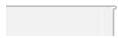



Department of Information Engineering  
University of Padova, ITALY

# *Reactive power pricing strategy*

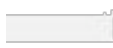
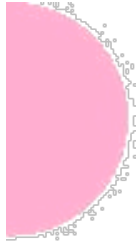
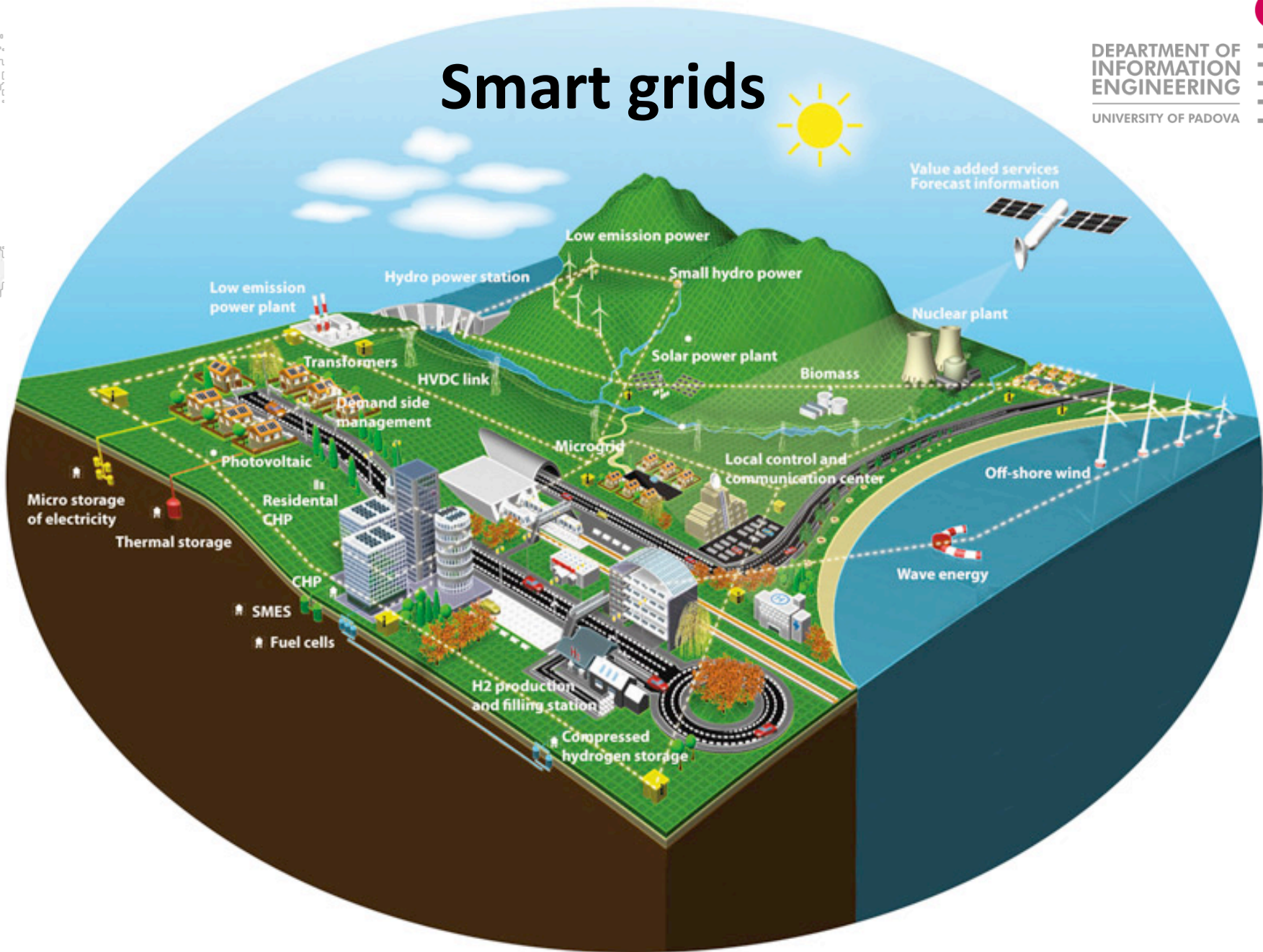
Giulia Maso, Martino Minella, Anna Polidoro

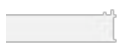


# Outline

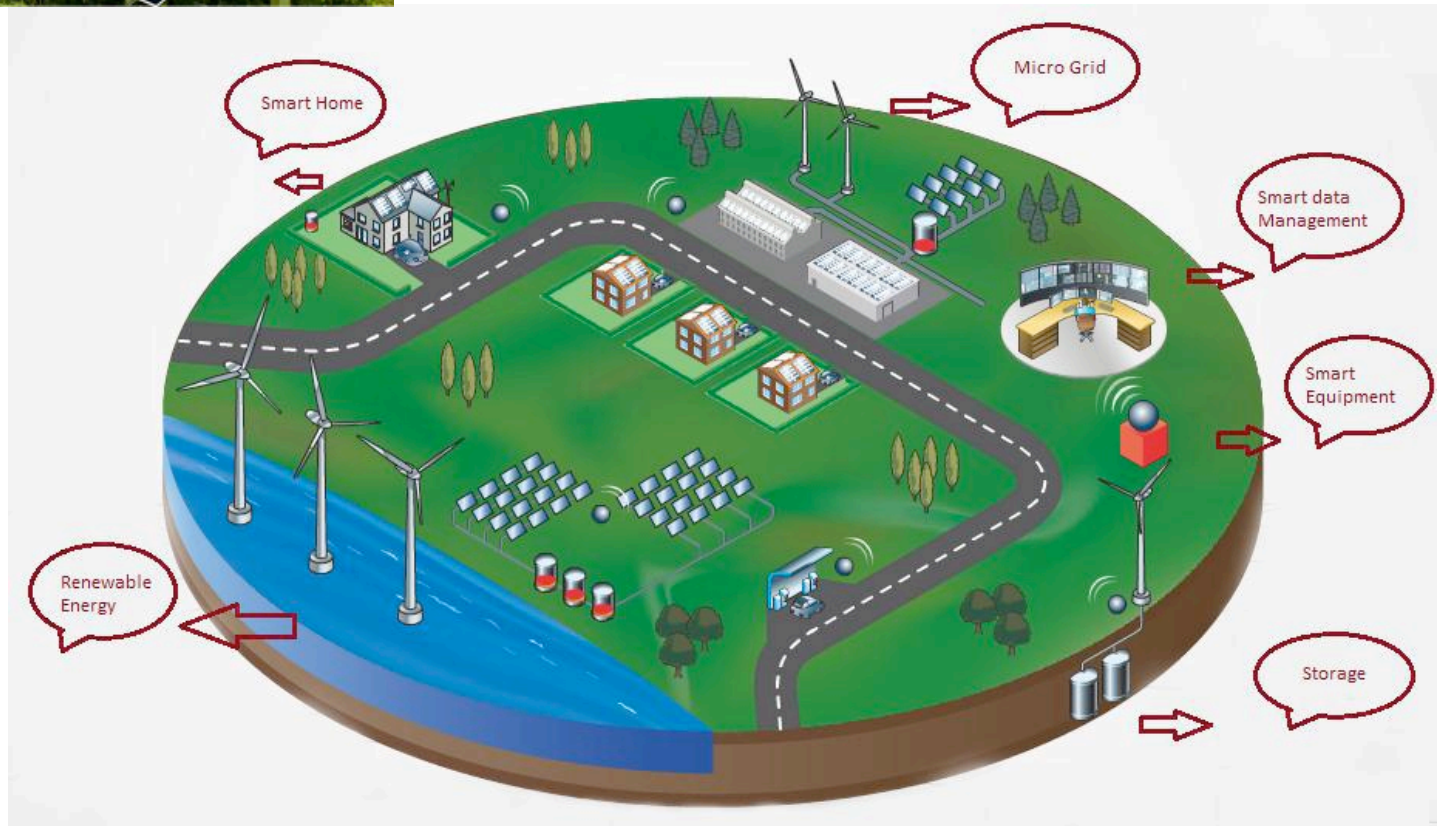
- 
- Smart Grids
    - Model
    - Reactive power compensation
  - Pricing Tools
    - Lagrange multipliers (centralized)
    - Gradient estimation (distributed)
  - Pricing Strategy
    - Shadow prices
    - Storage strategy

# Smart grids

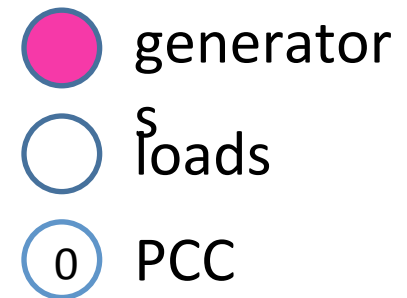
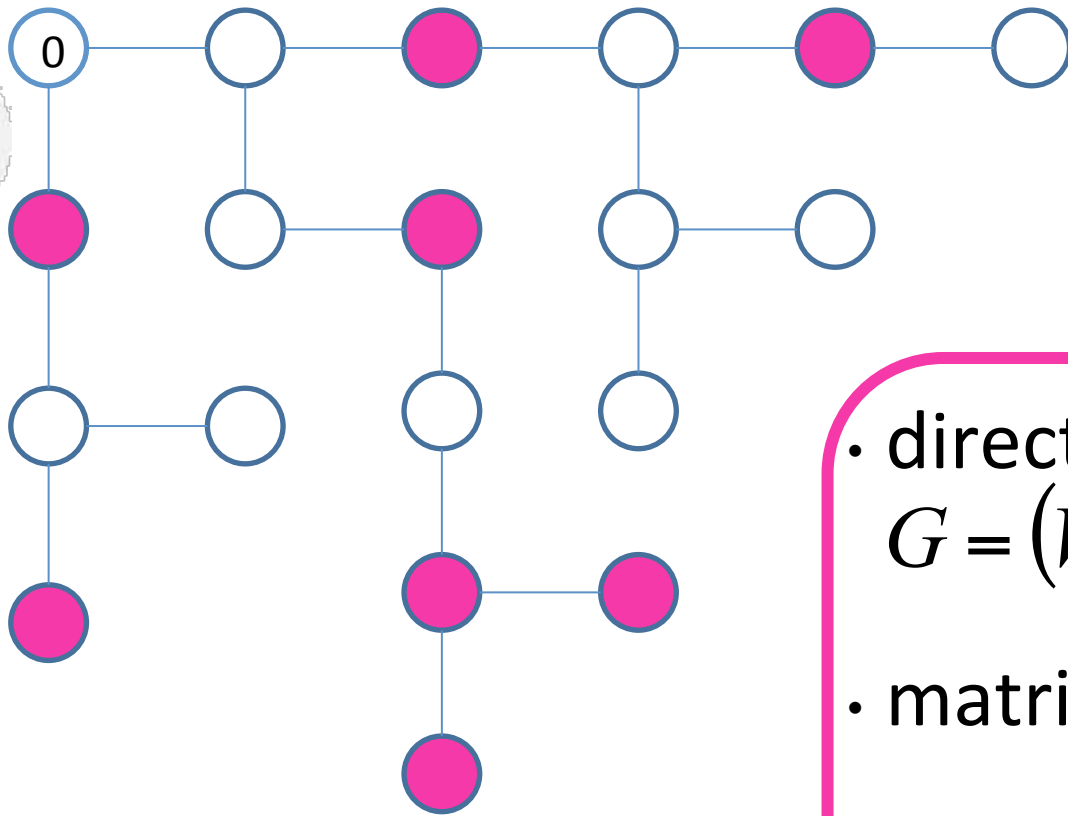




# Smart grids



# Smart grids - Model



- directed graph  
 $G = (V, E, \sigma, \tau)$
- matrix of incidence  $A$
- voltages and currents  
 $y(t) = |y| \sqrt{2} \sin(\omega_0 t + \angle y)$



# Smart grids - Model

## *Initial model equations*

- (KLC) and (KVL) laws

$$\mathbf{A}^T \boldsymbol{\xi} + \mathbf{i} = \mathbf{0}$$

$$\mathbf{A}\mathbf{u} + \mathbf{Z}\boldsymbol{\xi} = \mathbf{0}$$

- PCC  $\longrightarrow$  constant voltage generator

$$u_0 = U_0$$

- generic node  $\longrightarrow$  exponential model

$$u_v \bar{i}_v = s_v \left| \frac{u_v}{U_0} \right|^{\eta_v}, \forall v \in V \setminus \{0\}$$

# Approximate model(1)

**Laplacian matrix,  $L = A^T Z^{-1} A$**

**Green matrix,  $X$  satisfying:**

$$\begin{cases} XL = I - 11_0^T \\ X1_0 = 0 \end{cases}$$

Solution for the currents:

$$i = Lu$$

## Approximate model(2)

The system can be rewritten in the following form:

$$\begin{cases} u = Xi + U_0 \mathbf{1} \\ u_v \bar{i}_v = s_v \left| \frac{u_v}{U_0} \right|^{\eta_v}, \forall v \in V \setminus \{0\} \\ \mathbf{1}^T i = 0 \end{cases}$$



# Smart grids - Compensation

*Reactive power* flows contribute to:

- power losses on the lines
- voltage drop
- grid instability



Problem of optimal reactive power compensation



Bolognani, S., and Zampieri, S. (2011)

Distributed control strategy for optimal reactive power compensation in smart microgrids.

# Smart grids - Compensation

$$J' = i^{-T} \operatorname{Re}(x)i = \frac{1}{|U_0|^2} p^T \operatorname{Re}(x)p + \frac{1}{|U_0|^2} q^T \operatorname{Re}(x)q + \frac{1}{|U_0|^2} \tilde{J}(U_0, s)$$

where it has been used the Taylor approximation of  $i(U_0)$  for large  $U_0$



Being  $\tilde{J}(U_0, s)$  infinitesimal, we have an *uncoupling phenomenon*



**QUADRATIC LINEARLY CONSTRAINED PROBLEM**

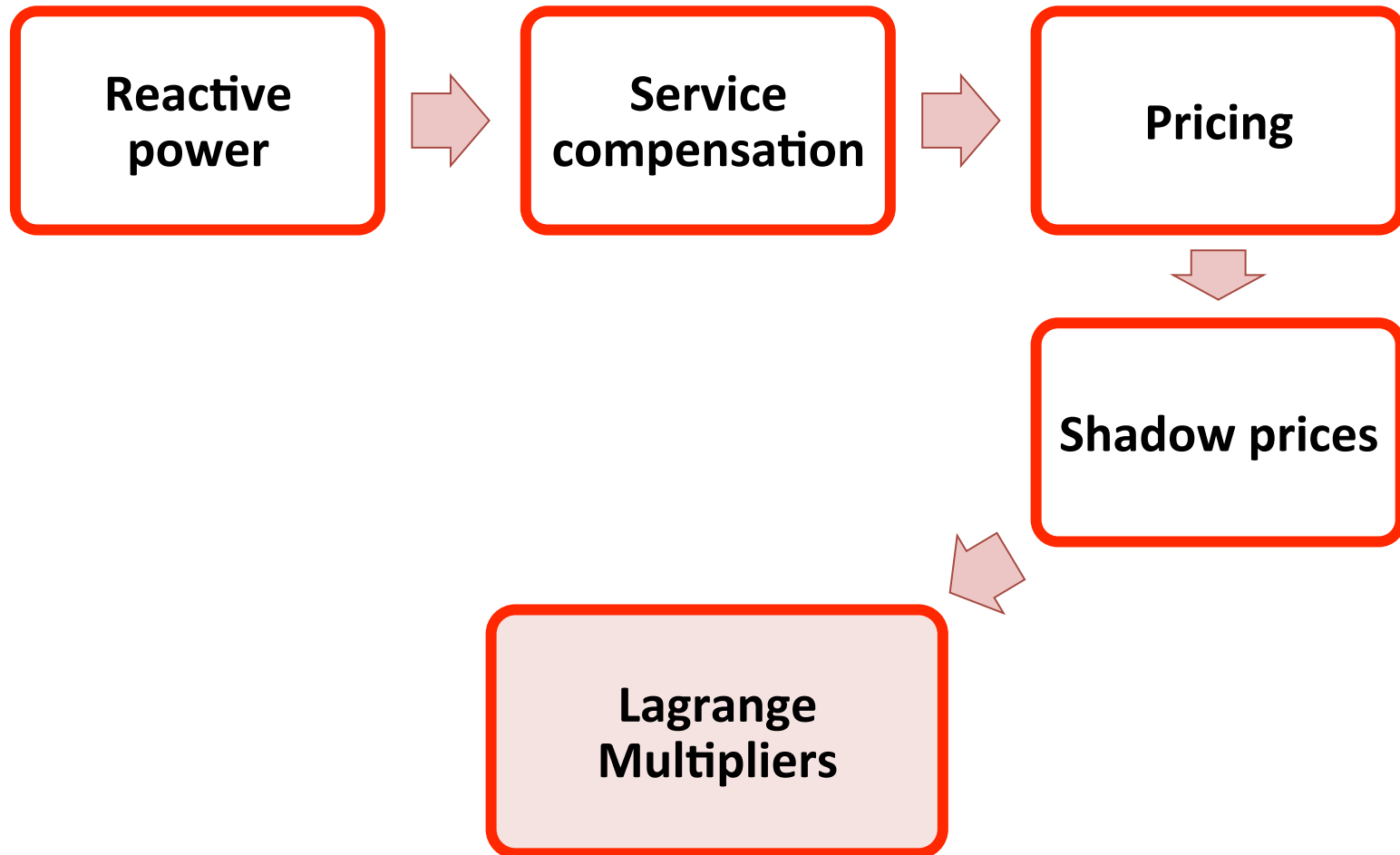
# Smart grids - Compensation

## QUADRATIC LINEARLY CONSTRAINED PROBLEM

$$\min_q J(q), \quad \text{where } J(q) = \frac{1}{2} q^T \operatorname{Re}(x)q,$$

$$\text{subject to } \mathbf{1}^T q = 0$$

$$q_v = \operatorname{Im}(s_v) \quad \forall v \in V \setminus C$$



# Lagrange Multipliers-Theory(1)

## Duality theory



- Primal

$$\min f_0(x) \text{ s.t } f_i(x) \leq 0, h_i(x) = 0$$

- Lagrangian

$$g(\lambda, \nu) = \inf L(x, \lambda, \nu)$$

- Dual

$$\max g(\lambda, \nu) \text{ s.t } \lambda \geq 0$$

Primal+dual   $\lambda^*, \nu^*$

# Lagrange Multipliers-Theory(2)

$$\lambda_i^* = - \frac{\partial p^*(0,0)}{\partial u_i}$$

$p^*$  Primal solution

$u_i$  Constraint perturbation

Optimal Lagrange multipliers



LOCAL SENSITIVITIES

# Lagrange Multipliers-Application(1)

- Objective function  $J(q)$
- Constraints on loads and compensators

$$q = Q_l, q \leq Q_c$$

- Lagrangian

$$L(q, \lambda) = J(q) + \lambda^T (q - Q)$$

- Solution

$$\lambda_l^* = -\frac{2}{|u_0^2|} D^{-1} Q_l$$






# Lagrange Multipliers-Application(2)



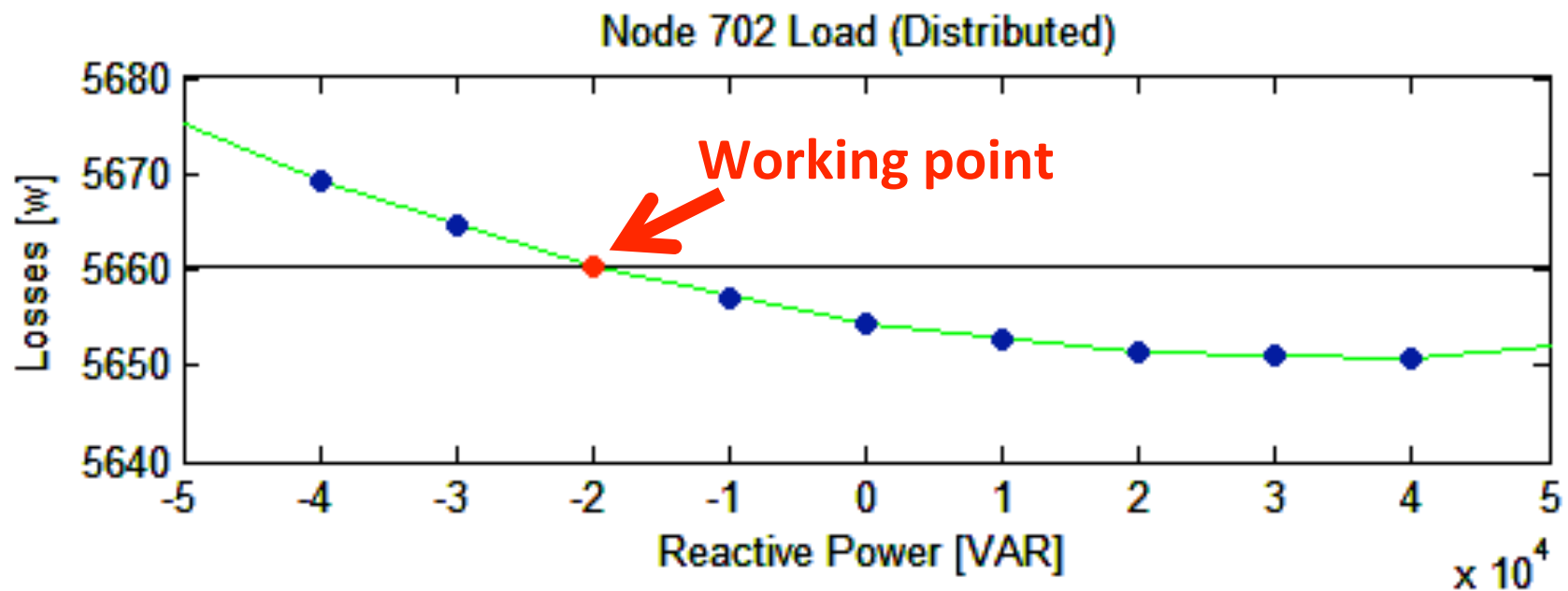
Solution requires global knowledge of network topology

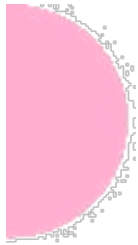
Centralized algorithm

- 
- Centralized unit
  - High computational cost with large number of nodes
  - Broadband communication system
  - Change in network topology

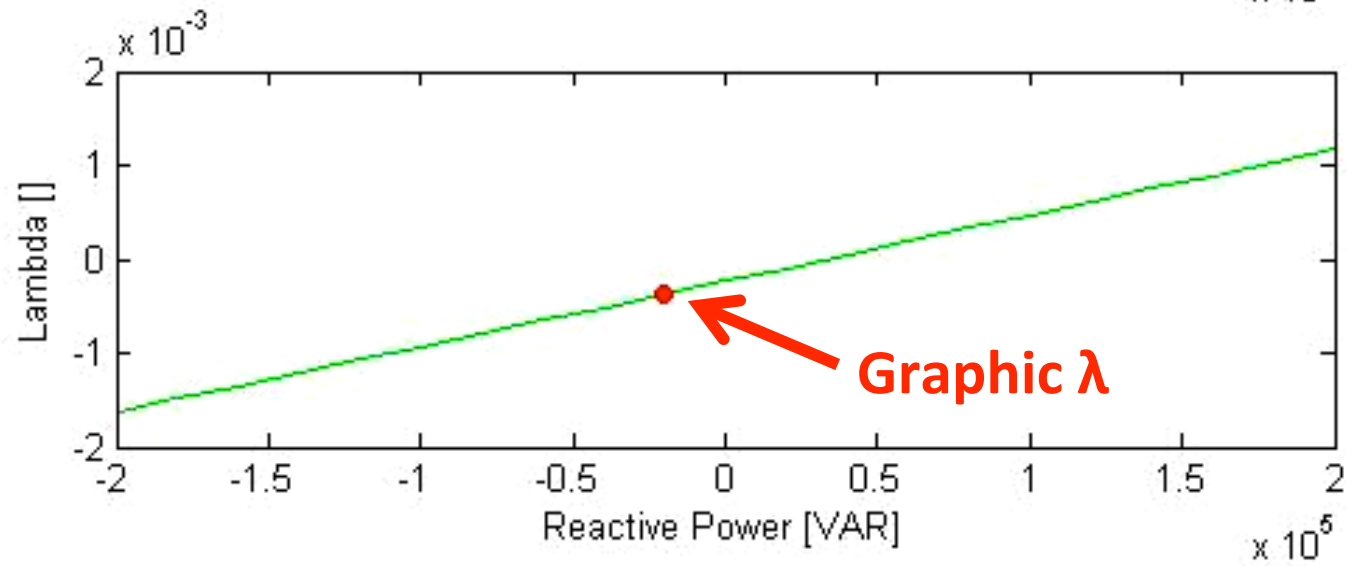
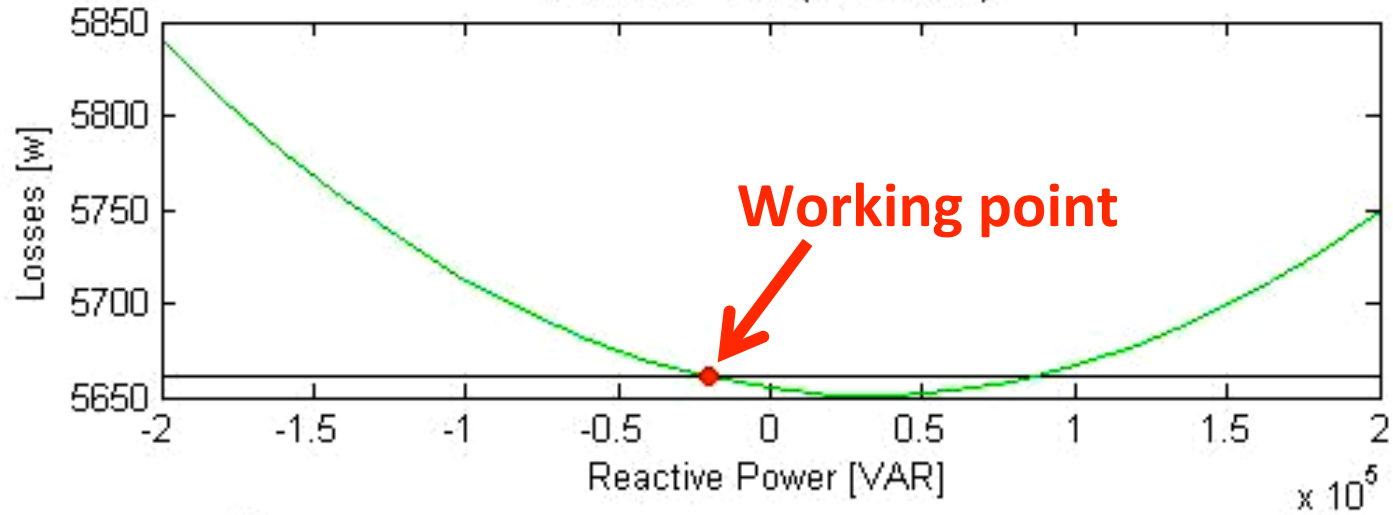
# Lagrange multipliers-Graphic

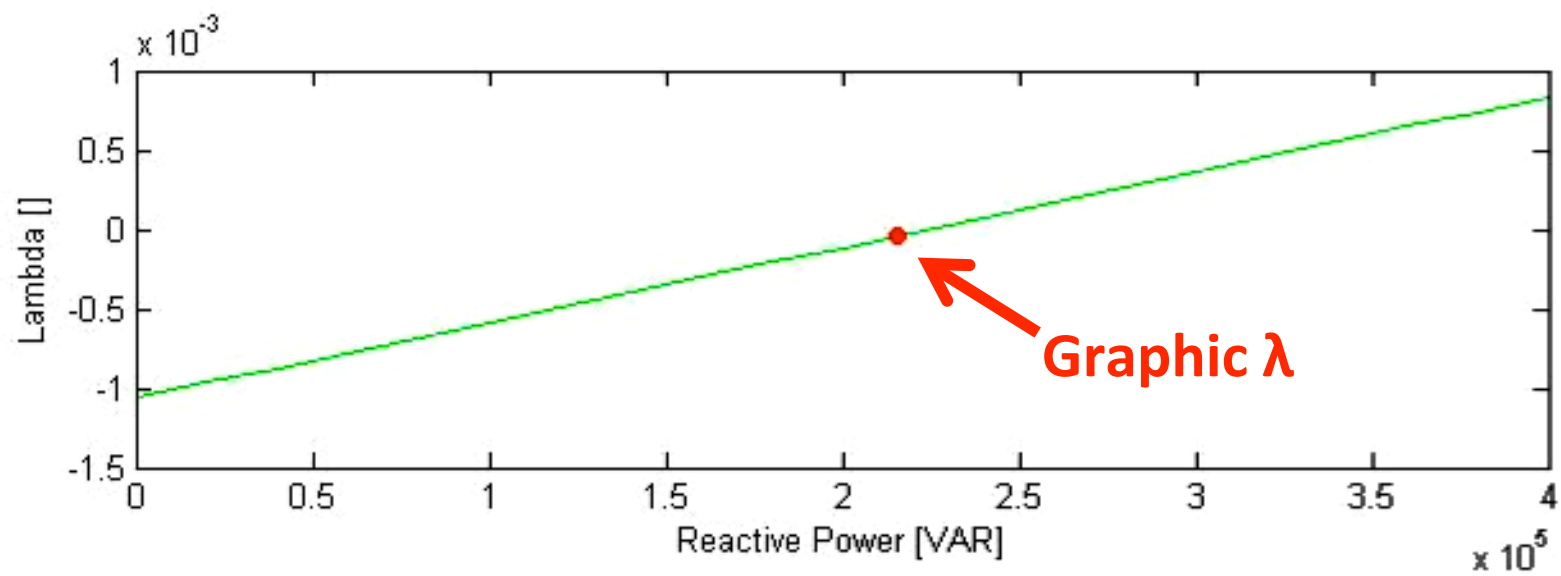
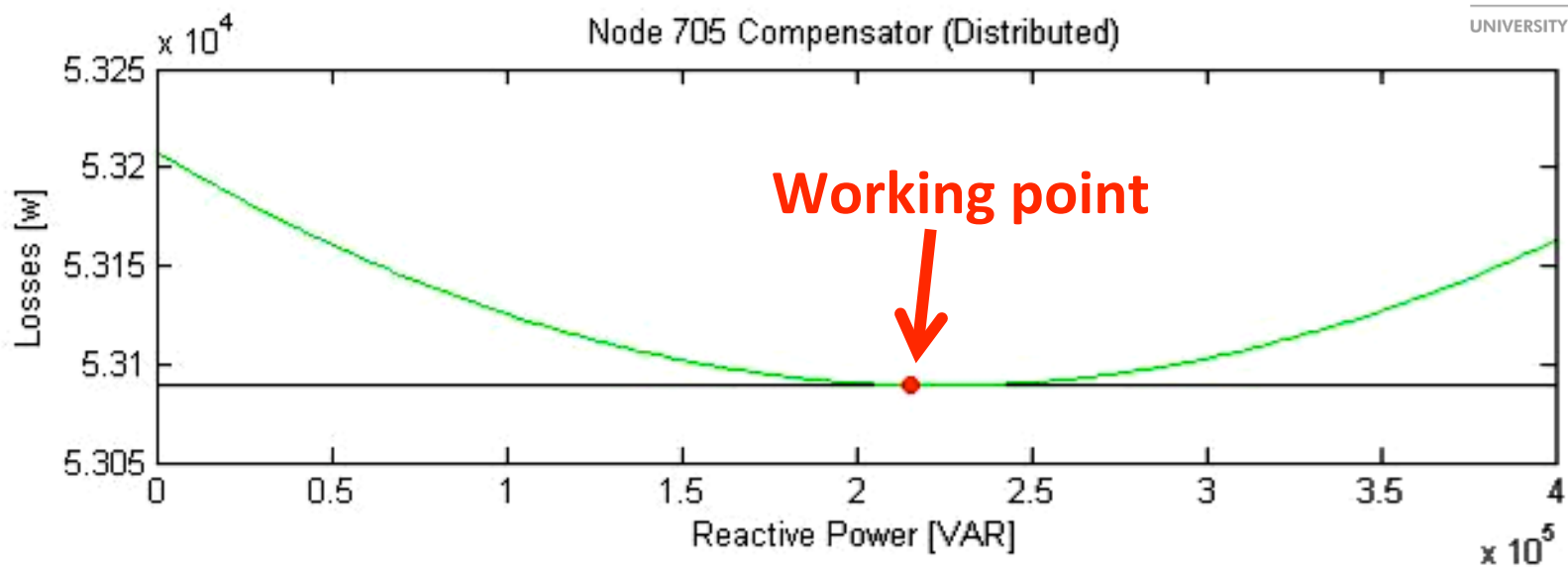
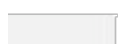
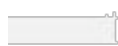
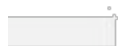
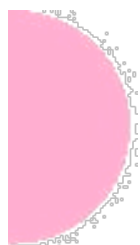
Exploiting the perturbation theory of duality we identify the losses parabola





Node 702 Load (Distributed)





# Gradient estimation

Beginning from the Lagrangian with constraints on both

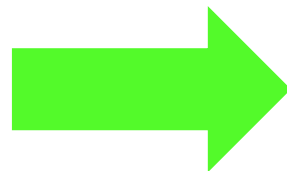
loads and cor

$$q(\lambda) = \frac{|u_0^2|}{2} \text{Re}(\mathbf{X})^{-1} \lambda$$

Solving for  $\lambda$ :

$$\lambda(q) = -\frac{2\text{Re}(\mathbf{X})}{|u_0^2|} q$$

$\text{Re}(\mathbf{X})q$



$\text{Re}(\mathbf{X})q$

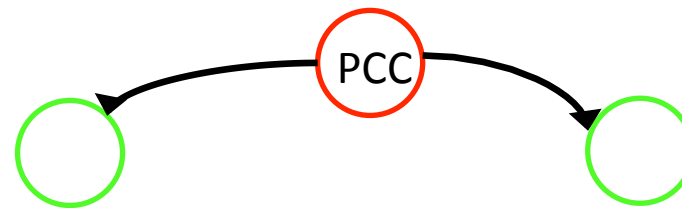


**estimation**

# Gradient estimation (1)

- Using PCC voltage

Each node receives information from the PCC



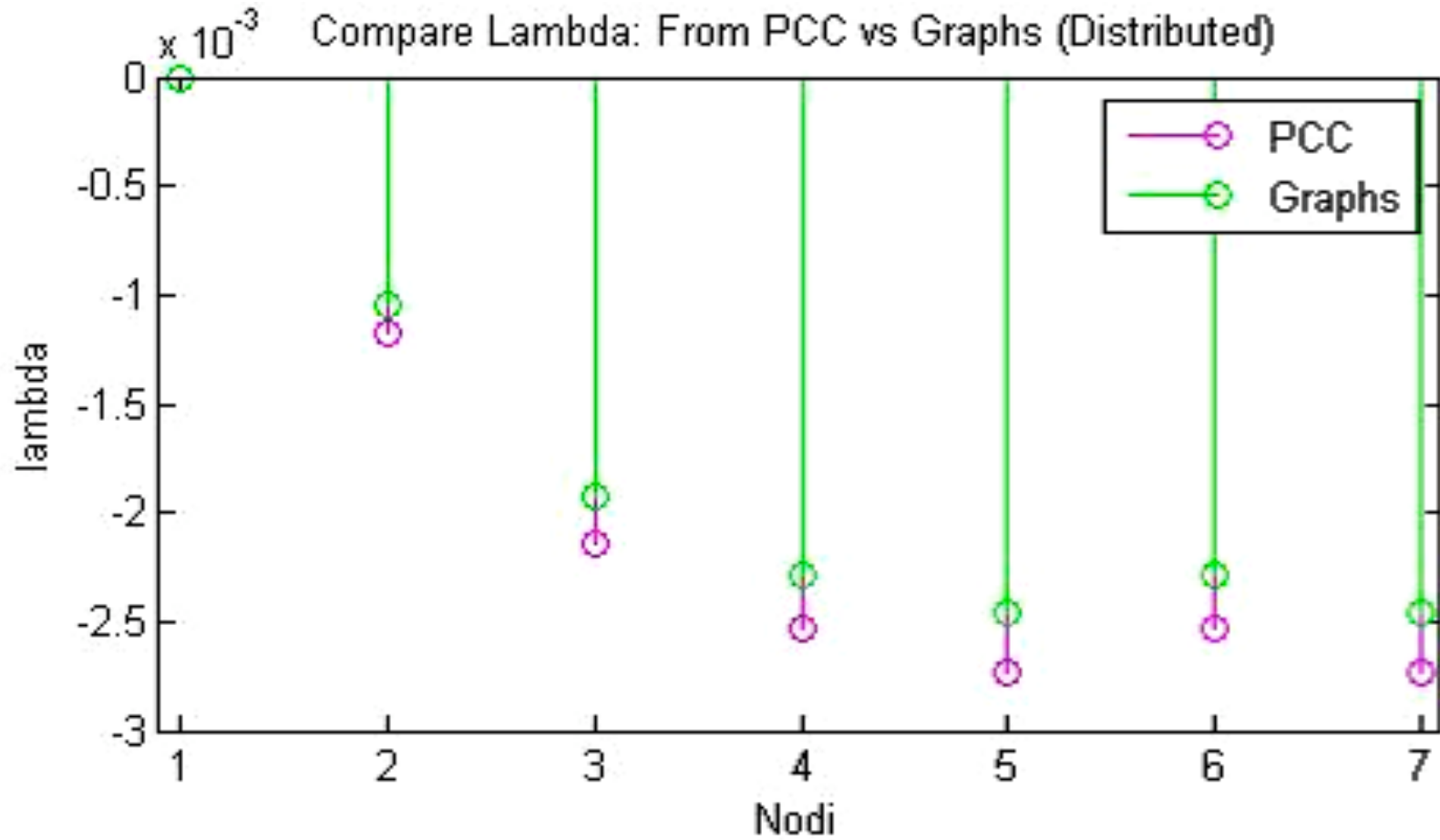
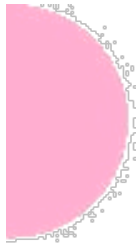
$$\lambda(u) = 2 \cos \theta \operatorname{Im} \left[ \frac{e^{-j\theta} (u - u_0 \mathbf{1})}{u_0} \right]$$

$\theta$  phase shift

- constant
- between node and PCC



overestimate results

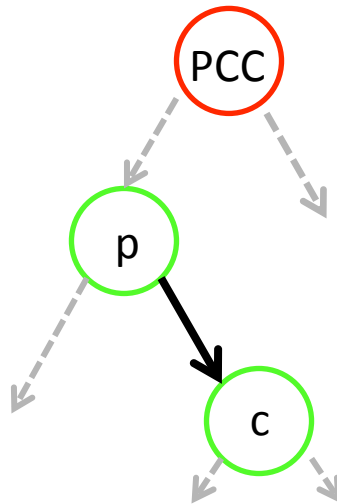




## Gradient estimation (2)

- Distributed

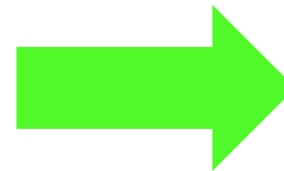
Two nodes exchange information between each other



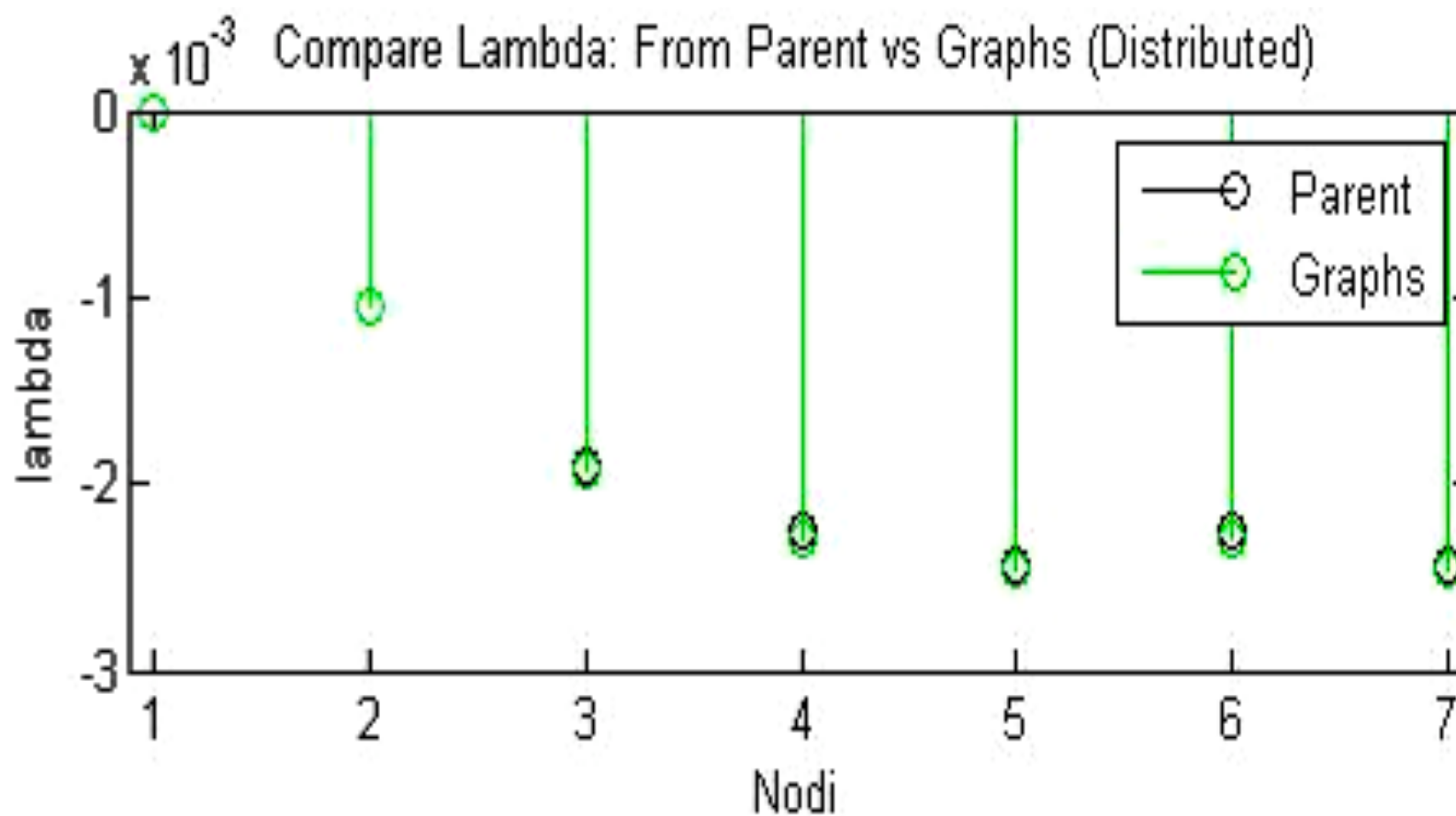
$$\lambda_c = \lambda_p + \frac{\cos \theta^2}{|u_0^2|} \text{Im}[e^{-j\theta} (\bar{u}_p + \bar{u}_c)(u_p - u_c)]$$

$\Theta$  phase shift


- Between the two nodes results



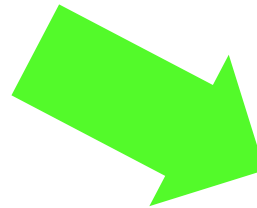
underestimate



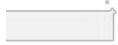
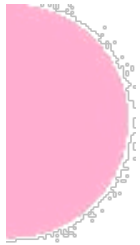
# Validation test for $\lambda$ estimation



Real  $\lambda$   
analysis

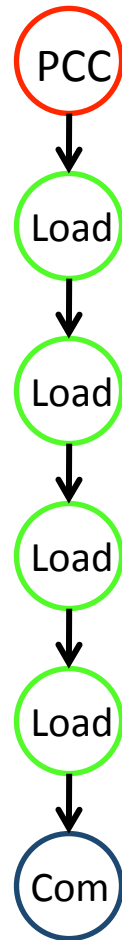


Estimate  $\lambda$   
analysis

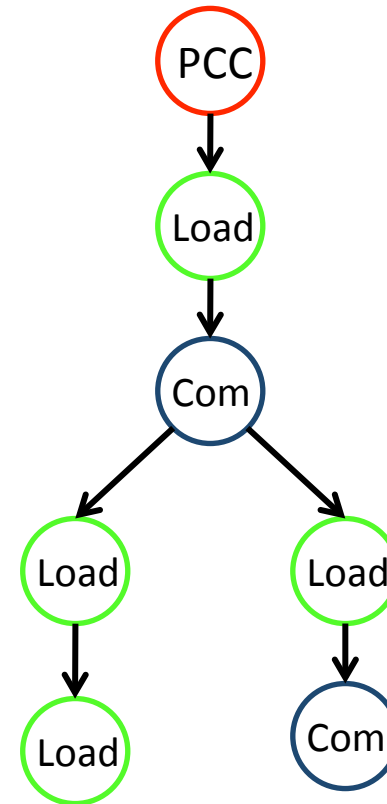


# Test Grid

## Aligned nodes

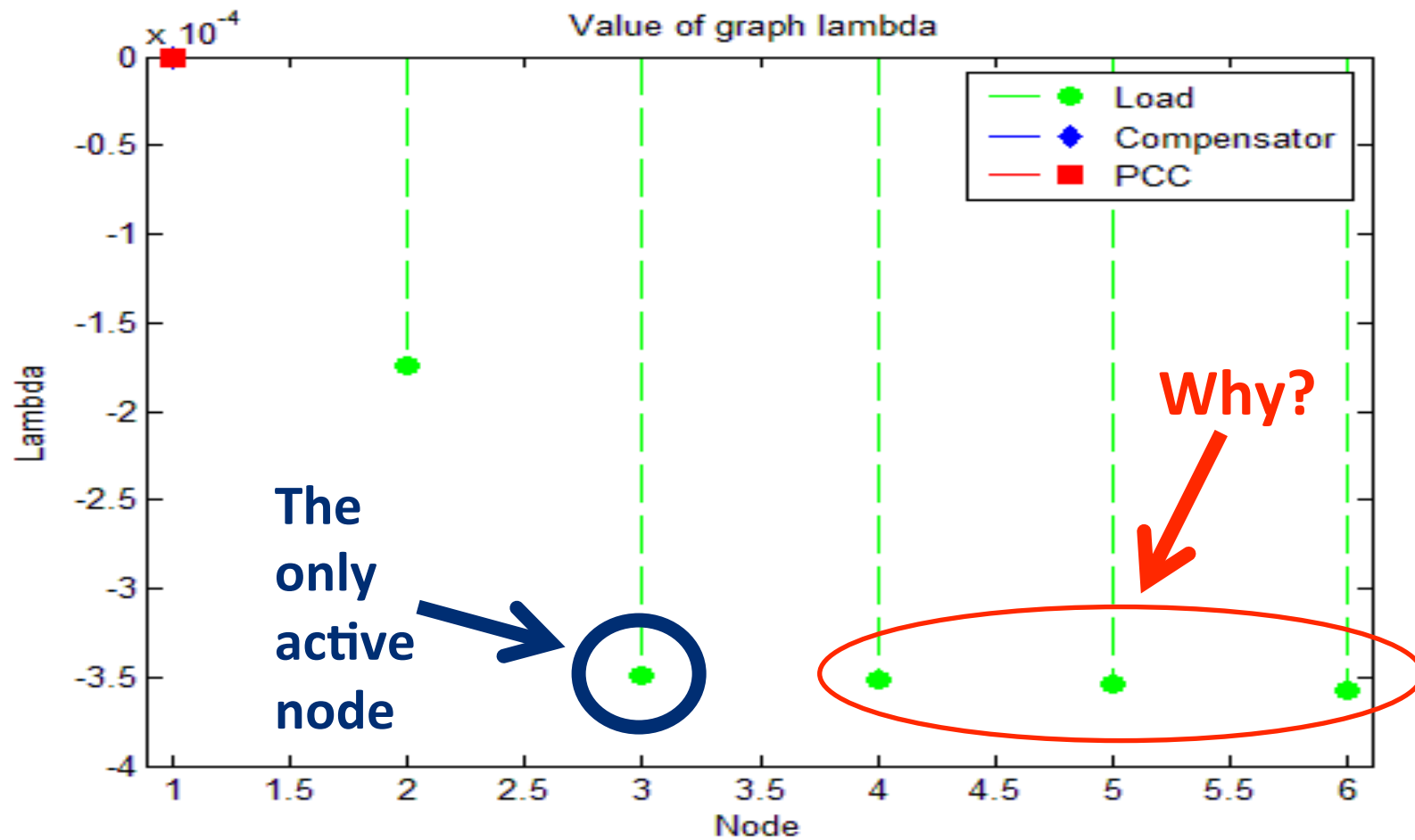


## Symmetric bifurcation



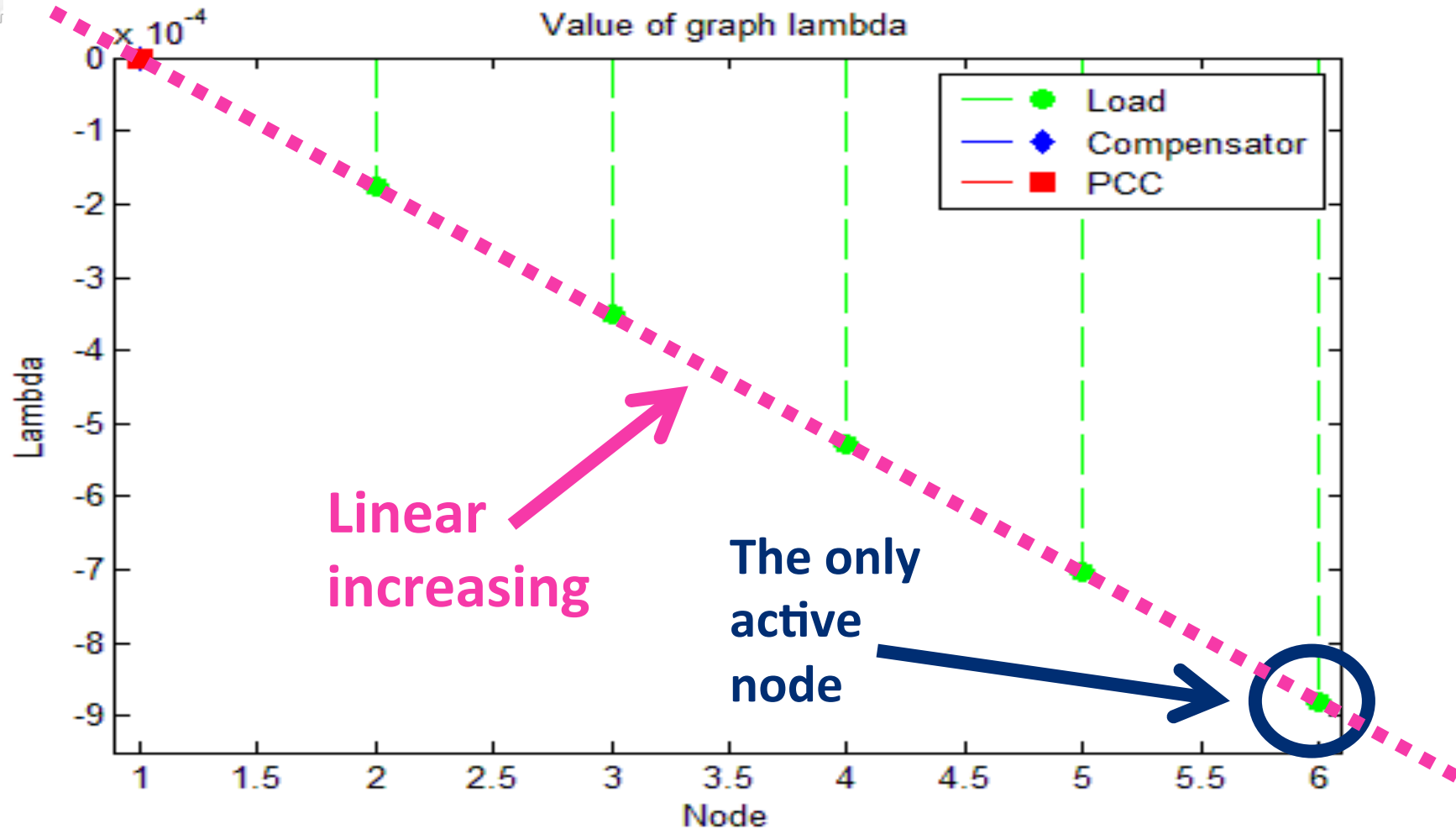
# 1° observation

Branch with no power flowing ( $\lambda \neq 0$ )



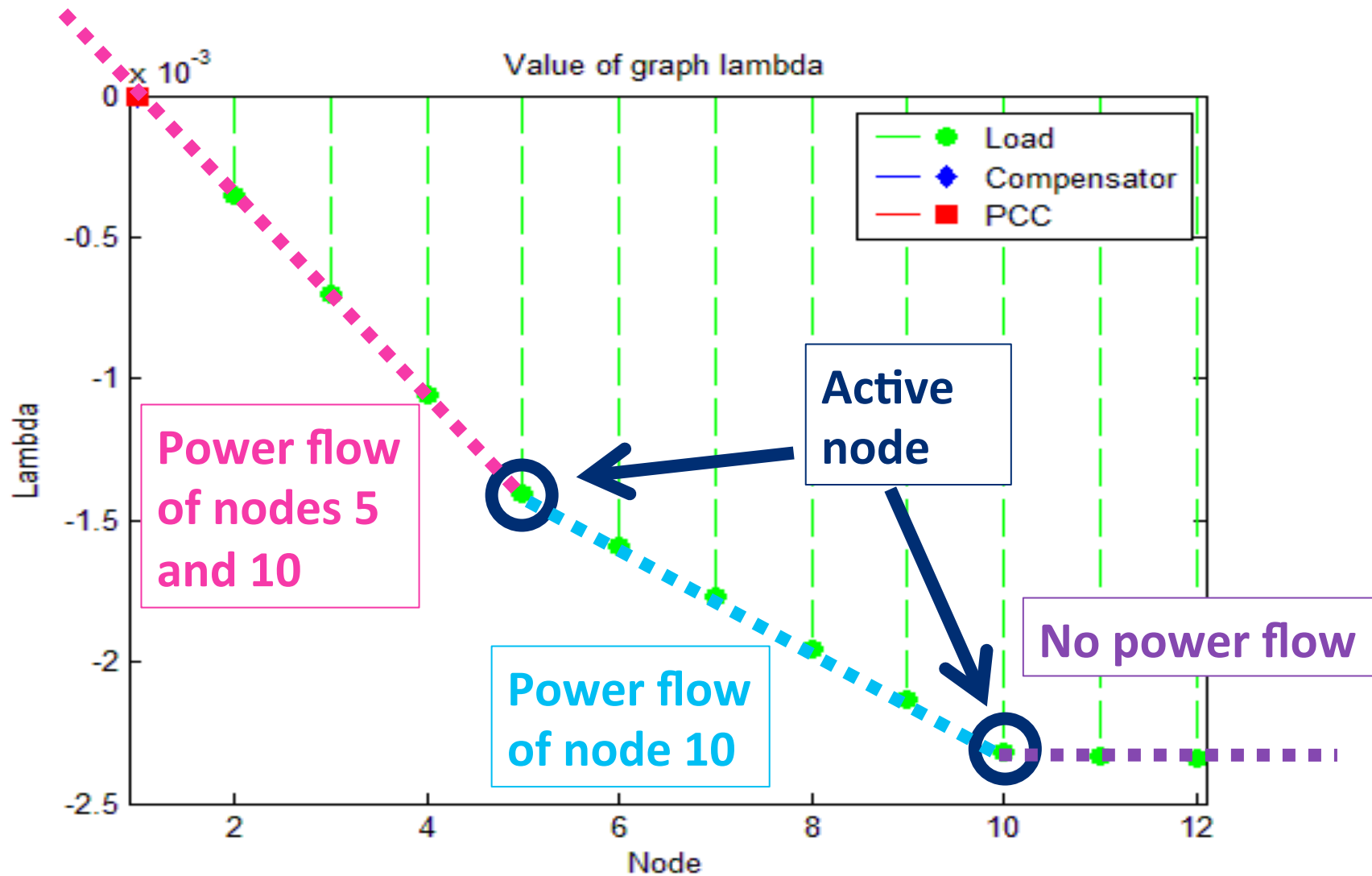
# 2° observation

Linear increasing of  $\lambda$  in a branch with constant power flowing



# 3° observation

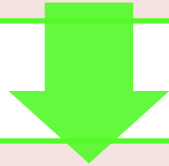
Superposition of the various effects



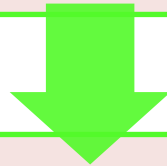


# Performance of the $\lambda$ estimation

Simple grid



Different absorptions

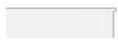
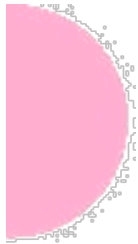


Many compensators



-Not homogeneous grid

-Depth tree



# Hypothesis of no homogeneity

If we have different impedance phase angles:

$$\mathbf{X} = e^{j\theta} X$$

then the assumption done on  $\text{Re}(\mathbf{X})$  isn't true  
and we can't extract the phase angles from  $\mathbf{X}$



Anyway, the homogeneous hypothesis is a  
realistic assumption in the smart microgrid



# Depth tree

The error increases with the increase of depth tree. This is due to two errors:

$$\lambda_c = \lambda_p + \frac{\cos \theta^2}{|u_0^2|} \text{Im}[e^{-j\theta} (\bar{u}_p + \bar{u}_c)(u_p - u_c)]$$

from parent  $\lambda$

from upgrade



Nevertheless :

- we can consider compensator information
- generally, we have 12-20 levels of depth



# Parent-child communication strategies

Ordered

- Right upgrades
- Time:  $\# \text{ levels} - 1$



Randomized

- Wrong upgrades
- Time:  $\geq \# \text{ nodes} - 1$



Centralized

- Only voltage needed
- Time: 1 step



# Shadow prices interpretation



$\lambda_i$  tells us approximately how much more profit the process could make for a small increase in availability of resource  $q_i$

**Lagrange Multiplier = Shadow Price**

However, the cost function  $f_0(x)$  doesn't consider all the benefits related to reactive power

~~**Lagrange Multiplier = Shadow Price**~~

# Storage strategy

$f_0(x)$  doesn't consider:

- voltage constraints
- congestion constraints



We define a storage strategy in order to evaluate what is truly convenient for a compensator:

**Sell or Store** active power?

# Compensator limitations

A compensator provides an apparent power  $A$  that is function of the active power  $P$  and of the reactive power  $Q$ .

These quantities are linked by Boucherot theorem:

$$\overline{A}^2 = \overline{P}^2 + \overline{Q}^2$$

Where bars indicate the available active power or the reactive power required.

The inverter installed on the compensator is characterized by an apparent power limitation  $M$ . Thus, we have two cases:

- $M \geq \bar{A}$  → No limitation
- $M < \bar{A}$  → Limitation is active

**We must decide whether to sell or to store active power**



# What to do in case of limitation?

## Time $t=0$

At the initial time we suppose to provide the whole active power and produce a quantity  $Q(t=0)$  of reactive power

The corresponding inverter limitation is:

$$M(t_0)^2 = P(t_0)^2 + Q(t_0)^2 = \bar{P}^2 + Q(t_0)^2$$

Where the reactive power tends to zero.

## Time t=1

Suppose to increase the reactive power to:

$$Q(t_1) = Q(t_0) + dQ$$

Due to active limitation, we must decrease the active power sold and store a certain quantity:

$$dS(t_1)^2 = Q(t_1)^2 - Q(t_0)^2 \Rightarrow dS(t_1) = dQ \sqrt{\left(1 + 2 \frac{Q(t_0)}{dQ}\right)}$$

For any production increment of reactive power we can consider an equal storage quantity:

$$dS = dQ$$

# Cost function

storage isn't free

considering the storage inefficiency  $\eta$

$$dC = \eta dS \$P = \eta dQ \$P$$

Where  $\$P$  is the unit price of active power

# Gain function using $\lambda$

For an infinitesimal variation of reactive power we assume a linear increasing of active power

$$dP = \lambda dQ$$

From which we obtain the gain function:

$$dG = \lambda dQ \$P$$

Where  $\$P$  is the unit price of active power

# Profits inequality

To have profits we need to comply with:

$$dG \geq dC$$

Solving the inequality we obtain:

$$1 \leq \frac{\lambda}{\eta}$$

**Never true**

$$\lambda < 0.05$$

$$\eta = 0.1 - 0.07$$

We have a confirmation that  $\lambda$  hasn't all the necessary information for pricing



## Gain function with Q price

Assuming to know the correct reactive power price  $\$Q$ , we can define the gain:

$$dG = dQ \$Q$$

Solving the profit inequality, we obtain:

$$\$Q \geq \eta \$P \cong 0.1 \$P$$

It is plausible that in some cases reactive power importance is very high even higher than the active power one

# Conclusions

$\lambda \neq$  shadow price for

- Voltage limits
- Risk of congestion

**Pricing**  **Storage strategy**

## Future developments

- Define a new cost function
- Build different Lagrangians
- Abandon Lagrange theory