Vasudha

AI & IOT for Sustainability

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Vasudha Cluster Outline & Partnerships:

1. Fault detection and localization in solar PV cells
2. Tackling “range anxiety” of EV drivers
3. Detection of faults and anomalies in EV batteries
4. Price and Carbon Arbitrage with Battery Storage
5. Active Contract and market participation by multi sources

TATA POWER SOLAR

ASHOK LEYLAND

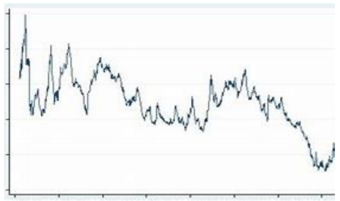
sse Airtricity

AYANA RENEWABLE POWER PRIVATE LIMITED

Why Decision Making is Complex?

Introduction of Renewable Energy Resources

Variable Renewable Resource Generators



- Availability is uncertain
- Dependent on nature

Electricity Market Participation:

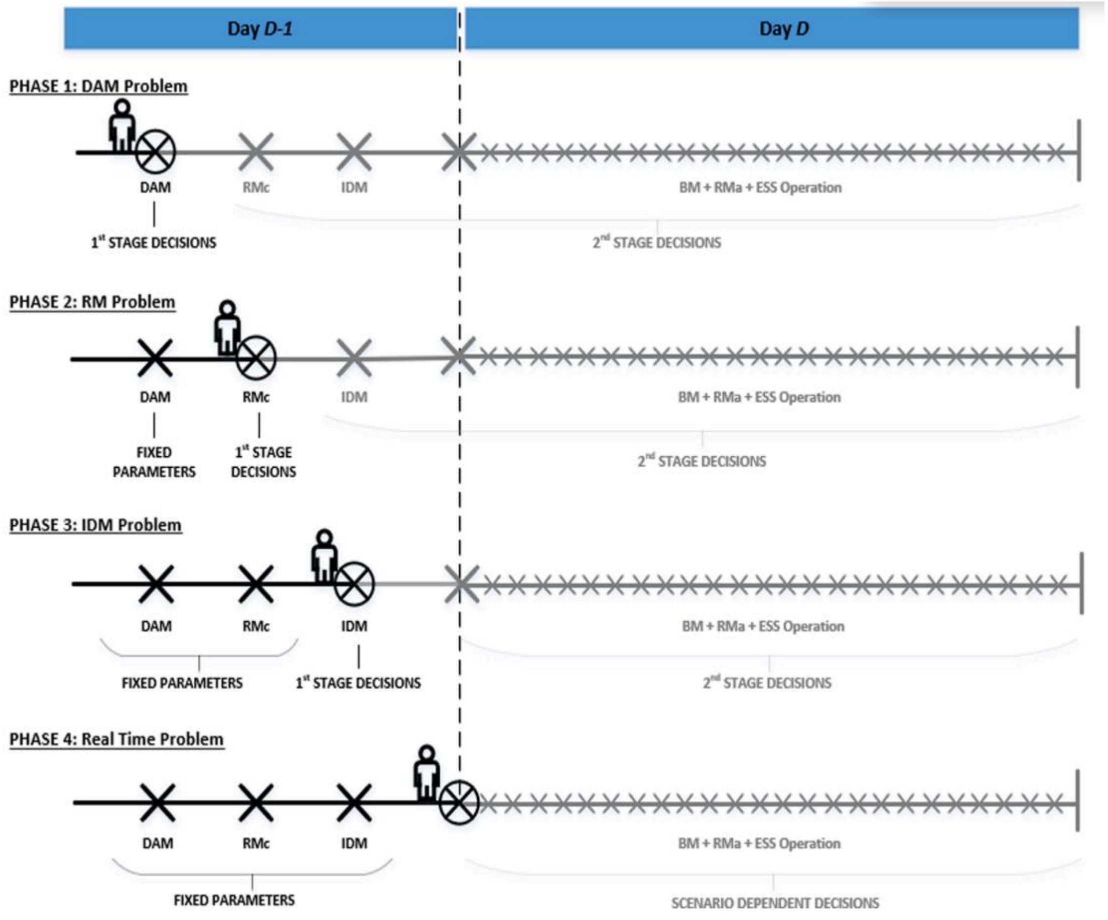
- Different gate closure timings
- Different mechanisms and properties.

Market Participation :

Sequential Commitments leading up to the time of actual participation

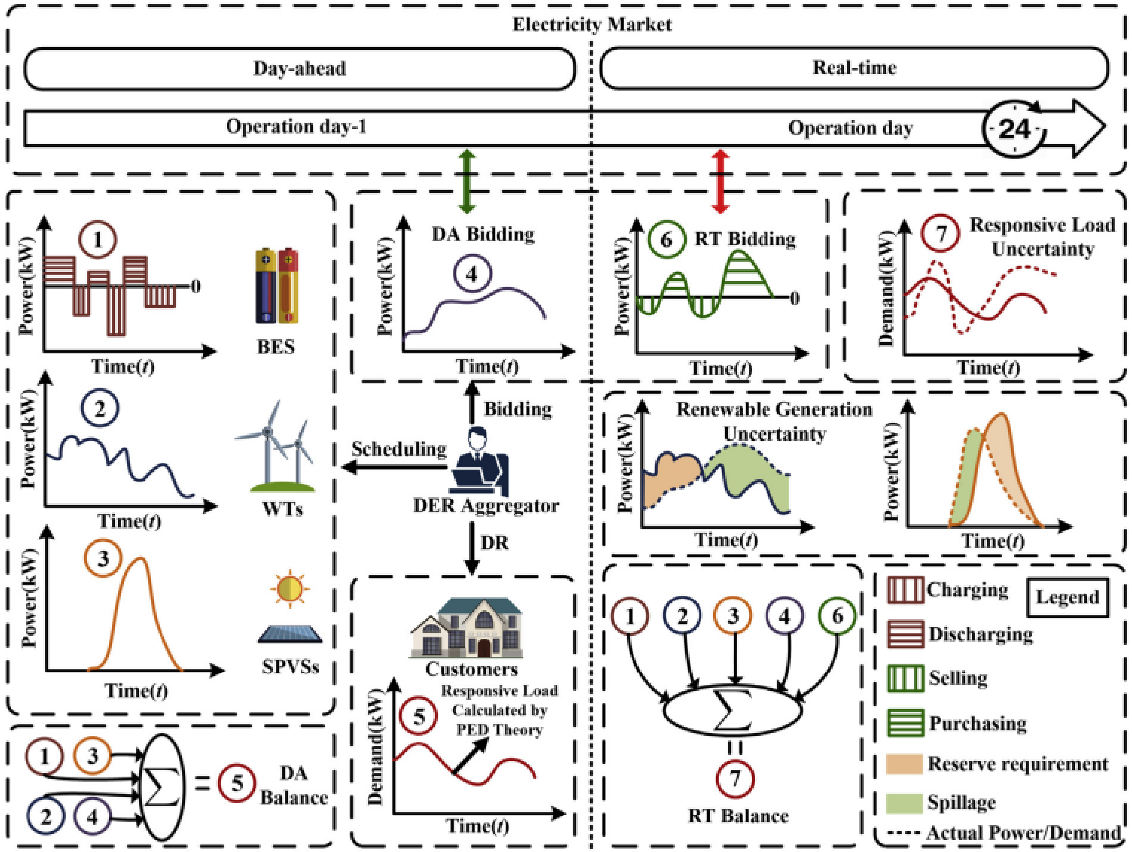
Market Bidding Windows:

Link: paper



Example of Market Mechanisms:

Link: paper



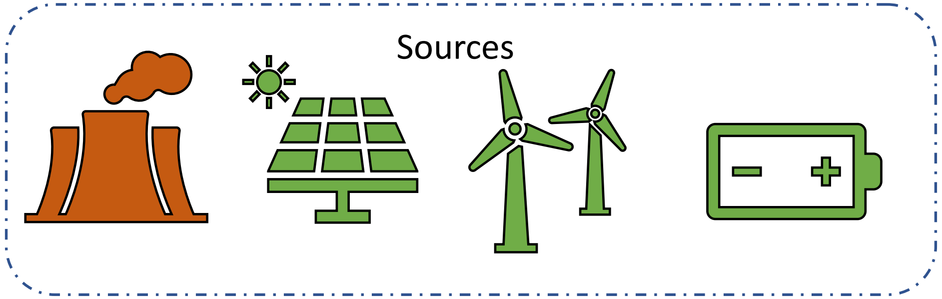
Subject to penalties because of deviation from the committed schedules

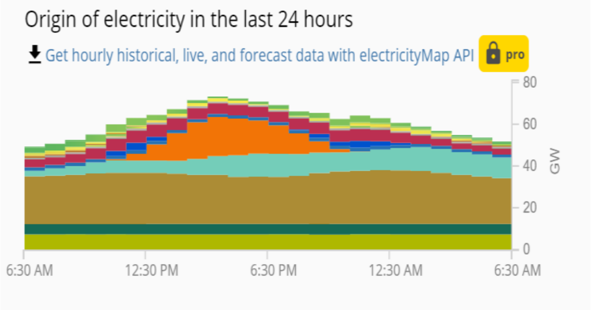
Problem Formulation: SSE Airtricity

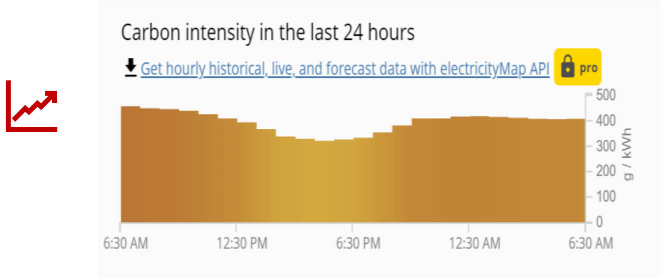
Reduce CO_2eq footprint with batteries

Renewable Energy provider in Ireland has deployed Lithium-ion Batteries to its consumers. It is required to operate these batteries in such a manner that it would help **reduce carbon footprint.**

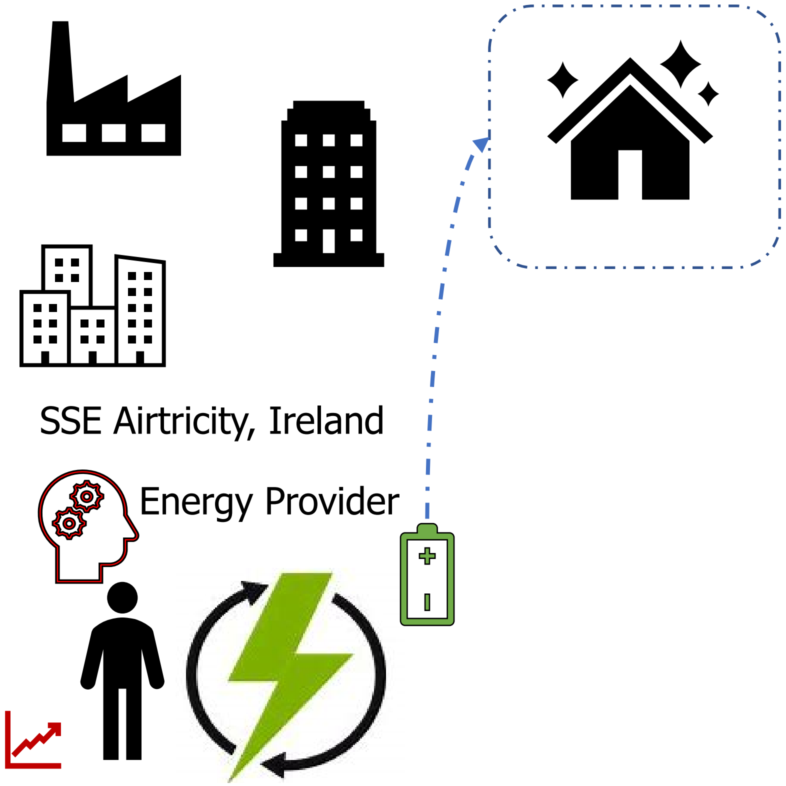
Energy Producer







f_n(sources available + demand contracts)



How to go greener

- Battery Configurations
- Grid Variance
- Optimization Parameters
- Computational Approach

Take actions to go greener:
Accurate charging and discharging schedules

Modelling considerations:

Carbon Intensity: Uncertainty in Forecast, Arbitrage opportunity

Battery Characteristics: Capacity, Efficiency, Degradation, Charging/discharging

Problem Formulation: Ayana

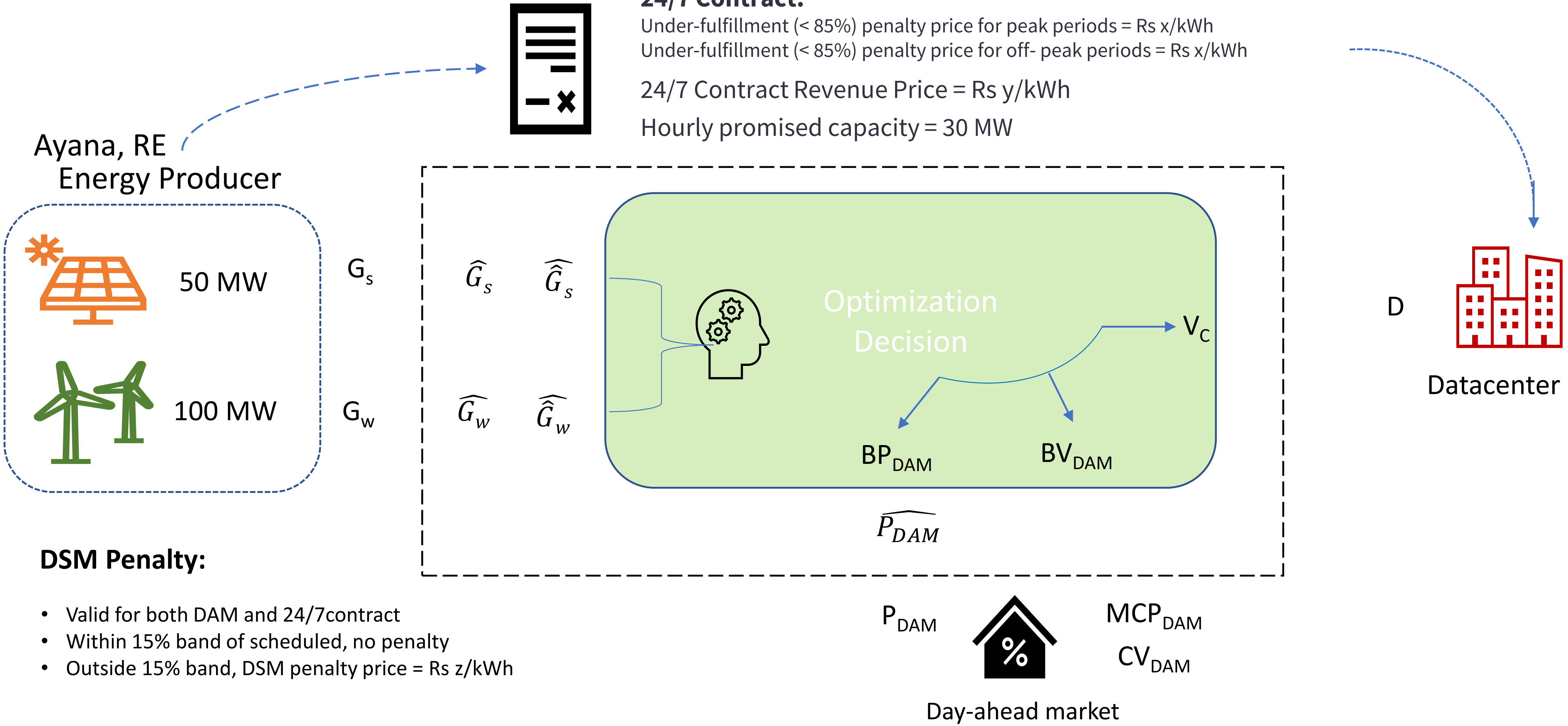
Profit Maximization for multi-source producer by market and contract participation

24/7 Contract:

Under-fulfillment (< 85%) penalty price for peak periods = Rs x/kWh
Under-fulfillment (< 85%) penalty price for off- peak periods = Rs x/kWh

24/7 Contract Revenue Price = Rs y/kWh

Hourly promised capacity = 30 MW



DSM Penalty:

- Valid for both DAM and 24/7contract
- Within 15% band of scheduled, no penalty
- Outside 15% band, DSM penalty price = Rs z/kWh

Take actions to maximize profit:
Accurate profile orchestration of contract and market

What is DSM?

It's Deviation Settlement Mechanism, which is issued by electricity regulatory transmission commissions, where producers are penalized:

0->11:45 pm forecasts, for 1:15 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
1->12:00 am forecasts, for 1:30 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
2->12:15 pm forecasts, for 1:45 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
3->12:30 am forecasts, for 2 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
4->12:45 am forecasts, for 2:15 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
5->1:00 am forecasts, for 2:30 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
6->1:15 am forecasts, for 2:45 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
7->1:30 am forecasts, for 3 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
8->1:45 am forecasts, for 3:15 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
9->2:00 am forecasts, for 3:30 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
10->2:15 am forecasts, for 3:45 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]
11->2:30 am forecasts, for 4 am: [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23, ... ,95]

"The schedule by RE generators or lead generator or principal generator may be revised by giving advance notice to the concerned RLDC. Such revisions shall be effective from 4th time block (i.e., after 45mins), the first being the time-block in which notice was given. There may be one revision for each time slot of one and half hours starting from 00:00 hours of a particular day subject to maximum of 16 revisions during the day."

-CERC

Approaches used to tackle the problem:

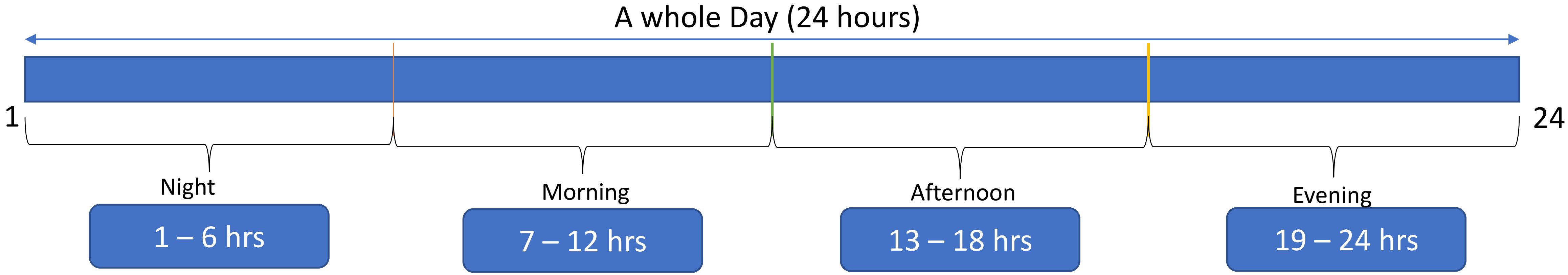
Optimization Problem:

- Rule-Based Heuristics / Greedy
- Mixed-Integer Programming
- Reinforcement Learning

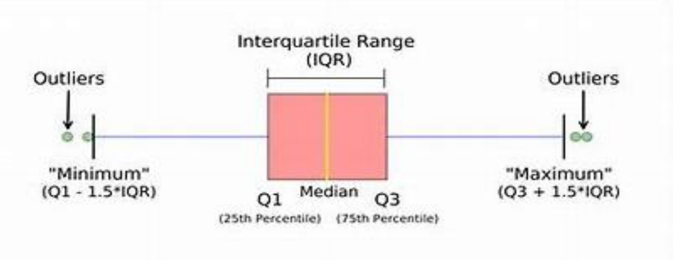
Actions to be taken for optimization:

- SSE: Build up accurate charging and discharging schedules
- Ayana: Build up Accurate profile orchestration of contract and market

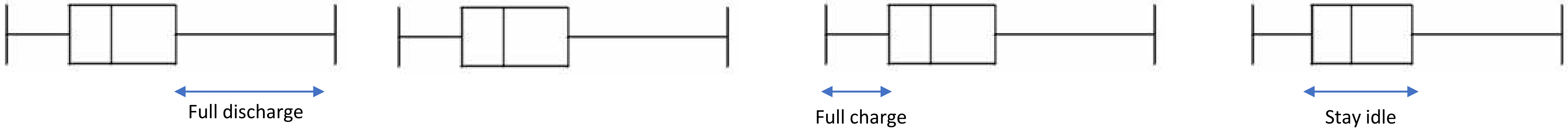
Rule-Based Heuristics



Carbon Emissions distribution:



Actions on battery :



Mixed-Integer Programming

$$\min \sum_{t=1}^{T} [(x_t C_t - y_t D_t) \cdot \Delta t \cdot Em_t + \lambda \cdot BCost \cdot C_t \cdot \Delta_t]$$

$$s.t.\ 0 \le x_t \le 1 \forall t$$

% charging state

$$0 \le y_t \le 1 \forall t$$

% discharging state

$$0 \le x_t + y_t \le 1$$

% battery can be either charging or discharging

$$Soc_t = SoC_{init} + \sum_{k=1}^{t-1} (\rho x_t C_t - y_t D_t) \cdot \Delta t / Nom$$

% state of charge in the battery at any given time slot

$$DoD \le Soc_t \le 1$$

%state of charge in the battery should be within it's depth of discharge and 1

$$Soc_{t-1} \cdot Nom + \rho x_t C_t \cdot \Delta t \le Nom$$

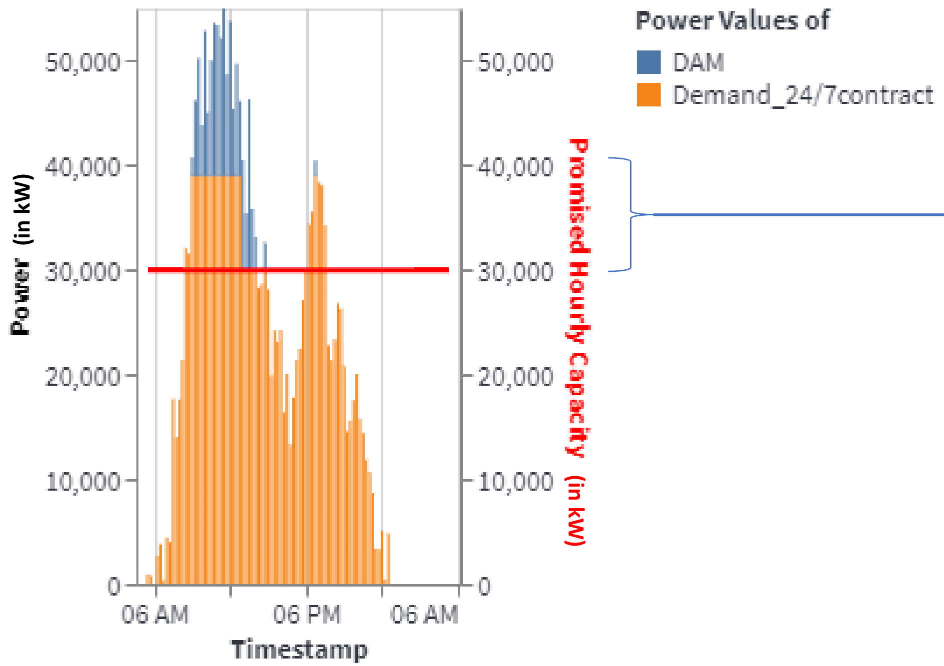
$$Soc_{t-1} \cdot Nom - y_t D_t \cdot \Delta t \ge DoD \cdot Nom$$

$$Soc_{min} \le Soc_T \le 1$$

% at the end of the day, minimum SoC need to maintained

- x_t - Charging state of the battery in t (1 = charging)
- y_t - Discharging state of the battery in t (1 = discharging)
- t - each time step in the planning horizon
- T - total time steps in planning horizon
- $\Delta t = 24/T$ - time step in hours
- Nom - Nominal or maximum caacity of the battery in KWh
- DoD - Depth of Discharge (DOD) (%) – The percentage of battery capacity that has been discharged expressed as a percentage of maximum capacity.
- Soc - State of Charge (SOC)(%) – An expression of the present battery capacity as a percentage of maximum capacity.
- Soc_{init} - Initial state of the charge at the time of start of planning horizon
- Soc_{min} - Minimum state of the charge that need to be maintained at the end of planning horizon
- ρ - Charging efficiency of the battery
- Em_t - forecast carbon emissions at time step t
- λ - weighting factor between carbon emissions and battery degradation costs
- $BCost$ - Amortized battery degradation cost per KWh of charging cycle
- C_t - Charging power (KW) from battery storage system in time step t. This would be derived from battery charge rate (at present, can be assumed constant). Battery storage system can be charged and discharged with limited current charge mode under constant power, constant load or constant current. This formulation assumes constant power charge/ discharge.
- D_t - Discharging power (KW) from battery storage system in time step t. This would be derived from battery discharge rate (at present, can be assumed constant)
- Soc_t -State of charge (%) at time t

Rule-Based Heuristics



Volume Distribution in (100, 130)%

Baseline 1

Day Ahead Market

Baseline 2

24/7 Contract

There is no requirement of having decisions to be made based on the prices and penalty minimization. By this technique we are taking a safer approach to incur less 24/7contract penalty.

AYANA
RENEWABLE POWER PRIVATE LIMITED

Mixed-Integer Programming

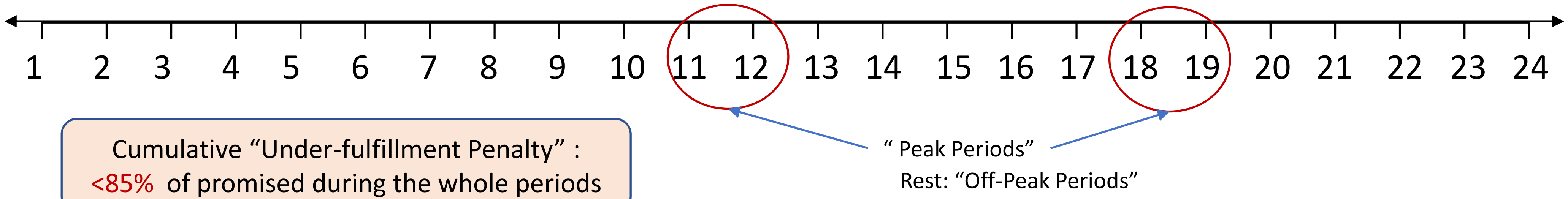
Level 0: Day Ahead Commitment

- **Objective - Partition generation between RTC and DAM**
- **Decision variables:**
  - DAM Bid Volume + DAM Bid price
  - RTC Volume
- **Decision Time:** 2pm (Day T-1)

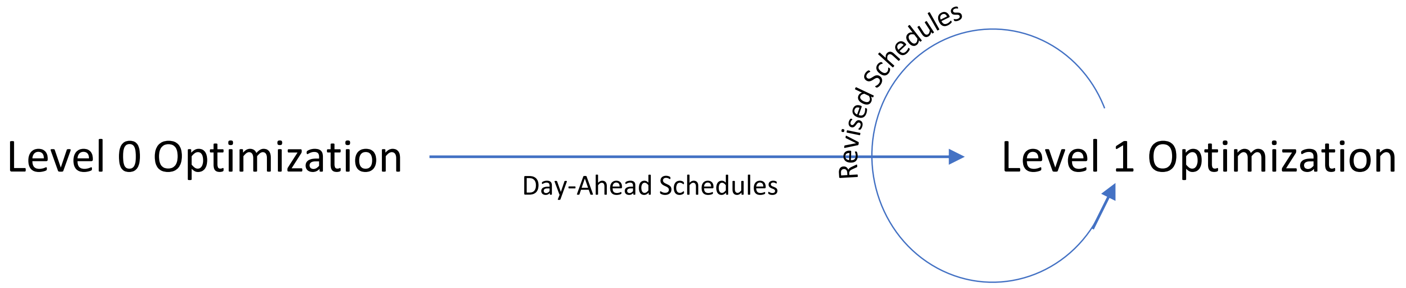
Level 1: Intraday Revisions

- **Objective - Reduce DSM Penalty**
- **Decision variables:** RTC Volume, DAM Volume
- **Decision Time:** Every 1.5 hours (>45 mins before commitment)

Primary Objective = Profit Maximization for the day: 24/7 Revenue + DAM Revenue – “Penalties”



Cumulative “Under-fulfillment Penalty” :
<85% of promised during the whole periods



“Deviation Settlement Mechanism” [DSM]
Penalty: day-ahead & revised schedules

Observation and Results

- SSE Airtricity (Carbon footprint reduction with Battery Storage)
- Ayana RE (Active Market and Contract Participation for renewable monetization)

Link to the Results: Vasudha

Solcast Data:

Location: [14.2862348, 77.3987393]

Pavagada, Karnataka, India

Data Time Period: 1st Jan 2020 - 25th Dec 2021

Sample Time : 15mins

Columns to be used:

- Period end[UTC],
- ghi estimated actual[W/m^2],
- ghi fcst +1h[W/m^2],
- ghi fcst dayahead[W/m^2],
- wind speed 10m[m/s],

Information to Gather:

- Solar Generation
- Wind Generation

IEX Market Data:

Location: S1 area considered which includes the following states:

South Region |Andhra Pradesh, Telangana, Karnataka, Pondicherry (Yanam), South Goa

Data used: Day Ahead market (DAM) prices

Data Time Period: 1st Jan 2016 – 30th Nov 2021 (For current use: 1st Jan 2020 – 31st Dec 2020 taken to be synchronous with solcast data)

Sample Time: 15mins

Columns to be used:

- Datetime index
- S1

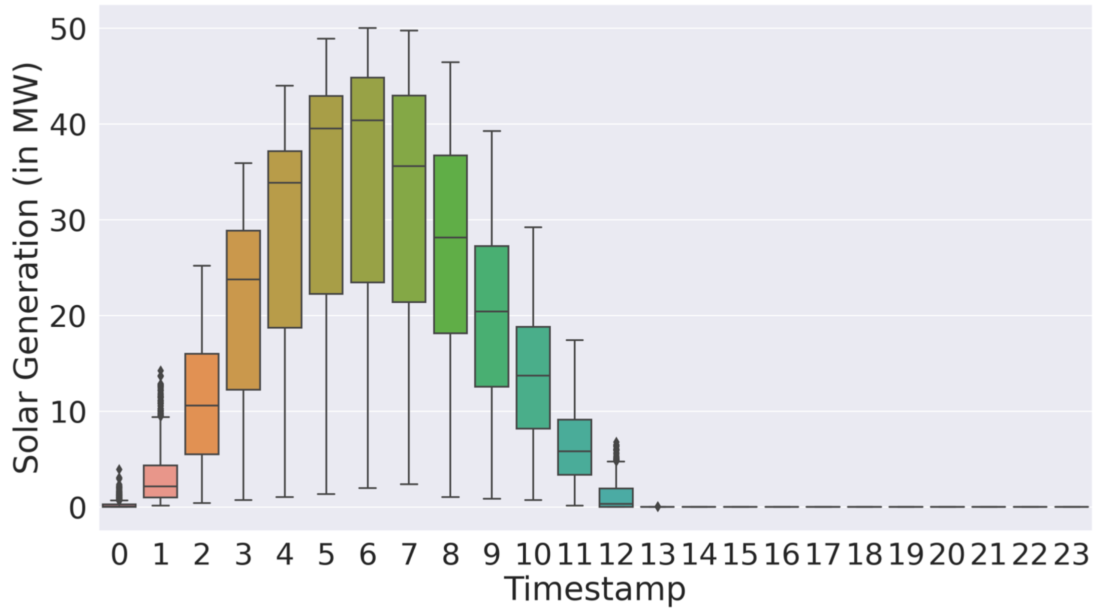
Information to Gather:

- Day Ahead Market Price

Data used: 1st Jan'20 to 31st Dec'20, 15mins sampled

Solar Generation Data:

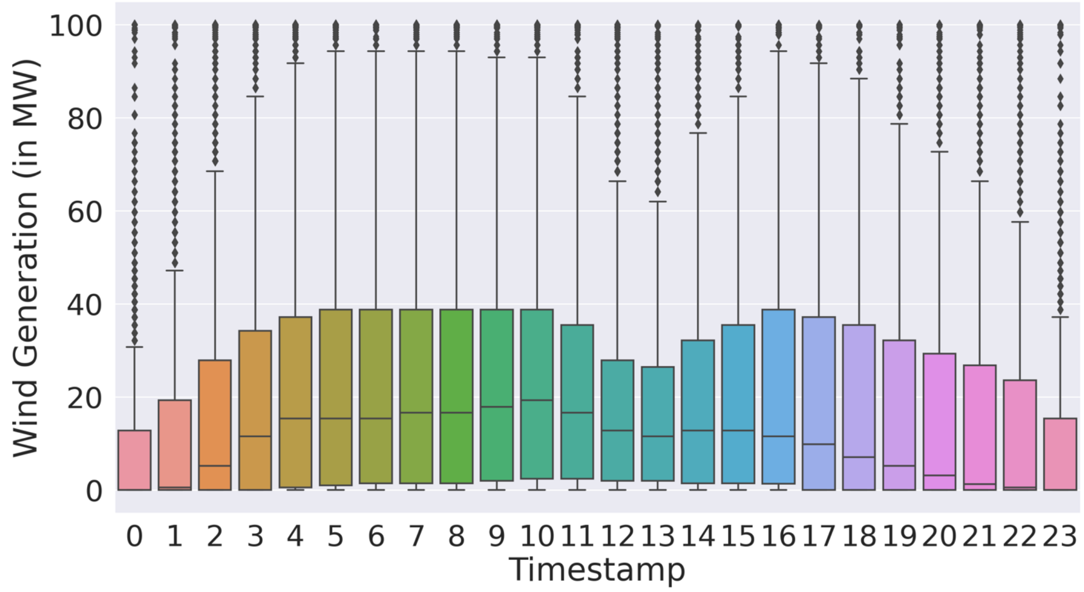
Variation of Solar power across the year, shown over a day



Approx Solar Capacity : 50 MW

Wind Generation Data:

Variation of Wind power across the year, shown over a day

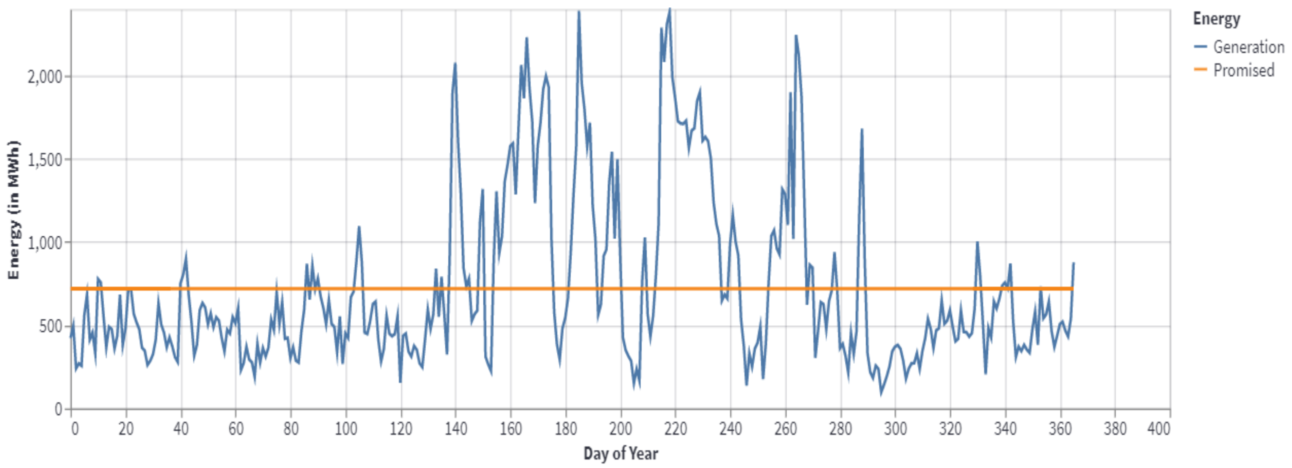


Approx wind Capacity : 100 MW

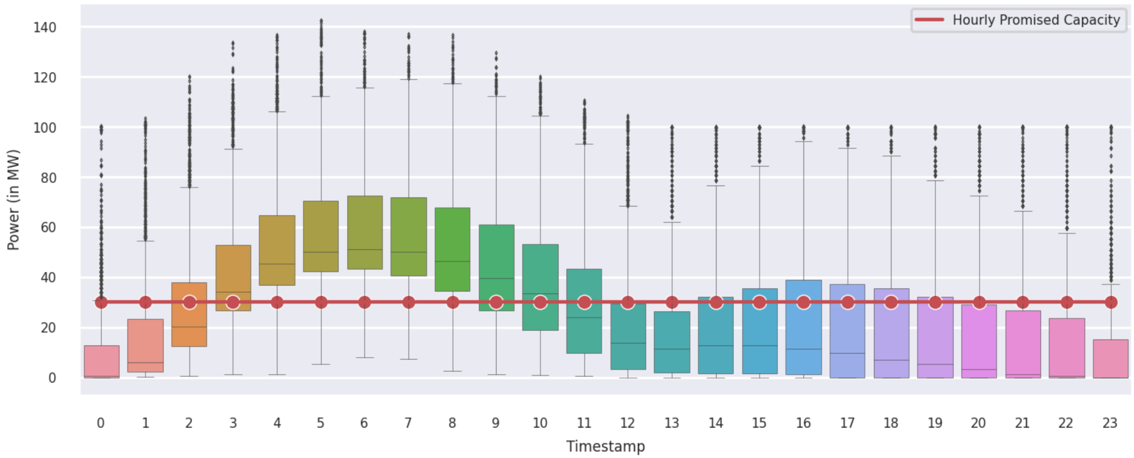
Note: Slide 4 and Slide 5 shows how we arrived at these values for solar and wind from the solcast data

Setting the RTC constants for the formulation:

Showing promised supply over a day:



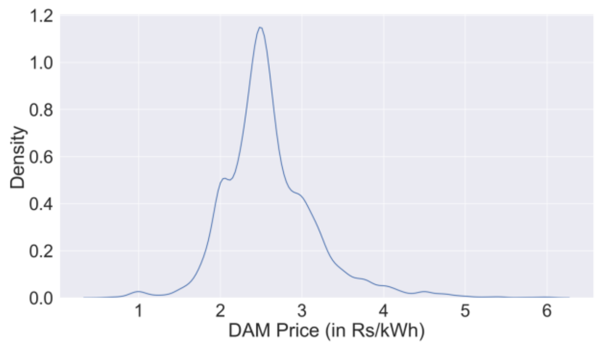
Showing Hourly promised capacity :



Max Total Energy (Solar+Wind) generated in a day ~ 2500 MWh

Hence Volume Constants,

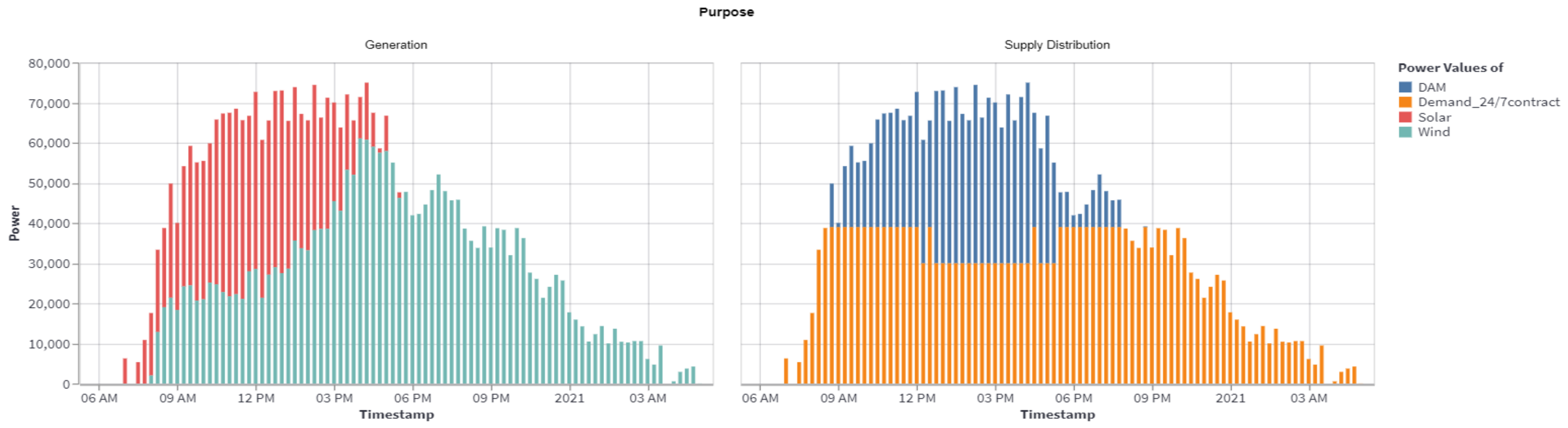
- Promised supply over a day = 2500/3.5 ~ 720 MWh
- Hourly promised capacity = 720 MWh /24 = 30 MW

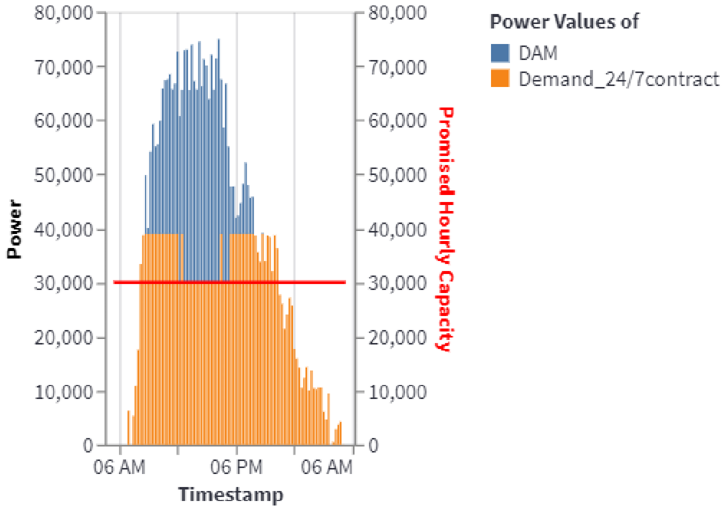


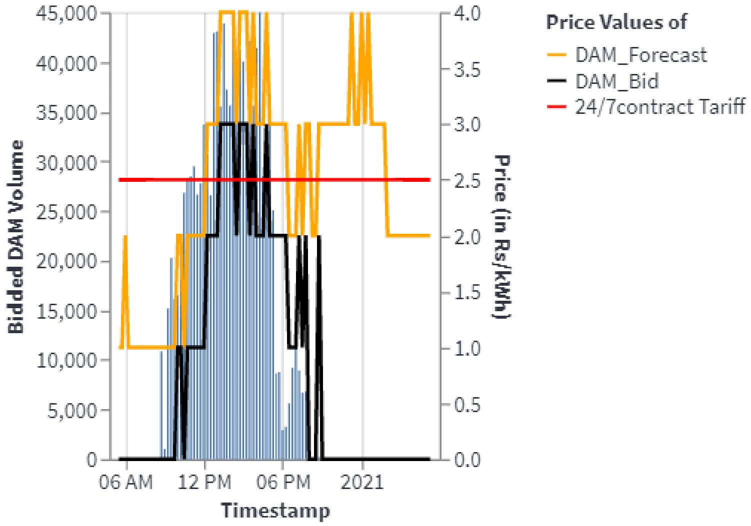
- RTC contract revenue price = Rs 2.5/kWh
- RTC Daily Penalty price = Rs 1/kWh
- DSM Penalty price = Rs 0.5/kWh

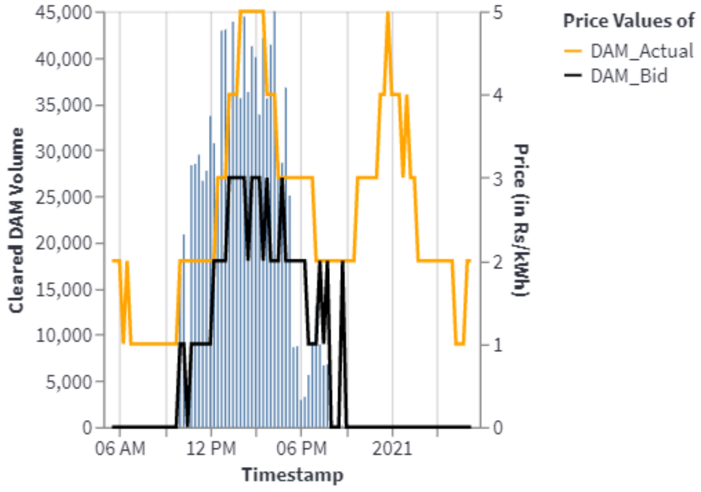
Results for a Day: Level - 0 (Day ahead optimization)

Demand Response and Surplus Management



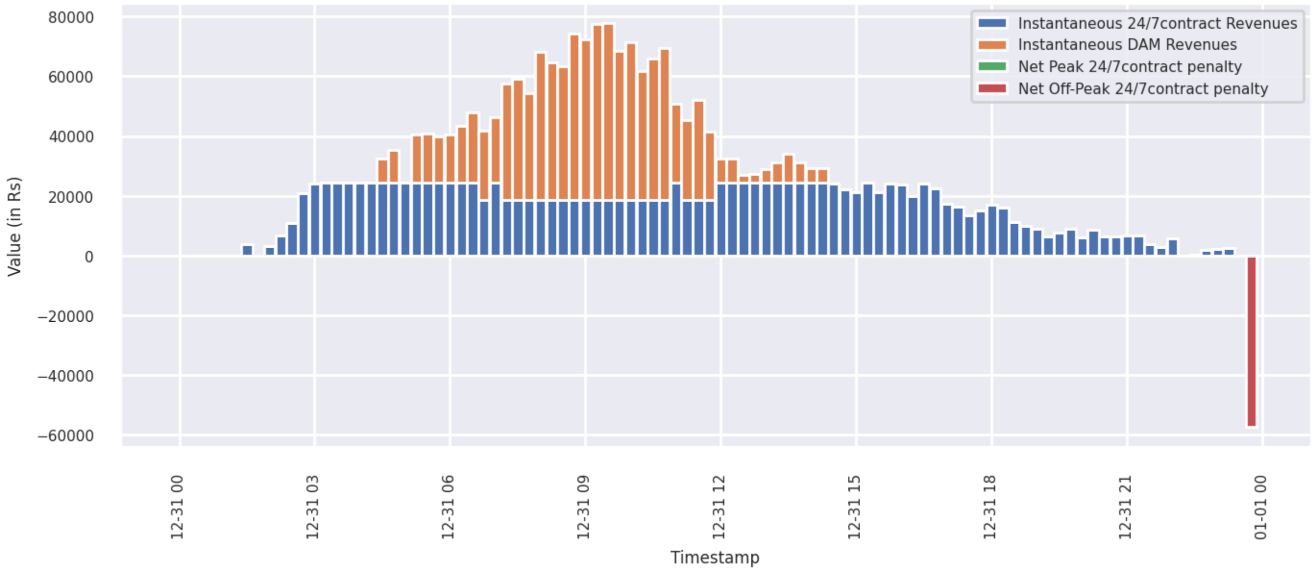




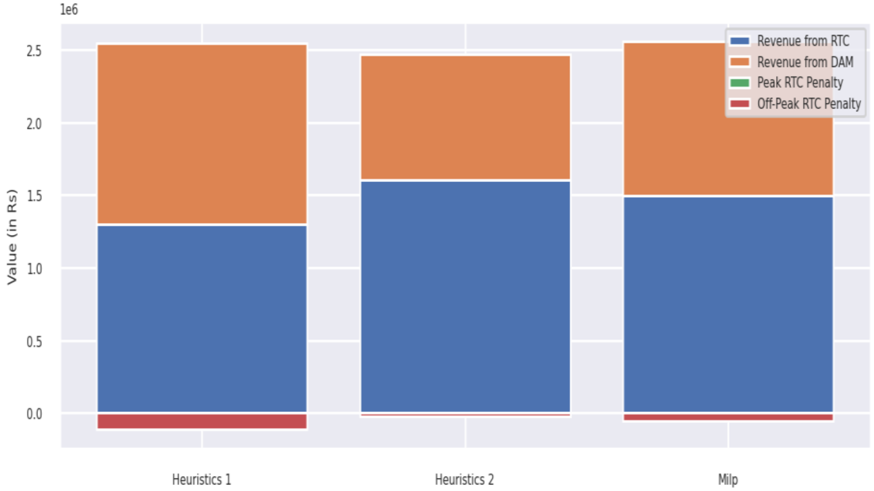


Level - 0 (Day ahead optimization) :

Expected Income for the next day using MILP:

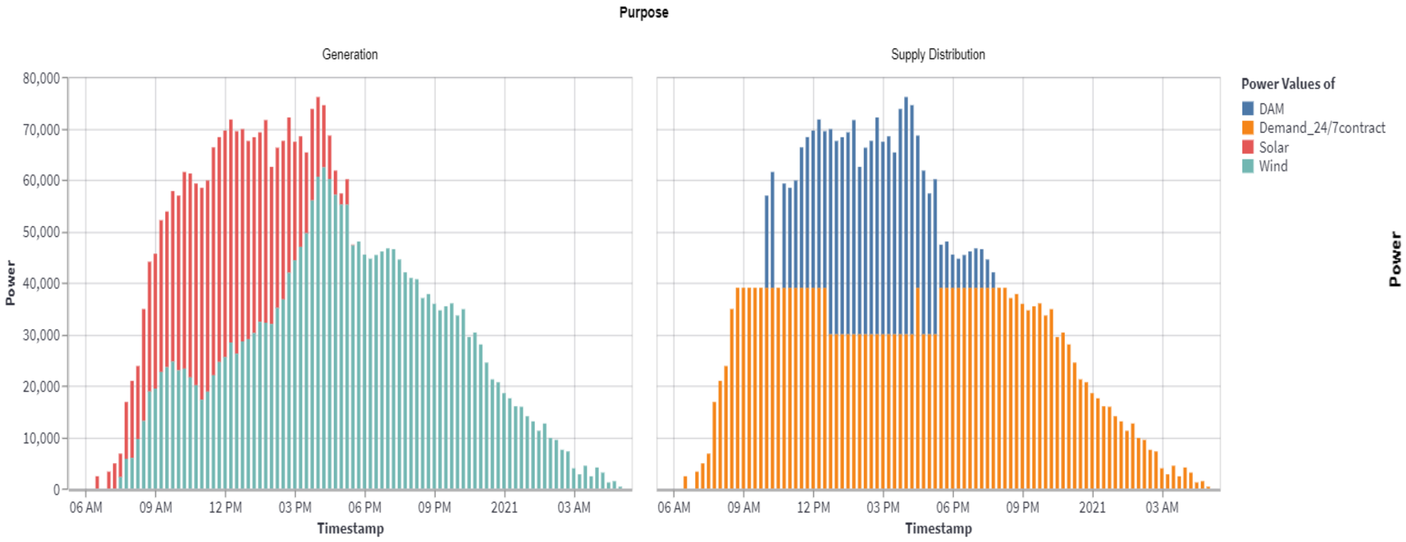


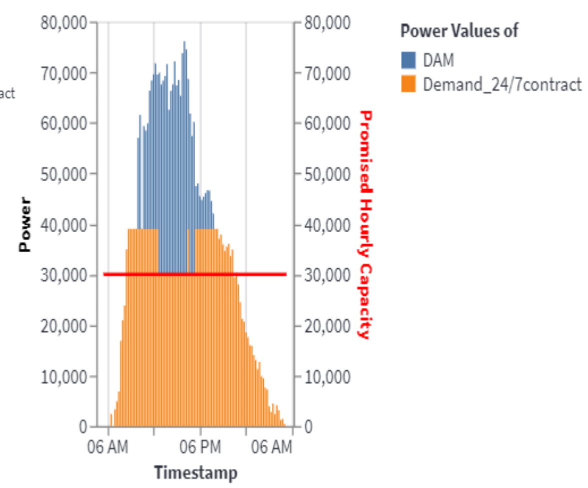
Method Comparisons:

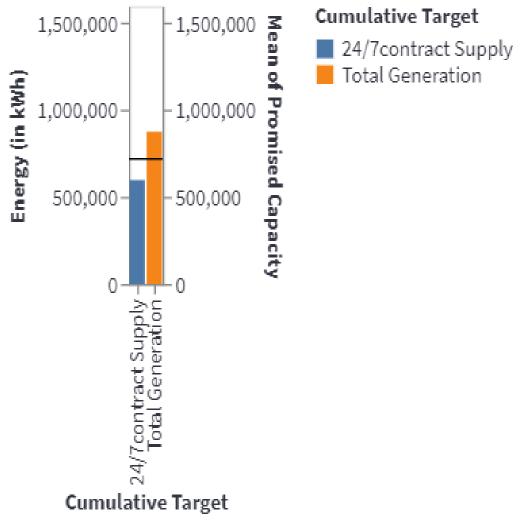


Optimization Method	24/7contract Revenue (in Rs)	DAM Revenue (in Rs)	Peak 24/7contract Penalty (in Rs)	Off-Peak 24/7contract Penalty (in Rs)	Income (in Rs)	Income (in Rs/MW installed capacity
Heuristics 1	1302505.62	1245831.1	0	108997.75	2439338.97	16262.26
Heuristics 2	1603670.62	867904.62	0	23574.25	2448001	16320.01
MILP	1496795.62	1063827.63	0	57324.25	2503299	16688.66

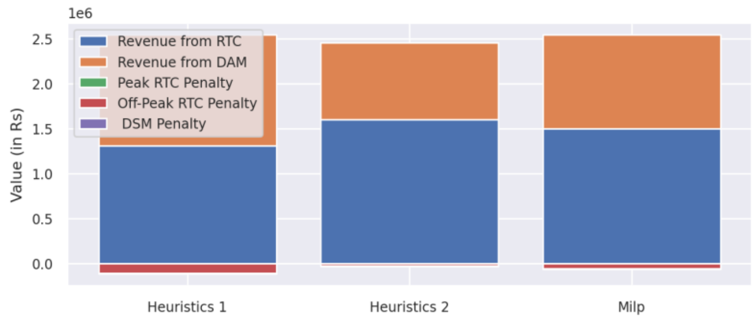
Level - 1 (Revised Intraday optimization) :

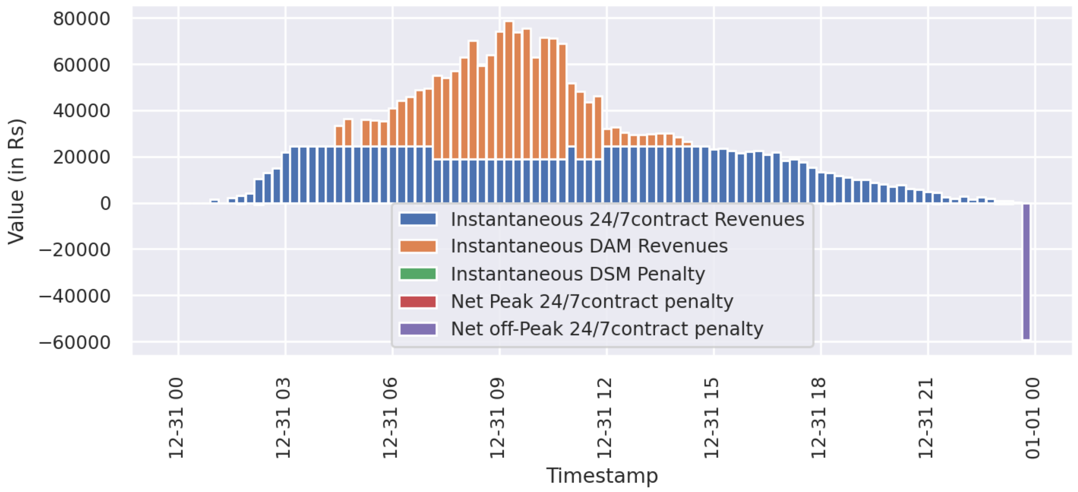






Expected Income:

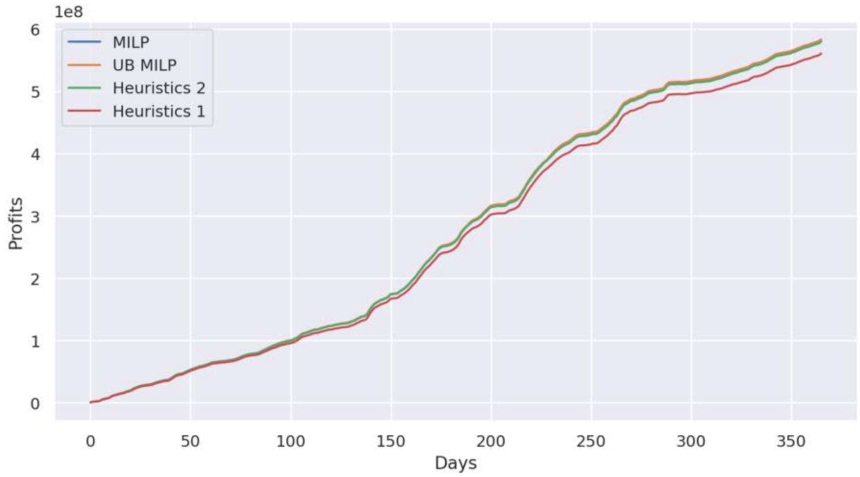




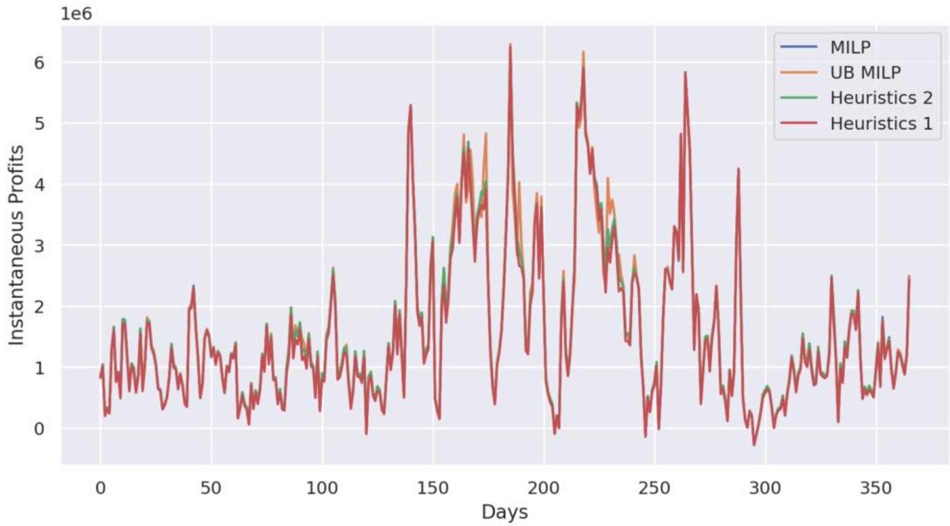
Optimization Method	24/7contract Revenue (in Rs)	DAM Revenue (in Rs)	Peak 24/7contract Penalty (in Rs)	Off-Peak 24/7contract Penalty (in Rs)	DSM Penalty (in Rs)	Income (in Rs)	Income (in Rs/MW installed capacity
Heuristics 1	1305449.38	1235392.47	0	107820.25	4306	2426182.8	16174.55
Heuristics 2	1601261.88	854740.52	0	25495.25	4306	2426201.15	16174.67
MILP	1500011.88	1043936.09	0	59245.25	5431	2479271.72	16528.48

Yearly Income:

Cumulative addition of profits over the days for the year:



Daily profits over the days for the year:



Optimization Method	24/7contract Revenue (in Rs)	DAM Revenue (in Rs)	Peak 24/7contract Penalty (in Rs)	Off-Peak 24/7contract Penalty (in Rs)	DSM Penalty (in Rs)	Income (in Rs)	Income (in Rs/MW installed capacity
Heuristics 1	396284770	241177795.18	7471072.75	65576126.5	1989100.62	560869577.72	3739130.52
Heuristics 2	473664426.25	167856310.39	4239948	55248392.25	2148483.38	579883913.01	3865892.75
MILP	469624260	174376855.09	4410113.5	56152094.5	2169191.75	581269715.34	3875131.44
UB MILP	468122302.5	178633952.58	4464221	56447152	2136129.12	583708752.95	3891391.69

DQN agent used.

Reinforcement Learning

States: $s_t = (c_t, \ldots, c_{t+(H-1)}, c_{t+H}, SoC_t)$

c_t - Forecasted carbon intensity values for horizon H
SoC_t – State of Charge at time t

Actions: $A_t = (-P_e^{max}, 0, P'^{max}_e)$

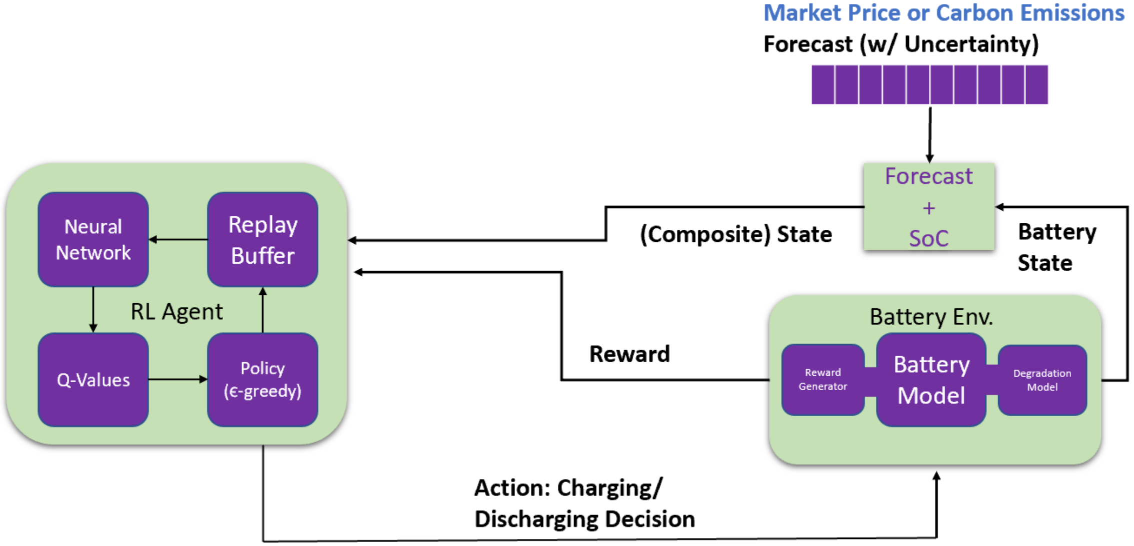
Charge/discharge completely, Charge/discharge at 50% rate, Do nothing

- P'^{max}_e is the max rate of discharging power (in kW) = $P * \eta_{dis}$
- P_e^{max} is the max rate of charging power (in kW) = P / η_{ch}

η_{dis} discharging efficiency and η_{ch} charging efficiency

Reward: $$Rt = \left(ct * \frac{P_{e\,t}}{P_e^{max}} - \alpha_d * \frac{|P_{e\,t}|}{P_e^{max}}\right) * Ts$$

Incorporates both carbon savings from arbitrage and battery degradation cost



Degradation:

Degradation model provides amortized cost and carbon footprint impact of the battery for every charge/discharge cycle over its lifetime

$Q_t := Q_{t-1} * \lambda$
where λ is the reduction factor, here 0.998.

Degradation coefficient =
$$\alpha_{d,j} = \frac{Q_{s\,j} - Qc_j}{\sum_{i=1}^{T'} |Pe'_i|} * C_B$$

TD3 agent used.

Reinforcement Learning

Level - 0 (Day ahead optimization)

States:

$$s_t = \{\widehat{S}_t, D_{rtc,t}, I_{p,t}, I_{op,t}, \widehat{PD}_{dam,t}, Drtc_{lp,t}, Drtc_{lop,t}\}$$

Actions:

$$a_t = \{BV_{dam,t}, BP_{dam,t}, V_{rtc,t}, V_{excess,t}\}$$

Next state s_{t+1}:

$\widehat{S}_{t+1} \sim \widehat{Gs}_{t+1}, \widehat{Gw}_{t+1}$

$D_{rtc,t+1} \sim$ Demand RTC at t+1

$I_{p,t+1} \sim$ Indicator for peak periods

$I_{op,t+1} \sim$ Indicator for offpeak periods

$\widehat{PD}_{dam,t+1} \sim PD_{dam}$ forecast for hour t+1

$Drtc_{lp,t+1} = Drtc_{lp,t} - (V_{rtc,t} + V_{excess,t}) * I_{p,t}$ for peak periods

$Drtc_{lop,t+1} = Drtc_{lop,t} - (V_{rtc,t} + V_{excess,t}) * I_{op,t}$ for offpeak periods

Reward:

$r_t \epsilon \mathcal{R}$ at time t has the following components,

$$revenue_t = V_{rtc,t} * price_{rtc} + V_{excess,t} * price_{excess} + V_{dam,t} * dam_{price}$$

$$penalty^{peak}_{rtc,T} = (V_{rtc,T} + V_{excess,T} - promised_{supply} * peak_T) * penalty_{peak}$$

$$penalty^{opeak}_{rtc,T} = (V_{rtc,T} + V_{excess,T} - promised_{supply} * offpeak_T) * penalty_{offpeak}$$

$$r_t = \alpha_1 * e^{revenue_t} + (-\alpha_2 * e^{-penalty^{peak}_T} - \alpha_3 * e^{-penalty^{opeak}_T})$$

$$penalty^{peak}_{rtc} = \sum_{t=0}^{23}(V_{excess,t} + V_{rtc,t} - 0.85 * Hrpromised_{supply} * I_{p,t}) * penalty_{peak}$$

$$penalty^{opeak}_{rtc} = \sum_{t=0}^{23}(V_{excess,t} + V_{rtc,t} - 0.85 * Hrpromised_{supply} * I_{op,t}) * penalty_{offpeak}$$

$$true\ reward_t = revenue_t - penalty_t$$

Level - 1 (Revised Intraday optimization) :

States:

Consider values uptil horizon for Source total and Cleared DAM Volume, also include "index of previous revision" and "noticed schedules and previously scheduled actions -> uptil the horizon"

Actions:

Consider values uptil horizon for Volume to RTC and Volume to Excess RTC, also include "revise/not". [a binary output]

Reward:

$$DSMpenalty_{rtc,t} = |SV_{rtc} - (V_{rtc,t} + V_{excess,t})| * I^{rtc}_{thr,t} * dsm_{penalty}$$

$$DSMpenalty_{dam,t} = |SV_{dam,t} - V_{dam,t}| * I^{dsm}_{thr,t} * dsm_{penalty}$$

$$r_t = \alpha_1 * e^{revenue_t} + (-\alpha_3 * e^{DSMpenalty_{dam,t}} - \alpha_4 * e^{DSMpenalty_{rtc,t}}) + (-\alpha_2 * e^{-penalty^{peak}_T} - \alpha_3 * e^{-penalty^{opeak}_T})$$

$$true\ reward_t = revenue_t - penalty_t$$

noticed schedules [1] / previous schedules [0]

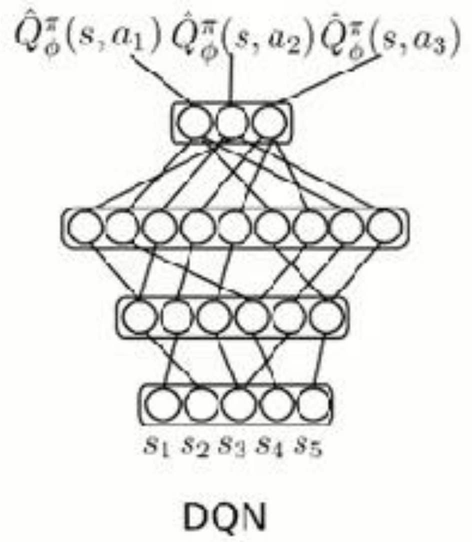
np.round(action[-1])

Reward Addition: ([Penalty calculated from previous schedule] – [Penalty calculated from noticed schedule]) *A * alpha

$A = a^2 + a - 1$ (a := np.round(action[-1]))

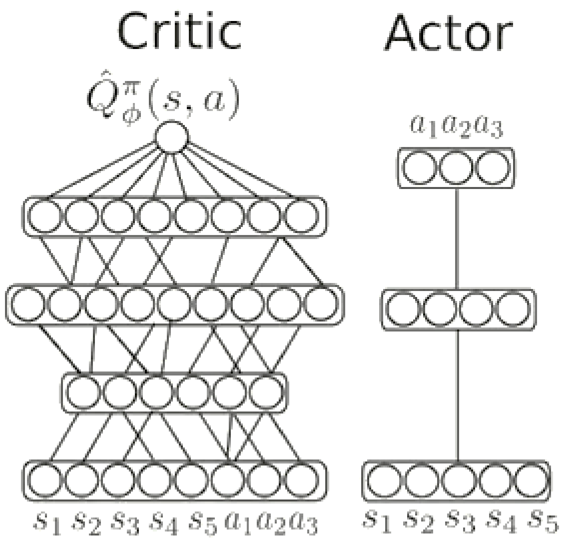
Why different RL algos DQN -> TD3 ?

Select the best action that has highest Q value.



- In DQN, the state is given as input and we have 1 o/p neuron per action where the output Q value of the network says the value of being in that state taken the action.
- Valid for discrete space, difficult for continuous space, since then there will be infinite output nodes.

$$Q(\mathbf{s}_t,\mathbf{a}_t) \leftarrow Q(\mathbf{s}_t,\mathbf{a}_t) + \alpha[r_t + \gamma \max_{\mathbf{a}\in A} Q(\mathbf{s}_{t+1},\mathbf{a}) - Q(\mathbf{s}_t,\mathbf{a}_t)]$$



Train a side estimator to have the best action

Deterministic policy gradient theorem: the true policy gradient is

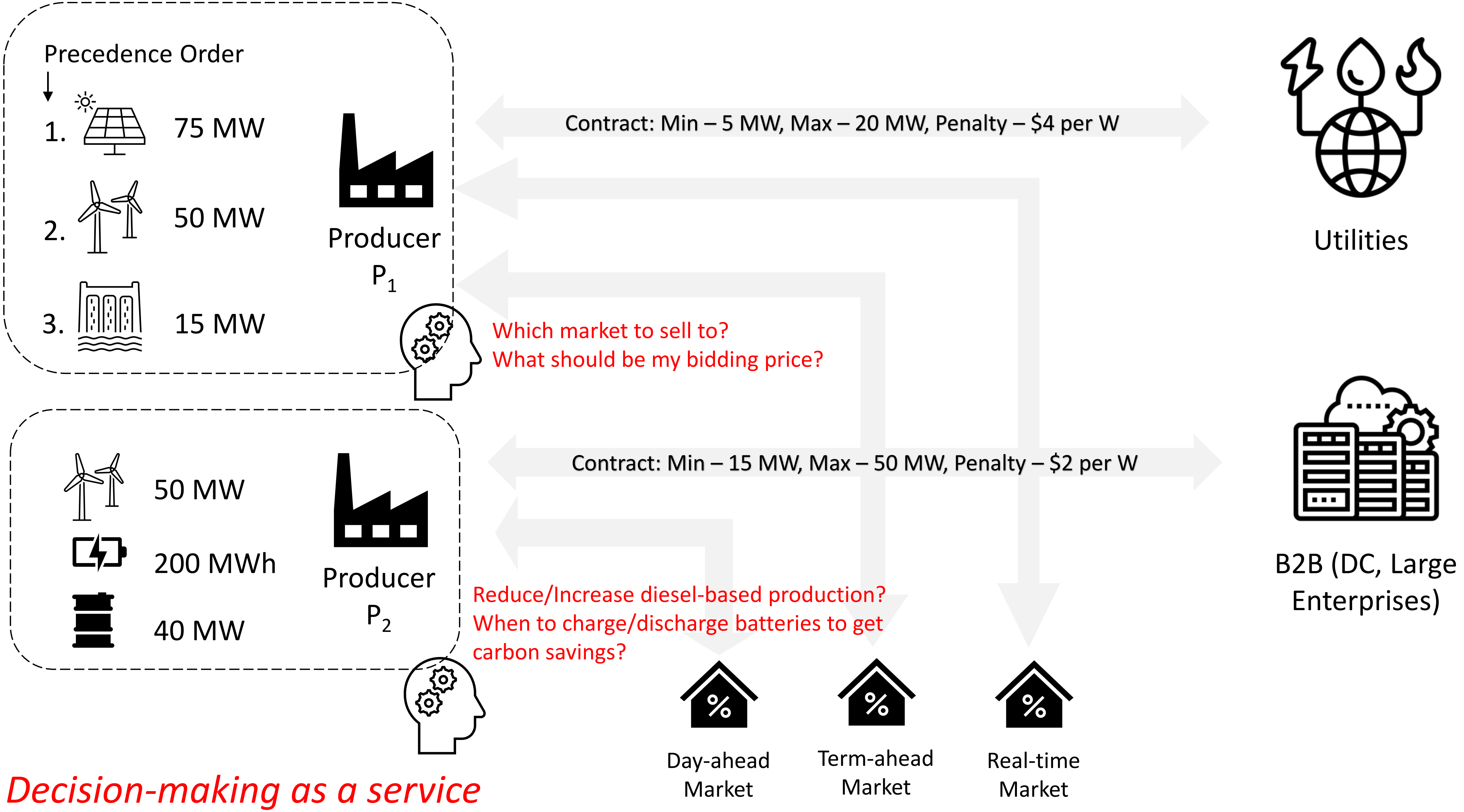
$$\nabla_{\theta}\pi(\mathbf{s}_t,\mathbf{a}_t) = \mathbb{E}_{\mathbf{s}_t,\mathbf{a}_t\sim\pi_{\theta}(.)}[\nabla_a \hat{Q}^{\pi_\theta}_{\phi}(\mathbf{s}_t,\mathbf{a}_t)\nabla_{\theta}\pi(s|\boldsymbol{\theta})]$$

TD3

Twin Delayed DDPG

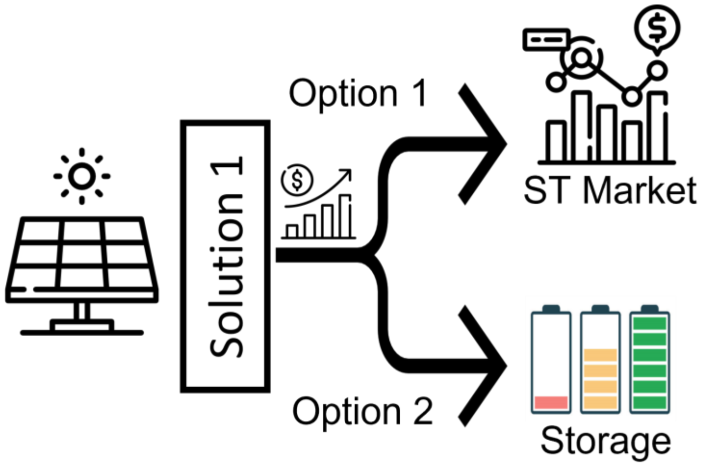
Limitations of DDPG:
Learned Q function dramatically overestimates Q values , which leads to policy breaking, exploits the errors in Q function.

Decisions in renewables monetization and orchestration

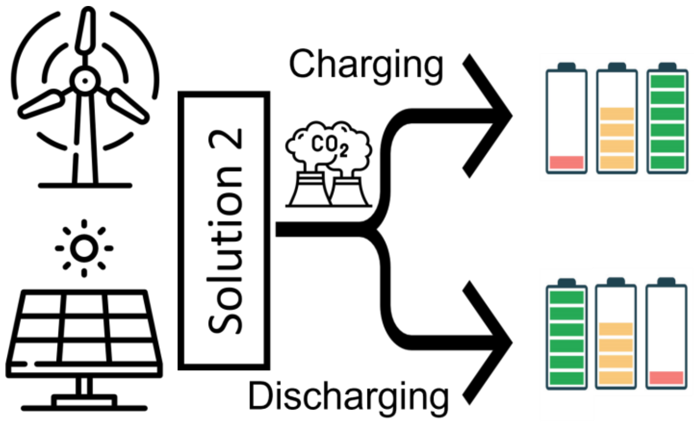


Decision-making as a service

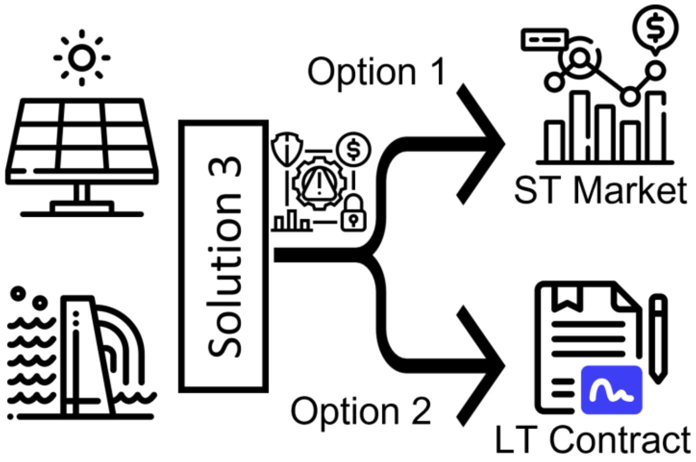
In Short...



Variations in type, quantity of energy sources



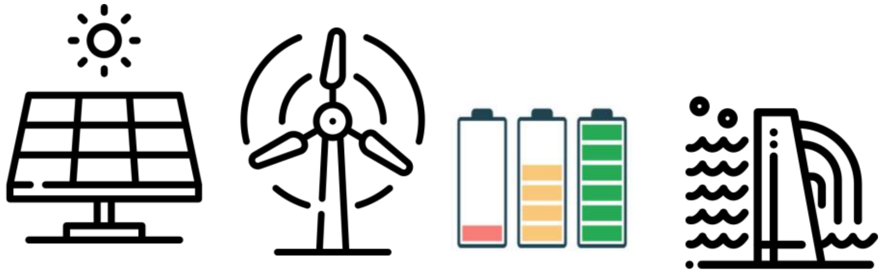
Variations in objective and optimization scheme



Variations in type of decisions (participants, actions allowed)

Decision Management Abstractions

Energy sources



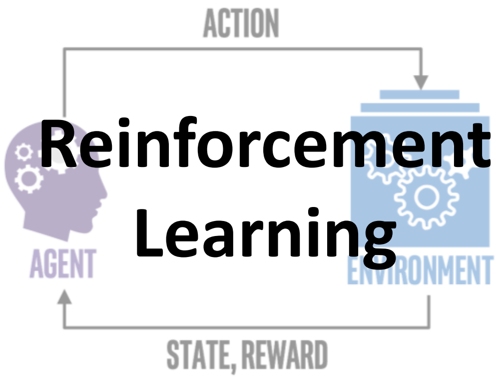
Solar Wind Storage Hydro

Markets and Contracts

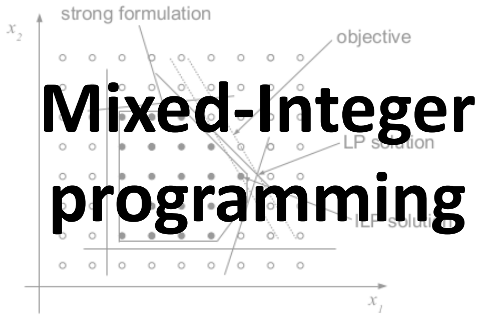
LT Contract

ST Market

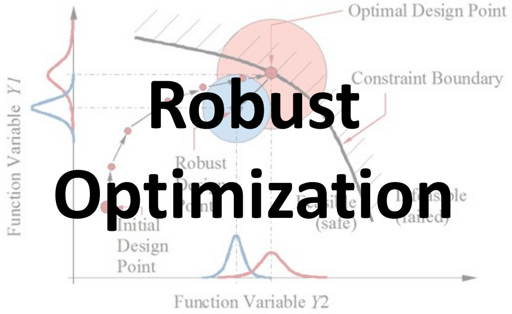
Decision Engine



Reinforcement Learning



Mixed-Integer programming



Robust Optimization

Thank You!