



Decentralized Control of RES by Fast Market-based MAS

IRP 1.2

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Work in Progress

Optimal bidding with planning ahead of DERs in real-time market-based control under uncertainty

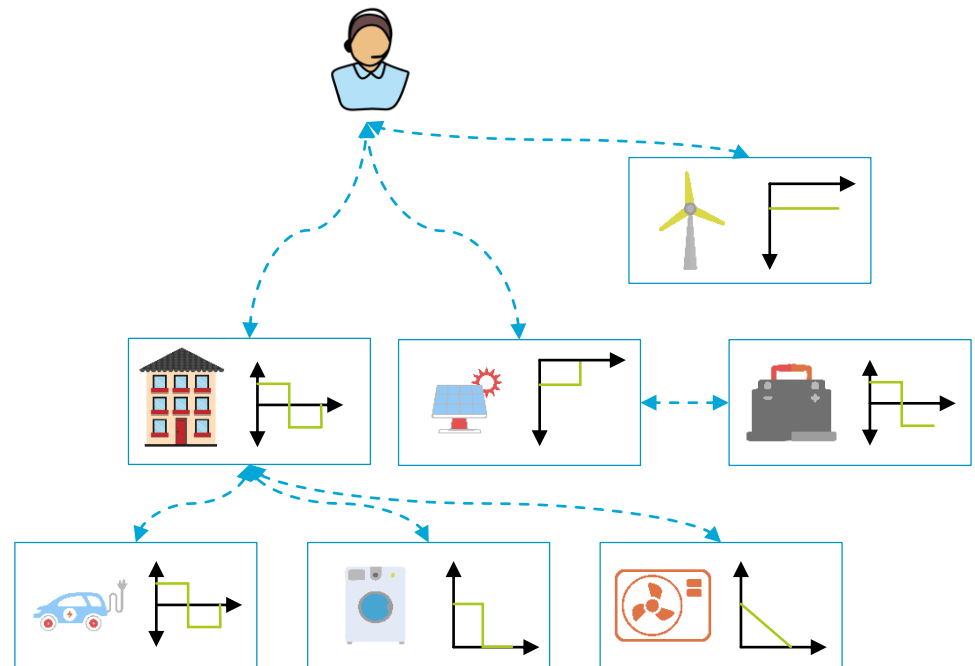


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Introduction

- Flexibility utilization through real-time market-based control.
- Flexible/inflexible device agents in automated market.
- Agents bid subject to
 - Uncertainty.
 - Local constraints.
 - Local objective.
- Market is cleared, clearing price communicated.
- Local control actions are taken based on market price and bid.



Introduction

Top-down Switching

- No privacy/ No autonomy.
- Highly scalable/ No openness.
- Response unknown.

Price-based Control

- Full privacy/ Full autonomy.
- Highly scalable/ Open.
- Response unknown.

Centralized Optimization

- No privacy/ No autonomy.
- Poor scalability/ No openness.
- Response known.

Market-based Control

- High privacy/ High autonomy.
- Highly Scalable/ Open.
- Response known.

Challenges

Lack of planning ahead in real-time MBC

► Leads to Sub-optimal use of flexibility over time.

- Multi-settlement markets:
 - Complex bidding, risk of gaming.
- Iterative/negotiation mechanisms:
 - Long/uncertain clearing time, dependence on initial conditions.
- Cooperative mechanisms:
 - Not suitable with self-interested agents.
- Central scheduling:
 - Lack of privacy.

Research Problem

Inefficient utilization of flexibility within distribution grids with high penetration of DERs.

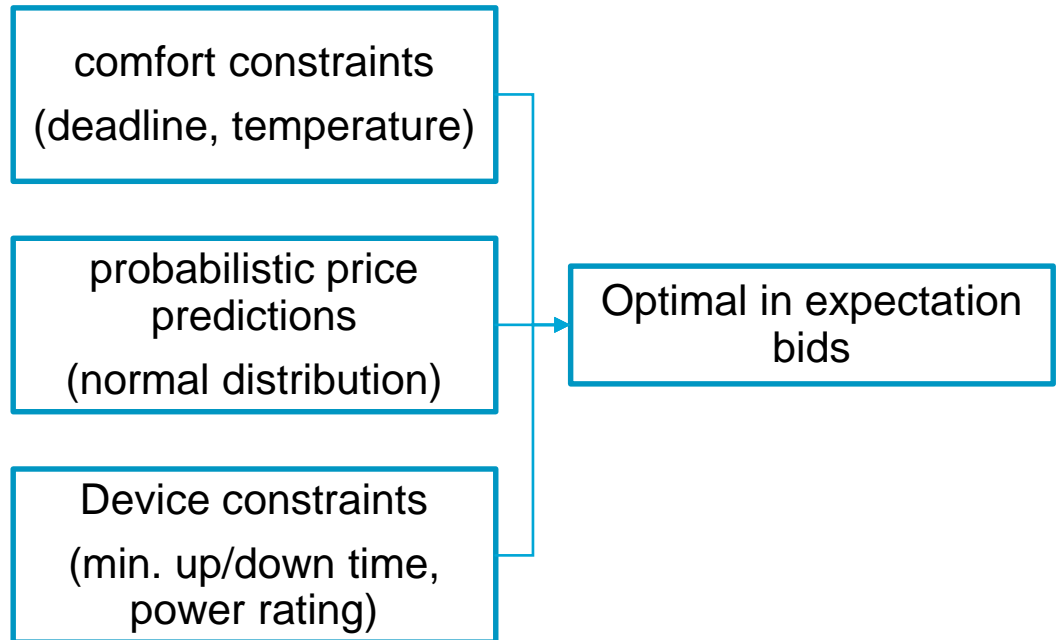
Optimal bidding with
planning ahead

Effect of regularly updated
price predictions

Decentralized network
constraint management

Overview

- Optimal-in-expectation bidding algorithms.
- Speed, scalability are required.
- Limitations
 - Small computational capability.
 - Heterogeneity.
- Challenges
 - Continuous state-space, action space.
 - Time dependency.



Methodology

- In Literature,
 - Uncertainty in neglected (i.e. deterministic planning).
 - Simplified models/assumptions.
 - Complex, unscalable.
-
- MDP,
 - Planning over multiple time-steps with uncertainty.
 - Threshold policies,
 - Scalability.
 - Specialized algorithms,
 - Heterogeneity.

Complete information

Optimal in expectation

Deterministic

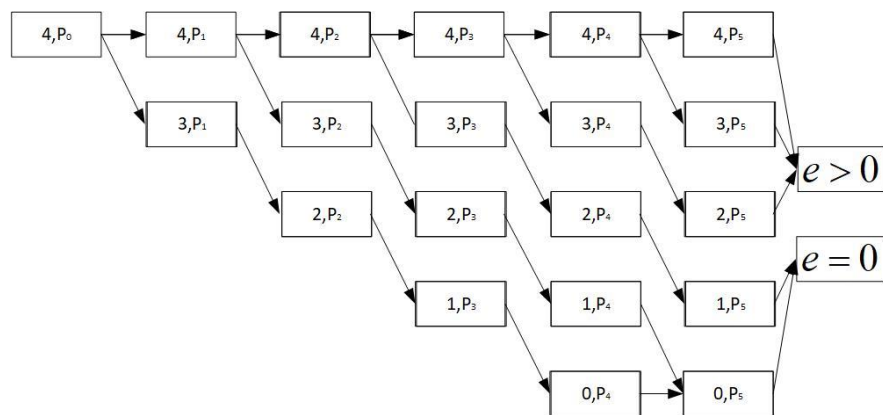
Naive

MDP Model

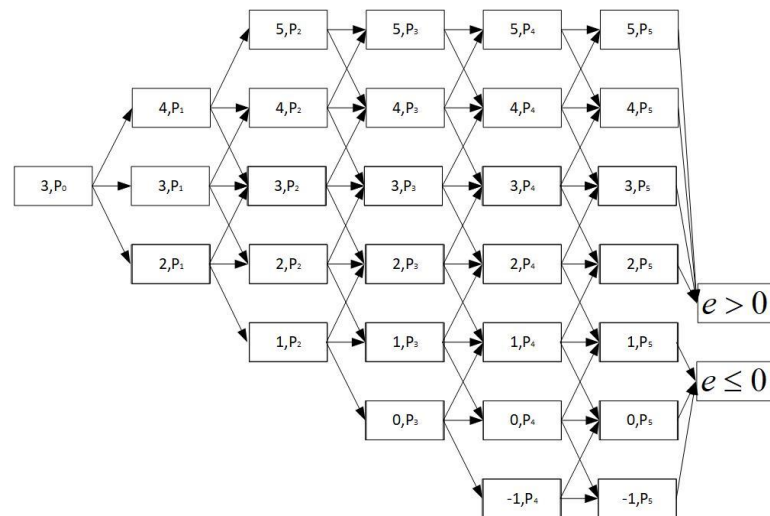
- Discrete time steps indexed by t .
- First bid is formulated and submitted at $t = 0$.
- The last bid a device submits is formulated and submitted at $t = T - 1$.
- T is the deadline set by the device owner.
- Price Predictions \bar{P}_t, σ_t .
- A device's energy reserve/state-of-charge (SOC) has a minimum and maximum E_{min} , E_{max} at any time.
- A device has a power rating of D .
- e is the required energy to fulfill a device's task.
- the state of a device at any time step is a vector of the required energy to fulfil the device's task e_t , and the real-time price $s_t = (e_t, P_t)$.
- Actions are represented by $a \in [-1, 1]$.

$$c(s_t, a) = aP_tD + c_i(s_t, a)$$

MDP Model



MDP model for uninterruptible time-shiftable device



MDP model for electric vehicle

Uninterruptible time-shiftable devices

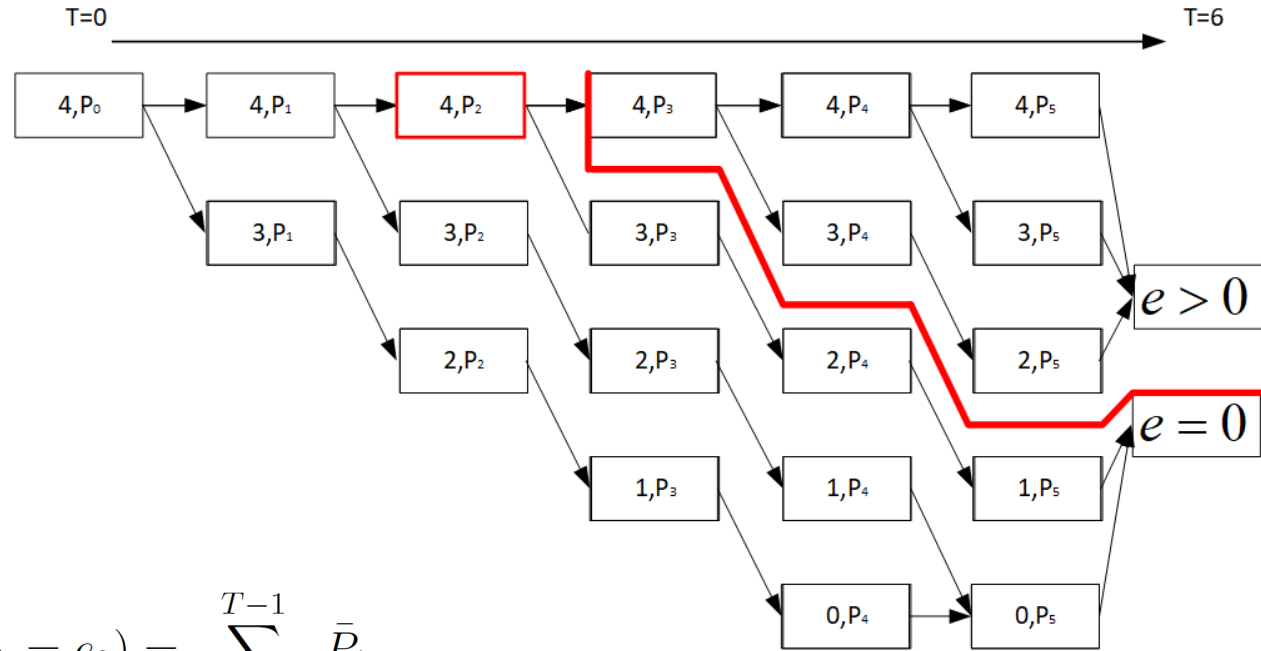
$$A_t = \begin{cases} \{1, 0\} & e_t = e_0 \\ \{1\} & 0 < e_t < e_0 \\ \{0\} & e_t = 0 \end{cases}$$

$$e_t \in \{\max(0, e_0 - Dt), \dots, e_0\} \quad \forall t$$

$$\Pr(s_{t+1} = (j, P) | s_t = (e, P_t), a_t = a) = \begin{cases} \Pr(P_{t+1} = P) & j = e - aD \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$V(s_T) = \begin{cases} 0 & e_T = 0 \\ \infty & \text{otherwise} \end{cases}$$

$$V(s_t, a) = c(s_t, a) + \mathbb{E}V(s_{t+1})$$



$$C_0\left(T - \frac{e_0}{D}\right) = \mathbb{E}V^*(s_{T-\frac{e_0}{D}} = e_0) = \sum_{i=T-\frac{e_0}{D}}^{T-1} \bar{P}_i$$

$$P_t^{th} = \max \left\{ \min \left\{ \left(C_o(t+1) - \sum_{i=1}^{D-1} \bar{P}_{t+i} \right), P_{t,max} \right\}, P_{t,min} \right\}$$

$$C_o(t) = \phi_h(t) \cdot C_o(t+1) + \phi_l(t) \cdot \left[average(P_{t,min}, P_t^{th}) + \sum_{j=1}^{D-1} \bar{P}_{t+j} \right]$$

Optimal bidding policy

$$b^*(t) = \begin{cases} 1 & 0 < e_t < e_0 \\ 0 & e_t = 0 \\ 1 & e_t = e_0, t \geq T - \frac{e_0}{D} \\ 1 & e_t = e_0, t < T - \frac{e_0}{D}, P_t \leq P_t^{\text{th}} \\ 0 & e_t = e_0, t < T - \frac{e_0}{D}, P_t > P_t^{\text{th}} \end{cases}$$

Electric Vehicles

$$e_0 = E_{T,\text{req}} - E_0$$

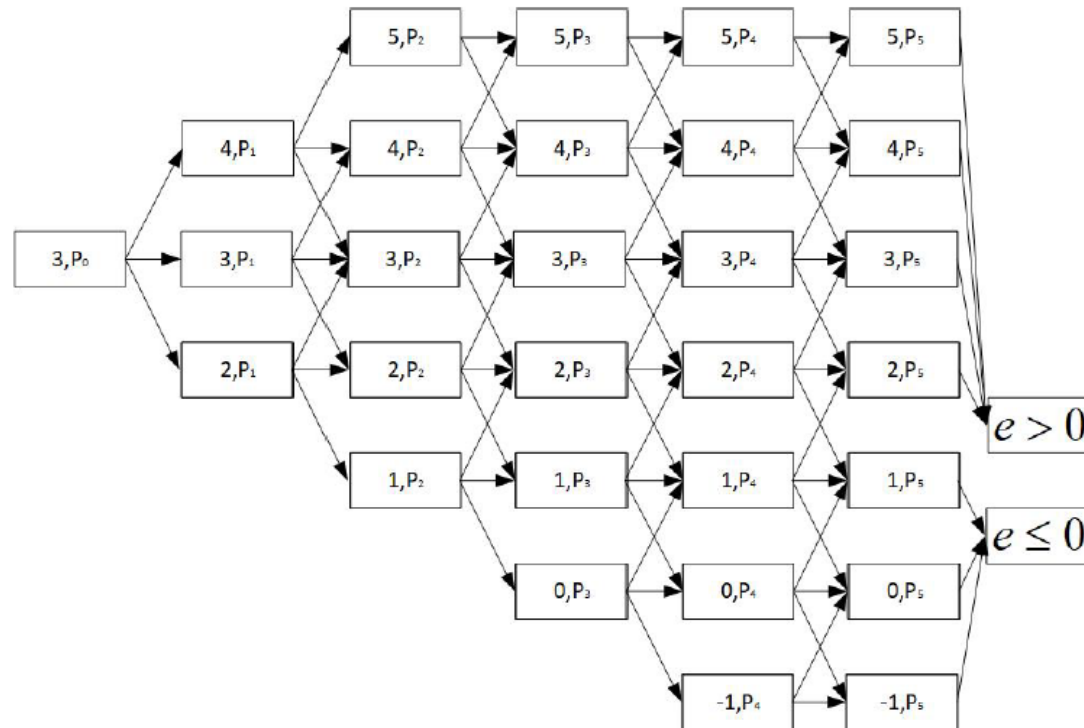
$$E_t = E_{T,\text{req}} - e_t.$$

$$A_t = \begin{cases} \{0, -1\} & E_t = E_{\max} \\ \{1, 0, -1\} & E_{\min} < E_t < E_{\max} \\ \{0, 1\} & E_t = E_{\min} \end{cases}$$

$$e_t \in \{\max(e_{\min}, e_0 - Dt), \dots, e_0, \dots, \min(e_{\max}, e_0 + Dt)\}$$

$$c_i(s_t, a) = \begin{cases} (1 - \eta)DP_t & a = -1 \\ 0 & \text{otherwise} \end{cases}$$

Electric Vehicles

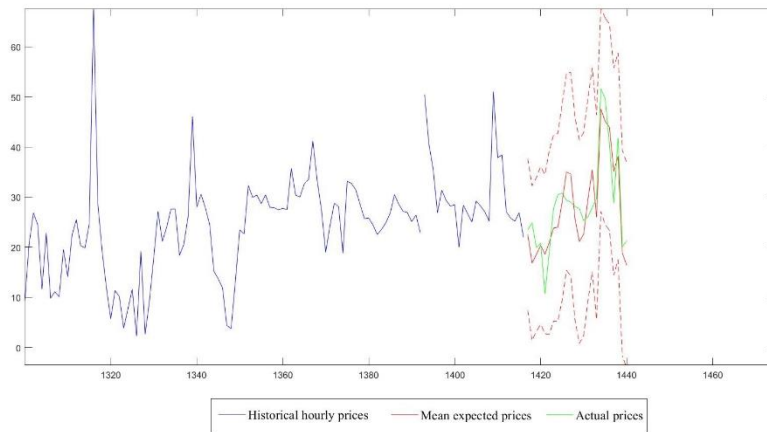


Optimal Bidding Policy

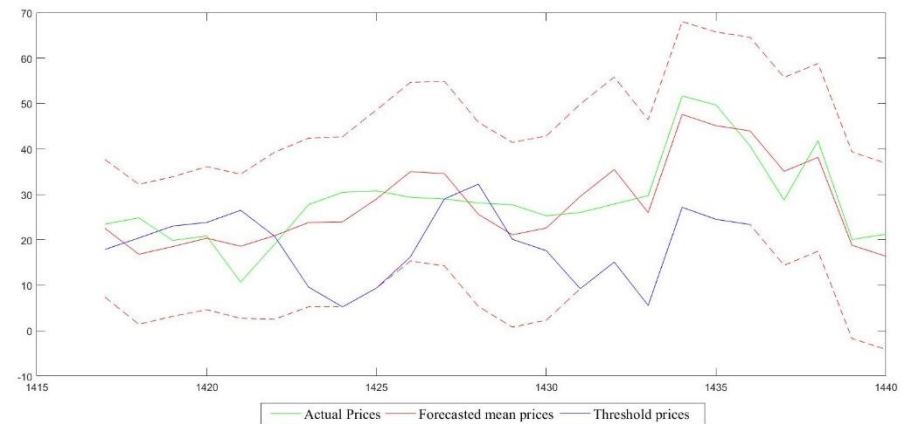
$$b^*(t) = \begin{cases} 1 & e_t \geq (T - t)D \\ -1 & e_t \leq (T - t)D \\ 1 & e_t = (T - t - 1)D \vee e_t = e_{\max}, P_t \leq P_t^{\text{th}} \\ 0 & e_t = (T - t - 1)D \vee e_t = e_{\max}, P_t > P_t^{\text{th}} \\ 0 & e_t = -(T - t - 1)D \vee e_t = e_{\min}, P_t \leq P_t^{\text{th}} \\ -1 & e_t = -(T - t - 1)D \vee e_t = e_{\min}, P_t > P_t^{\text{th}} \\ 1 & \text{otherwise, } P_t \leq P_t^{\text{th, low}} \\ 0 & \text{otherwise, } P_t^{\text{th, low}} < P_t \leq P_t^{\text{th, high}} \\ -1 & \text{otherwise, } P_t > P_t^{\text{th, high}} \end{cases}$$

Preliminary Result

Price forecasts for one day



Threshold prices vs. actual prices



THANK YOU



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