Maintenance of Energy Consumption: Prediction and Management

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Research Focus:
Data Science, Machine Learning, Optimization

Field:
Finance, Economic, Energy

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AGENDA

01
Research Roadmap

02
Prediction

Developed Models

03
Management

Developed Systems

04
Discussion

Research Plan

01

Research Roadmap

Roadmap

Prediction

Predict the energy consumption of tasks, AGVs

Management

Manage the energy usage, charging, pricing (priority)

Scheduling

Schedule the tasks assign to AGVs

02

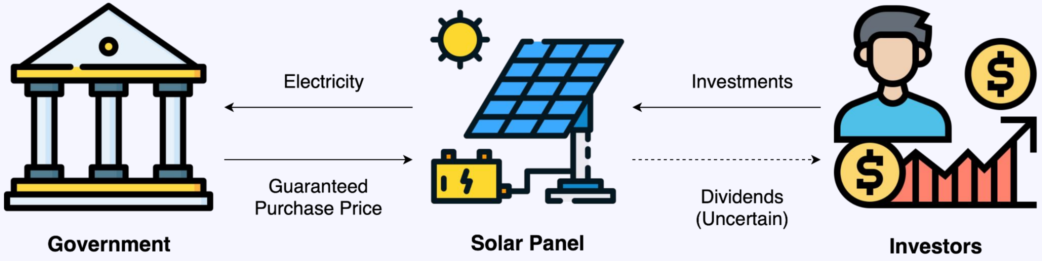
Prediction

Developed Models

- "**An IoT-based Data-Driven Hedge System of Solar Power Generation**", *IEEE Internet of Things Journal*, 2021.

Goal: Predict solar power generation

Hedge low-radiation risk



Developed Models

- **“Multi-Head Learning Model for Power Consumption Prediction of Uncrewed Ground Vehicles**”, submitted to AAAI 2023.

  Goal: Predict the power consumption (watt) of UGV

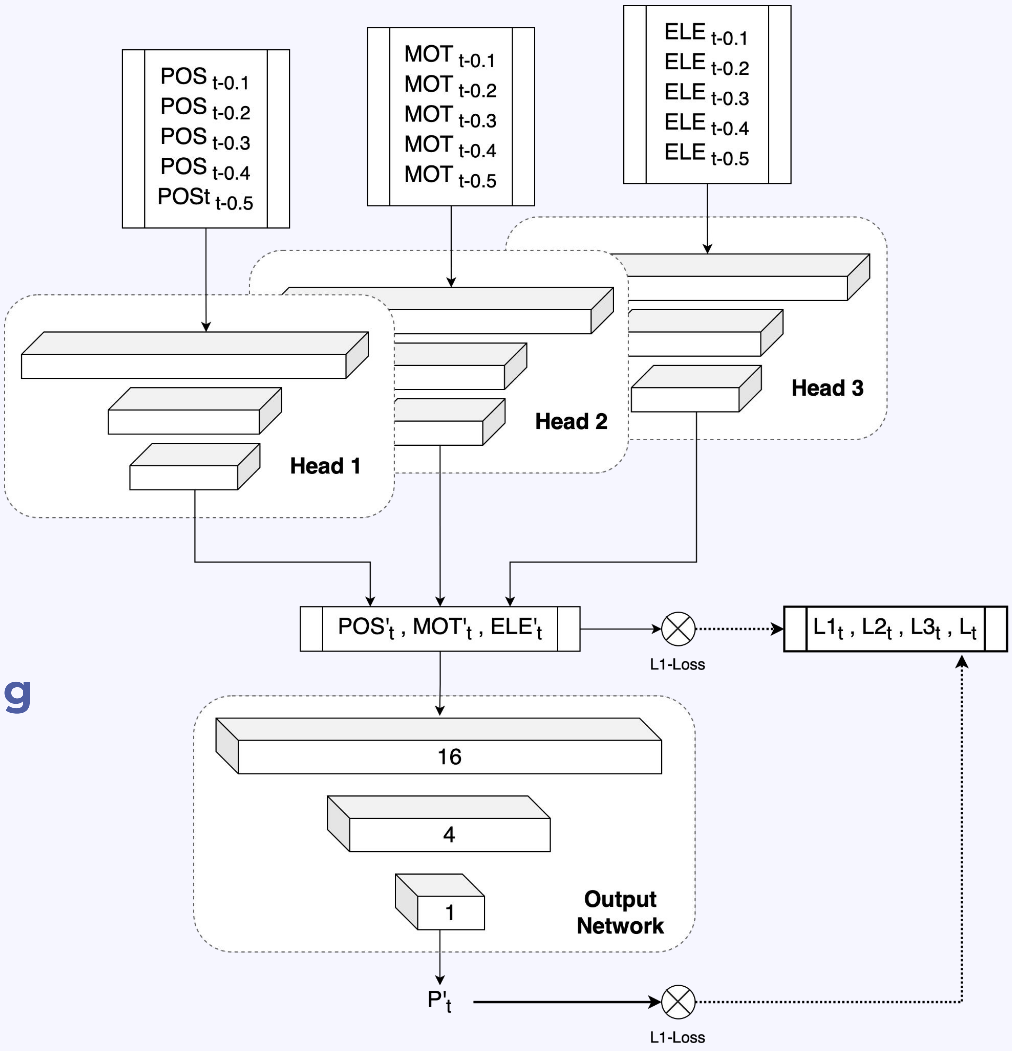
Dataset: “Energy consumption data for package delivery with an Uncrewed Ground Vehicle”

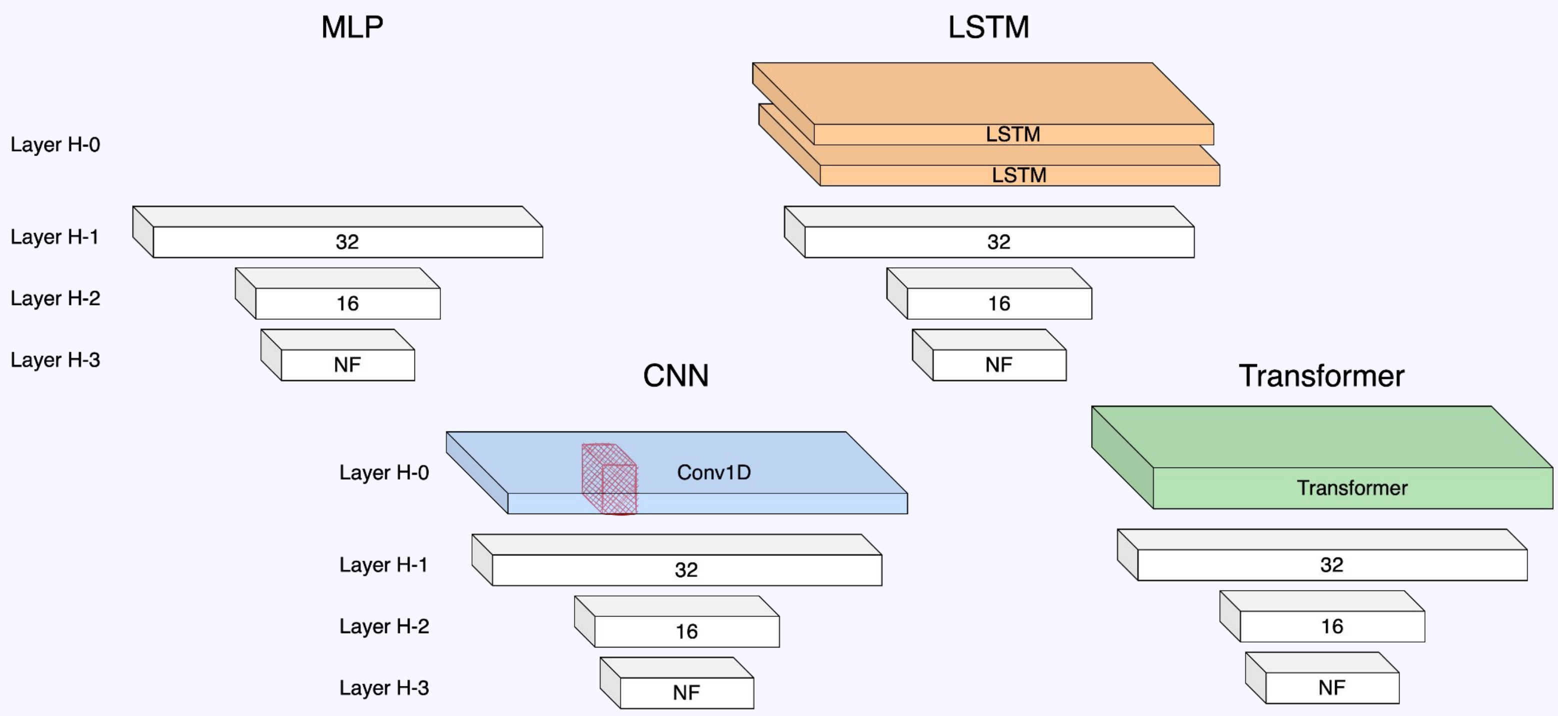
- 10 HZ data of Husky A200 UGV
- Different routes and payloads
- Features: position, motor, electronic info
- Predict: power consumption (watt or A · V)

Transfer Learning

- Route A - Source: 24 trials for training, 10 for testing
- Route B - Target: 25 trials for training, 10 for testing
- Route C - FewShot: 7 trials for training, 10 for testing
- Route D - ZeroShot: 5 for testing

2SMH: 2-stage multi-head learning




MLP
Layer H-0
Layer H-1
32
Layer H-2
16
Layer H-3
NF
LSTM
LSTM
LSTM
32
16
NF
CNN
Layer H-0
Conv1D
Layer H-1
32
Layer H-2
16
Layer H-3
NF
Transformer
Transformer
32
16
NF

MAE Evaluation

0.1 second after

Network	Linear					CNN				
Route	A	B	C	D	Aver.	A	B	C	D	Aver.
Benchmark	34.5	16.1	22.2	116.4	47.3	44.8	16.5	21.1	112.1	48.6
EMH	43.3	**15.7**	24.0	133.8	54.2	**44.6**	**15.1**	25.0	117.4	50.5
2SMH	**32.4**	16.2	29.9	**81.4**	**40.0**	**34.2**	**15.3**	**16.6**	**80.7**	**36.7**

Network	LSTM					Transformer				
Route	A	B	C	D	Aver.	A	B	C	D	Aver.
Benchmark	109.5	41.5	47.3	216.6	103.7	109.6	41.5	47.3	216.5	103.7
EMH	**109.4**	**22.6**	**19.1**	217.1	**92.1**	**109.5**	**33.0**	**44.5**	216.8	**101.0**
2SMH	**85.0**	**15.9**	**17.0**	**194.9**	**78.2**	**109.5**	41.5	**32.2**	217.0	**100.0**

A: Source
B: Target
C: FewShot
D: ZeroShot

MAE Evaluation

0.5 second after

Network	Linear					CNN				
Route	A	B	C	D	Aver.	A	B	C	D	Aver.
Benchmark	63.0	26.6	37.9	171.4	74.7	63.3	25.5	35.1	156.6	70.1
EMH	65.7	**24.7**	67.4	**165.8**	80.9	**62.6**	**24.8**	37.8	178.7	76.0
2SMH	**60.3**	26.9	63.6	**137.6**	**72.1**	**61.4**	**25.1**	**30.6**	**126.8**	**60.9**

Network	LSTM					Transformer				
Route	A	B	C	D	Aver.	A	B	C	D	Aver.
Benchmark	109.9	41.5	47.3	214.7	103.3	109.9	41.5	47.3	214.9	103.4
EMH	**109.4**	**27.2**	**31.4**	217.3	**96.3**	**109.5**	41.5	**46.3**	217.0	103.6
2SMH	**108.6**	**24.6**	**30.3**	**190.6**	**88.5**	**109.5**	**35.6**	**43.7**	217.0	**101.4**

A: Source
B: Target
C: FewShot
D: ZeroShot

MAE Evaluation

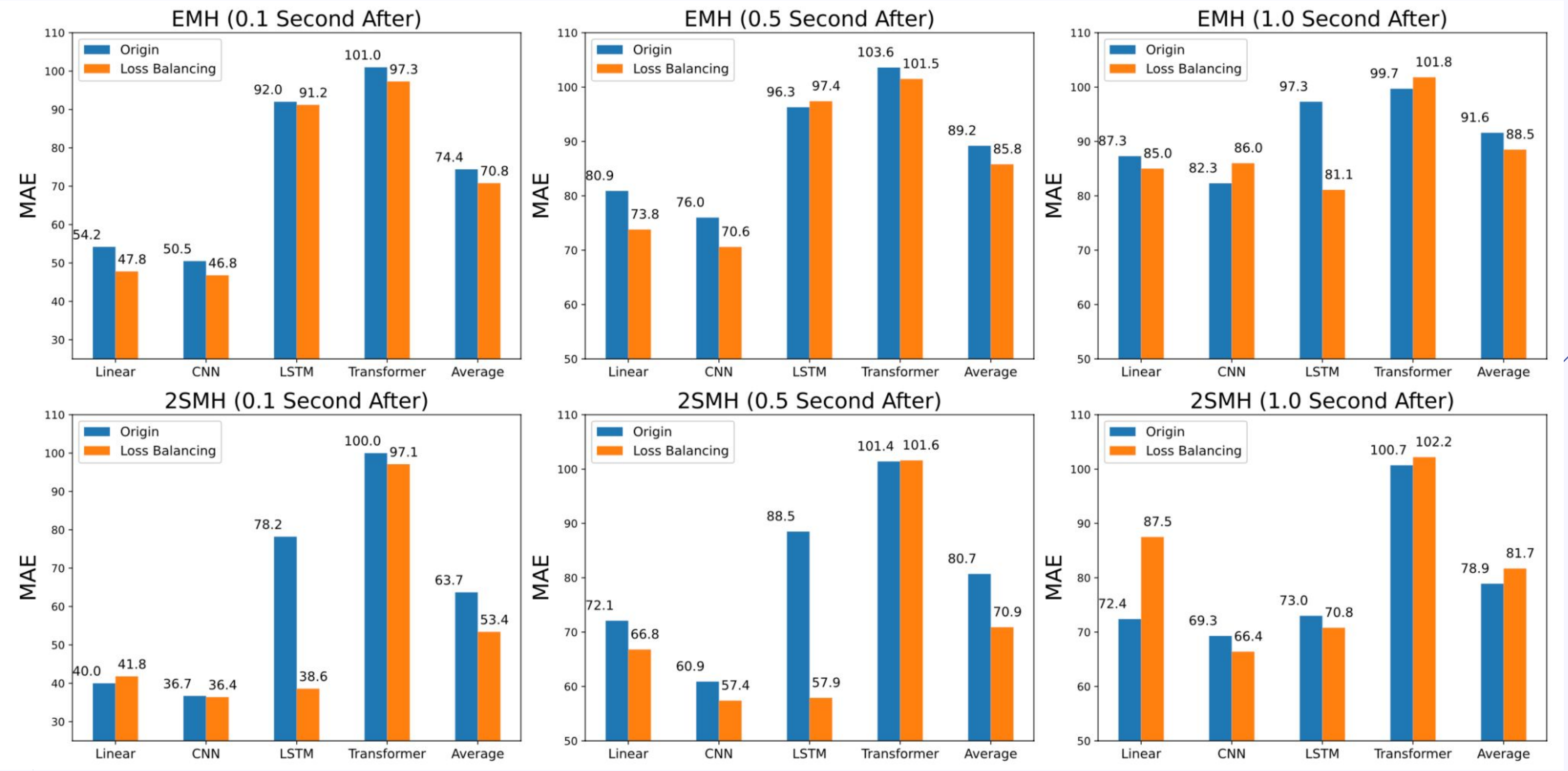
1.0 second after

Network	Linear					CNN				
Route	A	B	C	D	Aver.	A	B	C	D	Aver.
Benchmark	73.7	32.3	47.4	160.6	78.5	71.6	29.5	39.6	257.3	99.5
EMH	82.4	**28.2**	**44.6**	193.9	87.3	77.1	**27.6**	59.9	**164.7**	**82.3**
2SMH	75.7	**26.6**	**41.5**	**145.8**	**72.4**	71.8	**29.2**	**34.1**	**142.3**	**69.3**

Network	LSTM					Transformer				
Route	A	B	C	D	Aver.	A	B	C	D	Aver.
Benchmark	109.6	41.5	47.9	216.6	103.9	109.3	41.5	47.3	217.8	104.0
EMH	**106.2**	**29.9**	**37.2**	**215.8**	**97.3**	109.5	**37.4**	**34.9**	**217.0**	**99.7**
2SMH	**83.2**	**29.3**	**33.7**	**145.8**	**73.0**	109.4	**35.0**	**41.0**	**217.4**	**100.7**

A: Source
B: Target
C: FewShot
D: ZeroShot

Loss Balance



Transfer Mechanisms

Time	0.1 S	0.5 S	1.0 S
Benchmark	75.8	87.9	96.5
Benchmark-TWN	76.1	87.3	92.1
EMH	**74.4**	89.2	**91.7**
EMH-LB	**70.8**	**85.8**	**88.5**
EMH-LB-TWN	**69.1**	**78.0**	**89.7**
EMH-LB-TON	**70.3**	**77.8**	**82.6**
2SMH	**63.7**	**80.7**	**78.9**
2SMH-LB	**53.4**	**70.9**	**81.7**
2SMH-LB-TWN	**50.8**	**70.2**	**77.9**
2SMH-LB-TON	**47.0**	**69.9**	**76.5**

Developed Models

- **“Multi-Head Learning Model for Power Consumption Prediction of Uncrewed Ground Vehicles**”, submitted to AAAI 2023.

  Goal: Predict the power consumption (watt) of UGV

  Contribution:

  A. Propose 2-stage multi-head learning
  B. Multi-task for time-series prediction
  C. High transferability

03

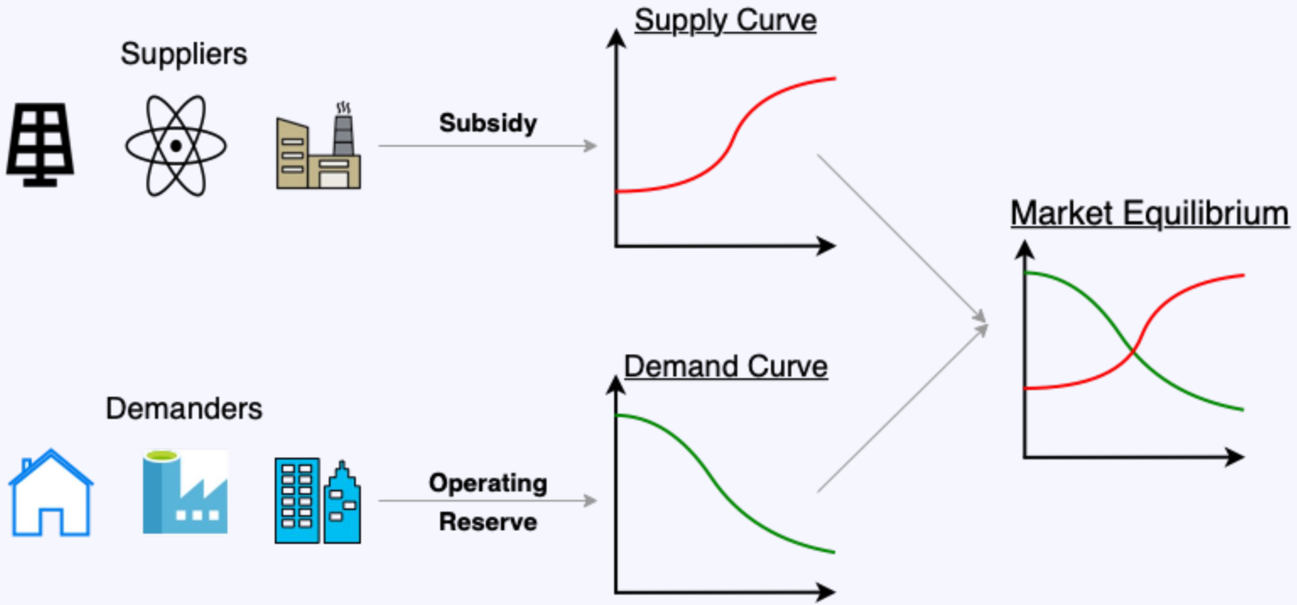
Management

Developed Models

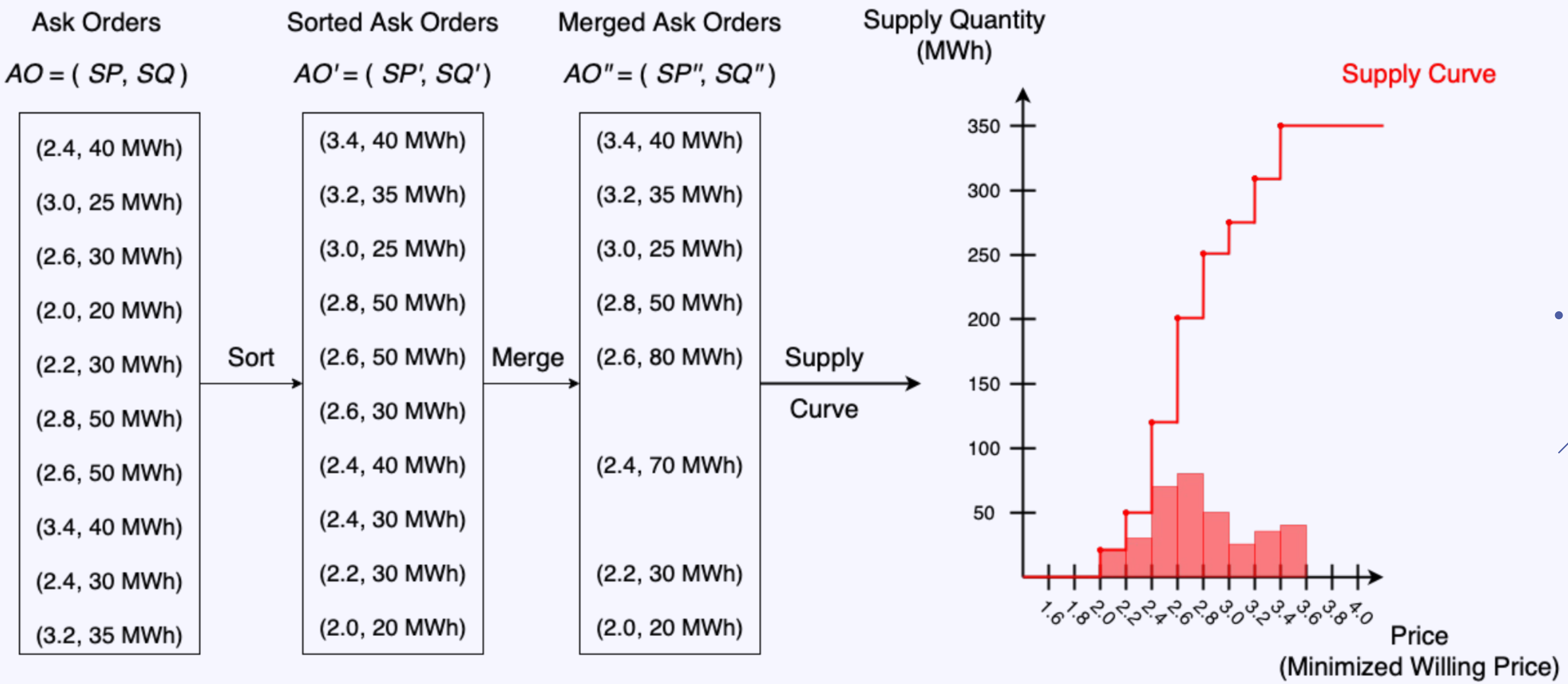
- **“Call Auction-Based Energy Management System with Adaptive Subsidy and Dynamic Operating Reserve”**, *Sustainable Computing: Informatics and Systems*, 2022.

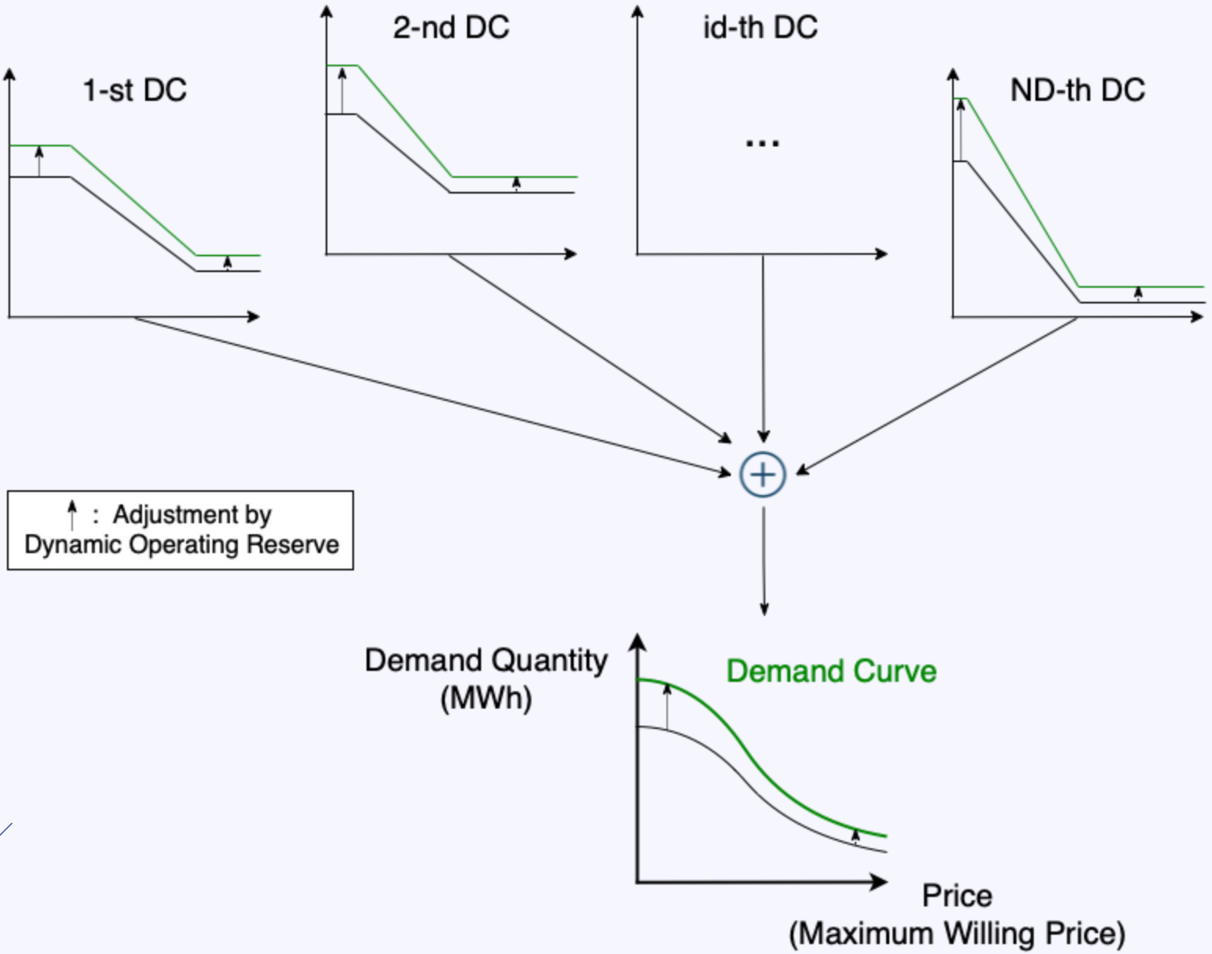
  Goal: Maintain operating reserve rate at a stable level

  Achieve the target distribution of energy supply



Suppliers
Subsidy
Supply Curve
Market Equilibrium
Demand Curve
Demanders
Operating
Reserve


Ask Orders
AO = (SP, SQ)
(2.4, 40 MWh)
(3.0, 25 MWh)
(2.6, 30 MWh)
(2.0, 20 MWh)
(2.2, 30 MWh)
(2.8, 50 MWh)
(2.6, 50 MWh)
(3.4, 40 MWh)
(2.4, 30 MWh)
(3.2, 35 MWh)
Sort
Sorted Ask Orders
AO' = (SP', SQ')
(3.4, 40 MWh)
(3.2, 35 MWh)
(3.0, 25 MWh)
(2.8, 50 MWh)
(2.6, 50 MWh)
(2.6, 30 MWh)
(2.4, 40 MWh)
(2.4, 30 MWh)
(2.2, 30 MWh)
(2.0, 20 MWh)
Merge
Merged Ask Orders
AO'' = (SP'', SQ'')
(3.4, 40 MWh)
(3.2, 35 MWh)
(3.0, 25 MWh)
(2.8, 50 MWh)
(2.6, 80 MWh)
(2.4, 70 MWh)
(2.2, 30 MWh)
(2.0, 20 MWh)
Supply
Curve
Supply Quantity
(MWh)
Supply Curve
350
300
250
200
150
100
50
1.6
1.8
2.0
2.2
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
Price
(Minimized Willing Price)


1-st DC
2-nd DC
id-th DC
...
ND-th DC
: Adjustment by
Dynamic Operating Reserve
Demand Quantity
(MWh)
Demand Curve
Price
(Maximum Willing Price)

Dynamic Operating Reserve Rate:

$$DMOR_d = \alpha \times DMOR_{d-1} + (1-\alpha) \times NM_d$$

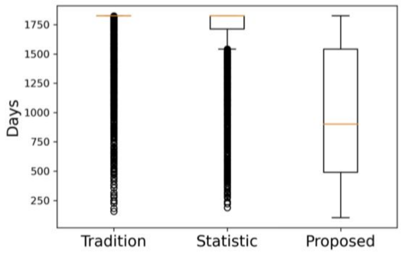
$$NM_d = DMOR_{d-1} + (TarORR - ORR_{d-1})$$

Adaptive Subsidy

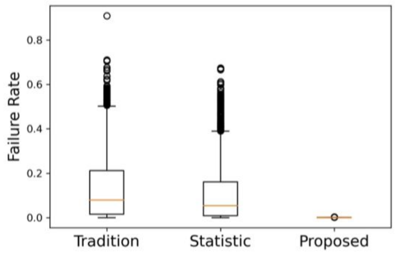
Algorithm 1 Self-financing algorithm for adaptive subsidy

$Remains = 0$;
for each d-th day **do**
  $Income = \text{Sum}(\ \{(EquP_{d-1} - TarP_{its}) \times TarQ_{its} \ \mid \ EquP_{d-1} > TarP_{its}\}\ )$;
  $Expend = \text{Sum}(\ \{(TarP_{its} - EquP_{d-1}) \times TarQ_{its} \ \mid \ TarP_{its} > EquP_{d-1}\}\ )$;
  $Balance = Income - Expend + Remains$;
  if $Balance > 0$ **then**
    $MSI = \frac{Remains - Expend}{Income}$;
    for each its-th type suppliers **do**
      if $TarP_{its} < EquP_{d-1}$ (negative subsidy) **then**
        $AdjIncome = (EquP_{d-1} - TarP_{its}) \times TarQ_{its} \times MSI$;
        $SUB_{its,d}$ = subsidy that just charge $AdjIncome$ from its-th type suppliers;
      if $TarP_{its} >= EquP_{d-1}$ (positive subsidy) **then**
        $SUB_{its,d} = TarP_{its} - EquP_{d-1}$;

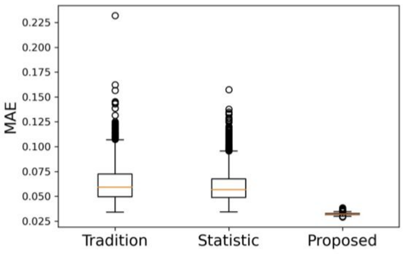
	Tradition	Statistic	Proposed
Average Convergence Day	1725	1686	**989**
Average Failure Rate	13.09%	10.12%	**0.03%**
MAE of Operating Reserve Rate	6.3%	6.0%	**3.2%**
MAE of Supply Distribution	22.9%	21.7%	**8.5%**



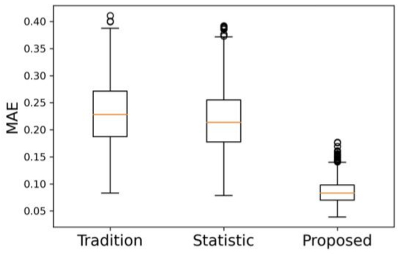
(a) Convergence Day



(b) Failure Rate



(c) MAE of Operating Reserve Rate



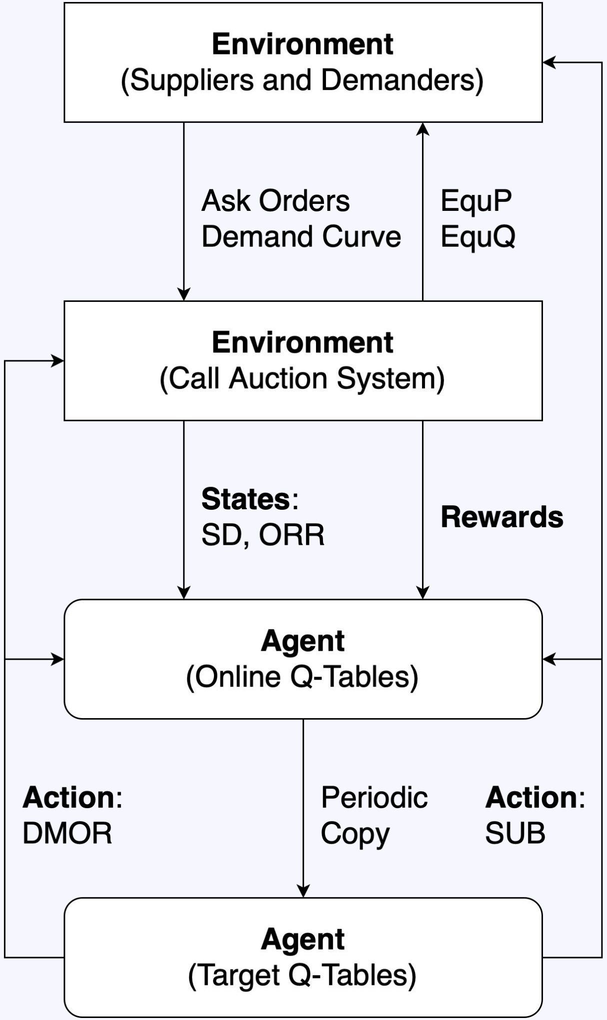
(d) MAE of Supply Distribution

Developed Models

- **"Double-Environmental Q-Learning for Energy Management System in Smart Grid"**, submitted to AAAI 2023.

  Contribution:

  A. Q-learning-based decision making
  B. Clear states and intuitive actions
  C. High interpretability


Environment
(Suppliers and Demanders)
Ask Orders
Demand Curve
EquP
EquQ
Environment
(Call Auction System)
States:
SD, ORR
Rewards
Agent
(Online Q-Tables)
Action:
DMOR
Periodic
Copy
Action:
SUB
Agent
(Target Q-Tables)

0.10	Tradition	Statistic	CAEMS	DEQEMS
CONVERGE	1710	1704	955	**633**
MAESD	23.0%	21.4%	8.5%	**6.7%**
MAEORR	6.4%	6.1%	**3.2%**	3.4%
FAIL	13.24%	11.24%	**0.03%**	**0.03%**

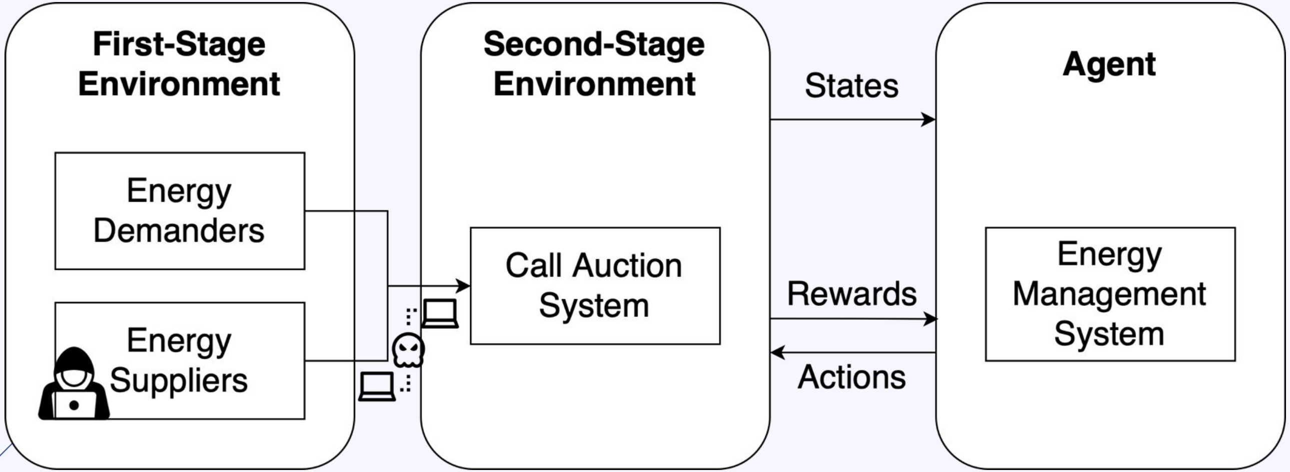
0.15	Tradition	Statistic	CAEMS	DEQEMS
CONVERGE	1726	1699	978	**651**
MAESD	23.2%	22.5%	8.1%	**7.0%**
MAEORR	6.3%	5.9%	**2.9%**	3.1%
FAIL	3.10%	1.94%	**0.00%**	**0.00%**

0.20	Tradition	Statistic	CAEMS	DEQEMS
CONVERGE	1796	1797	1023	**680**
MAESD	25.0%	25.1%	8.0%	**6.8%**
MAEORR	5.8%	5.2%	**2.7%**	2.8%
FAIL	0.09%	0.04%	**0.00%**	**0.00%**

What if get attacked?

Malicious Suppliers

Man-in-the-middle



Developing Models

- **“Secure Q-Learning for Energy Management System in Smart Grid”**

  Contribution:

  A. Anomaly detection by deep learning
  B. Fuzzy control module

04

Discussion

Connect with CoBotAGV

- AGV (supplier) select tasks (demander)
- Based on priority of weight, urgency, … (price)
- Limited by the battery level (quantity)

	Price	**Quantity**
AGV	Reward	Battery Level
Task	Priority (weight, urgency)	Energy Consumption

Research Plan

Referenced from:

"**Hybridization of evolutionary algorithm and deep reinforcement learning for multi-objective orienteering optimization**", *IEEE Transactions on Evolutionary Computation*

AGV	Problem	Method
Task Selection	Knapsack	Multi-Objective Optimization
Path Arrangement	Traveling Salesman	Deep Reinforcement Learning

Roadmap

Prediction

1 Accepted
1 Submitted

Management

1 Accepted
1 Submitted
1 Writing

Scheduling

1 Planned

Current Issues

1. Data from CoBoatAGV
   a. Power Consumption (motor, battery, …)
   b. Charging Information
2. Tasks of CoBoatAGV
   a. Types of tasks
   b. Types of anomaly

Future Works

1. Refine prediction models to fit CoBotAGV
2. Develop scheduling methods
    a. Task selection
    b. Path arrangement
3. Establish management system for CoBotAGV

Thank You for Your Listening ! Questions or Suggestions?

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Thank You for Your Listening !

Questions or Suggestions?

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