Resource Management under Uncertainties, Risks and Information Incompleteness in Next Generation (NextG) Networks

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Tutorial

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Outline

- **Introduction**
- **Contract Theory:** Resource Management under Incomplete/Asymmetric Information
  - Principles, Models & Taxonomies
  - Contract Design
  - Application Examples
- **Game Theory:** Distributed Resource Management
  - Principles
  - Games in Normal Form
  - Games in Satisfaction Form
  - Standard Common-Pool-Resource Game
- **Prospect Theory:** Risk-Aware Resource Management
  - Principles
  - Fragile Common-Pool-Resource Game
  - Application Examples

Introduction

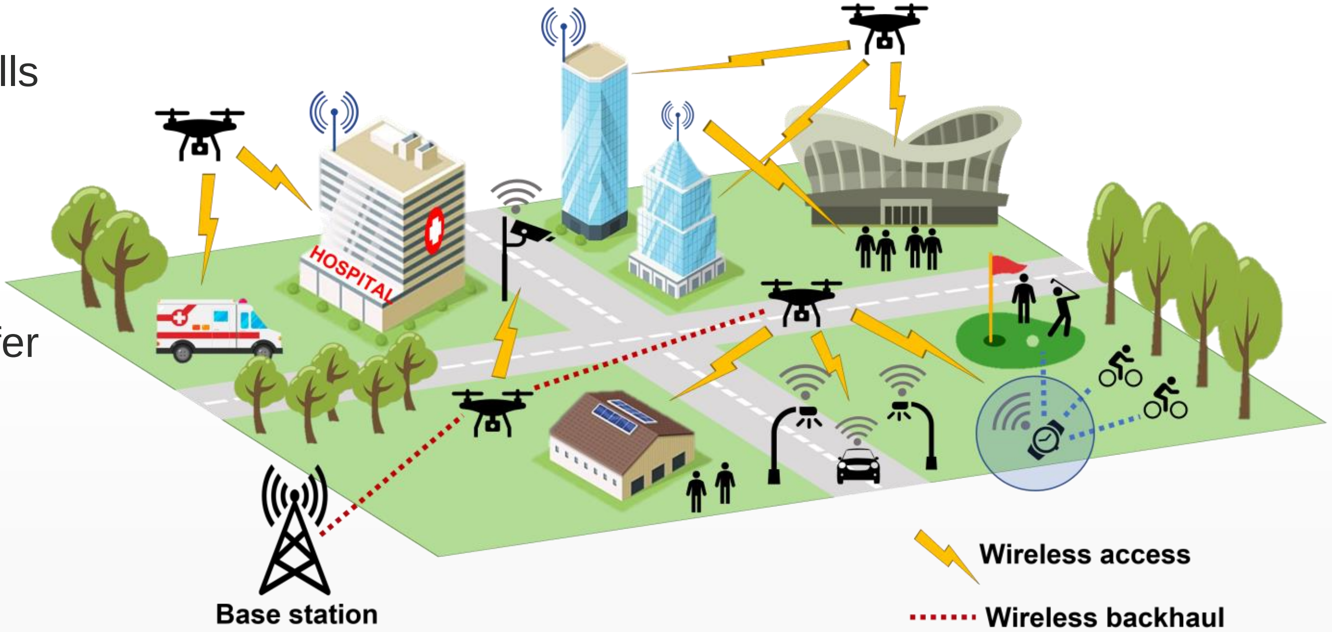
6G Wireless Communication Networks

Technologies

- Heterogeneous network deployments
- Dense deployment of mmWave small cells
- UAV-assisted communications
- 3D-networking (terrestrial, satellite)
- Integrated access & backhaul networks
- Joint wireless information & power transfer

Stakeholders

- Mobile network operators
- Service providers
- Small-cell holders
- End-users



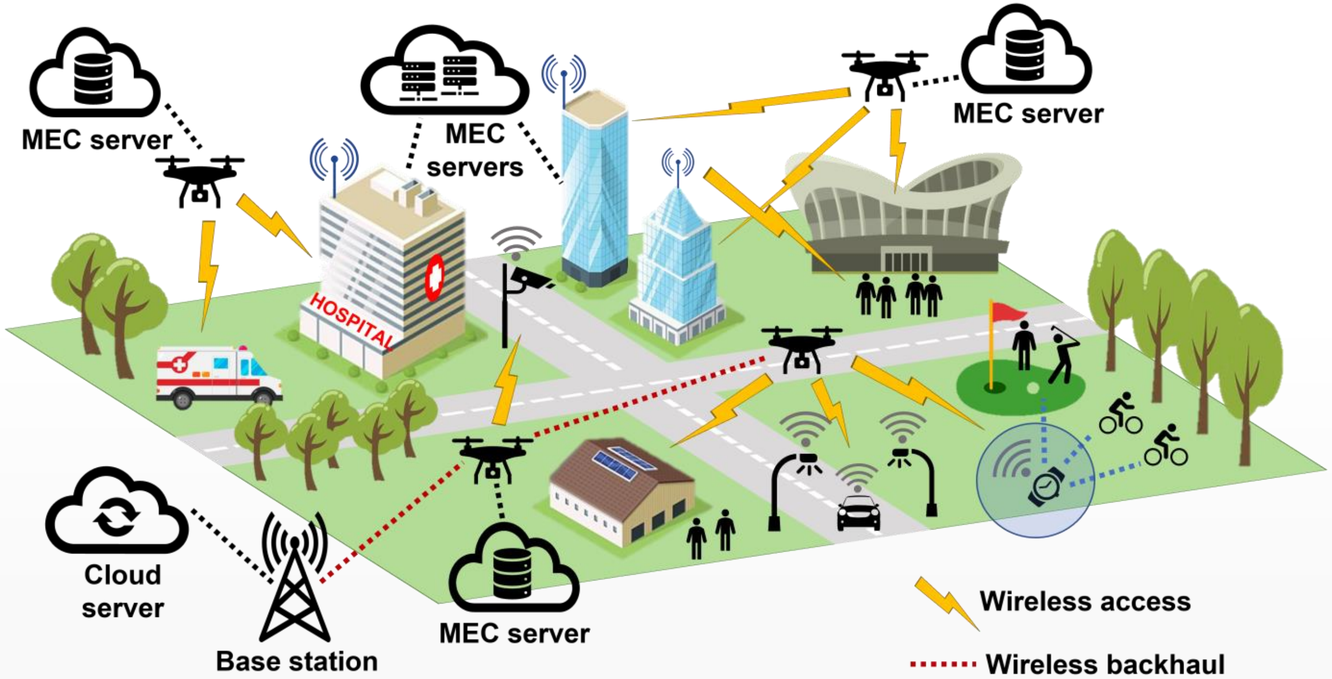
6G Wireless Computing Networks

Technologies

- Multi-access edge computing
- Heterogeneous multi-layer computing
- Delay-tolerant computing
- Collaborative mobile edge computing

Stakeholders

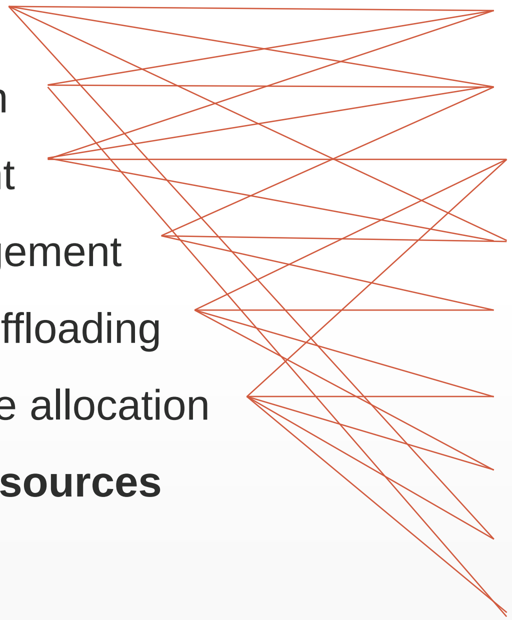
- Cloud providers
- Edge providers
- Network providers
- Cloud tenants
- Cloud service brokers
- End-users



Resource Allocation Problems

Allocated Resources

- User association
- Spectrum allocation
- Power management
- Interference management
- Computation task offloading
- Computing resource allocation
- **Combination of resources**



Objectives

- Rate maximization
- Energy efficiency maximization
- Energy consumption minimization
- Interference mitigation
- Delay minimization
- Profit maximization
- System utility maximization
- Load balancing
- Fairness
- **Multiple objectives**

Challenges

- Congested and demanding environment
- Multiple entities and stakeholders
- Different and contradicting objectives
- Common/shared resources
- Interdependent behaviors, interactions and decisions

Competitive distributed environment

Economic-driven approaches & solutions

- Distributed resource management
  - → Mitigates signaling overhead
  - → Alleviates single point of failure burden
  - → Enables dynamic and autonomous decision making
  - → Decreases algorithmic complexity
  - → Improves security and privacy
- Accounts for resource/service pricing and network’s profit

Traditional Economic Models Limitations

Traditional economic models assume players':

1. rationality and completeness of information
2. willingness to invest more personal resources or pay higher fee to enjoy better service
3. risk-neutral behavior

≠

Realistic 6G networks are characterized by:

1. partial/incomplete information and dynamicity
2. need for sparing resource management and mitigation of unjustified resource drainage
3. risk-averse behavior associated with the common resources' over-exploitation

Contract Theory

- Creates mutually agreeable contracts between economic players
  - e.g., employer - employees
- Reconciles players’ conflicting goals
- Accounts for the employer’s partial/incomplete information
- Distinguishes employees according to their personal/private characteristics
- Allows employees’ autonomous decision making based on their current state

Games in Satisfaction Form

- Promotes QoS satisfaction instead of maximization
- Promotes fair allocation of resources
- Meets players' QoS prerequisites
- Reduces energy consumption or unnecessary expenses
- Provides a distributed resource management framework

Prospect Theory

- Formulates players' utility functions
- Accounts for players' relative sensitivity to gains and losses, or satisfaction and risk
- Discriminates between a safe resource and a resource prone to failure
- Can be used along with typical optimization or game-theoretic methodologies
- Provides realistic modeling of player behavior against the shared nature of communication and computing resources

Contract Theory: Resource Management under Incomplete/Asymmetric Information

Contract Theory

- Studies the interactions between a **principal** and a **agent/agents** under **asymmetric/incomplete information** cases, by introducing cooperation between them.
  - Employment contracts
  - Insurance contracts
  - Venture capital contracts
- The principal is unaware of the agents' personal characteristics, i.e., **private information**.
- Outcome: **Contract bundles** for the agents {
  - **effort** provided to the principal
  - **reward** offered by the principal

Contract Theory Breakthrough Timeline

1940s – 1950s

- Simple exchange of goods
- Allocation / Sharing of risk

1960s – 1970s

- Private information
- Hidden actions

1980s – 1990s

- Long-term contracting
- Dynamic contracting

2014

- **Jean Tirole Nobel Prize**
- ”for his analysis of market power and regulation”

2016

- **Oliver Hart & Bengt Holmström Nobel Prize**
- “for their contributions to contract theory”

Adverse Selection Problem (1)

Hidden information problem

The plan I tell my teacher

"I want to study at the university"

The secret plan

Become a basketball player

Adverse Selection Problem (2)

- Hidden information **before contract agreement**
- Asymmetric/Incomplete information
  - The **agents' characteristics** are their **private information**
  - The principal has **statistical knowledge** of the agents' private information
- The principal distinguishes the agents into different **types**
- Revelation principle
  - The principal designs a **menu of contracts tailored to the different agent types**
  - The principal makes sure that each agent type has the incentive to **select only the contract destined to this type**

Adverse Selection Problem (3)

Principal:
Designs menu of contracts based on its statistical knowledge about the agent types

Agent:
Selects the one contract that best fits its type, i.e., private information

Agent:
Provides the required effort to the principal

Principal:
Makes revenue from the agent’s effort

Principal:
Offers to the agent a reward

Moral Hazard Problem (1)

Hidden action problem

What the teacher thinks I do

What I actually do

Moral Hazard Problem (2)

- Hidden action **after contract agreement**
- Asymmetric/Incomplete information
  - The **agents' actions** are their **private information**
  - The principal **is unaware** of the agents' **actions**, but can **observe** their ultimate **performance**
- The principal **rewards good performance** or **punishes bad performance**
- There is **no menu of contracts**
- The agent **autonomously selects** the amount of **action** that leads to a desired reward

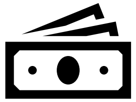
Moral Hazard Problem (3)

Agent:

Selects to perform an action

Principal:

Observes the agent’s performance, which is a noisy signal of its performed action



Principal:

Makes revenue from the agent’s performance

Principal:

Offers to the agent a reward proportional to its performance

Mixture of Adverse Selection & Moral Hazard (1)

- **Two** levels of asymmetric/Incomplete information

Hidden information, i.e., agent types → → Hidden action

- **Two-stage reward** offered by the principal

Down payment → → Installment payment

- The principal designs a **menu of two-stage payments tailored to the different agent types**
- The principal **rewards good performance via the installment payment**
- The agent **autonomously selects** the amount of **payment and action** that lead to a desired reward

Mixture of Adverse Selection & Moral Hazard (2)

Principal:
Designs a menu of payments based on its statistical knowledge about the agent types

Agent:
Selects the one payment method that best fits its type

Principal:
Provides the agent with the down payment

Agent:
Selects to perform an action

Principal:
Observes the agent's performance, which is a noisy signal of its performed action

Principal:
Makes revenue from the agent's performance

Principal:
Provides the agent with the installment payment, i.e., reward proportional to its performance

Contract Theory Taxonomies

- Adverse Selection Problem
- Moral Hazard Problem
- Mixture of Adverse Selection & Moral Hazard Problem

- Static Contracting
- Repeated Contracting

- Bilateral Contracting (One-to-One)
- Multilateral Contracting (One-to-Many)

- One-Dimensional Contract
- Multi-dimensional Contract

} types, efforts/actions, rewards

- Complete Contract
- Incomplete Contract

Contract Design

- **Outcome:** Agent’s optimal bundles of {effort , reward}
- **Procedure:** Optimization problem solved by the principal
  - **Objective:** Maximize the principal’s personal utility
  - **Constraints:** Guarantee the agent’s participation in the contract

How to guarantee the agent’s participation?

- **Individual Rationality (IR) condition:** The agent’s utility under this contract is greater than or equal to its reservation utility when not participating in the contract.
- **Incentive Compatibility (IC) condition:** The agent’s utility is maximized when selecting the bundle of {effort , reward} that best fits its private information.

Contract Design – Adverse Selection (1)

- Single principal
- Set of agents: $N = \{1, \ldots, |N|\}$

Static, multi-lateral, one-dimensional and complete contract model

- $\theta_n, \forall n \in N$: agent's type, representing its level of capability, competeness, willingness, etc.

  ↳ **Agent's private information**

Contract bundle: $\{p_n, r_n\}$

- $p_n, \forall n \in N$: agent's effort required by the principal
- $r_n, \forall n \in N$: agent's reward offered by the principal

Contract Design – Adverse Selection (2)

Principal's expected utility function:

$$U = \sum_{\forall n \in N} \lambda_n (p_n - c r_n)$$

- λ_n: agent's n probability of being of type θ_n, such that $\sum_{\forall n \in N} \lambda_n = 1$
- $c \in \mathbb{R}^+$: principal's unit cost of offered rewards

➡ **Principal's statistical knowledge over the agent types**

Agent's n utility function:

$$V_n = \theta_n e(r_n) - k p_n, \forall\, n \in N$$

- $e(\cdot)$: agent's n evaluation function of reward r_n, such that $e(0) = 0, e'(\cdot) > 0, e''(\cdot) < 0$
- $k \in \mathbb{R}^+$: agent's n unit cost of provided effort

Contract Design – Adverse Selection (3)

Principal's optimization problem:

$$max_{\{p_n, r_n\}\forall n \in N} \sum_{\forall n \in N} \lambda_n (p_n - c r_n)$$

$$\theta_n e(r_n) - k p_n \geq 0, \forall\, n \in N$$ → **Individual Rationality (IR) condition**

$$\theta_n e(r_n) - k p_n \geq \theta_n e(r_{n'}) - k p_{n'}, \forall\, n, n' \in N, n \neq n'$$ → **Incentive Compatibility (IC) condition**

- Non-convex optimization problem
- Includes $|N|$ IR and $|N|(|N|$-1) IC conditions coupled to each other

Contract Design – Adverse Selection (4)

Consider $\theta_1 < \cdots < \theta_n < \cdots < \theta_{|N|}$.

- **Proposition 1:** For any feasible contract, it must hold: $r_n > r_{n'} \Leftrightarrow \theta_n > \theta_{n'}$ and $r_n = r_{n'} \Leftrightarrow \theta_n = \theta_{n'}$
- **Proposition 2:** A higher-type agent, i.e., $\theta_1 < \cdots < \theta_n < \cdots < \theta_{|N|}$, will receive a greater reward, i.e., $r_1 < \cdots < r_n < \cdots < r_{|N|}$, and will provide a higher effort, i.e., $p_1 < \cdots < p_n < \cdots < p_{|N|}$.
- **Proposition 3:** A higher-type agent, i.e., $\theta_1 < \cdots < \theta_n < \cdots < \theta_{|N|}$, will receive a greater utility, i.e., $V_1 < \cdots < V_n < \cdots < V_{|N|}$.
- **Proposition 4:** All IR conditions can be reduced to the lowest agent type's IR conditions, i.e., $\theta_1 e(r_1) - kp_1 = 0$, which also holds with equality. ***(Reduces IR conditions)***
- **Proposition 5:** All IC conditions between agents n and n', $\forall n \neq n'$ can be reduced to the local IC conditions between agents n and $n-1$, $\forall\, n$. ***(Reduces IC conditions)***

Contract Design – Adverse Selection (5)

Principal's **equivalently transformed** optimization problem:

$$max_{\{p_n, r_n\} \forall n \in N} \sum_{\forall n \in N} \lambda_n (p_n - c r_n)$$

$$\theta_1 e(r_1) - k p_1 = 0$$ → **Reduced IR condition**

$$\theta_n e(r_n) - k p_n = \theta_n e(r_{n-1}) - k p_{n-1}, \forall\, n \in N$$ → **Reduced IC condition**

$$r_1 < \cdots < r_n < \cdots < r_{|N|}$$ → **Monotonicity condition**

- Easily handled as a convex optimization problem
- Includes 1 IR and $(|N| - 1)$ IC conditions

Contract Design – Moral Hazard (1)

- Single principal
- Single agent

Static, bilateral, one-dimensional and complete contract model

- a: agent's autonomously selected action → **Agent's private information**
- $q = a + \varepsilon, \varepsilon \sim N(0, \sigma^2)$: agent's actual performance observed by the principal

- $w = t + sq$: agent's reward offered by the principal
- t: agent's fixed reward
- sq: agent's variable reward with its actual performance

Contract Design – Moral Hazard (2)

Principal's expected utility function:

$$U = \mathbb{E}[q - w]$$

➡ **Principal's statistical knowledge over the agent's action**

- $\mathbb{E}$: expectation operator

Agent's utility function:

$$V = -e^{-\eta\,(w-\psi(a))}$$

➡ **Constant Absolute Risk Aversion (CARA) utility form**

- $\eta \in \mathbb{R}^{+}$: agent's coefficient of risk aversion
- $\psi(a) = \frac{1}{2}Ca^2$: agent's cost of provided effort
- $\mathrm{C} \in \mathbb{R}^{+}$: agent's unit cost of provided effort

Contract Design – Moral Hazard (3)

Principal's optimization problem:

$$max_{\{a,w\}}\mathbb{E}[q - w]$$

$$\mathbb{E}\left[-e^{-\eta\,(w-\psi(a))}\right] \geq V\,(\bar{w}, a = 0)$$ → **Individual Rationality (IR) condition**

$$a \in argmax_a \mathbb{E}\left[-e^{-\eta\,(w-\psi(a))}\right]$$ → **Incentive Compatibility (IC) condition**

Contract Theory vs Other Theories

Properties	Contract Theory	Market Equilibrium	Auction Theory	Stackelberg or Matching Game
Information asymmetry	✓	✓	✓	✗
Iterative procedure	✗	✓	✓	✓
One party’s profit maximization	✓	✗	✓	✗
Both parties’ profit maximization	✗	✗	✗	✓
Supply-demand equalization	✗	✓	✗	✗

Application Examples of Contract Theory (1)

1. Power allocation in UAV-assisted Non-Orthogonal Multiple Access (NOMA) wireless networks → **Adverse Selection**

   M. Diamanti, G. Fragkos, E. E. Tsiropoulou and **S. Papavassiliou**, "Unified User Association and Contract-Theoretic Resource Orchestration in NOMA Heterogeneous Wireless Networks," in **IEEE Open Journal of the Communications Society**, vol. 1, pp. 1485-1502, **2020**, doi: 10.1109/OJCOMS.2020.3024778.

   M. Diamanti, E. E. Tsiropoulou and **S. Papavassiliou**, "Resource Orchestration in UAV-assisted NOMA Wireless Networks: A Labor Economics Perspective," **ICC 2021 - IEEE International Conference on Communications, 2021,** pp. 1-6, doi: 10.1109/ICC42927.2021.9500715.

2. Computing resource trading in collaborative Mobile Edge Computing (MEC) networks → **Mixture**

   M. Diamanti and S. Papavassiliou, "Trading in Collaborative Mobile Edge Computing Networks: A Contract Theory-based Auction Model," **2022 18th International Conference on Distributed Computing in Sensor Systems (DCOSS), 2022**, pp. 387-393, doi: 10.1109/DCOSS54816.2022.00068.

3. Incentives towards multi-layer delay-tolerant computing → **Adverse Selection Moral Hazard**

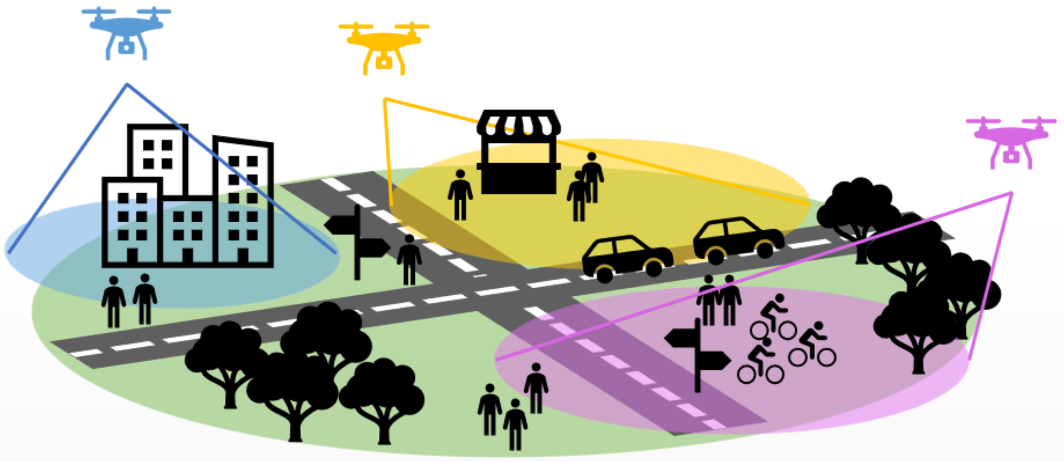
   M. Diamanti, P. Charatsaris, E. E. Tsiropoulou and S. **Papavassiliou**, "Incentive Mechanism and Resource Allocation for Edge-Fog Networks Driven by Multi-Dimensional Contract and Game Theories," in **IEEE Open Journal of the Communications Society**, vol. 3, pp. 435-452, **2022**, doi: 10.1109/OJCOMS.2022.3154536.

   M. Diamanti, E. E. Tsiropoulou and S. Papavassiliou, "An Incentivization Mechanism for Green Computing Continuum of Delay-Tolerant Tasks," **ICC 2022 - IEEE International Conference on Communications, 2022**, pp. 3538-3543, doi: 10.1109/ICC45855.2022.9838752.

Application Examples of Contract Theory (2)

Power allocation in UAV-assisted Non-Orthogonal Multiple Access (NOMA) wireless networks

- Set of users: $U = \{1, \dots, |U|\}$
- Set of UAVs: $\mathrm{C} = \{1, \dots, |C|\}$
- Set of users served by UAV c: $U_c = \{1, \dots, |U_c|\}$



The system bandwidth is divided into $|C|$ orthogonal frequency bands:

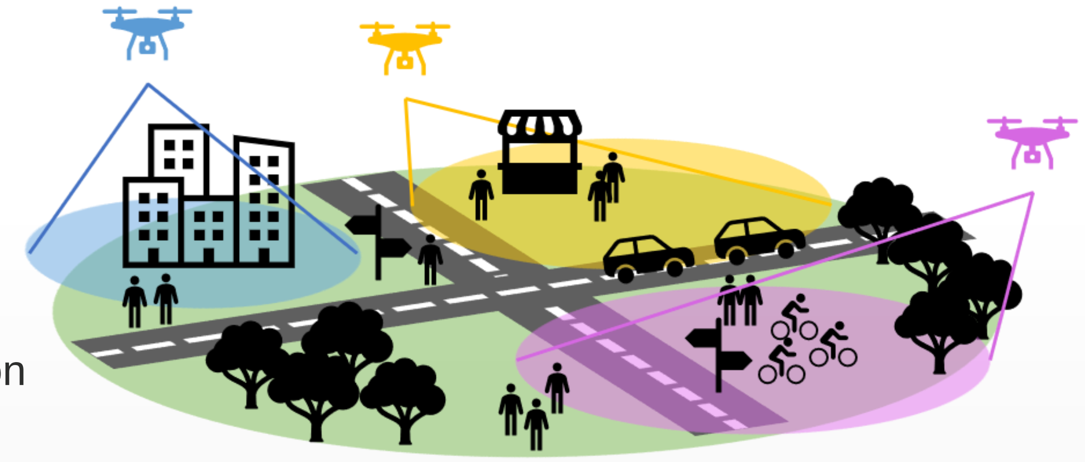
- B_c: UAV's c available bandwidth
- $G_{u,c}$: channel gain of user u served by UAV c
- $I_{u,c}$: interference sensed by user u served by UAV c, calculated as $I_{u,c} = \sum_{\forall j<u} G_{j,c}\, p_{j,c}$
- $p_{u,c}$: uplink transmission power of user u served by UAV c

Application Examples of Contract Theory (3)

Power allocation in UAV-assisted Non-Orthogonal Multiple Access (NOMA) wireless networks

Motivation:

- Users' channel conditions **change dynamically** and in an unpredictable manner.
- UAVs have **statistical knowledge** of the users' Channel State Information (CSI).
- Users autonomously select the uplink transmission power to the UAVs that best fits their CSI.
- UAVs reward users proportionally to the interference that they sense, in order to motivate them utilize the common spectrum resources



Application Examples of Contract Theory (4)

Power allocation in UAV-assisted Non-Orthogonal Multiple Access (NOMA) wireless networks

Consider a single UAV c serving $|U_c|$ users.

- User's u type:

$$\theta_{u,c} = \frac{G_{u,c}}{\sum_{u=1}^{|U_c|} G_{u,c}}, \theta_{u,c} \in (0,1]$$

➡ **User's private information**

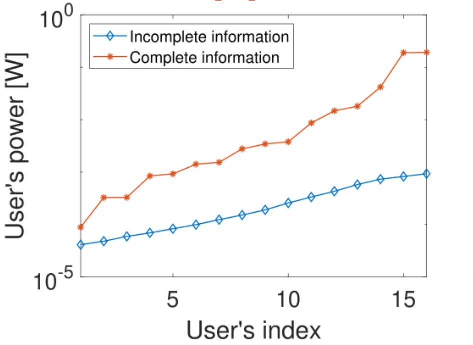
Contract bundle: $\{p_{u,c}, r_{u,c}\}$

- User's u effort provided to UAV c: $p_{u,c} \in (0,1]$
- User's u reward offered by UAV c : $r_{u,c} = \rho\, I_{u,c}, r_{u,c} \in (0,1]$
  ρ: constant reward factor

Application Examples of Contract Theory (5)

Power allocation in UAV-assisted Non-Orthogonal Multiple Access (NOMA) wireless networks

(a)



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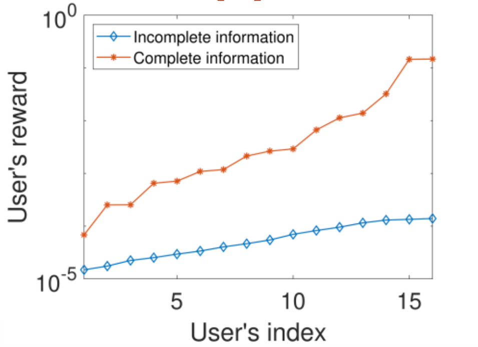

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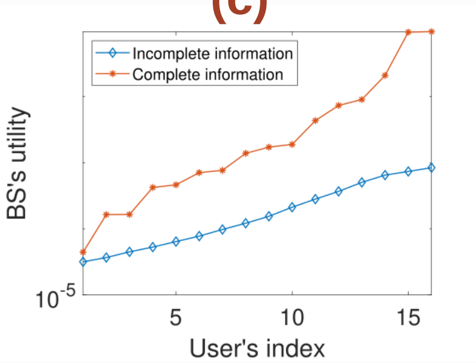

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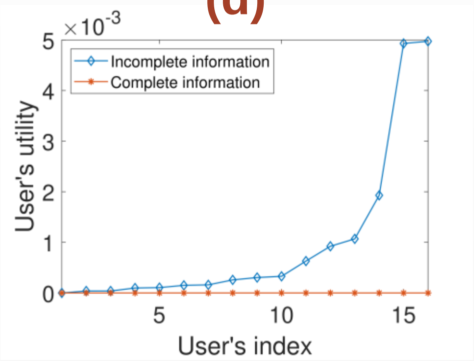
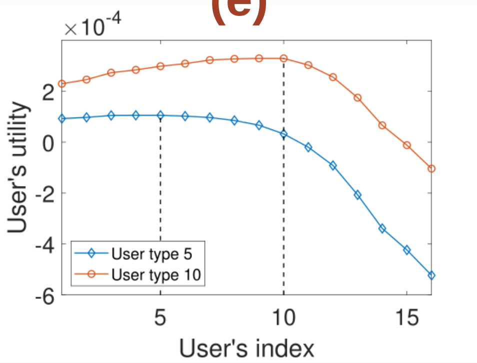


(e)



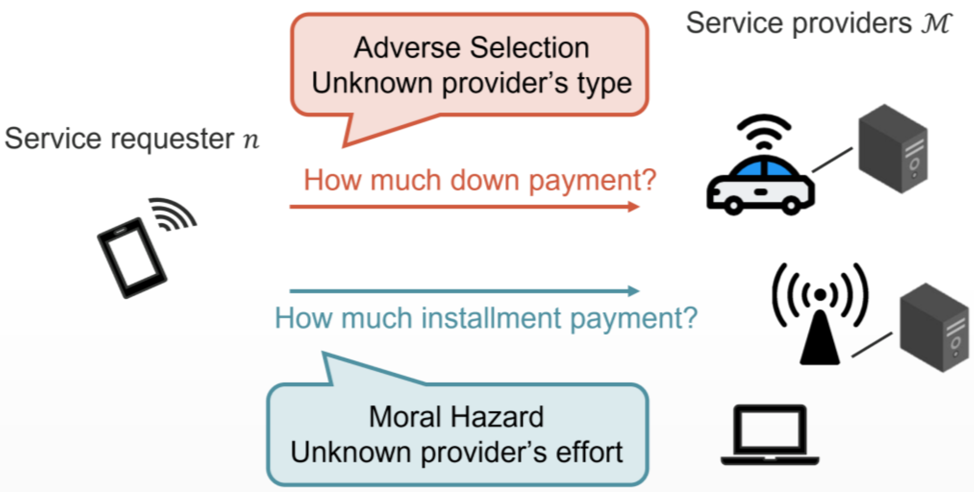
Application Examples of Contract Theory (11)

Computing resource trading in collaborative Mobile Edge Computing (MEC) networks

Consider a collaborative MEC network:

- Service requester n
- Service providers set $\mathcal{M} = \{1, \ldots, M\}$

- W_n [CPU cycles]: requester's n computation task
- τ_n [sec]: requester's n QoS prerequisite

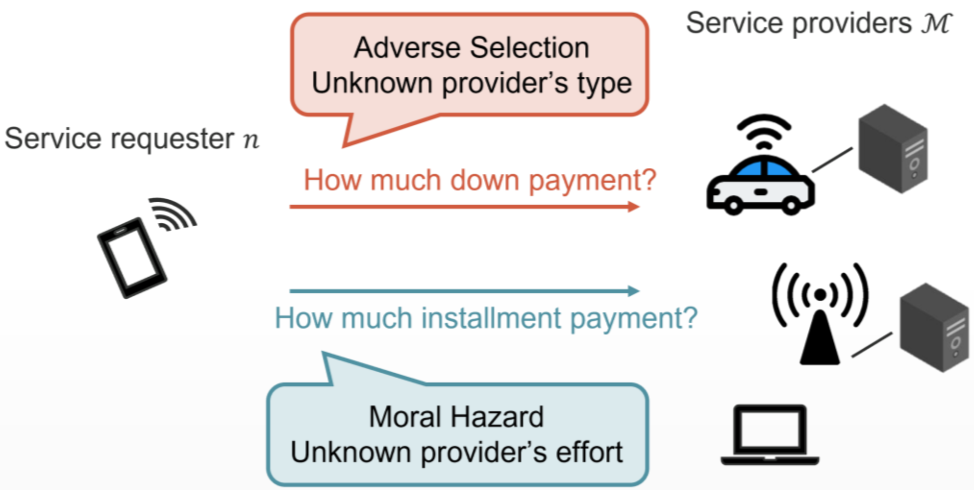


- $f_{n,m}$ [CPU cycles/sec]: provider's m allocated computing power to requester n, $0 \leq f_{n,m} \leq F_m$
- F_m [CPU cycles/sec]: provider's m total computing power

Application Examples of Contract Theory (12)

Computing resource trading in collaborative Mobile Edge Computing (MEC) networks

Motivation:



- User devices play the role of **computing service providers** to facilitate other users' computation demands **without intervention of remote server**
- Collaborative MEC is founded on the delivery of adequate economic incentives to settle the service providers' costs
- An **auction** is usually used to determine the most appropriate service provider, the quality of its offered computing service and its reward
- The **auction** should **account for** the joint problem of **Adverse Selection & Moral Hazard**

Application Examples of Contract Theory (13)

Computing resource trading in collaborative Mobile Edge Computing (MEC) networks

- Service provider's m type:

$$\theta_{n,m} = \frac{\frac{T_m}{k_m W_n F_m^2}}{max\left\{\frac{T_m}{k_m W_n F_m^2}, \forall m\right\}}, \theta_{n,m} \in [0,1]$$

- Service provider's m effort:

$$e_{n,m} = \frac{f_{n,m}}{F_m}, e_{n,m} \in [0,1]$$

T_m: probability of dedicating computing resources for τ_n sec (at most)

k_m: energy consumption coefficient

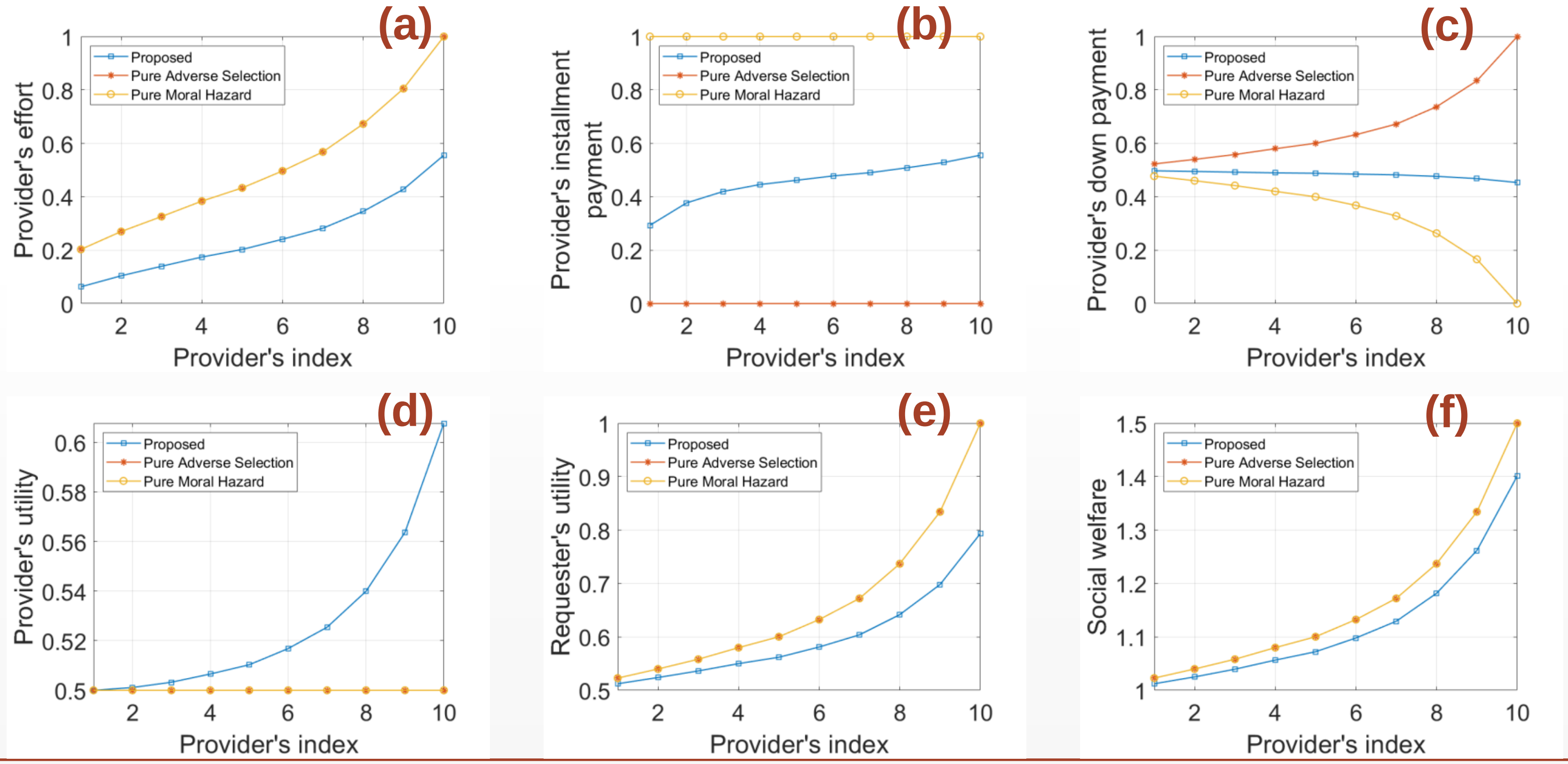
Service provider's private information

Contract Bundle: $\{p_{n,m}, q_{n,m}\}$

- Down payment: $p_{n,m} \in \mathbb{R}^+$
- Installment payment: $q_{n,m} \in [0,1]$

Application Examples of Contract Theory (14)

Computing resource trading in collaborative Mobile Edge Computing (MEC) networks



Summary

- Contract theory principles
- Contract theory problems → Adverse Selection; Moral Hazard; Mixture
- Contract theory taxonomies
- Contract design
- Contract theory vs other theories → Market Equilibrium; Auction Theory; Stackelberg or matching Game
- Application examples →
  - Power allocation in UAV-assisted Non-Orthogonal Multiple Access (NOMA) wireless networks
  - Incentives towards multi-layer delay-tolerant computing
  - Computing resource trading in collaborative Mobile Edge Computing (MEC) networks

Game Theory: Distributed Resource Management

What is Game Theory?

- Game theory (GT) is a formal study of conflict and cooperation.
- It is concerned with situations where “players” interact / take decisions in a such a way that an individual decision / action influences the collective one and vice versa.
- As an example, fishers fishing as much as possible can collectively hurt themselves by over-fishing.
- GT provides a framework to study complex interactions among interdependent rational players.

Some History

- **20's**: Borel and von Neumann formalize the notion of "mixed strategy" along with the idea of "solving" a game via a minimax strategy.
- **40's**: Military applications of game theory.
- **40's**: Von Neumann and Morgenstern publish their book titled "Theory of Games and Economic Behavior".
- **50's**: Nash formalizes the notion of equilibrium of a game.
- **70's – 80's**: Game theory is applied to biological problems.
- **90's –**: Era of algorithmic game theory.

Basic Concepts

- A game in *strategic (or normal) form* is tuple $G = (\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{u_i\}_{i\in\mathcal{N}})$ where:
  - $\mathcal{N} = \{1, \dots, N\}$ is a finite set of players
  - $\mathcal{S}_i$ is the set of available strategies / choices for player $i \in \mathcal{N}$
  - $u_i\colon \mathcal{S} \to \mathbb{R}$ is the utility (payoff) function for player i, where $\mathcal{S} \coloneqq \mathcal{S}_1 \times \cdots \times \mathcal{S}_N$.
- $\mathcal{S}_{-i}$ denotes $\prod_{j\in\mathcal{N}\setminus\{i\}} \mathcal{S}_j$, and elements in $\mathcal{S}_{-i}$ are denoted by $\boldsymbol{s}_{-i}$.
- Moreover, $\boldsymbol{s} = (s_1, \dots, s_n) \in \mathcal{S}$ is occasionally written $\boldsymbol{s} = (s_i, \boldsymbol{s}_{-i})$, for $i \in \mathcal{N}$, $s_i \in \mathcal{S}_i$ and $\boldsymbol{s}_{-i} \in \mathcal{S}_{-i}$.
- The **goal** of each player is to maximize her own payoff.

Remarks / Assumptions

- The utility function captures the concept of “strategic interdependence”: the utility of a player depends also on the other players’ actions.
- A player *prefers* strategy s_i to $s_{i'}$ if $u_i(s_i, \boldsymbol{s}_{-i}) \geq u_i(s_i', \boldsymbol{s}_{-i})$.
- A player will always prefer a strategy that maximizes the (expected) utility, given its belief of the others players’ strategies.

Solution Concepts

- “Solving” a game means finding a strategy profile that is “acceptable” by all players.
- Examples include:
  - Dominating strategies
  - Nash equilibria: no communication or bargaining
  - Generalized Nash equilibria
  - Satisfaction equilibria
  - Correlated equilibria
  - ...

Nash Equilibrium (NE)

- A *Nash equilibrium* of a game $G = (\mathcal{N}, \{\mathcal{S}_i\}_{i \in \mathcal{N}}, \{u_i\}_{i \in \mathcal{N}})$ is a strategy profile $\boldsymbol{s}^* \in \mathcal{S}$ having the property that for each $i \in \mathcal{N}$ it holds

$$u_i(s_i^*, \boldsymbol{s}_{-i}^*) \geq (s_i, \boldsymbol{s}_{-i}^*), \text{ for all } s_i \in \mathcal{S}_i.$$

- In other words, no player can improve her utility by unilaterally changing strategy.

Prisoner's Dilemma

- Payoff is 3 minus the number of years served in prison.
- Which decisions will be chosen by the prisoners?
- **Best response**: a strategy which provides the maximum utility against the strategies chosen by the other players.
- **Nash equilibrium**: a pair of strategies for which each player has chosen a best response.
- **Social Optimum**: a pair of strategies that maximizes the aggregate utility.

	S	C
S	$2,2$	$0,3$
C	$3,0$	$1,1$

In Prisoner's dilemma, (C, C) is the unique NE, and (S, S) is the unique SO.

Matching Pennies

	H	T
H	$+1, -1$	$-1, +1,$
T	$-1, +1$	$+1, -1$

- In general, Nash equilibria may not exist.

Some Bad News about NEs

- Existence is not guaranteed.
- There may be (infinitely) many NEs.
- Different NEs may give different utilities, and a NE may not be the best option from a utility point of view.

Satisfaction Equilibria

- A game in *satisfaction form* is tuple $\hat{G} = (\mathcal{N}, \{\mathcal{S}_i\}_{i\in\mathcal{N}}, \{f_i\}_{i\in\mathcal{N}}, \{T_i\}_{i\in\mathcal{N}})$ where:
  - $\mathcal{N} = \{1, \dots, N\}$ is the set of players
  - $\mathcal{S}_i$ is the strategy set of player $i \in \mathcal{N}$
  - $u_i(s_i, \boldsymbol{s}_{-i})$: represents the player's i payoff (i.e., utility function), and

$$f_i(\boldsymbol{s}_{-i}) = \{s_i \in \mathcal{S}_i : u_i(s_i, \boldsymbol{s}_{-i}) \geq T_i\}$$

denotes the set consisting of all strategies of player i that allow her satisfaction regarding the threshold $T_i \in \mathbb{R}_+$. In other words, the set $f_i(\boldsymbol{s}_{-i})$ consists of all strategies of player i that guarantee a payoff which is above a fixed threshold value T_i, given the strategies, $\boldsymbol{s}_{-i}$, of all remaining players.

Satisfaction Equilibria

- An action profile of the N players $\boldsymbol{s}^+ = (s_1^+, \ldots, s_N^+)$ is a satisfaction equilibrium (SE) for the game in satisfaction form $\hat{G}$ if the following holds true:

$$s_i^+ \in f_i(\boldsymbol{s}_{-i}^+), \forall i \in \mathcal{N}.$$

Let us remark that a Satisfaction Equilibrium is not necessarily unique. In order to further distinguish the elements of the set consisting of the Satisfaction Equilibria of a game in satisfaction form, we utilize the concept of *Efficient Satisfaction Equilibrium (ESE),* where each player of the game achieves her minimum prerequisites while simultaneously being penalized with the minimum possible "effort". The notion of effort, associated to a given strategy of a player, is formalized through the concept of a *cost function*.

Efficient Satisfaction Equilibrium (ESE)

- For each $i \in \mathcal{N}$, the cost function, denoted c_i, is a map $c_i: \mathcal{S}_i \rightarrow [0,1]$. It is noted that strategy s_i requires *lower effort* from player i than strategy s_i' if it holds $c_i(s_i) < c_i(s_i')$.
- **Efficient Satisfaction Equilibrium (ESE):** An action profile $\boldsymbol{s}^* = (s_1^*, \dots, s_N^*)$ is an ESE point for the game in satisfaction form $\hat{G}$, with cost functions $\{c_i\}_{i \in \mathcal{N}}$, if the following two conditions hold:
  - $s_i^* \in f_i(\boldsymbol{s}_{-I}^*)$, for all $i \in \mathcal{N}$
  - $c_i(s_i) \geq c_i(s_i^*)$, for all $i \in \mathcal{N}$, and all $s_i^* \in f_i(\boldsymbol{s}_{-I}^*)$.
- In other words, an ESE is an SE whose coordinates minimize the player’s experienced cost. Once again, the game $\hat{G}$ might possess a multitude of ESEs, and the following definition underscores the prospective best ESE of a game (provided it exists).

Optimal Efficient Satisfaction Equilibrium (OESE)

- An action profile $\boldsymbol{s}^{\dagger} = (s_1^{\dagger}, \dots, s_N^{\dagger})$ is an OESE for the game in satisfaction form $\hat{G}$, with cost functions $\{c_i\}_{i \in \mathcal{N}}$ and Σ_{ese} the set consisting of all action profiles that are ESEs, if the following two conditions hold:
  - $s_i^{\dagger} \in f_i(\boldsymbol{s}_{-I}^{\dagger})$, for all $i \in \mathcal{N}$
  - $c_i(s_i) \geq c_i(s_i^{\dagger})$, for all $i \in \mathcal{N}$, and all $s_i^{*} \in f_i\left(\boldsymbol{s}_{-I}^{\dagger}\right)$
  - $c_i(s_i^{*}) \geq c_i(s_i^{\dagger})$, for all ESEs $\boldsymbol{s}^{*} \in \Sigma_{ese}$, and all $i \in \mathcal{N}$.
- In other words, an OESE is an ESE whose coordinates achieve the overall minimum cost for the player compared to all other available ESEs. If $\hat{G}$ possesses an ESE, then the set consisting of all ESEs has a minimal element, i.e., a point that is coordinate-wise better than any other in the set. Similarly, one could pinpoint the minimal element of the set of SEs of $\hat{G}$, when such a strategy profile exists.

Optimal Satisfaction Equilibrium (OSE)

- An action profile $\boldsymbol{s}^{opt} = (s_1^{opt}, \dots, s_N^{opt})$ is an OSE for the game in satisfaction form $\hat{G}$, with cost functions $\{c_i\}_{i \in \mathcal{N}}$ and Σ_{se} the set consisting of all action profiles that are SEs, if the following two conditions hold:
  - $s_i^{opt} \in f_i(\boldsymbol{s}_{-I}^{opt})$, for all $i \in \mathcal{N}$
  - $c_i(s_i^{+}) \geq c_i(s_i^{opt})$, for all SEs $\boldsymbol{s}^{+} \in \Sigma_{se}$, and all $i \in \mathcal{N}$.

- One can argue that, when the only objective of a player is to reach a certain prerequisite on her profits, the OSE (provided it exists) is the best possible equilibrium because of the fact that, for such an action profile, all players are satisfied and each player is penalized with the least possible cost.

CPR Games

- A Common Pool Resource (CPR) game is an instance of a resource sharing game where a CPR, which is prone to failure due to over-exploitation, is shared among several players.
- Each player has a fixed initial endowment and is faced with the task of investing in the common-pool resource without forcing it to fail.
- The return from the CPR may be subject to uncertainty.

The Tragedy of the Commons

- A CPR is shared by N users. Each user has to decide the amount x_i she wants to exploit from the CPR.
- Let $x_T := \sum_i x_i$ be the sum of the amounts.
- If $x_T \geq 1$, then the CPR is overloaded and collapses: the utility of each user is equal to 0.
- Otherwise, the utility of player i is equal to $u_i = x_i(1 - x_T)$.
- In other words, increasing the amount of each player will not always increase the utility.
- The optimal choice of x_i depends on the choices of the other players.

The Tragedy of the Commons

- If the strategies of the other players are fixed, then the “best response” of player i can be determined:
- It holds $u_i = x_i \cdot (1 - x_i - \sum_{j \neq i} x_j)$.
- Differentiating w.r.t. x_i and setting the result equal to zero yields: $2x_i = 1 - \sum_{j \neq i} x_j$, and therefore $x_i = 1 - x_T$.
- Adding up to the last equations for all i yields: $x_T = \frac{N}{N+1}$ and thus $x_i = \frac{1}{N+1}$ and $u_i = \frac{1}{(N+1)^2}$.
- Now, if each player chooses $x_i = \frac{1}{2N}$, then the utility will be equal to $u_i = \frac{1}{4N}$.
- Observe that $\frac{1}{4N}$ is asymptotically larger than $\frac{1}{(N+1)^2}$.
- Each player will increase her utility by moving form the “rational” solution $\frac{1}{(N+1)^2}$ to the solution $\frac{1}{4N}$.

The Standard CPR Game

- Suppose that N players have access to a CPR. Each player has an available endowment, which is assumed to be equal to 1.
- Let $F(\cdot)$ be a "nice"[1] concave function. The utility of player i equals

$$u_i(x_i, x_T) = \begin{cases} 1, & \text{if } x_i = 0, \\ (1 - x_i) + \dfrac{x_i}{x_T} \cdot F(x_T), & \text{if } x_i > 1. \end{cases} \quad (1)$$

- The user may split her endowment between a "safe resource" and the CPR.
- The game is **symmetric**: all players have the same endowment, same strategy space, same utility function. This implies that if $(x_1, \dots, x_N)$ is a NE of the game, then $x_1 = \cdots = x_N$.
- If $(x_1, \dots, x_N)$ is a NE of the game, it holds $x_T = N \cdot x_i$.

[1] $F(0) = 0, F'(0) > 1, F'(N) < 0$.

The Standard CPR Game

- Differentiating (1) w.r.t. x_i and setting the result equal to zero, one obtains:

$$-1 + \frac{x_i}{x_T} \cdot F'(x_T) + F(x_T) \cdot \frac{x_T - x_i}{(x_T)^2} = 0. \qquad (2)$$

- Substituting $x_T = N \cdot x_i$ into (2), one has:

$$-1 + \frac{1}{n} \cdot F'(Nx_i) + F(Nx_i) \cdot \frac{N-1}{N^2 x_i} = 0. \qquad (3)$$

- Let us now compare the equilibrium solution to another solution.

The Standard CPR Game: A Global Solution

- If $u = \sum_i u_i$, then $u(\boldsymbol{x}) = N - x_t + F(x_T)$, which is to be maximized subject to the constraint $0 \leq x_T \leq N$.
- The unique solution is characterized by the condition:

$$-1 + F'(x_{\mathrm{T}}) = 0. \quad (4)$$

- Since (3) and (4) have different solution, it follows that the equilibrium point is not an optimum.

Moral Lesson

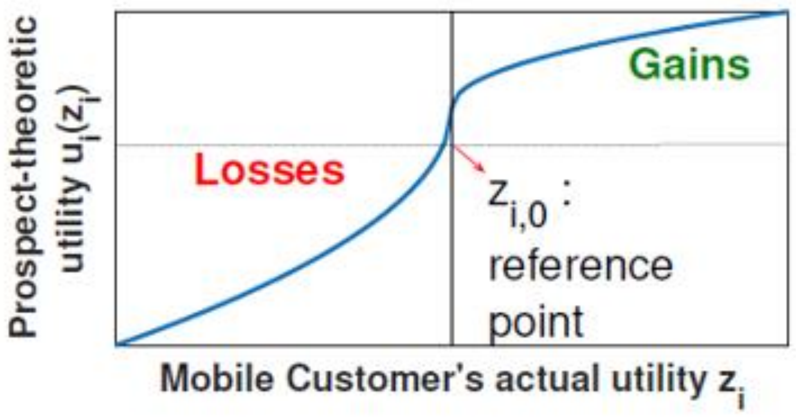
- The equilibrium solution may not be "globally optimal".
- This is due to the assumption that players are not allowed to collaborate.
- Players are selfish: each tries to maximize her own utility, given the choices of the remaining players.
- Collaboration may increase utility.

Prospect Theory: Risk-Aware Resource Management

Prospect Theory

- Captures the uncertain outcomes of a decision-making process
- Models the behavior of the individuals' decision-making process
- Considers four fundamental attributes:
  - Reference dependence → The perceived satisfaction is determined based on the derived gains or losses with respect to a reference point.
  - Loss aversion → The loss of an amount imposes greater dissatisfaction than the pleasure from gaining the same amount.
  - Diminishing sensitivity → A risk averse behavior is pursued in gains and a risk seeking attitude is adopted in losses.
  - Probability weighting → The likelihood of very low possibility events is overestimated, whereas the highly expected events are underestimated.

Prospect Theory



Value function. Sensitivity is different to losses and gains, with respect to a reference point.

Relative per user outcome

Reference point

$$v_i(z_i) = \begin{cases} (z_i - z_0)^{a_i}, & \text{when } z_i = z_0 \\ -k_i(z_0 - z_i)^{\beta_i}, & \text{otherwise} \end{cases}$$

Risk aversion parameter reflects the impact of losses compared to gains in user's utility

Sensitivity of user i with regards to a gain or a loss $a_i = \beta_i, a_i, \beta_i \in (0,1]$

A Fragile CPR Game

- This game is similar to the Standard CPR Game, with the additional ingredient that the performance of the CPR is subject to uncertainty.
- In particular, the CPR collapses with the probability that is an increasing function of x_T, denoted $p(x_T)$.
- The utility for each player in the Fragile CPR Game is given by:

$$u_i(x_i, \boldsymbol{x}_{-i}) = \begin{cases} \left(x_i \cdot (R(x_T) - 1)\right)^{a_i}, & \text{with probability } 1 - p(x_T), \\ -k_i \cdot x_i^{a_i}, & \text{with probability } p(x_T). \end{cases} \quad (5)$$

- Hence, the expected utility of player i is equal to $E_i = x_i^{a_i} \cdot F_i(x_T)$, where

$$F_i(x_T) = (R(x_T) - 1)^{a_i} \cdot \left(1 - p(x_T)\right) - p(X_T), \quad (6)$$

where F_i is the *effective rate of return*.

A Fragile CPR Game

- Assumption: Consider a Fragile CPR Game that satisfies the following:
  - The function $p(\cdot)$ is twice continuously differentiable and satisfies $p(0) = 0$ and $p(x_T) = 1$, whenever $x_T \geq 1$.
  - For all $i \in [n]$ and all $x_T \in (0,1)$ it holds $\frac{\partial}{\partial x_T} F_i(x_T), \frac{\partial^2}{\partial x_T^2} F_i(x_T) < 0$, where F is given by (6).
- In other words, the first assumption states that the CPR fails for sure, when the investment is “high”, thus rendering the Fragile CPR Game to be subject to the “tragedy of the commons”.
- The particular choice of the total investment of the players, x_T, is decisive, since it may cause the CPR to either be in a *secure state* (i.e., a state for which $p(x_T)$ is small), or a *fragile state* (i.e., a state for which $p(x_T)$ is large).

A Fragile CPR Game

- Consider a Fragile CPR Game that satisfies the aforementioned assumption.
- **Theorem** (Hota et al. 2016): The Fragile CPR Game admits a unique Nash equilibrium. Furthermore, the best response dynamics converge to the Nash equilibrium.

An Application in Computing Networks

Risk-aware Data Offloading in UAV-assisted MEC Systems

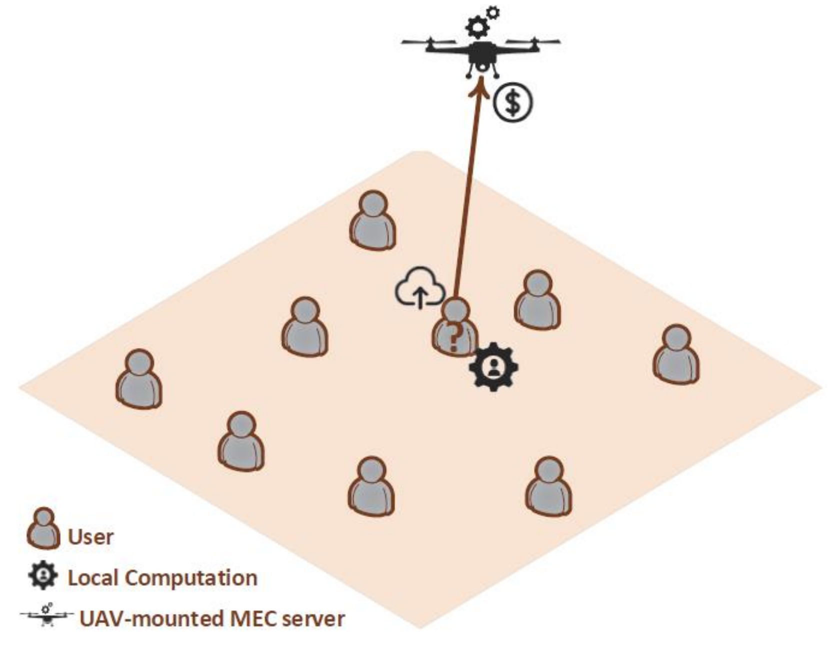
Mitsis, G.; Tsiropoulou, E.E.; **Papavassiliou, S**. Data Offloading in UAV-Assisted Multi-Access Edge Computing Systems: A Resource-Based Pricing and User Risk-Awareness Approach. ***Sensors*** **2020**, *20*, 2434. https://doi.org/10.3390/s20082434

- Users set $\mathcal{N} = \{1, \dots, \mathrm{N}\}$
- A single UAV-mounted MEC server

The user n has a computing application $A_n = (b_n, d_n)$:

- b_n [bits]: total input data
- d_n [CPU cycles/bit]: intensity

Goal: Determine each user's n optimal amount of data b_n^{MEC} [bits] to be offloaded to the UAV-mounted MEC server.



An Application in Computing Networks

Risk-aware Data Offloading in UAV-assisted MEC Systems

- $\hat{t}_n$ [sec]: required **time** to process the task locally, $\hat{t}_n = \frac{d_n}{f_n}$
  f_n [CPU cycles/sec]: computing capability of user's device
- $\hat{e}_n$ [sec]: required **energy** to process the task locally, $\hat{e}_n = \gamma_n d_n$
  γ_n [Joule/CPU cycle]: coefficient of consumed energy per CPU cycle
- c_n: **cost** of processing the task at the UV-mounted MEC server, $c_n(b_n^{MEC}) = \frac{c d_n b_n^{MEC}}{b_n}$
  c [1/CPU cycles]: constant pricing factor per CPU cycle
  b_n^{MEC} [bits]: amount of data offloaded at the UAV-mounted MEC server

An Application in Computing Networks

Risk-aware Data Offloading in UAV-assisted MEC Systems

- User's prospect-theoretic utility:

$$P_n(U_n) = \begin{cases} \left(U_n - U_{n,0}\right)^{a_n}, & \text{if } U_n \geq U_{n,0} \\ -k_n\left(U_{n,0} - U_n\right)^{\beta_n}, & \text{otherwise} \end{cases}$$

- User's actual perceived satisfaction from offloading at the UAV-mounted MEC server:

$$U_n(\boldsymbol{b}^{MEC}) = \begin{cases} \frac{1}{\hat{t}_n \hat{e}_n} b_n, & \text{If } b_n^{MEC} = 0 \\ \frac{1}{\hat{t}_n \hat{e}_n}(b_n - b_n^{MEC}) + b_n^{MEC} ROR(d_\tau) - c_n(b_n^{MEC}), & \text{If } b_n^{MEC} \neq 0 \text{ and MEC survives} \\ \frac{1}{\hat{t}_n \hat{e}_n}(b_n - b_n^{MEC}) - c_n(b_n^{MEC}), & \text{If } b_n^{MEC} \neq 0 \text{ and MEC fails} \end{cases}$$

An Application in Computing Networks

Risk-aware Data Offloading in UAV-assisted MEC Systems

- User's total demand function:

$$d_\tau(\boldsymbol{b}^{MEC}) = -1 + \frac{2}{1 + e^{-\theta \sum_{n=1}^{N} \frac{d_n b_n^{MEC}}{b_n}}}$$

→ Continuous, strictly increasing function w.r.t. users' total amount of offloaded data $\boldsymbol{b}^{MEC}$

- UAV-mounted MEC server's Rate of Return (ROR):

$$ROR(d_\tau) = 2 - e^{d_\tau - 1}$$

→ Continuous, monotonically decreasing, and concave function w.r.t. users' total demand of computing resources d_τ

- UAV-mounted MEC server's probability of failure:

$$Pr(d_\tau) = d_\tau^2$$

→ Square function

An Application in Computing Networks

Risk-aware Data Offloading in UAV-assisted MEC Systems

- User's expected prospect-theoretic utility function:

$$\mathbb{E}(U_n) = P_n^{surv}(U_n)\big(1 - Pr(d_\tau)\big) + P_n^{fail}(U_n)Pr(d_\tau)$$

- Pricing and risk-aware data offloading problem solved by each user:

$$max_{b_n^{MEC}} \ \mathbb{E}[U_n(b_n^{MEC}, \boldsymbol{b}_{-\boldsymbol{n}}^{\boldsymbol{MEC}})]$$

$$0 \le b_n^{MEC} \le b_n$$

The solution of the problem can be proved to be a pure NE point.

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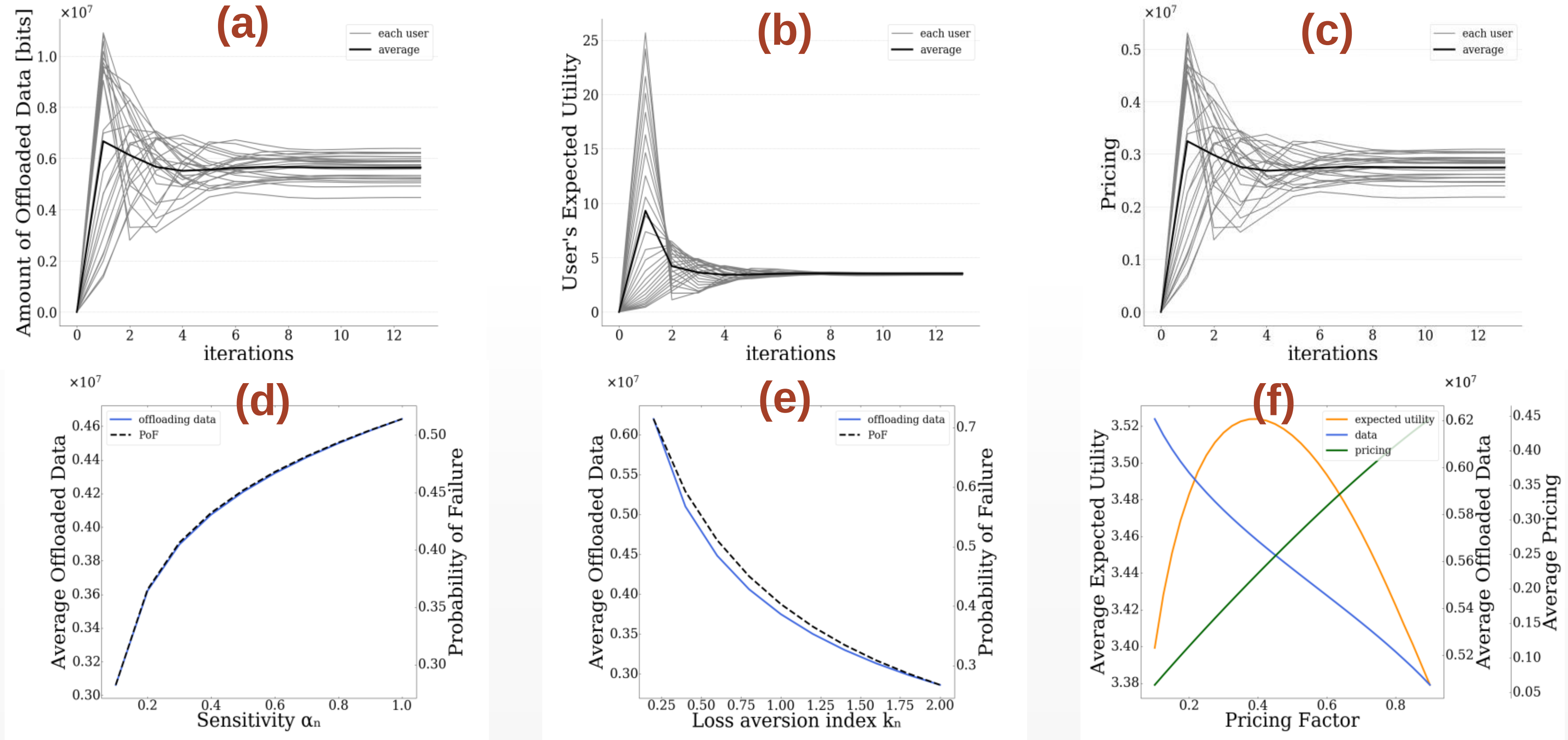
Risk-aware Data Offloading in UAV-assisted MEC Systems



A Fragile Multi-CPR Game

- What happens if the players are allowed to share more than one CPR?
- Intuitively, one would expect larger utilities as well as lower probabilities of forcing the CPR to fail.

A Fragile Multi-CPR Game

- Consider N players, each having an initial endowment equal to 1, and m CPRs.
- Each player chooses $\boldsymbol{x}_i = (x_{i1}, \ldots, x_{im})$, such that $x_{ij} \geq 0$ and $\sum_j x_{ij} \leq 1$ and invests x_{ij} in the j-th CPR.
- The *utility* of player $i \in [n]$ from the j-th CPR is given by:

$$u_{ij}\left(x_{ij}, \boldsymbol{x}_T^{(j)}\right) = \begin{cases} \left(x_{ij} \cdot \left(R_j\left(x_T^{(j)}\right) - 1\right)\right)^{a_i}, & \text{with probability } 1 - p_j(x_T^{(j)}), \\ -k_i x_{ij}^{a_i} & \text{with probability } p_j(x_T^{(j)}). \end{cases} \quad (7)$$

A Fragile Multi-CPR Game

- The utility of each player is equal to

$$V_i = \sum_{j=1}^{m} u_{ij}(x_{ij}, \boldsymbol{x}_T^{(j)}).$$

- We assume that the performance of a CPR is independent of the performances of the remaining CPRs.

Generalized Nash Equilibrium (GNE)

- Assume further that for each player $i \in \mathcal{N}$ there exists a correspondence $\theta_\iota \colon \mathcal{S}_{-\iota} \rightarrow 2^{\mathcal{S}_\iota}$ mapping every element $\boldsymbol{s}_{-i} \in \mathcal{S}_{-i}$ to a set $\theta_\iota(\boldsymbol{s}_{-i}) \subset \mathcal{S}_i$.
- θ_ι is referred to as a *constraint policy* and may be thought of as determining the set of strategies that are feasible for player $i \in \mathcal{N}$, given the choices of all other players $\boldsymbol{s}_{-i} \in \mathcal{S}_{-i}$.
- A GNE is a strategy profile $\boldsymbol{s}^* \in \mathcal{S}$ having the property that for each $i \in \mathcal{N}$ it holds
  - $s_i^* \in \theta_\iota(\boldsymbol{s}_{-i}^*)$ for all $i \in \mathcal{N}$
  - $u_i(s_i^*, \boldsymbol{s}_{-i}^*) \geq u_i(s_i, \boldsymbol{s}_{-i}^*)$, for all $s_i \in \theta_\iota(\boldsymbol{s}_{-i}^*)$.

A Fragile Multi-CPR Game

- **Theorem**: Consider a Fragile multi-CPR Game with $n \geq 1$ players and $m \geq 1$ CPRs. Then, the game admits a GNE. Furthermore, if $m \leq n$, the set consisting of all GNEs of the game of Lebesgue measure zero.

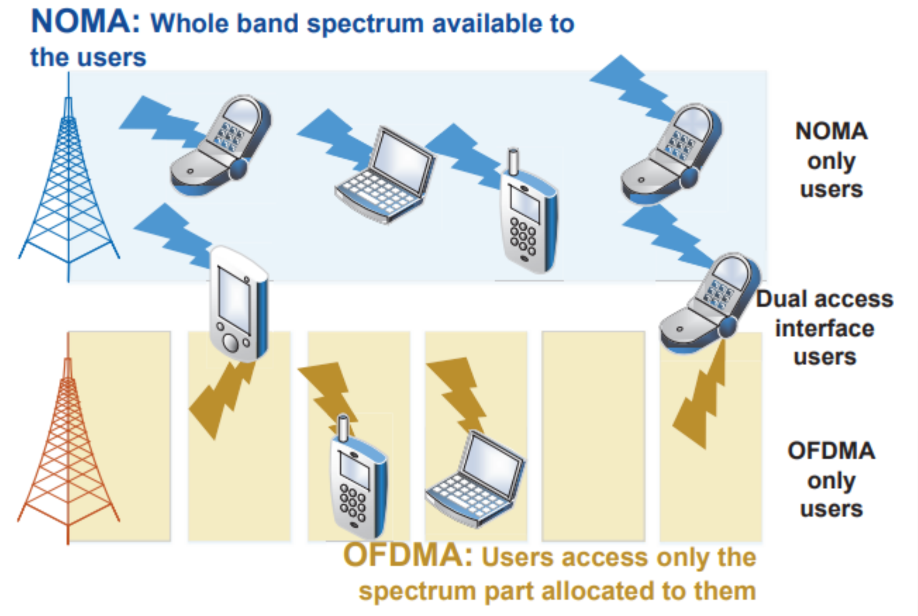
A Fragile Multi-CPR Game: Open Questions

- We believe that the set consisting of all GNEs of a Fragile multi-CPR game is finite.
- Computer experiments suggest that the best response dynamics of the game converge.
- What happens when the CPRs are not independent?

An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

P. Promponas, **C. Pelekis**, E. E. Tsiropoulou and **S. Papavassiliou**, "Games in Normal and Satisfaction Form for Efficient Transmission Power Allocation Under Dual 5G Wireless Multiple Access Paradigm," in **IEEE/ACM Transactions on Networking**, vol. 29, no. 6, pp. 2574-2587, Dec. **2021**, doi: 10.1109/TNET.2021.3095351.



- Users/Transmitters set $\mathcal{K} = \{1, \dots, K\}$
- A single Base Station (BS)

Each user has a dual communication interface to transmit data either using NOMA or OFDMA technique.

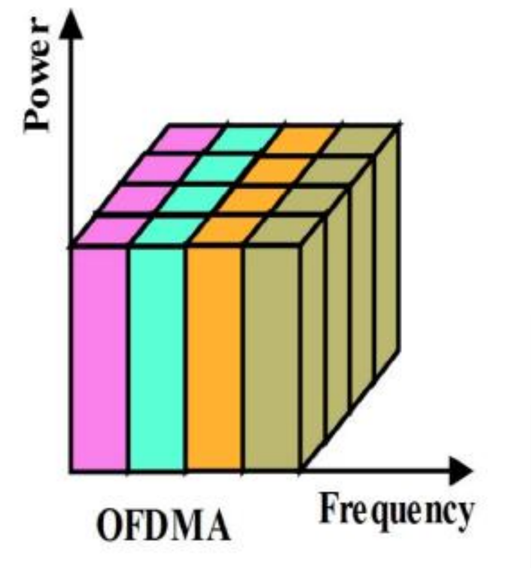
- h_k: channel power gain between user k and BS
- $p_k \in [0, p_k^{max}]$: uplink transmission power of user k to BS
- $x_k \in [0,1]$: percentage of transmission power investment of user k to NOMA

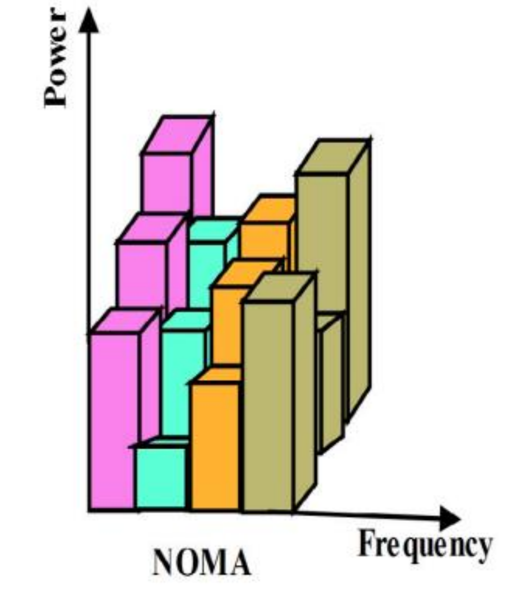
An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

- **Orthogonal Frequency Division Multiple Access (OFDMA):** User transmissions are performed over different time and frequency resources

- **Power-domain Non-Orthogonal Multiple Access (NOMA):** User transmissions are multiplexed in the power domain, over the same resource (e.g., time, frequency)





The emergence of smart devices brings dual transmission access capabilities, enabling spectrum sharing under different wireless access techniques simultaneously.

An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

- Each UE's **goal** is to opportunistically choose its **optimal transmission power level** $\boldsymbol{p_k} \in [\mathbf{0}, \boldsymbol{p_k^{max}}]$ and **transmission power split** $\boldsymbol{x_k} \in [\mathbf{0}, \mathbf{1}]$ over the NOMA and the OFDMA, to fulfil its QoS prerequisites.
  - $p_k^N = x_k \cdot p_k$: transmission power over NOMA
  - $p_k^O = (1 - x_k) \cdot p_k$: transmission power over OFDMA
- User's k utility function:

$$U_k(p_k, x_k; \boldsymbol{p}_{-k}, \boldsymbol{x}_{-k}) = u_k^O(p_k, x_k) + u_k^N(\boldsymbol{p}, \boldsymbol{x}) - c_k(p_k)$$

where $u_k^O(p_k, x_k) = A \cdot \log_2\left(1 + \frac{h_k p_k^O}{\sigma^2}\right)$, $u_k^N(\boldsymbol{p}, \boldsymbol{x}) = A \cdot \log_2\left(1 + \frac{h_k p_k^N}{\sum_{j>k} h_j p_j^N + \sigma^2}\right)$ and $c_k(p_k) = \lambda_k p_k$

→ **achievable data rate with OFDMA** → **achievable data rate with NOMA** → **linear cost function**

An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

Dual Access Technology Game

- **Theorem**: The dual access technology game admits a NE.
  Furthermore, the Best Response Dynamics converge to a NE.

An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

Dual Access Technology Game in Satisfaction Form

- A strategy profile $\boldsymbol{a} = (\boldsymbol{a}_1, \ldots, \boldsymbol{a}_K)$, where $\boldsymbol{a}_k = (p_k, x_k)$, for the players in the Dual Access Technology Game is a *satisfaction equilibrium* (SE) if for all k it holds

$$\boldsymbol{a}_k \in F_k(\boldsymbol{a}_{-k}) \coloneqq \{(p_k, x_k): U_K(p_k, x_k; \boldsymbol{p}_{-k}, \boldsymbol{x}_{-k}) \geq T_k\}$$

  where $\{T_k\}_k$ are user-defined thresholds, and $U_K(p_k, x_k; \boldsymbol{p}_{-k}, \boldsymbol{x}_{-k}) = u_k^O(p_k, x_k) + u_k^N(\boldsymbol{p}, \boldsymbol{x})$.

- SE may not be unique.

Satisfaction equilibrium (SE)

An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

Dual Access Technology Game in Satisfaction Form

- Suppose that for each player k there is an associated *cost function* $c_k[0,1] \rightarrow [0,1]$ which satisfies: $c_k(\boldsymbol{a}_k) < c_k(\boldsymbol{a}'_k)$, if and only if, $\boldsymbol{a}_k$ requires a lower effort by player k than action $\boldsymbol{a}'_k$.
- A strategy profile $\boldsymbol{a} = (\boldsymbol{a}_1, \dots, \boldsymbol{a}_K)$ is an *efficient satisfaction equilibrium* (ESE) if for all k it holds
  - $\boldsymbol{a}_k \in F_k(\boldsymbol{a}_{-k})$
  - $c_k(\boldsymbol{a}'_k) \geq c_k(\boldsymbol{a}_k)$, for all $\boldsymbol{a}'_k \in F_k(\boldsymbol{a}_{-k})$

Efficient Satisfaction equilibrium (ESE)

An Application in Wireless Networks

Risk-aware & QoS-based Power Allocation under Dual Wireless Access

Dual Access Technology Game in Satisfaction Form

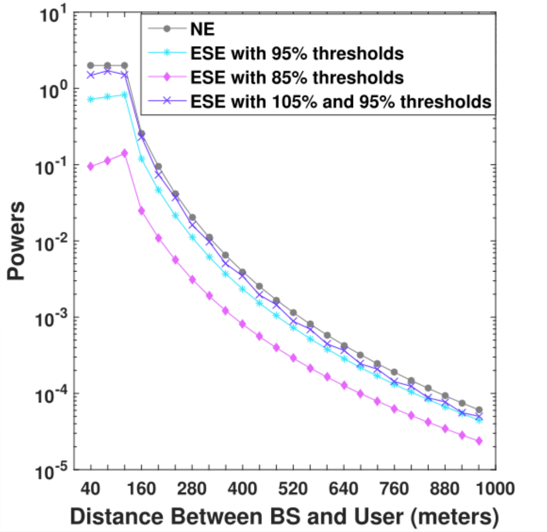
- The best response of a player k is defined as

$$BR_k(\boldsymbol{a}_{-k}) = \{\boldsymbol{a}_k = (p_k, x_k) : \boldsymbol{a}_k = argmin_{\boldsymbol{a}_k \in F_k(\boldsymbol{a}_{-k})} c_k(p_k)\}$$

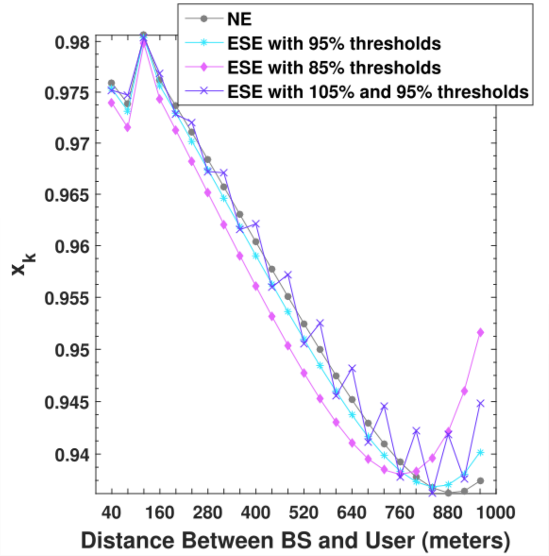
- **Theorem**: Suppose that each user has a non-empty BR-set when the rest of the users choose a BR-strategy. Then, the Dual Access Technology game in satisfaction form admits a unique ESE. Furthermore, the best response dynamics converge to the ESE.

An Application in Wireless Networks

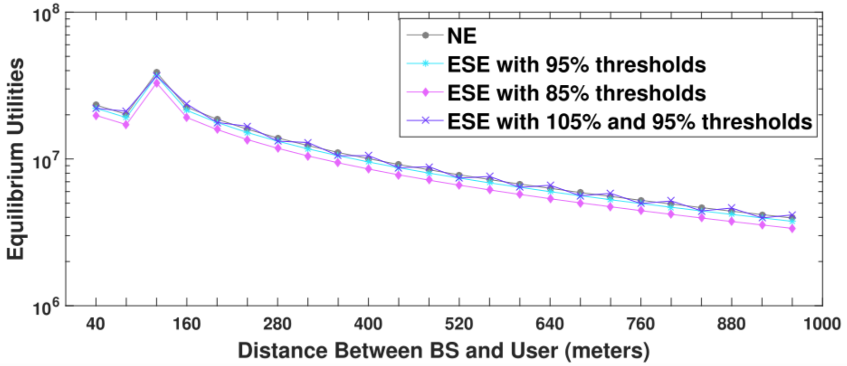
Risk-aware & QoS-based Power Allocation under Dual Wireless Access



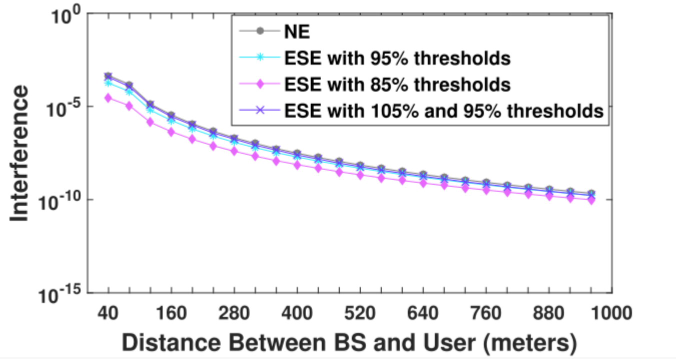
(a)



(b)



(c)



(d)

Summary

- Game theory principles
- Games in Normal Form
- Games in Satisfaction Form
- The tragedy of the commons
- Standard CPR game
- Prospect theory
- Fragile CPR game
- Application example in computing networks
- Application example in dual-access wireless networks

Thank you !

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