



Optimal IoT control in Smart Homes

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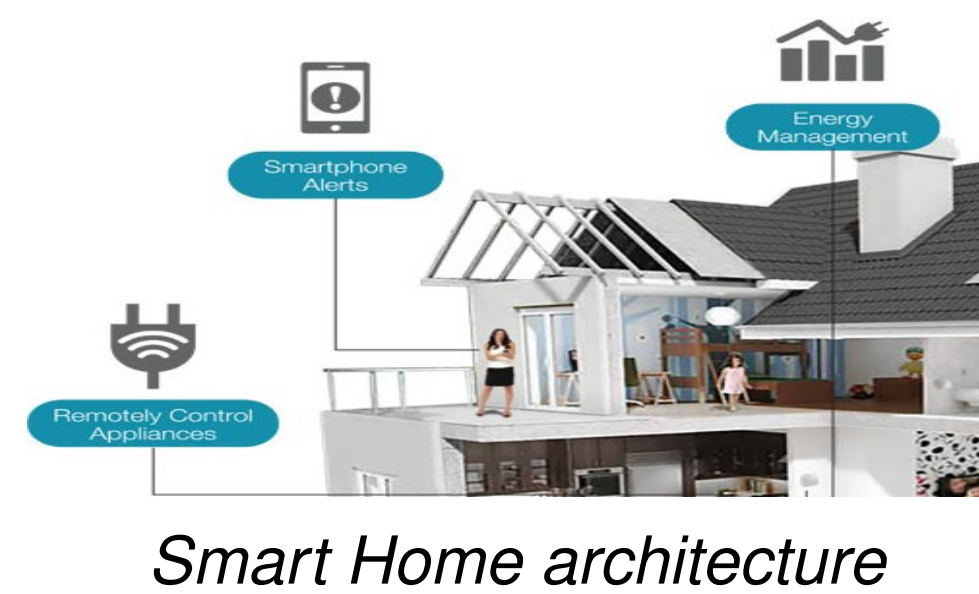


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Introduction and Motivation

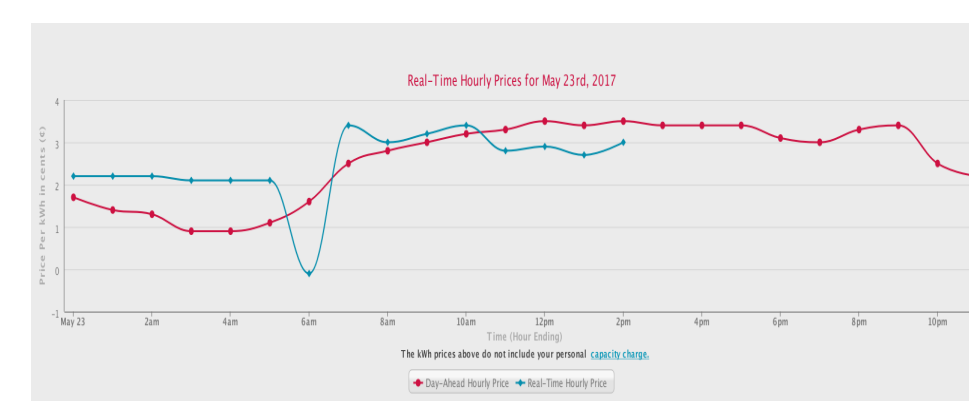
Goal

- To design an intuitive **dishwasher** that can be activated at an **optimal time** during the day via voice command through **Amazon Echo Dot**.



Negative Prices

- Happens when electricity supply is greater than the demand.
- Customers are actually **being paid** to use electricity during negative priced hours



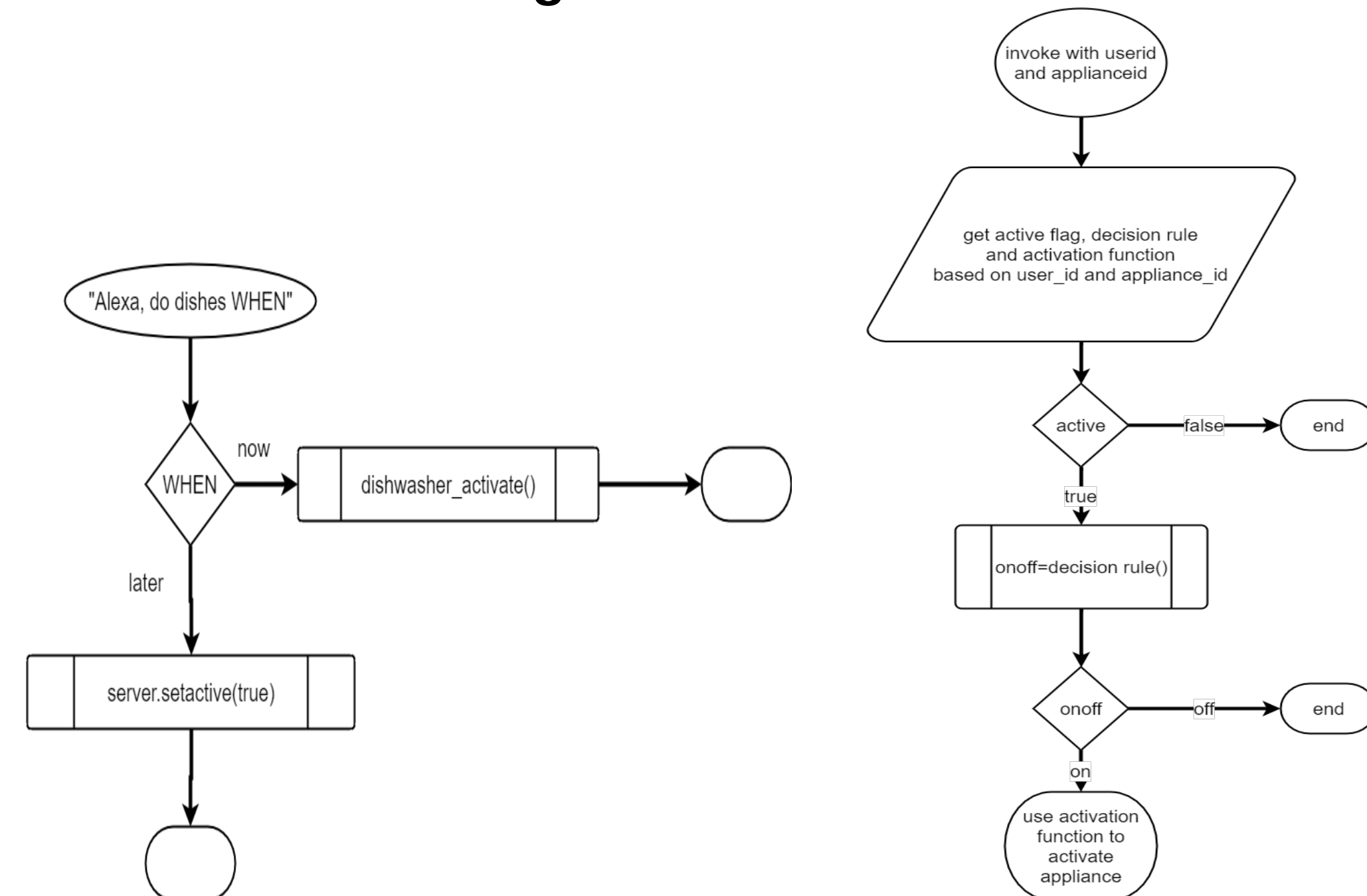
Negative Prices observed May 14, 2017

System Components and Implementation

Setup Components



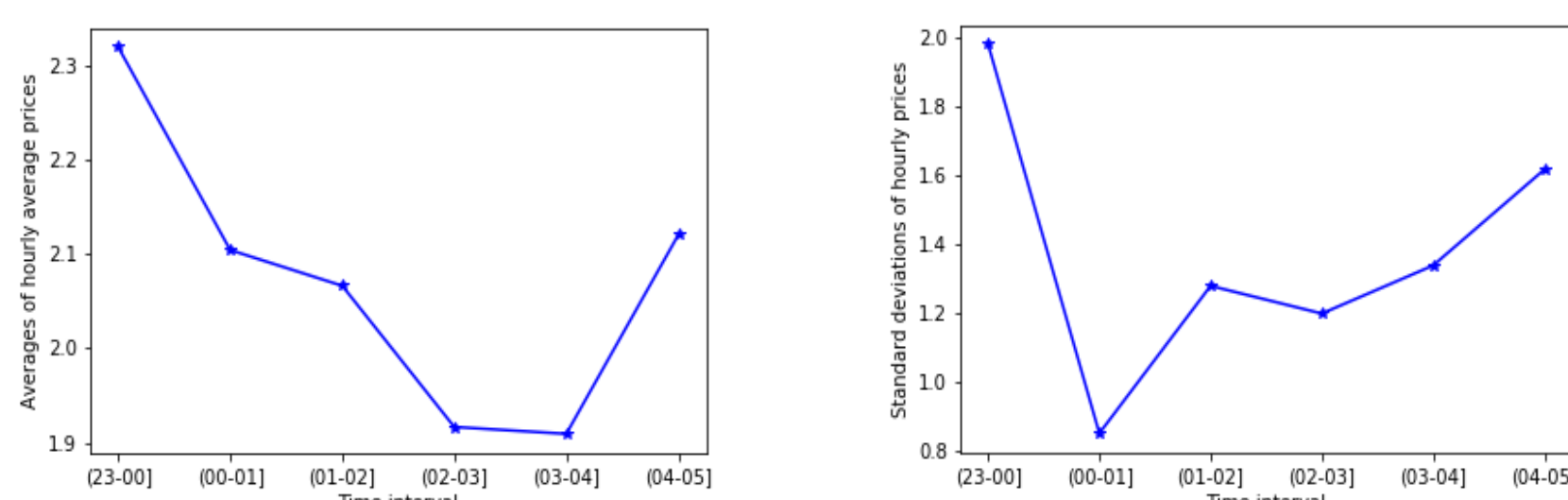
Decision Logic for Alexa and Cloud Watch



Price Modeling

Trade off

Mean price is low around 4 AM, but the variance is also large at that time.

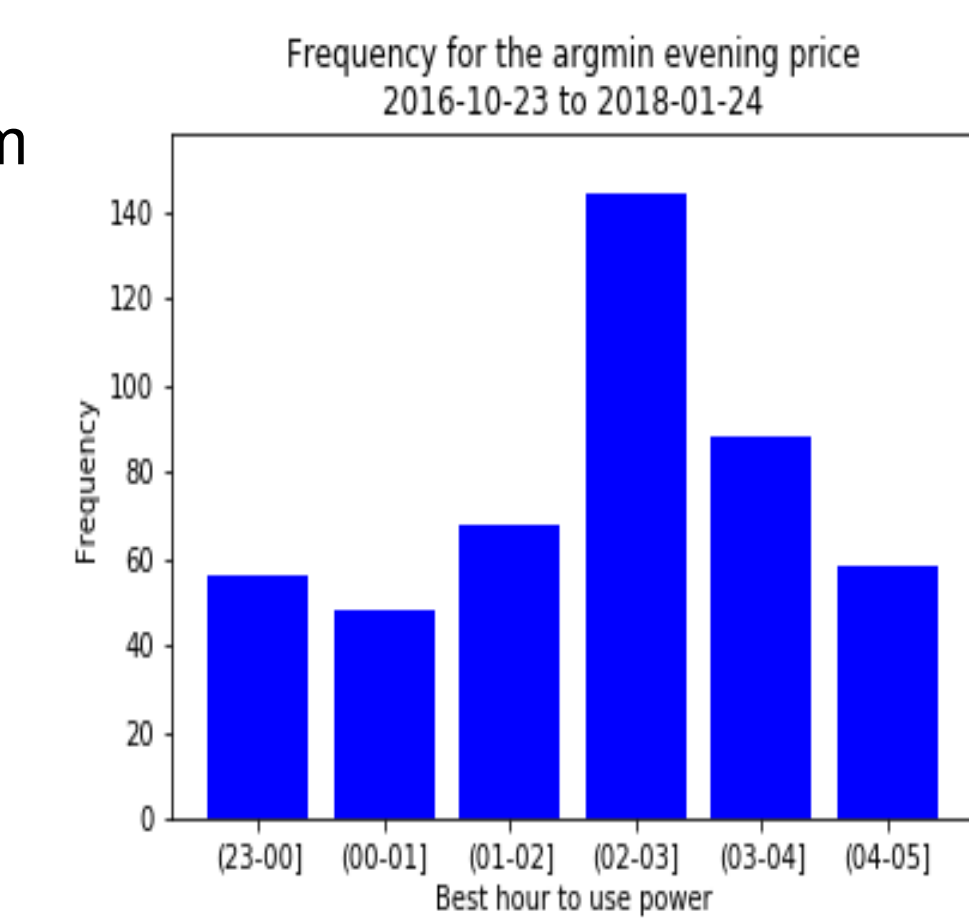


Some Notations

- \bar{P} - Retroactive averages for any usage in time interval $(t-60, t]$
$$\bar{P} = \frac{1}{12} \sum_{i=0}^{11} P_{t-5i}$$
- $T_{runtime}$ - Cycle running time for the appliance
- $\delta = \frac{1}{12}$ (5 minutes)
- $\Delta = 24$ (a days' worth of time)
- $T_{min} = 1, T_{max} = 5$ (Activate time between 11 PM and 5 AM)
- $N = \{T_{min}, T_{min} + 1 \dots T_{max}\}$
- D_c - No. of days in the past to train policies

Argmin Policy

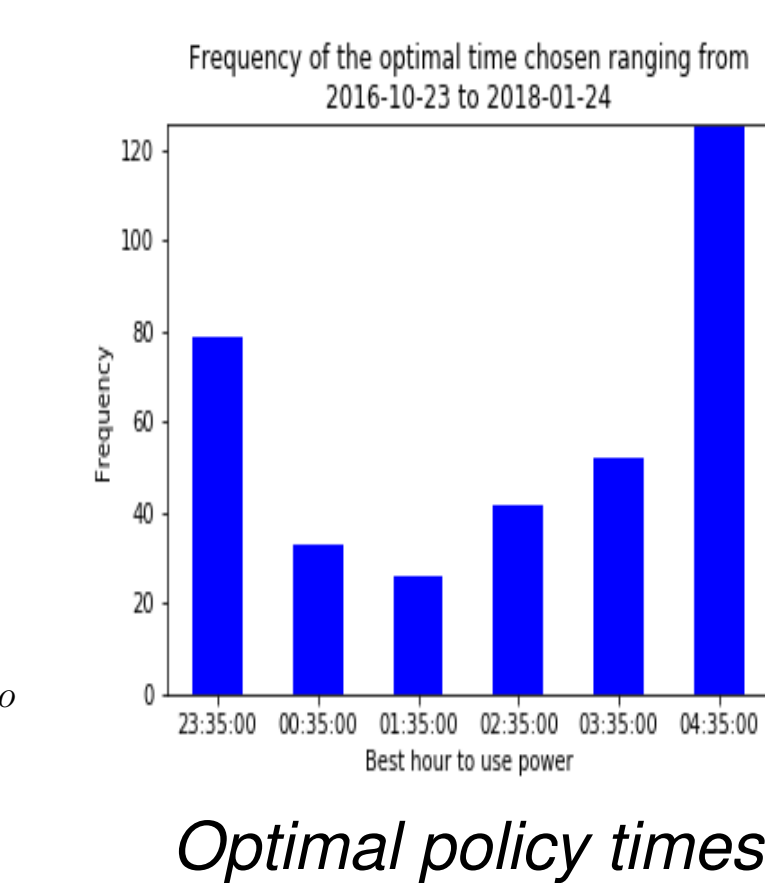
- Find the **most frequented** times of least prices from the past.
- d days ago, τ_d was the cheapest time:
$$\tau_d = \operatorname{argmin}\{\bar{P}_{n-\Delta d} : n \in N\}$$
- Frequency count of the τ_d 's:
$$F_n = \frac{1}{D_c} \sum_{d=1}^{D_c} 1_{\{\tau_d=n\}}$$
- Activate the appliance if
$$F_n = \max\{F_{n'} : n' \in \{n, n+1 \dots T_{max}\}\}$$



Histogram for the Argmin prices

Hybrid Model

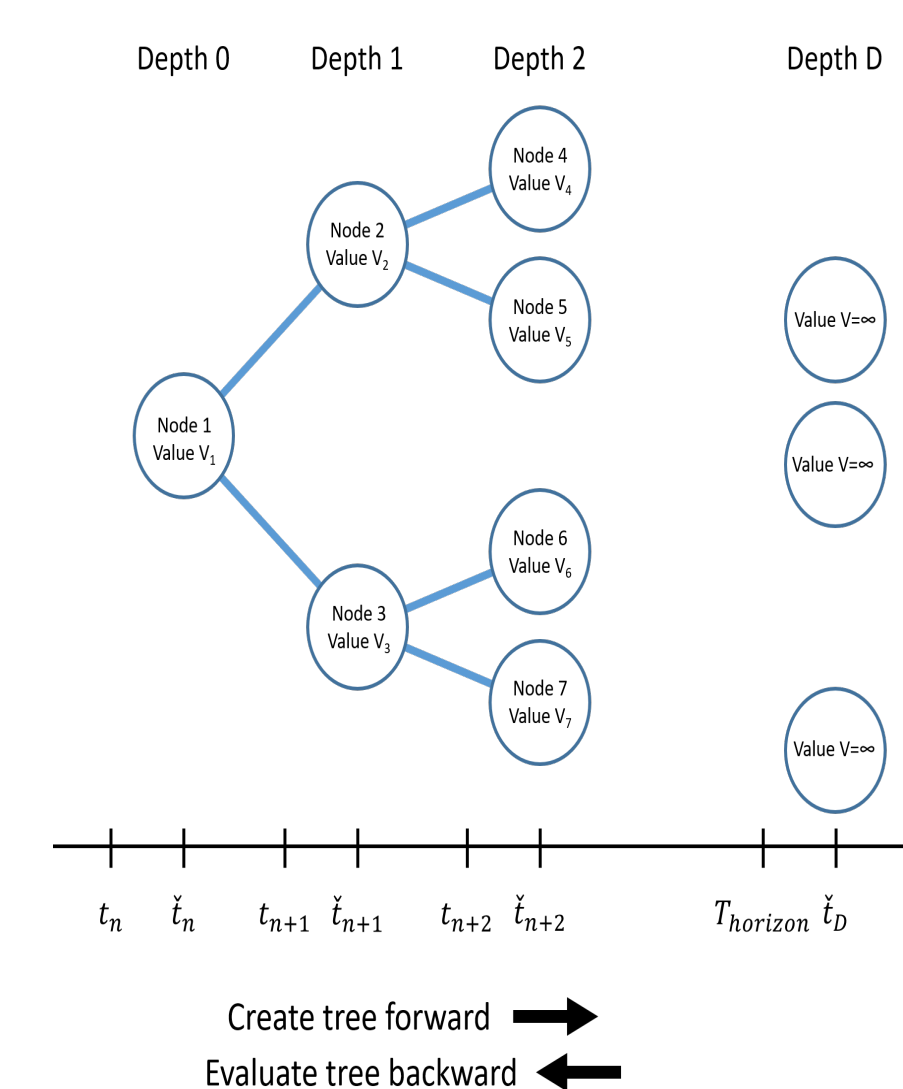
- Optimal time to decide activation = $\delta J_{maxinfo}$ where:
$$J_{maxinfo} = \left\lceil \frac{1 - T_{runtime}}{\delta} \right\rceil - 1$$
- Decision Interval:
$$D_n = (n - 1 + \delta J_{maxinfo}, n - T_{runtime})$$
- Seasonality using historical averages:
$$\bar{P}_n^H = \frac{1}{D_c} \sum_{d=1}^{D_c} \bar{P}_{n-\Delta d}$$
- Initial Regression:**
 - Known spot prices for current hour $\{P_{n-1+j\delta}\}_{1 \leq j \leq J_{maxinfo}}$
 - Historical averages (\bar{P}_n^H)
- Hourly Regression:**
 - Prior 5-minute spot price (P_{n-1})
 - Historical averages (\bar{P}_n^H)



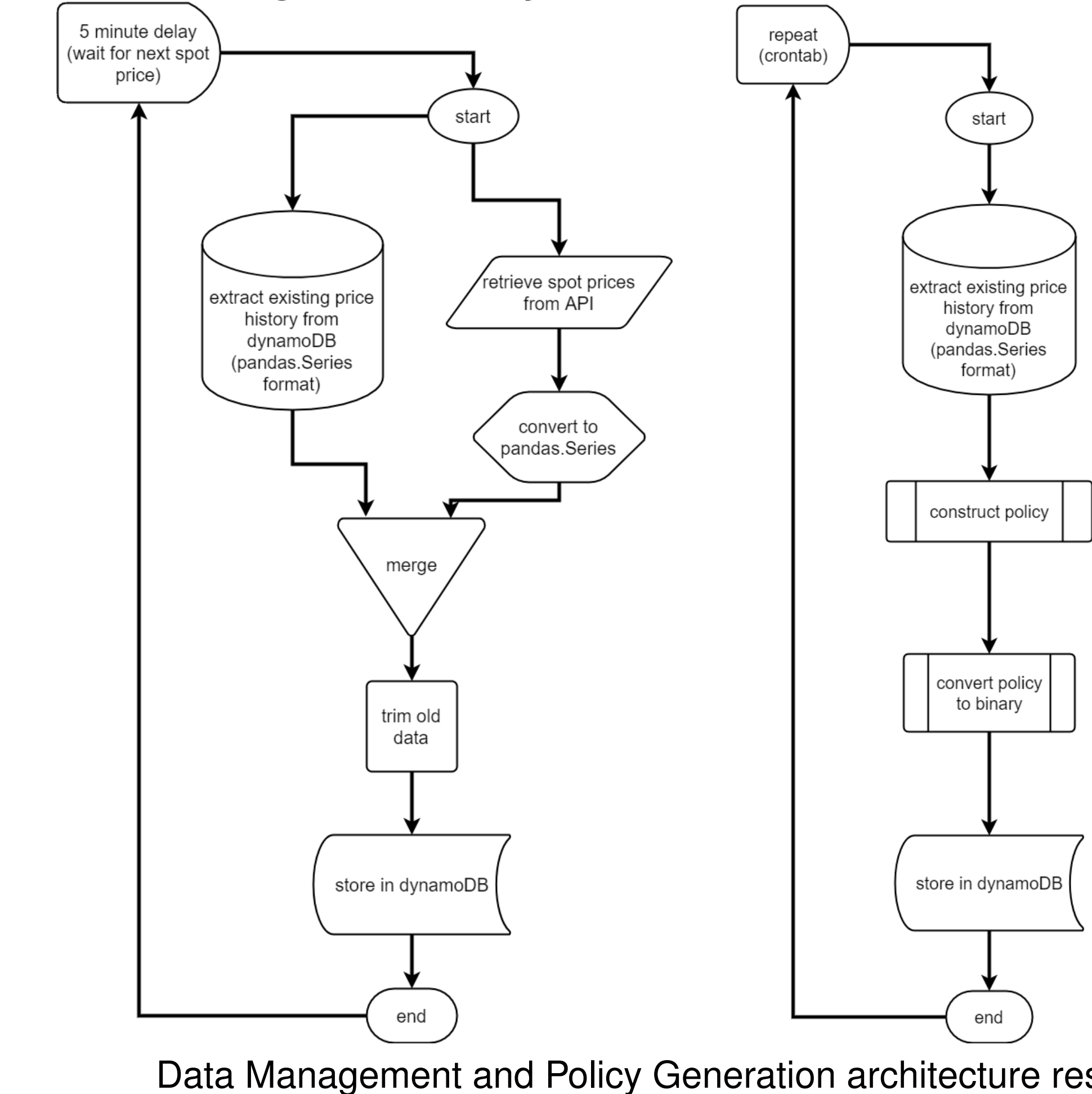
Optimal policy times

Optimal Stopping Policy

- Constructed: Forward Direction
- Evaluated: Backward Direction.
- The **Exercise price** (\bar{P}_n^E) of consuming energy is computed at each of the future nodes.
- Continuation value** (V_n) = ∞ at end node.
- Continuation value $V_n = E[\bar{P}_{n+1}^E \wedge V_{n+1}]$ for $n < T_{max}$.
- Optimal Time: Exercise Price < Continuation Price:**
$$\tau^* = \operatorname{Min}\{n : \bar{P}_n^E < V_n\}$$
 where $V = E[\bar{P}_\tau^E]$



AWS Decision logic for Policy Generation



Project Impact and Results

Economic Impact

- WiFi** accessible with inexpensive and fast installation
- Can be extended to **any electrical appliance** with a switch leading to energy savings
- Can Establish a **"Smart Grid"** preventing overloading and power outages.
- Particle Photon: \$19, Relay Shield: \$30, Lifetime Electricity Savings
- Results when back tested on a year's data:

	Mean (average prices)	Mean (policy prices)	Average Savings
Argmin Policy	2.04873	1.86045	9.2 %
Optimal Policy	2.04873	1.83445	10.5 %

Table 1: Savings from the Argmin and Optimal Stopping policies in a single cycle

Future Research

Extensions

- Implementation and comparison of **Machine Learning** models predicting price patterns
- Inclusion of consumer demand and **weather** conditions as well for the forecast

Acknowledgements

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