面向高可靠通信的资源管理

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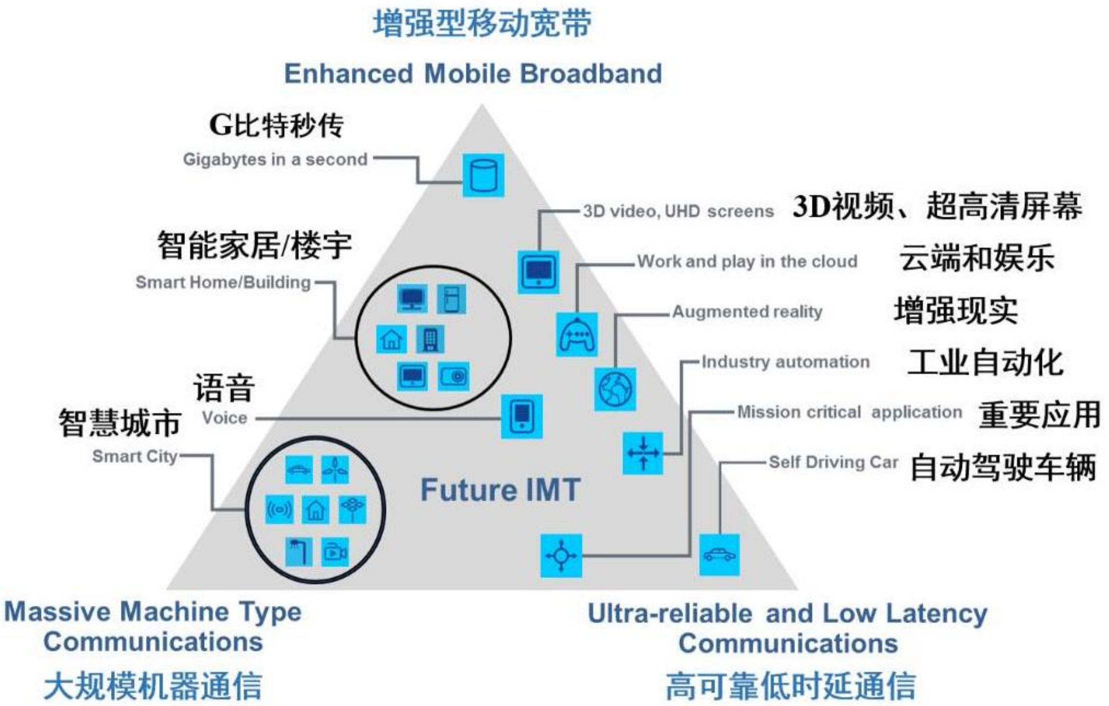
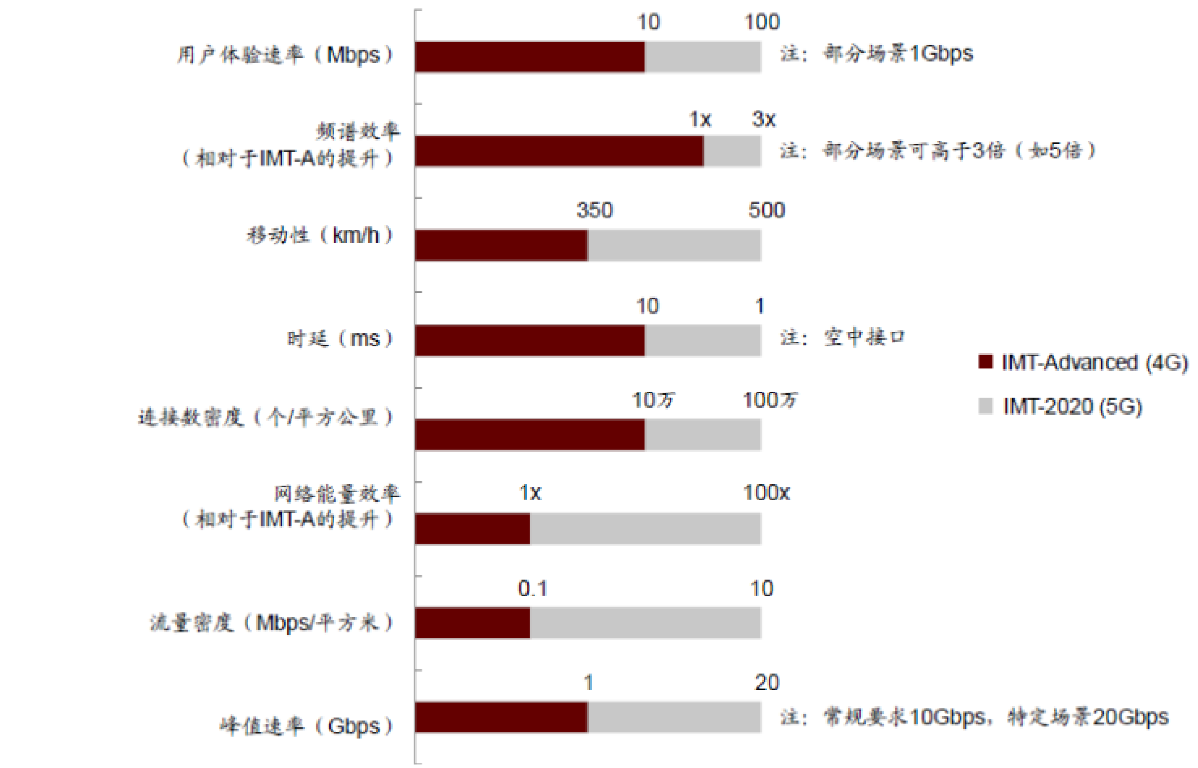
研究背景

5G应用



图表 5G技术和4G技术的对比



新型应用

	工业无线网络需求	现有工业无线网络(IEEE 802技术体系)	现有5G
时延	闭环时延<2ms	端到端时延百毫秒	端到端时延几十毫秒
可靠性	高于99.9999%	高于99.99%	高于99.999%
安全性	防止用户标识信息被截获、篡改	机器数字空间认证信息易被截获、篡改	用户标识信息易被截获、篡改
高速率	峰值速率1Gbps (99.9999%可靠性下)	峰值速率54Mbps (99.99%可靠性下)	峰值速率100Mbps (99.999%可靠性下)
环境感知	物理环境、无线环境	无	无

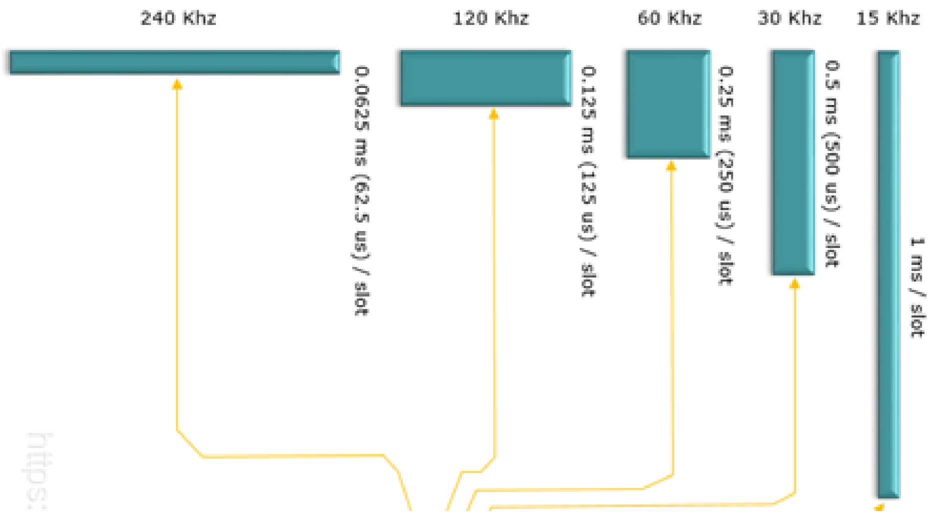
但现有5G仍无法满足工业级信息交互需求

5G超可靠低时延技术

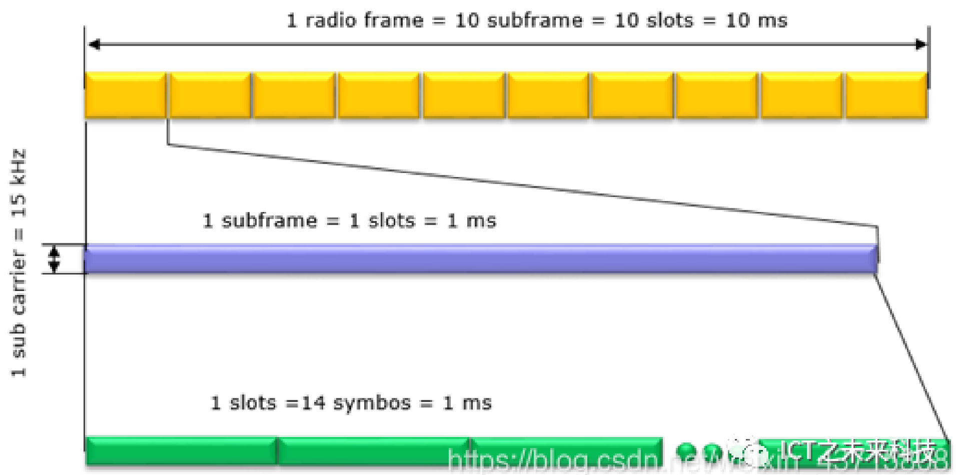
Feature	C	NR
Comm. types	Broadcast	Broadcast, Groupcast, Unicast
MCS	Rel. 14: QPSK, 16-QAM Rel. 15: 64-QAM	QPSK, 16-QAM, 64-QAM
Waveform	SC-FDMA	OFDM
Re-transmissions	Blind	HARQ
Feedback channel	Not Available	PSFCH
Control & data multiplexing	FDM	TDM
DMRS	Four/sub-frame	Flexible
Sub-carrier spacing	15 kHz	sub-6 GHz: 15, 30, 60 kHz mmWave: 60, 120 kHz
Scheduling interval	one sub-frame	slot, mini-slot or multi-slot
Sidelink modes	Modes 3 & 4	Modes 1 & 2
Sidelink sub-modes	N/A	Modes 2(a), 2(d)

➢ 关键技术增强

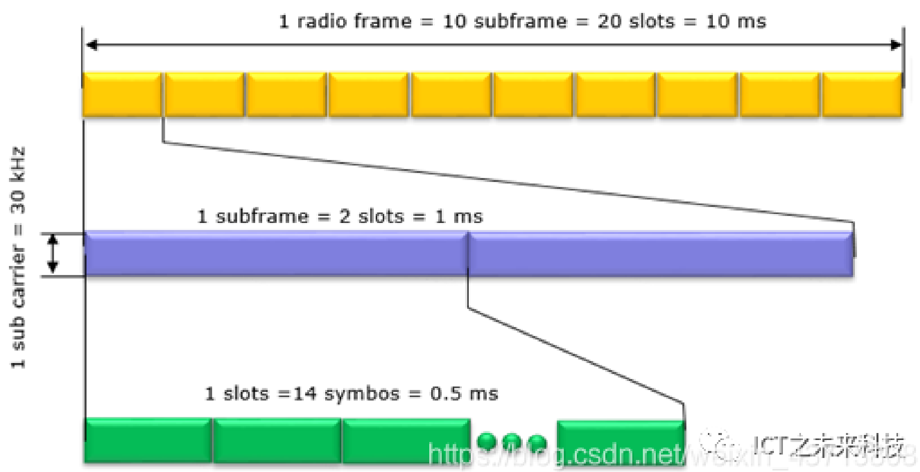
- 灵活的载波间隔
- 时隙，迷你时隙和多时隙调度
- Sidelink反馈信道（PSFCH）



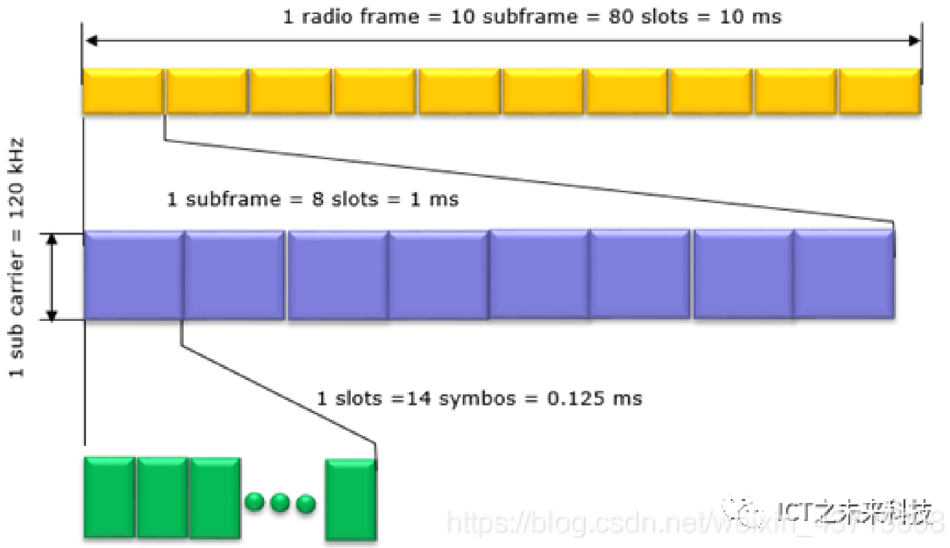
灵活的载波间隔



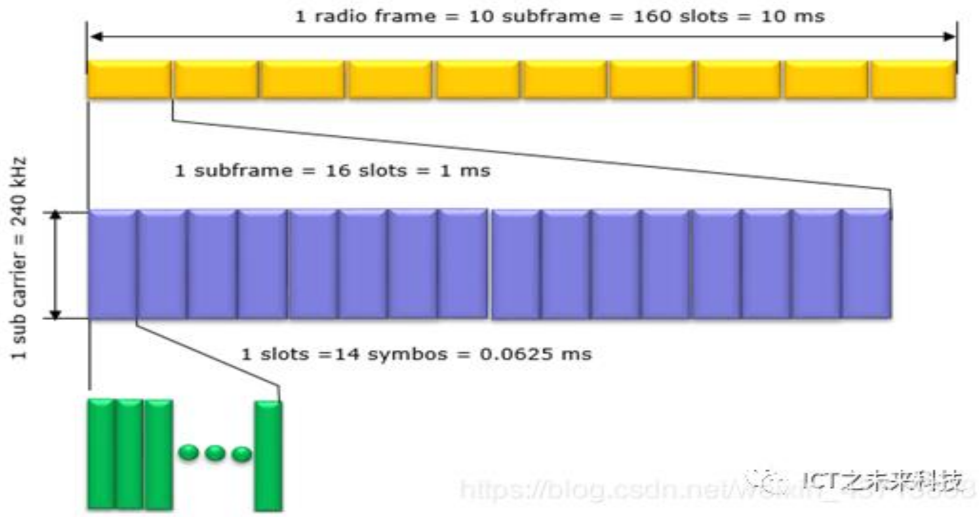
载波宽度15KHz



载波宽度30KHz



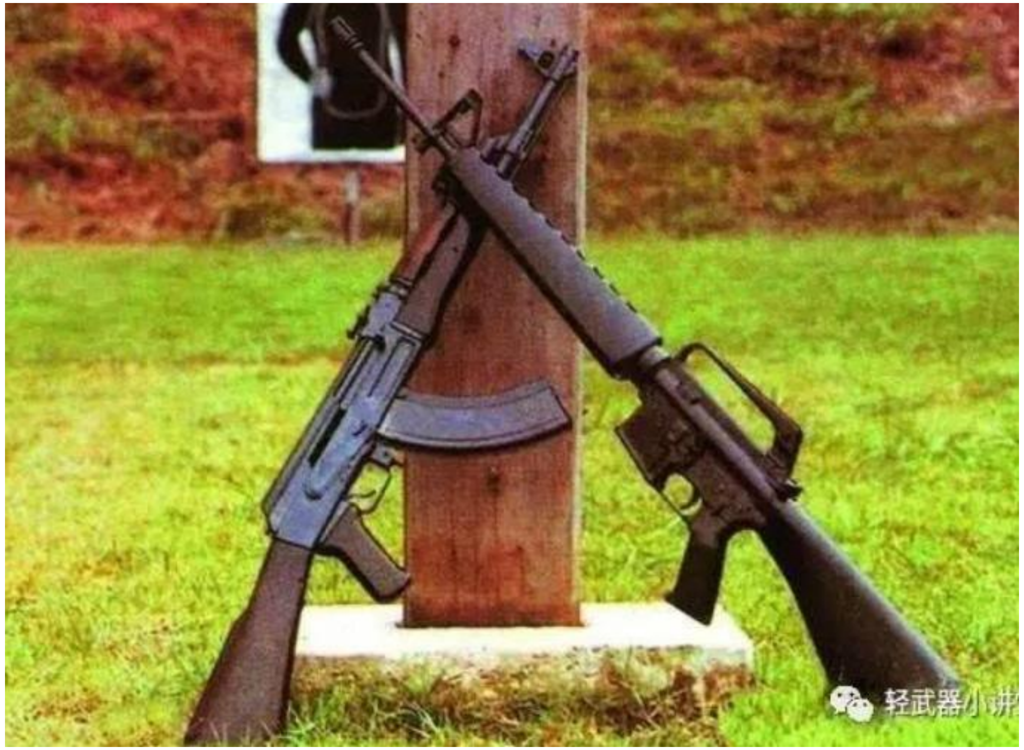
载波宽度120KHz



载波宽度240KHz

高可靠通信

越南战争时期的美军



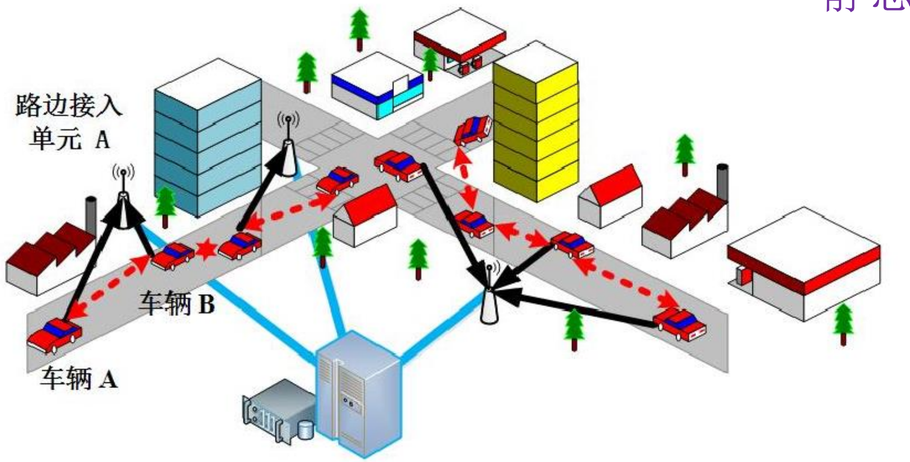
AK74和M16

启示：严丝合缝的系统VS高可靠的系统

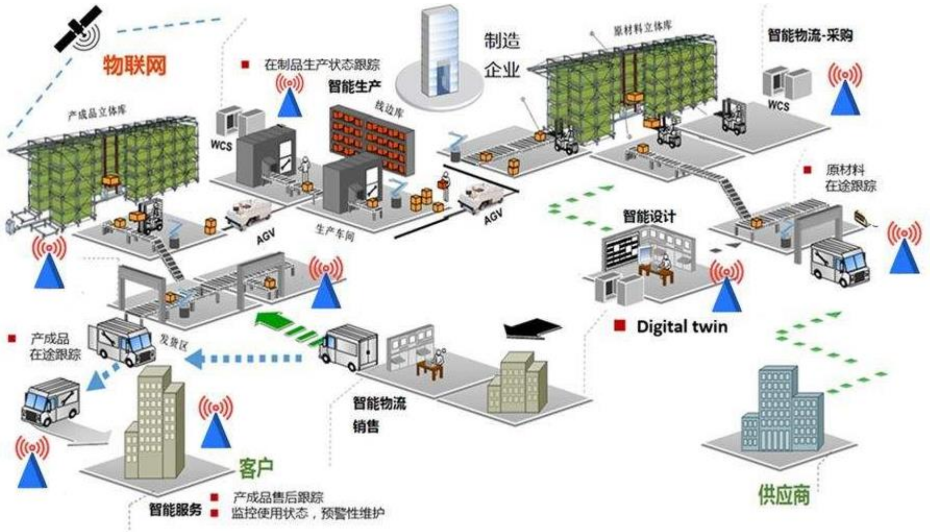
技术挑战

➢ 车联网

- 动态散射体
- 静态散射体



➢ 工业互联网



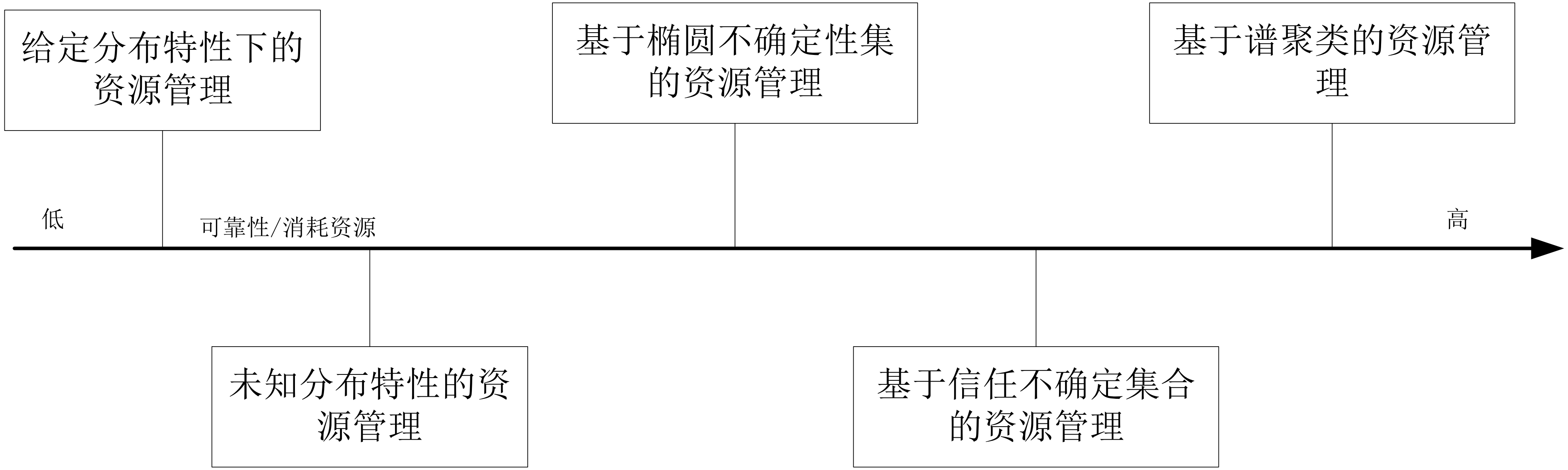
➢ 高动态无线信道特点

- 时间非平稳
- 深衰落
- 明显的多普勒效用
- 不同车流量下信道的统计特性不同

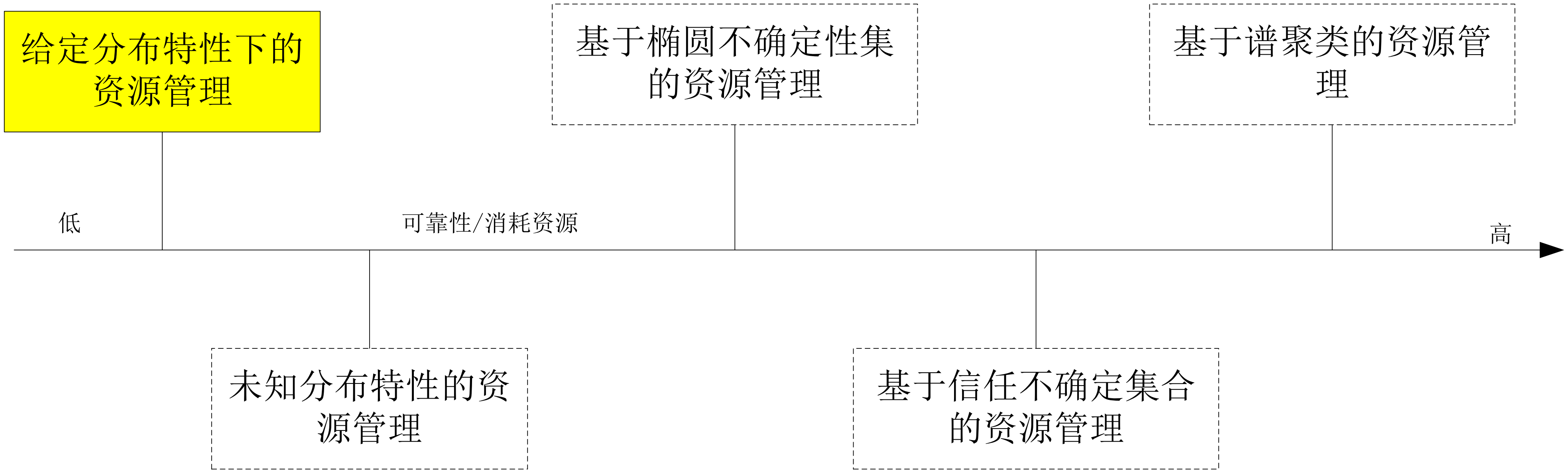
➢ 先前系统设计的不足

- 孤立的存在
- 和环境缺少交互
- 自适应性差

面对不可靠信息的资源管理

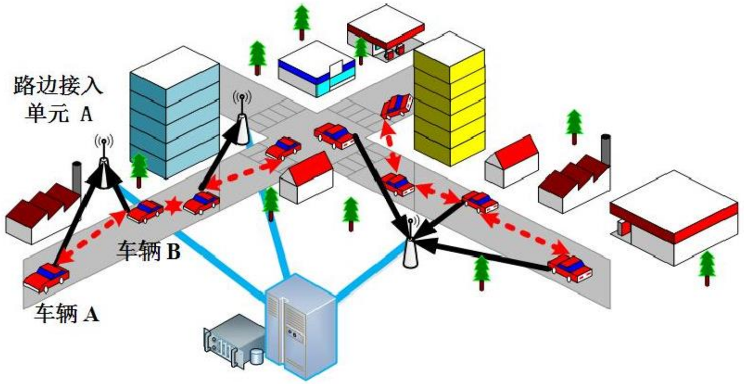


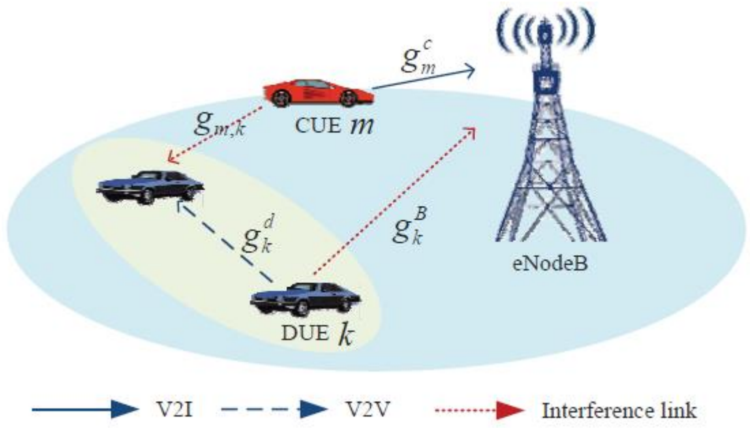
给定CSI分布特性的资源管理



给定CSI分布特性的资源管理

- System model





- Channel power gain

$$g_k^d = h_k^d \beta_k^d \varrho D_k^{-\iota} \triangleq |h_k^d|^2 \alpha_k^d,$$

- Small-scale channel gain

$$h = \varepsilon \hat{h} + \sqrt{1-\varepsilon^2} e.$$

- ε is determined by the high dynamic conditions

- SINR

$$\gamma_k^d = \frac{p_k^d \alpha_k^d \left(\varepsilon^2 |\hat{h}_k^d|^2 + (1-\varepsilon^2)|e_k^d|^2 \right)}{\sigma^2 + \sum_{m \in \mathcal{M}} x_{m,k} p_m^c \alpha_{m,k} \left(\varepsilon^2 |\hat{h}_{m,k}|^2 + (1-\varepsilon^2)|e_{m,k}|^2 \right)},$$

给定CSI分布特性的资源管理

The resource allocation problem

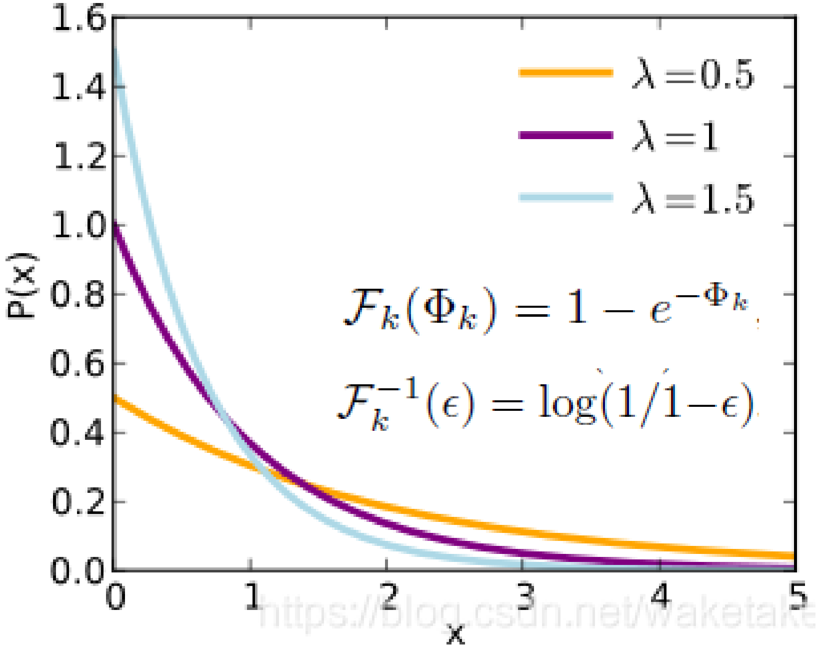
$$
\begin{aligned}
\max_{\{x_{m,k}\}\{p_m^c\}\{p_k^d\}} \; & \sum_{m=1}^{M} B\log_2(1+\gamma_m^c) \\
\text{s.t.} \quad & \gamma_m^c \geq \gamma_{min}^c, \forall m \in \mathcal{M}, \\
& \Pr\left\{\gamma_k^d \geq \gamma_{min}^d\right\} \geq 1-\epsilon, \forall k \in \mathcal{K}, \\
& \sum_{k=1}^{K} x_{m,k} \leq 1, x_{m,k} \in \{0,1\}, \forall m \in \mathcal{M}, \\
& \sum_{m=1}^{M} x_{m,k} \leq 1, \forall k \in \mathcal{K}, \\
& 0 \leq p_m^c \leq P_{max}^c, \forall m \in \mathcal{M} \\
& 0 \leq p_k^d \leq P_{max}^d, \forall k \in \mathcal{K},
\end{aligned}
$$

Decompose into power allocation subproblem and spectrum allocation subproblem.

$$
\begin{aligned}
C_{m,k} = \; & \max_{\{p_m^c\}\{p_k^d\}} B\log_2\left(1+\frac{p_m^c g_m^c}{\sigma^2+p_k^d g_k^B}\right) \\
\text{s.t.} \quad & \Pr\left\{\frac{\Theta_k^d+\Lambda_k^d X}{\Phi_{m,k}+\Omega_{m,k} Y} \leq \gamma_{min}^d\right\} \leq \epsilon, \\
& \frac{p_m^c g_m^c}{\sigma^2+p_k^d g_k^B} \geq \gamma_{min}^c, \\
& 0 \leq p_m^c \leq P_{max}^c, 0 \leq p_k^d \leq P_{max}^d,
\end{aligned}
$$

where $\Theta_k^d = p_k^d \alpha_k^d \varepsilon^2 |\hat{h}_k^d|^2$, $\Lambda_k^d = p_k^d \alpha_k^d (1-\varepsilon^2)$, $\Phi_{m,k} = \sigma^2 + p_m^c \alpha_{m,k} \varepsilon^2 |\hat{h}_{m,k}|^2$ and $\Omega_{m,k} = p_m^c \alpha_{m,k}(1-\varepsilon^2)$. Both $X = |e_k^d|^2$ and $Y = |e_{m,k}|^2$ are exponential random variables with unit mean.

给定CSI分布特性的资源管理



$\mathcal{F}_k(\cdot)$ is the cumulative distribution function (CDF)

$$\Phi_k$$

$$\begin{aligned}\text{outage}_k &= \mathbb{E}\left[\mathcal{F}_k(\Psi_k)\right] \leq \mathcal{F}_k(\mathbb{E}[\Psi_k]) \\ &= \mathcal{F}_k\left(\frac{\gamma_{min}^d(\Phi_{m,k} + \Omega_{m,k}\mathbb{E}[Y]) - \Theta_k^d}{\Lambda_k^d}\right) = \mathcal{F}_k(\Phi_k),\end{aligned}$$

The QoS requirement can further be given as

$$outage_k \leq \mathcal{F}_k(\Phi_k) \leq \epsilon.$$

The QoS requirement is

$$\Phi_k \leq \mathcal{F}_k^{-1}(\epsilon) \Rightarrow \frac{\Theta_k^d + \Lambda_k^d \mathcal{F}_k^{-1}(\epsilon)}{\Phi_{m,k} + \Omega_{m,k}} \geq \gamma_{min}^d.$$

Obtain the solution

$$\frac{p_k^d \hat{g}_k^d}{\sigma^2 + p_m^c \hat{g}_{m,k}} \geq \gamma_{min}^d,$$

给定CSI分布特性的资源管理

V2I QoS Constraint

$$\frac{p_m^c g_m^c}{\sigma^2 + p_k^d g_k^B} \geq \gamma_{min}^c,$$

V2V QoS Constraint

$$\frac{p_k^d \hat{g}_k^d}{\sigma^2 + p_m^c \hat{g}_{m,k}} \geq \gamma_{min}^d,$$

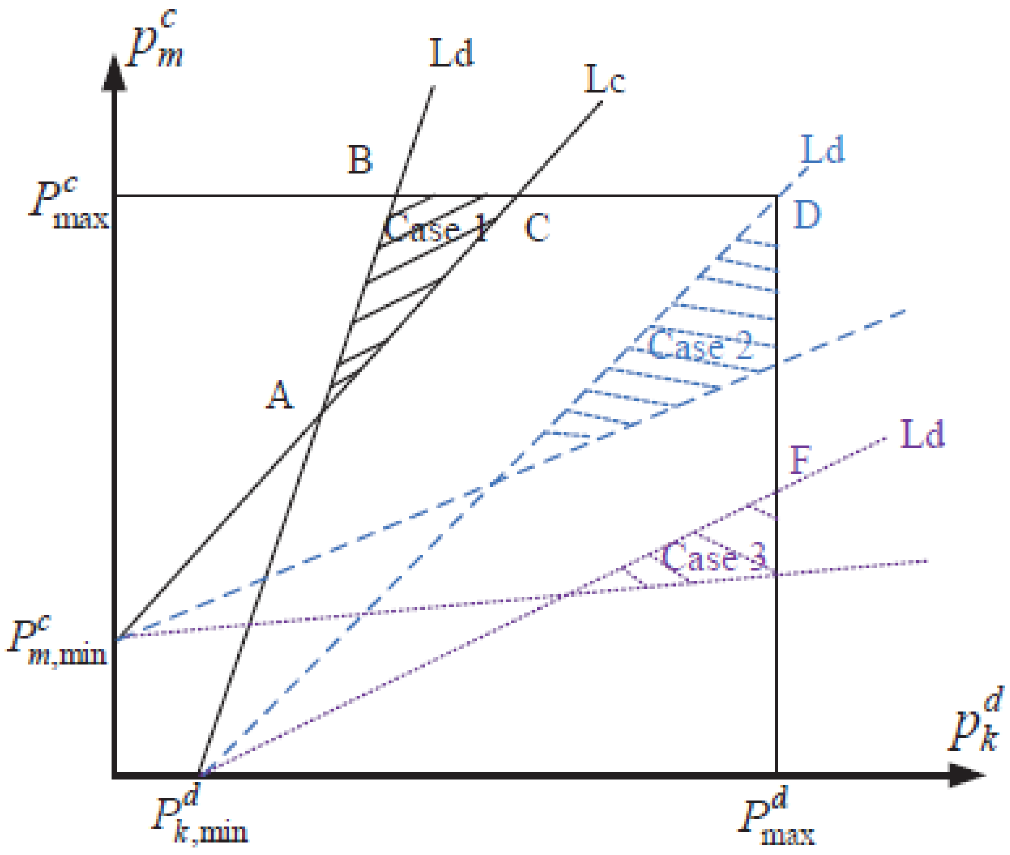
The optimal solution can be obtained

$$(p_m^{c,*}, p_k^{d,*}) = \underset{(p_m^c, p_k^d) \in \Omega}{\arg\max} \left\{ \log_2 \left(1 + \frac{p_m^c g_m^c}{\sigma^2 + p_k^d g_k^B} \right) \right\}$$

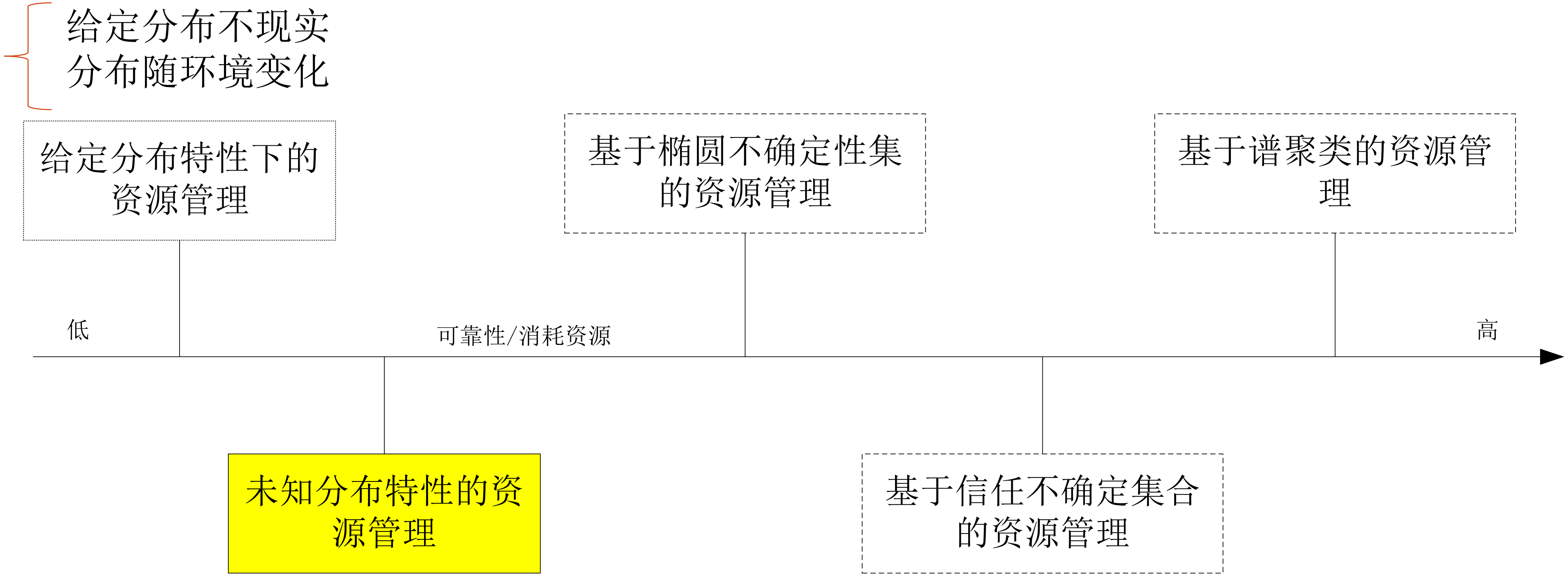
where

$$\Omega = \begin{cases} \{(P_{c,max}^d, P_{max}^c)\}, \text{if} \frac{P_{max}^d \hat{g}_k^d}{P_{max}^c \hat{g}_{m,k} + \sigma^2} > \gamma_{min}^d \\ \{(P_{max}^d, P_{max}^c)\}, \quad \text{if} \frac{P_{max}^d \hat{g}_k^d}{P_{max}^c \hat{g}_{m,k} + \sigma^2} = \gamma_{min}^d \\ \{(P_{max}^d, P_{d,max}^c)\}, \text{if} \frac{P_{max}^d \hat{g}_k^d}{P_{max}^c \hat{g}_{m,k} + \sigma^2} < \gamma_{min}^d \end{cases}$$

Feasible region of power control problem



未知CSI分布特性的资源管理



未知CSI分布特性的资源管理

Collect multiple samples of the uncertain CSI

$$\mathcal{D} = \{\xi_1, \xi_2, \cdots, \xi_N\}$$

The first-order moment of uncertain CSI

$$\bar{g} = \frac{1}{N}\sum_{k=1}^{N} \xi_k.$$

The second-order moment

$$\Sigma = \frac{1}{N-1}\left[\sum_{i=1}^{N-1} \xi_i \xi_i^T - \frac{1}{N-1}\left(\sum_{i=1}^{N} \xi_i\right)\left(\sum_{i=1}^{N} \xi_i\right)^T\right]$$

The QoS constraint reformulated as distributionally robust constraint

$$\inf_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{P}\left(\frac{p_k^d g_k^d}{\sigma^2 + p_m^c g_{m,k}} \geq \gamma_{min}^d\right) \geq 1-\epsilon.$$

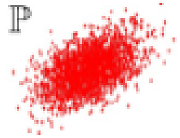
Deterministic Optimization

$$\inf_{\mathbf{x}} f(\mathbf{x}, \xi) \quad \text{s.t. } \mathbf{x} \in X$$

ξ

Stochastic Programming

$$\inf_{\mathbf{x}} \mathbb{E}_{\mathbb{P}}\{f(\mathbf{x}, \xi)\} \quad \text{s.t. } \mathbf{x} \in X$$

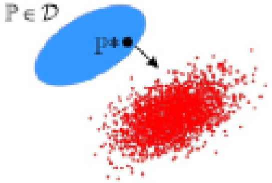


Robust Optimization

$$\inf_{\mathbf{x}} \sup_{\xi\in U} f(\mathbf{x}, \xi) \quad \text{s.t. } \mathbf{x} \in X$$

DR Optimization

$$\inf_{\mathbf{x}} \sup_{\mathbb{P}\in\mathcal{D}} \mathbb{E}_{\mathbb{P}}\{f(\mathbf{x}, \xi)\} \quad \text{s.t. } \mathbf{x} \in X$$



The feasible set of chance constraint

$$\left\{p_m^c, p_k^d \in \mathbb{R}^+ : \inf_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{P}\left(\frac{p_k^d g_k^d}{\sigma^2 + p_m^c g_{m,k}} \geq \gamma_{min}^d\right) \geq 1-\epsilon\right\}$$

未知CSI分布特性的资源管理

(CVaR) conditional expectation for evaluating the loss above the $(1-\epsilon)$-quantile of the loss distribution.

$$\mathbb{P}\text{-CVaR}(L(\mathrm{g})) = \inf_{\beta\in\mathbb{R}} \left\{ \beta + \frac{1}{\epsilon}\mathbb{E}_{\mathbb{P}}\left[(L(\mathrm{g}) - \beta)^{+} \right] \right\}$$

Define the loss function as $\dfrac{p_k^d g_k^d}{\sigma^2 + p_m^c g_{m,k}} \geq \gamma_{min}^d$

$$L(\mathrm{g}) = \sigma^2 \gamma_{min}^d + \gamma_{min}^d p_m^c g_{m,k} - p_k^d g_k^d.$$

The solution can be obtained

$$\sup_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{P}\text{-CVaR}_{\epsilon}(L(\mathrm{g})) \leq 0 \Rightarrow$$

$$\inf_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{P}\left(\frac{p_k^d g_k^d}{\sigma^2 + p_m^c g_{m,k}} \geq \gamma_{min}^d \right) \geq 1-\epsilon.$$

$$\begin{aligned} &\sup_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{P}\text{-CVaR}_{\epsilon}(L(\mathrm{g})) \\ &= \sup_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \inf_{\beta\in\mathbb{R}} \left\{ \beta + \frac{1}{\epsilon}\mathbb{E}_{\mathbb{P}}\left[(L(\mathrm{g}) - \beta)^{+} \right] \right\} \\ &= \inf_{\beta\in\mathbb{R}} \left\{ \beta + \frac{1}{\epsilon} \sup_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{E}_{\mathbb{P}}\left[(L(\mathrm{g}) - \beta)^{+} \right] \right\}, \end{aligned}$$

Lemma 1: Suppose that $f : \mathbb{R}^2 \to \mathbb{R}$ is a measurable function and define the worst-case expectation as $\varpi = \sup_{\mathbb{P}\in\mathcal{P}} \mathbb{E}_{\mathbb{P}}\left[(f(\mathrm{g}))^{+} \right]$, where $\mathcal{P}$ represents the usual set of all probability distributions on $\mathbb{R}^2$ with given mean $\bar{\mathrm{g}}$ and covariance matrix Σ. Then

$$\varpi = \inf_{\mathrm{M}\in\mathbb{S}^3} \left\{ \langle \Omega, \mathrm{M} \rangle : \mathrm{M} \succeq 0, \left[\mathrm{g}^T \; 1\right] \mathrm{M} \left[\mathrm{g}^T \; 1\right]^T \geq f(\mathrm{g}), \forall \mathrm{g} \in \mathbb{R}^2 \right\}$$

where

$$\Omega = \begin{bmatrix} \Sigma + \bar{\mathrm{g}}\bar{\mathrm{g}}^T & \bar{\mathrm{g}} \\ \bar{\mathrm{g}}^T & 1 \end{bmatrix}$$

is the second-order moment matrix of g.

未知CSI分布特性的资源管理

The CVaR is computed as

$$\sup_{\mathbb{P}\in\mathcal{P}_{\mathcal{G}}} \mathbb{P}\text{-CVaR}_{\epsilon}\,(L(\mathrm{g})) = \min_{\beta,\mathbf{M}} \beta + \frac{1}{\epsilon}\mathrm{Tr}(\Omega^T \mathbf{M})$$

$$\text{s.t.}\, \beta \in \mathbb{R}, \mathbf{M} \in \mathbb{S}^3, \mathbf{M} - \mathbf{\Phi} \succeq 0,$$

The power allocation problem can be reformulated as the following optimization problem

$$C_{m,k} = \max_{\{p_m^c\},\{p_k^d\},\beta,\mathbf{M}} B\log_2\left(1 + \frac{p_m^c g_m^c}{\sigma^2 + p_k^d g_k^B}\right)$$

$$\begin{aligned} \text{s.t.} \quad & \beta + \frac{1}{\epsilon}\mathrm{Tr}(\Omega^T \mathbf{M}) \le 0, \\ & \beta \in \mathbb{R}, \mathbf{M} \in \mathbb{S}^3, \mathbf{M} - \mathbf{\Phi} \succeq 0, \\ & \text{(7d)}. \end{aligned}$$

Algorithm 2 Bisection Search for Solving Problem (37)

Set termination threshold $0 < \zeta < 1$;
Set $p^d_{k,min} = 0$ and $p^d_{k,max} = P^d_{max}$;
while $p_k^d < P^d_{max} - \zeta$ **do**
  set $p_k^d = (p^d_{k,min} + p^d_{k,max})/2$; Solve (38) to obtain p_m^c;
  if $p_m^c > P^c_{max} + \zeta$ **then**
    $p^d_{k,max} = p_k^d$
  else if $p_m^c < P^c_{max} - \zeta$ **then**
    $p^d_{k,min} = p_k^d$
  else if $P^c_{max} - \zeta < p_m^c < P^c_{max} + \zeta$ **then**
    break
  end if
end while
Output the optimal transmit powers $p_m^{c,*}$ and $p_k^{d,*}$.

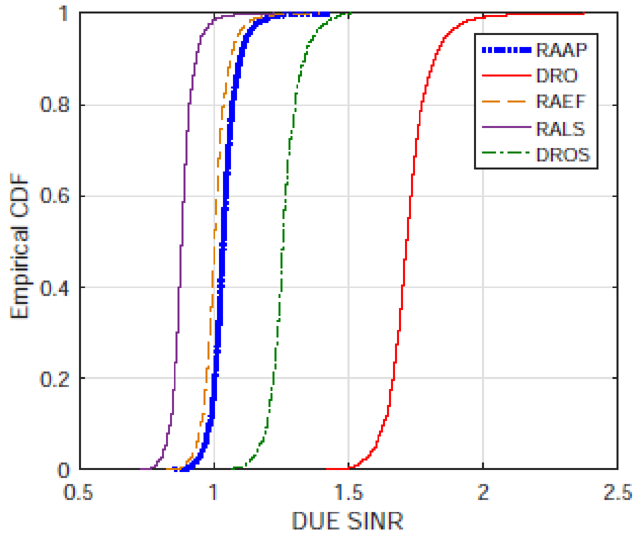


Fig. 4. V2V feasibility probability under the target SINR, assuming $\gamma^c = 2$, $\gamma^d = 1$, vehicle speed $v = 100$km/h and $P^c_{max} = P^d_{max} = 30$ dBm.

未知CSI分布特性的资源管理

Collect multiple samples of the uncertain CSI

$$\mathcal{D} = \{\xi_1, \xi_2, \cdots, \xi_N\}$$

The support $s > 0$ can be estimated as

$$s = \max_{1 \le i \le N} (\boldsymbol{\xi}_i - \bar{\mathbf{g}})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\xi}_i - \bar{\mathbf{g}}).$$

Rewrite the uncertainty set S as the following semi-infinite constraint

$$(\mathbf{g} - \bar{\mathbf{g}})^T \boldsymbol{\Sigma}^{-1} (\mathbf{g} - \bar{\mathbf{g}}) \le s \Leftrightarrow$$

$$\begin{bmatrix} \mathbf{g} \\ 1 \end{bmatrix}^T \begin{bmatrix} \boldsymbol{\Sigma}^{-1} & -\boldsymbol{\Sigma}^{-1}\bar{\mathbf{g}} \\ -\bar{\mathbf{g}}^T \boldsymbol{\Sigma}^{-1} & \bar{\mathbf{g}}^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{g}} - s \end{bmatrix} \begin{bmatrix} \mathbf{g} \\ 1 \end{bmatrix} \le 0.$$

Lemma 2. *Suppose $f_i(\mathbf{g}) = \mathbf{g}^T \mathbf{A}_i \mathbf{g}$ with $\mathbf{A}_i \in \mathbb{S}^3$ be quadratic functions of $\mathbf{g} \in \mathbb{R}^3$ for $i = 0, \cdots, p$. Then, $f_0(\mathbf{g}) \ge 0$ for all $\mathbf{g}$ with $f_i(\mathbf{g}) \le 0, i = 1, \cdots p$ if there exists constants $\tau_i \ge 0$ such that*

$$\mathbf{A}_0 + \sum_{i=1}^{p} \tau_i \mathbf{A}_i \succeq \mathbf{0}. \tag{44}$$

QoS constraint condition

$$\sup_{\mathbb{P} \in \mathcal{P}_{\mathcal{G}}} \mathbb{P}\text{-CVaR}_\epsilon \left(L(\mathbf{g})\right) = \min_{\beta, \mathbf{M}} \beta + \frac{1}{\epsilon} \mathrm{Tr}(\boldsymbol{\Omega}^T \mathbf{M})$$
$$\text{s.t.} \beta \in \mathbb{R}, \mathbf{M} \in \mathbb{S}^3, \mathbf{M} - \boldsymbol{\Phi} \succeq 0,$$

The QoS constraint is transformed into

$$\begin{aligned} \sup_{\mathbb{P} \in \mathcal{P}_{\mathcal{G}}} \mathbb{P}\text{-CVaR}_\epsilon (L(\mathbf{g})) = & \min_{\beta, \mathbf{M}, \tau^1, \tau^0} \beta + \frac{1}{\epsilon} \mathrm{Tr}(\boldsymbol{\Omega}^T \mathbf{M}) \\ \text{s.t. } & \beta \in \mathbb{R}, \mathbf{M} \in \mathbb{S}^3, \\ & \mathbf{M} + \tau^1 \mathbf{W} - \boldsymbol{\Phi} \succeq \mathbf{0}, \\ & \mathbf{M} + \tau^0 \mathbf{W} \succeq \mathbf{0}, \tau^1, \tau^0 \ge 0, \end{aligned}$$

The power control problem

$$\begin{aligned} C_{m,k} = & \max_{\{p_m^c\}, \{p_k^d\}, \beta, \mathbf{M}, \tau^1, \tau^0} B \log_2 \left(1 + \frac{p_m^c g_m^c}{\sigma^2 + p_k^d g_k^B}\right) \\ \text{s.t.} \quad & \beta + \frac{1}{\epsilon} \mathrm{Tr}(\boldsymbol{\Omega}^T \mathbf{M}) \le 0, \\ & \beta \in \mathbb{R}, \mathbf{M} \in \mathbb{S}^3, \\ & \mathbf{M} + \tau^1 \mathbf{W} - \boldsymbol{\Phi} \succeq \mathbf{0}, \\ & \mathbf{M} + \tau^0 \mathbf{W} \succeq \mathbf{0}, \tau^1, \tau^0 \ge 0, \end{aligned}$$

未知CSI分布特性的资源管理

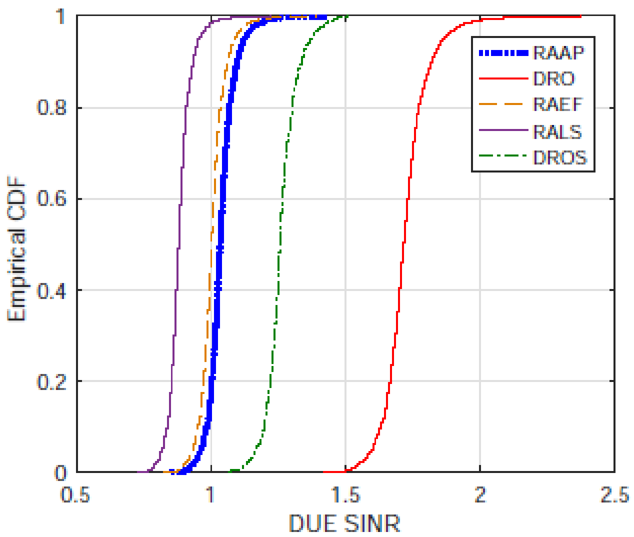


Fig. 4. V2V feasibility probability under the target SINR, assuming $\gamma^c = 2$, $\gamma^d = 1$, vehicle speed $v = 100$km/h and $P^c_{max} = P^d_{max} = 30$ dBm.

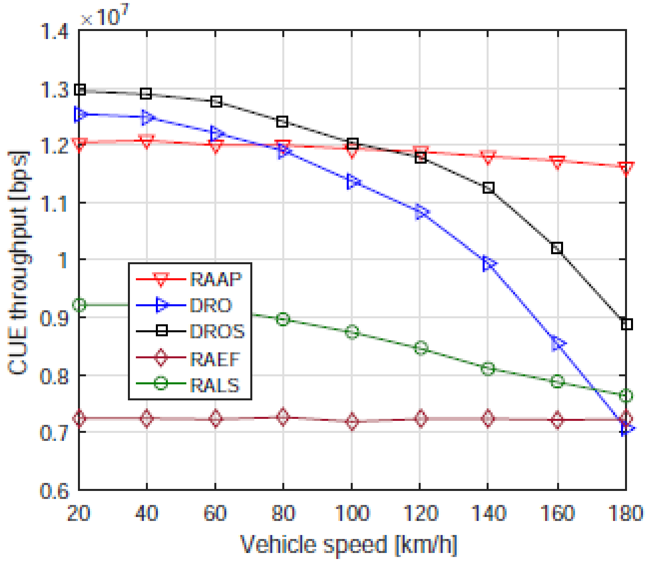


Fig. 9. CUE throughput versus the vehicle speed, assuming $\gamma^c = 2$, $\gamma^d = 1$ and $P^c_{max} = P^d_{max} = 30$ dBm.

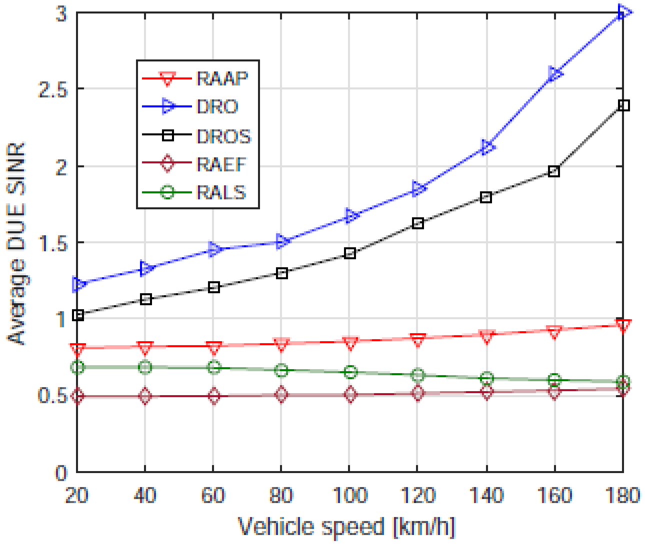
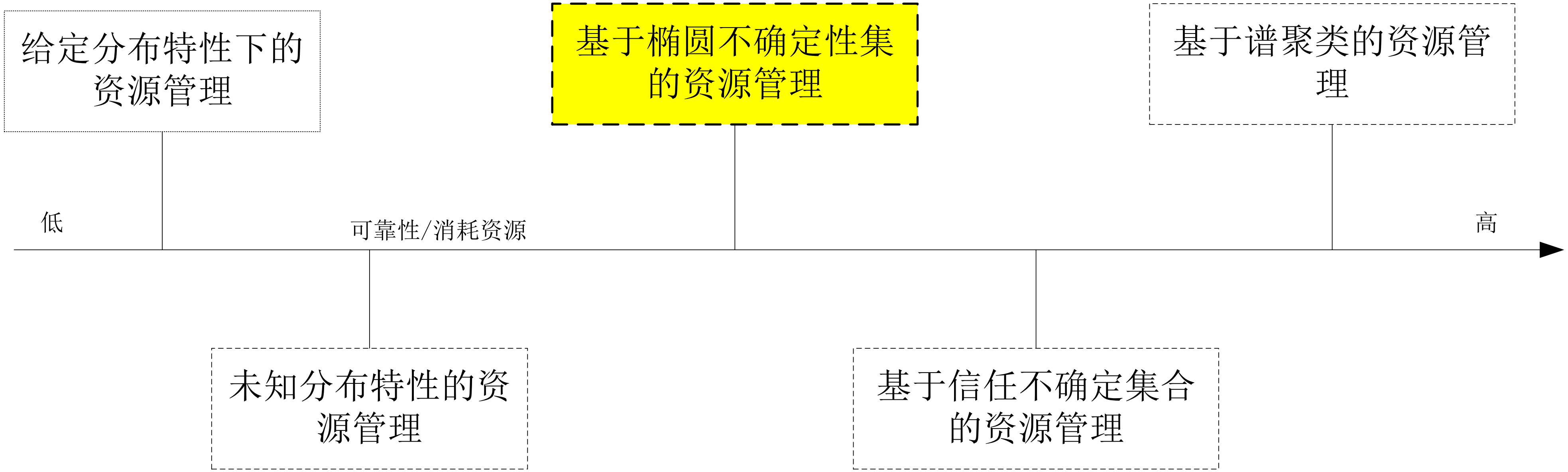


Fig. 10. Average DUE SINR versus the vehicle speed, assuming $\gamma^c = 2$, $\gamma^d = 1$ and $P^c_{max} = P^d_{max} = 30$ dBm.

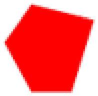
基于椭圆不确定集的资源管理



Robust Optimization

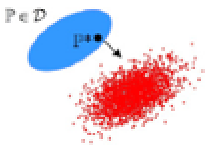
$$\inf_{\mathbf{x}} \sup_{\xi \in U} f(\mathbf{x}, \xi)$$
$$\text{s.t. } \mathbf{x} \in X$$

$\xi \in U$

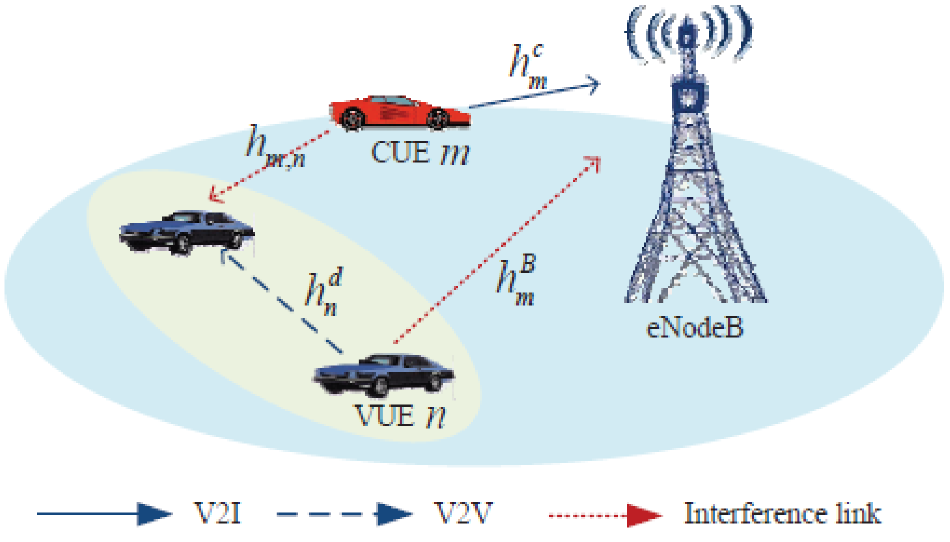


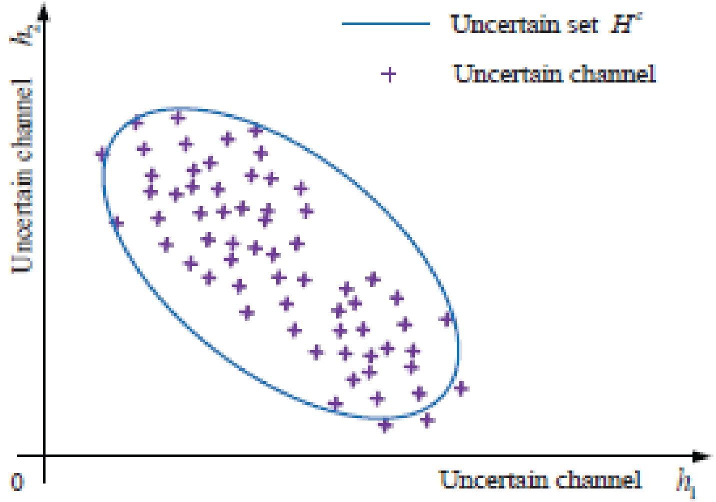
DR Optimization

$$\inf_{\mathbf{x}} \sup_{\mathbb{P} \in \mathcal{D}} \mathbb{E}_{\mathbb{P}}\{f(\mathbf{x}, \xi)\}$$
$$\text{s.t. } \mathbf{x} \in X$$



基于椭圆不确定集的资源管理





Ultra-reliable communications constraint

$$\Pr\left\{\gamma_n^d \geq \gamma_{req}^d\right\} \geq 1-\epsilon,$$

We use ellipsoid sets to model the uncertainties of the channel realizations

$$\mathcal{H}^c = \{\mathbf{h}^c : \mathbf{h}^c = \bar{\mathbf{h}}^c + \mathbf{B}^c\mathbf{u}, \mathbf{u}^T\mathbf{u} \leq 1\},$$

$$\mathcal{H}^c = \{\mathbf{h}^c : (\mathbf{h}^c - \bar{\mathbf{h}}^c)^T \mathbf{\Sigma}^{-1}(\mathbf{h}^c - \bar{\mathbf{h}}^c) \leq s_c\},$$

基于椭圆不确定集的资源管理

Collect multiple samples of the uncertain CSI

$$\mathcal{D} = \{\xi_1, \xi_2, \cdots, \xi_N\}$$

1) Shape Learning

The center is

$$\bar{\mathbf{h}}^c = \frac{1}{D_1}\sum_{k=1}^{D_1} \xi_k,$$

The correlation between each element is

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma}_1 & & \\ & \ddots & \\ & & \boldsymbol{\Sigma}_M \end{bmatrix}$$

$$\Sigma_m^{i,j} = \frac{1}{D_1}\sum_{k=1}^{D_1}(\xi_k^{2(m-1)+i} - \bar{\mathbf{h}}^c_{2(m-1)+i})^T(\xi_k^{2(m-1)+j} - \bar{\mathbf{h}}^c_{2(m-1)+j})$$

2) Size Calibration:

$$t(\xi) = (\xi - \bar{\mathbf{h}}^c)^T \boldsymbol{\Sigma}^{-1}(\xi - \bar{\mathbf{h}}^c)$$

Then, the k∗ = ⌈(1−δ)D2⌉-th values t(1)≤ · · · ≤ t(D−D1) in ascending order is the upper bound of (1 − δ)-quantile

$$\mathcal{H}^c = \{\mathbf{h}^c : \mathbf{h}^c = \bar{\mathbf{h}}^c + \mathbf{B}^c\mathbf{u}, \mathbf{u}^T\mathbf{u} \le 1\},$$

The QoS constraint can be computed as

$$\begin{aligned} \min \quad & \mathbf{p}^c\mathbf{h}^c \ge \boldsymbol{\sigma}^c, \\ \text{s.t.} \quad & \mathbf{h}^c = \bar{\mathbf{h}}^c + \mathbf{B}^c\mathbf{u}, \mathbf{u}^T\mathbf{u} \le 1, \end{aligned}$$

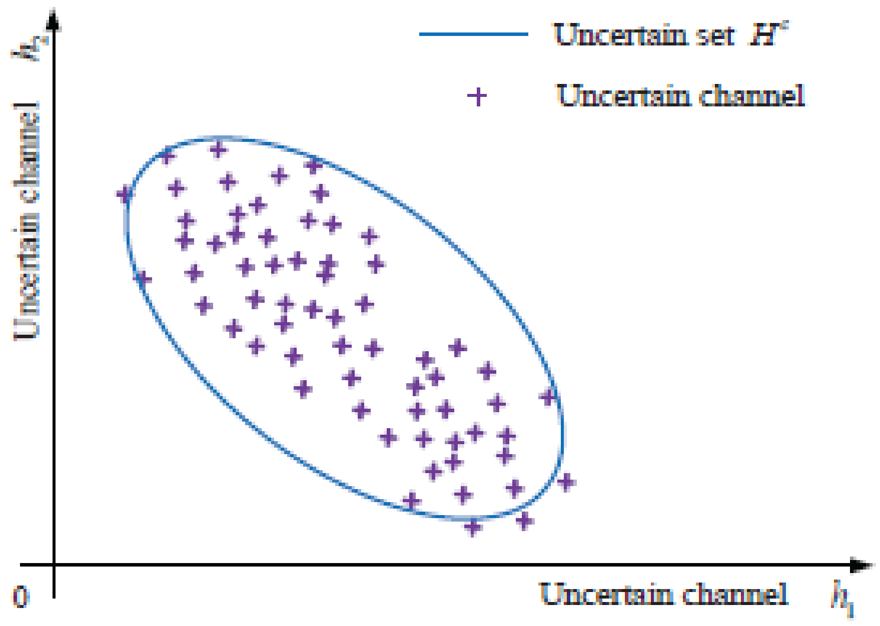
The robust counterpart is

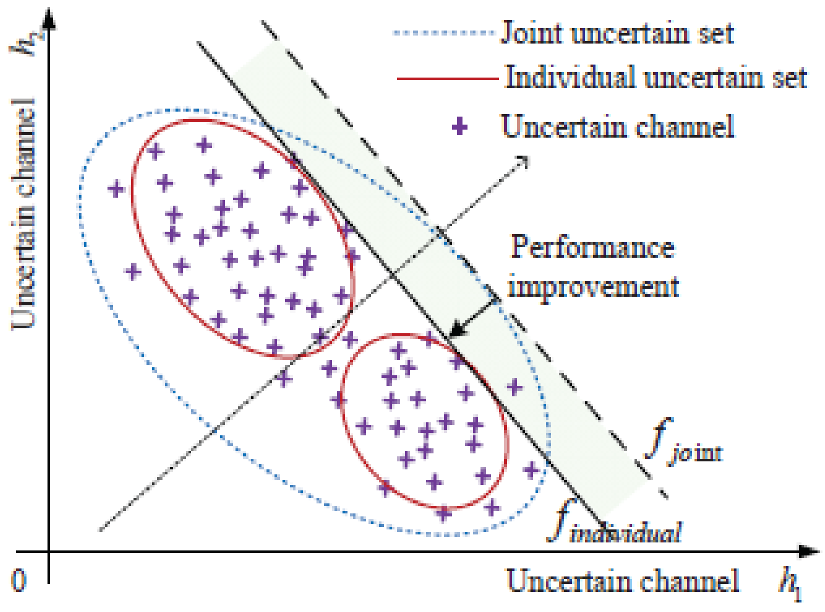
$$\begin{aligned} & \mathbf{p}^d\mathbf{h}^d \ge \boldsymbol{\sigma}, \mathbf{h}^d = \bar{\mathbf{h}}^d + \mathbf{B}^d\mathbf{u}, \mathbf{u}^T\mathbf{u} \le 1 \\ \Leftrightarrow & \inf_{\|\mathbf{u}\|\le 1} \mathbf{p}^d(\bar{\mathbf{h}}^d + \mathbf{B}^d\mathbf{u}) = \mathbf{p}^d\bar{\mathbf{h}}^d - \|\mathbf{p}^d\mathbf{B}^d\|. \end{aligned}$$

基于椭圆不确定集的资源管理

The robust counterpart is

$$
\begin{aligned}
\min \quad & w_1 \sum_m p_m^c + w_2 \sum_n p_n^d \\
\text{s.t.} \quad & \mathbf{p}^c \bar{\mathbf{h}}^c - \|\mathbf{p}^c \mathbf{B}^c\| \geq \boldsymbol{\sigma}^c, \\
& \mathbf{p}^d \bar{\mathbf{h}}^d - \|\mathbf{p}^d \mathbf{B}^d\| \geq \boldsymbol{\sigma}^d, \\
& \text{(4d), (4e)},
\end{aligned}
$$





基于椭圆不确定集的资源管理

Collect multiple samples of the uncertain CSI

$$\mathcal{D} = \{\xi_1, \xi_2, \cdots, \xi_N\}$$

1) Shape Learning

The center is

$$\bar{\eta}_m^c = \frac{1}{D_1}\sum_{k=1}^{D_1} \xi_k^m \quad \text{and} \quad \bar{\varphi}_n^d = \frac{1}{T_1}\sum_{k=1}^{T_1} \theta_k^n,$$

The correlation between each element is

$$\boldsymbol{\Sigma}_m = \begin{bmatrix} \Sigma^{1,1} & \Sigma^{1,2} \\ \Sigma^{2,1} & \Sigma^{2,2} \end{bmatrix}, \boldsymbol{\Lambda}_n = \begin{bmatrix} \Lambda^{1,1} & \Lambda^{1,2} \\ \Lambda^{2,1} & \Lambda^{2,2} \end{bmatrix},$$

2) Size Calibration:

$$t_{\boldsymbol{\xi}}(\boldsymbol{\xi}) = \max_{m=1,\cdots,M} (\boldsymbol{\xi}_m - \bar{\eta}_m^c)^T \boldsymbol{\Sigma}_m^{-1} (\boldsymbol{\xi}_m - \bar{\eta}_m^c),$$

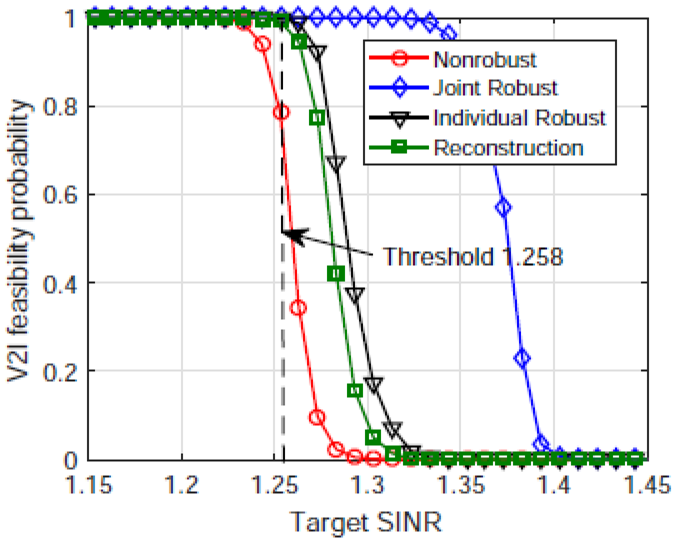
Robust optimization problem

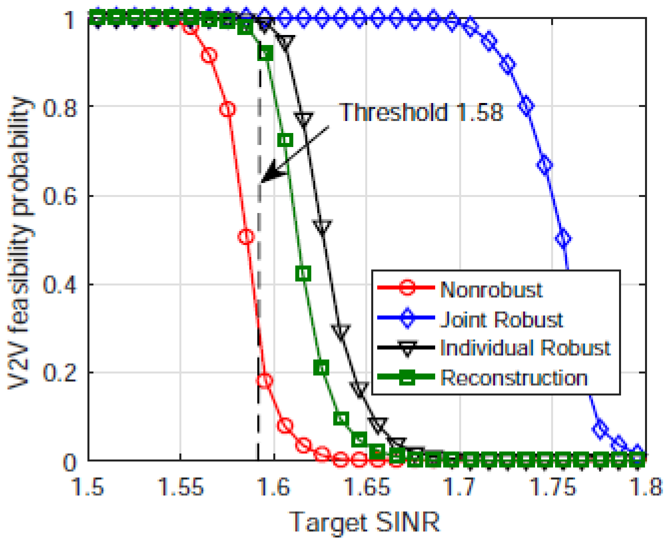
$$\begin{aligned} \min \quad & w_1 p_m^c + w_2 p_n^d \\ \text{s.t.} \quad & \mathbf{p}_m^c \boldsymbol{\eta}_m^c \geq \sigma^2, \boldsymbol{\eta}_m^c = \bar{\boldsymbol{\eta}}_m^c + \mathbf{B}_m^c \boldsymbol{\mu}, \boldsymbol{\mu}^T \boldsymbol{\mu} \leq 1, \\ & \mathbf{p}_n^d \boldsymbol{\varphi}_n^d \geq \sigma^2, \boldsymbol{\varphi}_n^d = \bar{\boldsymbol{\varphi}}_n^d + \mathbf{B}_n^d \boldsymbol{\mu}, \boldsymbol{\mu}^T \boldsymbol{\mu} \leq 1, \\ & (29\text{d}), (29\text{e}). \end{aligned}$$

The robust counterpart can be written as

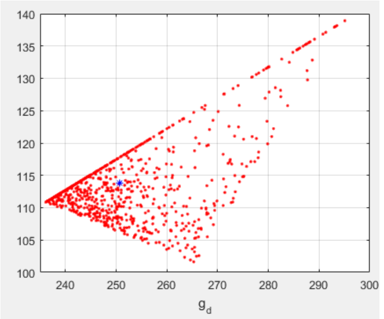
$$\begin{aligned} \min \quad & w_1 p_m^c + w_2 p_n^d \\ \text{s.t.} \quad & \mathbf{p}_m^c \bar{\boldsymbol{\eta}}_m^c - \|\mathbf{p}_m^c \mathbf{B}_m^c\| \geq \sigma^2, \\ & \mathbf{p}_n^d \bar{\boldsymbol{\varphi}}_n^d - \|\mathbf{p}_n^d \mathbf{B}_n^d\| \geq \sigma^2, \\ & (29\text{d}), (29\text{e}). \end{aligned}$$

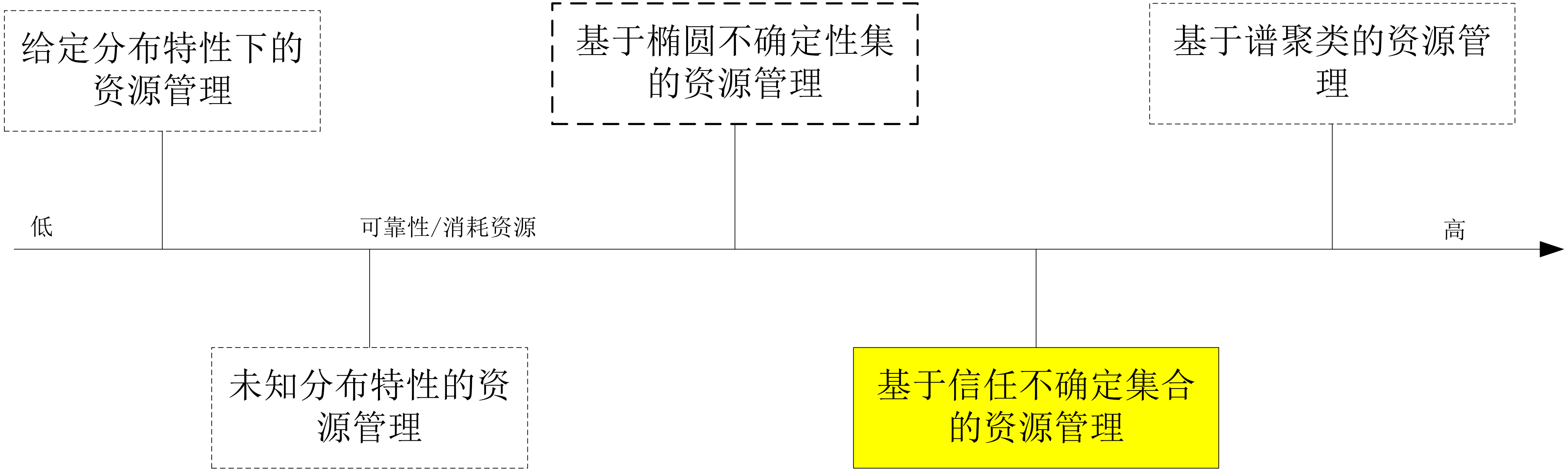
基于椭圆不确定集的资源管理





基于椭圆不确定集的资源管理





基于信任不确定集的资源管理

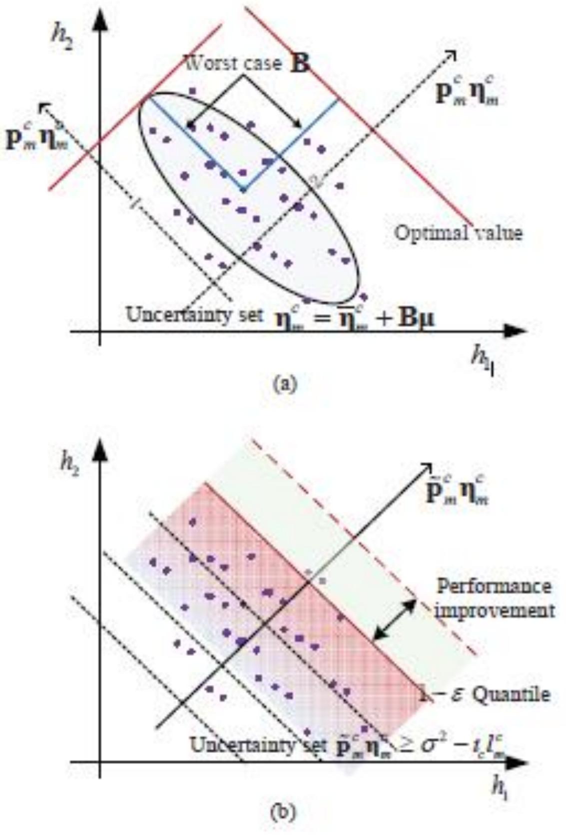


Fig. 4. Performance improvement through reconstructing the ellipsoid set as an affine set. $\mathbf{p}_m^c \eta_m^c$ is the possible increasing direction of the network performance. $\mathbf{B}$ indicates the worst case of CSI error. $\tilde{\mathbf{p}}_m^c \eta_m^c$ is the reliable increasing direction of the network performance. $\tilde{\mathbf{p}}_m^c \eta_m^c \geq \sigma^2 - \iota_c l_m^c$ is the uncertainty set constructed along the reliable increasing direction.

The QoS constraint

$$\gamma_m^c \geq \gamma_{req}^c \Rightarrow \frac{p_m^c h_m^c}{\gamma_{req}^c} - p_n^d h_n^B \geq \sigma^2, \forall m. \quad \mathcal{H}_m^c = \{\eta_m^c | \tilde{\mathbf{p}}_m^c \eta_m^c \geq \sigma^2 - \iota_c l_m^c\},$$

The values is calibrated by letting

$$t_{\xi}(\xi) = \max_{m=1,\cdots,M} \left\{ \left(\sigma^2 - \tilde{\mathbf{p}}_m^c \xi_m\right) / l_m^c \right\},$$

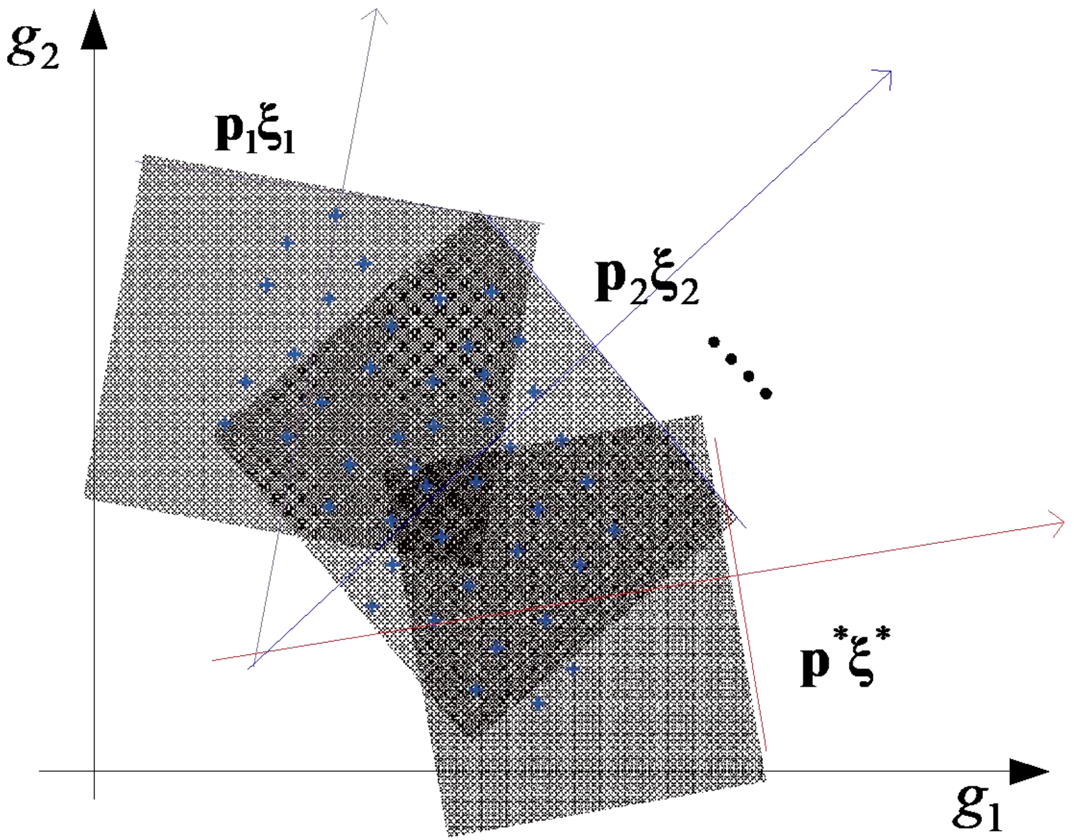
Robust counterpart

$$\begin{aligned} \min_{\varphi_n^d} \quad & \mathbf{p}_n^d \varphi_n^d \\ \text{s.t.} \quad & \tilde{\mathbf{p}}_n^d \varphi_n^d \geq \sigma^2 - \iota_d l_n^d. \end{aligned} \qquad \begin{aligned} \max \quad & y_n^d(\sigma^2 - \iota_d l_n^d) \\ \text{s.t.} \quad & y_n^d \tilde{\mathbf{p}}_n^d \leq \mathbf{p}_n^d, y_n^d \geq 0 \end{aligned}$$

Robust problem

$$\begin{aligned} \min \quad & w_1 p_m^c + w_2 p_n^d \\ \text{s.t.} \quad & y_m^c(\sigma^2 - \iota_c l_m^c) \geq \sigma^2, \\ & y_m^c \tilde{\mathbf{p}}_m^c \leq \mathbf{p}_m^c, y_m^c \geq 0, \\ & y_n^d(\sigma^2 - \iota_d l_n^d) \geq \sigma^2, \\ & y_n^d \tilde{\mathbf{p}}_n^d \leq \mathbf{p}_n^d, y_n^d \geq 0, \end{aligned}$$

基于信任不确定集的资源管理



The values is calibrated by letting

$$t_\xi(\xi) = \max_{m=1,\cdots,M} \left\{ \left(\sigma^2 - \tilde{\mathrm{p}}^c_m \xi_m\right) / l^c_m \right\},$$

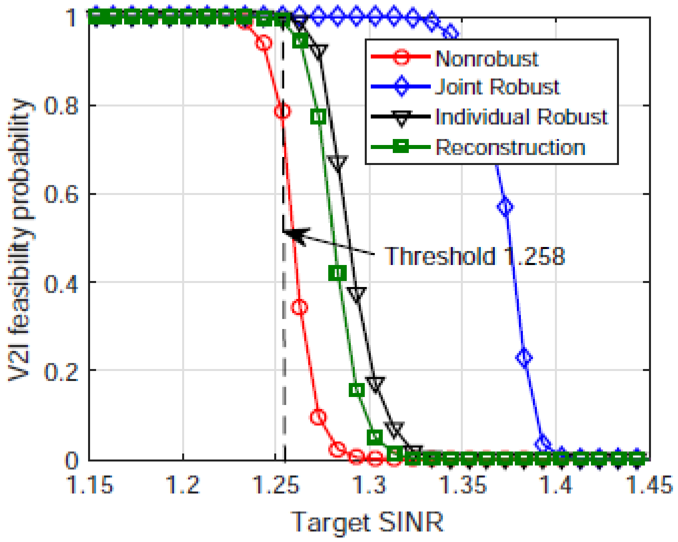
Robust counterpart

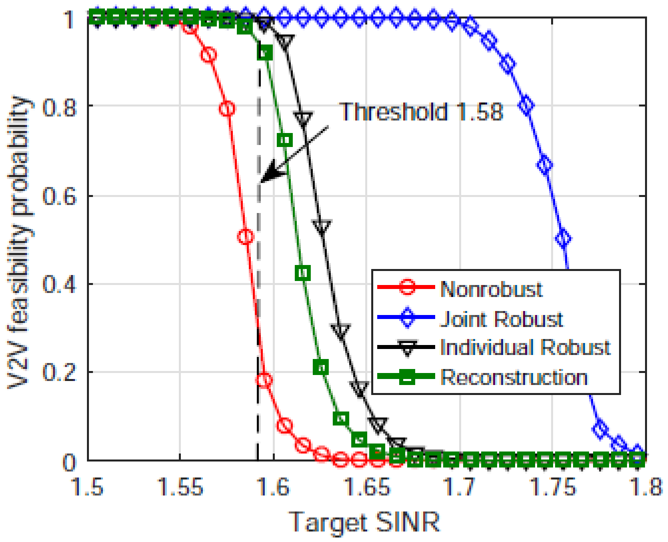
$$\begin{array}{ll} \min\limits_{\varphi^d_n} & \mathrm{p}^d_n \varphi^d_n \\ \text{s.t.} & \tilde{\mathrm{p}}^d_n \varphi^d_n \geq \sigma^2 - \iota_d l^d_n. \end{array} \qquad \begin{array}{ll} \max & y^d_n(\sigma^2 - \iota_d l^d_n) \\ \text{s.t.} & y^d_n \tilde{\mathrm{p}}^d_n \leq \mathrm{p}^d_n, y^d_n \geq 0 \end{array}$$

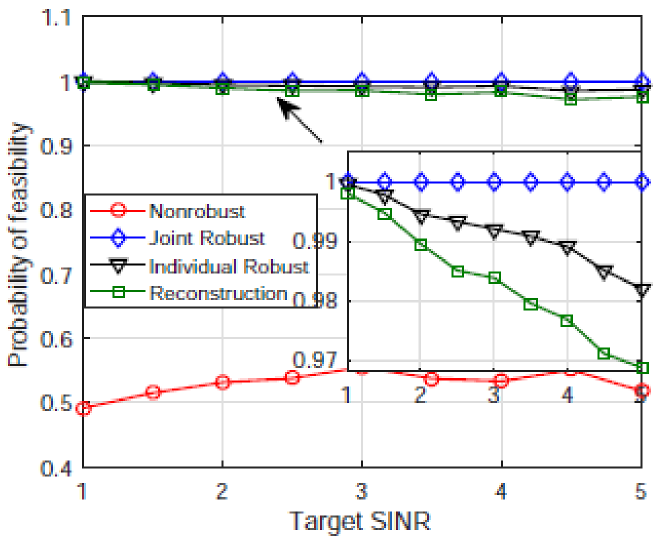
Robust problem

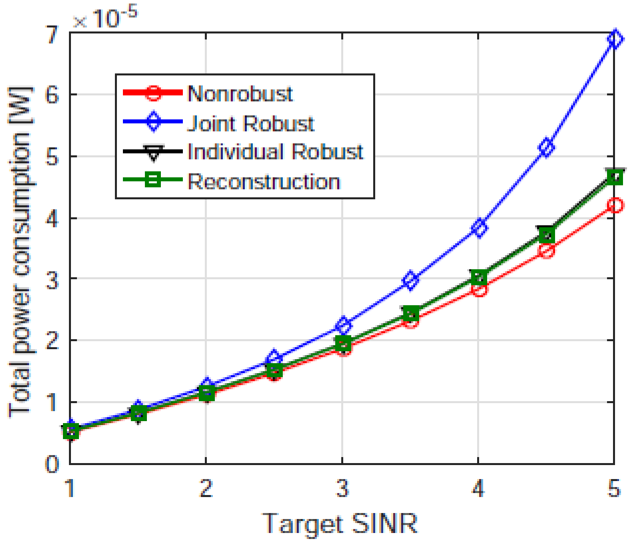
$$\begin{array}{ll} \min & w_1 p^c_m + w_2 p^d_n \\ \text{s.t.} & y^c_m(\sigma^2 - \iota_c l^c_m) \geq \sigma^2, \\ & y^c_m \tilde{\mathrm{p}}^c_m \leq \mathrm{p}^c_m, y^c_m \geq 0, \\ & y^d_n(\sigma^2 - \iota_d l^d_n) \geq \sigma^2, \\ & y^d_n \tilde{\mathrm{p}}^d_n \leq \mathrm{p}^d_n, y^d_n \geq 0, \end{array}$$

基于信任不确定集的资源管理

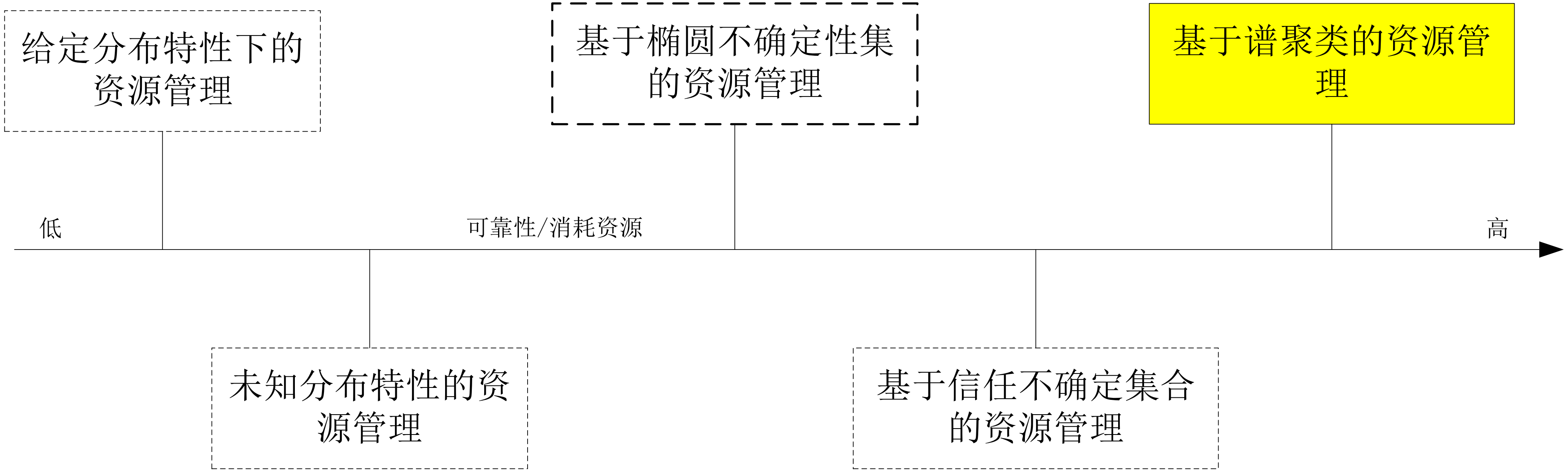




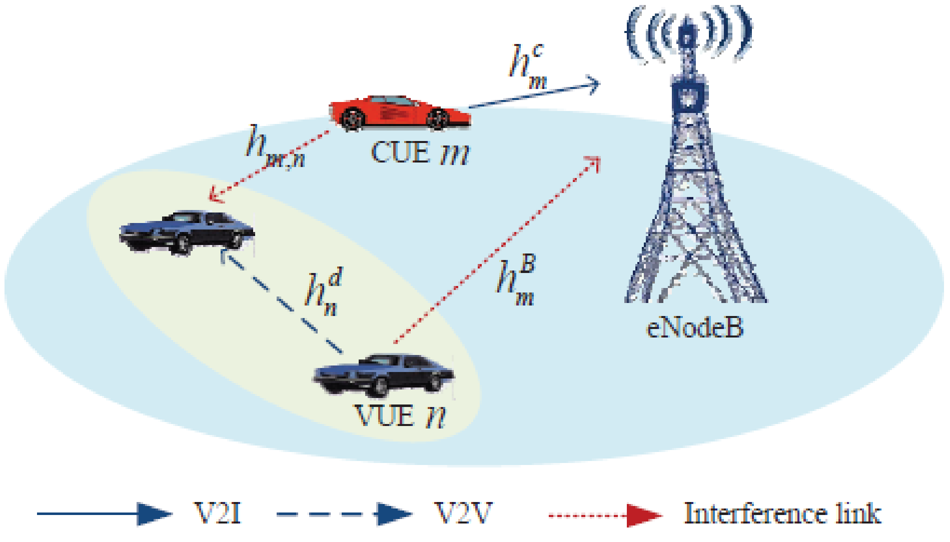




基于谱聚类的资源管理


给定分布特性下的资源管理
基于椭圆不确定性集的资源管理
基于谱聚类的资源管理
低
可靠性/消耗资源
高
未知分布特性的资源管理
基于信任不确定集合的资源管理

基于谱聚类的资源管理



- Small-scale channel gain

$$h = \varepsilon \hat{h} + \sqrt{1-\varepsilon^2}e.$$

- SINR

$$\gamma_k^d = \frac{p_k^d \alpha_k^d \left(\varepsilon^2 |\hat{h}_k^d|^2 + (1-\varepsilon^2)|e_k^d|^2\right)}{\sigma^2 + \sum_{m\in\mathcal{M}} x_{m,k} p_m^c \alpha_{m,k} \left(\varepsilon^2 |\hat{h}_{m,k}|^2 + (1-\varepsilon^2)|e_{m,k}|^2\right)},$$

- Channel power gain

$$g_k^d = h_k^d \beta_k^d \varrho D_k^{-\iota} \triangleq |h_k^d|^2 \alpha_k^d,$$

- QoS requirements

$$\Pr\{\gamma_d \geq \gamma_{min}^d\} \geq \Pr\{\mathbf{g} \in \mathcal{G}\} \geq 1-\epsilon,$$

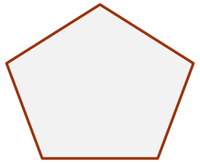
基于谱聚类的资源管理

Symmetrical-geometry-based learning approach

➢ *Polytope Model*

$$\mathcal{P} = \{\mathbf{g} \mid\ | g_d - \bar{g}_d | + | g_{c,d} - \bar{g}_{c,d} | \le \Gamma\},$$

1) Shape Learning:



$$\bar{\mathbf{g}} = \frac{1}{N}\sum_{k=1}^{N} \boldsymbol{\xi}_k.$$

2) Size Calibration:

$$t_p(\boldsymbol{\xi}) = | \boldsymbol{\xi}(1) - \bar{g}_d | + | \boldsymbol{\xi}(2) - \bar{g}_{c,d} |$$

QoS constraint computed as

$$\begin{aligned} \min \quad & \mathbf{p}^T \mathbf{g} \\ \text{s.t.} \quad & \mathbf{M}_p(\mathbf{g} - \bar{\mathbf{g}}) \le \boldsymbol{\Gamma}. \end{aligned}$$

Lagrange dual as

$$\begin{aligned} \max \quad & -(\boldsymbol{\Gamma} + \mathbf{M}_p \bar{\mathbf{g}})^T \mathbf{x} \\ \text{s.t.} \quad & -\mathbf{M}_p^T \mathbf{x} \le \mathbf{p}, \mathbf{x} \ge 0, \end{aligned}$$

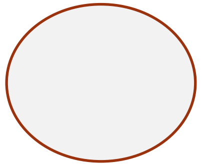
Robust counterpart

$$\begin{cases} -(\boldsymbol{\Gamma} + \mathbf{M}_p \bar{\mathbf{g}})^T \mathbf{x} \ge \gamma_{min}^d, \\ -\mathbf{M}_p^T \mathbf{x} \le \mathbf{p}, \mathbf{x} \ge 0. \end{cases}$$

➢ *Ellipsoidal*

$$\mathcal{E} = \{\mathbf{g} : (\mathbf{g} - \bar{\mathbf{g}})^T (\mathbf{g} - \bar{\mathbf{g}}) \le \Lambda\},$$

1) Shape Learning:



$$\bar{\mathbf{g}} = \frac{1}{N}\sum_{k=1}^{N} \boldsymbol{\xi}_k.$$

2) Size Calibration:

$$t_e(\boldsymbol{\xi}) = (\boldsymbol{\xi} - \bar{\mathbf{g}})^T (\boldsymbol{\xi} - \bar{\mathbf{g}})$$

QoS constraint computed as

$$\begin{aligned} \min \quad & \mathbf{p}^T \mathbf{g} \\ \text{s.t.} \quad & \mathbf{g} = \bar{\mathbf{g}} + \zeta \mathbf{u}, \mathbf{u}^T \mathbf{u} \le 1. \end{aligned}$$

Since

$$\inf_{\|\mathbf{u}\| \le 1} \mathbf{p}^T (\bar{\mathbf{g}} + \zeta \mathbf{u}) = \mathbf{p}^T \bar{\mathbf{g}} - \zeta \| \mathbf{p}^T \|,$$

Robust counterpart

$$\mathbf{p}^T \bar{\mathbf{g}} - \zeta \|\mathbf{p}^T\| \ge \gamma_{min}^d,$$

➢ *Box Uncertainty Set*

$$\mathcal{B} = \{| \mathbf{g}(i) - \bar{\mathbf{g}}(i) | \le \Psi, i = 1, 2\},$$

1) Shape Learning:

$$\bar{\mathbf{g}} = \frac{1}{N}\sum_{k=1}^{N} \boldsymbol{\xi}_k.$$

2) Size Calibration:

$$t_b(\boldsymbol{\xi}_i) = \max_{i=1,2} | \boldsymbol{\xi}_i - \bar{\mathbf{g}}_i |$$

QoS constraint computed as

$$\begin{aligned} \min \quad & \mathbf{p}^T \mathbf{g} \\ \text{s.t.} \quad & \mathbf{M}_b(\mathbf{g} - \bar{\mathbf{g}}) \le \boldsymbol{\Psi}. \end{aligned}$$

Lagrange dual as

$$\begin{aligned} \max \quad & -(\boldsymbol{\Psi} + \mathbf{M}_b \bar{\mathbf{g}})^T \mathbf{y} \\ \text{s.t.} \quad & -\mathbf{M}_b^T \mathbf{y} \le \mathbf{p}, \mathbf{y} \ge 0, \end{aligned}$$

Robust counterpart

$$\begin{cases} -(\boldsymbol{\Psi} + \mathbf{M}_b \bar{\mathbf{g}})^T \mathbf{y} \ge \gamma_{min}^d, \\ -\mathbf{M}_b^T \mathbf{y} \le \mathbf{p}, \mathbf{y} \ge 0. \end{cases}$$

基于谱聚类的资源管理

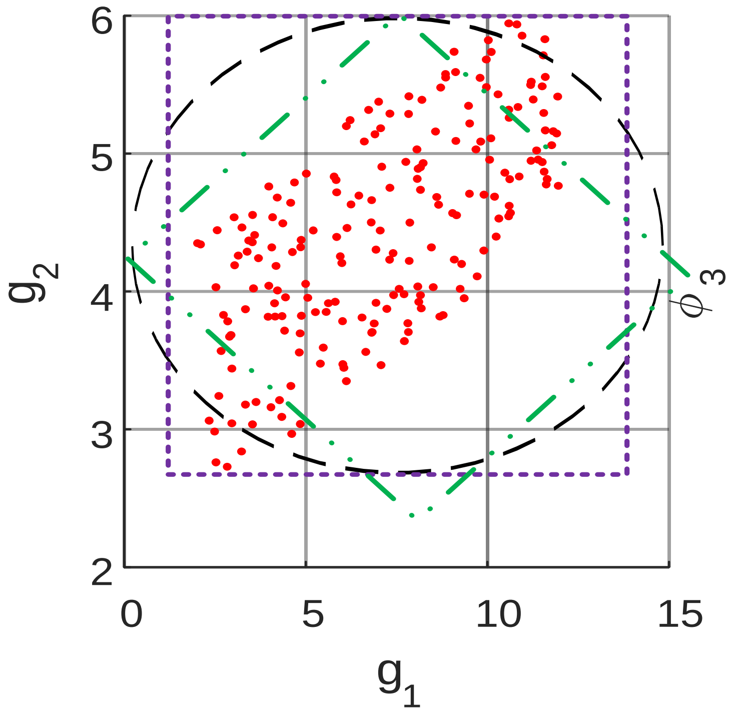
- 功率分配问题

$$
\begin{aligned}
\max_{p_c, p_d} \quad & B \log_2 \left(1 + \frac{p_c g_c}{\sigma^2 + p_d g_{d,B}} \right) \\
\text{s.t.} \quad & \left\{ \begin{array}{l} -(\mathbf{\Gamma} + \mathbf{M}_p \bar{\mathbf{g}})^T \mathbf{x} \geq \gamma_{min}^d, \\ -\mathbf{M}_p^T \mathbf{x} \leq \mathbf{p}, \mathbf{x} \geq 0. \end{array} \right. \\
& \mathbf{p}^T \bar{\mathbf{g}} - \zeta \| \mathbf{p}^T \| \geq \gamma_{min}^d, \\
& \left\{ \begin{array}{l} -(\mathbf{\Psi} + \mathbf{M}_b \bar{\mathbf{g}})^T \mathbf{y} \geq \gamma_{min}^d, \\ -\mathbf{M}_b^T \mathbf{y} \leq \mathbf{p}, \mathbf{y} \geq 0. \end{array} \right.
\end{aligned}
$$

Algorithm 1 Bisection Search-Based Power Allocation

Set termination threshold $0 < \zeta < 1$;
Set $p_{k,min}^d = 0$ and $p_{k,max}^d = P_{max}^d$;
while $p_k^d < P_{max}^d - \zeta$ **do**
  set $p_k^d = (p_{k,min}^d + p_{k,max}^d)/2$; Solve (30) to obtain p_m^c;
  if $p_m^c > P_{max}^c + \zeta$ **then**
    $p_{k,max}^d = p_k^d$
  else if $p_m^c < P_{max}^c - \zeta$ **then**
    $p_{k,min}^d = p_k^d$
  else if $P_{max}^c - \zeta < p_m^c < P_{max}^c + \zeta$ **then**
    break
  end if
end while
Output the optimal transmit powers $p_m^{c,*}$ and $p_k^{d,*}$.

- 学习到的不确定性集合



(a)

基于谱聚类的资源管理

- **Use SVC to cover the uncertain CSI in high-dimensional space**
  - Define nonlinear mapping

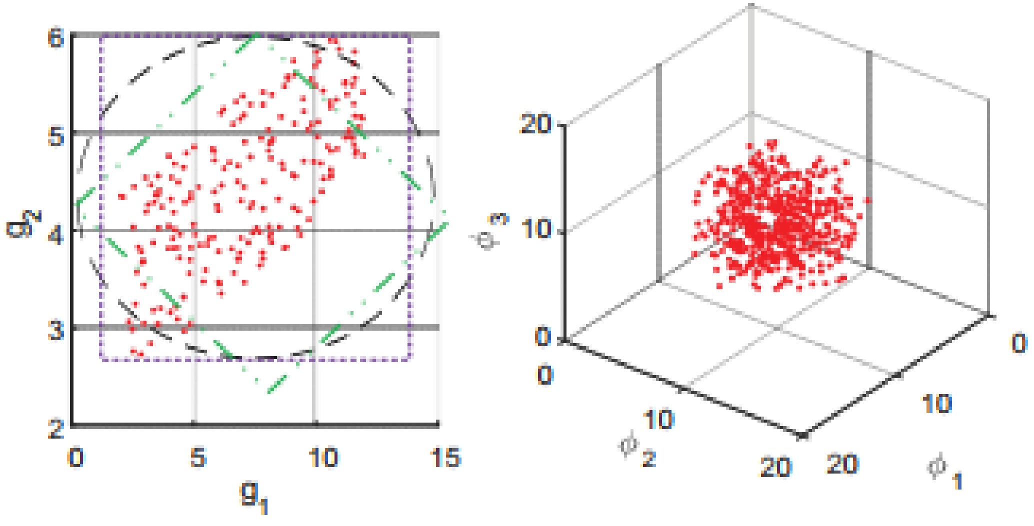
$$\phi(\boldsymbol{\xi}_i) : \mathbb{R}^2 \mapsto \mathbb{R}^K$$

to map the CSI samples into a high-dimensional features

  - seek the smallest sphere to enclose the CSI samples in high-dimensional features space

$$\begin{aligned} \min_{R,\boldsymbol{\rho},\{\psi_i\}} \quad & R^2 + C\sum_{i=1}^{N}\psi_i \\ \text{s.t.} \quad & \|\phi(\boldsymbol{\xi}_i) - \boldsymbol{\rho}\|^2 \le R^2 + \psi_i, i = 1, \cdots, N, \\ & \psi_i \ge 0, i = 1, \cdots, N, \end{aligned}$$

set $C = 1/(\epsilon N)$ to control the sphere covering the CSI samples with $(1 - \epsilon) \times 100\%$ confidence.



(a)

(b)

基于谱聚类的资源管理

- The dual problem is formulated as

$$\min_{\lambda} \sum_{i=1}^{N}\sum_{j=1}^{N} \lambda_i\lambda_j K(\xi_i,\xi_j) - \sum_{i=1}^{N} \lambda_i K(\xi_i,\xi_i)$$
$$\text{s.t.} \quad 0 \le \lambda_i \le C, i = 1,\cdots N,$$
$$\sum_{i=1}^{N} \lambda_i = 1,$$

KKT conditions

$$\begin{cases} \frac{\partial L}{\partial R} = 0 \to \sum_{i=1}^{N} \lambda_i = 1, \\ \frac{\partial L}{\partial \rho} = 0 \to \rho = \sum_{i=1}^{N} \lambda_i \phi(\xi_i), \\ \frac{\partial L}{\partial \psi_i} \to \lambda_i + \eta_i = C. \end{cases}$$

Obtain the following desirable geometric interpretations

$$\begin{cases} \|\phi(\xi_i) - \rho\|^2 < R^2 \to \lambda_i = 0, \eta_i = C, \\ \|\phi(\xi_i) - \rho\|^2 = R^2 \to 0 < \lambda_i < C, 0 < \eta_i < C, \\ \|\phi(\xi_i) - \rho\|^2 > R^2 \to \lambda_i = C, \eta_i = 0. \end{cases}$$

We give definitions of all support vectors and boundary support vectors

$$\mathcal{F} = \{i \mid \lambda_i > 0, \forall i\} \text{ and } \mathcal{B}_v = \{i \mid 0 < \lambda_i < C, \forall i\}$$

The radius of the sphere

$$R^2 = \|\phi(\xi_l) - \rho\|^2 = \|\phi(\xi_l) - \sum_{i=1}^{N} \lambda_i \phi(\xi_i)\|^2$$
$$= K(\xi_l,\xi_l) - 2\sum_{i=1}^{N} \lambda_i K(\xi_l,\xi_i) + \sum_{i=1}^{N}\sum_{j=1}^{N} \lambda_i\lambda_j K($$

The feasible set of uncertain CSI

$$\mathcal{S}_\epsilon(\mathcal{N}) = \left\{ \mathrm{g} \mid K(\mathrm{g},\mathrm{g}) - 2\sum_{i=1}^{N} \lambda_i K(\mathrm{g},\xi_i) + \sum_{i=1}^{N}\sum_{j=1}^{N} \lambda_i\lambda_j K(\xi_i,\xi_j) \le R^2 \right\}$$

The kernel function plays a key role

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- Commonly used functions

Gaussian kernel:

$$K(\boldsymbol{\xi}_i, \boldsymbol{\xi}_j) = \exp(-q\|\boldsymbol{\xi}_i - \boldsymbol{\xi}_j\|^2)$$

Sigmoid kernel:

$$K(\boldsymbol{\xi}_i, \boldsymbol{\xi}_j) = \tanh(a \cdot \boldsymbol{\xi}_i^T \cdot \boldsymbol{\xi}_j + r)$$

Polynomial kernel:

$$K(\boldsymbol{\xi}_i, \boldsymbol{\xi}_j) = (\boldsymbol{\xi}_i^T \cdot \boldsymbol{\xi}_j + 1)^d$$

inevitably complicate the application in power allocation.

$$\mathcal{S}_\epsilon(\mathcal{N}) = \left\{ \mathbf{g} \mid K(\mathbf{g}, \mathbf{g}) - 2\sum_{i=1}^{N} \lambda_i K(\mathbf{g}, \boldsymbol{\xi}_i) + \sum_{i=1}^{N}\sum_{j=1}^{N} \lambda_i \lambda_j K(\boldsymbol{\xi}_i, \boldsymbol{\xi}_j) \le R^2 \right\}$$

- Proposed kernel functions

$$K(\boldsymbol{\xi}_i, \boldsymbol{\xi}_j) = \sum_{k=1}^{2} \Xi_k - \|\mathbf{Q}(\boldsymbol{\xi}_i - \boldsymbol{\xi}_j)\|_1,$$

Q can be constructed as $\mathbf{Q} = \boldsymbol{\Sigma}^{-\frac{1}{2}},$

$$\boldsymbol{\Sigma} = \frac{1}{N-1}\left[\sum_{i=1}^{N-1} \xi_i \xi_i^T - \frac{1}{N-1}\left(\sum_{i=1}^{N} \xi_i\right)\left(\sum_{i=1}^{N} \xi_i\right)^T\right].$$

Ξ_k is chosen as

$$\Pi_k > \max_{1 \le i \le N} \mathbf{q}_k^T \xi_i - \min_{1 \le i \le N} \mathbf{q}_k^T \xi_i.$$

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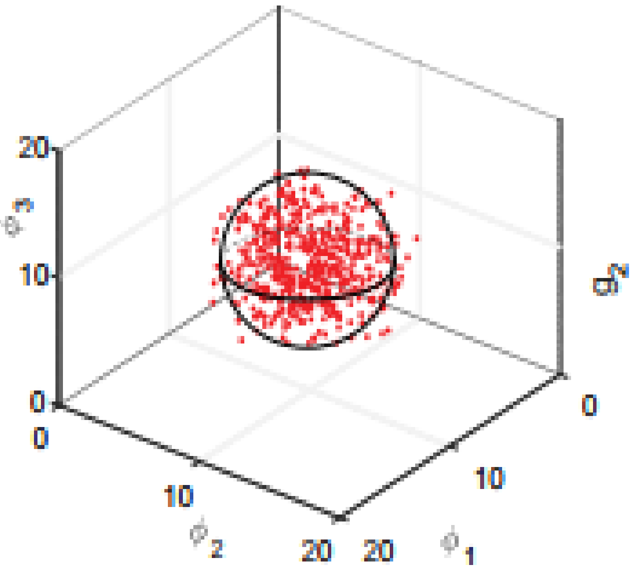
- The explicit expression of data-driven uncertainty set is represented as

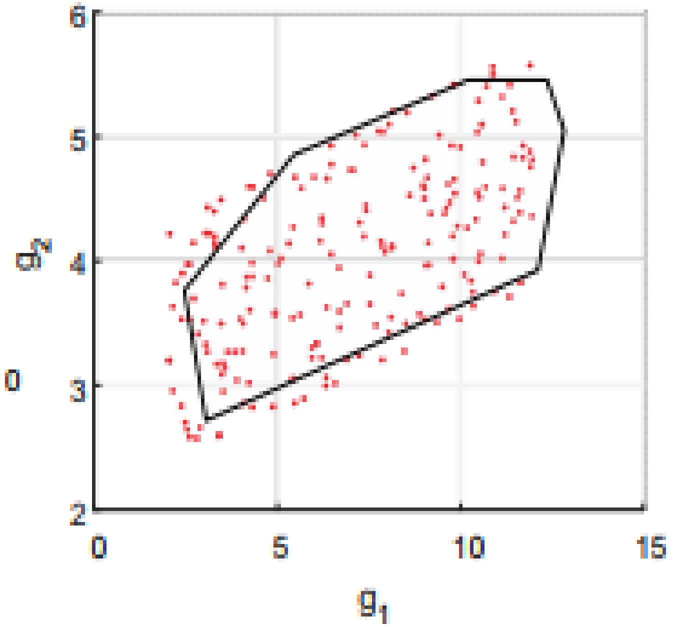
$$\mathcal{S}_\epsilon(\mathcal{N}) = \left\{ \mathbf{g} \,\middle|\, \sum_{i\in\mathcal{F}} \lambda_i \|\mathbf{Q}(\mathbf{g}-\boldsymbol{\xi}_i)\|_1 \le \sum_{i\in\mathcal{F}} \lambda_i \|\mathbf{Q}(\boldsymbol{\xi}_l-\boldsymbol{\xi}_i)\|_1, l\in\mathcal{B}_v \right\}$$

let $\varrho = \sum_{i\in\mathcal{F}} \lambda_i \|\mathbf{Q}(\boldsymbol{\xi}_l-\boldsymbol{\xi}_i)\|_1, l\in\mathcal{B}_v$

$$\mathcal{S}_\epsilon(\mathcal{N}) = \left\{ \mathbf{g} \,\middle|\, \begin{array}{c} \exists \mathbf{v}_i, i\in\mathcal{F} \text{ s.t.} \\ \sum_{i\in\mathcal{F}} (\lambda_i \cdot \mathbf{v}_i^T \mathbf{1}_{2\times 1}) \le \varrho \\ -\mathbf{v}_i \le \mathbf{Q}(\mathbf{g}-\boldsymbol{\xi}_i) \le \mathbf{v}_i, i\in\mathcal{F} \end{array} \right\}.$$



(a)



(b)

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- The chance QoS constraint

$$
\begin{aligned}
\min_{\mathbf{g},\{\mathbf{v}_i\}} \quad & \mathbf{p}^T\mathbf{g} \\
\text{s.t.} \quad & \sum_{i\in\mathcal{F}} (\lambda_i \cdot \mathbf{v}_i^T \mathbf{1}_{2\times 1}) \le \varrho, \\
& -\mathbf{v}_i \le \mathbf{Q}(\mathbf{g}-\boldsymbol{\xi}_i) \le \mathbf{v}_i, i \in \mathcal{F}.
\end{aligned}
$$

Dual problem

$$
\begin{aligned}
\max_{\kappa,\{\varphi_i\},\{\omega_i\}} \quad & \sum_{i\in\mathcal{F}} (\omega_i - \varphi_i)^T \mathbf{Q}\boldsymbol{\xi}_i - \varrho\kappa \\
\text{s.t.} \quad & \sum_{i\in F} (\omega_i - \varphi_i)^T \mathbf{Q} - \mathbf{p} = \mathbf{0}, \\
& \omega_i + \varphi_i - \lambda_i \cdot \kappa \cdot \mathbf{1} = \mathbf{0}, \forall i \in \mathcal{F}, \\
& \kappa \ge 0, \varphi_i, \omega_i \in \mathbb{R}_+^2.
\end{aligned}
$$

- The intractable chance constraint can be replaced by the following linear constraint

$$
\begin{cases}
\sum_{i\in\mathcal{F}} (\omega_i - \varphi_i)^T \mathbf{Q}\boldsymbol{\xi}_i - \varrho\kappa \ge \gamma_{min}^d, \\
\sum_{i\in\mathcal{F}} (\omega_i - \varphi_i)^T \mathbf{Q} - \mathbf{p} = \mathbf{0}, \\
\omega_i + \varphi_i - \lambda_i \cdot \kappa \cdot \mathbf{1} = \mathbf{0}, \forall i \in \mathcal{F}, \\
\kappa \ge 0, \varphi_i, \omega_i \in \mathbb{R}_+^2.
\end{cases}
$$

The power allocation problem

$$
\begin{aligned}
\max_{p_c, p_d} \quad & B \log_2 \left(1 + \frac{p_c g_c}{\sigma^2 + p_d g_{d,B}}\right) \\
\text{s.t.} \quad & \begin{cases}
\sum_{i\in\mathcal{F}} (\omega_i - \varphi_i)^T \mathbf{Q}\boldsymbol{\xi}_i - \varrho\kappa \ge \gamma_{min}^d, \\
\sum_{i\in\mathcal{F}} (\omega_i - \varphi_i)^T \mathbf{Q} - \mathbf{p} = \mathbf{0}, \\
\omega_i + \varphi_i - \lambda_i \cdot \kappa \cdot \mathbf{1} = \mathbf{0}, \forall i \in \mathcal{F}, \\
\kappa \ge 0, \varphi_i, \omega_i \in \mathbb{R}_+^2.
\end{cases}
\end{aligned}
$$

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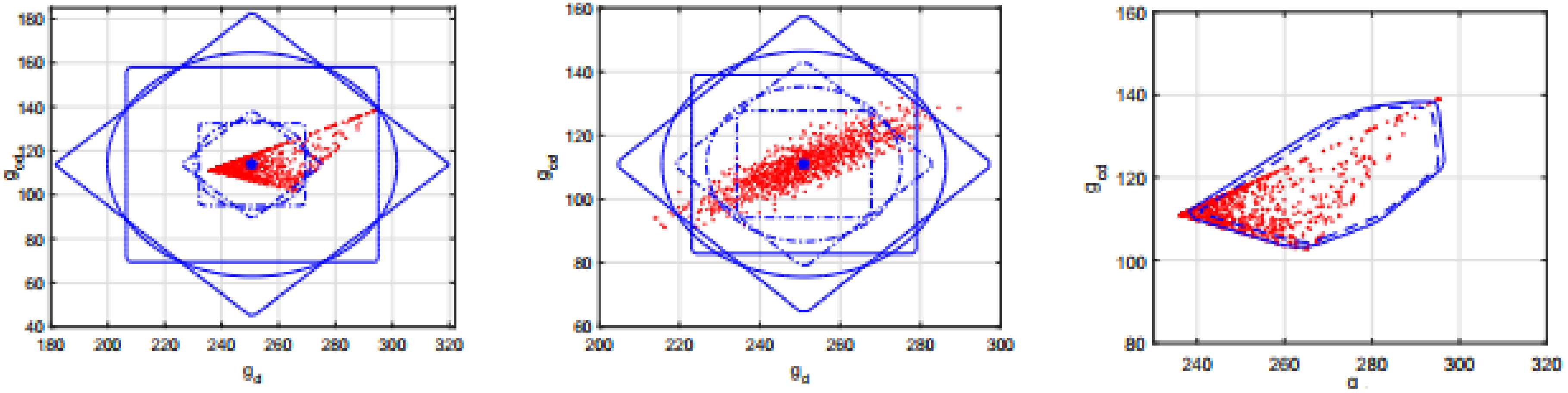
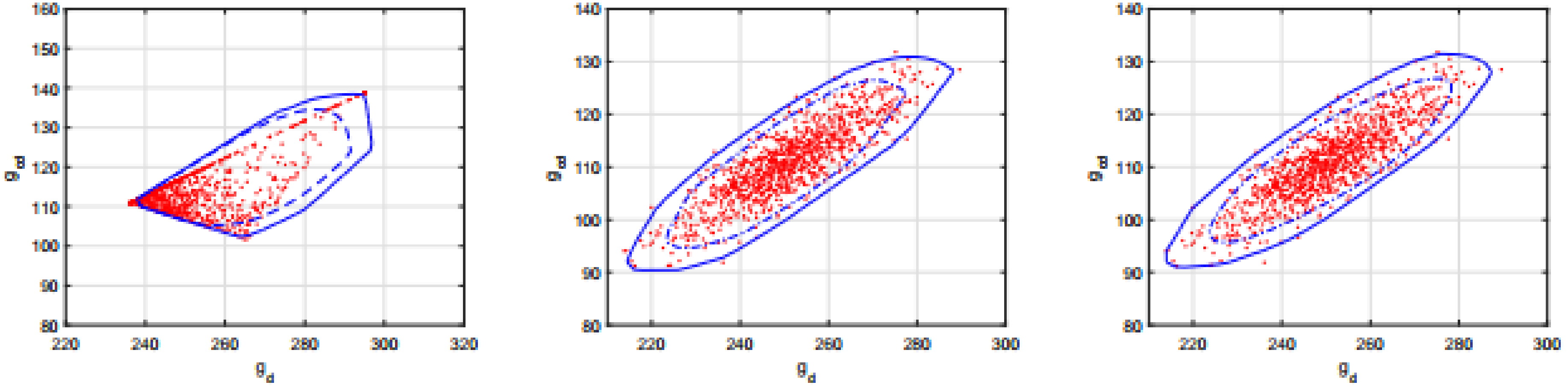


(a) Symmetrical-geometry-based uncertainty set under truncated exponential.

(b) Symmetrical-geometry-based uncertainty set under gaussian.

(c) Quantile-SVC approach under truncated exponential.



(d) SVC under truncated exponential.

(e) Quantile-SVC approach under gaussian.

(f) SVC under under gaussian.

Fig. 4. Learning results of the uncertainty sets, where the solid line and the dotted line correspond to $\epsilon = 0.01$ and $\epsilon = 0.05$ respectively

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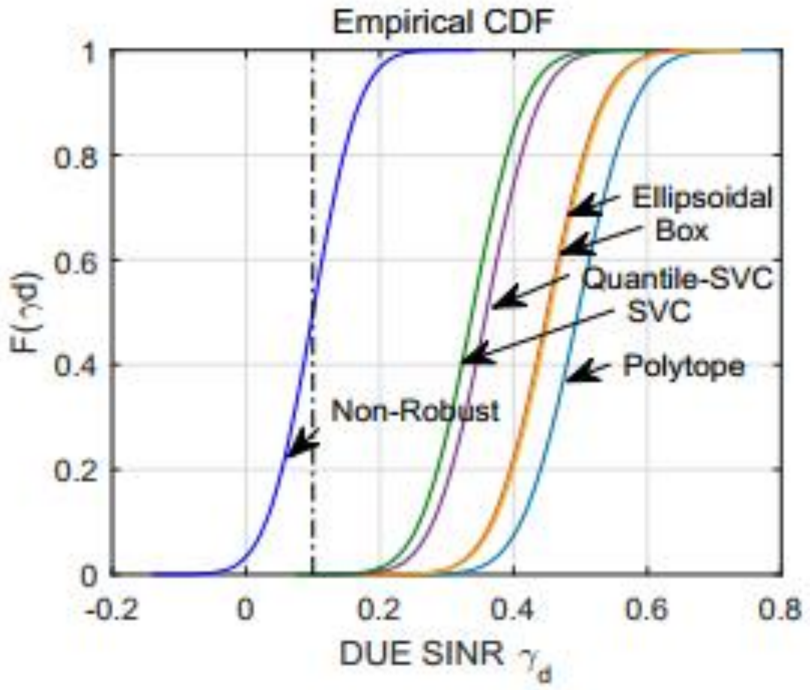

Fig. 7. DUE SINR cumulative distributions under Gaussian uncertainties, assuming $P^c_{max} = P^d_{max} = 20$dBm, QoS requirements $\gamma^c_{min} = 5$, $\gamma^d_{min} = 0.1$ and outage probability $\epsilon = 0.05$.

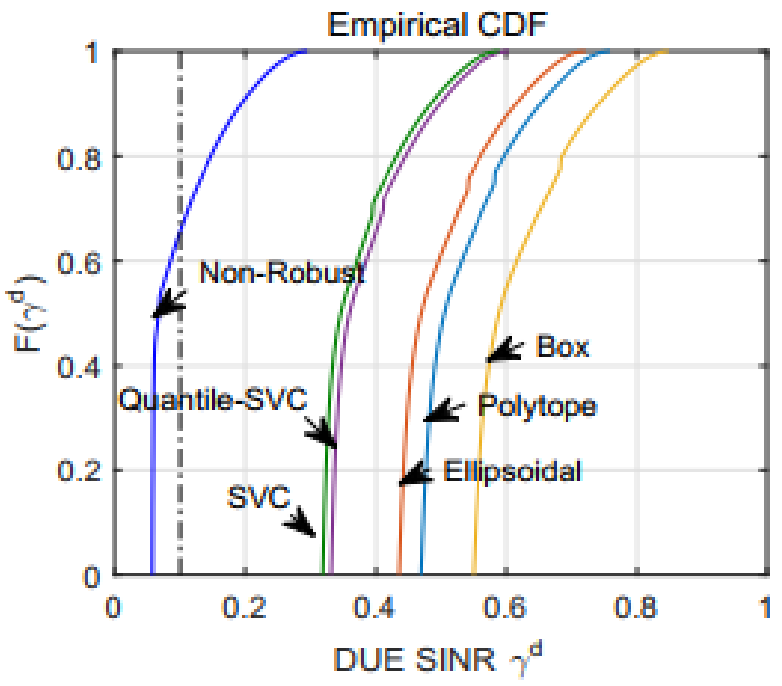

Fig. 8. DUE SINR cumulative distributions under exponential uncertainties, assuming $P^c_{max} = P^d_{max} = 20$dBm, QoS requirements $\gamma^c_{min} = 5$, $\gamma^d_{min} = 0.1$ and outage probability $\epsilon = 0.05$.

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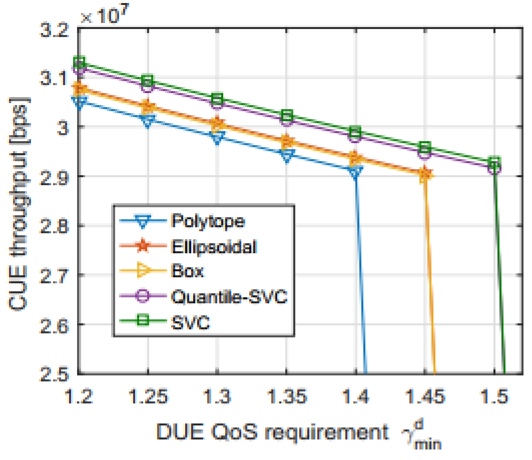

Fig. 11. CUE throughput versus DUE QoS requirement, assuming $P^c_{max} = P^d_{max} = 20$dBm, CUE QoS requirement $\gamma^c_{min} = 5$ and outage probability $\epsilon = 0.05$.

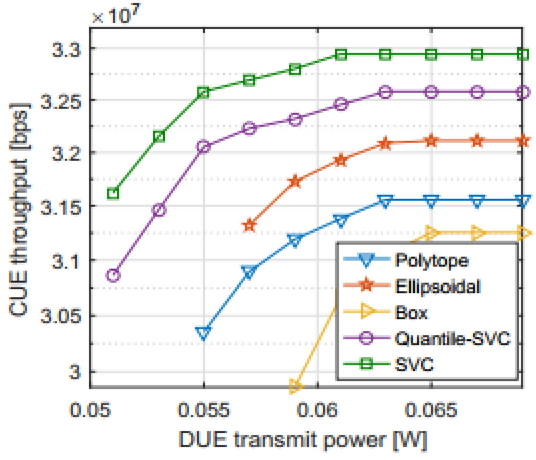

Fig. 13. CUE throughput versus DUE transmit power, assuming $P^c_{max} = 20$dBm, CUE QoS requirement $\gamma^c_{min} = 5$, DUE QoS requirement $\gamma^c_{min} = 1$ and outage probability $\epsilon = 0.05$.

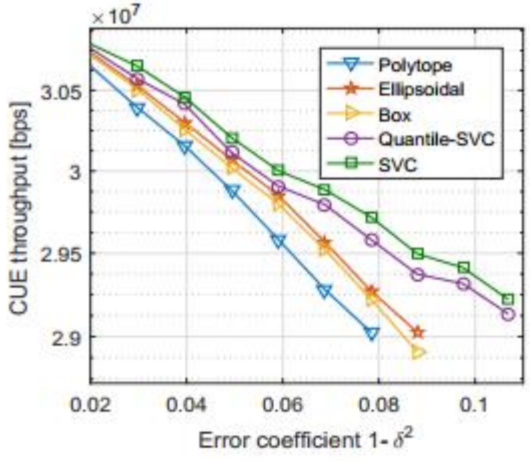

Fig. 15. CUE throughput versus channel estimation error coefficient, assuming $P^c_{max} = P^d_{max} = 20$dBm, CUE QoS requirement $\gamma^c_{min} = 5$, DUE QoS requirement $\gamma^c_{min} = 1.5$ and outage probability $\epsilon = 0.05$.

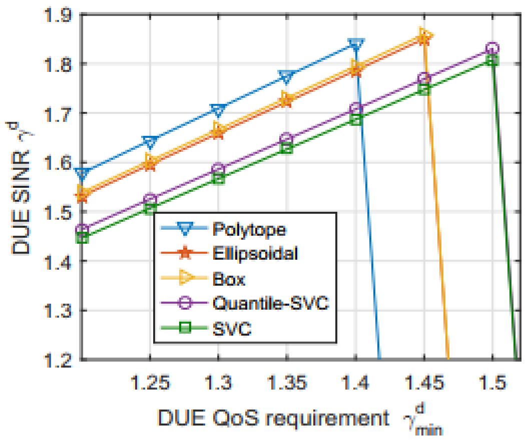

Fig. 12. DUE SINR versus DUE QoS requirement, assuming $P^c_{max} = P^d_{max} = 20$dBm, CUE QoS requirement $\gamma^c_{min} = 5$ and outage probability $\epsilon = 0.05$.

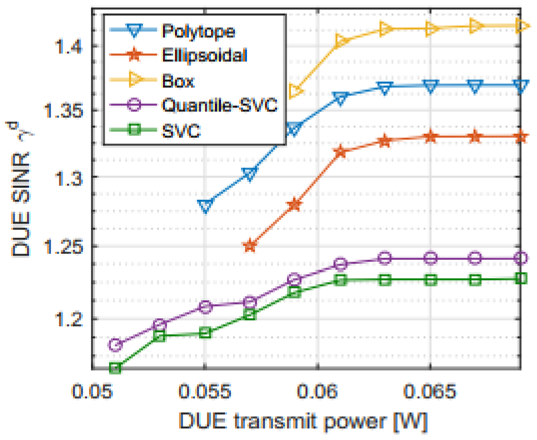

Fig. 14. DUE SINR versus DUE transmit power, assuming $P^c_{max} = 20$dBm, CUE QoS requirement $\gamma^c_{min} = 5$, DUE QoS requirement $\gamma^c_{min} = 1$ and outage probability $\epsilon = 0.05$.

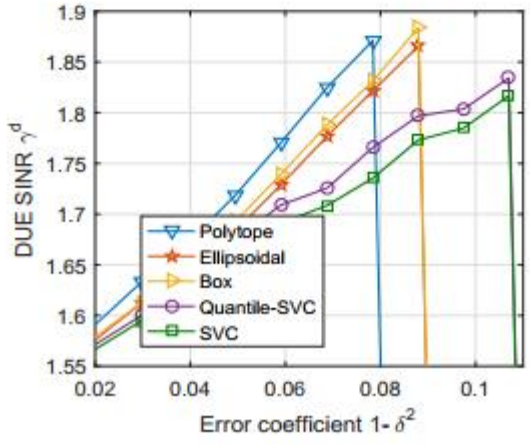

Fig. 16. DUE SINR versus channel estimation error coefficient, assuming $P^c_{max} = P^d_{max} = 20$dBm, CUE QoS requirement $\gamma^c_{min} = 5$, DUE QoS requirement $\gamma^c_{min} = 1.5$ and outage probability $\epsilon = 0.05$.

谢 谢