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Allocation of computing tasks in distributed MEC servers co-powered by renewable sources and the power grid

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Scenario

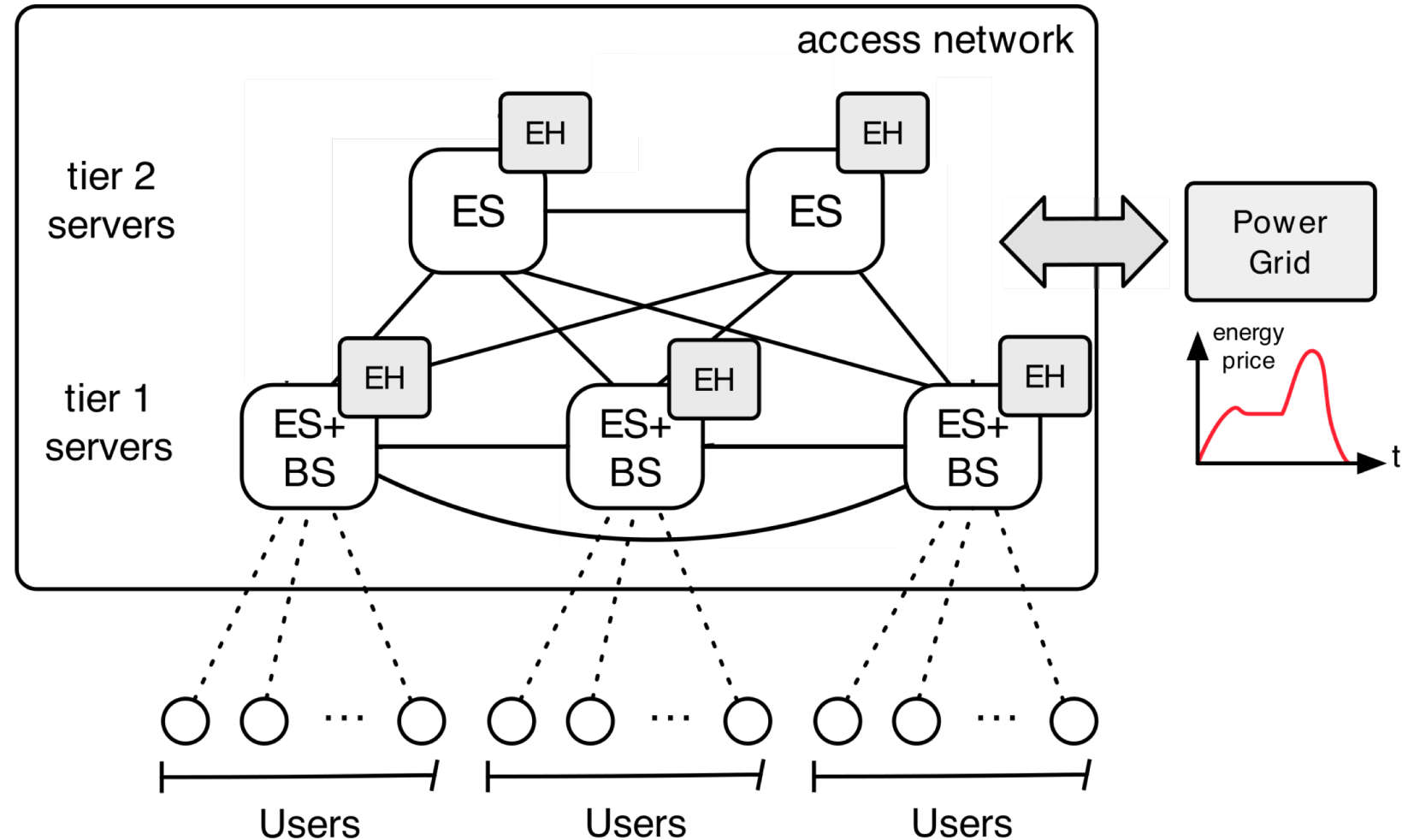


Radio Access Network

MEC architecture

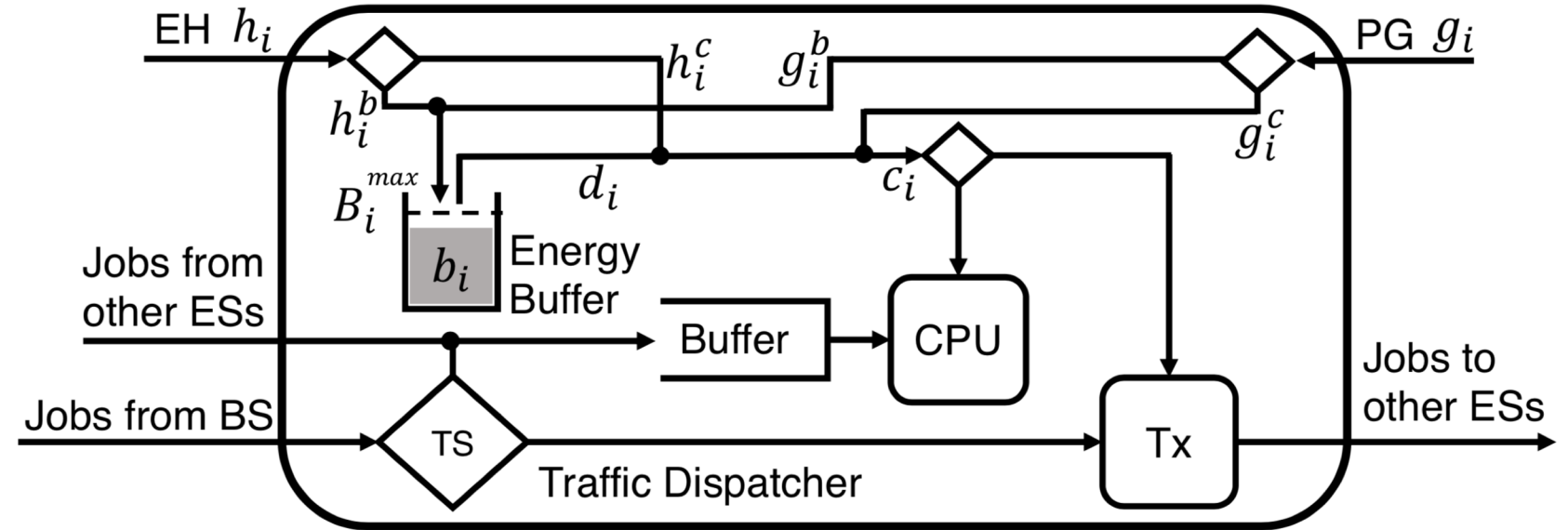
- ❖ Tier-1 servers
 - Co-located with BSs
 - ❖ Tier-2 servers
- Servers have to process users' jobs, that must be dispatched among the servers

Time is slotted





Scenario: Edge Server



- ❑ Processing unit
- ❑ Communication unit
- ❑ Energy harvesting (e.g., photovoltaics)
- ❑ Energy purchase from power grid
- ❑ Energy storage (e.g., battery)



Objective: minimize the monetary cost incurred by the servers in the energy purchases from the power grid, while executing the offloaded jobs.

Proposal: online algorithm that

- ❑ dispatches the job flows among the servers
- ❑ decides when to buy energy
- ❑ manages the batteries

Accounting for the fact that users jobs' flows, energy harvested and grid energy price are variable over time and unknown a priori.



Optimization problem

$$\begin{aligned} & \text{minimize} && \sum_{k=1}^T p(k) \sum_{i \in \mathcal{M}} g_i(k) \\ & g_i^b(k), g_i^c(k), h_i^b(k), && \\ & h_i^c(k), d_i(k), r_{ij}(k), && \\ & i \in \mathcal{M}, j \in \mathcal{M} \setminus \{i\}, 0 \leq k \leq T && \end{aligned}$$

subject to:

- Linear relations between energy consumption and job processing
- Linear relations between energy consumption and communications
- Battery levels evolution
- Job flow conservation
- Maximum harvested energy
- Maximum battery drained
- Maximum battery capacity
- Non-negativity of variables

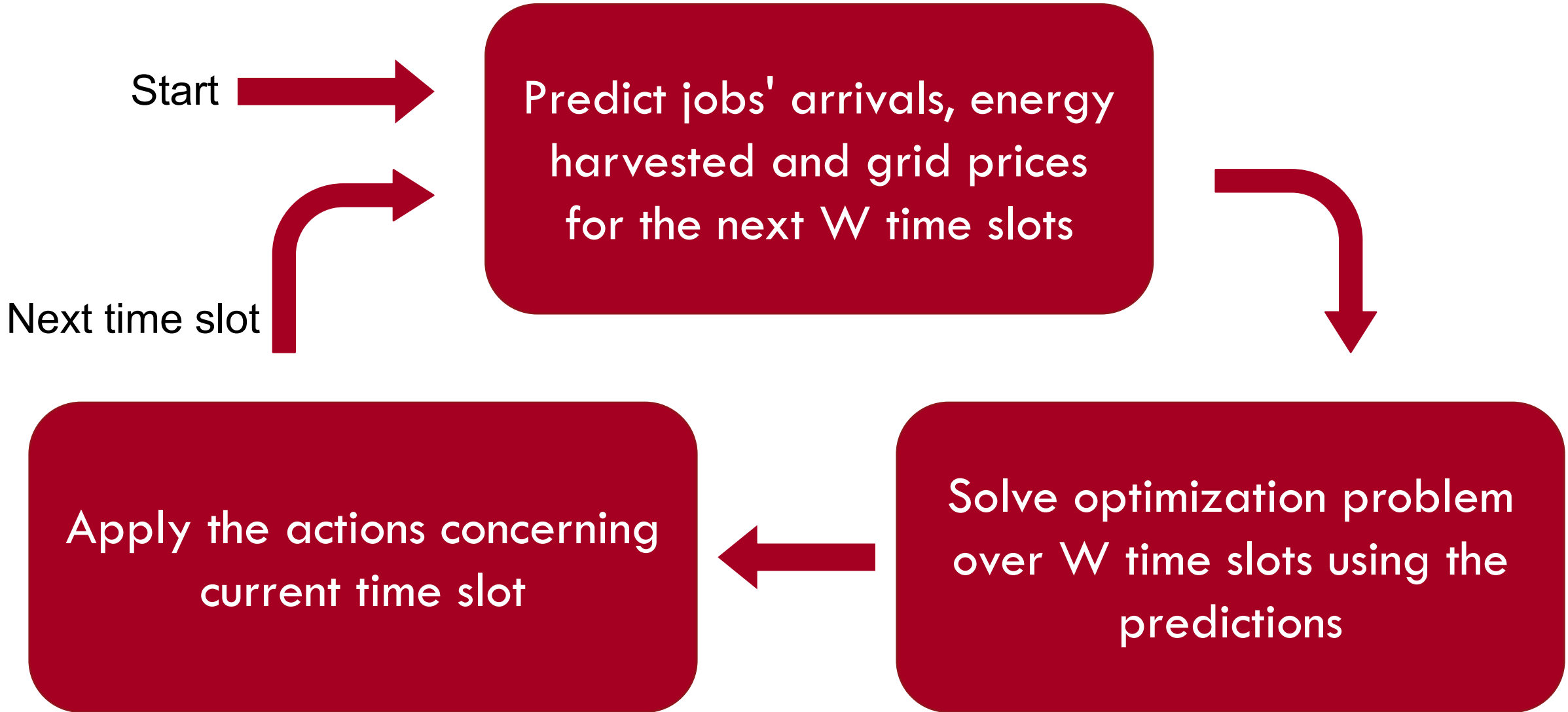
$T = \#$ of time slots
 $\mathcal{M} =$ set of servers
 $p(k) =$ energy price
 $g_i(k) =$ purchased energy



How to deal with uncertainty?

- ❑ Grid energy price: available one day ahead (“one day ahead Market”)
- ❑ Jobs’ arrivals: average load profiles of each BS are used as job flow predictions
- ❑ Energy harvested: Long Shot-Term Memory (LSTM) neural networks are used as predictor for future harvested energy availability
 - ❑ 1 hidden layer consisting of 40 neurons
 - ❑ Trained for 80 epochs over 4 years of harvested energy measurements
 - ❑ Outputs the forecasts for W time slots, by using the most recent $L=24$ samples

Online algorithm



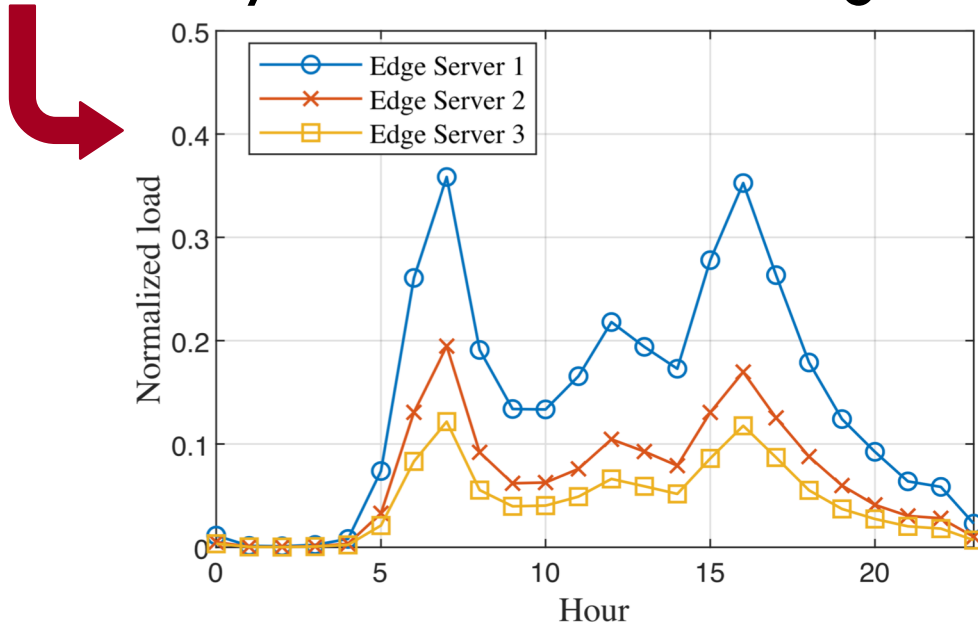


Simulations

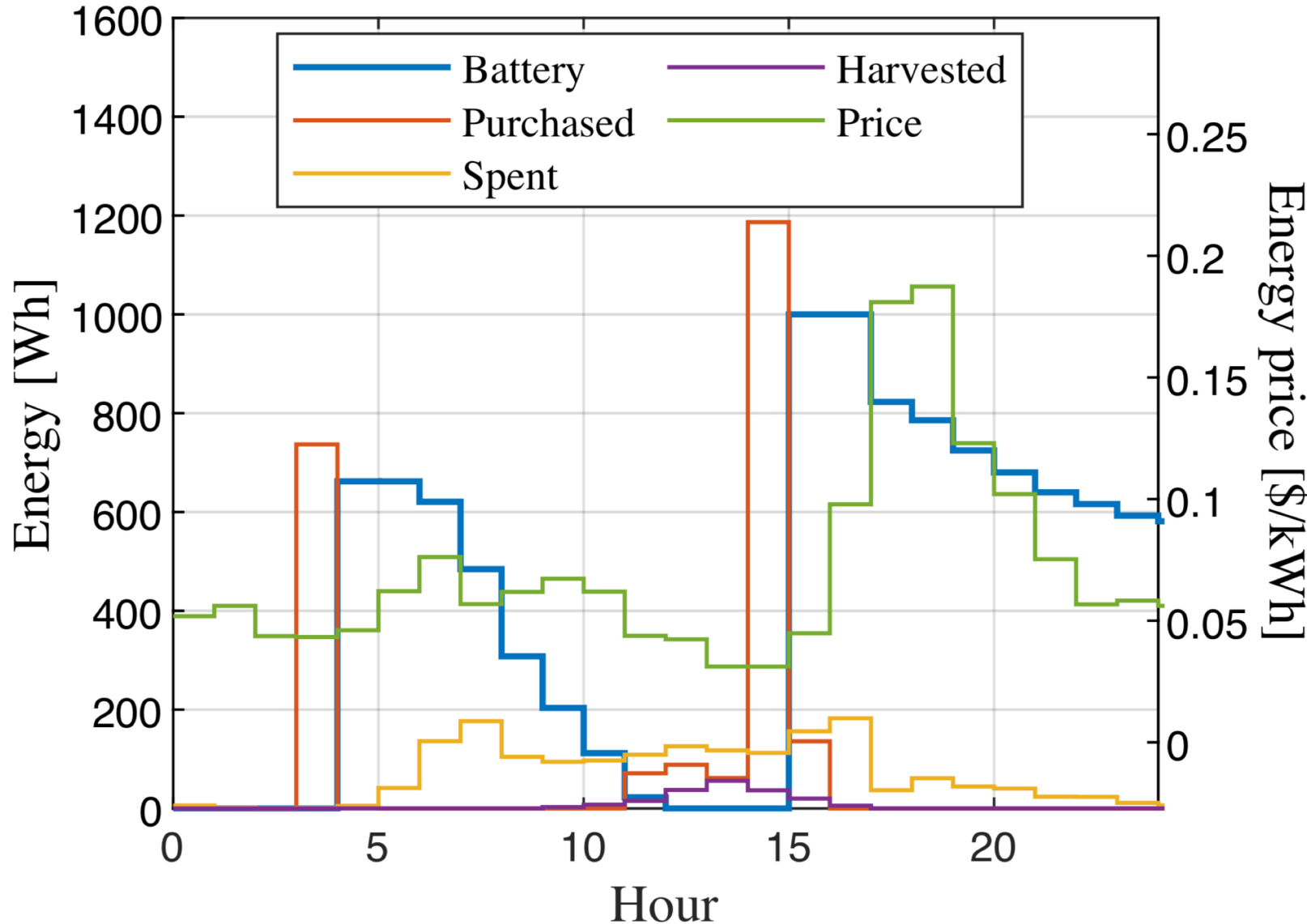
- $T = 360h$; time step = $1h$; 3 tier-1 servers; 2 tier-2 servers

Inputs:

- Energy harvested: real traces available on the SolarStat tool
- Grid energy price: from US National Grid database
- Job flows: synthetic time series generated with SUMO



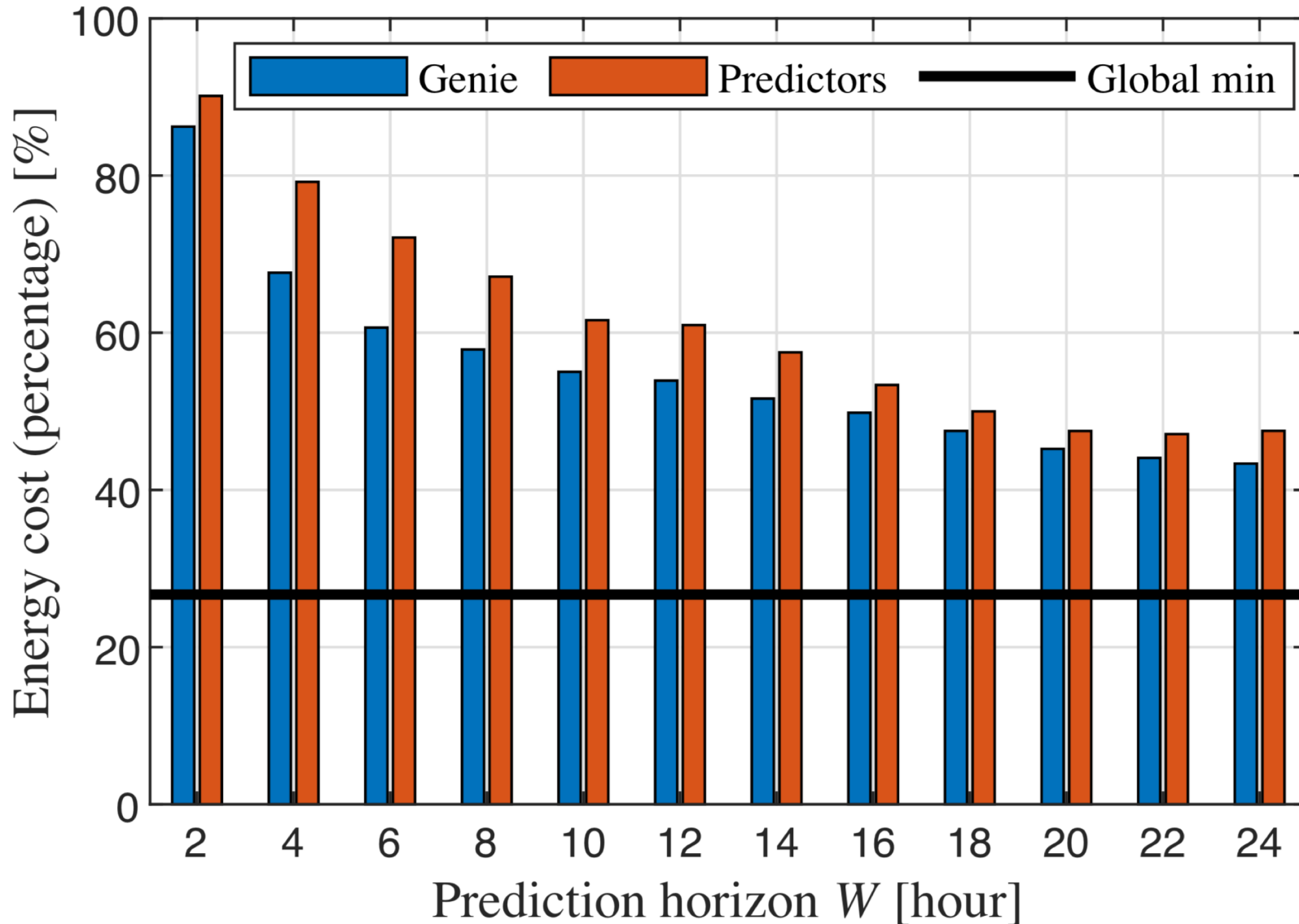
Results



Plot shows the energy price and the state evolution of server 1 (in tier 1) obtained using $W = 24$ hours.

The ES purchases energy from the power grid on energy price's [local minima](#).

Results



Plot shows the energy cost achieved by Genie predictors and our Predictors, while varying the length of the prediction horizon W (results in percentage with respect to the energy cost incurred with $W = 1$).

With our Predictors, setting $W = 4$ hours allows reducing the energy expenses by 20%. With $W = 18$ hours, the **energy cost is halved**.

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