

Théorie des jeux pour la négociation entre la production d'énergie et les tâches informatique dans un datacenter à énergies renouvelables

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Context

Does using IT technologies have any consequences ?

⇒ IT consumes a huge amount of energy

- ▶ sending an email with an attach file consumes as much as one low-power bulb of high power for one hour

⇒ Data Centers in the US consumed 91 billions of kWh in 2013

⇒ Data Centers in Europe consumed 56 billions of kWh in 2013

▶ increasing the energy efficiency of data-centers

▶ supplying data-centers with only green energy

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Data Centers reached 4% of the global energy consumption in 2015

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DATAZERO : an innovative data-center model



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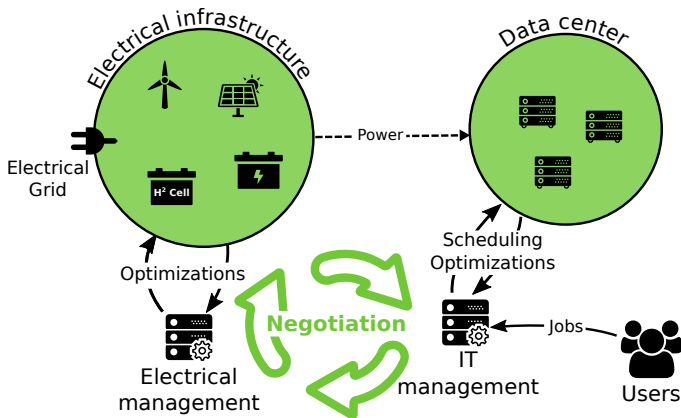
Adapting the IT load to
the available power
&
Adapting the power to
the incoming IT load



while using a mix of only green energy sources (without grid power usage)



DATAZERO : the big picture

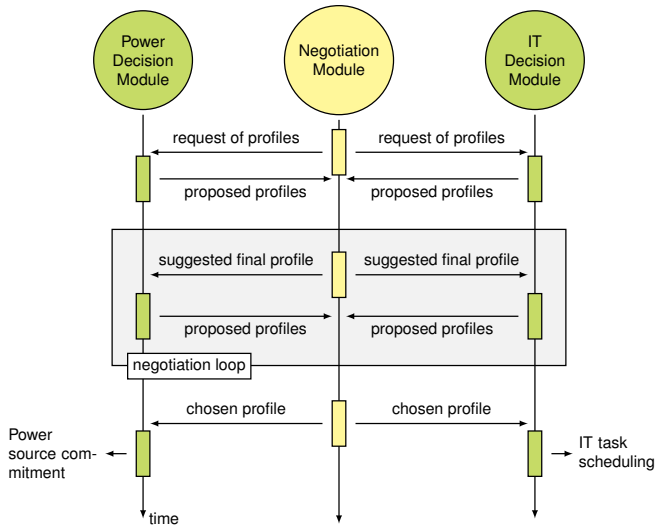


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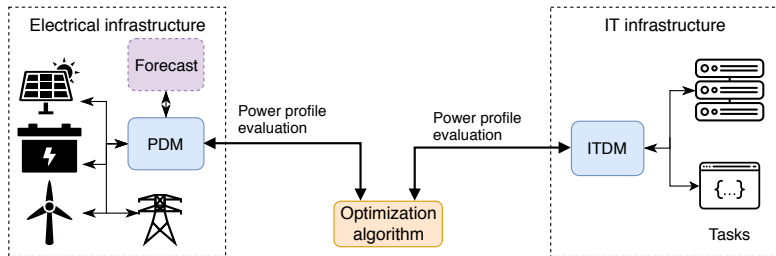
Negotiation between ITDM and PDM

Context and overview of the problem

Problem statement

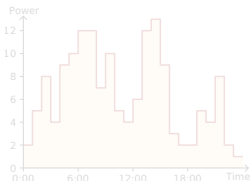


Infrastructure and negotiation

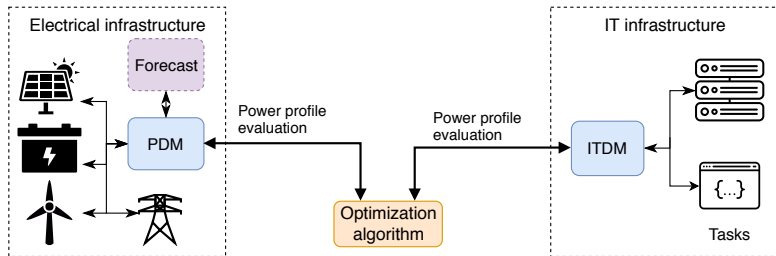


Separated IT and electrical optimizations

- ▶ Ability to evaluate power plan impact
- ▶ Internal objective (utility)
- ▶ Black box functions $\mathbb{R}^T \rightarrow \mathbb{R}$
- ▶ Computationally expensive

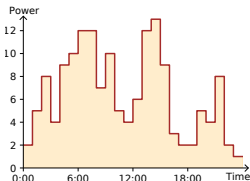


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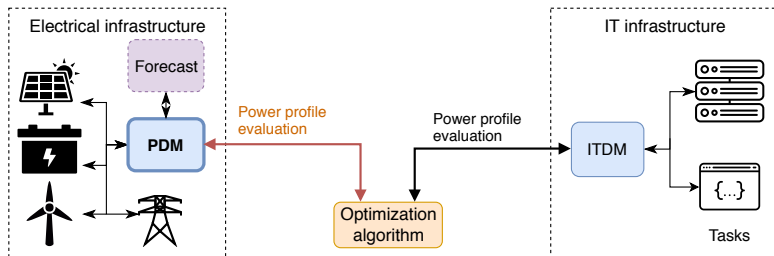


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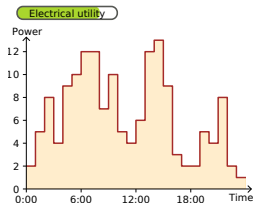


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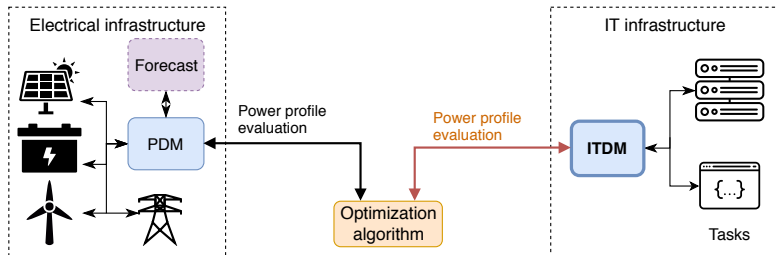


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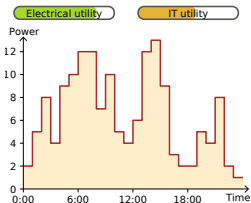


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- ▶ Each DM has one or more objectives to satisfy
- ▶ Objectives may differ between DM
 - ▶ QoS related for ITDM, environmental impact for PDM

Managing different objectives

3 options studied :

- ▶ Finding a set of good solutions (set of possible trade-offs) (Pareto-based approach)
- ▶ Maximizing the weighted sum of the utilities, under the constraint of a distance between the two resulting profiles (SAN approach)
- ▶ Playing a game between the PDM and the ITDM so that each one maximizes its profit (GAN approach)

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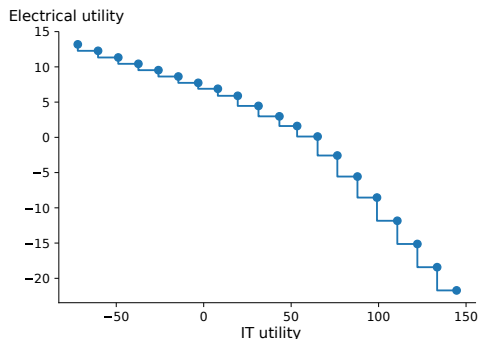
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Pareto front

- ▶ Find Pareto front (best trade-offs)

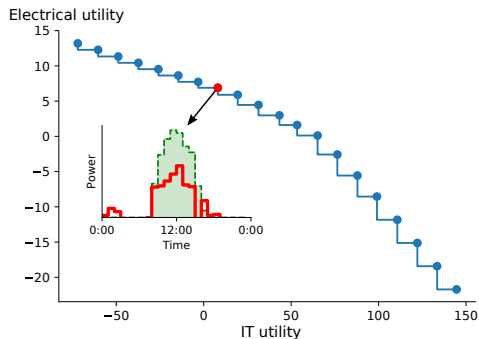


Multi-Objective Evolutionary Algorithms

- ▶ Well studied area, various approaches
- ▶ Focused on SPEA2 (genetic algorithm). Maximization of the hypervolume of solutions

Pareto front : Multi-objective optimization and heuristics

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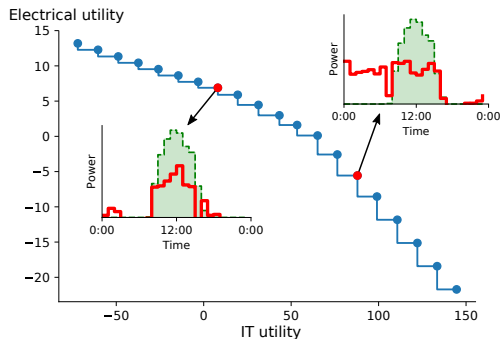


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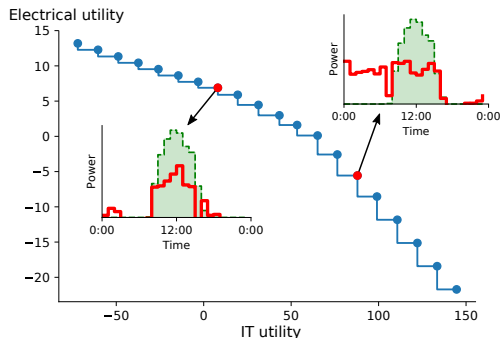
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Multi-Objective Evolutionary Algorithms

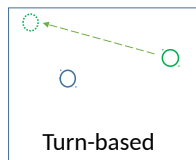
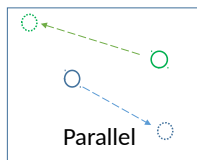
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SAN and GAN : Turn based approaches

Overview of SAN and GAN approaches

Main points

- ▶ Both algorithms are based on scheduling
 - ▶ DMs generate multiple scheduling solutions
 - ▶ Then we find negotiation solution from those scheduling solutions
- ▶ Both SAN and GAN negotiates in turn-based strategy
 - ▶ When ITDM runs scheduling (to follow PDM), PDM does not, and vice versa
 - ▶ We define 2 modes : "Follow PDM" mode (FLW_PD) and "Follow ITDM" mode (FLW_IT)
 - ▶ For both SAN and GAN (for the entire of the presentation), the whole system is executed **under only 1 mode** at a time



SCHEDULING BASED NEGOTIATION (SAN)

Definitions

- ▶ The set of ITDM profiles is $\{x_1, x_2, \dots, x_m\}$
- ▶ The set of PDM profiles is $\{y_1, y_2, \dots, y_n\}$
- ▶ Depending on each specific context, a profile may also be named "hint" or "candidate"

2 stages

- ▶ Stage 1 : Checking for matched pair
 - ▶ Decision variable : the pair {PDM profile, ITDM profile} :
 $\{x \in \{x_1, x_2, \dots, x_m\}, y \in \{y_1, y_2, \dots, y_n\}\}$
 - ▶ Objective : maximize sum of utility

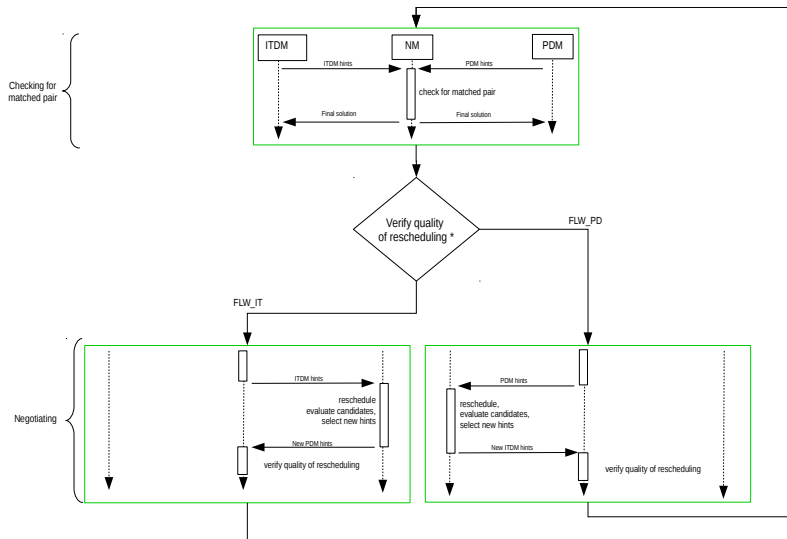
$$\max_{\{x,y\}} (u(x) + u(y)) \quad (1)$$

- ▶ Constraint : $d(x, y) < \epsilon$
where $d()$ is the distance between x and y
- ▶ If we can't find any matched pair, run Stage 2 : Negotiating.

Stage 2 : Negotiating :

- ▶ General mechanism
 - ▶ At a time, the whole system is executed **under only 1 mode** : follow ITDM (FLW_IT) or follow PDM (FLW_PD)
 - ▶ NM decides to switch between two modes using "*verify quality of rescheduling*"
 - ▶ Repeat until matched pair found
- ▶ Two modes :
 - ▶ FLW_IT : Follow the ITDM
 - ▶ NM sends the ITDM hints to PDM
 - ▶ PDM uses an algorithm (e.g. greedy, linear program) to find multiple scheduling solutions as candidates
 - ▶ PDM evaluates quality of candidates by "*weighted similarity*" to hints
 - ▶ PDM selects candidates with high "*weighted similarity*" as its news hints and sends back to NM
 - ▶ FLW_PD : Similar to FLW_IT, following the PDM

Algorithm



(*) verify quality of rescheduling: compare "distance between the best ITDM hint and the best PDM hint" before and after rescheduling

Formulation

- ▶ Mean Square Error between profile $x = \{x_1, \dots, x_T\}$ and $y = \{y_1, \dots, y_T\}$:

$$d(x, y) = \frac{1}{T} \sum_{i=1}^T (x_i - y_i)^2 \quad (2)$$

- ▶ Pearson correlation between them :

$$d(x, y) = \frac{\sqrt{\sum_{i=1}^T (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^T (y_i - \bar{y})^2}}{\sum_{i=1}^T (x_i - \bar{x})(y_i - \bar{y})}, \quad (3)$$

Formulation : Weighted similarity

$$w(x, Y) = \sum_{n=1}^N (u(x) + u(y^n)) \frac{1}{d(x, y^n)}, \quad (4)$$

Or, if we want to adjust impact of utility and distance :

$$w(x, Y) = \sum_{n=1}^N \left(\alpha(u(x) + u(y^n)) + (1 - \alpha) \frac{1}{d(x, y^n)} \right), \quad (5)$$

where $Y = \{y^1, \dots, y^n, \dots, y^N\}$ and $y^n = \{y_1^n, \dots, y_T^n\}$, and the values are normalized to (0,1]

Example

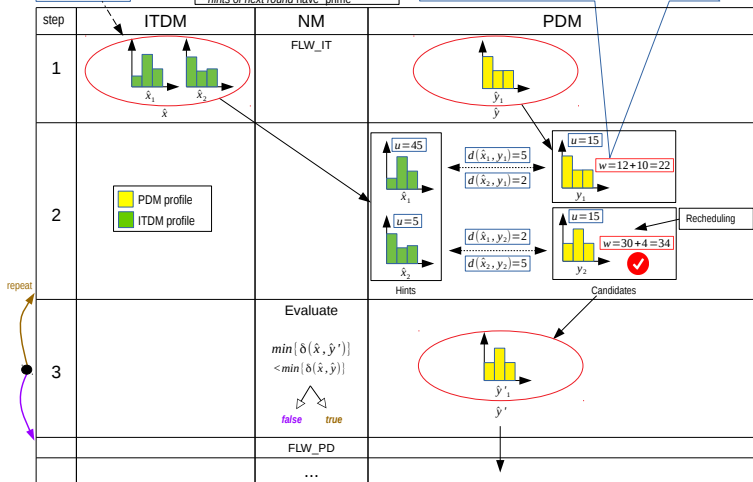
Example

Follow ITDM



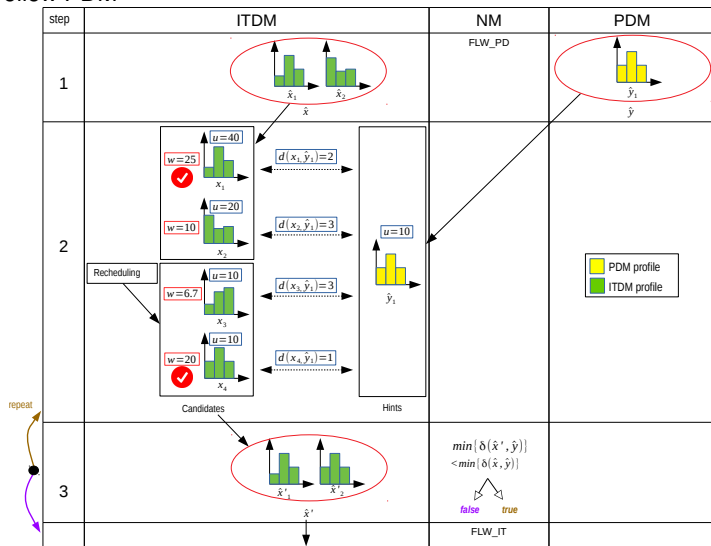
Notation:
 - candidates don't have "hat"
 - hints have "hat"
 - hints of next round have "prime"

$$w = \frac{45 + 15}{d(\hat{x}_1, y_1)} + \frac{5 + 15}{d(\hat{x}_2, y_1)} = \frac{60}{5} + \frac{20}{2} = 12 + 10 = 22$$



Example

Follow PDM





GAME BASED NEGOTIATION (GAN)

Model



Game players

ITDM:

- Objective:  
 - max {payment from users – payment to PDM}
- Decision variables:
 - price
 - scheduling

revenue - cost

PDM:

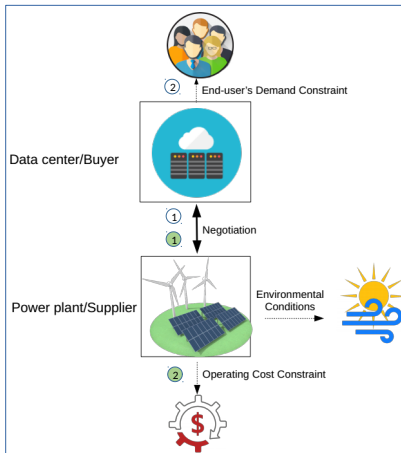
- Objective:  
 - max {payment from ITDM – (opex + capex cost)}
- Decision variables:
 - purchased power
 - scheduling

Game model

Hybrid model

- Non-cooperative: each player maximizes their own utility
- Cooperative: sometimes a player follows the other's suggestion

Supplier-buyer game diagram



Motivation

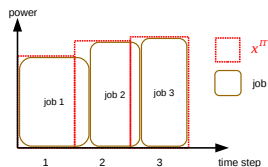
- ▶ The buying-selling nature of the system
 - ▶ Selling : PDM is selling power → controls the price
 - ▶ Buying : ITDM is buying power → decide the order/purchase
- ▶ Advantages of pricing
 - ▶ Power source availability can be reflected in price
 - ▶ Through price, pattern of order reflects pattern of PDM's desirable supply → drive demand toward supply

Preliminary

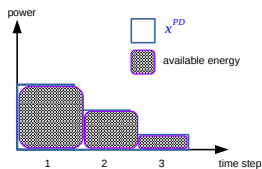
- ▶ Players are selfish
 - ▶ They try to maximize their utility
 - ▶ Each player negotiates just because he foresees some benefit
 - ▶ We introduce *incentive pricing mechanism* : each player tries to find offers that are attractive to the other player.
- ▶ An unexpected situation may occurred : all players can't foresee their benefit and stop negotiate without reaching any agreement.
 - ▶ From the view of the whole system, this situation is unacceptable, no transaction is done, the players obtain zero utility
 - ▶ If this situation occurred, we introduce *sacrifice mechanism*, in which the players gradually sacrifice their utility until they reach an agreement.

Definition 1

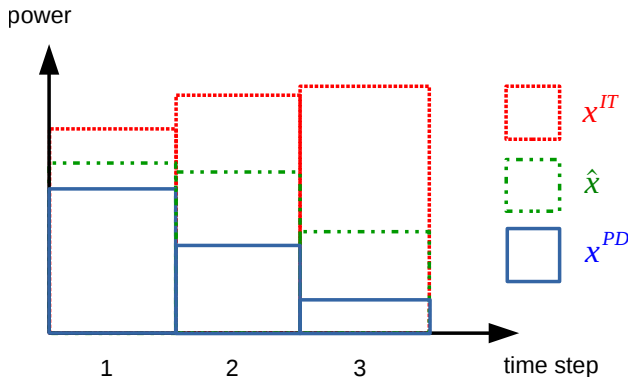
- ▶ T : Time window
- ▶ \hat{x}, x^{IT}, x^{PD} are profiles
- ▶ $\hat{x} = \{\hat{x}_1, \hat{x}_2, \dots, \hat{x}_T\}$, $x^{IT} = \{x_1^{IT}, x_2^{IT}, \dots, x_T^{IT}\}$ $x^{PD} = \{x_1^{PD}, x_2^{PD}, \dots, x_T^{PD}\}$



(a)

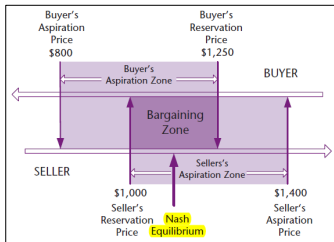


(b)

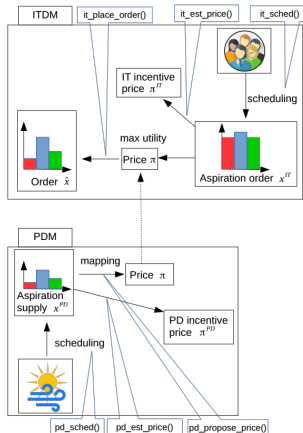


Definition 2

► $\pi = \{\pi_1, \pi_2, \dots, \pi_T\}$, $\pi^{IT} = \{\pi_1^{IT}, \pi_2^{IT}, \dots, \pi_T^{IT}\}$, $\pi^{PD} = \{\pi_1^{PD}, \pi_2^{PD}, \dots, \pi_T^{PD}\}$



2006_Krause_Bargaining Stances and Outcomes in Buyer-Seller Negotiations: Experimental Results (The Journal of Supply Chain Management)



Negotiation Model

Turn-based play

- ▶ There are 3 variables :
 - ▶ ITDM local variable $it_mod = \{FLW_IT, FLW_PD\}$,
 - ▶ PDM local variable $pd_mod = \{FLW_IT, FLW_PD\}$,
 - ▶ global variable $mod = \{FLW_IT, FLW_PD\}$.
- ▶ **The mode of the system is only depended on mod .** Two local variables only show the capability of the DMs.
- ▶ At a time, the system is executed **under only one mode**
- ▶ However, each player is selfish, he always wants the other player to follow himself, i.e., $it_mod = FLW_IT$, $pd_mod = FLW_PD$. In this situation, the negotiation can't be processed.
- ▶ Therefore
 - ▶ if ITDM is also **capable of** following PDM, we will set $it_mod = FLW_PD$
 - ▶ if PDM is also **capable of** following ITDM, we set $pd_mod = FLW_IT$

Negotiation solution

- ▶ Stopping criteria : \hat{x} approximates both x^{IT} and x^{PD}
- ▶ Final solution is the last \hat{x}

Incentive pricing mechanism :

- ▶ ITDM follows PDM : when x^{PD} and π^{PD} are attractive * :
it_cost(aspiration supply, PD incentive price) < it_cost(order, price) :

$$c(x^{PD}, \pi^{PD}) < c(\hat{x}, \pi) \quad (6)$$

- ▶ PD follows ITDM : when ITDM's offers are attractive :
pd_revenue(aspiration order, IT incentive price) > pd_revenue(order, price)

$$r(x^{IT}, \pi^{IT}) > r(\hat{x}, \pi) \quad (7)$$

(*) next page

(*) How π^{PD} can be attractive to ITDM :

- ▶ Given :
 - ▶ Definition : x^{PD} is the PDM's desirable supply
 - ▶ Then, the cost associated with this supply is lower than the cost associated with other supplies
- ▶ As a result
 - ▶ the PDM estimates the amount of cost it can reduce when it provides the ITDM with x^{PD} , instead of \hat{x} .
 - ▶ the PDM computes a π^{PD} such that its total utility increases

$$u(x^{PD}, \pi^{PD}) > u(\hat{x}, \pi) \quad (8)$$

How π^{IT} can be attractive to PDM : similarly

Sacrifice mechanism

- ▶ Unexpected situation : both ITDM and PDM are not capable of following each other, but an agreement is not reached
- ▶ Solution : ITDM gradually increases its *sacrifice variable* α :

$$\alpha \leftarrow \alpha + \gamma \quad (9)$$

then the incentive pricing mechanism at ITDM becomes :

$$c(x^{PD}, \pi^{PD}) - \alpha < c(\hat{x}, \pi) \quad (10)$$

- ▶ Similarly, incentive pricing mechanism at PDM becomes :

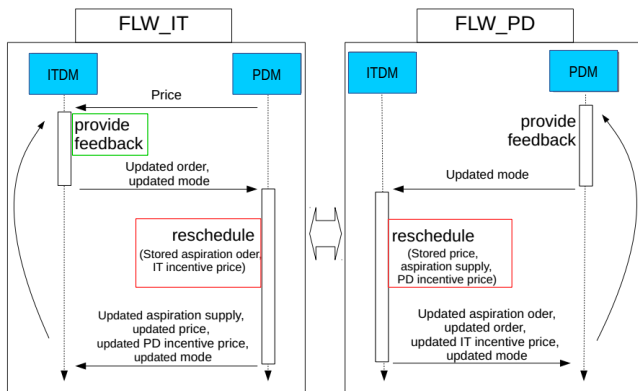
$$r(x^{IT}, \pi^{IT}) + \alpha > r(\hat{x}, \pi) \quad (11)$$

Algorithm

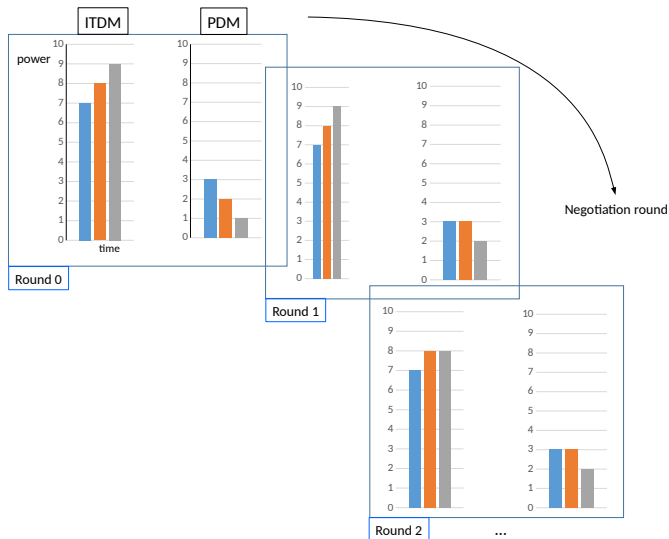
Algorithm

Note :

- ▶ At a time, the whole system is executed under **only one mode** : FLW_IT or FLW_PD
- ▶ DMs only exchange data that have been updated/modified, other data can be stored and reused



Graphical interpretation of the algorithm



ITDM Formulation

$$u(x, \pi) = r(x) - c(x, \pi) = \sum_{i=1}^J u_i(x) - \sum_{k=1}^T \pi_k x_k, \quad (12)$$

where

- ▶ $r(\cdot)$: revenue of ITDM
- ▶ $c(\cdot)$: ITDM's payment to PDM
- ▶ J : the number of ITDM's jobs
- ▶ $u_i(\cdot)$: the payment of the users' i -th job to ITDM

The payment from users is computed based on the Amazon EC2 pricing

PDM Formulation

$$u(x, \pi, S) = r(x, \pi) - c(x, S) = \sum_{i=1}^T \pi_i x_i - \sum_{j \in S} c_j^{OP}(x) c_j^{CAP} \quad (13)$$

where

- ▶ $c_j^{OP}(\cdot)$: operational rate of the j-th power source component
- ▶ $c_j^{CAP}(\cdot)$: the capital cost
- ▶ S is the number of utilized power source components

- ▶ `it_sched()` : Generate x^{IT} from the scheduling solution, such that
 - ▶ Utility $u(x^{IT}, \pi)$ is maximized
 - ▶ Revenue of x^{IT} must be larger than revenue of previous round's aspiration order \dot{x}^{IT}
 - ▶ And x^{IT} has to be closer to x^{PD} than previous round's aspiration order \dot{x}^{IT}

$$x^{IT} = \arg \max_x u(x, \pi) \quad (14)$$

$$s.t \quad r(x) > r(\dot{x}^{IT}) \quad (15)$$

$$d(x, x^{PD}) < d(\dot{x}^{IT}, x^{PD}) \quad (16)$$

- ▶ `it_place_order()` : ITDM finds \hat{x} that maximizes the ITDM's utility function $u(x, \pi)$

$$\hat{x} = \arg \max_x u(x, \pi) \quad (17)$$

- ▶ `it_est_price()` : ITDM estimates new π^{IT} that is more attractive to PDM than previous round's IT incentive price $\dot{\pi}^{IT}$, while keeping the ITDM's total utility non-decreased :

$$p = \pi^{IT} = \dot{\pi}^{IT} \quad (18)$$

$$\text{while } u(x^{IT}, p) \geq u(\hat{x}, \pi) \quad (19)$$

$$\pi^{IT} = p \quad (20)$$

$$p_i = p_i + p_i/N, \quad i = 1, \dots, T \quad (21)$$

where N is an integer, set through experiment parameters

- ▶ `pd_propose_price(x^{PD})` : the price π is generated such that

$$\pi_i = \frac{1}{x_i^{PD}}, \quad i = 1, \dots, T \quad (22)$$

where x_i^{PD} is normalized to $(0,1]$

- ▶ `pd_est_price()` : Similar to `it_est_price()`, PDM estimates a new π^{PD} that is more attractive to ITDM than previous round's PD incentive price $\dot{\pi}^{PD}$, while keeping PDM's utility non-decreased :

$$p = \pi^{PD} = \dot{\pi}^{PD} \quad (23)$$

$$\text{while } u(x^{PD}, p) \geq u(\hat{x}, \pi) \quad (24)$$

$$\pi^{PD} = p \quad (25)$$

$$p_i = p_i - p_i/N, \quad i = 1, \dots, T \quad (26)$$

- ▶ `pd_sched()` : Generate x^{PD} from the scheduling solution, such that
 - ▶ Utility $u(x^{PD}, \pi, S)$ is maximized
 - ▶ Cost of x^{PD} must be smaller than cost of previous round's aspiration supply \dot{x}^{PD}
 - ▶ New price π has to be closer to π^{IT} than the previous round's price $\dot{\pi}$

$$x^{PD} = \arg \max_x u(x, \pi, S) \quad (27)$$

$$s.t \quad c(x) < c(\dot{x}^{PD}) \quad (28)$$

$$d(\pi, \pi^{IT}) < d(\dot{\pi}, \pi^{IT}) \quad (29)$$

where $\pi \leftarrow \text{pd_propose_price}(x)$

Example

Simplified example

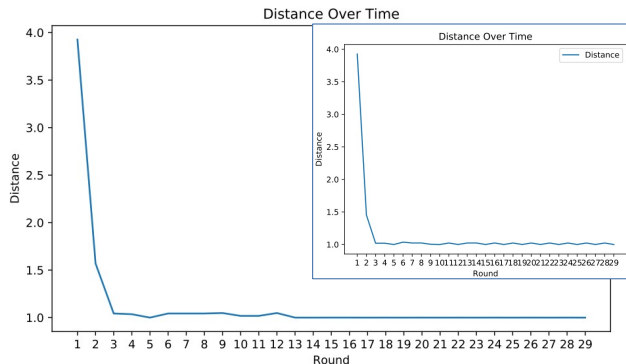
round	row	PD-Player	Common Space	IT-Player
1	1	<p>power</p> <p>time</p> <p>x^{PD}</p>	<p>$\pi^{PD} = [7,6]$</p> <p>$\pi = [8,6]$</p> <p>\hat{x}</p> <p>$\pi^{IT} = [3,3]$</p>	<p>70 70</p> <p>x^{IT}</p> <p>Scheduling solution</p>
	2	<p>Assume $\begin{cases} r(x^{IT}, \pi^{IT}) + \alpha = 0.25 \\ r(\hat{x}, \pi) = 0.22 \end{cases}$</p> <p>$r(x^{IT}, \pi^{IT}) + \alpha > r(\hat{x}, \pi) \rightarrow \text{true}$</p>		<p>Assume $\begin{cases} c(x^{PD}, \pi^{PD}) - \alpha = 0.13 \\ c(\hat{x}, \pi) = 0.15 \end{cases}$</p> <p>$c(x^{PD}, \pi^{PD}) - \alpha < c(\hat{x}, \pi) \rightarrow \text{true}$</p>
	3	$pd_pre = FLW_{IT}$	$mod = FLW_{IT}$	$it_pre = FLW_{PD}$
2	4	<p>30 40</p> <p>x^{PD}</p>	<p>$\pi^{PD} = [7,6]$</p> <p>$\pi = [7,6]$</p> <p>\hat{x}</p> <p>$\pi^{IT} = [3,3]$</p>	
	5	<p>Assume $\begin{cases} r(x^{IT}, \pi^{IT}) + \alpha = 0.25 \\ r(\hat{x}, \pi) = 0.28 \end{cases}$</p> <p>$r(x^{IT}, \pi^{IT}) + \alpha > r(\hat{x}, \pi) \rightarrow \text{false}$</p>		<p>Assume $\begin{cases} c(x^{PD}, \pi^{PD}) - \alpha = 0.16 \\ c(\hat{x}, \pi) = 0.17 \end{cases}$</p> <p>$c(x^{PD}, \pi^{PD}) - \alpha < c(\hat{x}, \pi) \rightarrow \text{true}$</p>
	6	$pd_pre = FLW_{PD}$	$mod = FLW_{PD}$	$it_pre = FLW_{PD}$
3	7		<p>$\pi^{PD} = [7,6]$</p> <p>$\pi = [7,6]$</p> <p>\hat{x}</p> <p>$\pi^{IT} = [6,5]$</p>	<p>40 50</p> <p>x^{IT}</p> <p>New scheduling solution</p>
	8	<p>Assume $\begin{cases} r(x^{IT}, \pi^{IT}) + \alpha = 0.23 \\ r(\hat{x}, \pi) = 0.24 \end{cases}$</p> <p>$r(x^{IT}, \pi^{IT}) + \alpha > r(\hat{x}, \pi) \rightarrow \text{false}$</p>		<p>Assume $\begin{cases} c(x^{PD}, \pi^{PD}) - \alpha = 0.16 \\ c(\hat{x}, \pi) = 0.14 \end{cases}$</p> <p>$c(x^{PD}, \pi^{PD}) - \alpha < c(\hat{x}, \pi) \rightarrow \text{false}$</p>
	9	$pd_pre = FLW_{PD}$		$it_pre = FLW_{IT}$
	10	<p>$d(x^{PD}, \hat{x}) > \epsilon$</p> <p>repeat</p>		<p>$d(x^{PD}, \hat{x}) > \epsilon$</p>

EXPERIMENT

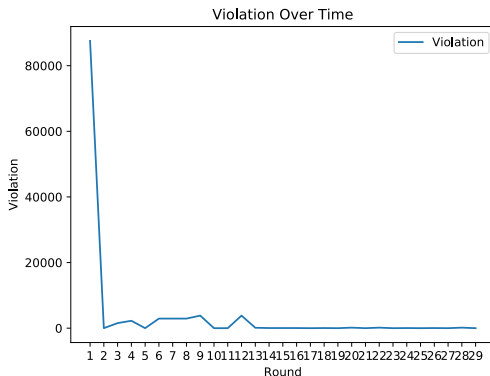
Real PDM & ITDM

- ▶ PDM weather information : 1 month
- ▶ Time window : 3 days or 72 hours
- ▶ Timestep : 1 hour or 3,600,000 ms
- ▶ PDM sizing : $\approx 1\text{kW}$
- ▶ Run time : ≈ 10 minutes

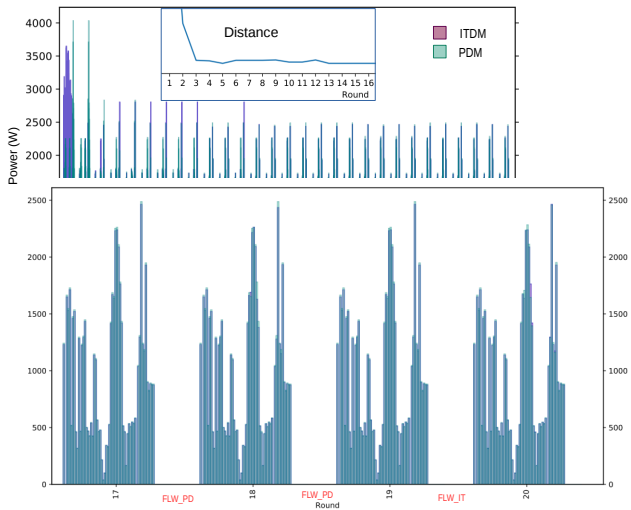
- ▶ Calculation : using Pearson correlation
- ▶ Distance is not always decreasing because the profiles are evaluated by both utility and distance
- ▶ Negotiation results depend a lot on the series of utilities from DMs



- ▶ Calculation : sum of the amount that the ITDM profiles exceeds PDM's profiles
- ▶ A significant reason for this result : DMs scheduling algorithms



Power level



Visit www.datazero.org for more information !!