Mechanism Design Theory in Control Engineering

A Tutorial and Overview of Applications in Communication, Power Grid, Transportation, and Security Systems

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Abstract

This article provides an introduction to the theory of mechanism design and its application to engineering problems. Our aim is to provide the fundamental principles of mechanism design for control engineers and theorists, along with state-of-the-art methods in engineering applications. We start our exposition with a brief overview of game theory, highlighting the fundamental notions necessary to introduce mechanism design. Then we offer a comprehensive discussion of the principles of mechanism design. Finally, we explore four key applications in engineering, i.e., communication networks, power grids, transportation, and security systems.

Introduction

Over the last seventy years, the theory of mechanism design was developed as an approach to efficiently align the individuals' and system's interests in problems where individuals have private preferences [1]. It can be viewed as the art of designing the rules of a game to achieve a desired outcome. Mechanism design has broad applications spanning many fields, including microeconomics, social choice theory, computer science [2], and control engineering. Applications in engineering include communication networks [3], social media [4], transportation routing [5], online advertising [6], smart grid [7], multi-agent systems [8], and resource allocation problems [9].

Eric Maskin has provided an example that best illustrates the theory of mechanism design in simple terms [10]. Suppose we want to divide a cake between two children, e.g., Mary and

Bill (see Fig. 1). Our intent is to divide the cake fairly so that each child is satisfied with their portion. Obviously, one way for a fair division is when Mary thinks she has at least half of the cake, and so does Bill. However, *how can we achieve such a fair division?* If we are sure that the children see the cake the same way we do, we can just cut it in half and give each child one of the pieces. Mary and Bill will each think they have half the cake and will live happily ever after. In reality, though, Mary and Bill can be expected to see things differently than us. Children do not always regard our "fair" division as really fair. Bill might think that Mary's piece is bigger and feel somewhat shortchanged. So, even if we intend to accomplish a fair division, in practice, we are not in the position to obtain it because we know nothing about the children's perspective. *Do they see it as we do or not? Is there a "mechanism" (e.g., a protocol) that, if followed, will result in a fair division even if we do not have enough information about the fairness of the division?* Well, one potential mechanism is to have Bill cut the cake, and then Mary would choose the portion she would like. The above mechanism is called *divide-and-choose mechanism*. Since Bill is accountable for the fair division of the cake, he will do his best to have it equally cut. He knows that if the pieces are disparate, Mary will choose the bigger one. So, the cake is equally cut. Mary chooses her portion, and she is happy with that, as well as Bill, who chooses the other one. Hence, through the divide-and-choose mechanism, we have accomplished the desired outcome.

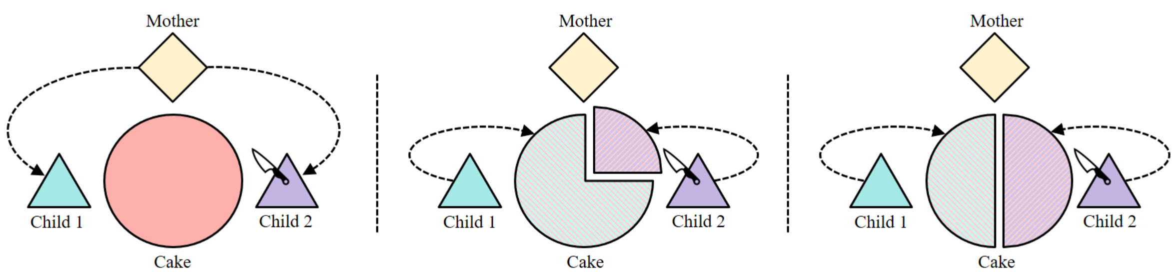

Figure 1: An illustration of the divide-and-choose mechanism, showcasing the fair division of a cake. In the scenario, Bill is tasked with dividing the cake into two perceived equal parts while Mary chooses her preferred portion. This method ensures a satisfying outcome for both children, regardless of their individual perceptions of fairness.

The theory of mechanism design represents the confluence of microeconomics [11]–[22], and social choice theory [23], [24], while it equally draws from auctions [25], optimization [26], [27], and game theory [28]–[33]. The theory was developed to implement system-wide optimal solutions to problems involving multiple rational individuals (agents), each with private information about preferences and conflicting interests [1]. It all started with Leonid Hurwicz, who asked what is the best way for a centralized entity to manage a system of selfish agents with conflicting interests, each trying to make a decision and reach an equilibrium. He was most interested in problems in which the efficiency of the equilibrium depends on the availability (and thus, truthfulness) of the agents' information. Hurwicz's rigorous answer established the theoretical framework to study this problem and other similar ones. The key idea behind his seminal work [34]–[36] was to recognize that the solution depends on the agents' behavior and how they value their information. In economics, this translates to "a rational and intelligent agent will act as a utility maximizer and will not report their private information truthfully without a guaranteed compensation." Hurwicz developed a methodology to elicit the private information of any agent by offering appropriate incentives. Hurwicz's theoretical framework was revolutionary in economics and engineering, and many other scholars started expanding the theory. Robert Myerson and Eric Maskin contributed immensely to the theory and expanded the mathematics behind "reverse-engineering," the process of achieving a desirable goal (e.g., social welfare, revenue). The importance, significance, and impact of Hurwicz, Myerson, and Maskin's work were recognized and awarded the Nobel Memorial Prize in Economic Sciences in 2007 [37].

Control Example

Here, we offer a control dynamical system example (following closely [38]), in which we can easily identify where mechanism design can be used.

We assume linear dynamics for a dynamical system of the following form:

$$x_{t+1} = Ax_t + Bu_t, \tag{S1}$$

where $x_t \in \mathbb{R}^n$ is the state vector, and $u_t \in \mathbb{R}^m$ is the input signal. For this system, we suppose that there are a total of $|\mathcal{I}|$ interconnected and non-overlapping subsystems, where $\mathcal{I}$ denotes the set $\{0, 1, \ldots, |\mathcal{I}|\}$. We say that each $i \in \mathcal{I}$ represents an agent. In addition, we define $\mathcal{N}_i$ as the set of neighboring agents for agent i. For time step $t = 1, 2, \ldots, T$, we denote by $x_t^{(i)} \in \mathbb{R}^{n_i}$ the state vector of agent i, and so we have $x_t = (x_t^{(1)}, \ldots, x_t^{(|\mathcal{I}|)})$ and $\sum_{i=1}^{|\mathcal{I}|} n_i = n$. Next, we partition the inputs, i.e., $u_t^{(i)} \in \mathbb{R}^{m_i}$. In a similar fashion, we have $u_t = (u_t^{(1)}, \ldots, u_t^{(|\mathcal{I}|)})$ and $\sum_{i=1}^{|\mathcal{I}|} m_i = m$.

We are ready now to discuss an agent's problem. First, no agent directly provides control inputs into the system. The diagonal block A_{ii} of A gives the dynamics for the ith agent. Different agents may influence each other, so the off-diagonal blocks A_{ij} represent the impact of agent j on agent i. For the purposes of this example, we assume that agent i's input can only affect the states of their subsystem. Thus, we have that the input matrix

$B = \mathrm{diag}(B_1, \ldots, B_{|\mathcal{I}|})$ is a block-diagonal matrix. Based on this, the dynamics for agent i are

$$x_{t+1}^{(i)} = A_{ii} x_t^{(i)} + B_i u_t^{(i)} + \sum_{j \in \mathcal{N}_i} A_{ij} x_t^{(j)}. \tag{S2}$$

It is natural for any agent i to be aware of their own dynamics, so A_{ii} and B_i are known to agent i. However, no agent has complete information of the component $\sum_{j \in \mathcal{N}_i} A_{ij} x_t^{(j)}$, which is part of their dynamics. Hence, a "social planner" (central computer or system coordinator) is required to intervene and provide a "mechanism" (or a process) handling whatever information each agent knows, ensuring in the end, all agents can compute their dynamics. We consider that for each agent i the state is $\mathbb{X}_i = \{G_x^{(i)} x^{(i)} \leq g_x^{(i)}\}$, and also that the input constraints are given by $\mathbb{U}_i = \{G_u^{(i)} u(i) \leq g_u^{(i)}\}$, where $\{G_x^{(i)}, G_u^{(i)}\}_{i=1}^{|\mathcal{I}|}$ and $\{g_x^{(i)}, g_u^{(i)}\}_{i=1}^{|\mathcal{I}|}$ are matrices and vectors with appropriate dimensions, respectively. Now, the (strictly) convex cost function of agent i is

$$v_i(x^{(i)}, u^{(i)})) = g_i(x_T^{(i)}) + \sum_{t=0}^{T-1} l_i \left(x_t^{(i)}, u_t^{(i)} \right), \tag{S3}$$

where $l_i(\cdot, \cdot)$ and $g_i(\cdot)$ are the stage and terminal costs, respectively.

As discussed earlier, agents know their dynamics and any agent i's cost function is private information. This raises a big problem: *How can we analyze such a problem when information is asymmetric between all the agents?* For a moment, suppose a social planner is tasked with implementing a control input in the system and has complete knowledge about the dynamics of the system, i.e., matrices A and B, and constraints for any $i \in \mathcal{I}$, $\mathbb{X}_i, \mathbb{U}_i$. The social planner's problem is a convex minimization program:

$$\min_{x,u} \sum_{i=1}^{M} \left(g_i(x_T^{(i)}) + \sum_{k=0}^{T-1} l_i(x_t^{(i)}, u_t^{(i)}) \right) \tag{S4}$$

$$\begin{aligned} \text{subject to: } & x_{t+1} = A x_t + B u_t, && t = 1, \ldots, T-1, \\ & x_t^{(i)} \in \mathbb{X}_i \text{ and } u_t^{(i)} \in \mathbb{U}_i, && \forall i \in \mathcal{I}, \quad t = 1, \ldots, T, \\ & x_0^{(i)} = \bar{x}_0^{(i)}, && \forall i \in \mathcal{I}. \end{aligned} \tag{S5}$$

This problem could be solved using standard convex optimization techniques. However, our assumption that the social planner has complete information on all the agents' costs is too strong. Without this knowledge, the objective function is effectively unknown. To find an efficient trajectory/solution to this problem, the social planner must elicit the missing information from all the agents. Since the agents are strategic, we cannot simply ask them to report their private information, as misreporting can lead to a better outcome for them. This is where the theory of mechanism design enters and provides a powerful theoretical framework to provide a solution to this information elicitation problem. By designing appropriate incentives (rewarding an agent for reporting their private information truthfully) or disincentives (penalizing them for misreporting), we can ensure that our system's strategic agents have it in their best interest to disclose their true information, thereby facilitating an optimal solution to optimal control problem that aligns with the collective interest (e.g., efficient trajectories for a group of drones).

This article has two main objectives: (1) to provide a tutorial on the theory of mechanism design and (2) to present how the theory of mechanism design can yield solutions to engineering problems. The take-away messages of this article are as follows:

1) Although mechanism design originates from economics, primarily aiming to align individual and system-wide economic interests, it has found applications in various engineering fields.
2) Mechanism design provides a powerful theoretical framework for solving objective-first and information-elicitation problems.
3) Although most of the literature has focused on static and simplified economic models, there is great potential in solving dynamic real-world engineering problems.
4) The future challenge lies in developing dynamic, robust, and computationally tractable mechanisms, especially in dynamic and unpredictable engineering control problems.

We start our exposition by providing a brief overview of key notions of game theory. Next, we offer the general framework and fundamental principles of mechanism design. Then, we provide mechanism design problem formulations of different engineering applications. Finally, we offer some concluding remarks and a discussion of the future of mechanism design in control engineering.

Game Theory

Game theory is arguably one of the cornerstones of economics for studying competition and strategic behavior and lies at the intersection of mathematics and social science. The first theoretical formulation of a game is thanks to John von Neumann [39]. Von Neumann's work established the notion that every problem in economics (for that matter, in engineering and computer science) is essentially a competition of resources between selfish agents, each striving to make a decision that benefits them only. Thus, von Neumann introduced game theory as a means to study "interactions in the presence of conflict of interest" [40]. Game theory models the conflicting (or cooperative) interaction between agents (also referred to as "players") and provides a principled way of predicting the outcome of this interaction using equilibrium analysis.

The study of games is most appealing and intuitive to scientists, engineers, and scholars across many fields as it provides the mathematics to answer what a selfish agent (human, corporation, machine) is going to decide and how under different yet certain conditions.

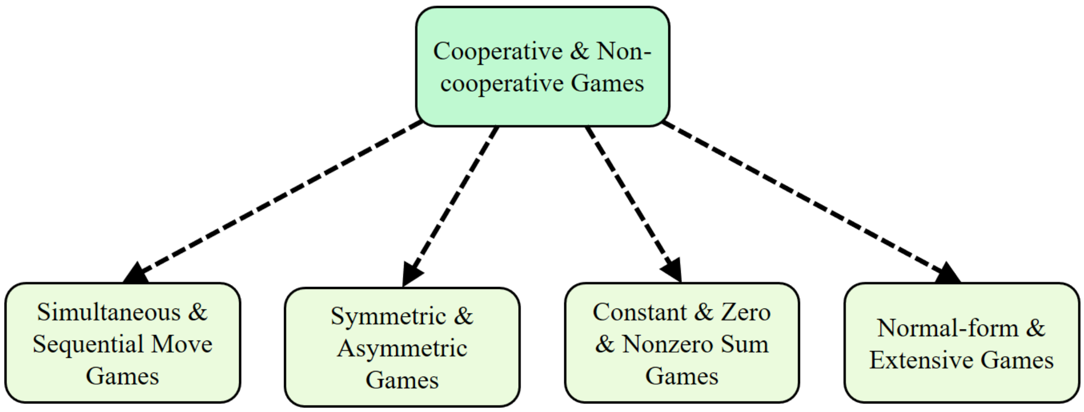

Figure 2: A classification of the different types of games.

Although game theory is quite extensive, in this article, we focus on providing only a snapshot of the fundamental notions and a simple classification of games (see Fig. 2). A *game* is a mathematical model of the strategic interaction of at least two agents (e.g., bidders in an auction, corporations, countries, robots, autonomous cars) whose *actions* (or decisions) can affect the other agents' *payoff*. The agents play against each other, often competing over the utilization of a limited resource (e.g., Tragedy of the Commons [41]), by taking an action, which defines the agent's behavior in the game; depending on the application, an action can be either a bid in an auction, or the selection of a route on the road network, or simply what to bet on a coin flip. An agent's action leads to a payoff, meaning that there exists a function that maps the agents' actions to a real number. For example, a vehicle may have to decide on route A or route B. The payoff from choosing either route can be in terms of travel time, so route A may result in 30 minutes, and route B may result in 25 minutes. These actions can be taken *simultaneously* (e.g., rock-paper-scissors), or *sequentially* (e.g., monopoly, chess). Agents may *cooperate* towards reaching an ideal solution (e.g., signing a contract). This cooperation can take the form of an alliance to find the "common ground" in terms of what actions each should take. If agents do not choose or are unable to cooperate, then the game is called *non-cooperative*, and it most naturally models strictly competitive "play" among all agents.

Due to the broad applicability of game theory, there have been a myriad of applications in economics and engineering as well as in computer science, and so specific games have been given a name. For example, *normal-form games* (we offer an overview of these games in Sidebar: Games and the Nash Equilibrium), *matrix games*, *differential, static, dynamic games* [42]–[46], *Bayesian and stochastic games* [47], *zero-sum games* [48], [49], and *one-shot and repeated games*, *Stackelberg games* [50], [51], *finite and continuous games* [52], and *hybrid games* [53], [54].

Sidebar: Games and the Nash Equilibrium

We present an overview of essential notions from non-cooperative game theory. A finite normal-form game is a tuple $\mathcal{G} = \langle \mathcal{I}, \mathcal{S}, (u_i)_{i \in \mathcal{I}} \rangle$, where $\mathcal{I} = \{1, 2, \ldots, n\}$ is a finite set of n agents (most commonly referred to as players) with $n \geq 2$; $\mathcal{S} = S_1 \times \cdots \times S_n$, where S_i is a finite set of actions available to player $i \in \mathcal{I}$ with $s = (s_1, \ldots, s_n) \in \mathcal{S}$ being the strategy profile; $u = (u_1, \ldots, u_n)$, where $u_i : \mathcal{S} \to \mathbb{R}$, is a real-valued payoff (or utility) function for player $i \in \mathcal{I}$.

Actions are the possible moves a player can make at any given point in the game. For example, in a simple game of rock-paper-scissors, the actions available to a player are to play either rock, paper, or scissors. A strategy, on the other hand, is a complete plan of actions a player will take given any possible situation in the game. It is a specification of what actions a player will take in response to every possible action of the other players. For example, in the game of chess, a strategy might specify a player's opening move, how they will respond to each possible opening move of their opponent, how they will respond to each possible counter-move, and so on. Of course, for any player in any game, one strategy that is available to them is to select an action and play it [S2]. In game theory, we call such strategies "pure strategies." Alternatively, a game-theoretic player could randomize their strategy (which action to choose) over some probability distribution. Such strategies are called "mixed strategies." For the remainder of this article, we will focus on pure strategies and use the terms action and strategy interchangeably.

Games model the *strategic interactions* of competing players. These interactions rely on the information of the players. Thus, in game theory "who knows what" plays a crucial role. If all players in a game have full access to all available information (payoff or utility functions, players' strategies, and game dynamics), then we say this is a game with *complete information*. In contrast, even if one player has limited or missing information, then we say that this is a game with *incomplete information*. In most cases, players are uninformed about the game's characteristics (types, utility functions, or strategies). If at least one player is not fully aware of all actions/strategies of all other agents, then we say this is a game with *imperfect information*. For example, every one-shot simultaneous-move game is a game of imperfect information. Another important notion in game theory is the notion of *common knowledge*, which characterizes a game's information as follows: if every player knows a specific information (e.g., an action), then we can expect any other player to know that every other player knows it as well.

One of the key assumptions in game theory is that the players are *rational*. A player is said to be rational if they always make decisions in pursuit of their own objectives (e.g., maximize their own expected payoff). Another key assumption in game theory is that the players are *intelligent*. This implies that each player in the game knows everything about the game and they are competent enough to make any inferences about the game.

In all games, players make decisions and reach an *equilibrium*. We call different notions of equilibria a *solution concept*. One such equilibrium is the *dominant strategies equilibrium*, in which any agent has a strategy that, regardless of what other players might decide to do, this strategy is the best possible (results in the highest possible payoff). The dominant strategies equilibrium is quite strong, and it can be hard (almost impossible) to have it in a game of competing players under different scenarios. The most celebrated solution concept in game theory is the *Nash equilibrium* (NE). A player's NE strategy is the best response to the NE strategies of the other players. In other words, a player cannot be better off if they depart from their NE strategy if all other players choose their NE strategies. Thus, no player has an incentive to deviate from a NE strategy. More formally, let S_i be the set strategies of player i, $s_i, s_i' \in S_i$ be two strategies of player i, and S_{-i} be the set of all strategy profiles of the remaining players. Then, s_i strictly dominates s_i' if, for all $s_{-i} \in S_{-i}$, we have $u_i(s_i, s_{-i}) > u_i(s_i', s_{-i})$. Also, a strategy is (strictly) dominant if it (strictly) dominates any other strategy. A player i's best response to the strategy profile

$$s_{-i} = (s_1, \ldots, s_{i-1}, s_{i+1}, \ldots, s_n) \tag{S1}$$

is the strategy $s_i^* \in S_i$ such that $u_i(s_i^*, s_{-i}) \geq u_i(s_i, s_{-i})$ for all $s_i \in S_i$. A strategy profile $s^* = (s_1^*, \ldots, s_n^*)$ is a NE if, for each player i, $u_i(s_i^*, s_{-i}^*) \geq u_i(s_i', s_{-i}^*)$, for all $s_i' \in S_i$.

Next, for completeness, we define the notion of Pareto domination. An outcome of a game is any strategy profile $s \in \mathcal{S}$. Intuitively, an outcome Pareto dominates some other outcome as long as it improves the utility of at least one player without reducing the utility of any other. Let $\mathcal{G}$ and $s', s \in \mathcal{S}$. Then a strategy profile s' Pareto dominates strategy s if $u_i(s') \geq u_i(s)$, for all $i \in \mathcal{I}$, and there exists some $j \in \mathcal{I}$ for which $u_j(s') > u_j(s)$. Pareto domination is a useful notion to describe the social dilemma in a game. However, Pareto-dominated outcomes are often not played in game theory; an NE will always be preferred by rational players. For further discussion of the game theory notions presented above, see [S1], [S2].

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The History of Mechanism Design

Game theory is concerned with the analysis of games. Mechanism design, on the other hand, involves designing games with desirable outcomes. Mechanism design was considered a consequence of debates about the relative merits of socialism, communism, and capitalism, the most important of which was the *socialist calculation debate* [55]. Mechanism design attempted to provide a scientific basis for addressing the above debate by constructing a theoretical framework for considering systems other than capital markets for allocating the means of production [56]. It also took a mathematically rigorous approach to the comparison of a specific arrangement to capitalism in terms of efficacy and productivity. In the last half-century, economics has adopted the study of mechanism design as the systematic analysis of resource allocation in institutions and processes. The above extremely fundamental development reveals the roles of information, communication, control, incentives, and agent processing capacity in decentralized resource allocation. Moreover, it allows the identification of sources of market failure. Leonid Hurwicz, a Polish-American economist and mathematician, was the first to introduce the concept of *incentive compatibility*, a cornerstone notion in which agents are incentivized to act in accordance with the desired outcomes of a social planner. It ensures that truth-telling or behaving according to the system's rules is the best strategy for each agent, leading to the successful implementation of the system's objectives. Hurwicz also provided a methodology for mechanisms that are incentive compatible and how exactly these mechanisms can guarantee the desired outcomes [57]. Hurwicz's contributions in establishing mechanism design's theoretical foundations were key in providing efficient solutions to resource allocation problems. Jean-Jacques Laffont, a French economist, through his studies in public and information economics, participated in the translation of the foundational economic theory into the language and tools that today appear not only in game theory but also in studies of the organization of firms and markets as well as in the applied economics of regulation, taxation, and public goods provision [58]. Pure and applied research in economics was connected through the studies about transactions among economic agents in terms of information and incentives. As one can see from Fig. 3, the insights and better theoretical understanding of how incentives influence strategic economic problems have transformed the discipline of economics. The theory's interdisciplinary applicability has helped scientists and engineers architect efficient systems by designing the right incentive to drive the agents' behavior and thus achieve the desirable objective. Other excellent historical surveys on the theory of mechanism design are reported in [59], [60].

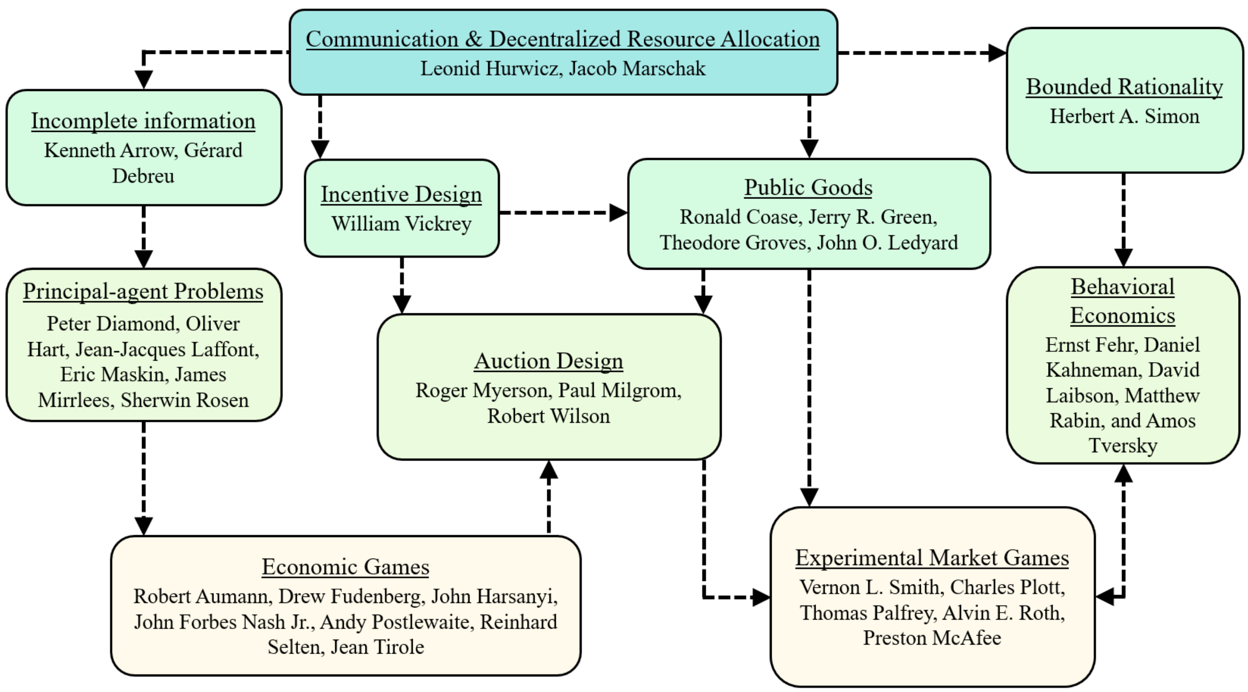

Figure 3: A snapshot of the key theoretical "chapters" of the theory of mechanism design and its related fields. We use arrows to showcase the influence of the different ideas and what notions first inspired specific works. For example, Vickrey's work in incentive design inspired both the design of auctions and problems in public goods.

The theory of mechanism design since the 1950s has been rigorously studied by numerous economists and mathematicians to provide insights and solutions to different economic topics (e.g., public goods, markets, and auctions). The theory started with the seminal contributions of Leonid Hurwicz [35], [57] and Jacob Marschak [61] (see Fig. 3), who both were interested in resource allocation problems (e.g., communication) and the means of controlling (through incentives) agents. In parallel, Kenneth Arrow, Gérard Debreu, and Herbert A. Simon also worked on problems with incomplete information and how to bound rationality.

In 1961, William Vickrey's seminal work [25] on auctions was published, paving the way for Hurwicz's theoretical framework to be applied as a means of designing incentives based on the agents' information for a simple yet formidable problem of an auction. Arrow and Debreu's work was instrumental in establishing the interconnected relation of information and decision-making and its role in influencing behavior in the efficient allocation of limited resources.

Much later in the 1970s and 1980s, Peter Diamond, Oliver Hart, Jean-Jacques Laffont, Eric Maskin, James Mirrlees, and Sherwin Rosen worked independently on "principal-agent problems" focusing on how one can design a contract between a principal (e.g., institution, corporation) and a rational agent efficiently. As a continuation of Vickrey's work, Ronald Coase, Jerry R. Green, Theodore Groves, and John Ledyard made significant contributions to the design of incentives for public goods problems (e.g., road infrastructure, public parks, television and radio broadcasts, national security). Furthermore, Roger Myerson, Paul Milgrom, and Robert Wilson expanded the Vickrey auction to address more complicated scenarios and complex problems.

At the same time, many economists continued developing and studying games; a few examples are Robert Aumann, Drew Fudenberg, John Harsanyi, John Forbes Nash Jr., Andy Postlewaite, Reinhard Selten, and Jean Tirole. An essential extension of game theory is the development of methodologies for agents who might not act as rational and intelligent agents. Key questions in this area are: (I) *Do agents make optimal decisions at all times?* (ii) *Do agents make sacrifices when deciding on their utility?* (iii) *Do agents always optimize for their own benefit?* To answer these questions, the fields of behavioral economics and experimental game theory were developed first by Herbert A. Simon and then by notable contributors such as Ernst Fehr, Daniel Kahneman, David Laibson, Matthew Rabin, and Amos Tversky, as well as Vernon L. Smith, Charles Plott, Thomas Palfrey, Alvin E. Roth, and Preston McAfee. Several survey papers on the theory of mechanism design can be found in [62]–[65].

Although we have only focused on the history of mechanism design from the economics point of view, there have been numerous key contributions in engineering and computer science. Thus, we have dedicated the second part of this article to stress the contributions and engineering applications of mechanism design.

The Theory of Mechanism Design

Most generic control systems can be viewed as a specification of how decisions are made as a function of the information that is known by the agents in the system [66]–[70]. What interests us in most cases is *efficiency*, i.e., realizing the best possible allocation of resources with the best use of information to achieve an outcome where collectively agents are satisfied, and there is no overutilization of the system's resources [30]. One key challenge in ensuring efficiency in a control system is the fact that different agents may have conflicting interests and act selfishly. In other words, systems that incorporate strategic decision-making, if they remain uninfluenced, are not guaranteed to exhibit optimal performance. This is well-known to be the case in control theory and economics [71], [72]. There are various theories and approaches that attempt to guarantee efficiency in such systems and can provide solutions of varying degrees of success. One way to study such problems is *information design* (see Sidebar: Information Design). Another theory is mechanism design, in which we are concerned with how to implement system-wide optimal solutions to problems involving multiple selfish agents, each with private information about their preferences [73], [74]. For example, within the context of mobility, agents are the travelers, and their private information can be either tolerance to traffic delays, value of time, preferred travel time, or any disposition to a specific mode of transportation [75]. Given that each traveler/driver/passenger "competes" with everyone else to reach their destination first, we want to ensure that given this inherent conflict of interest, we can still guarantee uncongested roads, no traffic accidents, and no travel time delays. Mechanism design can help us design the rules of systems where information is decentralized (different agents know different aspects of the system), and agents do not necessarily have an immediate incentive to cooperate [76]. In particular, mechanism design helps us design rules that align all agents' decision-making by providing the right incentives to achieve a well-defined objective for the system (e.g., aggregate optimal performance and system-level efficiency). Thus, mechanism design entails solving an optimization problem with sometimes unverifiable and always incomplete information structure [18]. We call such a problem *an incentive design and preference elicitation problem*.

Sidebar: Information Design

In this sidebar, we offer a quick overview of an alternative approach to mechanism design based on the work reported in [S3], [S4]. As we have seen so far, information plays a crucial role in game-theoretic models and mechanism design. However, information in such cases is used to evaluate the utility functions and study equilibria. In mechanism design, in particular, information is used to design the best possible incentives (in the form of payment functions) to guide efficient allocations. In contrast, in *information design*, the social planner manages a system's information (instead of its resources), and it is their task to devise a careful process for the efficient allocation of information (instead of monetary incentives for the allocation of resources). Thus, the goal of information design is to influence the agents' behavior based on how much information may become available.

This draws vital insights from behavioral economics as it treats the agents' cognitive abilities to adapt their behavior based on what is available to them.

It is standard in mechanism design to consider as a given the "informational environment" (e.g., who knows what and who does not know what yet seeks to learn) and focus on the design of appropriate incentives based on the desirable outcome (equilibrium behavior) among strategic agents. Information design simply considers non-fixed informational environments and sets the rules that the agents and the social planner commit to respect. Of particular interest are environments with incomplete information as strategic agents compete over resources against each other and seek to learn more about their competitors (other agents). For example, an agent can improve their strategy if they have more accurate beliefs about the payoffs and states of other agents.

In the last ten years, information design has been growing rapidly, finding key applications in economics, engineering, and finance. One example is the study of the optimal design of information under a Bayesian framework between two agents who attempt to communicate over a network [S5]–[S7]. Other applications are grade disclosure and matching markets [S8], voter mobilization [S9], traffic routing [S10], rating systems [S11], and transparency regulation in financial markets [S12], price discrimination [S13], and stress tests in banking regulation [S14]. Furthermore, similar methodologies have been used to design auction-based mechanisms to sell and buy information [S15]–[S17].

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The Building Blocks of Mechanism Design

We start our exposition by considering a system consisting of a finite group of agents, each competing with each other for a limited, fixed allocation of resources. Each agent evaluates different allocations based on some private information that is known only to them. We consider a *social planner*, playing the role of a centralized entity whose task is to align the selfish and conflicting interests of the agents with the overall system's objective (e.g., an efficient allocation of resources or the maximization of social welfare). As illustrated in Fig. 4, four components exist. There is a group of agents, each making a decision based on their personal information. Decisions then are reported as messages to the social planner, who is tasked to design the rules of which it can be determined what each agent gets.

Next, we provide a formal mathematical presentation of the social planner's task through the lens of optimization theory. We consider a set of selfish agents $\mathcal{I}$, $|\mathcal{I}| = n \in \mathbb{N}$, with preferences over different outcomes in a set $\mathcal{O}$. Each agent $i \in \mathcal{I}$ is assumed to possess private information, denoted by $\theta_i \in \Theta_i$. Since an agent i's θ_i can influence their decision-making in a

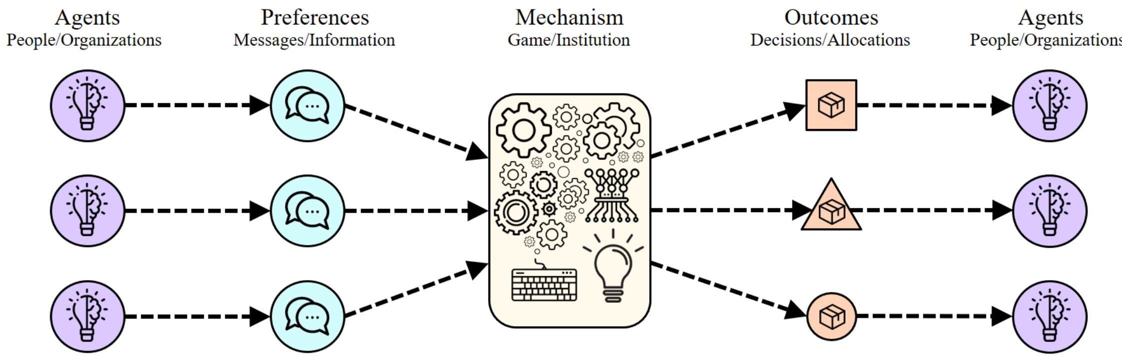

Figure 4: A visualization of how an arbitrary control system (agents, preferences, allocations) can be viewed under a mechanism design framework.

significant way, we call θ_i the *type* of agent i. We write $(\theta_i)_{i\in\mathcal{I}} = \theta$, $\theta \in \Theta$, where $\Theta = \prod_{i\in\mathcal{I}} \Theta_i$, to represent the type profile of all agents. An agent i's preferences over different outcomes can be represented by a utility function $u_i : \mathcal{O} \times \Theta_i \to \mathbb{R}$. Although the exact form of u_i can vary depending on the application of the problem [77]–[80], what is common in the literature [2], [8], [76] is a *quasilinear function* of the form

$$u_i(o, \theta_i) = v_i(o, \theta_i) - p_i(\theta_i), \tag{1}$$

where $v_i : \mathcal{O} \times \Theta_i \to \mathbb{R}_{\geq 0}$ represents an arbitrary valuation function, and $p_i \mapsto \mathbb{R}$ is a monotonically increasing function. If outcome $o \in \mathcal{O}$ represents an allocation of a resource, then p_i can be thought of as a transfer of agent i's wealth or a cost imposed to agent i for that particular allocation o. Intuitively, a quasilinear function defined as in (1) ensures that the marginal value of v_i does not depend on how large p_i becomes, and vice-versa. Furthermore, (1) assumes u_i is linear with respect to p_i. Next, we can naturally define the *social welfare* as the collective summation of all agents' valuations, i.e.,

$$SW(o, \theta) = \sum_{i\in\mathcal{I}} v_i(o, \theta_i). \tag{2}$$

If our system objective is to maximize (2), then immediately we observe that there is an important obstacle, i.e., any agent i may misreport their type θ_i in the hopes of increasing their own utility. So, the question is now: *How can we incentivize agents to report their type truthfully?* The answer is through the appropriate design of p_i. So, our next step is to outline the building blocks that can help us design p_i. Formally, we can define a *mechanism* as the tuple $\langle f, p\rangle$ composed of a *social choice function* (SCF) $f : \Theta \to \mathcal{O}$ and a vector of *payment functions* $p = (p_i)_{i\in\mathcal{I}}$, with $p_i : \Theta \to \mathbb{R}$. In words, a mechanism $\langle f, p\rangle$ defines the rules by which we can implement a system objective by mapping the agents' types to an outcome (in the means of the SCF) while using the payments to ensure the optimality or efficiency of that outcome. It is important to note here that the above is an example of a *direct mechanism*, in which information is directly communicated between the agents and the social planner (see Sidebar: Fundamental Results for other specifications). Next, we state the social planner's problem as follows

$$\max_{o \in \mathcal{O}} SW(o, \theta) \tag{3}$$

$$\text{subject to: } \hat{\theta}_i = \theta_i, \quad \forall i \in \mathcal{I}, \tag{4}$$

$$\sum_{i \in \mathcal{I}} v_i(o, \theta_i) \geq \sum_{i \in \mathcal{I}} v_i(o', \theta_i), \quad \forall o' \in \mathcal{O}, \tag{5}$$

$$\sum_{i \in \mathcal{I}} p_i(s(\theta)) \geq 0, \quad \forall \theta \in \Theta, \tag{6}$$

$$v_i(f(s(\theta))) - p_i(s(\theta)) \geq 0, \quad \forall i \in \mathcal{I}, \quad \forall \theta \in \Theta, \tag{7}$$

where $\hat{\theta}_i$ denotes the reported type of agent i, $s(\cdot)$ is the equilibrium strategy profile (e.g., NE). Constraints (4) ensure the truthfulness in the agents' reported types, (5) imposes an efficiency condition, (6) makes certain that no external payments are required, and (7) incentivizes all agents to participate in the mechanism voluntarily. If we could know for certain the true types of all agents, then we could solve the optimization problem (3) - (7) using standard optimization techniques. However, as this is unreasonable to expect from selfish agents, the social planner needs to elicit $\theta = (\theta_i)_{i \in \mathcal{I}}$ by designing the appropriate $p = (p_i)_{i \in \mathcal{I}}$.

The social planner faces now two critical questions: the *preference aggregation*, which asks what is the best outcome $o \in \mathcal{O}$ for any given type profile $\theta \in \Theta$, and the *information elicitation*, which asks how one can extract truthfully the type $\theta_i \in \Theta$ of any agent $i \in \mathcal{I}$. The theory of mechanism design essentially helps us answer both questions by providing the mathematical framework to construct mechanisms $\langle f, p \rangle$ that can achieve our desirable outcome. In the next subsection, we discuss one such mechanism that elicits the private information of agents truthfully.

Sidebar: Fundamental Results

One key characteristic of mechanism design is the communication of information in the system. Agents have private information, which is vital to the social planner's objective. Part of any mechanism is to specify how the private information is communicated from the agents to the social planner, and thus, all mechanisms fall under two categories: *direct* and *indirect*. Given any system, if the agents report their private information (preferences) directly to the social planner, then we say that the agents' preferences are observable to the social planner. In contrast, if the agents do not (or cannot) report their private information to the social planner, then the social planner has to "observe" the agents' preferences indirectly through signals or behavior. Formally, an indirect mechanism is defined as the specification of $\langle \mathcal{M}, g \rangle$, a collection of messages $\mathcal{M} = (\mathcal{M}_i)_{i \in \mathcal{I}}$ and an outcome function g. A direct mechanism is defined as the tuple $\langle f, p \rangle$. One key question in mechanism design now is the following: *If an outcome can be implemented in an indirect mechanism, then can it also be implementable in a direct mechanism where information (types) is observable?* This is answered by the *revelation principle*.

The revelation principle is one of the most fundamental and significant results in the theory of mechanism design. It serves as the cornerstone, establishing that the solution of any indirect mechanism can most surely be replicated by a direct mechanism. This allows us to limit the scope of how many mechanisms we need to investigate and focus rather on mechanisms in which agents communicate privately and directly with the social planner. Thus, the goal remains to elicit the private information truthfully [S18]–[S22]. For example, let us take a city's transportation network with a finite number of cars. Suppose each car has its own travel preferences (private information). We are interested in finding the optimal traffic flow. If such a flow exists when all the cars only share information that is indirectly related to their true preferences, then thanks to the revelation principle, there is also an optimal flow in which all cars report their preferences truthfully, and thus, we can achieve the same optimal traffic flow. So, by devising systems where cars are incentivized to be truthful, we can efficiently manage the city's traffic. Mathematically, we have the following theoretical setup: suppose some arbitrary mechanism $\langle \mathcal{M}, g \rangle$ implements some SCF f in a *dominant strategy equilibrium*. This means that SCF f is truthfully implementable in dominant strategy equilibrium if and only if for each agent $i \in \mathcal{I}$, there exists functions $m_i : \Theta_i \to \mathcal{M}_i$ such that for $\theta_i \in \Theta_i$ and $g(m(\theta)) = f(\theta)$ the profile $(m_i(\theta_i))_{i \in \mathcal{I}}$ is a dominant strategy. Hence, it can be seen that the revelation principle holds immediately after noting that $f(\theta) = g(m(\theta))$ for each $\theta \in \Theta$. Therefore, there are two key theoretical insights we can draw from the revelation principle: (i) for the implementation of an SCF, it is only sufficient to focus on a system's main attributes; (ii) in systems, decentralization cannot prevail centralization. As we will see in later sections, though, decentralization and the specifics of a problem can offer valuable insights and are worth investigating indirect mechanisms.

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The Vickrey-Clarke-Groves Mechanism

A well-established and broadly-used mechanism that has been successful in widely different applications (e.g., auctions, public projects, and cost-minimization problems) is the Vickrey-Clarke-Groves (VCG) mechanism [12], [16], [25]. The VCG mechanism ensures the existence and implementation of a dominant strategy equilibrium, which is an efficient solution and allows selfish agents to make a decision (alternatively, choose a strategy) that is best no matter what other agents may decide. Agents are also incentivized to truthfully report their private preferences and have no reason (e.g., chance of receiving negative utility) not to participate in the mechanism. However, the VCG mechanism is known to be an extravagant mechanism, i.e., it can generate big surpluses (i.e., taxation may be extremely high for all agents).

In the previous subsection, we reviewed the main concepts of mechanism design and formulated the incentive design and preference elicitation problem. In words, we asked: *How can we design the payments $p = (p_i)_{i \in \mathcal{I}}$ so that every agent makes the decision that agrees with what we have chosen as the system's objective (e.g., efficiency)?* To answer this question, in this subsection, we review the VCG mechanism, one of the most successful mechanisms, as it incentivizes agents to be truthful and guarantees efficiency.

As discussed earlier, a mechanism is a tuple $\langle f, p \rangle$. In a VCG mechanism, the SCF f is defined as an allocation rule (who gets what) based on the optimization problem (3) - (7), i.e.,

$$f(\hat{\theta}) = \arg \max_{o \in \mathcal{O}, \hat{\theta}_i \in \Theta_i} SW(o, \hat{\theta}_i), \tag{9}$$

where $\hat{\theta} = (\hat{\theta}_i)_{i \in \mathcal{I}}$. In words, assuming that the agents disclose their true information, (9) provides the social planner, who attempts to maximize the social welfare, a formal mathematical framework to compute the allocations of each agent under the right incentives.

Recall that the central idea of a VCG mechanism is determining the allocation of a resource to agents by eliciting truthfully any private information agents might hold. To achieve this, VCG mechanisms propose payments that serve as incentives for the agents to report their private information. The critical question is: *How can we ensure truthfulness if an agent can influence their payment by what they report?* The VCG mechanism answers this question by asking each agent to pay for the external effect they impose on the other agents. This is the total utility (or welfare) loss other agents experience due to this specific agent's presence in the mechanism. As such, it does not depend on their own declared valuation. Thus, the VCG mechanism charges each agent the following payment:

$$p_i(\hat{\theta}) = \sum_{j \neq i} v_j(f(\hat{\theta}_{-i})) - \sum_{j \neq i} v_j(f(\hat{\theta})), \tag{10}$$

where $\hat{\theta}_{-i}$ denotes the type profile of all agents except agent i. Note that the payments defined in (10) do not depend on an agent i's own declaration $\hat{\theta}_i$. Let us assume for a moment that all agents declare their types truthfully. Then, the first sum in (10) computes the value of the social welfare with agent i not participating in the mechanism. The second sum in (10) computes the value of the social welfare of all other agents $j \neq i$ with agent i participating in the mechanism. Thus, agent i when they report $\hat{\theta}_i$ are made to pay the *marginal effect* of their decision (in our case, that is agent i's reported type $\hat{\theta}_i$). In other words, this particular design of the payments in (10) internalizes an agent i's social externality. In this context, "externality" refers to the impact that an agent's actions have on the welfare of all other agents. Borrowed from economics, the notion of externalities is often used to describe situations where the actions of one individual or group have consequences (positive or negative) for others. In our particular setting, the externality is how agent i's decision affects the welfare of all other agents.

The VCG mechanism represented by the SCF f defined by (9) and the payment functions p defined by (10) satisfies the following properties:

1) For any agent, truth-telling is a strategy that dominates any other strategy that is available for that agent. We say then that truth-telling is a *dominant strategy*. Note that such strategies are "always optimal" no matter what the other agents decide.
2) The VCG mechanism successfully aligns the agents' individual interests with the system's objective. In our case, that objective was to maximize the social welfare of all agents. We call this property *economic efficiency*.
3) For any agent, the VCG mechanism incentivizes them to voluntarily participate in the mechanism as no agent loses by participation (in terms of utility).

4) The VCG mechanism ensures no positive transfers are made from the social planner to the agents. Thus, the mechanism does not incur a loss. We call this *weakly budget balanced*.

The VCG mechanism essentially ensures the realization of a *socially-efficient outcome*, i.e., satisfying Properties (1) - (3) in a system of selfish agents, where each possesses private information. The VCG mechanism induces a dominant strategy equilibrium, maximizing the social welfare while ensuring no agent is hurt by participating.

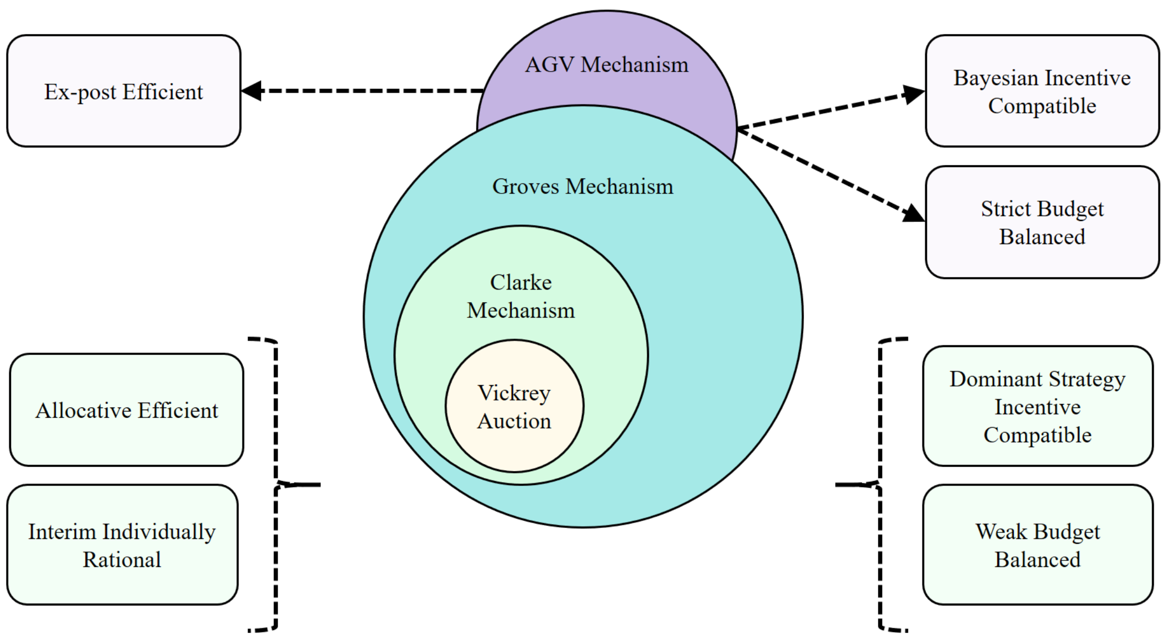

Figure 5: A visualization of the VCG and AGV mechanisms and their possible properties.

Other mechanisms exist, each with different properties and tradeoffs between efficiency, optimality, and information. One classic example is the Arrow and d'Aspremont and Gerard-Varet (AGV) mechanism that offers an efficient solution, incentivizes all agents to report their private information truthfully, and most importantly, all transactions between the agents and the social planner equal to zero (i.e., budget-balanced). The key characteristic of the AGV is its solution concept *Bayesian-Nash equilibrium* that operates under the assumption of a *common prior*, i.e., agents hold beliefs on what other agents might do. Furthermore, implementation theory focuses on decentralized mechanisms and setting up more rigorously the messaging process between agents and the social planner. Inspired by economics and engineering applications, *distributed mechanisms* (see [81]–[85]) and *dynamic mechanisms* (see [86]–[88]) have also been developed to tackle how decisions can be made locally within a system and also by relaxing some of the strong assumptions on information and prior beliefs, respectively.

We conclude this section with the following remark. Although the main motivation of mechanism design is the microeconomic study of institutions and relies heavily on game-theoretic techniques, it is a powerful theory providing a systematic methodology in the design of systems of asymmetric information [89], [90], consisting of strategic agents, whose performance must attain a specified system objective. The remaining article shall present how we can use this theory to design a socially-efficient system consisting of rational and intelligent agents who compete with each other for the utilization of a limited number of resources.

Engineering Applications

In this section, we explore various engineering applications of mechanism design.

Communication Networks

Communication networks are typically modeled as resource allocation problems (e.g., the bandwidth in wired/wireless communication is the resource, and a "network manager" needs to allocate efficiently among the agents) with a finite set of strategic agents. There are many different focused areas in communications, such as flow control, routing, channel scheduling, and power control. There are numerous ways to model the utility of an agent in a communication network. Still, one key assumption is considering network utilities for the agents as a concave function. Naturally, game-theoretic studies [91]–[96] have been extensively focused on routing/congestion games, networked games, and dynamic games. The main results are the existence and uniqueness of an NE, its computation, and deriving algorithms to learn/attain an NE. A completely different approach is to formulate the communication network as a *convex optimization problem* (e.g., maximize network utility of all agents) subject to network constraints [97], [98]. Typically, a communication problem is formulated as follows. We consider a communication network of n strategic agents, where $\mathcal{I}$ corresponds to the set of agents. Each agent is rational and intelligent and possesses private information. In addition, each agent $i \in \mathcal{I}$ is endowed with a utility function $u_i : \mathcal{X} \times \mathbb{R}$, where $\mathcal{X}$ is the set of allocations. In such problems, we consider *quasilinear* utility functions of the form

$$u_i(\mathbf{x}_i, p_i) = v_i(\mathbf{x}_i) - p_i, \tag{11}$$

where $\mathbf{x}_i = (x_i^1, x_i^2, \ldots, x_i^{k_i})$ is a k_i-dimensional vector and denotes the allocation made to agent $i \in \mathcal{I}$. Intuitively, a quasilinear function defined above ensures that the marginal value of v_i does not depend on how large p_i becomes, and vice-versa. Furthermore, u_i is linear with respect to p_i, which represents the tax paid by agent $i \in \mathcal{I}$. Based on this information so far, we get the following optimization problem

$$\max_{\mathbf{x}} \sum_{i \in \mathcal{I}} v_i(\mathbf{x}_i) \tag{12}$$

$$\text{subject to: } \sum_{i \in \mathcal{S}_j} h_{ij}(\mathbf{x}_i) \leq c_j, \quad \forall j = 1, 2, \ldots, m_c, \tag{13}$$

$$\mathbf{x}_i \geq 0, \quad \forall i \in \mathcal{I}, \tag{14}$$

where $m_c \in \mathbb{N}$ is the number of network constraints (e.g., the capacity of a link in the network) and $\mathcal{S}_j$ is the set of agents associated with the j-th constraint (e.g., number of agents using a particular link in the network). For each $j = 1, \ldots, m_c$, h_{ij} is a general function that, depending on the specifics of the problem, may model how we can measure the bandwidth allocation in the network. Next, agents hold private information that is not known to the social planner. An example is the valuation functions $(v_i)_{i \in \mathcal{I}}$. Thus, the social planner cannot directly address the above maximization problem without the agents' valuation functions. We say information is decentralized among the agents in the communication network, and it is the task of the social planner to devise a mechanism to elicit the necessary information from the agents and ensure the efficient allocation of resources. This is a clear and natural application of *implementation theory* in an engineering problem (see Sidebar: Implementation Theory).

Sidebar: Implementation Theory

In this sidebar, we present the fundamentals of *implementation* theory following the formulation of an indirect and decentralized resource allocation mechanism closely inspired by the framework presented in [S37]. One key characteristic of implementation theory is that it considers informationally decentralized systems. Thus, the goal is to devise a mechanism that handles this "asymmetry" in information and provide a set of rules that induce a game. This game will have an equilibrium, achieving our desired outcome among strategic agents. So, *what are the building blocks of this theory?* First, we need to specify a set of messages that all agents have access to and can use to communicate information. Based on this information, agents make decisions that affect the reaction of the network manager. Once the communication between the network manager and the agents is complete, we say that the mechanism induces a game; strategic agents then compete for the network's resources. In this line of reasoning, we formally define below what we mean by indirect mechanism and induced game. An indirect mechanism can be described as a tuple of two components, namely $\langle \mathcal{M}, g \rangle$. We write $\mathcal{M} = (\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_n)$, where $\mathcal{M}_i$ defines the set of possible messages of agent $i \in \mathcal{I}$. Thus, the agents' complete message space is $\mathscr{M} = \mathcal{M}_1 \times \cdots \times \mathcal{M}_n$. The component g is the outcome function defined by

$g : \mathscr{M} \to \mathcal{O}$ which maps each message profile to the output space

$$\mathcal{O} = \{(x_1, \ldots, x_n), (p_1, \ldots, p_n) \mid x_i \in \mathbb{R}_{\geq 0},\ p_i \in \mathbb{R}\}, \tag{S2}$$

i.e., the set of all possible allocations to the agents and the monetary payments made or received by the agents. The outcome function g determines the outcome, namely $g(\mu)$ for any given message profile $\mu = (m_1, \ldots, m_n) \in \mathcal{M}$. The payment function $p_i : \mathcal{M} \to \mathbb{R}$ determines the monetary payment made or received by an agent $i \in \mathcal{I}$. A mechanism $\langle \mathcal{M}, g \rangle$ together with the utility functions $(u_i)_{i \in \mathcal{I}}$ induce a game $\langle \mathcal{M}, g, (u_i)_{i \in \mathcal{I}} \rangle$, where each utility u_i is evaluated at $g(\mu)$ for each agent $i \in \mathcal{I}$. Let m_{-i} be the message profile of all agents except agent $i \in \mathcal{I}$, i.e., $m_{-i} = (m_1, \ldots, m_{i-1}, m_{i+1}, \ldots, m_n)$. Next, consider a game $\langle \mathcal{M}, g, (u_i)_{i \in \mathcal{I}} \rangle$. The solution concept of NE is a message profile μ^* such that $u_i(g(m_i^*, m_{-i}^*)) \geq u_i(g(m_i, m_{-i}^*))$, for all $m_i \in \mathcal{M}_i$ and for each $i \in \mathcal{I}$, where $m_{-i} = (m_1, \ldots, m_{i-1}, m_{i+1}, \ldots, m_n)$. Note that an NE requires complete information. But, we can interpret an NE as the fixed point of an iterative process in an incomplete information setting [S24], [S25]. This is in accordance with John Nash's interpretation of an NE, i.e., the complete information NE can be a possible equilibrium of an iterative learning process.

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Using implementation theory and taking advantage of an optimization-based formulation, the focus is to carefully design the outcome function g, i.e., design the payment function p_i such that the allocations $\mathbf{x}$ are efficient for all agents. The standard analysis of such problems is as follows: first, we show that at least one NE exists for the game induced by the mechanism $\langle \mathcal{M}, g \rangle$. Then, since agents are considered to be strategic, we need to ensure that the outcome function (and thus, the payment functions) induce *voluntary participation*, i.e., at any NE, no agent may lose utility from participating in the mechanism. So, in other words, all agents may, at the very least, have neutral utility ($u_i = 0$). Naturally, in communication networks, as well as any other engineering applications, we need to be mindful of all monetary transactions in the system. Thus, by checking the sum of all the payments of all the agents, we need to ensure it is zero at NE, which, in that case, we say the mechanism is *budget balanced*. The next two properties are related to the optimal solution of the optimization problem. *Can we ensure that all NE of the induced game $\langle \mathcal{M}, g, (u_i)_{i\in\mathcal{I}} \rangle$ are equivalent to the optimal solution?* If yes, then we say that the mechanism fully implements the efficient allocation vector $\mathbf{x}^*$ at an NE. Rarely, we might have an ideal mechanism that results in a unique NE. Finally, depending on the network's topology and other physical constraints of our problem of interest, we need to check feasibility, i.e., the allocation $\mathbf{x} = (x_1, \ldots, x_n)$ for each agent is feasible satisfying all the constraints at NE. This methodology has been widely used in the communication networks literature. In Table 1, we provide a snapshot of recent work that mostly focuses on the utility maximization problem.

In the following subsection, we focus on one particularly interesting method that has been studied extensively in communication networks (inspired by the economics literature). Of course, other mechanisms have also been investigated in the literature [99]–[103].

TABLE 1: A summary of recent papers on utility maximization problems in communication networks.

Communication Networks with a Maximization Problem				
Reference	Framework	Constraints	Implementation	Budget Balanced
[104]	Flow Control	System-wide	Partial	No
[68]	Flow Control	System-wide	Full	Yes
[105]	Flow Control	System-wide	Full	Yes
[97]	Flow Control	System-wide	Partial	Yes
[98]	Joint Flow Control & Multipath Routing	System-wide	Full	No
[106]	Power allocation & Spectrum sharing	System-wide	Full	Yes
[107]	Electric Vehicles	System-wide	Full	Yes
[108]	Networked Public Goods	Local	Full	Yes
[83]	Networked Public Goods	System-wide	Full	Yes
[82]	Network Utility Max	System-wide & Linear	Full	Yes

VCG-based Mechanisms for Communications Networks

How can we allocate a fixed amount of an infinitely divisible resource among a finite set of strategic agents? This is a classic problem in communication problems where pricing plays a key role [68], [109], [110]. Under natural network constraints, and if our desired outcome is to achieve efficiency, then our starting point is the *Kelly mechanism* [111]. Briefly, the Kelly mechanism asks each agent to act as a bidder in an auction and announce a bid. Then, the allocation of the single resource is conducted in proportion to the agents' bids. For each allocation, the social planner will receive a payment (or tax) equal to the amount the agent's bid in a proportional way. For example, if an agent bids a higher amount for a larger proportion of the resource, the Kelly mechanism asks the agent to pay more proportionally to their bid. In economics, we call this a "market-clearing price." Such a price has many desirable characteristics as it ensures the bare minimum communication (one-dimensional messages), and the social planner only needs to communicate back a single price per resource unit. Both characteristics are ideal as they ensure the mechanism is practical and easily implementable for large-scale systems. The usefulness of the Kelly mechanism led to extensive research and the birth of *scalar-parameterized mechanisms* (as the only communication between agents and the social planner is a scalar). Mathematically, the allocation function for agent $i \in \mathcal{I}$ in the Kelly mechanism is given by $x_i = (c \cdot p_i)/(\sum_{j \in \mathcal{I} \setminus \{i\}} p_j)$, where p_i is the payment agent i has to make, and $c \in \mathbb{N}$ is the capacity of a single resource.

Following a similar methodology, a special formulation of the VCG mechanism for an auction setting was introduced in [112], [113]. The problem was for a single divisible good under two different scenarios. At first, Semret [113] studied non-differentiable pseudo-utility functions between a social planner and multiple agents. In [112], the case was that agents seek bundles of links of a communication network (e.g., route), and each agent's utility function depends on the minimum allocation received along their route. The key approach here was that for each link of the network, a completely new and different auction was run. Both works have been somewhat generalized for multiple divisible links [114], [115]. A general convex VCG-based mechanism was introduced in [68] following [104], which, just like in the Kelly mechanism, only required one-dimensional bid signals from all agents. Following this work, [105] proposed a VCG-based mechanism with agents reporting a two-dimensional bid, i.e., a per-unit price β and a maximum quantity d_i that agent $i \in \mathcal{I}$ is willing to pay for the resource. Thus, the valuation function takes the form of

$$\hat{v}_i(x_i) = \beta \cdot \min\{x_i, d_i\}. \tag{14}$$

The benefit of this mechanism is that it provides the equilibrium of the induced game (auction in this case), resulting in an optimal solution of the utility maximization problem based on the reported by the agents' utility functions. Each agent pays for their allocation exactly the externality they impose on the other agents by participating in this mechanism. Of course, other mechanisms have been investigated, explored, and developed in great length [99]–[103].

Power Grid Systems

Over the last few decades, considerable efforts have been made to decarbonize our society's increasing energy demands [116] and reassess the efficiency of the existing methods of producing, managing, and consuming electricity [117]. Since the 1980s [118]–[120], *demand-size management* (DSM) programs have been the standard way to study power-grid systems, their efficiency, and recently, their transformation to smart grid systems thanks to automation. According to the Department of US Energy Information Administration: "Demand-side management (DSM) programs consist of the planning, implementing, and monitoring activities of electric utilities which are designed to encourage consumers to modify their level and pattern of electricity usage." Hence, it is no surprise that the next-generation smart power grids utilize information and communication technologies as well as improved computational and sensor capabilities. That is why smart power grid systems are excellent examples of cyber-physical systems characterized by an overlay of information, algorithms, and enhanced operational programs to generate, transmit, distribute, and use electricity [121].

There are multiple methodologies for DSM programs, but depending on the application and modeling choices, we can say that there are four main categories: (i) *energy efficiency*, (ii) price-based *demand response*, (iii) incentive-based demand response, (iv) market-based models. For the purposes of this article, our focus will be on the last category, i.e., *market-centric* grid control. The key architectural structure for such models is as follows: there are *generators*, *loads*, *distribution grids*, and *aggregators*, all playing important roles as participants in the market. There is an *independent system operator* (ISO) who is tasked to manage all and any transactions for electricity in the market [122]. The goal of such a model is to provide the "right" incentives and set of rules in order for the overall power generation to match the load at all times cost-effectively and in an efficient manner [121]. The main approach to achieve this goal is for the ISO to assume complete control of the market and, by introducing an auction, derive the incentives (e.g., electricity payments) for the efficient power and energy allocation under different scenarios. For example, we can consider different regulations and constraints in the production or distribution of electricity. Such modeling has been studied extensively over the last ten years, as efforts to provide more sustainable consumption and production of electricity to homes from factories have been a top priority [123]–[127]. Two key challenges that have been studied in the literature are: (i) *How can we design the right monetary payments in selling electricity to consumers in day-ahead or real-time settings?* (ii) *How can we ensure the efficient and balanced production and distribution of electricity as well as the control of the electrical voltage frequency?* In parallel to market-based approaches, game-theoretic models have also been studied and explored in an effort to understand the strategic interactions between producers (e.g., production centers or factories) and consumers (e.g., households, buildings) [128]–[133]. This means that both producers and consumers are assumed selfish (rational and intelligent), and thus, make decisions (how much electricity to produce, how much electricity to consume) according to their own individual self-interest [134].

Suppose our goal is to develop a pricing mechanism for a DSM program in which we want to encourage efficient energy consumption among consumers. If we adopt the mechanism design approach, then we set a system-wide socially efficient objective that we want to achieve (this could be properties such as truthfulness, efficiency, and budget balanced). *What if, though, all household appliances that use electricity from our consumers are jointly scheduled?* One way to tackle this issue (since it causes severe computational complexity) is to use the technique *consumer-level control*, in which we attempt to determine the total electricity consumption in each time step. Then, we schedule enough production/distribution for the consumer's appliances to operate at the "desired" electricity usage levels [135], [136]. However, additional information from the consumers might be necessary, and as it has been shown [7], this information is private, and consumers have no reason to report it truthfully. Hence, mechanism design can be used to solve this information elicitation problem by the appropriate design of incentives [137]. The literature can be categorized as follows: (i) auction-based mechanisms (primarily extensions of the VCG), (ii) market-based mechanisms [138]–[144], and (iii) indirect mechanisms for bidding and pricing models. In the following subsection, we review a general market-based framework of a smart grid system.

Electricity Markets

In this subsection, we offer a general formulation of an electricity market followed by its natural extension to an optimal mechanism design problem. Our exposition follows the work in [145].

We consider a smart power grid system consisting of agents (e.g., producers, consumers), a power grid network, and the electricity demand from the agents. In this general framework, we also consider that the information is uncertain. Electricity production incurs a cost that needs to be covered by the producers. To capture this, we introduce a *production cost function*. Thus, it is natural to expect all producers to be selfish, and so their goal is to cover, at the very least, their cost when selling the produced electricity. In general, there are two ways we can model this problem: (i) use of *bid function*, which directly maps electricity quantity into a payment; (ii) use of *supply function*, which directly maps payments to the produced quantity. As we discussed earlier, there is an ISO that aggregates the demand size. In mechanism design terms, ISO plays the role of a social planner and is tasked to elicit any private information, gather the bids and payments from the agents, and allocate the electricity that has been produced. Next, consider that $i \in \mathcal{I}$ refers to a node (some producer) of an arbitrary network $\mathcal{G}$, where $\mathcal{I}$ is the set of nodes. Each $i \in \mathcal{I}$ may produce $q_i \in \mathbb{R}$ quantity of electricity. As this is an interconnected power grid system, we say that the quantity of electricity that is sent from some node $i \in \mathcal{I}$ to node $j \in \mathcal{I}$ is denoted by $h_{i,j} \in \mathbb{R}$. At each node $i \in \mathcal{I}$, we assume that there is demand for electricity $d_i \in \mathbb{R}$. Each node is asked by the ISO to report a bid denoted by $b_i(q_i) \in \mathbb{R}$, and at the same also report the maximum quantity $\bar{q}_i$ node $i \in \mathcal{I}$ can produce. Next, we can add constraints to our problem to capture the specifics of the power grid network. We have $\mathbf{h} = (h_{i,j})_{i,j \in \mathcal{I}} \in \mathcal{H}$ such that $h_{i,j} \leq h_{i,j}^{\max}$. The goal of the ISO is to derive the allocation of electricity such that the total cost of production is minimized for the nodes (or producers), respect all constraints, and ensure the supply of electricity is at least greater than the demand (that way the power grid system can safely meet the demand) [145]. Next, we add a nodal constraint of the form

$$q_i + \sum_{j \in \mathcal{I}} (h_{j,i} - h_{i,j}) - \sum_{j \in \mathcal{I}} \frac{c_{j,i}(h_{j,i}) + c_{i,j}(h_{i,j})}{2} \geq d_i, \tag{15}$$

where $c_{i,j}(\mathbf{h})$ represents the loss from the distribution of electricity with quantity $\mathbf{h}$ from node $i \in \mathcal{I}$ to node $j \in \mathcal{I}$. This constraint is critical to ensure that the demand at each node is satisfied, considering the electricity produced, the amount received from other nodes, the amount sent to other nodes, and the losses from distribution between nodes. We are ready to state the allocation of the electricity optimization problem: for each $h \in \mathcal{H}$, we have

$$\min_{(q_i)_{i \in \mathcal{I}}, \mathbf{h}} \sum_{i \in \mathcal{I}} b_i(q_i) \tag{16}$$

$$\text{subject to: } q_i + \sum_{j \in \mathcal{I}} (h_{j,i} - h_{i,j}) - \sum_{j \in \mathcal{I}} \frac{c_{j,i}(h_{j,i}) + c_{i,j}(h_{i,j})}{2} \geq d_i, \tag{17}$$

$$q_i \in [0, \bar{q}_i], \tag{18}$$

$$h_{i,j} \geq 0. \tag{19}$$

We consider that there exists a probability distribution f_i over a set of potential production cost functions. Each node $i \in \mathcal{I}$ is characterized by a type, say θ_i, representing a production cost function that depends on the quantity q_i. So, based on the mechanism design expectation that no node $i \in \mathcal{I}$ will report their true production cost function θ_i truthfully, we need to formulate an optimization problem and design appropriate incentives in order to have efficient production and distribution of electricity in the power grid network. We have

$$\min_{q_j, h_{i,k}, p_j} \sum_{j \in \mathcal{I}} \mathbb{E}[p_j(\theta)] \tag{20}$$

$$\text{subject to: } q_j(\theta) + \sum_{i \in \mathcal{I}} (h_{i,j} - h_{j,i}) - \sum_{i \in \mathcal{I}} \frac{c_{i,j}(h_{i,j}) + c_{j,i}(h_{j,i})}{2} \geq d_j, \tag{21}$$

$$\mathbb{E}[p_j(\theta)] - \theta_j(q_j(\theta)) \geq \mathbb{E}[p_j(b)] - \theta_j(q_j(b)), \tag{22}$$

$$\mathbb{E}[p_j(\theta)] - \theta_j(q_j(\theta)) \geq 0, \tag{23}$$

$$h_{i,j}, p_j \geq 0, \tag{24}$$

where $\theta = (\theta_i)_{i \in \mathcal{I}}$ is the profile of production cost functions. To solve the above optimization problem, we need a mechanism with allocation and payment rules (q, p) that minimizes the expected payments of all nodes. Some key approaches to find the optimal (q, p) are to analyze first a NE based on *Bayesian Bertrand games* [146], study the quadratic externalities of the system or study the Walrasian equilibrium and replicate the techniques used in wholesale electricity auctions [147], [148]. Of course, there are many other techniques for this problem, i.e., stochastic market mechanisms [149] and energy-reserve co-optimized markets [150]. Of course, there are other methodologies of electricity markets in power grid systems or electric mobility that take a different approach, such as designing stochastic repeated games [151], [152].

Transportation Systems

Commuters in big metropolitan areas have continuously experienced the frustration of congestion and traffic jams [153]. Several studies have shown the benefits of *emerging mobility systems* (e.g., ride-hailing, on-demand mobility services, shared vehicles, self-driving cars) in reducing energy and alleviating traffic congestion in several different transportation scenarios [154]–[163]. For some recent and comprehensive surveys on the methodologies and techniques used in smart mobility-on-demand systems, see [164]–[166].

Routing/Congestion Games

We start this subsection with a motivational example. Suppose we have a simple transportation network $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with two routes A and B (one shorter than the other), where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of edges/roads. The agents (in this case, the drivers) start at origin $o \in \mathcal{V}$ and need to choose either route A or B to reach a final destination $d \in \mathcal{V}$. If all drivers choose the shortest route, then naturally, congestion will occur, and all drivers will experience travel delays. So, the goal here is to find the best possible coordination of traffic through the different routes from o to d. We can model this as a game in which the drivers play against each other and have two possible actions (route A or route B), thus leading to several possible outcomes. In the simple case of two players, the number of possible outcomes is the combination of choices between these two players, i.e., (i) both players choose route A; (ii) player 1 chooses route A and Player 2 chooses route B; (iii) player 1 chooses route B and Player 2 chooses route A; (iv) both players choose route B. *Which one is the best equilibrium?* The answer to this question has been studied extensively over the last twenty years in the form of noncooperative *routing games*, in which selfish agents compete for the best route in traffic of a transportation network [167]. Most interestingly, the generalization of routing games was developed by economist Robert W. Rosenthal in 1973 [168], [169], in which the theoretical framework of *congestion games* was introduced as noncooperative games of competing agents whose strategies are subsets of resources in the system (transportation network). The agents' utility then depends only on the number of other agents who have chosen the same or overlapping strategy [170], [171]. Moreover, the final cost of an agent can be computed as the sum of the costs of the strategy's elements (route, origin-destination pair). Mathematically, following the formulation of congestion games in [2] closely, we have $n \in \mathbb{N}$ agents with set $\mathcal{I} = \{1, \ldots, n\}$ and a network $\mathcal{G}$. The set of strategies of each agent $i \in \mathcal{I}$ is a set of subsets of the set of edges $\mathcal{E}$. We call these *paths* or *routes*. For each edge $e \in \mathcal{E}$, there exists a *congestion function* $c_e : \mathcal{I} \to \mathbb{R}_{\geq 0}$. Additionally, denote by $\mathcal{P} = \{(\mathcal{P}_i, \ldots, \mathcal{P}_n)\}$ the set of paths (i.e., the strategies). The congestion of edge $e \in \mathcal{E}$ is some function $\ell(\mathcal{P})$ that can measure how many agents utilize one particular edge of agent $i \in \mathcal{I}$. Then, agent i's utility is given as

$$u_i = \sum_{e \in \mathcal{P}_i} c_e(\ell(\mathcal{P})). \tag{25}$$

If the set of agents is infinite, then the game is *nonatomic* [172]. This notion, together with Rosenthal's congestion game framework, allowed the formulation of general traffic networked games with an infinite number of agents, each with a negligible effect on the system's overall performance. Hence, nonatomic congestion games (and their special case: routing games) have been the standard model of transportation systems, communication routing networks, and computer science [173]–[182]. Moreover, this framework of congestion games has been proven to be quite flexible for a number of models and applications (see [167]).

Another example to showcase the flexibility and the theoretical prowess of nonatomic congestion games is the traffic routing model [183]. Agents are characterized as different origin-destination pairs in a transportation network of which its edges are the resources. The core assumption here is that agents compete for limited (easily congested) resources. Thus, the strategies of the agents are represented as the possible paths between an origin and a destination. To each path, a cost is associated, and it models the travel latency or travel delays based on the traffic along the path. The goal in this model is to find an equilibrium closest to the *social optimum*: a multicommodity flow of minimum total delay. In [183], the *Wardrop equilibrium* was introduced as the collective strategies of all agents in the network with the shortest paths. The significance behind the Wardrop traffic model under the congestion game framework is that it allows us to study the efficiency of equilibria. Both NE and Wardrop equilibria fail to minimize the social cost and, thus, are overtly inefficient. Thus, to improve the game-theoretic analysis, in 1999, Koutsoupias and Papadimitriou [184], [185] proposed the inefficiency of equilibria to be studied through the lens of worst-case analysis. In their seminal work, they introduced the "Price of Anarchy," which represents the ratio of the worst social cost evaluated at an NE to the cost of an optimal solution [170]. This key notion was extensively studied in transportation, communication, and computer science problems (e.g., selfish routing) [170], [176], [186]–[189].

Auction-based Approaches for Intelligent Transportation Systems

Traffic congestion persists to be one key challenge for the next-generation smart cities. The cost incurred by travel delays, traffic accidents, and fuel consumption has been estimated to be in the billions of US dollars per capita annually. That is why, over the last twenty years, *Intelligent Transportation Systems* (ITS) have been introduced to provide solutions and make transportation in urban areas, as well as highways, safer, efficient, and convenient for travelers and drivers. ITS are a multidisciplinary field as they incorporate multiple technologies such as wireless communication, navigation, sensing, and computing technologies [190]. For example, ITS have been applied in-vehicle navigation, traffic signal control, emergency notification, and collision avoidance system. Naturally, communication is vital in such systems including *vehicle-to-vehicle* and *vehicle-to-infrastructure* (V2I) communication [191], in which advanced wireless communication allows vehicles to communicate crucial traffic information (e.g., speed, position, acceleration, traffic conditions, congestion, traffic warnings) and vehicles to infrastructure (some central authority/coordinator).

As we discussed earlier in this section, a key approach to the analysis of ITS can be based on auctions. Vickrey's work [192] established *congestion pricing* as a way to control congestion efficiently by requiring the travelers/drivers in the transportation system to pay tolls (as a function of the existing congestion, time, location, vehicle type) [193]. Dynamic pricing has also been introduced, notably [194], [195]. In contrast to congestion pricing, an auction-based technique focuses on establishing an auction with competing vehicles reporting bids for "time-slots" for them to travel in high-demand urban areas during peak hours [196]. Alternatively, taking advantage of V2I technologies, a *combinatorial auction* can be formulated to determine the right toll prices for vehicles [197] (in such auctions, buyers compete with each other and bid to acquire multiple different but related goods). Based on [196], we have the following framework: there is a set of agents $\mathcal{I}$, where each agent $i \in \mathcal{I}$ makes a total of $m_i \in \mathbb{N}$ bids to enter the high-demand urban area. Time is modeled as a set of discrete steps, i.e., $\mathcal{T} = \{1, 2, \dots, T\}$,

$T \in \mathbb{N}$. Each time interval represents the duration of an agent's stay in the area. So, each agent $i \in \mathcal{I}$ bids a monetary payment of value $p_{ij} \in \mathbb{R}$ for the right to visit the urban area a number of $c_{ij} \in \mathbb{N}$ times. Next, we have the following binary variables:

$$d_{ij}(t) = \begin{cases} 1, & \text{if } c_{ij} \text{ consists of time interval } t, \\ 0, & \text{otherwise.} \end{cases} \tag{26}$$

In addition, we have

$$x_{ij}(t) = \begin{cases} 1, & \text{if } c_{ij} \text{ is accepted,} \\ 0, & \text{otherwise.} \end{cases} \tag{27}$$

Thus, the optimization problem is formulated as follows:

$$\max_{x} \sum_{i \in \mathcal{I}} \sum_{j=1}^{m_i} p_{ij} \cdot x_{ij}, \tag{28}$$

$$\text{subject to: } \sum_{i \in \mathcal{I}} \sum_{j=1}^{m_i} d_{ij}(t) \cdot x_{ij}(t) \leq D_{\max}, \quad \forall t \in \mathcal{T}, \tag{29}$$

$$\sum_{j=1}^{m_i} x_{ij} \leq 1, \quad \forall i \in \mathcal{I}, \tag{30}$$

where $D_{\max}$ is the maximum number of vehicles that are allowed to be in the specific urban area. This optimization problem is rather difficult to solve as it is combinatorial, and depending on its size, it can be almost impossible to solve in finite time. However, the auction-based congestion pricing [196] can provide good-enough solutions. In [197], a similar yet improved combinatorial optimization problem is proposed, and using VCG-based incentives provides an efficient solution in the alleviation of traffic.

More recently, auctions and mechanism design have been used in ridesharing [5], [198] and autonomous vehicles public transportation problems [199]. We summarize some of the latest papers in this area in Table 2.

Security Systems

It is well-known that cyber-defense remains a top priority for many organizations across different sectors. Part of this is because cyber-attacks are continuous and have the ability to bring down vital systems. Although there are many different angles to study security in a system of multiple agents, one approach is to assume security is an economic good or resource and adopt game-theoretic approaches to study how we can find the best possible processes (via the appropriate design of incentives) for an efficient security investment [206], [207]. The main assumption in this approach is that the interactions between strategic agents in a system in which

TABLE 2: A summary of auction-based mechanisms for transportation systems.

Auction-based mechanisms for transportation systems			
Reference	Model	Auction Type	Scenarios
[200]	Dynamic Ride-sharing	Combinatorial double auction	One-to-one assignment
[201]	Dynamic Ride-sharing	Vickrey	One-to-one assignment with detours
[202]	Dynamic Ride-sharing	Combinatorial double auction	One-to-one assignment with detours
[199]	Dial-a-Ride problem	VCG	One-to-many
[203]	Dial-a-Ride problem	Combinatorial double auction	One-to-many
[204], [205]	Dial-a-Ride problem	VCG	One-to-one assignment with detours

security is of crucial importance can constitute a game. The objective of such a game is the provision of security in the means of investments by the agents. Thus, we say that security is a public good. This approach was first introduced by [208] as a way for a "security game" to study airlines' baggage checking systems and what incentives are best. In parallel, Varian [209] studied security games for the reliability of computer systems. Afterward, security games were extensively studied in different fields and applications [208]–[213]. There are two surveys on this topic [214], [215].

The Design of Security Games

What is a security game? In general, interconnected systems of multiple agents who each depend on each other can be vulnerable to attacks by outsiders and external forces. Thus, any agent is encouraged to invest in the system's security measures not only to protect themselves but also to protect the other agents. Interconnectedness implies a positive externality. Consequently, the provision of security can be modeled naturally as the provision of a *public good* (non-rivalrous commodity) [1]. Thus, a security game models the strategic interactions of agents in a security system where each is asked to invest their own resources to secure the system from external attacks. Mathematically, we consider a network of $n \in \mathbb{N}$ agents (e.g., networked computer servers, corporate divisions, self-driving vehicles on a highway). The utilities of all agents are interdependent, and so $v_i(\mathbf{x})$. Each agent is assumed to possess a finite amount of resources $w_i \in \mathbb{N}$ available for investment, and we say that if an attack is successful against agent i's resources, then a loss $\ell_i \in (0, w_i]$ may be imposed to agent $i \in \mathcal{I}$. The agent is allowed to protect their resources; hence agent $i \in \mathcal{I}$ may invest $x_i \in \mathbb{R}_{\geq 0}$. However, this investment comes with a cost, represented by a general function $c_i : \mathbb{R}_{\geq 0} \to \mathbb{R}_{\geq 0}$ evaluated at the individual amount of investment x_i. We denote the vector of all agents' investments by $\mathbf{x} = \{x_1, \dots, x_n\} = \mathcal{X}$. Then, to capture how likely an attack may be successful or not, we introduce a risk function $r_i : \mathbb{R}^n_{\geq 0} \to [0, 1]$. Let $\mathbf{x}_{-i} = \{x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n\}$ capture the interdependence of all other agents' security. Then, the utility of an agent $i \in \mathcal{I}$ is of the form

$$v_i(\mathbf{x}) = w_i - \ell_i \cdot r_i(\mathbf{x}) - c_i(x_i). \tag{31}$$

Hence, the security game is given by the tuple $\langle \mathcal{I}, \mathcal{X}, (v_i)_{i\in\mathcal{I}} \rangle$ under a complete or incomplete information setting (depending on the problem).

The transformation of a security game to a mechanism design problem is straightforward. For a solution concept, we adopt the NE. Formally, we have

$$\tilde{x}_i = \arg\max_{x\geq 0} v_i(x_i, x_{-i}). \tag{32}$$

For completeness, the socially-optimal solution profile $\mathbf{x}^*$ can be computed as follows

$$\mathbf{x}^* = \arg\max_{x\geq 0} \sum_{i\in\mathcal{I}} v_j(\mathbf{x}). \tag{33}$$

Next, the total interdependent utility of agent $i \in \mathcal{I}$ is given by

$$u_i(\mathbf{x}, p_i) = v_i(\mathbf{x}) - p_i, \tag{34}$$

where p_i represents a payment/tax for agent $i \in \mathcal{I}$ when the investment profile is $\mathbf{x}$. Naturally, in a security system, it is imperative to design the right payments for all agents in order to incentivize voluntary participation. One approach for this is to introduce the notion of *exit equilibrium*: this is an equilibrium that takes into account the "external strategy" of an agent from the mechanism for the provision of non-excludable goods, such as security and investment. At an exit equilibrium, an agent may unilaterally opt out of the mechanism and decide to adopt their best response against the other agents who have chosen to participate in the mechanism [216]. Formally, we have

$$\hat{\mathbf{x}}^i_{-i} = \arg\max_{\mathbf{x}_{-i}\geq 0} \sum_{j\neq i} v_j(\mathbf{x}_{-i}, \hat{\mathbf{x}}^i_i), \tag{35}$$

$$\hat{\mathbf{x}}^i_i = \arg\max_{x_i\geq 0} v_i(\hat{\mathbf{x}}^i_{-i}, x_i). \tag{36}$$

Most notably, although this is quite an interesting notion of an exit equilibrium, [216] showed an impossibility result for mechanisms that induce a security game with social optimality, weak budget balanced, and voluntary participation. Most interestingly, two main approaches, i.e., the

VCG mechanism and the *externality mechanism* [217], [218] that have been quite successful in other applications fail to circumvent this theoretical obstacle. For the purpose of this article, we focus on the latter only.

The externality mechanism aims to redistribute the wealth that is collected from the agents and ensure a strong budget balance (all payments equal to zero). As shown in [218], this mechanism induces a game with social optimality, and voluntary participation, and maintains a balanced budget for cellular networks (which is an excludable public good). The payment function is given by

$$p_i(\mathbf{x}^*) = -\sum_{j \in \mathbb{I}} x_j^* \ell_i \frac{\partial r_i}{\partial x_j}(\mathbf{x}^*) - x_i^* \frac{\partial c_i}{\partial x_i}(x_i^*). \tag{37}$$

However, these taxes fail to induce voluntary participation for all agents, and thus, the system will be significantly vulnerable to attacks as its security cannot be guaranteed.

Security in Communication Systems

Security has been extensively studied in communication systems since the 1980s. With the advancement of communication technology, such as wireless networks, communication between systems, computers, and phones has never been as easy and quick. However, such systems admit vulnerabilities, and since they play a key role in the exchange of information, attacks are continuous and frequent. So, in this subsection, we briefly focus on auction-based mechanisms that offer solutions for various communication scenarios and the solutions we can derive.

Auctions have been used to model the economic-in-nature interactions between agents of a communication system that need to invest resources for the security and well-being of the system (e.g., prevent external attacks). Examples of auctions used to model security include *English auctions*, *Dutch auctions*, *Sealed-bid auctions*, *Double auctions*, *Share auctions*, and *Ascending-clock auctions*.

Both English and Dutch auctions are multiple-round auctions and allow buyers to exchange information (their bid) with other buyers. In economics, this type of disclosure in auctions is called *open-outcry*. In addition, the auctioneer in English auctions introduces a bid and keeps increasing it at each round, while in Dutch auctions, the opposite process occurs (high price decreasing until accepted). Thanks to the simplicity of the auction rules, such auctions have been used to defend and identify “malicious” agents in a system [225]. Sealed-bid auctions, as their name suggests, are characterized by their ensured privacy as buyers do not disclose their bids to anyone (examples are the first-price auction, Vickrey auction, and the VCG auction). The specifics of each auction have been summarized in Table 3 together with recent key applications [226]. For example, the VCG auction extends the Vickrey auction with multiple goods and

TABLE 3: A snapshot of papers on the security of communication systems.

Auction-based mechanisms for security in communication systems.			
Auction Type	Characteristics	Solution Concept	Scenario
English auction [219]	Winner pays second highest price	NE	Information integrity
Dutch auction [219]	Winner pays final price	NE	Black-hole attack
First-price sealed-bid auction [220]	Winner pays highest price	NE	Privacy or faked-sensing attack
Vickrey auction [220]	Winner pays second highest price	NE	User collusion/bid-rigging
VCG auction [221]	Vickrey auction with multiple goods	BNE	Eavesdropping attack
Share auction [222]	Matching of goods based on ratio of buyers' bids	NE	Distributed Denial-of-Service attack
Ascending-clock auction [223]	Increase price until demand equals supply	Walrasian equilibrium	False-name bids
Double auction [224]	Matching between sellers' demands and buyers' bids	Market equilibrium	Privacy

sets the proper rules to determine the winner (i.e., the buyer who gets the auctioned good). In particular, the VCG auction awards the good to the buyer, who then pays the second-highest bid. This is extremely important as it establishes the following principle: bid your true valuation and pay less than you expect. The VCG auction has been widely used in securing communication and wireless networks (e.g., to prevent agent misbehavior).

So far, the above-mentioned auctions are *one-sided*, meaning there is one auctioneer who tries to sell one or more goods to a finite number of buyers. In a double auction, there is still an auctioneer who manages an auction between multiple buyers, who each submit bids at the same time, and sellers, who each submit payment demands for their goods [224]. For example, an auctioneer can match the buyers and sellers as follows: list the bids in a descending order and the payment demands in an ascending order. Denote by p_m^{seller}, p_m^{buyer} for the payment demand of a seller and the bid of a buyer, respectively. Then, the auctioneer can find the largest index

$m \in \mathbb{N}$ for which we have

$$p_m^{\text{buyer}} \leq p_m^{\text{seller}}. \tag{38}$$

The next step is to set the final payment as

$$p^* = \frac{p_m^{\text{buyer}} + p_m^{\text{seller}}}{2}. \tag{39}$$

In economics, p^* is called *clearing price*. Using these prices, buyers get the good by paying p^*, and naturally, the seller receives p^*. This process can be repeated as many times as necessary, and it stops once all sellers' goods have been matched or sold to the buyers.

Lastly, share auctions are a type of auction that resembles a market and are used to model a resource allocation to multiple buyers. However, the resource needs to be divisible (e.g., bandwidth) [227]. Share auctions are as follows: buyers submit to an auctioneer a bid (how much bandwidth they require), and then the auctioneer computes a payment that is proportional to the buyer's bid. For example, suppose there are $K \in \mathbb{N}$ source-destination pairs of friendly jammers (sellers of friendly-jamming power) and eavesdroppers in a wireless communication network. The goal is to improve the secrecy capacity of a source. A buyer submits a bid in the form of asking for friendly-jamming power, say $\pi_i \in \mathbb{R}$. Thus, we can allocate the friendly-jamming power at each source $i \in \mathcal{I}$, i.e.,

$$\pi_i = \frac{b_i \pi_{\max}}{\beta + \sum_{k=1}^{K} b_k}, \tag{40}$$

where $\pi_{\max}$ is the maximum possible power, b_i is the source i's bid, and $\beta \in \mathbb{R}$. Finally, source $i \in \mathcal{I}$ pays $p_i = \lambda \pi_i$, where $\lambda \in \mathbb{R}$ is a payment per unit of power. Such auctions can be used to find the optimal bid between sources in the network and maximize the secrecy capacity change [228]. A comprehensive survey and tutorial can be found in [229], [230].

Conclusion

In this last section of our article, we offer a discussion on the theory of mechanism design and its engineering applications. First, we discuss the theoretical and practical limitations of the theory, some of the most notable criticisms, and how to move forward. We pay extra attention to offering key open questions in mechanism design and propose two main future research directions that we, as authors, believe have the greatest potential. Lastly, we conclude this article with a few remarks.

Traditionally, mechanism design has focused mainly on quasilinear static settings under somewhat simple structures for the agents' types or utility functions. Some particular (unrealistic) strong assumptions have pervaded, making it difficult for mechanisms to be implemented in real-life problems. Whether the set of agents remains fixed and known to the social planner or the evolution of information is not considered, the ability to design mechanisms that offer a superior way to design incentives and induce efficiency across a system still remains a formidable challenge in mechanism design. For example, the VCG mechanism, although a widely used mechanism, is not frugal, and depending on the application, it might overtax agents (thus, impose a heavy tax burden). Information and communication, as envisioned by Leonid Hurwicz, rely on the universal existence and authority of a central authority (a social planner). Agents are expected to fully disclose their private information, raising privacy concerns as well as computational costs to manage the sheer amount of information. Another key critique of the theory is the computational intractability of certain mechanisms as many fail to provide an iterative learning process (alternatively called tâtonnement process), i.e., there exists an algorithm for the equilibrium to be attained by the agents and social planner.

In general, from an engineering standpoint, mechanism design is characterized by its trade-off between the design of optimal and efficient solutions that all agents will accept and realistic and system-wide properties such as simplicity, robustness, and computational trackability. As control problems are commonly dynamic, complex, and unpredictable [231], it still remains an open question to devise mechanisms that are simple yet dynamic, robust, and trackable. At the same time, a key open question is to look at the intersection of mechanism design and machine learning, allowing mechanisms with incentives that lead to efficient equilibria that can be learned in dynamic environments (i.e., extending the typical mechanism to address dynamic control problems). It is the authors' belief that engineering applications (e.g., communication networks, information systems, transportation networks) of large-scale systems, which are dynamic in nature, impose rather crucial challenges to the theoretical framework of mechanism design, and thus, inspire novel new mechanisms that will circumvent some of the limitations of the theory. Over the last ten years, there has been extensive research from economists and mathematicians in expanding the theory of mechanism design for dynamic systems [6], [232]–[234]. The goal, of course, is to improve the applicability of these mechanisms in real-life problems and translate the usefulness of the theoretical insights into practice. Finally, game theory allows us to model the strategic interactions of systems consisting of multiple agents/players who compete over resources. The theory of mechanism design allows us to adopt an objective-first approach and model the best possible game and its rules. As new developments and applications are continuous, it remains to be seen the next chapters of mechanism design in engineering and its true impact in solving big problems.

Sidebar: Further Reading

There is a rich list of books in game theory, economic design, and mechanism design for the interested reader and especially for any first-year graduate students as a first resource to learn more about the field. The literature on game theory and its applications includes several excellent textbooks [S26]–[S31]. Most of the established theories of mechanism design can be divided into three categories: economics, auctions, and computer science (with general applications). The golden standard in microeconomics, which includes rigorous introductions to game-theoretic notions and mechanism design, is [S32]. A more focused on Nash-based mechanisms and matching markets textbook is [S34]. A recent book [S33] offers a more economics-inclined theory establishing the foundations of mechanism design. Excellent textbooks in implementation theory are [S35] (with an excellent chapter in [S31]). Robust mechanism design in economics has been mostly developed by Dirk Bergemann, who has compiled a decade's worth of work in [S36]. So far, most of the textbooks focus on the implementation of mechanisms and the efficient design of incentives. A completely different approach, one that is much closer to the first seminal paper by Leonid Hurwicz, is the study of mechanisms under informational efficiency focusing mostly on the preservation of privacy [S37] and the bounded size of the message space [S38]. However, a rather engineering-accessible textbook that offers a theoretical framework of mechanisms through fundamental results from linear programming is [S39]. Mechanism design has been instrumental in auction design, and many times, the methodologies and techniques of the two theories are interchangeable. Thus, here are some great general textbooks [S40], [S41], and a survey on combinatorial auctions [S42]. We end this part by offering excellent surveys from the economics literature [S43], [S44]. Of course, there have been numerous key contributions in mechanism design by computer scientists, and in many graduate programs, mechanism design is part of the curriculum. A well-known textbook that offers a survey of these contributions can be found in Chapters 9–16 of [S45] and in general [S46]. Additional resources in game-theoretic approaches and techniques of mechanism design can be found here (including dynamic incentive design) [S47]–[S50]. Lastly, a recent publication that discusses the latest developments, insights, and theoretical results in economic design is [S51].

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