

Scheduling of residential load with Real Time Pricing

Jürgen Herreiner
Master Wirtschaftsingenieurwesen

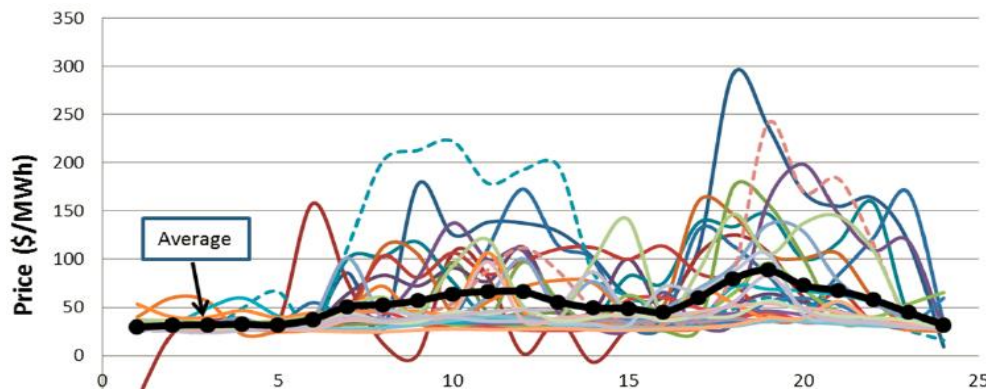
Institute for Industrial Production (IIP)
Chair of Energy Economics



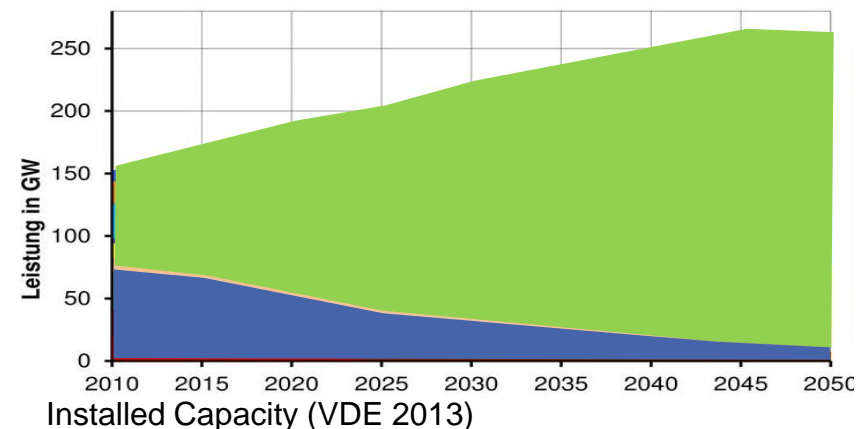
Motivation for Real Time Pricing

- Liberalization of the energy market
- Economic efficiency
- Climate Change
- Penetration with Renewable Energy Sources (RES)
- Decentralization
- How real-time is Real Time Pricing (RTP)
- RTP models in various countries

■ Con. power generation
 ■ RES



LMP at Newark Bay, USA Feb. 2013 (Hogan 2013)



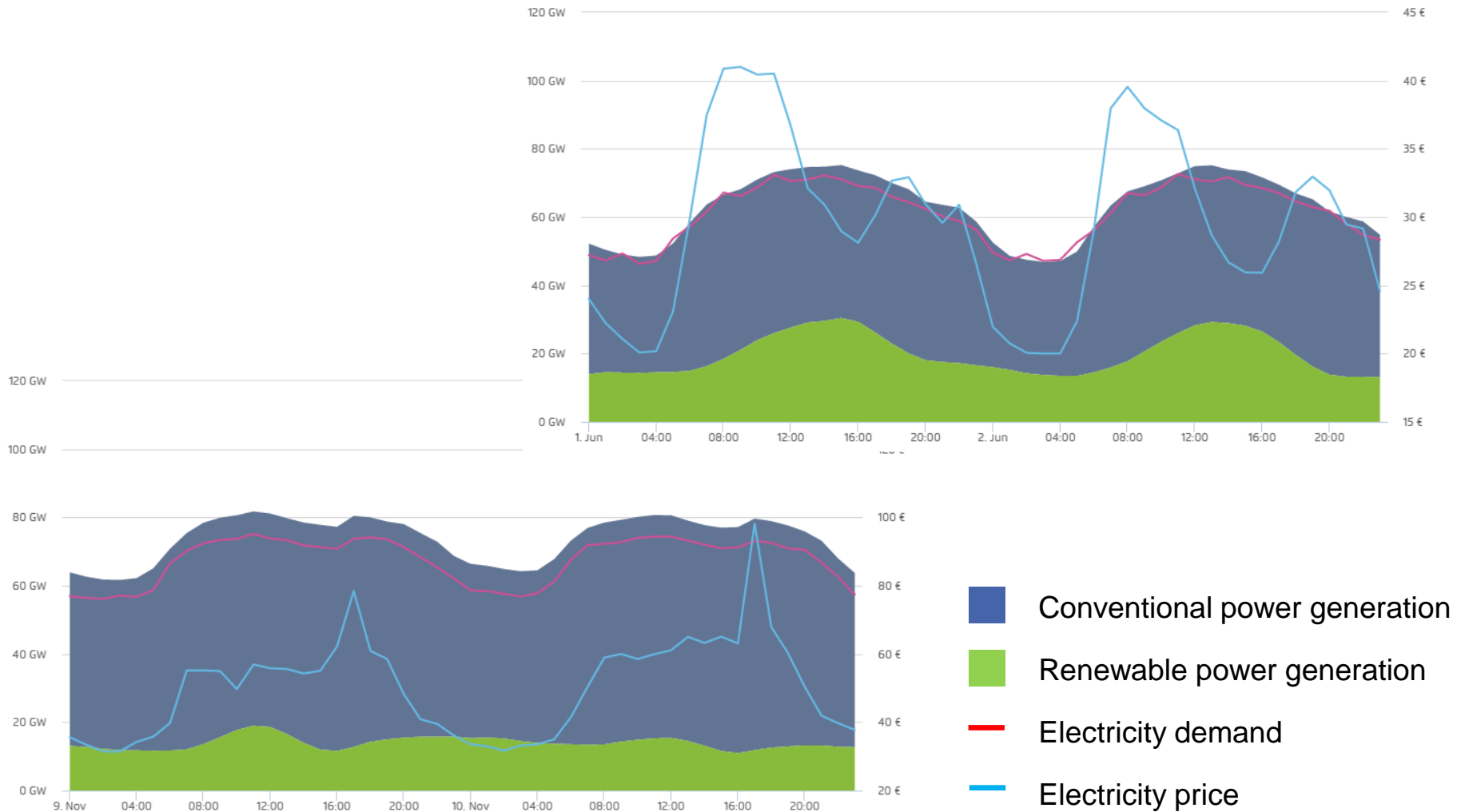
Agenda

- 1** Introduction
- 2** Overview of different scheduling models
- 3** Conclusion & outlook

Agenda

- 1** Introduction
- 2** Overview of different scheduling models
- 3** Conclusion & outlook

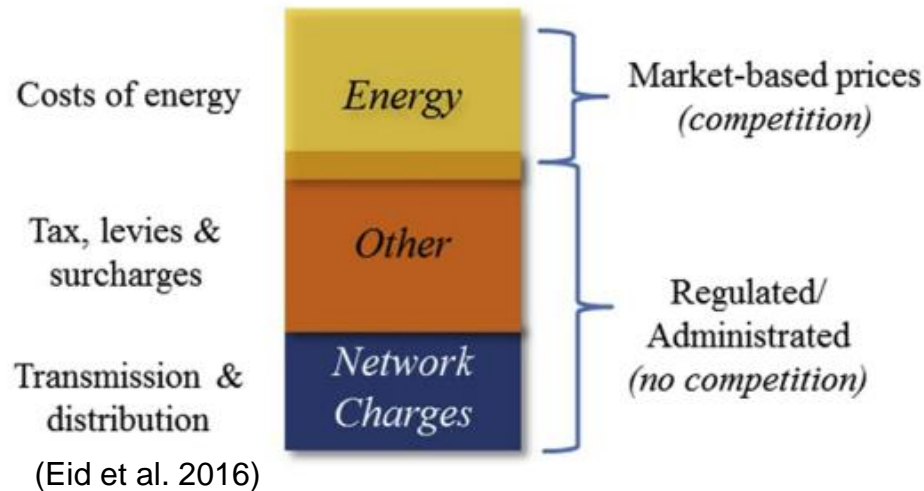
Electricity price, generation, consume



Agora-Energiewende 2016

Electricity Price (Eid et al. 2016)

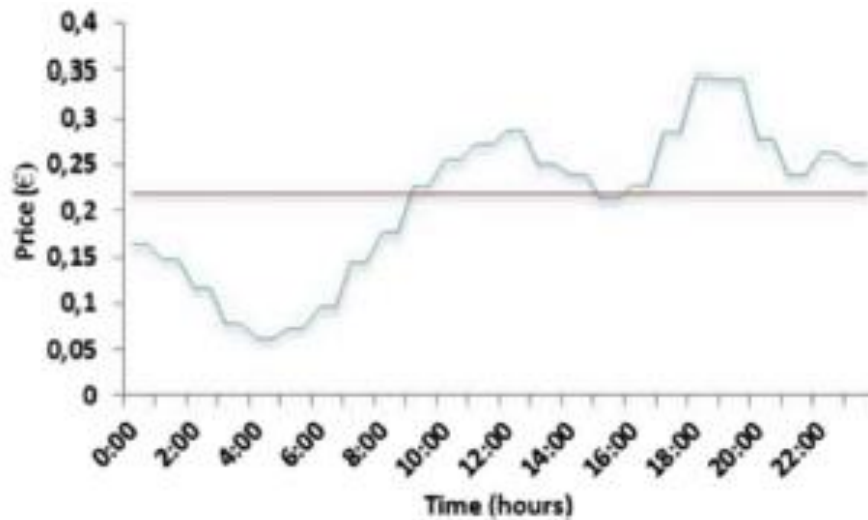
■ General composition of energy prices:



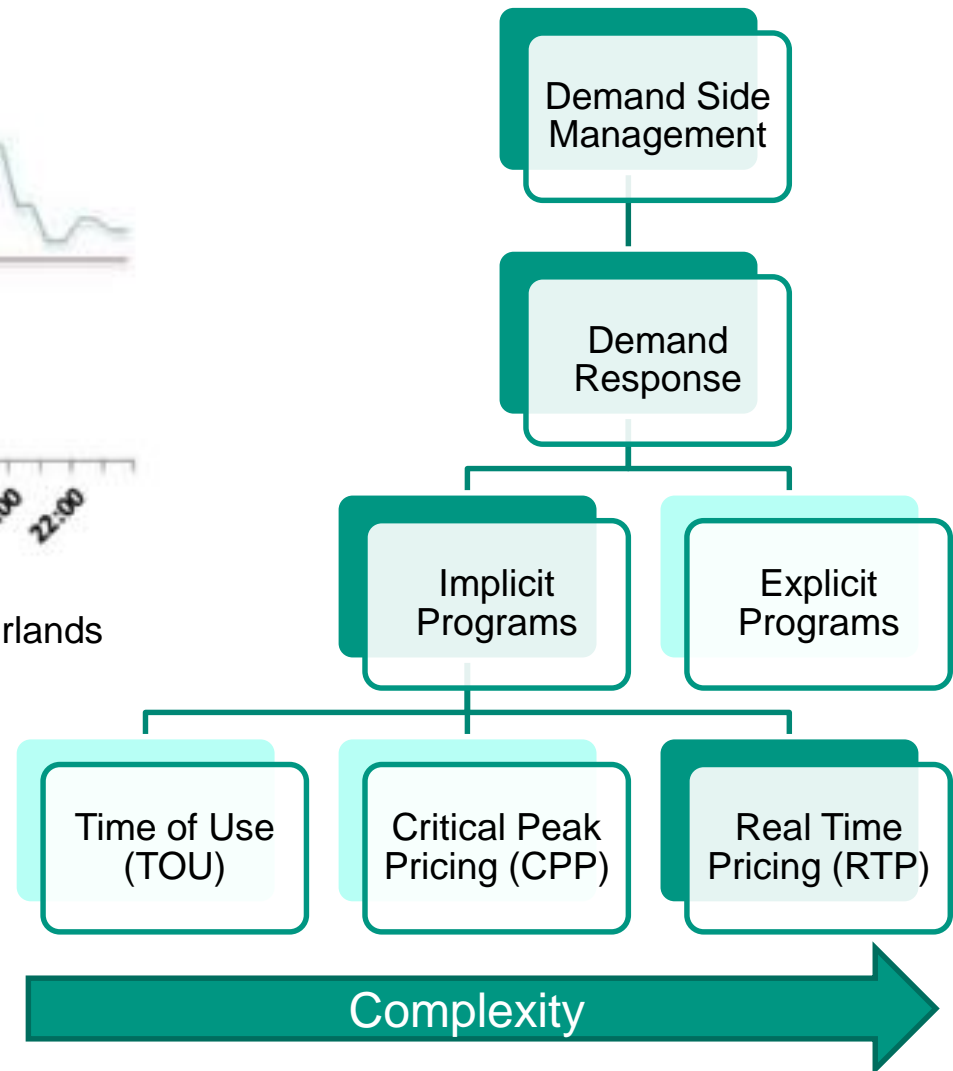
■ Possibilities of flexible pricing:

- Full Dynamic Prices, e.g. dynamic distribution & retail price
- Semi Dynamic Prices, e.g. fixed distribution & dynamic retail price
- Other arrangements, e.g. specific contract from aggregator

Categorization of Demand Response (DR)

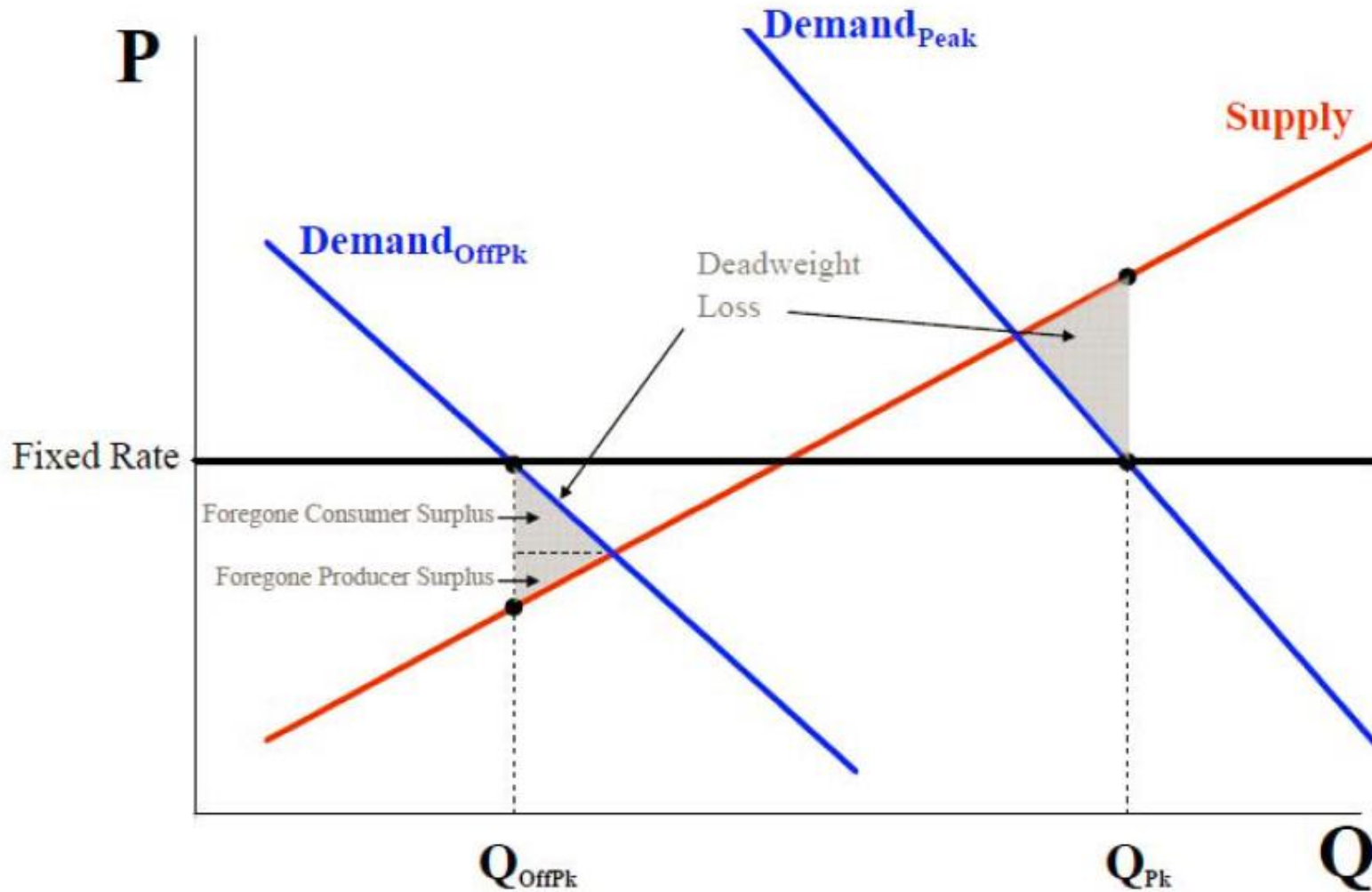


Day Ahead Prices & fixed rate in the Netherlands
(Eid et al. 2016)



Categories of DR (Moghaddam et al. 2011)

Relevance and state of the art



Economic efficiency loss (Hogan 2013)

Relevance and state of the art

Energy Economic

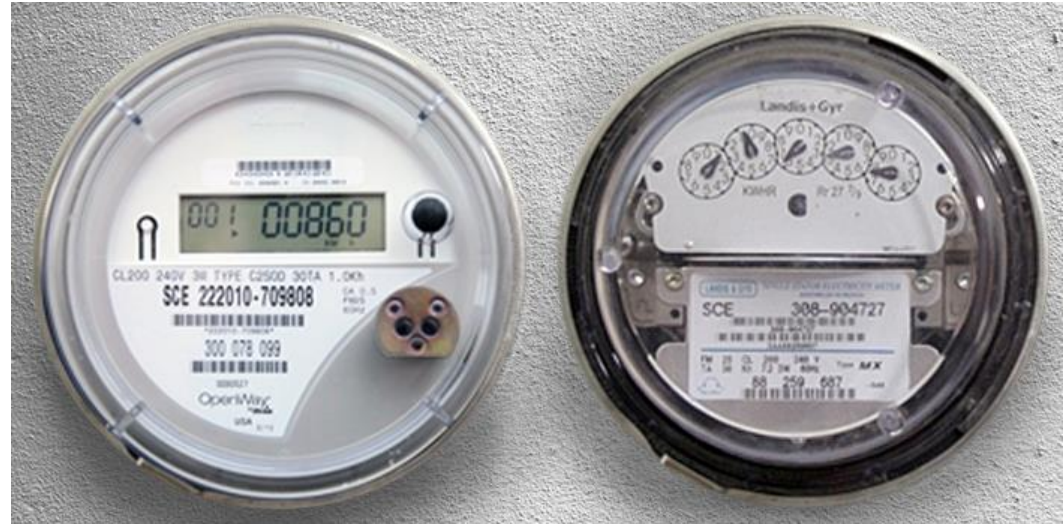
- Industrial DR
- Residential DR
 - Sweden with 100% Smart Meter roll out
 - RTP in Breda, Netherlands

Political

- EU
 - Energy Efficiency Directive (EED) – 2012/27/EU
- Germany
 - Amendment of the German energy law in 2016 – Design for electricity market 2.0
 - Digitalization of the “Energiewende”

Infrastructure

- Smart Meter
“A smart meter is an Internet-capable device that measures energy, water or natural gas consumption of a building or home.”¹
- Gateway
Hub for HAN,
WAN, LMN



(Devalo 2016)



(Lackman 2016)

¹<http://internetofthingsagenda.techtarget.com/definition/smart-meter>

Agenda

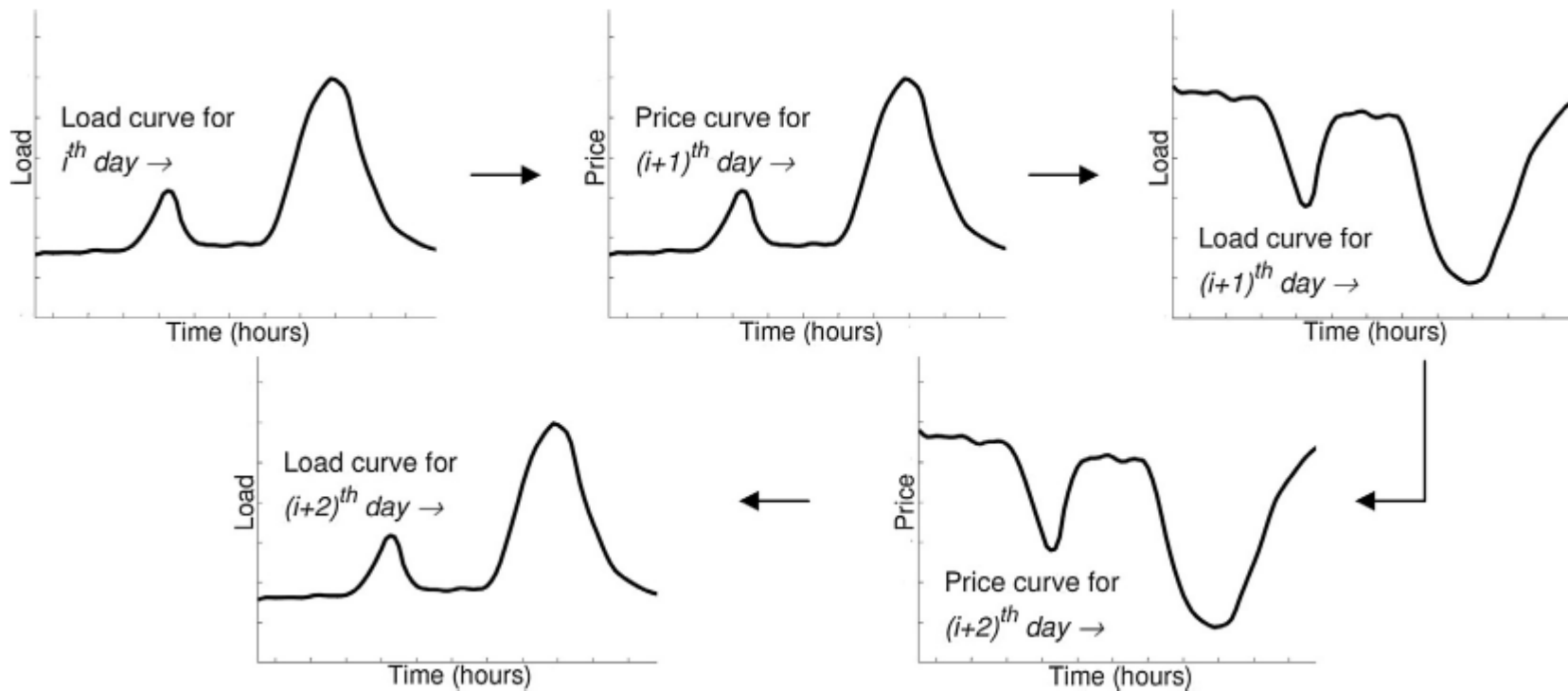
- 1** Introduction
- 2** Overview of different scheduling models
 - 2.1** Scheduling model with Inclining Block Rates
 - 2.2** Scheduling model with community focus
- 3** Conclusion & outlook

Categorization

	Chen et al. 2012	Edward et al. 2015	Chang et al. 2013	Mohensian -Rad et al. 2010	Anees & Chen 2016
Optimization model	Stochastic & robust optimization	Game theoretical approach	Stochastic optimization	Linear optimization	Linear optimization
Modified price prediction	Mixed	Yes	No	Mixed	Yes
Inclining Block Rates	No	No	No	Yes	Yes
Community focus	No	Yes	Mixed	No	Yes

Problem of Peak Load Shifting

- Primitive individual RTP optimization reduces the electricity bill, but has no beneficial influence on Peak to average (PAR)



Peak load shifting (Anees et al. 2016)

Agenda

- 1** Introduction
- 2** Overview of different scheduling models
 - 2.1** Scheduling model with Inclining Block Rates
 - 2.2** Scheduling model with community focus
- 3** Conclusion & outlook

Price Prediction in Real Time Electricity Pricing Environment

(Mohsenian-Rad et al. 2010)

■ Model architecture:



■ Parameters to be set by the consumer:

- Total energy needed for the operation of an appliance
- Possible beginning and ending time
- Maximum power level and minimum stand-by power level

Pricing

Inclining Block Rates

$$p^h(l^h) = \begin{cases} a^h, & \text{if } 0 \leq l^h \leq c^h \\ b^h, & \text{if } l^h > c^h. \end{cases}$$

Prediction

$$\hat{a}^h[t] = k_1 a^h[t-1] + k_2 a^h[t-2] + k_7 a^h[t-7], \quad \forall h \in \mathcal{H}$$

p^h price in hour h

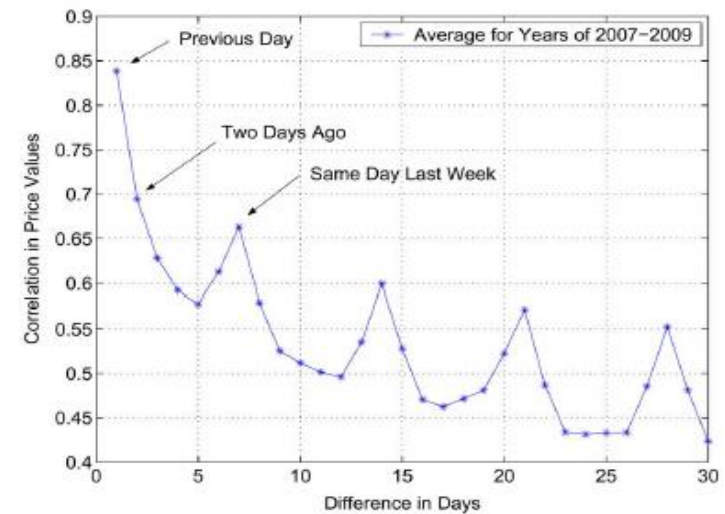
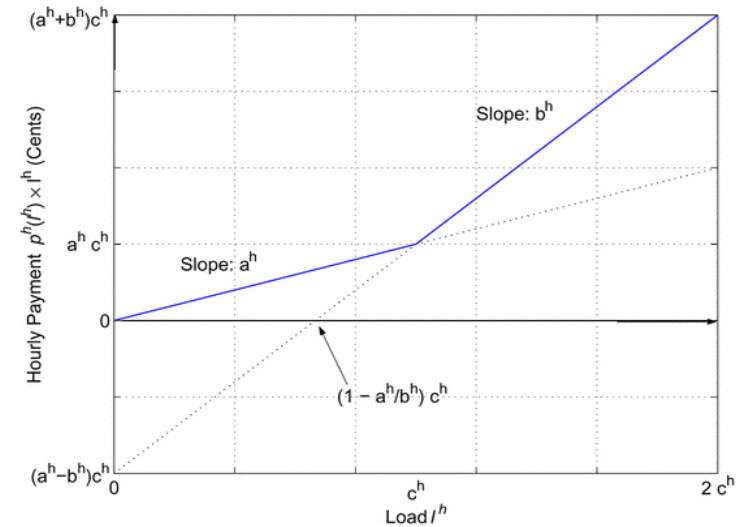
l^h consumption of consumer in hour h

a^h, b^h prices in hour h

\hat{a}^h predicted price in hour h

c^h threshold value in hour h

k_i price prediction coefficient for weekday i



Optimization problem & special cases

■ Optimization problem

$$\begin{aligned}
 \underset{x \in \mathcal{X}}{\text{minimize}} \quad & \sum_{h=1}^P \max \left\{ a^h \sum_{a \in \mathcal{A}} x_a^h, b^h \sum_{a \in \mathcal{A}} x_a^h + (a^h - b^h)c^h \right\} \\
 & + \sum_{h=P+1}^H \max \left\{ \hat{a}^h \sum_{a \in \mathcal{A}} x_a^h, \right. \\
 & \quad \left. \hat{b}^h \sum_{a \in \mathcal{A}} x_a^h + (\hat{a}^h - \hat{b}^h)c^h \right\} \\
 & + \lambda_{\text{wait}} \sum_{h=1}^H \sum_{a \in \mathcal{A}} \frac{(\delta_a)^{\beta_a - h} x_a^h}{E_a}
 \end{aligned}$$

X scheduling set

A set of appliances

x_a^h consumption of appliance a in h

H scheduling horizon

P price announcement horizon

λ_{wait} importance of the waiting cost

δ_a trade off control for each a

E_a required energy for a

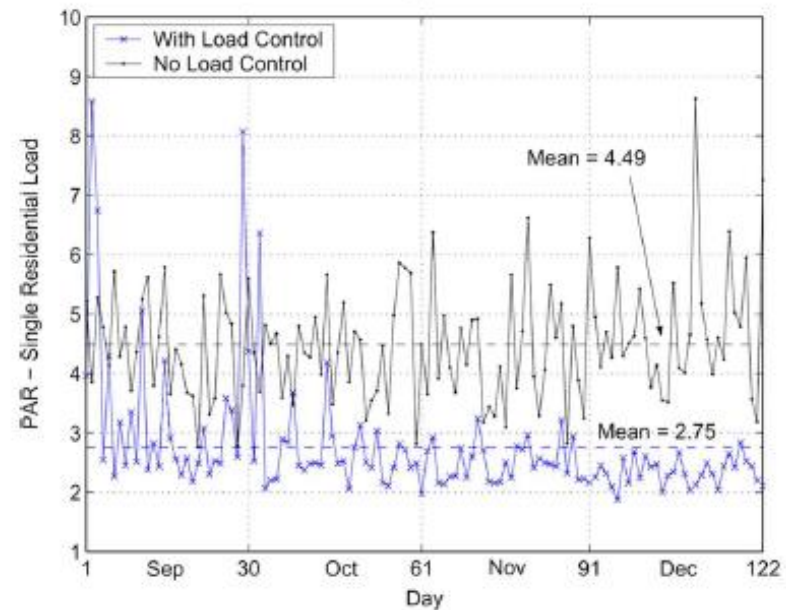
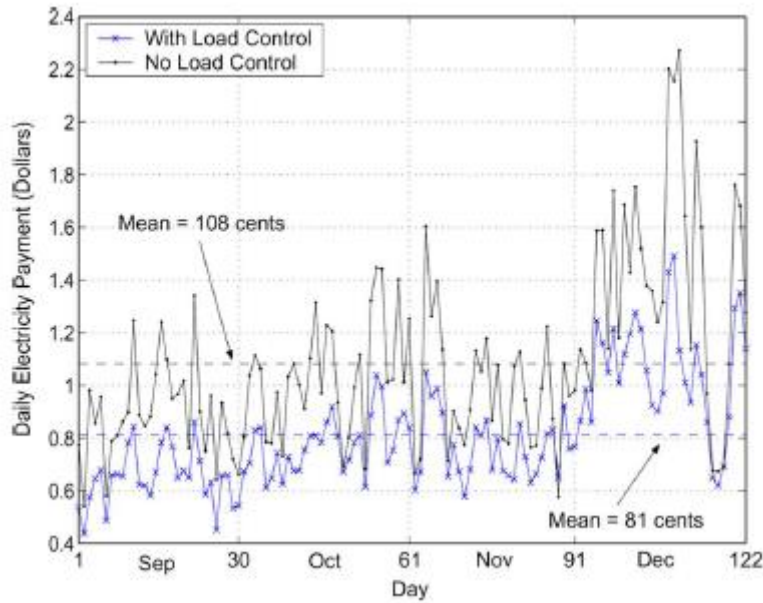
■ Special cases

- Discrete energy consumption level,
- Residential electricity storage, ...

Results

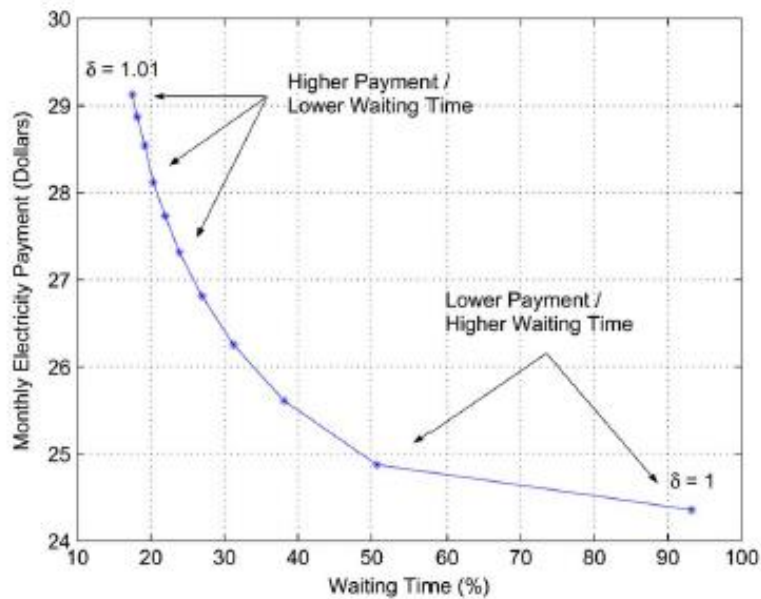
- Electricity bill reduced by 25%

- PAR reduced by 38%



Results

- Waiting Time decrease from 93.2% to 17.5%



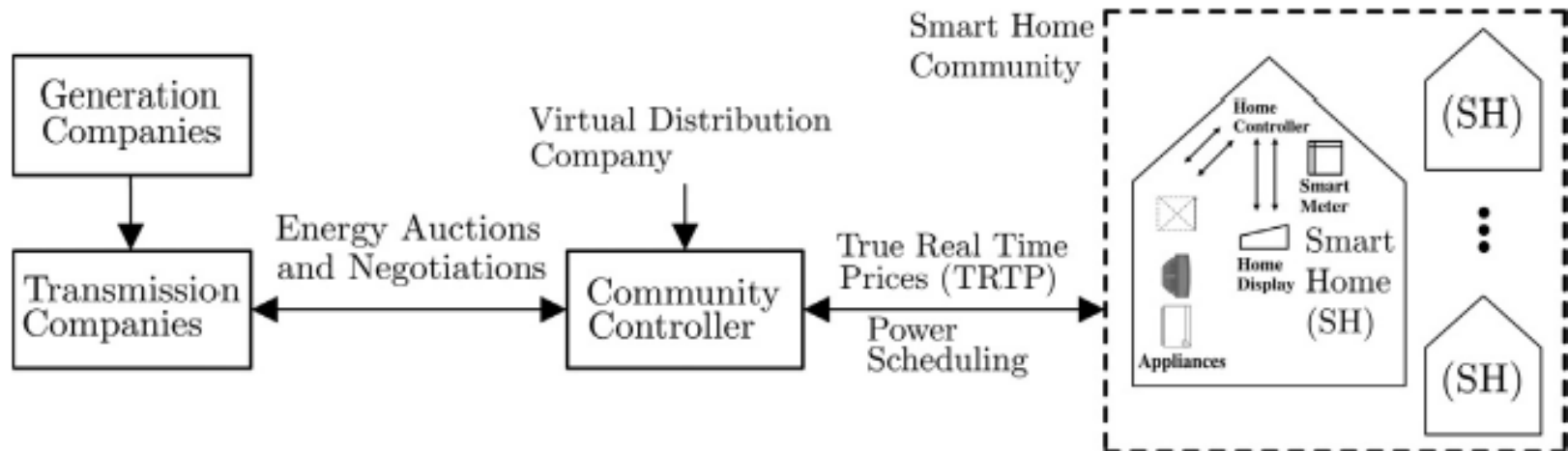
Agenda

- 1** Introduction
- 2** Overview of different scheduling models
 - 2.1** Scheduling model with Inclining Block Rates
 - 2.2** Scheduling model with community focus
- 3** Conclusion & outlook

True Real Time Pricing and combined power scheduling

(Anees & Chen 2016)

■ Combined Community



True Real Time Pricing

- Function of the combined load
- Time of use coefficients calculated ahead with the maximum, minimum and central ratio load and related prices

$$P_t = a_t L_t^2 + b_t L_t + c_t$$

a_t, b_t, c_t time of use coefficients

L_t total community load

Pricing

- IBR with two dynamic threshold values $\chi_{1(t)}, \chi_{2(t)}$ and threshold pricing constants ζ_1, ζ_2

$$P_t = \begin{cases} \{a_t L_t^2 + b_t L_t^2 + c_t\}, & \text{if } 0 \leq cns m_t \leq \chi_{1(t)} \\ \zeta_1 * \{a_t L_t^2 + b_t L_t^2 + c_t\}, & \text{if } \chi_{1(t)} < cns m_t \leq \chi_{2(t)} \\ \zeta_2 * \{a_t L_t^2 + b_t L_t^2 + c_t\}, & \text{if } cns m_t > \chi_{2(t)} \end{cases}$$

- Dynamic threshold values with threshold constants κ_1, κ_2

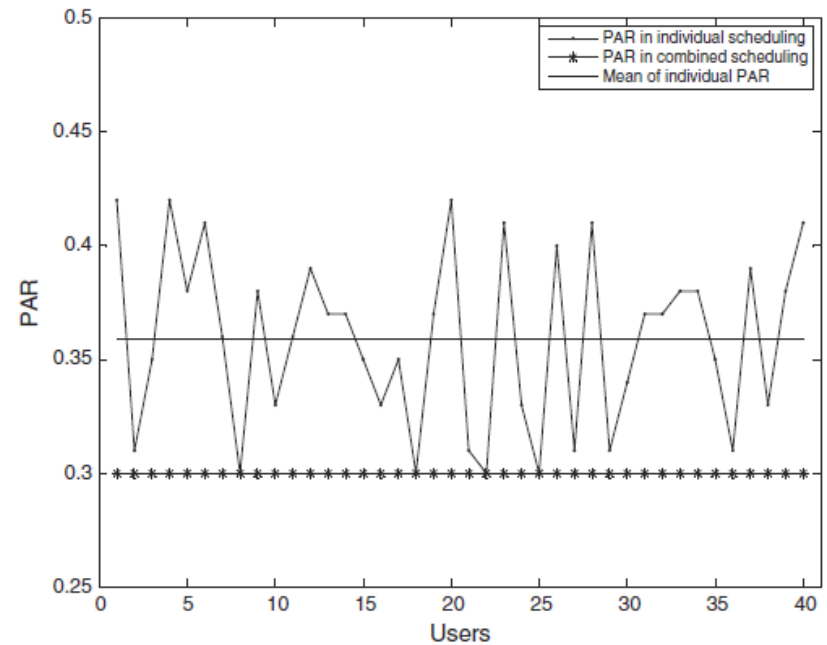
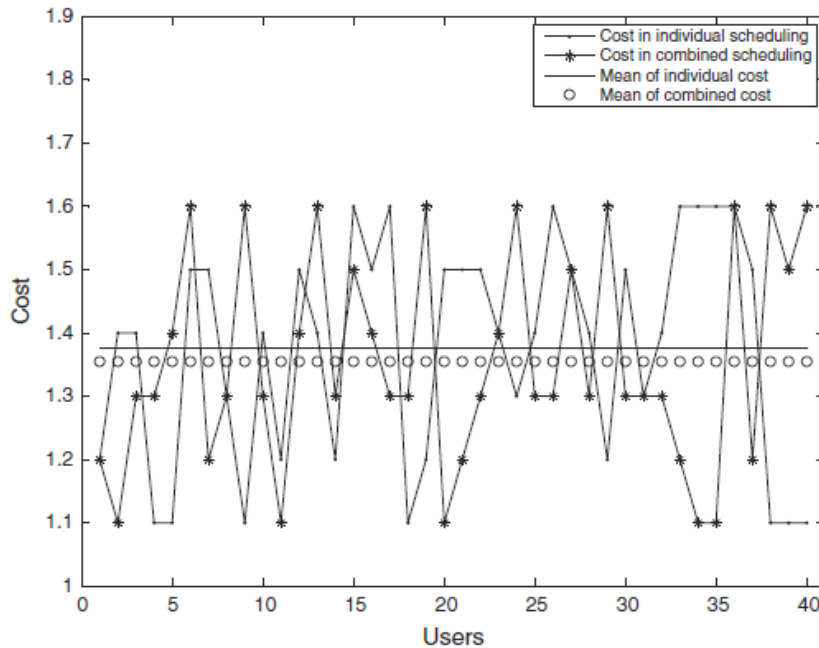
$$\chi_{1,t} \propto \kappa_1 \frac{1}{L_t} \quad \chi_{2,t} = \kappa_2 \chi_{1,t}$$

- Partial cost division

Results

- Electricity bill reduction of 1.5% by combined scheduling

- PAR reduction of 16% by combined scheduling



Agenda

- 1 Introduction
- 2 Overview of different scheduling models
- 3 Conclusion & outlook

Is Real Time Pricing Green? (Holland & Mansur 2008)

- IBR necessary to avoid peak load shift
- Changes in generation affect emissions
- Influence depending on specific power generation for a region

Future potential

- Increasing household knowledge
- Increasing automatism
- Coordination problem: e.g. oversupply of wind, but high transmission costs → security of supply as indicator and one final tariff
- IT security – news about hackers in Finnish electricity network, causing a shut down
- Frequency based pricing
- Blockchain Pricing

References

- Anees, A., & Chen, Y. P. P. (2016). True real time pricing and combined power scheduling of electric appliances in residential energy management system. *Applied Energy*, 165, 592-600.
- Chang, T. H., Alizadeh, M., and Scaglione, A., (2013). Real-Time Power Balancing Via Decentralized Coordinated Home Energy Scheduling. *IEEE Transactions on Smart Grid*, 4(3),1490-1504.
- Chen, Z., Wu, L., and Fu, Y. (2012). Real-Time Price-Based Demand Response Management for Residential Appliances via Stochastic Optimization and Robust Optimization. *IEEE Transactions on Smart Grid*, 3(4), 1822-1831.
- Deutscher Bundestag (2016). Entwurf eines Gesetzes zur Digitalisierung der Energiewende
- Deutscher Bundestag (2016). Gesetz zur Weiterentwicklung des Strommarktes (Strommarktgesetz. *Bundesgesetzblatt*
- Eid, C., Koliou, E., Valles, M., Reneses, J., & Hakvoort, R. (2016). Time-based pricing and electricity demand response: Existing barriers and next steps. *Utilities Policy*.

References

- Holland, S. P., & Mansur, E. T. (2008). Is real-time pricing green? The environmental impacts of electricity demand variance. *The Review of Economics and Statistics*, 90(3), 550-561.
- Mohsenian-Rad, A. H., & Leon-Garcia, A. (2010). Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE transactions on Smart Grid*, 1(2), 120-133.
- Schäfer, B. Matthiae, M. Timme, M. Witthaut, D. (2015). Decentral Smart Grid Control. *New Journal of Physics*.
- Stephens, E. R., Smith, D. B., and Mahanti, A., "Game Theoretic Model Predictive Control for Distributed Energy Demand-Side Management," in *IEEE Transactions on Smart Grid*, vol. 6, no. 3, pp. 1394-1402, May 2015.

Backup (Mohsenian-Rad et al. 2010)

$$\mathbf{x}_a \triangleq [x_a^1, \dots, x_a^H]$$

$$\sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a$$

$$\gamma_a^{\min} \leq x_a^h \leq \gamma_a^{\max}, \quad \forall h \in [\alpha_a, \beta_a].$$

$$\sum_{a \in \mathcal{A}} x_a^h \leq E^{\max}, \quad \forall h \in \mathcal{H}$$

$$\mathcal{X} = \left\{ \mathbf{x} \mid \begin{array}{l} \sum_{h=\alpha_a}^{\beta_a} x_a^h = E_a, \quad \forall a \in \mathcal{A}, \\ \gamma_a^{\min} \leq x_a^h \leq \gamma_a^{\max}, \quad \forall a \in \mathcal{A}, h \in [\alpha_a, \beta_a], \\ x_a^h = 0, \quad \forall a \in \mathcal{A}, h \in \mathcal{H} \setminus [\alpha_a, \beta_a], \\ \sum_{a \in \mathcal{A}} x_a^h \leq E^{\max}, \quad \forall h \in \mathcal{H} \end{array} \right\}$$

- Energy consumption scheduling vector for each appliance
- Total energy issued, has to be equal the total energy required
- Energy issued within the min stand by and max. power level
- Limit on the total energy consumption at each residential unit at each hour

Backup (Mohsenian-Rad et al. 2010)

$$\sum_{h=1}^H \sum_{a \in \mathcal{A}} \rho_a^h x_a^h$$

$$\rho_a^h = \frac{(\delta_a)^{\beta_a - h}}{E_a}, \quad \forall a \in \mathcal{A}, h \in [\alpha_a, \beta_a]$$

$$\rho_a^{\alpha_a} \leq \dots \leq \rho_a^{\beta_a}, \quad \forall a \in \mathcal{A}$$

$$\sum_{h=1}^H \frac{(\delta_a)^{\beta_a - h} x_a^h}{E_a} = 1, \quad \forall \mathbf{x} \in \mathcal{X}$$

$$\text{Waiting Time} = \frac{\mu_a - \alpha_a}{\beta_a - \alpha_a} \times 100$$

- Cost of waiting
- Model for the waiting parameter
- Cost increase with increasing waiting time
- If $\delta_a = 1$

Backup (Mohsenian-Rad et al. 2010)

$$\begin{aligned}
 & \underset{\substack{x \in \mathcal{X} \\ v^h, \forall h \in \mathcal{H}}}{\text{minimize}} \sum_{h=1}^H v^h + \lambda_{\text{wait}} \sum_{h=1}^H \sum_{a \in \mathcal{A}} \frac{(\delta_a)^{\beta_a - h} x_a^h}{E_a} \\
 & a^h \sum_{a \in \mathcal{A}} x_a^h \leq v^h, \quad \forall h \in \mathcal{P}, \\
 & b^h \sum_{a \in \mathcal{A}} x_a^h + (a^h - b^h)c^h \leq v^h, \quad \forall h \in \mathcal{P}, \\
 & \hat{a}^h \sum_{a \in \mathcal{A}} x_a^h \leq v^h, \quad \forall h \in \mathcal{H} \setminus \mathcal{P}, \\
 & \hat{b}^h \sum_{a \in \mathcal{A}} x_a^h + (\hat{a}^h - \hat{b}^h)\hat{c}^h \leq v^h, \quad \forall h \in \mathcal{H} \setminus \mathcal{P}.
 \end{aligned}$$

- Including auxiliary variables to achieve differentiability

Backup (Mohsenian-Rad et al. 2010)

- Avoiding load synchronization → random starting delay
- Announcing the consumption back to the utility → 2 way communication
- Load reduction requests → increasing prices
- Residential electricity storage → including negative loads for discharging, but price monitoring problem for the charging process
- Accommodating changes users' energy needs → recalculation with new situation and update of total energy usage