilemma (IPD) [7,8].

IPD allows two individuals to play together several times and to generate new strategies based on what they used in previous interactions. The moves of one player significantly determine the opponent's behaviours. The uniqueness of the IPD is that players cannot use the single dominant strategy of mutual defection and must favour more complex strategies. The players' approaches aim to maximize their payoffs.

Game developers face the complex challenge of promoting cooperative behaviour in large populations for the Iterated n-Players Prisoner's Dilemma (INPPD) [9]. The main concern is that incorporating an emulation of cooperative behaviours requires discovering a large population's strategy throughout the game [10]. The neighbourhood topologies representing the communication channels play a significant role in establishing effective cooperative behaviours [11–13].

This study emphasizes the significance of the population structures in developing and evolving the cooperative behaviour of INPPD. Prior research findings indicate that the evolution of cooperative behaviour

CONTACT Khaled Suwais Khaled.suwais@arabou.edu.sa Hitten District, Riyadh, 11861, Saudi Arabia

is a critical issue and the focus of numerous studies [Wang et al. 201510,14,15]. This study contributes to the development of an alternative neighbourhood topology capturing the essence of the universal structure in the evolving cooperative behaviour of INPPD. The alternative structure caters to the limitations existing in the current neighbourhood topologies that act as barriers to an effective exchange of experiences between players. The alternative neighbourhood topology has the advantage of providing good communication channels for improving players' game experience. This *local-universal* topology allows players to share experiences at the local and universal levels.

This paper first provides background information on INPDD in Section 2. The different existing neighbourhood topologies in game theory and INPPD are highlighted in Section 3, while Section 4 introduces our alternative *local-universal* topology. The various performance tests and the comprehensive supporting analysis of the results are outlined in Section 5. Finally, section 6 provides a concluding statement for the research paper.

2. Iterated *n*-players prisoner's dilemma (INPPD)

Researchers often use the IPD game to study the evolution of cooperative behaviour in biological and social systems. The two statements defining the INPPD are as follows [16]:

(i) The players receive higher payoffs in the game for defecting rather than cooperative behaviour, regardless of the actions of any of the players.
(ii) The players receive lower payoffs when both individuals choose defecting behaviour.

These two statements often create a dilemma among the players when they are unaware of each other's moves until they play their turn. Consequently, most players often hesitate to behave cooperatively since they assume that their opponents would choose a defecting behaviour. INPPD allows researchers to identify these dilemmas and establish various models promoting stable cooperation, reciprocity, co-evolutionary learning, altruism, and community structure [6]. The INPPD model also highlights a social dilemma, which occurs whenever there is a collective action. On the other hand, using INPPD can lead to less desirable outcomes in situations where the individual's defections occur at the expense of other players.

The players in INPPD have only two options: cooperating (C) or defecting (D). The payoffs received by the players depend on the number of existing cooperators (i). We define c_i and d_i (for all players, where $i = 0 \ldots n{-}1$) as a given player's payoff for cooperation or defection, respectively. Hence, each player should consider that i cooperators and $n{-}i{-}1$ defectors exist. Since player p will receive c_i or d_i when they cooperate or defect, respectively, they do not need information about the number of cooperators and defectors to compute the payoff.

The primary dilemma in the game is that the defecting strategy dominates the cooperative strategy. Thus, players do not choose the dominant strategy each time since they receive lower payoffs if they continue playing with the same strategy. Alternatively, if the player decides to cooperate and testify, and the other players choose to defect, they receive higher payoffs than their opponent. Therefore, it is easy for the players to establish a pattern for cooperation since it relies on rational behaviour. The players' fear of future punishments outweighs the benefits they gain if they adopt a defecting strategy.

In contrast to the real world, the social and biological systems are represented in the game by spatial models, and cooperation and defections occur among the different group members. Moreover, the existence of common finite resources leads to the development of new behaviours, where each individual uses more than their share of resources. These conditions can result in collective irrationality even among rational individuals.

Numerous recent studies have demonstrated interest in the evolution of cooperative behaviour. Most focus on the subject of anti-social punishment, which relies on both centralized and decentralized punishment. These studies indicate that punishments significantly impact the general evolution process. However, other findings suggest that cooperation has more advantages than defection, even when resulting in anti-social punishment [12,15,17].

The evaluation criteria chosen to assess the performance of different players depend on the payoff value that each individual could achieve in a game. Therefore, strategies that offer the largest payoffs are the best [18]. Additionally, players can achieve higher payoffs if they can predict their opponents' behaviour.

Players must be aware of the rules about the payoff matrix applicable throughout the game. The payoff functions involving INPPD should meet the following conditions [19]:

(i) *Condition 1: Monotonicity*

This condition states that the payoffs are higher for any additional cooperator if most players among n individuals have cooperated. Due to the inequality factor of monotonicity, the same rules apply to any additional defector.

The equations below represent the monotonicity condition:

$$c_i > c_{i-1}, \tag{1}$$

$$d_i > d_{i-1}, \tag{2}$$

where $i = 1, 2, \ldots, n{-}1$.

Table 1. Payoff matrix of INPPD.

	Number of cooperators among the remaining n−1 players				
	0	1	2	…	$n-1$
Player A Cooperate	c_0	c_1	c_2	…	$cn-1$
Defect	d_0	d_1	d_2	…	$dn-1$

(ii) *Condition 2: The dominance of defection over cooperation*

This condition states that rational players with short-term thinking will select defection due to the equation

$$d_i > c_i, \tag{3}$$

where $i = 0, 1, \ldots, n-1$ is the number of players who chose a given strategy, d_i is the corresponding payoff for players who chose defection, and c_i is the payoff for players who chose cooperation.

(iii) *Condition 3: Efficiency of cooperation over defection*

This condition, formulated in Equations (4) and (5), illustrates the increase of in-group payoffs once individuals start to cooperate:

$$(i+1)c_i + (n-i-1)d_{i+1} > ic_{i-1} + (n-i)d_i, \tag{4}$$

$$c_{n-1} > d_0, \tag{5}$$

Yao and Darwen [20] presented a model for INPPD that meets all three conditions. The representation of the data for the matrix is shown in Table 1. The rows and columns show the number of cooperators and the individuals' choices, respectively. The numerical values represent and satisfy the three INPPD conditions outlined above.

3. Players' communication topologies

Cooperation may be seen in community and natural systems when selfless action is rewarded despite the risk of exclusion. On the other hand, individual health appears to be contentious in Darwinian natural selection theory. Evaluating the genesis and sustainability of prosocial behaviours between selfish individuals becomes difficult [21–25]. Human beings collaborate when they are organized in an unchanging network of social relationships if the following rigorous criterion is met: the advantage of collaboration must surpass the entire cost of collaborating with all neighbours. A fundamental issue in biological evolution, community, and science is understanding why cooperative behaviour originates and persists among unconnected selfish individuals. Specific behavioural features are examined using evolving game theory to tackle this problem.

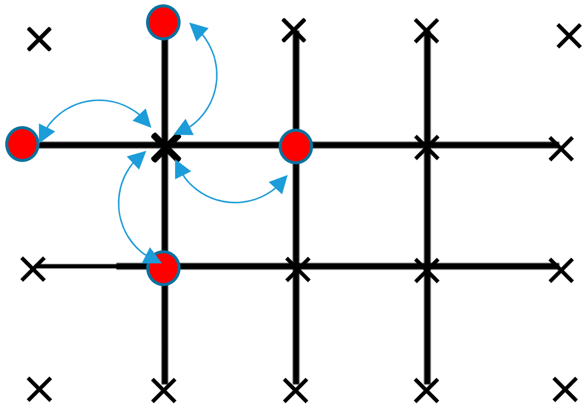

Figure 1. Representation of 20 players and neighbourhood communication over a game space.

Zhuang et al. [26] and Li et al. [27] investigate the evolutionary dynamics of a dilemma game on a network. The research primarily demonstrates that cooperative behaviour becomes the prevailing option when trust levels are above a specific threshold, allowing the network's whole community structure to be sustained. The prisoners' dilemma model depicts the social tension between self-interest and collaboration [28]. In the simplest form, if a particular system is not added to the community, the population faces a social dilemma in which defection dominates the system, and cooperation is abandoned.

The prisoners in the INPPD represent players in our game space. The interactions between the players depend on the neighbourhood topology of the game since it determines the individuals who play against each other [29,30]. Figure 1 illustrates the game space of 20 players, where the main player has several neighbours (denoted in red). The players can only interact with players who are within specific pre-defined neighbouring levels. Several studies indicate that this section of the research focuses on the static neighbourhood topologies' content.

Wu et al. [31] demonstrated the significance of community structure in the game. The researchers emphasize the importance of community structure for improving cooperation in spatial prisoner's dilemma games. Their findings show that the impact of spatial structure varies in terms of increasing cooperation depending on the game's dynamics.

Ye and Fan [32] applied a Particle Swarm Optimization (PSO) algorithm to the social dilemma and investigated the influence of PSO on the evolutionary passenger's dilemma game using a continual version. In the model, each individual changes their strategy based on two criteria: the most lucrative strategy in the past and the replication of the best strategy now available in the community. The simulation results showed that the suggested learning technique substantially enhances the development and perpetuation of cooperation. Furthermore, the PSO has a significant impact on interactions. Whenever the motivation is minimal, social contact aids high-value claims in the system, resulting in population variety over a wide strategy interval. The variance magnitude of strategy updating is represented by the velocity in this paradigm. However, the authors observed that this way of upgrading improves the network at the price of community turmoil and collapse. He et al. [28] suggested a novel trust management method based on game theory and a node-level penalty system to encourage social cooperation, while Pei et al. [33] investigated the motivational processes of collaboration. Under the effect of other-centered desires, actors are prepared to forego their benefit. This implies that trust is crucial since key data spreads more rapidly and efficiently on networks with a high trust rating.

Dong et al. [34] examined the influence of four common second-order reputation evaluation models on a 3D PD game. Using systematic Monte Carlo simulations, researchers show that the model's parameters encourage cooperating beyond geographic reciprocity in the examined prisoner's dilemma game and that the greater the reputation step size, the greater the collaboration. Chu et al. [35] argue that popularity and strategy evolve in lockstep and investigate how this setting influences the development of cooperation in structured populations. The authors used simulation to discover that this technique allows cooperation to survive. The finding improves our comprehension of cooperation in social systems. In addition, introducing popular selection based on heterogeneity can help ensure the long-term viability of collaboration. Players choose to mimic more popular neighbours as the vertex weight heterogeneity increases, leading to the development of cooperation.

Fu et al. [36] present a compensation system based on prior loyalty, in which a person who follows the cooperation strategy for a long time receives a bonus. As a result, surrounding defectors contribute equally to the incentive for a loyal cooperator. The findings of the PD game reveal that by setting adequate loyalty barriers and incentive variables, the amount of cooperation may be significantly increased. The spatial variation of collaborators and defectors and the temporal history of cooperator concentration are also investigated. In the spatial public goods game, the authors discovered that prior loyalty could enhance cooperation. Incentives based on past loyalty, as opposed to no incentives, are more favourable to establishing and developing large cooperative clusters. The evolution of cooperators' density and the changes in average payoff and health are investigated in a microscopic viewpoint to confirm the aforementioned result.

Guo et al. [37] investigated the influence of network topology on the development of cooperation using the PD game. The simulation findings suggest that network structure entropy is a critical factor in network collaboration and may accurately explain network influence on cooperation. The findings reveal that overall network entropy plays a common role in the networks' cooperation. The network structure entropy follows the evolution of the cooperator density in the PDG–DT model and exhibits an opposing evolution tendency when the starting network structure entropy increases. The network structure entropy is shown to be a significant aspect of the network evolutionary game and may be used to describe the effect of network structure on cooperation.

Griffin et al. [21] developed a model for strategic emulation in an arbitrary network of interacting players. The study illustrates a condition whereby the resultant difference equations progress to consensus via a discrete-time update. A simplified model for the transmission of trends or informational cascades in (e.g. interpersonal) networks is created using a variant of the model. Researchers show that when topological modifications are permitted in the graph structure of the extended PD game, the graph unites to a collection of unconnected groups and is mutually stable.

Wang et al. [38] proposed a preferential selection process in which players are more inclined to understand their contributing peers. The reciprocated incentive is continuously changed based on the adaptive link optimizing parameters and the desired intensity. Simulation experiments show that the suggested incentive system boosts cooperative development significantly. According to the findings, the reciprocated reinforcing mechanism considerably encourages the emergence of interaction. In addition, the adaptive modification of linkage weight and preferences impact factor promote collaboration.

Lee et al. [39] investigated an adaptable network of player pairs that coevolve while players try to maximize their gain in the Prisoner's Dilemma game. Researchers employed a node-based strategy model in which each player follows a single strategy with its neighbours, modifying that strategy and perhaps changing partners in reaction to perceived modifications in the network of player pairings and linked partners' strategies. The authors demonstrated that increasing the additional incentive facilitates cooperative behaviour by establishing large clusters for low defecting temptation. The suggested technique was implemented in a typical PD game with an undertaking in which players can select one of three strategies in every round of the game: collaboration, defection, or voluntary involvement. When considering self-interaction, the proportion of cooperative actions is significantly aided by constructing tight clusters, increasing the additional reward for low levels of defection temptation. As a result, self-interaction is critical in the evolution of cooperation.

Locodi and O'Riordan [40] proposed a topology for spatial evolutionary game theory that enables resilient cooperation; the standard PD is used as an interaction model. The authors discovered that the graph's size might be grown forever, making it more resilient as it grows. They provide a demonstration of this characteristic as well as the relevant graph restrictions. In addition, given the typical game payoffs, they identify the shortest graph with this characteristic.

Sinha et al. [41] presented the concept of cooperator and defector graphs and a novel type of game reward that is minimally affected by the fundamental network architecture. The authors show that with such a modest reliance, the core gameplay dynamics and the game's essence may be altered. If early cooperation is substantial, cooperation will most likely become the population's dominating approach. Additionally, the concept of topology-dependent payoffs is relevant for all network games, not only the prisoner's dilemma instance addressed here. Fluctuating habitats are those in which spatial and temporal variability contributes significantly to the evolutionary dynamics. Stojkoski et al. [42] expanded these findings by conducting systematic research on the dynamics of cooperation in changing settings with structured, diverse populations and individual entities bound to broad behavioural principles. They concluded that, in the face of environmental variations, cooperative dynamics might result in the formation of numerous network components, each of which has evolutionary features. The researchers also discovered that environmental fluctuations cause evolutionary behaviour, which might result in the formation of components. Furthermore, the authors showed that state-based generalized reciprocity improves the development of cooperation in volatile contexts by incorporating a simple behavioural updating criterion.

Wang and Du [43] looked at an asymmetrical situation in which the number of interacting neighbours for specific individuals differs significantly, resulting in a PD model with an optimum selection method. They discovered that when the proportion of the population is increased to a larger value, collaboration is improved substantially. They further demonstrate that microscopic events influence the outcomes. They discovered that when V increases, the influence of network reciprocity in the structure population becomes stronger. In the development of cooperative behaviour, the addition of eight replacement neighbours to the optimum selection model is critical. Szolnoki and Perc [44] proposed a strategy-neutral variation of the classic model in which the beneficial impact on evolutionary outcomes is not obvious. The authors proposed a relatively modest adjustment to the standard model, considering the possibility of a more cautious learner player who does not readily accept information about the model player. Regardless of the source, the population whose participants place a higher value on averaged information concerning the effectiveness of an alternative approach can achieve a higher level of cooperation – the greater the weight of this new knowledge in decision-making, the greater the potential for improvement.

Wang et al. [45] examined the impact of a trust-driven updating rule based on reputation in PD games on random networks. The findings reveal that when people renew their policies using this trust-based updating rule, their degree of cooperation increases considerably. The amount of collaboration improves when the heterogeneity parameter is increased. Furthermore, the authors investigate the impact of the association between node degree and reputation heterogeneity on cooperation resulting from individual effects. The simulation findings show that collaboration increases dramatically when people change their policies using this trust-driven updating mechanism. The simulations have proven that mimicking contributing players can help people cooperate.

In the following sub-sections, we introduce the well-known neighbourhood strategies used to develop cooperative behaviour among INPPD players.

3.1. Ring communication topology

The ring topology involves players' connection to their immediate neighbours in a one-dimensional space; therefore, the players can only interact with two neighbours. Due to the small size of these structures, players may be less cooperative since the player's knowledge is restricted to its neighbours. The emergence of cooperative behaviour among the players increases after n number of games for a population of n players. Experiencing the games may encourage the players with low payoff gains to alter their behaviour and cooperate. The ring topology has narrower levels for the INPPD players to experience.

3.2. Star communication topology

Star topology has a different structure since it allows all players to interact within the game. This structure primarily aims to help the players share the best experiences among the entire player population. The neighbourhood used by the players is the entire population. Using a star topology results in information moving among all players, and the majority of the group will display a tendency towards superior behaviour [46].

Star topology increases the efficiency of the game, especially among small populations. However, this type of topography requires processing a considerable amount of information, which poses a challenge. The exchange of large amounts of information among numerous players constitutes an additional issue.

3.3. Von Neumann communication topology

Von Neumann's topology has a different structure that entails another dimension while searching for algorithms that extend the neighbourhood structure. This topography allows the players to interact with the immediate four players surrounding them. This structure helps solve optimization challenges. Most studies indicate that von Neumann topologies are the most efficient among all neighbourhood topologies [47].

Bo and Sichman [48] proposed an INPPD model that utilizes the von Neumann topology as the primary form of communication between the layers. The cells at the edge of the lattice also have a neighbour on the opposite side of the lattice. Selection of the interacting player occurs randomly or sequentially.

3.4. Cluster communication topology

The cluster topology involves dividing the players into n number of groups. Each cluster can communicate with the other clusters. Specifically, each cluster has a diverse number of connections equal to the number of neighbouring clusters. The cluster topology typically features three or four different clusters. Although the players can interact through the connection, few inter-cluster connections exist among the individuals. O'Riordan and Sorensen [49] presented an INPPD model that displays a high degree of community structure, ensuring that the players insulate themselves from the defectors. The community structure involves the clustering process since a collection of nodes occurs in knit groups and thus features loose connections. Individuals from the other communities update their behaviour to match those of the neighbouring players. This study demonstrates that cooperation can spread through society (Li and O'Riordan 2013).

3.5. Random communication topology

If there are n players in a game, then there exist n random symmetrical connections between the individuals; hence, the links ensure that the players interact randomly. Moreover, the structure's lattice provides each player with immediate neighbours.

Chiong and Kirley [50] analyzed the effectiveness of co-evolutionary learning in neighbourhoods with both fixed and random structures. The randomly structured neighbourhoods present inner and outer structures. In this type of structure, the inner neighbourhood refers to a set of group members with eight immediate players. Conversely, the outer neighbourhood involves the selection of players from everywhere across the population.

Huang et al. [14] conducted a study to determine the impact of the ratio and strengths of the diverse connections on the players' behaviours. The researchers used this concept to model real-life circumstances. The study focuses on the importance of behavioural evolution in the evacuation process needing proper guidance for smaller groups. The authors also concentrate on the concept of the prisoner's dilemma, which shows that the group of players may be spread in different locations of the same building. The study's findings indicate that the topology supporting interconnected networks increases the likelihood of cooperation compared to the single regular lattice.

Schimit et al. [51] tried to use the games' strategies in a multi-agent context. In the study, the agents play two-player groups with the individuals depending on neighbours in cellular automata. The study's findings suggest that immediate punishments do not increase the players' level of cooperation. The researchers also established that the notion of tit-for-tat did not promote collaboration among the populations in the experiments.

This section concludes that choosing a suitable topography depends on the size of the game space and the number of individuals participating in each tournament. In the next section, we introduce an alternative neighbourhood topology that facilitates communication among large populations.

4. Local-Universal neighbourhood topology

This section provides information about an alternative neighbourhood topology relying on two levels: LVL1 and LVL2. LVL1 involves all the players in a given local community, and they must play against each other. Equation (6) illustrates the interaction of players within the same community for these local interaction levels:

$$P_i \in Li_{community} (\text{for } i = 2, \ldots n), \tag{6}$$

where P_i and $Li_{community}$ represent a given player and their local community, respectively.

The local-level interactions provide enough communication channels, facilitating effective communication among the community members. Individuals can play r number of games, which affects the behaviours of the same players within the same community. Such interactions encourage cooperation among the players. Figure 2 shows the interactions between one INPPD player and their four neighbours, represented in black and red, respectively. The arrows illustrate the tie communication lines between the members.

Restricting the player's interactions within a specific community to encourage cooperative behaviour can be beneficial. However, some communities lack the experience to evolve and become cooperative societies. Therefore, adding another communication channel between these communities is necessary.

Players can share information about the best players in their community with players in other communities. The linking of different communities makes the game more interesting since the players can share diverse experiences. LVL2 involves universal interactions and occurs by linking the various communities in a topography.

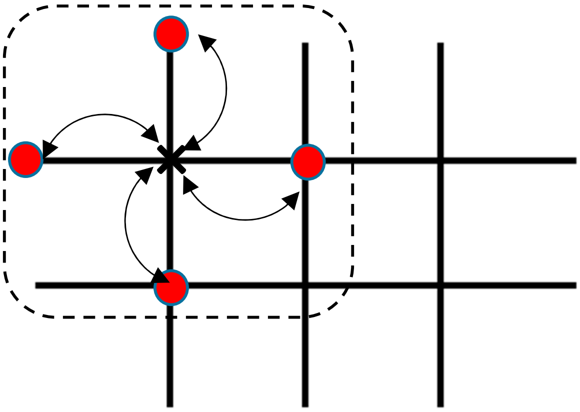

Figure 2. Local-level interactions in a community of five players.

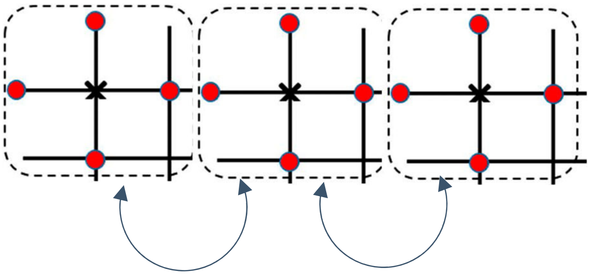

Figure 3. Universal-level interactions across three communities of five players.

The structure groups seven individuals in a set $S = P_1, P_7$ for each game, containing the main player. $S_1 \subset L_1$ and $S_2 \subset L_2$ represent four and two players, respectively. $P_i \in S$ is the main player, who is interacting with six players: four immediate players from S_1 and two other players from the universal set S_2. The corresponding algorithm is presented in Equation (7):

$$\text{Gamer}: \; Pi \leftrightharpoons [P_j \in S_1 \cup S_2], \tag{7}$$

where $i \neq j$ and $\leftrightharpoons$ illustrates the interaction between the players. Figure 3 below shows the universal level of interactions in a community of five players. The squares in the figure represent the communities within the whole population.

This new topology model allows the players to consider the behaviour of the other individuals in the community before choosing their moves. This affects the behaviours of the player in the other communities (C), as shown in Equation (8):

$$P_i \in C_{i-1} \cup P_j \in C_i \cup P_z \in C_{i+1}, \tag{8}$$

Figure 4 illustrates the connections between the players in the community and the integration with a neighbouring community.

The payoff matrix in Table 1 shows that the player who chooses to defect does not achieve payoffs as high as those achieved by players who cooperate. On the other hand, this new *local-universal* topology allows the defecting players to learn from the other communities.

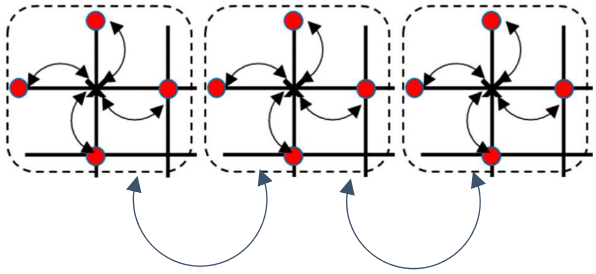

Figure 4. *Local-universal* neighbourhood topology.

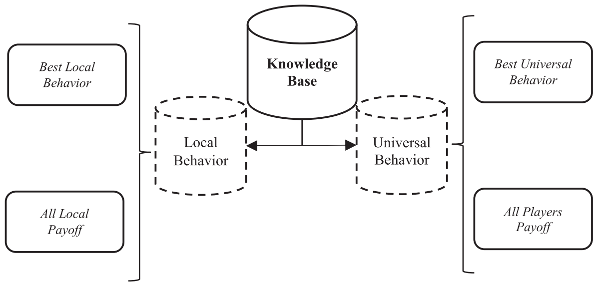

Figure 5. Structural design of the knowledge base.

Therefore, after several games, an evolving cooperative pattern may emerge among the previously defecting individuals.

Our proposed topological structure ensures that INPPD maintains the following specific properties:

(i) The evolving cooperative behaviour among the players in INPPD is facilitated by improved communication and better local interactions.

(ii) The evolving cooperation also occurs through sharing experiences among diverse communities, representing universal interaction and communication.

Therefore, an individual in a tournament of m games needs a knowledge base to track the players' behaviours both at the local and universal levels. Analyzing and predicting other players' moves significantly determines a player's payoffs. Using a knowledge base, players can gather data and knowledge about the players in their communities and those at the universal level. The designs for the supportive knowledge systems are described in Figure 5.

The knowledge base is divided into two sub-bases performing local and universal tracking. The first sub-base (local tracking) tracks the moves chosen by the participants in a community. In addition, the knowledge base identifies neighbours with the highest payoffs and records their highest-paying moves during the game. Tracking neighbours' moves facilitates the players' decision-making process as they can opt to align with the dominant behaviour among players. All players learn from their interactions with other players

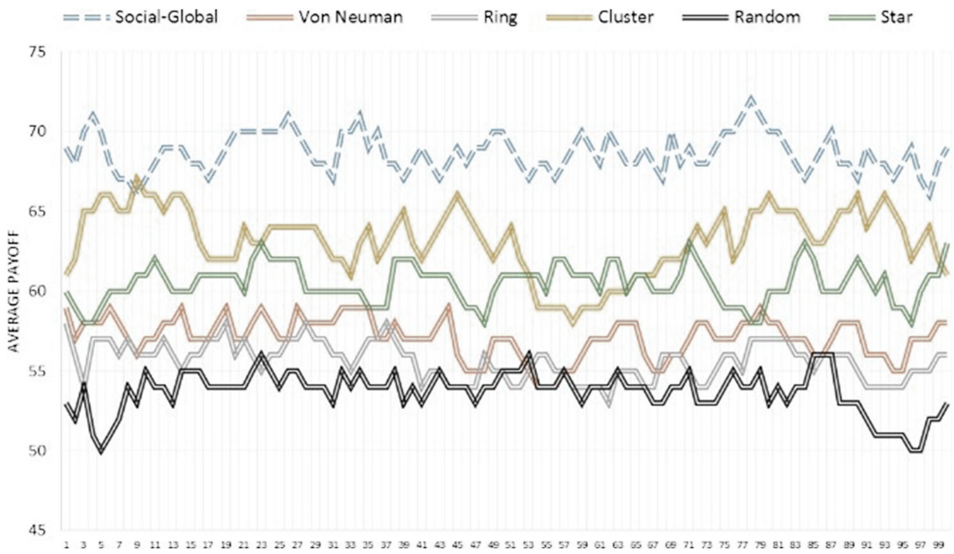

Figure 6. Average payoffs in INPPD societies while relying on diverse topologies in tournament 4.

in the tournament. The learning process allows players to adapt their behaviours and achieve better outcomes. This results in the development of cooperative behaviour within a community.

The second sub-base (universal tracking) is responsible for tracking each player's moves in the INPPD. This model tracks the moves resulting in the highest payoffs among the universal players and stores them. Using the universal tracking sub-base, players with lower payoffs can evolve their behaviours and become cooperative to match the behaviours of the other individuals in the population.

5. Performance tests and analysis

This section describes the comprehensive tests and analyses conducted to measure the performance of our proposed *local-universal* topology of players in the INPPD game. We based our evaluation on three primary factors: the ratio of cooperation among players, the average payoffs achieved by players while competing at the local and universal levels, and the best cooperative moves that the players make. These factors were selected because they are directly related to the cooperative behaviour conditions specified by Franken and Engelbrecht [52]. Our experiment was composed of four tournaments, each of which consisted of 1000 games. The population size for each of the four tournaments was 10, 30, 50, and 100 players, respectively. The experiment was implemented in a Java environment installed on a Lenovo machine with Intel Core i7®, 6 GB RAM, 500 GB HDD, 128 GB SSD, and Microsoft Windows 10 as the operating system.

The *local-universal* topology was tested against the Von Neumann, cluster, ring, star, and random neighbourhood topologies. The findings, presented in Figure 6, illustrate the average payoff achieved by players in INPPD. The players were grouped in communities and utilized different topologies in the first, second, third, and fourth tournaments, and each group utilized a different topology in each of the four tournaments. High payoffs in a game clearly indicate that the game provides effective neighbourhood interactions, allowing players to share experiences and information. The ability of the players to interact with each other effectively allows the players to choose the best course of action.

The average payoff of each player in a tournament was computed by summing the payoff of each move (C or D) taken by the player in one tournament and dividing by the total number of games in the tournament (i.e. 1000), as formulated in Equation (9), where g denotes the total number of games in a given tournament:

$$Avg.\,payoff = \frac{\sum_1^g payoff\,(move)}{g} \tag{9}$$

The maximum payoff that players can achieve in a game is reached when all the players within a community choose to cooperate. For instance, within a cooperative community of seven, each player can achieve $2(n-1) = 2(7-1) = 12$ points. Hence, if the whole community cooperates, all seven players can achieve $12 \times 7 = 84$ points together.

Our results, shown in Figure 6, indicate that the *local-universal* topology performs significantly better than the other topologies in tournaments with a larger population. In addition, the *local-universal* topology can achieve higher payoffs than other topographies for the same population size. Our topology also shows better performance with an increase in the size of the INPPD. Interaction and communication among players improve, and players can evaluate the data before making any decisions when the INPPD size increases; this results in higher payoffs. Our *local–universal* topology resulted in well-connected community members

Table 2. Descriptive statistics of six topologies.

	Mean	Std. dev.	Std. err.	95% conf. interval for mean Lower	Upper
Local-universal	47.38	4.941	.899	46.55	50.29
Von Neumann	38.99	7.988	1.460	35.03	43.11
Ring	38.85	5.449	.993	35.19	42.49
Star	40.04	1.977	.359	36.17	43.88
Random	38.22	3.551	.570	34.54	41.53
Cluster	41.31	6.321	.659	37.87	44.11

Table 3. one-way ANOVA tests for the payoff performance for the various topologies

	Sum of squares	*df*	Mean square	*F*	*p*-value
Between groups	1,838.399	5	369.879	11.599	.000
Within groups	5,536.998	173	31.819		
Total	7,385.979	178			

who interacted with the other communities in the population.

Statistical significance tests were carried out to identify the topology achieving the best results. Table 2 below shows the descriptive statistics of the six topologies. The study findings indicate that the *local–universal* topology's mean value is the highest compared to the rest. Results also show a 95% confidence interval for the means for all six tests. The 95% confidence interval of our group is 46.55, 50.29. The upper bounds of the means' 95% confidence interval are lower for the other five groups of tests. Therefore, in 95% of cases, the *local-universal* topology's mean value is higher than the mean value for the other topologies.

The Analysis of Variance (ANOVA) tests were conducted to measure the effectiveness of the *local-universal* topology against other topologies. The results show that our topology achieves higher mean averages than the other topologies. The null hypothesis assumes that the mean for all topologies is equal, while the alternative hypothesis assumes that all topologies are not equal. The results, shown in Table 3, reveal that the null hypothesis is invalid as the *p*-value is 0.000. Therefore, the mean of the *local-universal* topology is higher than that of the other topologies. This study relies on post hoc tests to prove the hypothesis.

Table 4 shows the 95% confidence interval of the differences between all the topologies. Our findings further indicate that the differences between the groups are positive. Hence, we conclude that the sample mean for the *local-universal* topology is significantly higher than for the other topologies. In our experiment, we also examined the average number of cooperative moves taken by all INPPD players as a testing factor for the effectiveness of the topology. This test assesses the evolution of cooperative behaviour between players. Figures 7–10 plot the average number of cooperation moves taken by all players in tournaments 1, 2, 3, and 4.

Table 4. Post hoc tests for the player performance using various topologies

(I) Group	(J) Group	Mean diff. (I-J)	sig.	95% conf. interval Lower	Upper
Local-universal	Von Neumann	9.35	.000	6.21	12.49
	Ring	9.60	.000	8.22	10.98
	Star	8.43	.001	6.55	10.31
	Random	10.36	.000	9.64	11.12
	Cluster	7.42	.001	4.69	10.11
Von Neumann	**Local-universal**	−9.37	.000	−12.51	−6.21
	Ring	.25	.325	−1.82	2.35
	Star	−.91	.199	−.13	1.97
	Random	1.00	.224	−.33	2.35
	Cluster	−1.93	.161	−5.53	1.64
Ring	**Local-universal**	−9.61	.000	−10.98	−8.24
	Von Neumann	−.26	.325	−2.34	1.83
	Star	−1.18	.421	−5.62	3.26
	Random	.75	.514	−.47	1.98
	Cluster	−2.20	.358	−6.61	2.22
Star	**Local-universal**	−8.43	.001	−10.31	−6.56
	Von Neumann	.91	.199	−1.97	.131
	Ring	1.17	.421	−3.24	5.60
	Random	1.92	.887	−1.6	5.35
	Cluster	−1.01	.578	−6.28	4.24
Random	**Local-universal**	−10.36	.000	−11.12	−9.59
	Von Neumann	−1.00	.224	−2.35	.339
	Ring	−.74	.514	−1.97	.479
	Star	−1.92	.887	−5.34	1.49
	Cluster	−2.94	.327	−10.28	4.37
Cluster	**Local-universal**	−7.41	.001	−10.11	−4.70
	Von Neumann	1.93	.161	−1.65	5.449
	Ring	2.21	.358	−2.21	6.61
	Star	1.01	.578	−4.24	6.26
	Random	2.94	.327	−4.37	10.24

The results indicate that our *local-universal* topology can promote the evolution of cooperative behaviour among INPPD players for diverse population sizes. However, as the topology sizes increase, other individuals become demotivated and abandon cooperative behaviours. The results further indicate that the gap between the *local-universal* topology and the other topologies increases with the population sizes. The efficiency ratio of the *local-universal* topology against other topologies was calculated; the results show that the *local-universal* topology is more efficient than other topologies in tournaments, as seen in (Table 5).

Franken and Engelbrecht [52] identified specific conditions demonstrating that the population is reaching cooperative behaviour during a game. The first condition states that a specific player with the largest payoffs has achieved a total number of cooperation moves ten times higher than the population size. The second condition states that the whole population must have reached an average total number of cooperative moves ten times higher than the population size.

To evaluate the ability of the *local-universal* topology to meet the requirements of the first condition, the behaviours of the best players in the population are analyzed for each tournament. Figure 11 presents the number of cooperative moves made by the best players in the first 2000 games for tournaments 1, 2, 3, and 4.

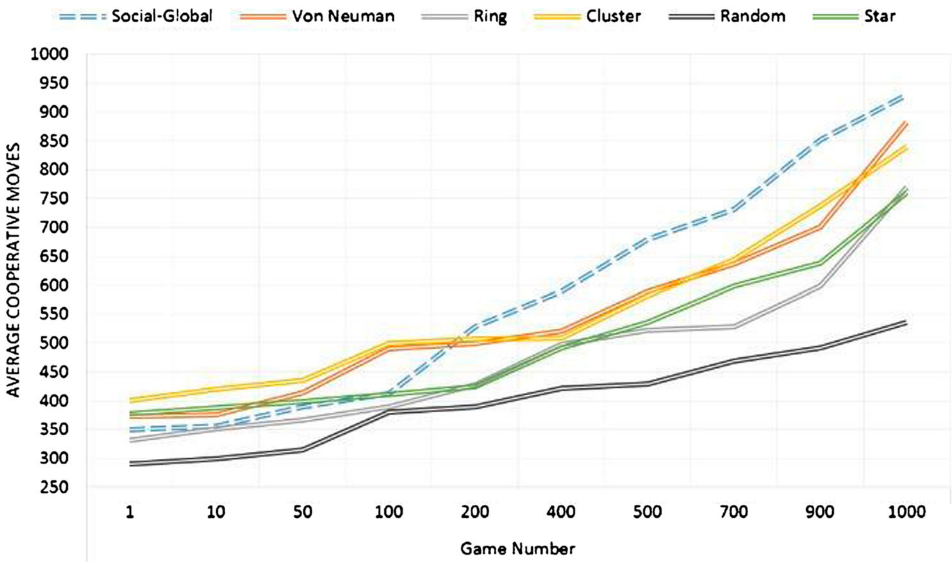

Figure 7. Average cooperative moves taken by INPPD players in the first tournament.

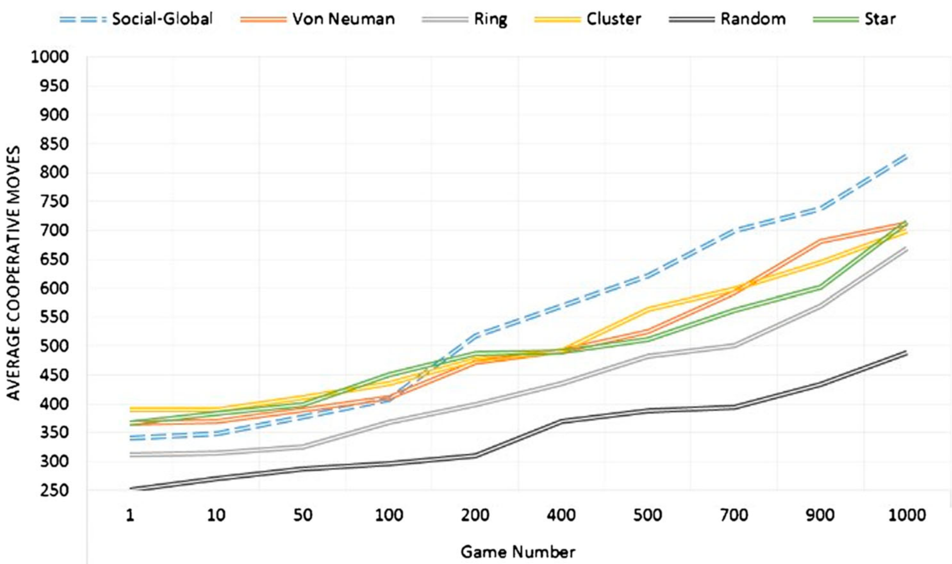

Figure 8. Average cooperative moves taken by INPPD players in the second tournament.

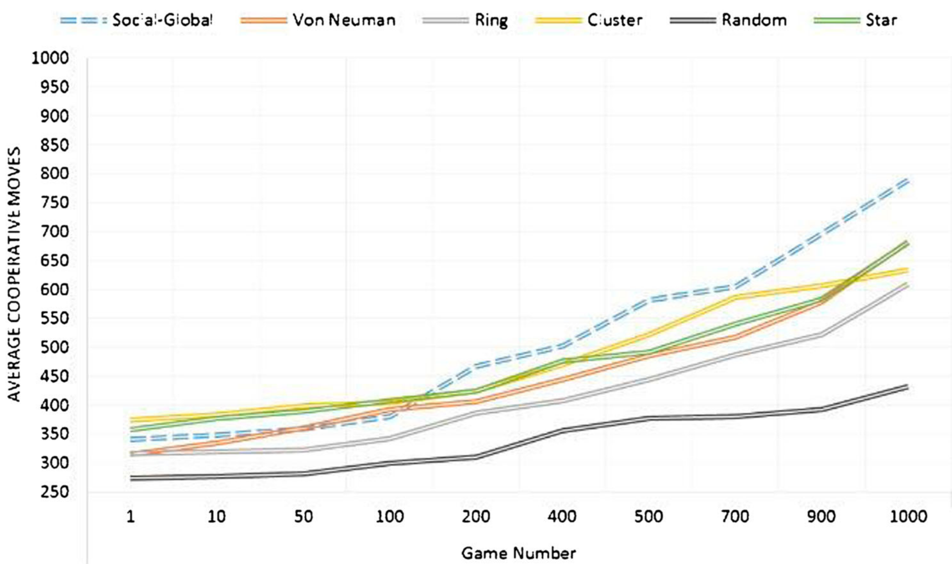

Figure 9. Average cooperative moves taken by INPPD players in the third tournament.

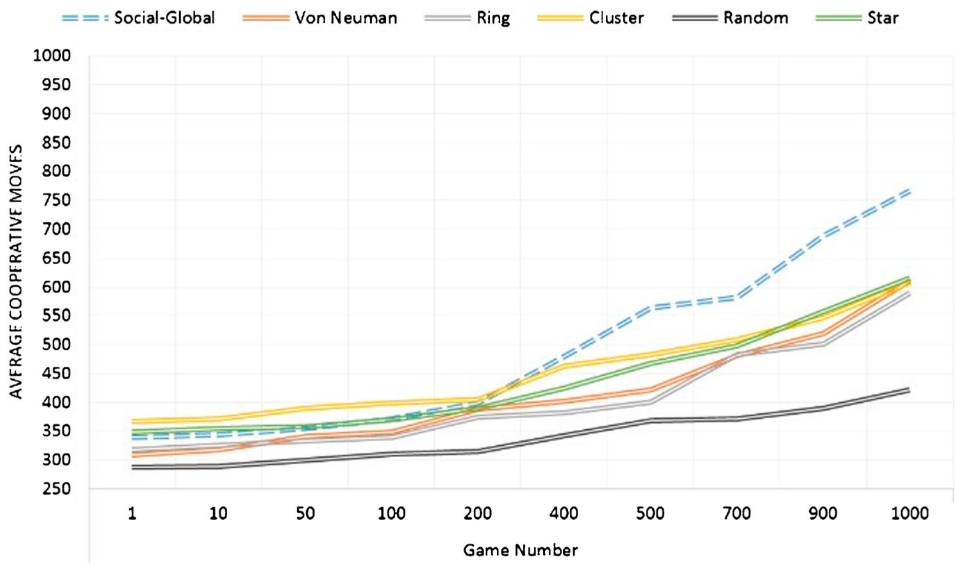

Figure 10. Average cooperative moves taken by INPPD players in the fourth tournament.

Table 5. Efficiency ratio of the local-universal topology against other topologies.

	Local-universal (tourn.1) (%)	Local-universal (tourn.2) (%)	Local-universal (tourn.3) (%)	Local-universal (tourn.4) (%)
Von Neumann	+10.4	+11.5	+11.6	+12.7
Ring	+12.1	+12.3	+13.1	+13.2
Cluster	+11.0	+11.7	+12.5	+12.7
Random	+15.6	+17.1	+18.3	+18.1
Star	+12.3	+11.7	+11.6	+12.4

The full lines represent ten times the population size for each tournament.

Figure 11 shows whether INPPD with various population sizes could meet the requirements of the first condition. Meeting this condition requires that the best player of each population make a number of cooperative moves exceeding ten times the population size for each tournament. The best player for an INPPD size of 100 made a number of cooperative moves of approximately 9.5 times the population size. Therefore, the first condition is not met with a population size of 100. This failure is likely related to the challenge of motivating players to be fully cooperative in a large population composed of rational players. On the other hand, when dealing with players in smaller population sizes, the best players tend to show full cooperation after 1300 games or less.

To meet the second condition outlined above, each player participating in the game must make ten times as many cooperative moves as there are individuals in the

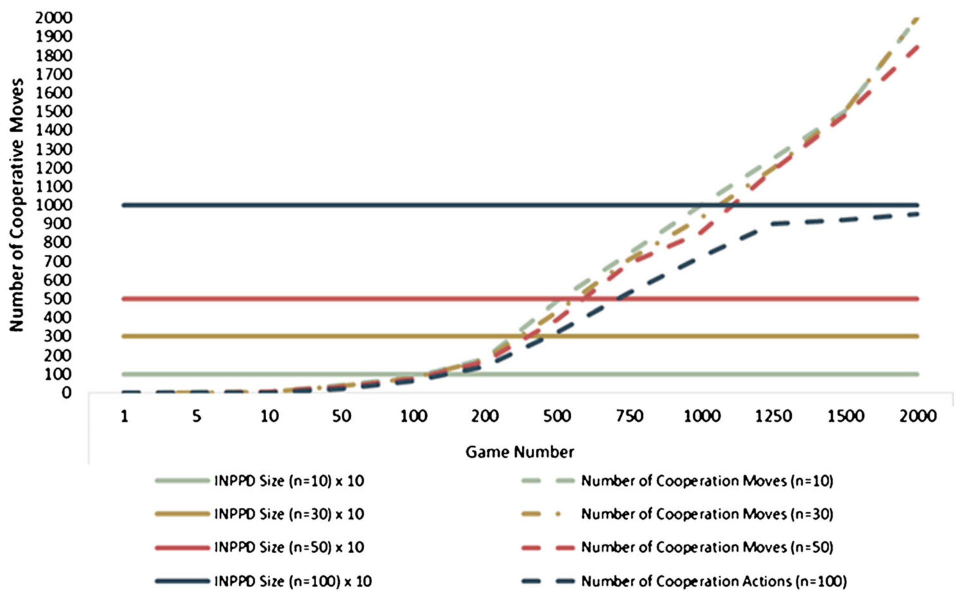

Figure 11. Population's behaviour in terms of the number of cooperative moves made by the best players.

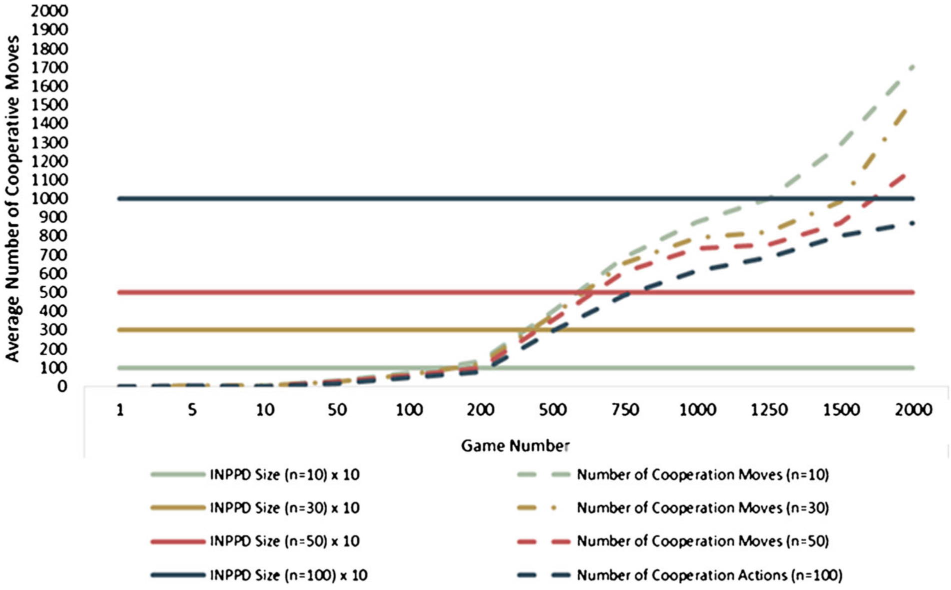

Figure 12. Population's behaviour in terms of the average number of cooperative moves made by each player.

population. The results, presented in Figure 12, indicate that *local-universal* topology helped the players develop cooperative behaviour.

The *local-universal* topology is effective in promoting the evolution of INPPD players' cooperative behaviour in all tournaments, except for the last tournament with a population of size 100. Furthermore, the findings indicate that the evolution of cooperative behaviour among the large population is non-trivial. Indeed, our topology succeeds in evolving cooperative behaviour among INPPD players to become nine times the population size.

As evidenced by the positive statistical analysis results, the *local-universal* topology achieved a high level of success, which primarily stems from its internal structure. Furthermore, the *local-universal* topology allows players to share their experience with other individuals from different communities. The high level of communication among diverse communities and the use of the knowledge base as a repository for previously taken moves helps reduce the number of defectors and increase the chances of evolving cooperation.

6. Conclusion

This study aims to establish the significance of communication in influencing the results from players within a population's structure. We first noted that the interactions between players are critical and may depend on the other players' performance. Although multiple studies assumed fixed positions for players in one community, this study provides an alternate model that facilitates local and universal interactions.

This paper presents a *local-universal* topology that contributes to the evolution of cooperative behaviour among INPPD players. Our research focuses on this topology because of its ability to facilitate the effective exchange of information between diverse players. The model design relies on establishing tight connections within the community and developing links to diverse societies globally. In addition, the players are supported by gaining access to a knowledge base that helps them learn from their own past experiences and that of other players in their local and universal communities.

We first tested the ability of our model to evolve cooperative behaviour, before comparing our model with other topologies. The findings of this study indicate that the *local-universal* topology can increase the development of cooperative behaviour among players. For example, the *local-universal* method is more effective in evolving cooperative behaviour among INPPD players by up to 17.3% against other topologies. Future research may focus on the impact of specific players' strategies in evolving cooperative behaviours using different communication topologies.

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No potential conflict of interest was reported by the author(s).

ORCID

Khaled Suwais http://orcid.org/0000-0001-6530-5022

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