

Combinatorial Power Allocation in AC Systems

Approximation, Hardness and Truthfulness for Complex-demand Knapsack Problem

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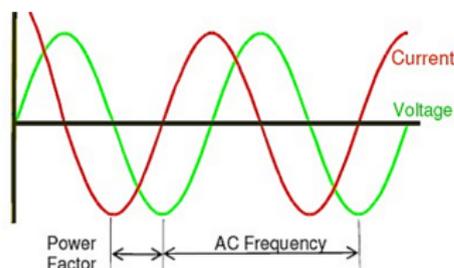
Paper: <http://www.SustainableNetworks.org/papers/cks.pdf>

Slides: <http://www.SustainableNetworks.org/slides/cks.pdf>

Story begins with Resource Allocation ...

- Resources are in different forms
 - E.g. time, space, bandwidth, ...
 - and *energy* (electricity is the most common form of energy)
- Smart grid (what is it?)
 - No precise definition, but broadly, modernizing electrical grid using information and communications technology
 - For example, enabling more efficient allocation of energy
- From *communication networking* to *electricity networking*
 - Similarities: Networked structures, Limited storage, Uncertainties in demands and supplies, ...
 - Differences: Homogeneous commodity (i.e. electricity), Periodic quantities (i.e. alternating current/AC)

- Circular motion of dynamo generator \Rightarrow Periodic current and voltage
- Phase between current and voltage



- Complex number representations: $V = |V|e^{i\omega t}$, $I = |I|e^{i(\omega t + \theta)}$,
- Power: $P = V \times I$ (also a complex number)
 - Active power: $\text{Re}(P)$
 - Reactive power: $\text{Im}(P)$
 - Apparent power: $|P|$

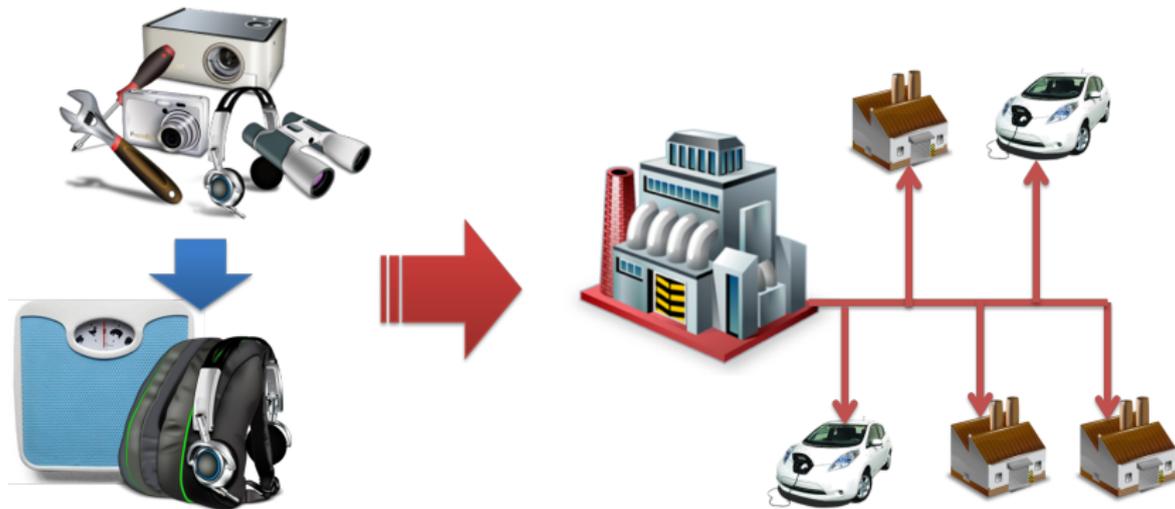
- Active power ($\text{Re}(P)$)
 - Can do useful work at loads
- Reactive power ($\text{Im}(P)$)
 - Needed to support the transfer of real power over the network
 - Capacitors generate reactive power; inductors to consume it
- Power factor ($\frac{\text{Re}(P)}{|P|}$)
 - Ratio between real power and apparent power
 - Regulations require maximum power factor
- Apparent power ($|P|$)
 - Magnitude of total active and reactive power
 - Cared by power engineers
 - Conductors, transformers and generators must be sized to carry the total current (manifested by apparent power)

Central Problem: Power Allocation

- Utility-maximizing allocation power to end-users
 - Subject to capacity constraints of total apparent power (or current, voltage)
- Elastic (splittable) demands \Rightarrow (Non-)Convex optimization
- Inelastic (unsplittable) demands \Rightarrow Combinatorial optimization
 - Minimum active/reactive power requirement
 - Challenge: Positive reactive power can cancel negative reactive power



From Knapsack to Inelastic Power Allocation



(Traditional) 1D Knapsack Problem

Definition (1DKS)

$$\max \sum_{k \in [n]} x_k u_k$$

subject to

$$\sum_{k \in K} x_k d_k \leq C, \quad x_k \in \{0, 1\} \text{ for } k \in [n]$$

- $[n] := \{1, \dots, n\}$: a set of users
- u_k : utility of k -th user if its demand is satisfied
- d_k : positive real-valued demand of k -th user
- C : real-valued capacity on total satisfiable demand
- x_k : decision variable of allocation
 - $x_k = 1$, if k -th user's demand is satisfied
 - $x_k = 0$, otherwise

Knapsack Problem for Power Allocation

- Complex-valued resources (e.g. AC power, current, voltage)
 - Discrete optimization mostly concerns real-valued resources
- Allocating complex-valued (AC) power among a set of users
- Inelastic user demands (i.e. fully satisfied or not)
- Maximizing total utility of satisfied users
- Subject capacity constraints
 - Active power and reactive power constraints
 - Apparent power constraint
- Optional:
 - Utility is private information reported by users
 - Selfish users tend to exaggerate their utility

2D Knapsack Problem

Definition (2DKS)

$$\max_{x_k \in \{0,1\}} \sum_{k \in K} x_k u_k \quad (1)$$

subject to

$$\sum_{k \in K} x_k d_k^R \leq C^R \text{ and } \sum_{k \in K} x_k d_k^I \leq C^I \quad (2)$$

- $d_k^R + \mathbf{i}d_k^I$: complex-valued demand of k -th user
- $C^R + \mathbf{i}C^I$: complex-valued power capacity
 - Real-part: Active power (d_k^R, C^R)
 - Imaginary-part: Reactive power (d_k^I, C^I)
- Well-known problem

Complex-demand Knapsack Problem

Definition (CKS)

$$\max \sum_{k \in K} x_k u_k$$

subject to

$$\left| \sum_{k \in K} x_k d_k \right| \leq C, \quad x_k \in \{0, 1\} \text{ for } k \in [n]$$

- d_k : complex-valued demand of k -th user ($d_k = d_k^R + \mathbf{i}d_k^I$)
- C : real-valued capacity of total satisfiable demand in apparent power

Complex-demand Knapsack Problem

Definition (CKS)

$$\max \sum_{k \in K} x_k u_k$$

subject to

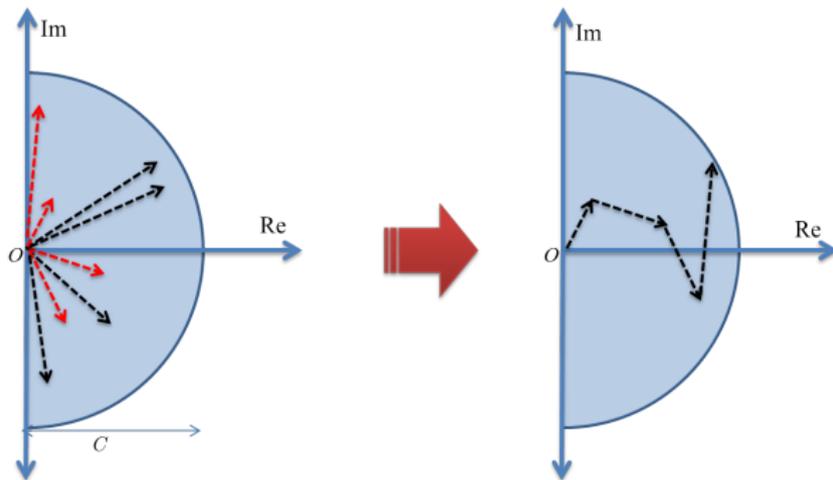
$$\left| \sum_{k \in K} x_k d_k \right| \leq C, \quad x_k \in \{0, 1\} \text{ for } k \in [n]$$

- It is a 0/1-quadratic programming problem:

$$\begin{aligned} \max \quad & \sum_{k \in [n]} x_k u_k \\ \text{s.t.} \quad & \left(\sum_{k \in [n]} d_k^R x_k \right)^2 + \left(\sum_{k \in [n]} d_k^I x_k \right)^2 \leq C^2 \\ & x_k \in \{0, 1\} \text{ for all } k \in [n]. \end{aligned}$$

- A new variant of knapsack problem

Complex-demand Knapsack Problem



Pictorially,

- Picking a maximum-utility subset of vectors, such that the sum lies within a circle

Definitions of Approximation Algorithms

- For set S of users, denote by $u(S) \triangleq \sum_{k \in S} u_k$
- Denote S^* an optimal solution of CKS

Definition

For $\alpha \in (0, 1]$ and $\beta \geq 1$, a bi-criteria (α, β) -approximation to CKS is a set S satisfying

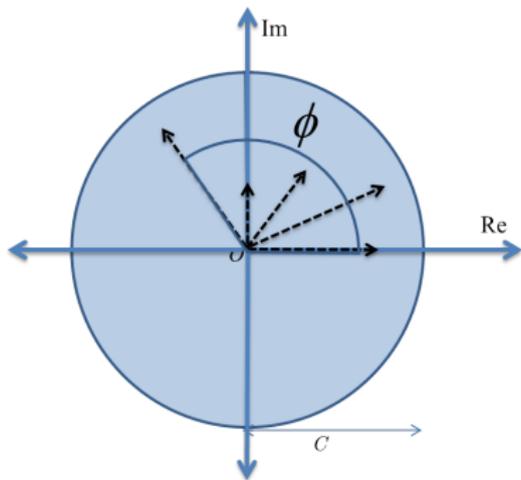
$$u(S) \geq \alpha \cdot u(S^*)$$
$$\left| \sum_{k \in S} d_k \right| \leq \beta \cdot C$$

- *Polynomial-time approximation scheme (PTAS)*: an algorithm computes $(1 - \epsilon, 1)$ -approximation in time polynomial in n for a fixed ϵ
- *Bi-criteria polynomial-time approximation scheme (PTAS)*: an algorithm computes $(1 - \epsilon, 1 + \epsilon)$ -approximation
- *Fully polynomial-time approximation scheme (FPTAS)*: PTAS and additionally requires polynomial running time in $1/\epsilon$

- FPTAS for 1DKS
 - Using dynamic programming and scaling (Lawler, 1979)
- No FPTAS for m DKS where $m \geq 2$
 - Reducing to equipartition problem (Gens and Levner, 1979)
- PTAS for m DKS where $m \geq 2$
 - Using partial exhaust search and LP (Freize and Clarke, 1985)
- Truthful (monotone) FPTAS for 1DKS
 - Monotonicity (Briest, Krysta and Vocking, 2005)
- Truthful bi-criteria FPTAS for multi-minded m DKS
 - Dynamic programming, scaling and VCG (Krysta, Telelis and Ventre, 2013)

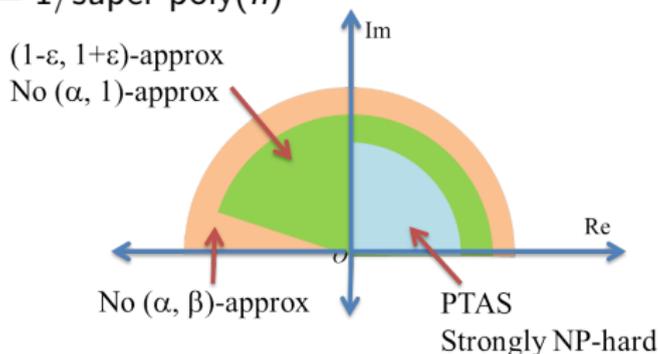
Some Definitions

- The problem is invariant under rotation
- Let ϕ be the maximum angle between any two demands
- Denote this restriction by $\text{CKS}[\phi]$
- Write $\text{CKS}[\phi_1, \phi_2]$ for $\text{CKS}[\phi]$ with $\phi \in [\phi_1, \phi_2]$



Approximability Results

- Write $\text{CKS}[\phi_1, \phi_2]$ for $\text{CKS}[\phi]$ with $\phi \in [\phi_1, \phi_2]$
- Positive results
 - PTAS for $\text{CKS}[0, \frac{\pi}{2}]$
 - Bi-criteria FPTAS for $\text{CKS}[0, \pi - \varepsilon]$ for $\varepsilon = 1/\text{poly}(n)$
- Inapproximability results
 - $\text{CKS}[0, \frac{\pi}{2}]$ is strongly NP-hard [Yu and Chau, 2013]
 - Unless $\text{P}=\text{NP}$, there is no $(\alpha, 1)$ -approximation for $\text{CKS}[\frac{\pi}{2}, \pi]$
 - Unless $\text{P}=\text{NP}$, there is no (α, β) -approximation for $\text{CKS}[\pi - \varepsilon, \pi]$ for some $\varepsilon = 1/\text{super-poly}(n)$

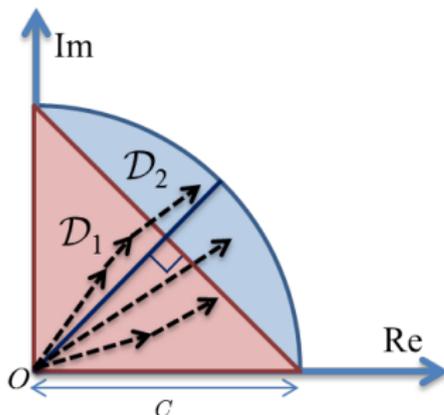


Summary of Results

	CKS[0, $\frac{\pi}{2}$]	CKS[0, $\pi - \varepsilon$]	CKS[$\pi - \varepsilon$, π]
Pure Inelastic	PTAS No FPTAS	Bi-criteria FPTAS No $(\alpha, 1)$ -approx	
Mixed with Elastic Demands (Linear Utility)	PTAS	Bi-criteria PTAS	Bi-criteria Inapproximable
Multi-minded Preferences	PTAS	Bi-criteria FPTAS	
Truthful Mechanism	Randomized PTAS	Deterministic Bi-criteria FPTAS	

Simple Algorithm ($(\frac{1}{2} + \epsilon)$ -Approx)

- Assume $\text{CKS}[0, \frac{\pi}{2}]$
- Let S^* be an optimal solution
- Intuition:
 - Case 1: $\sum_{i \in S^*} d_j$ lies in \mathcal{D}_1
 - Case 2: $\sum_{i \in S^*} d_j$ lies in \mathcal{D}_2 and $|S^*| = 1$
 - Case 3: $\sum_{i \in S^*} d_j$ lies in \mathcal{D}_2 and $|S^*| > 1$



- Case 1 and Case 2 are easy. And Case 3?

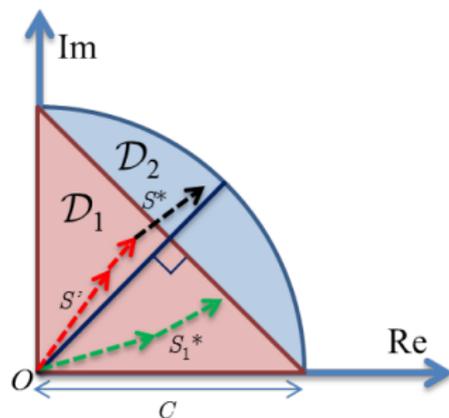
Simple Algorithm ($(\frac{1}{2} + \epsilon)$ -Approx)

- Case 3: $\sum_{i \in S^*} d_j$ lies in \mathcal{D}_2 and $|S^*| > 1$

Lemma

Let S_1^* be an optimal solution within \mathcal{D}_1 , and S^* be an optimal solution within $\mathcal{D}_1 \cup \mathcal{D}_2$, then

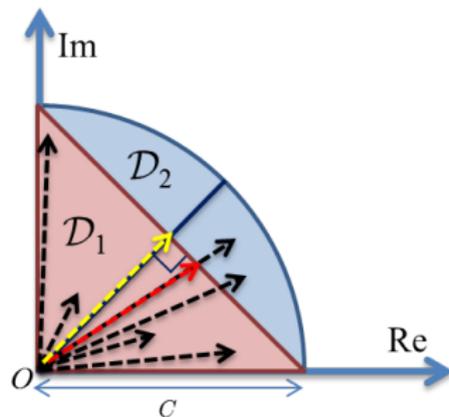
$$\sum_{j \in S^*} u_j \leq 2 \sum_{j \in S_1^*} u_j$$



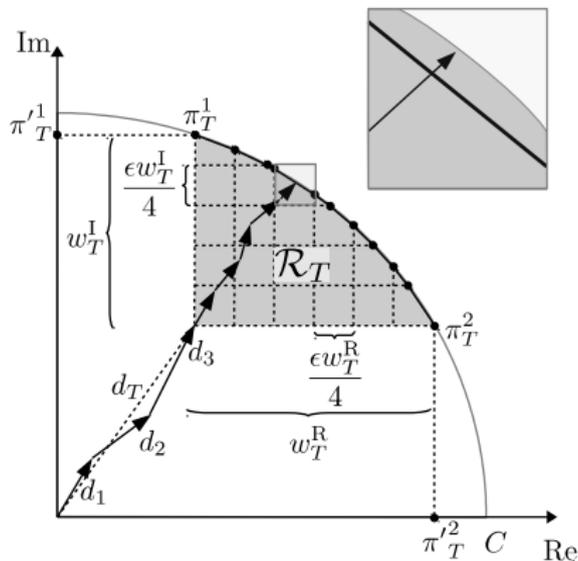
Simple Algorithm ($(\frac{1}{2} + \epsilon)$ -Approx)

$(\frac{1}{2} + \epsilon)$ -approximation algorithm for CKS $[0, \frac{\pi}{2}]$

- For each d_j , if d_j lies in \mathcal{D}_2 , only retain the part in \mathcal{D}_1
- Project each d_j onto 1DKS
- Apply FPTAS for 1DKS to solve $\{x_j\}$



- Polygonizing (inscribing polygon within) the circular feasible region
 - Approximate CKS by m DKS
- PTAS for m DKS with constant m cannot be applied directly
 - Consider optimal solution with large (in magnitude) demands and many small demands, each has the same utility
- Better solution (polygonizing + guessing by partial exhaustive search)
 - 1 Guess large demands (for a $\frac{1}{\epsilon}$ subset)
 - 2 Polygonizing by constructing a lattice on the remaining part of the circular region with cell size proportional to ϵ
 - 3 Find the maximum-utility set of demands in polygonized region (i.e. m DKS problem) where m is a constant depending on $1/\epsilon$
 - 4 Repeat for every $\frac{1}{\epsilon}$ subset and retain the best solution



- 1 Guess large demands (for a $\frac{1}{\epsilon}$ subset)
- 2 Polygonizing by constructing a lattice on the remaining part
- 3 Find the maximum-utility set of demands
- 4 Repeat for every $\frac{1}{\epsilon}$ subset and retain the best solution

PTAS for CKS[0, $\frac{\pi}{2}$]

CKS-PTAS for CKS[0, $\frac{\pi}{2}$]

- $\hat{S} \leftarrow \emptyset$
- For each subset $T \subseteq [n]$ of size at most $\min\{n, \frac{1}{\epsilon}\}$
 - Set $d_T \leftarrow \sum_{k \in T} d_k$
 - Obtain $S \leftarrow m\text{DKS-PTAS}[d_T]$ by polygonization within accuracy ϵ
 - If $u(\hat{S}) < u(S)$,
 - $\hat{S} \leftarrow S$
- Return \hat{S}

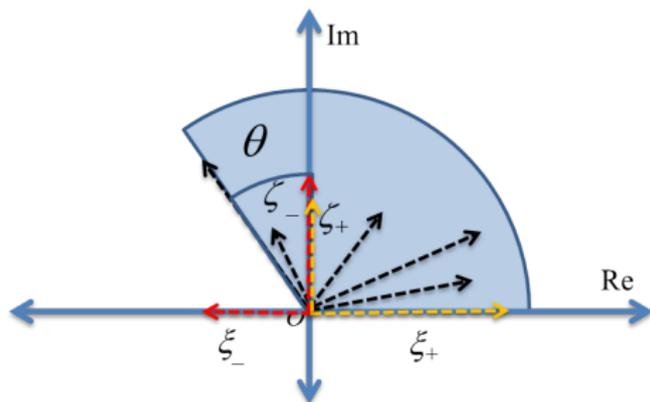
Theorem

For any $\epsilon > 0$, CKS-PTAS is a $(1 - 2\epsilon, 1)$ -approx to CKS[0, $\frac{\pi}{2}$]

Running time is $n^{O(\frac{1}{\epsilon^2})} \log U$, $U \triangleq \max\{C, \max\{d_k^R, d_k^I, u_k \mid k \in [n]\}\}$

Bi-criteria FPTAS for CKS[0, $\pi - \varepsilon$]

- CKS[0, $\frac{\pi}{2}$] ($\text{Re}(d) \geq 0, \text{Im}(d) \geq 0$) \Rightarrow no demands cancel others
- CKS[0, $\pi - \varepsilon$] ($\text{Re}(d) \leq 0$) \Rightarrow some demands can cancel others
- But $\theta < \pi$, $\Rightarrow \text{Im}(d) > 0$, when $\text{Re}(d) < 0$
- Intuition:
 - Let $S_+ \triangleq \{k \mid d_k^R \geq 0, k \in S\}$ and $S_- \triangleq \{k \mid d_k^R < 0, k \in S\}$
 - $\xi_+ = \sum_{k \in S_+} d_k^R \leq C(1 + \tan \theta)$, $\zeta_+ = \sum_{k \in S_+} d_k^I \leq C$
 - $\xi_- = \sum_{k \in S_-} -d_k^R \leq C \tan \theta$, $\zeta_- = \sum_{k \in S_-} d_k^I \leq C$



- Basic Ideas:

- ① Enumerate the guessed total projections on real and imaginary axes for S_+ and S_- respectively
- ② Assume that $\tan \theta$ is polynomial in n
- ③ Then solve two separate 2DKS exact problems that satisfy $(\xi_+ - \xi_-)^2 + (\zeta_+ + \zeta_-)^2 \leq C^2$
 - One in the first quadrant, while another in the second quadrant
- ④ But 2DKS exact is generally NP-Hard
 - Similar to bi-criteria FPTAS in m DKS
 - By scaling and truncating the demands makes the approximate problem solvable efficiently by dynamic programming
 - But violation is allowed \Rightarrow bi-criteria FPTAS

Bi-criteria FPTAS for $\text{CKS}[0, \pi - \varepsilon]$

CKS-BIFPTAS for $\text{CKS}[0, \pi - \varepsilon]$

- For all d_k and $k \in [n]$
 - Set $\hat{d}_k \leftarrow \hat{d}_k^R + \mathbf{i}\hat{d}_k^I \triangleq \left\lceil \frac{d_k^R}{L} \right\rceil + \mathbf{i} \left\lceil \frac{d_k^I}{L} \right\rceil$
- For all $\xi_+ \in \mathcal{A}_+, \xi_- \in \mathcal{A}_-, \zeta_+, \zeta_- \in \mathcal{B}$
 - If $(\xi_+ - \xi_-)^2 + (\zeta_+ + \zeta_-)^2 \leq C^2$
 - $F_+ \leftarrow \text{2DKS-EXACT}[\{u_k, \hat{d}_k\}, \frac{\xi_+}{L}, \frac{\zeta_+}{L}]$
 - $F_- \leftarrow \text{2DKS-EXACT}[\{u_k, \hat{d}_k\}, \frac{\xi_-}{L}, \frac{\zeta_-}{L}]$
 - If $F_+, F_- \neq \emptyset$ and $u(F_+ \cup F_-) > u(\hat{S})$
 - $\hat{S} \leftarrow \{F_+ \cup F_-\}$
- Return \hat{S}

Theorem

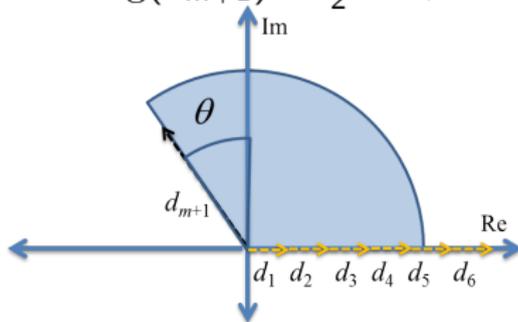
For any $\epsilon > 0$, CKS-BIFPTAS is $(1, 1 + \epsilon)$ -approximation for $\text{CKS}[0, \pi - \varepsilon]$. Running time is polynomial in both $n, \frac{1}{\epsilon}$ and $\tan \theta$.

Inapproximability of $\text{CKS}[\pi-\varepsilon, \pi]$

Theorem

Unless $P=NP$,

- No $(\alpha, 1)$ -approximation for $\text{CKS}[\frac{\pi}{2}+\varepsilon, \pi]$ where α, ε have polynomial length in n
- No (α, β) -approximation for $\text{CKS}[\pi-\varepsilon, \pi]$, where α and β have polynomial length, and ε depends exponentially on n .
- Hardness hold even if all demands are on the real line, except one demand d_{m+1} such that $\arg(d_{m+1}) = \frac{\pi}{2} + \theta$, for some $\theta \in [0, \frac{\pi}{2}]$



Inapproximability of $\text{CKS}[\pi-\varepsilon, \pi]$

Proof Ideas:

- Subset sum problem (SUBSUM):
 - An instance I is a set of positive integers $A \triangleq \{a_1, \dots, a_m\}$ and positive integer B ,
 - Decide if there exist a subset of A that sums-up to exactly B
- Mapping from SUBSUM to CKS
 - For each $a_k, k = 1, \dots, m$, define $d_k \triangleq a_k$
 - Define an additional $d_{m+1} \triangleq -B + \mathbf{i}B \cot \theta$
 - For all $k = 1, \dots, m$, let utility $u_k \triangleq \frac{\alpha}{m+1}$, and $u_{m+1} \triangleq 1$
 - Let $C \triangleq B \cot \theta$.
- Showing equivalence
 - $\text{SUBSUM}(I)$ is feasible \Rightarrow There is an (α, β) -approximation solution of utility at least α to CKS
 - There is (α, β) -approximation solution of utility at least α to CKS \Rightarrow There is an feasible solution to $\text{SUBSUM}(I)$

Inapproximability of CKS $[\pi-\varepsilon, \pi]$

Proof Ideas:

- Suppose there is (α, β) -approximation solution to CKS
- Since user $m+1$ has utility $u_{m+1} = 1$ and the rest of users utilities $\sum_{k=1}^m u_k < \alpha$, user $m+1$ must be included
- Therefore,

$$\left(\sum_{k=1}^m d_k^R x_k - B\right)^2 + B^2 \cot^2 \theta \leq \beta^2 C^2$$

$$\left(\sum_{k=1}^m d_k^R x_k - B\right)^2 \leq \beta^2 C^2 - B^2 \cot^2 \theta = B^2 \cot^2 \theta (\beta^2 - 1)$$

- SUBSUM is feasible, iff $|\sum_{k=1, \dots, m} a_k x_k - B| < 1$
- SUBSUM(I) is feasible when $B^2 \cot^2 \theta (\beta^2 - 1) < 1$
 - This occurs when $\beta = 1$, which proves the first claim
 - When θ is large enough such that $B^2 \cot^2 \theta (\beta^2 - 1) < 1$ (i.e., $\theta > \tan^{-1} \sqrt{B^2(\beta^2 - 1)}$), where B is not polynomial in n), which proves the second claim

Furthermore, Extensions of Basic Results

- ➊ Mixing elastic and inelastic demands (some x_k are fractional)
 - Combining demands with splittable and unsplittable demands
- ➋ Multi-minded preferences
 - More choices over multiple unsplittable demands
- ➌ Randomized truthful in expectation mechanisms for $\text{CKS}[0, \frac{\pi}{2}]$
 - Incentivizing users to report true utilities and demands
- ➍ Networked setting of inelastic power allocation
 - Sharing in electrical grid, Constrained by edge capacities

Mixing Elastic and Inelastic Demands

- Let \mathcal{N} be the set of users with inelastic demands
- Let \mathcal{E} be the set of users with elastic demands
 - Linear utility function
 - Utility of satisfying a demand $d_k x_k$ where $x_k \in [0, 1]$ is represented by $u_k x_k$, where u_k is maximum utility
- New optimization problem

$$\begin{aligned} (\text{CKS}_{\text{mx.lin}}) \quad & \max \sum_{k \in \mathcal{N} \cup \mathcal{E}} u_k x_k \\ \text{subject to} \quad & \left| \sum_{k \in \mathcal{N} \cup \mathcal{E}} d_k x_k \right| \leq C \\ & x_k \in \{0, 1\} \text{ for all } k \in \mathcal{N} \text{ and} \\ & x_k \in [0, 1] \text{ for all } k \in \mathcal{E}. \end{aligned}$$

- We extend PTAS and bi-criteria FPTAS of CKS to $\text{CKS}_{\text{mx.lin}}$, by first solving a convex programming problem

Multi-minded Preferences

- Non-single minded preferences: \mathcal{D} is a set of feasible demands
- Each agent can express multiple preferences over more than one unsplitable demand

$$\begin{aligned} (\text{NSMCKS}) \quad & \max \sum_{k \in \mathcal{N}} \sum_{d \in \mathcal{D}} v_k(d) x_{k,d} \\ \text{subject to} \quad & \left(\sum_{k \in \mathcal{N}} \sum_{d \in \mathcal{D}} d^{\text{R}} \cdot x_{k,d} \right)^2 + \sum_{k \in \mathcal{N}} \sum_{d \in \mathcal{D}} d^{\text{I}} \cdot x_{k,d} \leq C^2 \\ & \sum_{d \in \mathcal{D}} x_{k,d} = 1, \quad \text{for all } k \in \mathcal{N} \\ & x_{k,d} \in \{0, 1\} \text{ for all } k \in \mathcal{N}. \end{aligned}$$

- Multi-minded preferences:

$$v_k(d) = \begin{cases} \max_{d_k \in \mathcal{D}_k} \{v_k(d_k) : |d_k^{\text{R}}| \geq |d^{\text{R}}|, |d_k^{\text{I}}| \geq |d^{\text{I}}|, \\ \quad \text{sgn}(d_k^{\text{R}}) = \text{sgn}(d^{\text{R}}), \text{sgn}(d_k^{\text{I}}) = \text{sgn}(d^{\text{I}})\} & \text{if } d_k \in D_k, \\ 0, & \text{otherwise} \end{cases}$$

- Let $\mathcal{V} \triangleq \mathcal{V}_1 \times \cdots \times \mathcal{V}_n$, where \mathcal{V}_i is the set of all possible valuations of user i , and let Ω be a set of outcomes
- A randomized mechanism $(\mathcal{A}, \mathbb{P})$ is defined by
 - An allocation rule $\mathcal{A} : \mathcal{V} \rightarrow \mathcal{D}(\Omega)$
 - A payment rule $\mathbb{P} : \mathcal{V} \rightarrow \mathcal{D}(\mathbb{R}_+^n)$, where $\mathcal{D}(\mathcal{S})$ denotes the set of probability distributions over set \mathcal{S}
- The utility of player i when it receives the vector of bids $v \triangleq (v_1, \dots, v_n) \in \mathcal{V}$, is the random variable $U_k(v) = \bar{v}_k(x(v)) - p_i(v)$,
 - $x(v) \sim \mathcal{A}(v)$, and $p(v) = (p_1(v), \dots, p_n(v)) \sim \mathbb{P}(v)$;
 - \bar{v}_i denotes the true valuation of player i .
- A randomized mechanism is said to be *truthful in expectation*,
 - If for all i and all $\bar{v}_i, v_i \in \mathcal{V}_i$, and $v_{-k} \in \mathcal{V}_{-k}$, it guarantees that $\mathbb{E}[U_k(\bar{v}_k, v_{-k})] \geq \mathbb{E}[U_k(v_k, v_{-k})]$, when the true and reported valuations of player k are \bar{v}_k and v_k , respectively

Definition

- Abstractly speaking, the feasible set of a problem is a convex set $\mathcal{X} \subseteq [0, 1]^n$ for the relaxed version without integral constraints or $\mathcal{X}^{\mathcal{N}} \triangleq \{x \in \mathcal{X} \mid x_k \in \{0, 1\} \text{ for all } k \in \mathcal{N}\}$ with integral constraints
- For a convex polytope $\mathcal{Q} \subseteq [0, 1]^n$, we define $\beta \cdot \mathcal{Q} \triangleq \{\beta \cdot x \mid x \in \mathcal{Q}\}$
- An algorithm is called an (α, β) -LP-based approximation for $\mathcal{Q}^{\mathcal{N}}$, if for any $u \in \mathbb{R}_+^n$, it returns in polynomial time an $\hat{x} \in (\beta \cdot \mathcal{Q})^{\mathcal{N}}$, such that $u^T \hat{x} \geq \alpha \cdot \max_{x \in \mathcal{Q}} u^T x$

Theorem (Lavi-Swamy 2005)

If \mathcal{Q} is a convex polytope satisfying the packing property and admitting an α -LP-based approximation algorithm for $\mathcal{Q}^{\mathcal{N}}$. Then one can construct a randomized, individually rational, α -socially efficient mechanism on the set of outcomes $\mathcal{Q}^{\mathcal{N}}$, that is truthful-in-expectation and has no positive transfer.

- We extend the Lavi-Swamy theorem to non-linear problem (e.g. complex-demand knapsack problem CKS)
- CKS can be approximated by LP subproblems when $\text{CKS}[0, \frac{\pi}{2}]$
- We show that there is PTAS for $\text{CKS}[0, \frac{\pi}{2}]$ that admits a randomized, individually rational, α -socially efficient mechanism on the set of outcomes \mathcal{Q}^N , that is truthful-in-expectation and has no positive transfer
- Our results can be generalized to other non-linear problems
- Furthermore, we use VCG and dynamic programming to construct a truthful PTAS for $\text{CKS}[0, \pi - \varepsilon]$

Networked Setting of Inelastic Power Allocation

- Networked power flow is a difficult problem (non-convex)
- A simplified model of electrical grid $\mathcal{G} = (N, E)$
- Load $k \in \mathcal{R}$ has an internal impedance Z_{u_k} between its nodal voltage V_{u_k} and the ground, and requires an inelastic power demand d_k
- Consider a single source of generator at node $u_G \in N$
- We assume that the generation power is not limited and hence can feasibly support all loads, if not limited by edge capacity

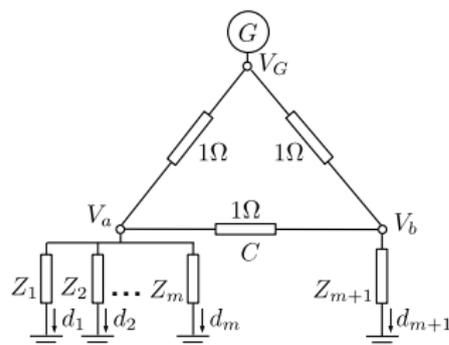
$$\begin{aligned} \text{(NETP)} \quad & \max_{x_k \in \{0,1\}} \sum_{k \in \mathcal{R}} u_k x_k \\ \text{subject to} \quad & \frac{V_{u_k}^2}{Z_{u_k}} = x_k d_k \text{ for all } k \in \mathcal{R} \\ & V_u - V_v = I_{(u,v)} Z_{(u,v)} \text{ for all } (u, v) \in E \\ & \sum_{v: \text{Neighbor}(u)} I_{(u,v)} = 0 \text{ for all } u \neq u_G \\ & |I_{(u,v)}| \leq C_{(u,v)} \text{ for all } (u, v) \in E \end{aligned}$$

Networked Setting of Inelastic Power Allocation

Theorem

Unless $P=NP$, there is no (α, β) -approximation for NETP (even considering a DC system)

- We consider the following gadget



- By equivalence of SUBSUM to NETP
- Open question: Then what can we do?

Conclusion and Implications

- A first study of combinatorial power allocation for AC systems
- Thorough approximation and hardness results
- Significance: A first step from communication networking to electricity networking
 - Knapsack \Rightarrow Complex-demand Knapsack
 - Commodity flow problem \Rightarrow Optimal power flow problem
 - Network design problem \Rightarrow Optimal islanding problem
- Open questions
 - Networked power allocation (e.g. tree, grid, star)
 - Coping with inapproximability (relaxing satisfiability)
 - Efficient incentive compatible mechanisms
 - Joint scheduling and power allocation

Paper: <http://www.SustainableNetworks.org/papers/cks.pdf>

Slides: <http://www.SustainableNetworks.org/slides/cks.pdf>