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Price of Anarchy and Price of Stability Mapping for Analyzing Topology Design of Communication Networks

Kanmani S. and M. Murali

Department of Computer Science and Engineering, SRM Institute of Science and Technology, India

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Corresponding Author:
Kanmani S.
Department of Computer Science and Engineering, SRM Institute of Science and Technology, India
Email: kanmanis@srmist.edu.in

Abstract: The goal of game theory is to model actions among players or users in a common space who deal with various situations and face various outcomes. The study of game theory is widely applied to a wide range of economic fields, including auctions, renewable energy, wireless sensor networks, and software defined networks. Resource allocation and cooperation between networks or terminals are important in the field of game theory networking. In order to infer concrete solutions for the players, game formulas are used. A solution is determined by classifying players and calculating the Price of Anarchy (PoA) and Price of Stability (PoS) in order to determine Nash equilibrium and evaluate efficiency. Using the Open Systems Interconnection (OSI) layer as a lens, this study examines a variety of applications of game theory in non-cooperative environments and communication systems. This study focuses on the 'presence of governing' or participation nodes in a set of players in a network. Also, a comparison of different research fields in game theory is made.

Keywords: Nash Equilibrium, Game Theory, PoA and PoS, OSI Layers, Optimization Models

Introduction

The concept of game theory (Nahir *et al*., 2013) encompasses the set of capabilities and opportunities involved in strategic decision making. It is a mathematical theory of strategic interactions among self-interested components. In game theory, the strategic interactions are modeled and associated with a set of feasible solution concepts that attempts to find out the rational output of the game. The concepts of machine intelligence have been widely applied in games as it constitutes a set of finite and organized tasks that can be explored with minimal information (Nahir *et al*., 2013). The modeling and solution concept of game theory is one of the appropriate frameworks used in modeling systems in the area of Computer Science (CS). In the context of networks, the concept of game theory serves as a tool for developing a cooperative dependency scheme for terminals, service providers, and nodes (Correia and Stoof, 2019). In addition, game theory models like the non-cooperative model have been widely used in modeling and analyzing routing and resource allocation problems (Felegyhazi *et al*., 2006). Designing dynamic communication networks requires taking into account factors such as wait time, cost, traffic, data rate, and the number of nodes. In some cases, nodes may refuse to cooperate while attempting to establish communication (Fang *et al*., 2017). Using predefined optimization parameters, computer network topology architecture seeks to find the best configuration for a network. The topology should be designed taking into account the cost, delay, and congestion of path establishment in an environment with non-cooperating nodes (Fischer *et al*., 2014).

In network development, the first design consideration is the cost of establishing a link. The consideration of directional links as well as the allowance of link costs with varying values across the network influences the cost of establishing a link (Demaine *et al*., 2012; Salehisadaghiani and Pavel, 2017). The link establishment cost should be analyzed at a single point during the network development phase before considering trade-offs and delays. Connection establishment differs from one graph topology to another. In networks, nodes are represented by various organizations, which determine the cost of establishing a link across the topology.

The subsequent consideration in network design is the path delay. The hop count can be easily determined after calculating the routing paths (Michalopoulou and Mähönen, 2012). Calculated by adding the no. of hops a unique node takes to reach its target, path delay is an indication of the amount of time taken for the path to be formed. A modification of Folk's theorem can improve the aspect of computer hop counting with the survival of Nash

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equilibrium in non-cooperative surroundings (Salehisadaghiani and Pavel, 2014).

Path congestion also known as the relying extent is the third design consideration in network development. High relaying volume is when a special node is utilized as communicated by a large no. of nodes. This results in an enormous increase in the level of traffic on the relay node (Demaine *et al*., 2012). This results in reduced bandwidth allocation and enhances packet loss. Most games are selected based on their type and application functions, rather than using a specific type for each situation. Noncooperative games are particularly suitable for developing the thought of broadcasting size in games of choice, where players make their own decisions.

By combining the design considerations, it is clear that the main aim of this study is the 'existence of governing' within a set of players or participating nodes in a network. This leads to the goal of stating that the calculation of the PoA is a major concern concerning competing players or nodes that are in equilibrium among all players. Eventually, the Price of Anarchy (PoA) is defined as the ratio of the worst equilibrium to the optimal solution in the present system, and the Price of Stability (PoS) is defined as the ratio of the best equilibrium to the optimal solution in the present system. Game theory is modeled to find the selfish nodes in a dynamic communication network. So, for this approach, a game is modeled as follows, $G = \{N, A, S_i, U\}$ where:

- $N = \{N_1, N_2 \dots\dots\dots N_n\}$ represents the number of players. In this study, nodes are considered players
- $A = \{A_1, A_2 \dots\dots\dots A_n\}$ represents the set of actions. In this study, it can be considered as an available resource such as maximum power to forward the data packet
- S_i represents a set of strategies for i^{th} player. In this study, two strategies are considered by each player that is the data packet is forwarded or not to be forwarded to the next node
- $U = \{U_1, U_2 \dots\dots\dots U_n\}$ represents the utility function or payoff of each player

Efficiency measure is defined with the welfare function denoted as $Welf: S \rightarrow \Re$. The welfare function is defined as $Welf\ (s) = \sum_{i \in N} U_i\ (s)$. The Price of Anarchy (PoA) is described as the ratio of the worst equilibrium to the optimal solution and is defined as follows:

$$POA = \frac{\text{Maximun } s \in S\ Welf\ (s)}{\text{Minimum } s \in E_{quill}\ Welf\ (s)}$$

- By the definition, $w.k.t$, $1 \leq$ Price of Stability $\leq$ Price of Anarchy

The PoA computation accurately depicts the behavior of network players or nodes. When a player or node behaves selfishly, the PoA parameter computation can be utilized to identify the pattern. As a result, we must compute the PoA or PoS for a networking environment in which nodes are expected to showcase their non-cooperative behavior.

The remaining sections are listed as pursues: Chapter 2 describes the general background of game theory, chapter 3 presents work related to this study, and chapter 4 analyses and discussed the results obtained by analyzing the state-of-the-art techniques presented in the literature. Lastly, chapter 5 concludes this study.

Game Theory

In a non-cooperative context, game theory application modeling is one of the difficult tasks that attracted a lot of concern from researchers in academia and industry. Many decision-making models use game theory as a method for developing candidate strategies for competing among players when the current approach fails to provide a desirable optimal solution (Durand *et al*., 2019). To achieve a desirable optimal solution, various game theory strategic models have been proposed in the literature. Networking principles such as flow control, bandwidth allocation, and routing (Banner and Orda, 2007) are embedded in current game theoretic models to underline the need for game theory and cooperation between networks (Martínez-Cánovas *et al*., 2016). Many authors have been studying the Nash equilibria (Nash Jr, 1950) of specific games to effectively address networking and resource allocation problems. Despite the improvements in performance achieved by several solutions, there exists a significant gap between these solutions and the optimum. From a networking perspective, topology design falls short of optimal solutions (Nahir *et al*., 2013). To achieve the required optimality in Nash equilibrium, the network game theoretic model must have a PoA and PoS.

In a game, there exists a predetermined group of players $P = \{1, 2, \dots\dots, p\}$ who choose a policy between $S = \{1, 2, \dots.., s\}$ anywhere utility u_i wants to be increased and $u_i\,(s)$: $S \rightarrow A$ is the utility function, where A denotes reply of players to the action of everybody. Payoff π_{ij} describes the payoff function assigned to player i for a particular action j (Romano and Pavel, 2019). Therefore, $G = (P, S_i, A, \pi_{ij})$ is the game model (G). Despite significant progress in game theory description, the time has come to reinvent the mapping between game theory and networks. The mapping network elements and game theory models are represented in Table 1.

Nash Equilibrium (NE)

NE in game theory describes a situation where the optimal result of a game has no incentive to deviate from the initial plan. In this case, the change in strategy of individual players does not unilaterally contribute to their profit or loss. To maximize their payoffs, players devise their equilibrium strategy.

Table 1: Mapping network elements with game theory model (Etesami and Başar, 2016)

Game element	Network element
Players'	Nodes, service providers, or customers
Strategies	An inference based on the player's actions with respect to network fields such as transfer, packet loss, new call, etc.
Actions	All types of actions performed by nodes to successfully communicate with network nodes
Payoffs	The utility functions u_i compute QoS metrics like throughput, propagation delay, etc.

As a result of a group of players choosing their strategies and one player alone changing them while the other players' strategies do not change, Nash equilibrium occurs as a result of the current strategy choices and payoffs (Dilkina *et al*., 2007). Nash equilibrium applications include prisoner's dilemma, traffic flow, currency crises, organizing auctions, penalty kicks in soccer, natural resource management, relegation challenges, marketing strategies, and many others (Zaw *et al*., 2020). A strategy is strictly dominated for a particular player *i*, if there exists $s_i' \in S_i$ such that:

$$u_i\left(s_i^{'}, s_{-i}\right) > u_i\left(s_i, s_{-i}\right) \forall s_{-i} \in S_{-i} \tag{1}$$

An individual player's strategy is called a strictly dominant strategy if, over time, he consistently receives the best results regardless of what his opponent does. In the case where several strategies are available with corresponding utility functions, the dominant strategy can be determined based on the utility functions of the player's previously pursued and current strategies.

To determine Nash equilibrium in a game, the various scenarios are modeled to achieve a set of results, and the optimal strategy is selected. To improve the Nash equilibrium determination process, an improved Nash equilibrium and level-k equilibrium are presented in frequent games (Das *et al*., 2019). Nash equilibrium reward profiles based on the concept of level-k equilibrium are proven to be Pareto optimality of a particular set of possible payout profiles. A minimum maximum reward profile is not required to calculate the Level K equilibrium. The outcome of a symmetric game is independent of the identity of the player (Chernov, 2019). Participants in evolutionary games are in the same position as they were when they first appeared, so they are approximately symmetrical. A minor perturbation cannot modify the genetic composition of a population in an evolutionarily stable state (Correia and Stoof, 2019; Etesami and Başar, 2016). Apart from the inherent conflict like random outcomes and artifacts in game dynamics, mutation, and crossover are also considered disturbances in the selection process. For the dynamic evolution game, the replication equation is expressed as an equation:

$$\dot{y}_i = y_i\,(u_i\,(y) - \bar{u}\,(y)) \tag{2}$$

where, $y = (y_1,\ldots\ldots,y_n)$ the distribution is a vector of the population and $i = 1, \ldots \ldots, n$, $u_i\,(y)$ is the fitness function or payoff of type *i* and $\bar{u}\,(y)$ is the mean population fitness:

$$\bar{u}\,(y) = \sum\nolimits_{j=1}^{n} y_j u_j\,(y) \tag{3}$$

In evolutionary stable states, scholars have made two contributions. The researchers first demonstrated that level-k equilibria are a general subset of Nash equilibria in continuous games that can be detected with symmetric players. As a second point, evolutionary steady states and continuous games cannot be analyzed using stability analysis.

Several important research areas in game theory are stability and optimization analysis. Cross layer optimization occurs in game theory for specific combinations of frameworks utilized to tackle troubles in the telecommunication area (Gadjov and Pavel, 2018). Layers cannot explicitly assign load control, network latency, or many other processes in OSI. Researchers have previously examined network structural operating points in game theory models Table 2.

Application Area in Hardware Layers of OSI

The Signal to Interference Noise Ratio (SINR) obtained by players is used to evaluate the topic design nodes in the application's regional performance. The use of each player or user is declining based on power but is increasing based on SINR (Nekouei *et al*., 2016). If all the power levels of the entire users are set, the power level of a player or node will be jointly reflected at the SINR level of the players or the ends. This is an application of game theory in the power control application area concerning CDMA networks (Wu *et al*., 2018). Similar applications, such as CDMA exist in game theory to decrease whole transmission power by altering transmission rate and power management techniques.

In game theory applications, selfish users receive an unreasonable rate of access to data connection layer channels. Users are unable to access channels due to this selfish behavior (Demaine *et al*., 2012; Komali *et al*., 2008). Consequently, the required for average access control needs to be incorporated in a specific way. Because many users are trying to send data as quickly as possible and they are working concurrently, access collapse occurs. This problem was partially solved by Slotted aloha. In this case, the time quantum is allocated using a specific synchronization approach. A user must wait for a slot boundary before he begins more transmitting when he needs to access a shared channel (Shi and Yang, 2019). However, the issue arises when two or users in the same slot attempt to transmit data at the same time (Salehisadaghiani and Pavel, 2014).

Table 2: Layers representation with game theory applications (Gadjov and Pavel, 2018)

OSI layer	Application area	Game theory specific application
Transport	Cell selection	Inter and intra cell games
	Admission or acceptance of Call	Among the service providers, the request distributes based on the service provider and customer environment, the acceptances were invited
	Load control	Completing a session based on the service provider and customer environment
Network	Routing	Forwarding and routing
Data link	Transmission medium and access control	Slotted aloha access Access control to interference channel
Physical	Spectrum allocation	Sharing of spectrum
	Power control	Transactions on the spectrum
	Cooperation in communication	CDMA networks Encode decode and forward cooperation
	MIMO networks or systems	Power management

Table 3: Different fields of research in game theory problem, method, and solutions

Domain	Reference Number	Problem	Solution	Approach/method used
Manufacturing field	Bysko and Krystek (2019)	Car sequencing problem	Use Genetic Algorithms (GA) or Ant Colony Optimizations (ACO) to optimize the structure of a car production line	Buffer slot assignment
		Color batching problem	ACO/heuristic computation	Buffer out the shuttle
Economics auctions	Ilie *et al*. (2018)	Optimizing bid strategy	3-tier crowd financing system	Semi truthful strategy
	Byde (2003)	Multi-agent allocation problem	Strategy optimization	Revenue equivalence theorem
Renewable energy	Ilie *et al*. (2018)	Selecting appropriate energy source nuclear waste	Molten salt thorium reactor Modular fission reactors	Hydropower plant Thermal energy transport or lossless electricity or smart distributed grid
Software Defined Networks (SDN)	Abderrahim *et al.* (2018)	Smart node placement problem	Mobile Edge Computing (MEC)	Embed MEC server in smart node
	Wang *et al.* (2019)	To create efficient Anomaly Detection Scheme (ADS)	Statistics or machine learning based ADS	Strategy selection module
	Killi *et al*. (2018)	Effective network partitioning for controller placement	Clustering/partitioning/ assignment heuristics	Spectral clustering K-means algorithm
Wireless Sensor Networks (WSN)	Abid and Boudriga (2013)	Behavior Detection of WSN	Detect and solve selfishness	Coverage eligibility rule, coverage maintenance protocol
	Agah *et al*. (2004)	Security monitor in WSN	To embed collaboration, reputation and QoS in network	Compute equilibrium at strategy pair
	Abd *et al*. (2015)	Nodes' lifetime depletion	To balance the traffic load on the network	To introduce a Three Dimensional Game-Theoretic Energy Balance (3DGTEB) protocol

In the network layer, packets are sent along routes, and routes are established. At the network layer, the concept of game theory helps to determine the best way to forward packets and choose whether to forward expected packets or not. Game theory is an important idea in this situation because nodes in the network must individually decide whether to take any action, taking into account the performance of other actions of the nodes (Frihauf *et al*., 2011).

The primary aspect to deal with at the transport layer is congestion control. Avoiding congestion should also be considered. The addition of new users should be limited to limit network load. Cell selection is a two-layer game where the primary layer is a cell-cell game in which the mobile terminal selects a cell based on a selection strategy and the second layer is an intra cell game (Wang *et al*., 2018).

Prior research on optimal topology design has not organized load control and call admission control. Since topology design relies entirely on dynamic networks, the current structural design or design based on Nash equilibrium is not optimal (Nash Jr, 1950).

To expand the study area in game theory, economics, Software Defined Networks (SDN), renewable energy, manufacturing industry, auction, wireless sensors, and many other fields take into account access problems and determine the research solution. Table 3 shows the numerous fields where the concept of game theory is applied to solve problems.

Table 3 presents the different application domains in game theory, problems, and approaches used to address the problem in the literature.

Discussion

This section discusses the various challenges in game theory, incentives in cooperation, objectives, and applications of game theory, and analysis of model data from record values of PoA and PoS for the transport layer.

Challenges in Game Theory

Networks present some challenges for game theory (Jin *et al*., 2020; Ahmadyan *et al*., 2016):

1. Nodes coherence: In game theory, players are assumed to be rational throughout a game. Let's assume players are asking for their interest fairly. However, this logical approach to nodes is not guaranteed when dealing with mobile terminals or nodes
2. Nodes cooperation: The goal of cooperative games is to improve players' payoffs by cooperating with each other. Peers may act selfishly in some cases to improve or maximize their profits. Nodes are encouraged to cooperate through incentives and selfish or immoral behavior is discouraged through mechanisms
3. Computation of payoff: Players' perceptions of their own performance and pleasure are important factors in calculating compensation. Using game theory, the application function calculates the self-profit-enhancing benefit based on the participants' game playing structure
4. Non-guaranteed existence of Nash equilibrium: If all players are not in Nash equilibrium, a frequent check is necessary for game theory. When there are numerous equilibria, the more efficient one should be evaluated

Incentives in Cooperation

For the best possible solution, collaboration across nodes is essential. However, cooperation between nodes cannot be guaranteed. The ability to cheat or act selfishly is most common when players or nodes are interacting in a sharing or communication environment (Law *et al*., 2012). Certain situations arise in which the player shouldn't perform selfishly. A node penalty value is generated using a reward or penalty to inform the respective nodes. It is important to reward resource providers and exclude selfish nodes from the network and resource pool. Incentive structures are in place (Roughgarden, 2015) to encourage participants to cooperate and reduce their selfish behaviors. Two major incentive systems that foster collaboration among players or nodes are reputation-based and credit based. In network routing formulations, a credit-based method has been utilized. Monetary benefits are provided to nodes to compensate users for packet forwarding received from the remaining nodes. Credit-based mechanisms enable the use of this monetary gain for retransmission, battery expenses, or packet loss. Also, Sprite is used for solving self-interested node routing issues. Whenever selfish nodes are connected to large scale nodes, this method is most advantageous. In contrast to the credit-based process, reputation is calculated centrally or at each node. By sharing resources, a player's reputation indicates their willingness to contribute to the network as a whole.

Game Theory and Next-Generation Networks

Heterogeneous networks provide global connectivity and common services to users. As a result, even when users switch networks, they receive a better QoS. Heterogeneous Services (Mihai-Alexandru *et al*., 2017) can support agents such as transparent gateways and common connectivity due to the simultaneous availability of multiple networks. Cooperation between nodes is a fundamental challenge for self-organized networks. With the notion of node, cooperation introduces a novel type of assortment between nodes, leading to improved communication reliability, coverage expansion, and reduced energy use. It is still possible to transmit packets at lower power levels and increase throughput even with the effects of channel variation and shadowing.

Defining Objectives in Game Theory Applications

To organize a network into a specific topology, goals for game theory-specific applications must be defined based on objective and computational parameters. This requires estimating and mapping the cost of anarchy and stability among players or users Table 4. Game type is a crucial factor to consider while comparing. The two types of games are cooperative and non-cooperative. In an n-player game, there is no need to analyze selfish node behavior when the players or nodes cooperate. It is accepted by all players that a set of rules must be followed when playing a game. Therefore, this study is primarily concerned with non-cooperative games in which equilibrium changes because players or nodes behave selfishly.

Table 5 displays sample data from the transport layer with Internet Protocol (IP) address, number of participants, and count of the hop, PoA, and PoS. Among the players connected to the network, hops are the distances traveled to reach a destination from the source (Clempner, 2022; Gkatzelis *et al*., 2022).

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Table 4: Calculation parameters of specific users or players based on game theory

Author	Game theory and year-specific application	Purpose	Computation parameter		Game type		Players/users		
			PoA	PoS	Non-cooperative	Cooperative	SP	Terminal	Link
Nahir *et al*. (2013)	Inter and intra cell Games service requirements	Cell that accomplishes	✓	X	✓	X	✓	✓	X
Romano and Pavel (2019)	Inter and intra cell games	Cell that accomplishes service requirements	✓	X	✓	X	✓	✓	X
Zaw *et al*. (2020)	Requests are distributed among service providers	Allocate requests providers	X	✓	✓	X	✓	X	X
Correia and Stoof (2019)	Requests are distributed among service providers	Assign requests to providers	X	✓	✓	X	✓	X	X
Fischer *et al*. (2014)	Call acceptance depends on the service provider and customer environment	To choose whether the service request is useful for players	✓	X	✓	X	✓	✓	X
Wang *et al*. (2018)	Call acceptance depends on the service provider and customer environment	To choose whether the service request is useful for players	✓	X	✓	X	✓	✓	X
Demaine *et al*. (2012)	Ending a session depends on the the environment of theclient and the service provider	To choose whether session termination affects the players	✓	X	✓	X	✓	✓	X
Chernov (2019)	Ending a session depends on the environment of the client and the service provider	To choose whether session termination affects players	✓	X	✓	X	✓	✓	X
Nekouei *et al*. (2016)	Forwarding and routing packets to send to players	To decide which	✓	X	✓	X	X	✓	X
Salehisadaghiani and Pavel (2017)	Slotted aloha access through random access	Reduce conflict	X	✓	✓	X	X	✓	X
Salehisadaghiani and Pavel (2014)	Access control for interrupt channel	Interruption shares access to the channels	✓	X	✓	X	X	✓	X
Felegyhazi *et al*. (2006)	CDMA networks power with minimum interference	To set transmission	X	✓	✓	X	X	✓	X
Jin *et al*. (2020)	Transactions and sharing on spectrum fairness	Distribution of to increase	X	✓	✓	✓	✓	✓	X

Table 5: Here are some sample values from the catalog for PoA and PoA for the transport layer

Network serial/IP address	No. of players	Hop count among players	PoA	PoS
103.40.196.170	122	61	0.988476	16.53
103.40.201.570	169	115	1.093460	40.57
103.40.198.121	217	178	1.678715	51.28
103.40.197.650	254	127	1.754702	61.09
103.40.202.740	69	51	2.069124	69.19
103.40.199.195	127	110	2.431693	76.95
103.40.203.212	177	102	1.126686	19.40
103.40.202.430	250	185	1.839270	51.66
103.40.198.120	70	57	2.003270	63.64
103.40.206.810	124	94	1.762510	62.26

PoA decreases over time as the no. of players and count of the hop increase while the cost of stability maximizes as the number of players and hop count increase. These phases are found in all four OSI levels with the same users. Additionally, we explain why we limited the study to only these four layers of OSI. A data link, a physical connection, a transport connection, and a network connection are all hardware layers, whereas a session, a presentation, and an application are software layers. Only the hardware layers are affected by player or user actions (the layers that transmit data).

A second disadvantage is that software developers tend to focus on how data is displayed at the other end, but hardware developers tend to focus on how data is navigated. Even if some nodes exhibit selfish behavior, topology selection and optimization can be used to improve network design after data successfully passes through hardware layers.

Conclusion and Future Work

Using game theory and other hierarchical concepts, incentive mechanisms can define constraints, make choices, compute reward matrices, and determine the action to be taken. Continuous monitoring of node activity is critical for progressing toward incentive mechanisms. To enhance the strategy profile of network participants, problems related to calculating the PoA and the PoS are addressed. Logical analysis of OSI layers improves communication efficiency even in non-cooperative environments where players/nodes exist. In the process, a research gap was discovered in the area of load and additive control in optimal topological design. As a further development or improvement, the modified Folk theorem can be used. Different optimization strategies are on their way to filling this research gap and should be explored and used to do so.

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Author's Contributions

Kanmani S.: Conception and designed, acquisition of data, analysis, and interpretation of data. drafted the article.

M. Murali: Reviewed article critically for significant intellectual content, and gave final approval of the version to be submitted and any revised version.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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