Towards Scalable and Privacy-Preserving Distributed Vehicle-to-Grid Services

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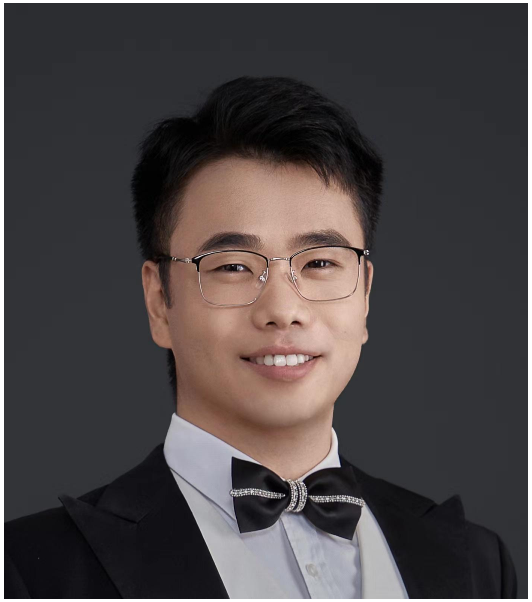
12.2023

Personal profile



Education

Harbin Institute of Technology
PhD, Information Engineering, 2022

Southern University of Sci & Tech
Joint PhD, Excellent Graduate

China Agricultural University
Bachelor, Electrical engineering, 2017

Awards & Honors

DAAD (Germany)
Alnet Fellow, 2023

SPPIES (Conference)
Best Paper, 2022

Tencent Technology
Rhino Bird Elite, 2022

Positions

Hong Kong University of Sci & Tech
Postdoc Researcher, 01.2023-now

Technical University of Munich
Visiting Scholar, 09.2023

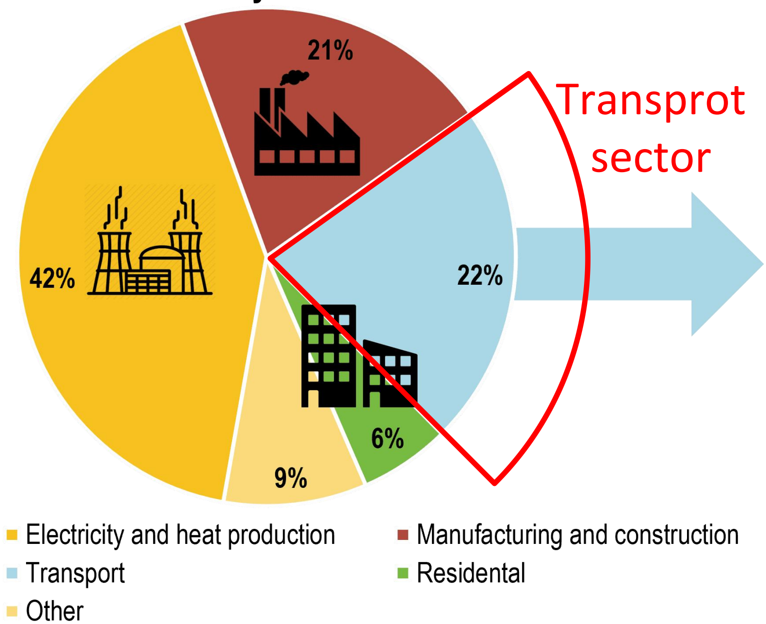
Tencent Technology
Internship, 05.2022-08.2022

Contents

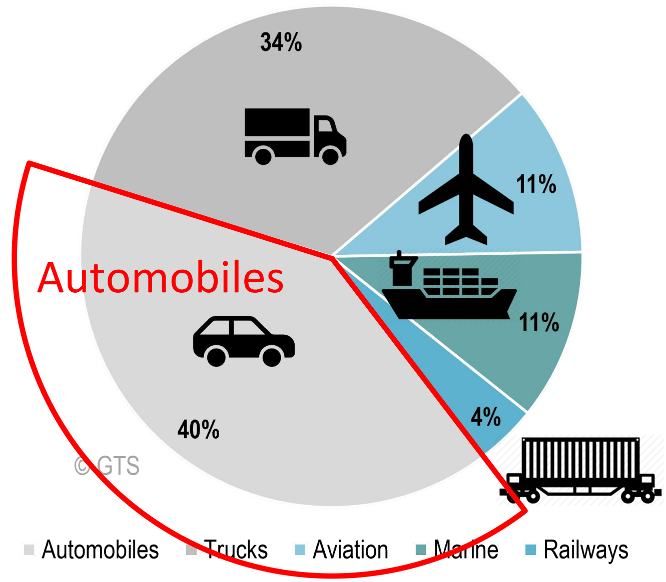
Introduction: Background

CO2 Emissions of Automobiles is Very Huge

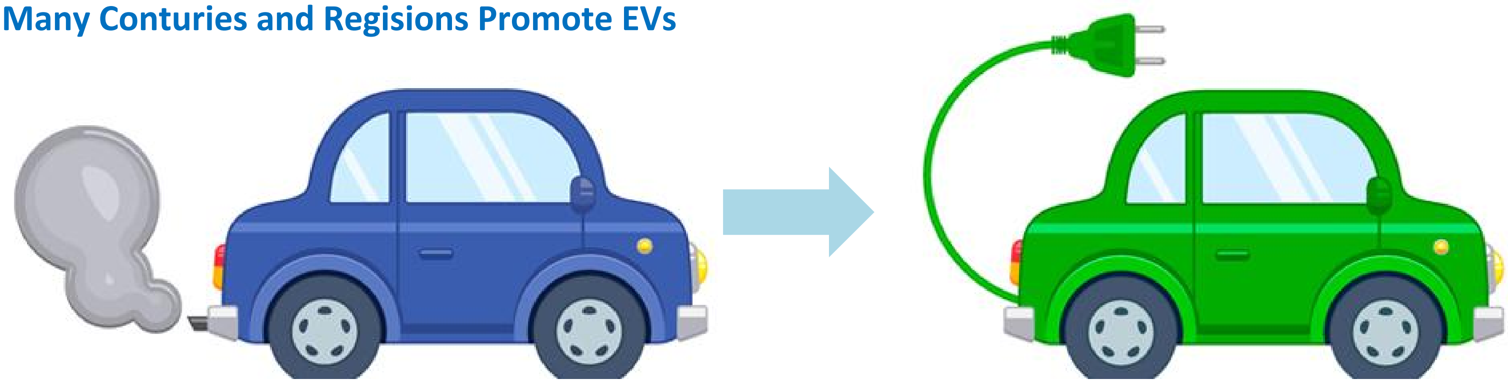
CO2 Emissions by Economic Sector



CO2 Emissions by the Transport Sector



Many Conturies and Regisions Promote EVs



The Development of EV in Hong Kong has 3 Milestones

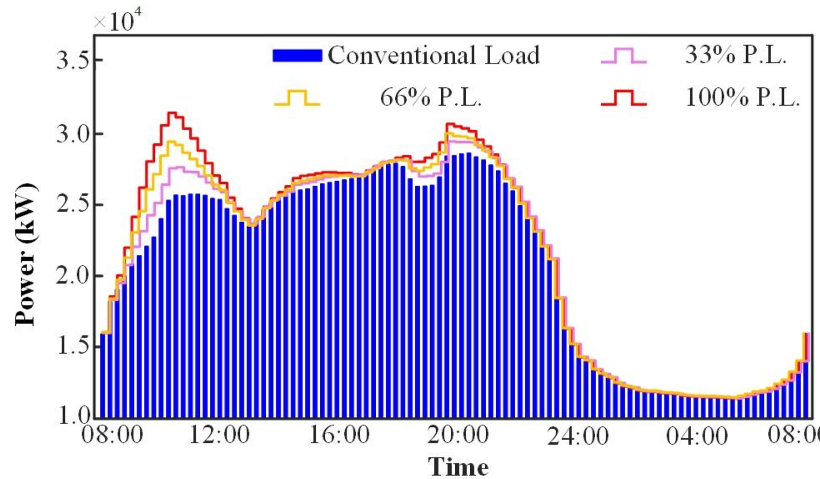
Private Charging Facilities

2025 ≥150 000

Public Charging Facilities

2025 ≥5000
(Plan to double in the future)

No new registration of fuel-propelled private cars including different types of hybrids in Hong Kong in 2035 or earlier



Increasing rate of load peak

Oct. 2023: 46,664 kW / 9,861,000 kW = **0.47%**

2025: 90, 000kW / 9,861,000 kW = **9.13%**

2050: 1,833,964 kW / 9,861,000 kW = **18.60%**

Many EVs Randomly Charging Cause Impact

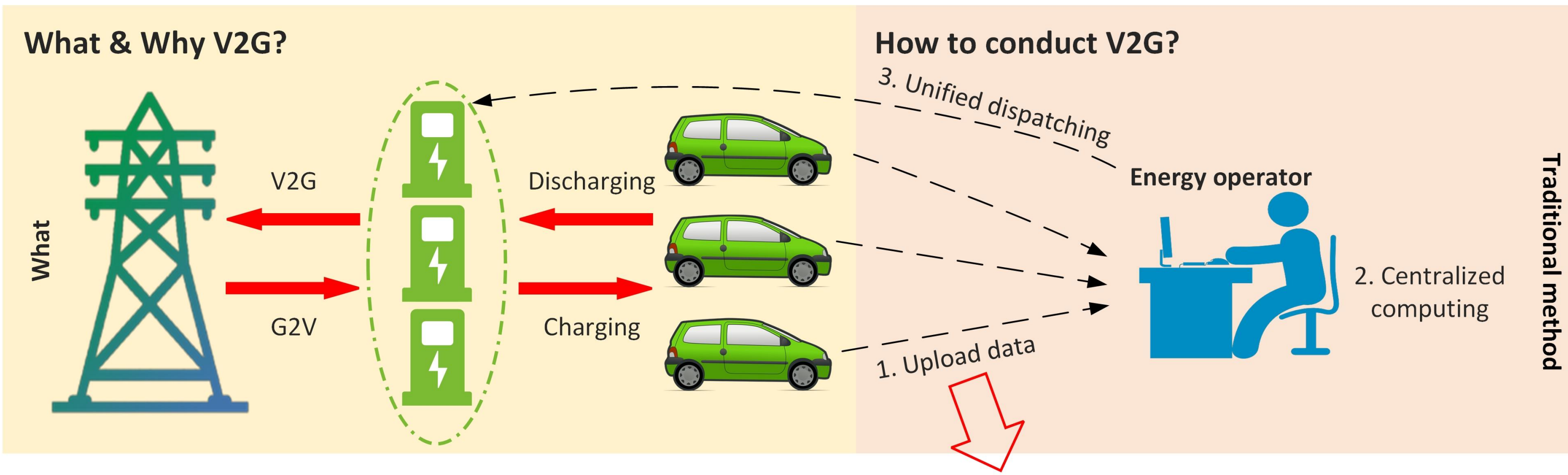
Calculation of load peak with unmanaged charging

- **Max conventional electricity load in 2021**
  - CLP Power: 7,477,000 kW
  - HKE: 2,384,000 kW
  - Total: 9,861,000 kW, assume that the total load peak will not change in the future
- **Amount of charging in HK**
  - Sept. 2023: 7,085 EV chargers for public use, including 3,950 medium chargers, 1,092 quick chargers and other 2,043 chargers are not specified, we assume they are medium chargers.
  - 2025: 150,000 for private charger and 5,000 for public charger
  - 2050: By Oct. 2023, the total number of EVs is 70,701, 7.7% of the total number of vehicles. So, total EVs in 2050 can be assumpted as 70,701 / 7.7% = 918,195. Let's assume that 3 vehicles share one private charger, which is 918,195 / 3 = 306,065. Let's assume that the public chargers are 10,000
- **Max EV charging load .**
  - Average charging power for private charger: 220 V * 16 A = **7 kW**
  - Average charging power for public charger: 380 V * 32 A = **12 kW**
  - Charging simultaneity factor for private charger : 0.8
  - Charging simultaneity factor for public charger : 1.0
  - Oct. 2023: (3,950 + 2,043) * 7 kW * 0.8 + 1,092 * 12 kW * 1.0 = 33,560 kW + 13,104 kW = **46,664 kW**
  - 2025: 150,000 * 7 kW * 0.8 + 5,000 * 12 kW * 1.0 = 840,000 kW + 60,000 kW = **900, 000kW**
  - 2050: 306,065 * 7 kW * 0.8 + 10,000 * 12 kW * 1.0 = 1,713,964 kW + 120,000 kW = **1,833,964 kW**
- **Load peak lift rate**
  - Oct. 2023: 46,664 kW / 9,861,000 kW = **0.47%**
  - 2025: 90, 000kW / 9,861,000 kW = **9.13%**
  - 2050: 1,833,964 kW / 9,861,000 kW = **18.60%**

Hong Kong: The Facts - Power and Gas Supplies (2022 Jul) (www.gov.hk)
Technical Guidelines on Charging Facilities for Electric Vehicles (emsd.gov.hk)
EVRoadmapEng17 3.indd (eeb.gov.hk)
Promotion of Electric Vehicles | Environmental Protection Department (epd.gov.hk)

How will the existing power grid cope with the impact of mass access to EVs?

Vehicle-to-grid (V2G) technology



Why

Grid
Power grid stability

Charging company
A new economic growth driver

EV user
Profitable for services

Government
Carbon neutrality

Overall society
Low carbon emission

Privacy leakage

Challenges

Kempton, Willett, and Jasna Tomić. "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue." *Journal of power sources* 144.1 (2005): 268-279.

V2G Problem of Minimizing Load Variance

$$\min \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{n=1}^{N} p_{n,t}^{EV} + p_t^{con} - p^{ave}\right)^2$$

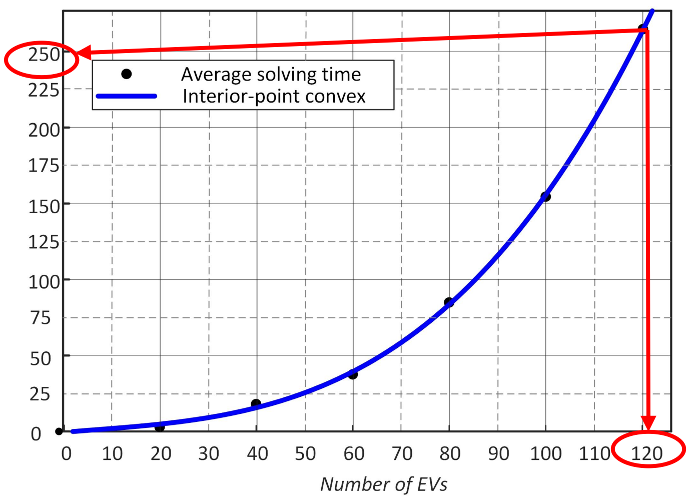
s.t.

$$SoC_n^{min} \le SoC_{n,t} \le SoC_n^{max}$$

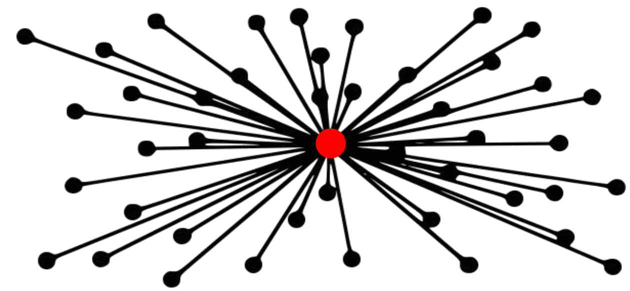
$$p_n^{dis,max} \le p_{n,t}^{EV} \le p_n^{ch,max}$$

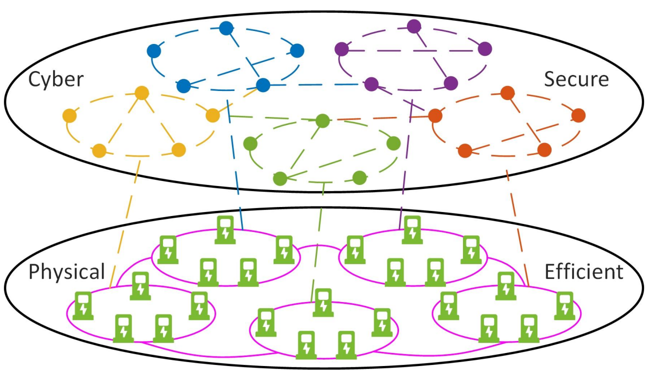
$$\eta_n^{ch}\Delta t \sum_{t=t_n^{arr}}^{t_i^{dep}} p_{n,t}^{EV} = \left(SoC_n^{dep} - SoC_n^{arr}\right)B_n = E_n$$

Solving time of minimizing load variance (quadratic programming)



Transform from Centralized to Distributed





Shang, Yitong, et al. "Computational performance analysis for centralized coordinated charging methods of plug-in electric vehicles: From the grid operator perspective." *International Transactions on Electrical Energy Systems* 30.2 (2020): e12229.

Brief Summary

1. Introduction
2. High Computational Performance Algorithm
3. High Information Security Method
4. High Stable Cyber-Physical-System Verification

Background
EV charging randomly

Current solution
V2G

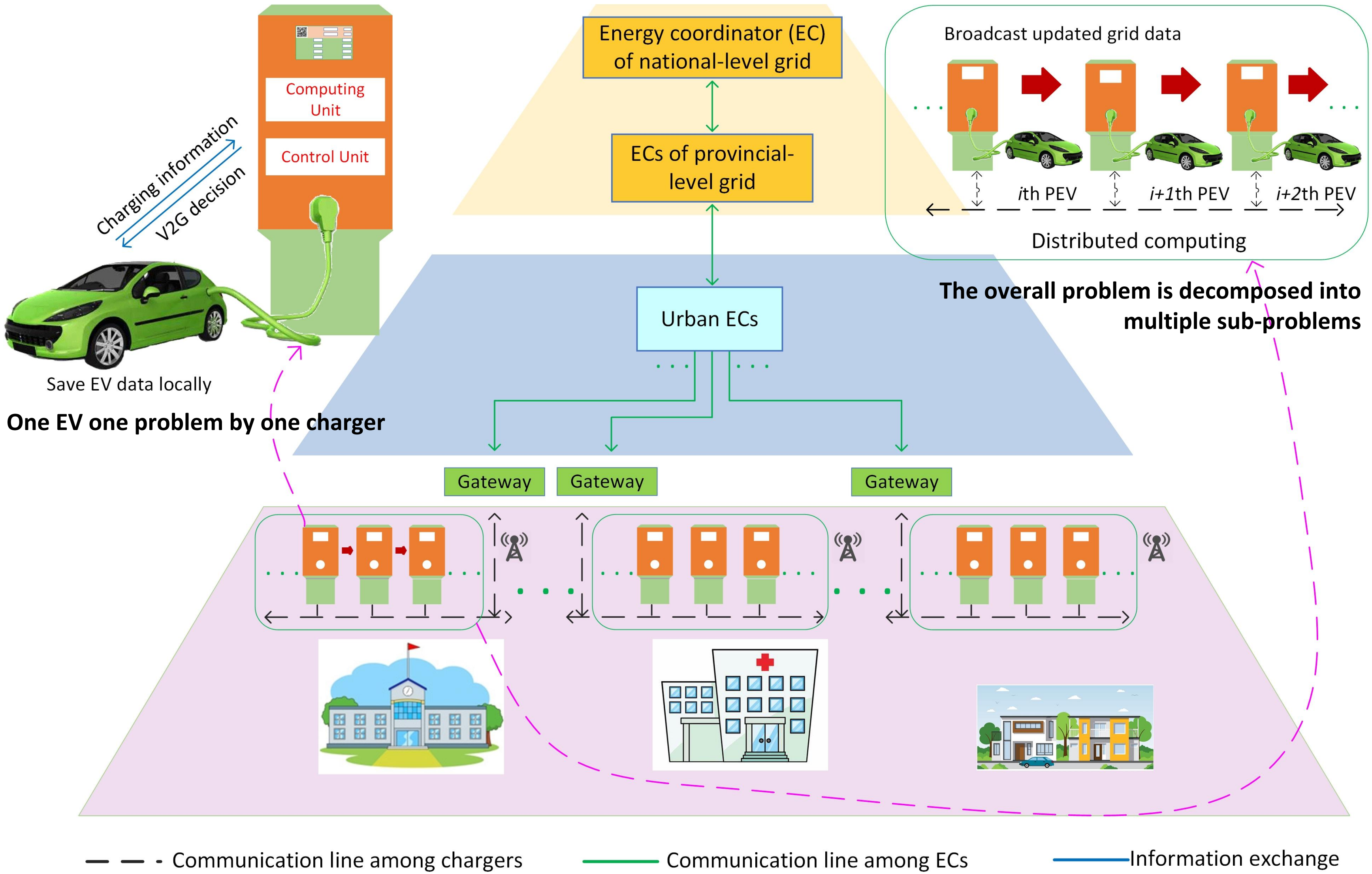
Potential issues
Privacy leakage and computational complexity

Proposed framework

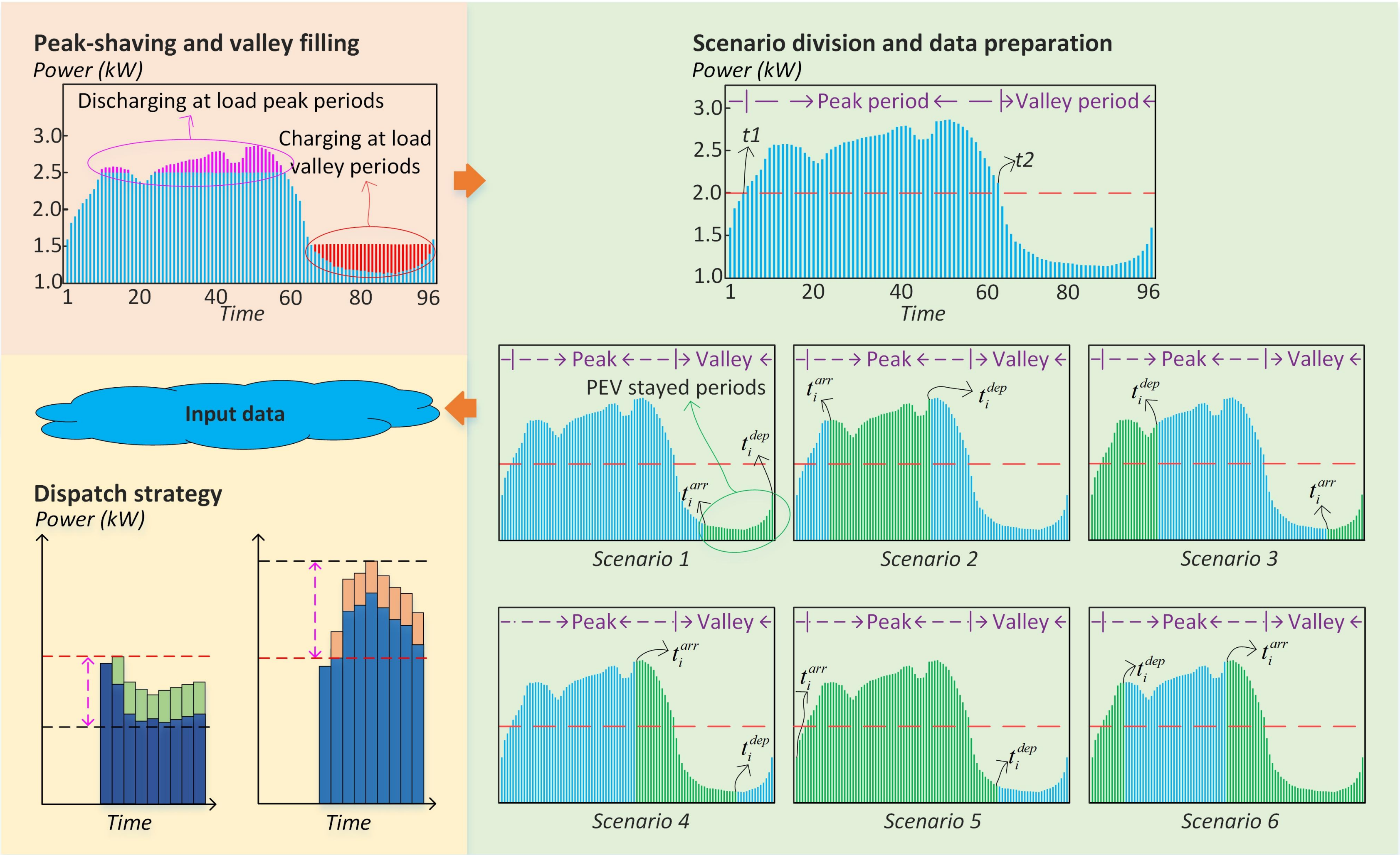
Contents

Design a Distributed Framework: Internet of smart charging points (ISCP)

✓ Three layers
✓ One key point
✓ Three advantages

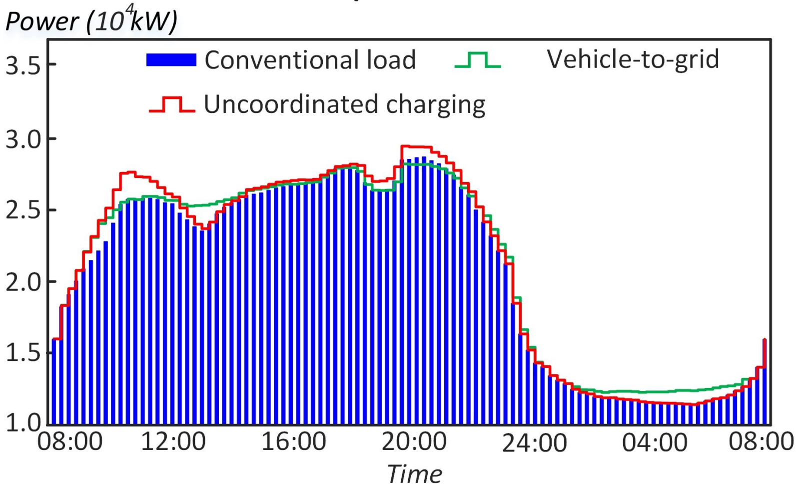


Distributed Load Flatting Strategy for One EV in ISCP

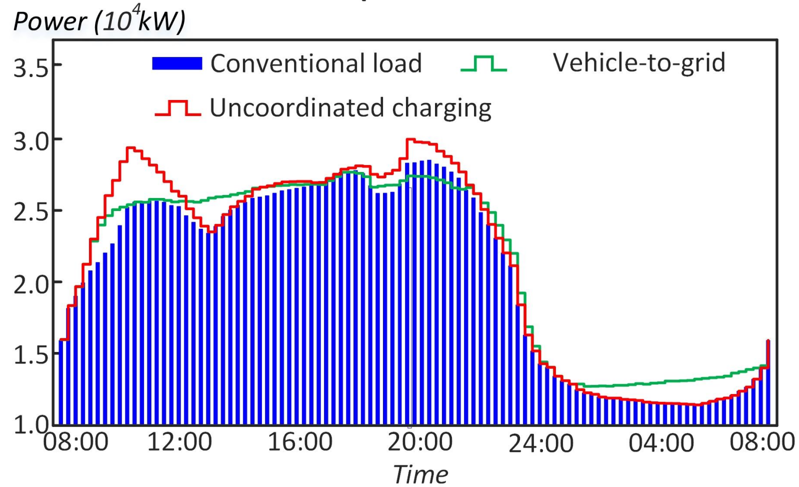


The Dispatch Results are Satisfied (Green Line) and the Computational Performance is Excellent

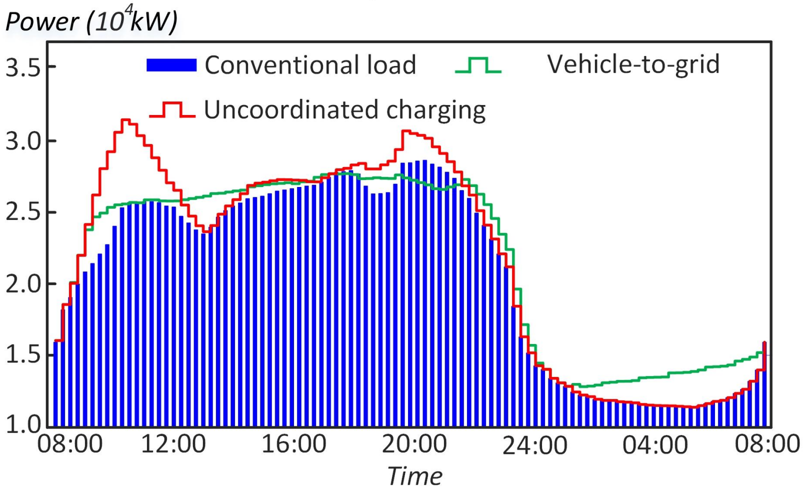
Load curve under 33% EV penetration



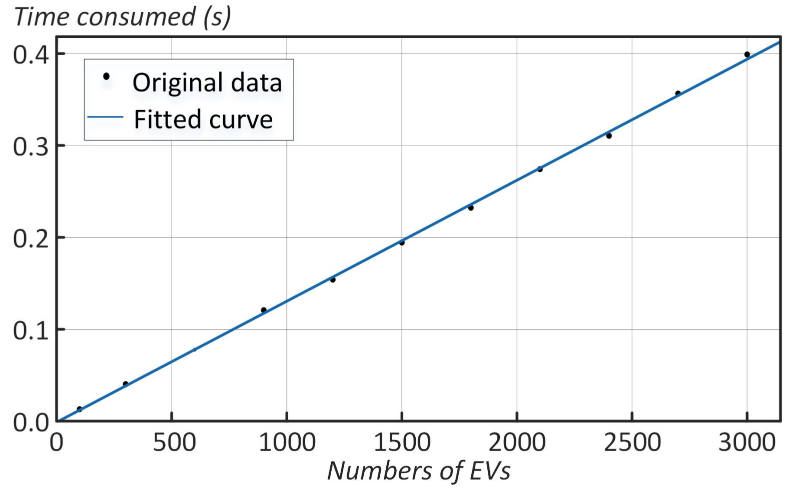
Load curve under 66% EV penetration



Load curve under 100% EV penetration



Computing time with EV increasing in one time slot



- Peak-shaving by **11.98%**
- Valley-filling by **12.68%**

- **About 0.4s** for **3000 EVs** under **ISCP**
- More than **250s** for **120 EVs** by **centralized** scheduling

Shang, Y., et al. "A centralized vehicle-to-grid scheme with distributed computing capacity engaging internet of smart charging points: case study." *International Journal of Energy Research* 45.1 (2021): 841-863.

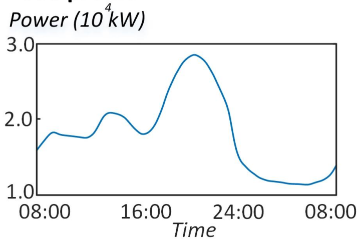
High Computational Performance: Strategy 2, Double Objective Functions

Distributed Load Flatting & PV Self-consumption Strategy for One EV in ISCP

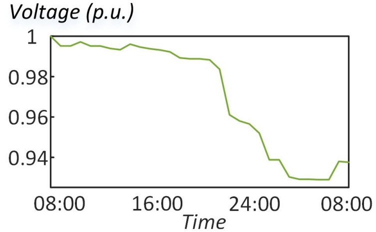
Step 1: Data collecting

- Collect the load profile of energy consumption
- Collect the energy output profile of solar panels
- Collect the node voltage value of distribution grid
- Collect the charging infomation value of PEV users

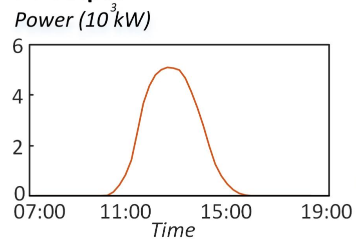
Load profile



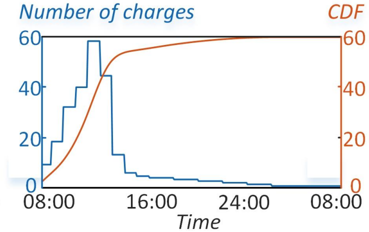
Voltage profile



PV output

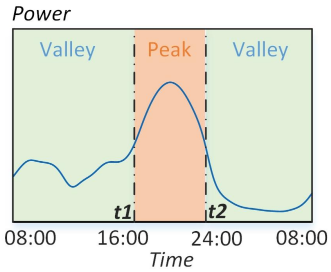


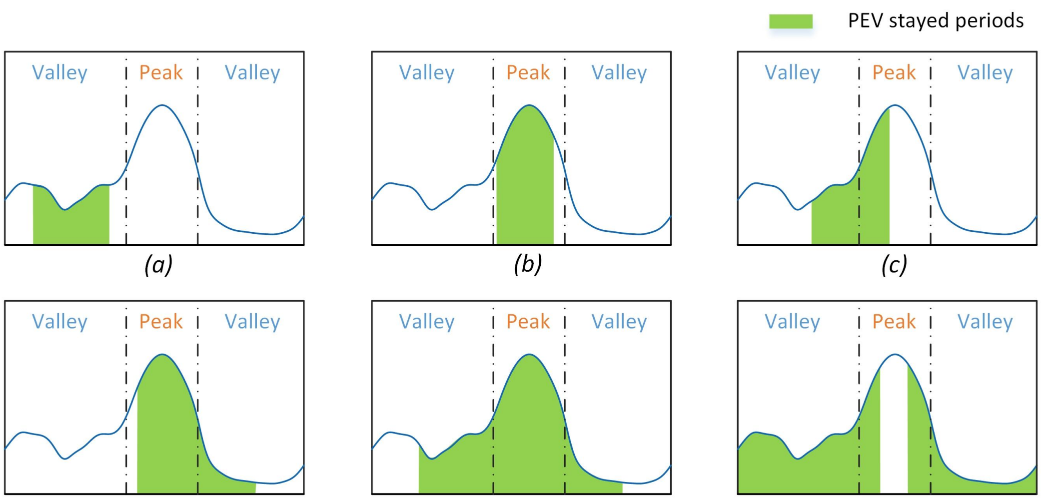
Charging information



Step 2: Data preprocessing

- Divide the peak and valley periods of net load
- Divide PEV charging scenarios





(a) (b) (c)

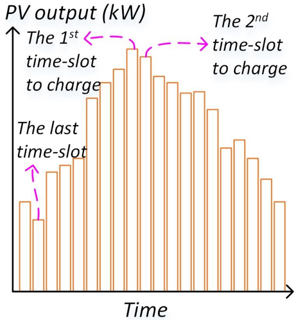
(d) (e) (f)

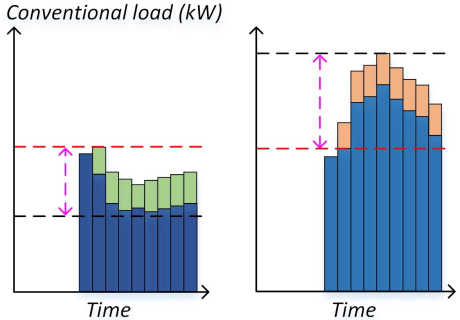
Distributed Load Flatting & PV Self-consumption Strategy for One EV in ISCP

- ✓ When PV output occors, it is different from the last single objective
- ✓ The strategy is EV charging from the highest PV output to the lowest PV output
- ✓ Use two weight factors to describe the importance of objective

Step 3: Dispatching strategy

- Charging from highest PV output to lowest PV output
- Dichotomy (water filling) algorithm

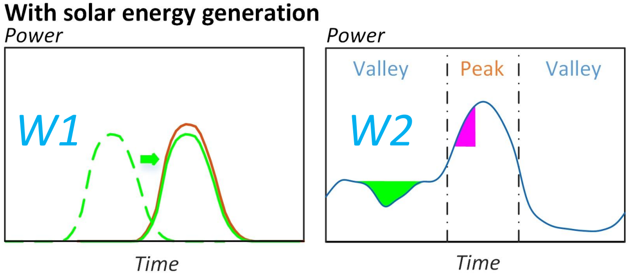




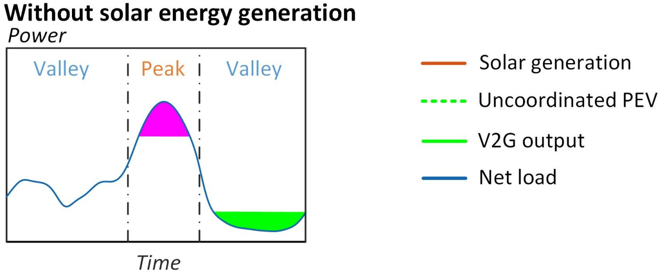
Step 4: Strategy execution

- Self-consumption of PV output by PEV charging
- Peak-shaving and valley-filling of net power load

With solar energy generation

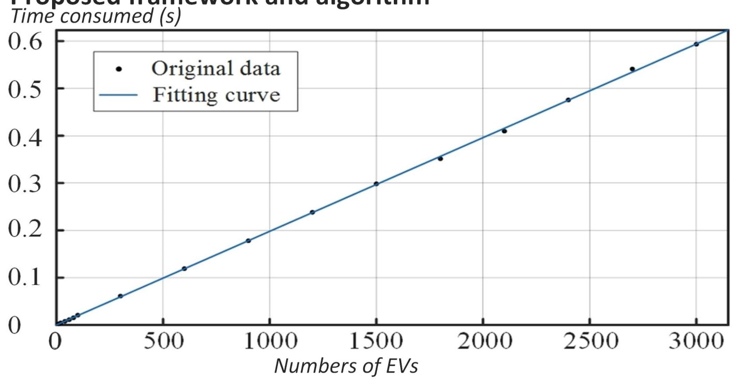


Without solar energy generation

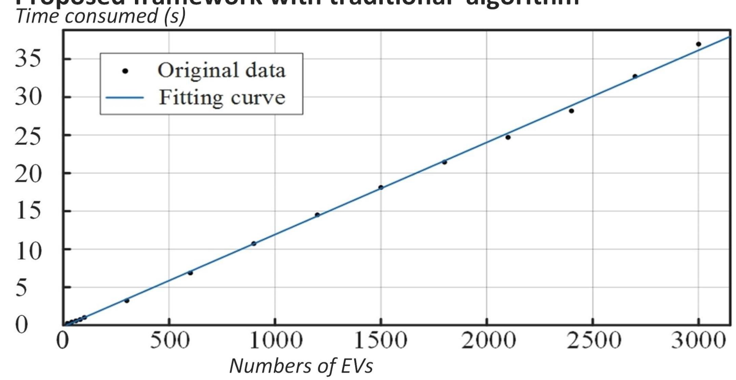


The Computational Performance is also Excellent, and Scheduling One EV Shows Microsecond Basis

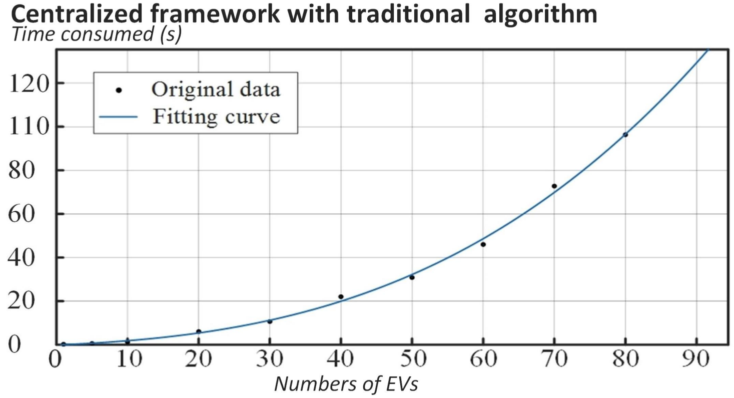
Proposed framework and algorithm



Proposed framework with traditional algorithm



Centralized framework with traditional algorithm



Execution time of the proposed scheme for single PEV in a single time interval

Condition	Case 1	Case 2	Case 3
Power flow (s)	0.000287	0.000205	0.000299
No Power flow (s)	0.000361	0.000394	0.000532

- **0.4s** for **3000 EVs** under **ISCP** with **efficient algorithm**, ***O(NTlog$_2$(T))***
- **35s** for **3000 EVs** under **ISCP** with **traditional algorithm, interior point method**, ***O(NT³)***
- **250s** for **120 EVs** by **centralized** scheduling, ***O((NT)³)***
- Scheduling **one EV** at **one-time slot** shows **microsecond** basis

Shang, Y., et al. "Internet of smart charging points with photovoltaic Integration: A high-efficiency scheme enabling optimal dispatching between electric vehicles and power grids." *Applied Energy* 278 (2020): 115640.

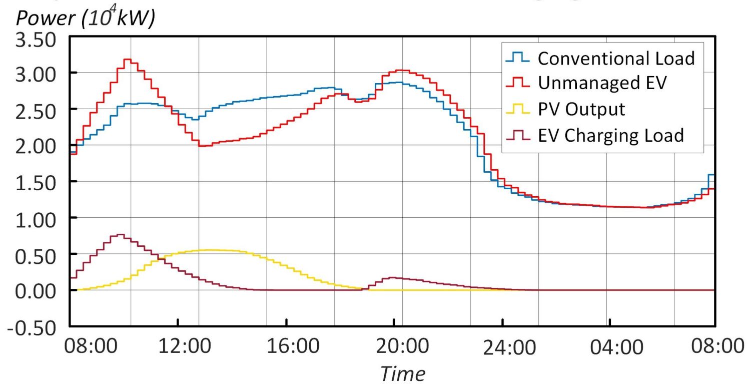
High Computational Performance: Dispatching Setting of Strategy 2

Modified distribution grid of SUSTech campus

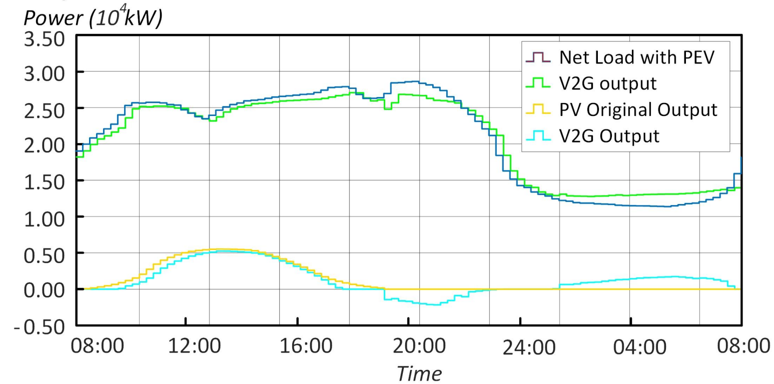
Energy consumption node　Charging station node

The Dispatch Results are Satisfied, Expecially in PV self-consumption

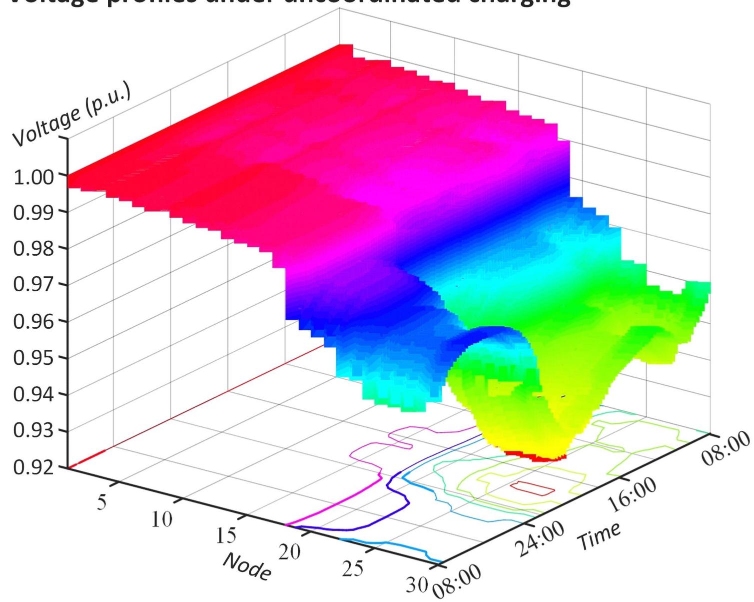
Dispatch results under uncoordinated charging



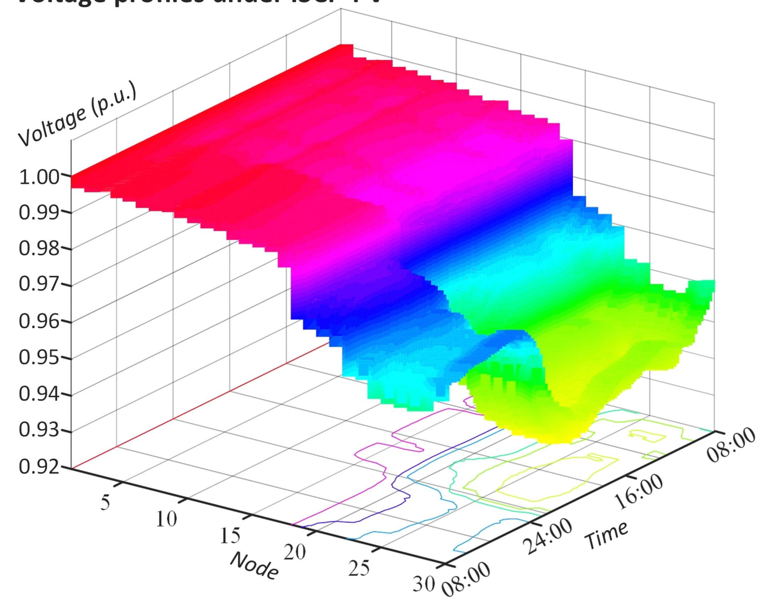
Dispatch results under ISCP-PV



Voltage profiles under uncoordinated charging



Voltage profiles under ISCP-PV



- Peak-shaving and valley-filling by 17.54% and 12.42%
- **PV self-consumption by V2G is 82.72%, which is 258.74% more than unmanaged charging**
- No voltage exceeds limit in ISCP scheme

Brief Summary

1. Introduction

2. High Computational Performance Algorithm

3. High Information Security Method

4. High Stable Cyber-Physical-System Verification

Strategy
One EV, one probelm, conducted by one charger

Objective
Load flatting and PV self-consumption

Advantages
Achieve good performance in a distributed manner

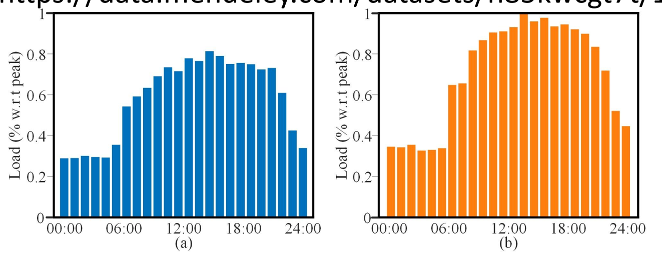
Potential issue
Require precise prediction of future state in advance.

Contents

Handling Uncertainties of Future Data by Data-driven Method

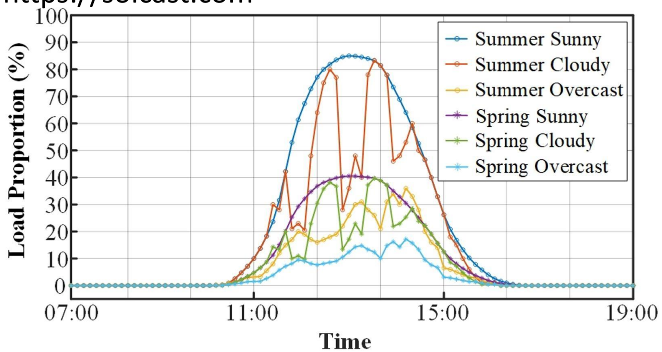
Conventional load

https://data.mendeley.com/datasets/n85kwcgt7t/1



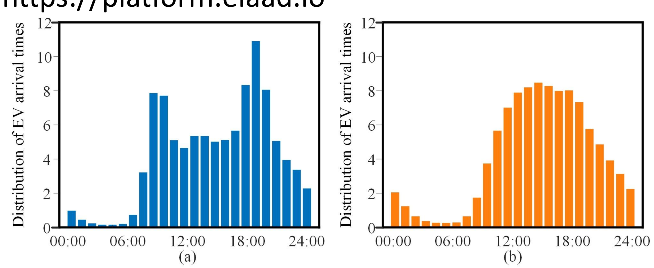
PV output

https://solcast.com

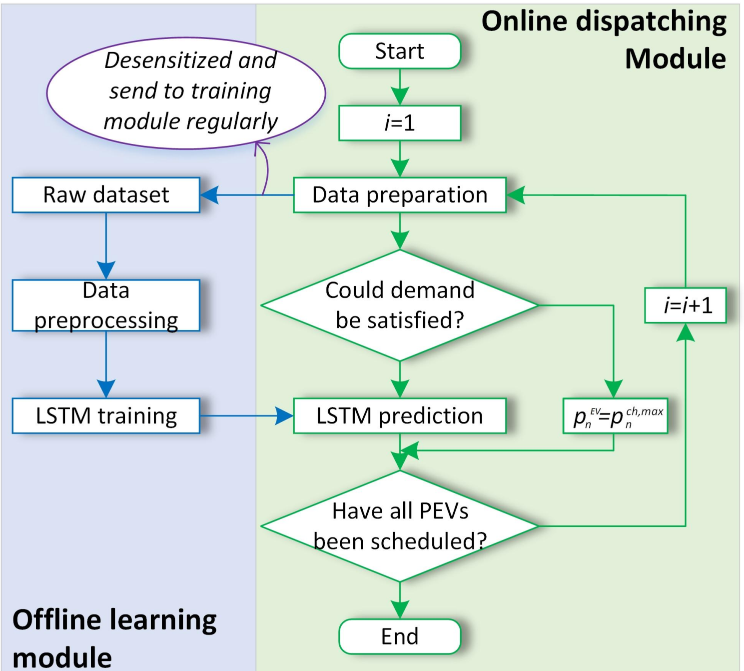


EV charging data

https://platform.elaad.io



Flowchart of offline learning and online dispatching

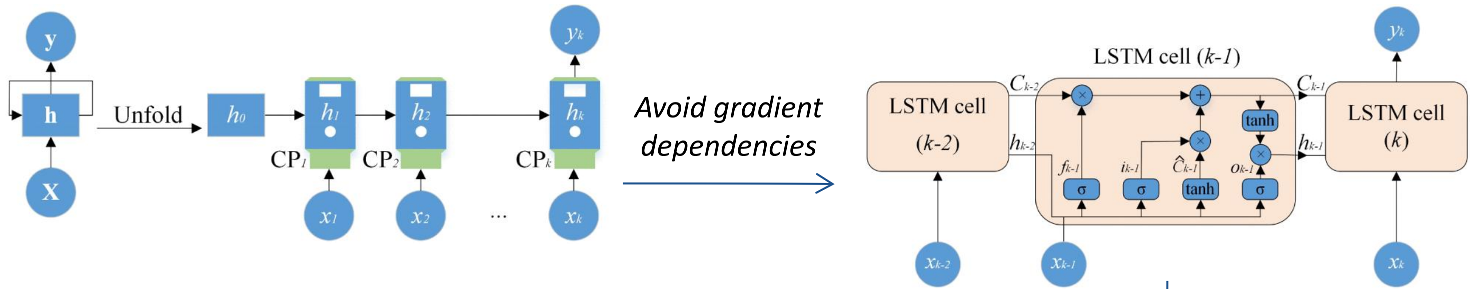


- ✓ **Offline learning: utilize the foregone future data from the dataset to compute label, and utilize the historical, current data, and label to train a learning model.**
- ✓ **Online dispatching: employ the end-to-end deep learning model conditioned on historical and current data to directly make scheduling decisions under uncertainties.**

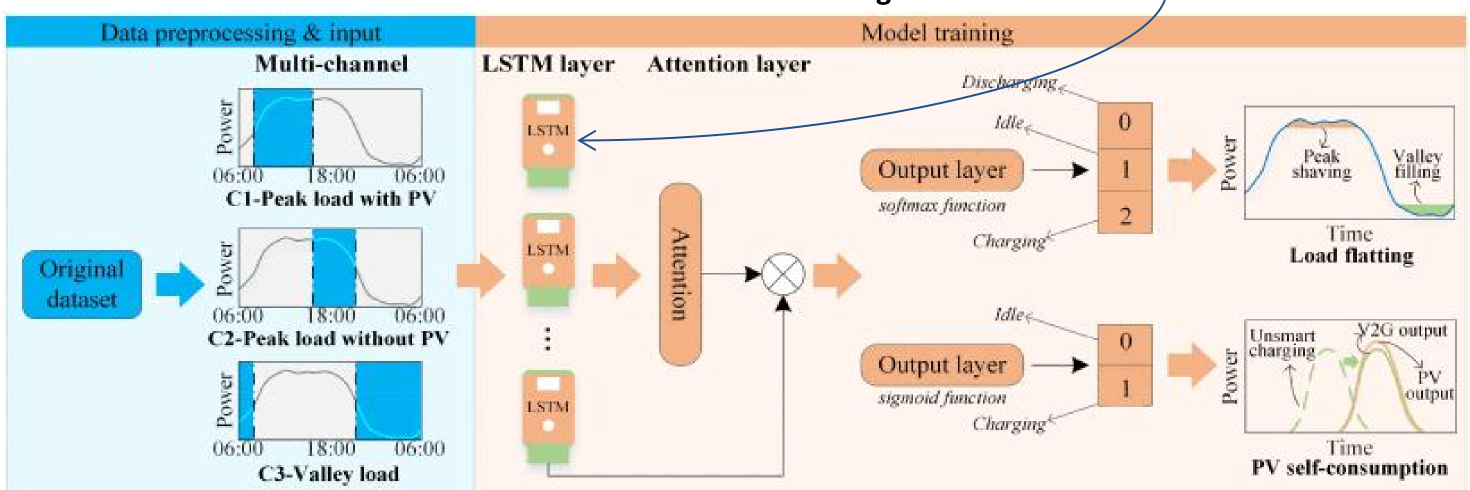
Shang, Y., et al. "ISCP-Data: a vehicle-to-grid dataset for commercial center and its machine learning application." 2021 IEEE 5th Conference on Energy Internet and Energy System Integration (EI2). IEEE, 2021.

Utilizing LSTM (a Variant of Recurrent Neural Network) and Attention Mechanism for Time Sequence Data

Structure of RNN **Structure of LSTM**

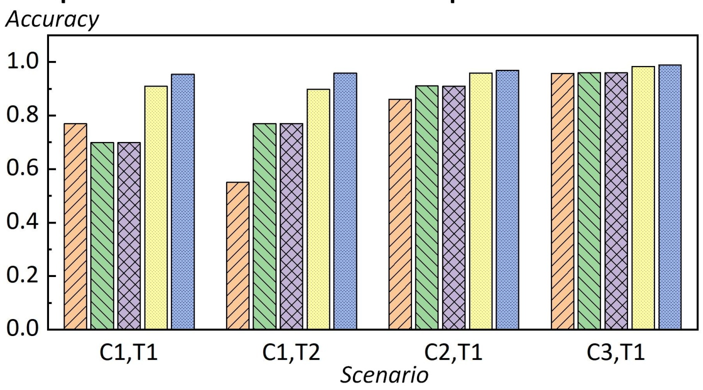


Overall network structure of the multichannel dual-task forecasting model.

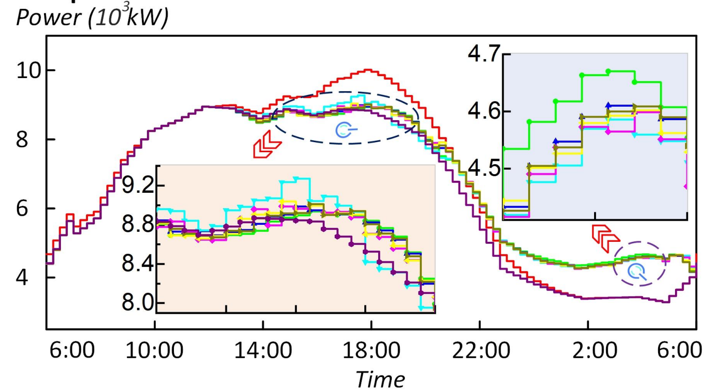


High Information Security 1: Results of Deep Learning Model

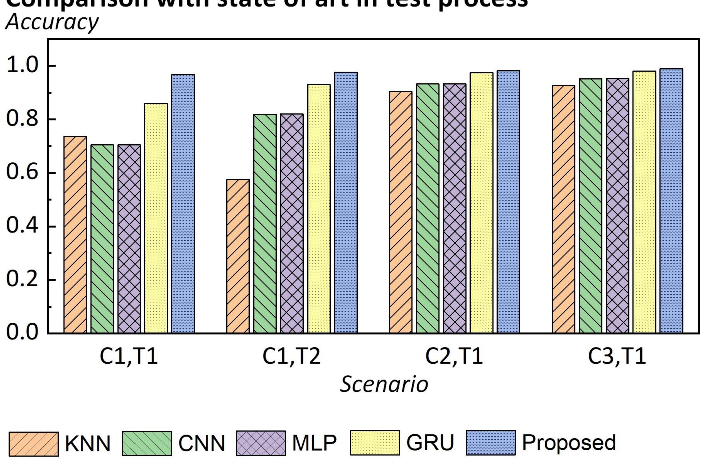
Comparison with state of art in train process



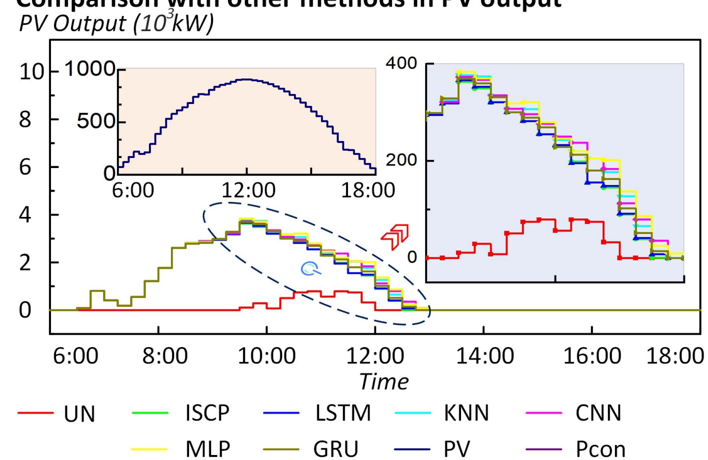
Comparison with other methods in conventional load



Comparison with state of art in test process



Comparison with other methods in PV output



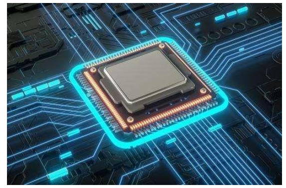
Qualitative analysis for different methods

Method	Computation time (s)		Handle uncertainties	Privacy-preserving	Scenarios adaptability
	80 EVs	1000 EVs			
Con1	96.3064	--	×	×	×
Con2	0.7408	12.9258	×	√	×
LSTM	0.0161	1.9784	√	√	√

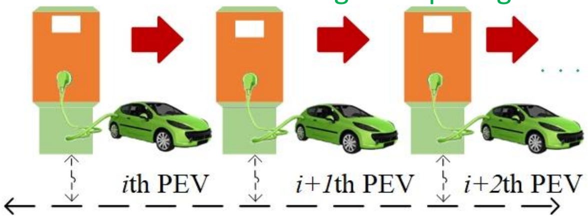
Shang, Y., et al. "Achieving efficient and adaptable dispatching for vehicle-to-grid using distributed edge computing and attention-based LSTM." *IEEE Transactions on Industrial Informatics* 18.10 (2021): 6915-6926.

High Information Security 2: Federated Learning for Handling Digital Asset Leakage

Past issues 1: EV users' privacy & computational complexity

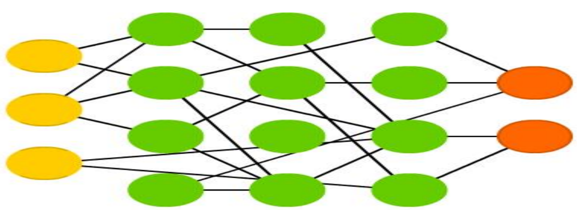



Solution 1: distributed edge computing

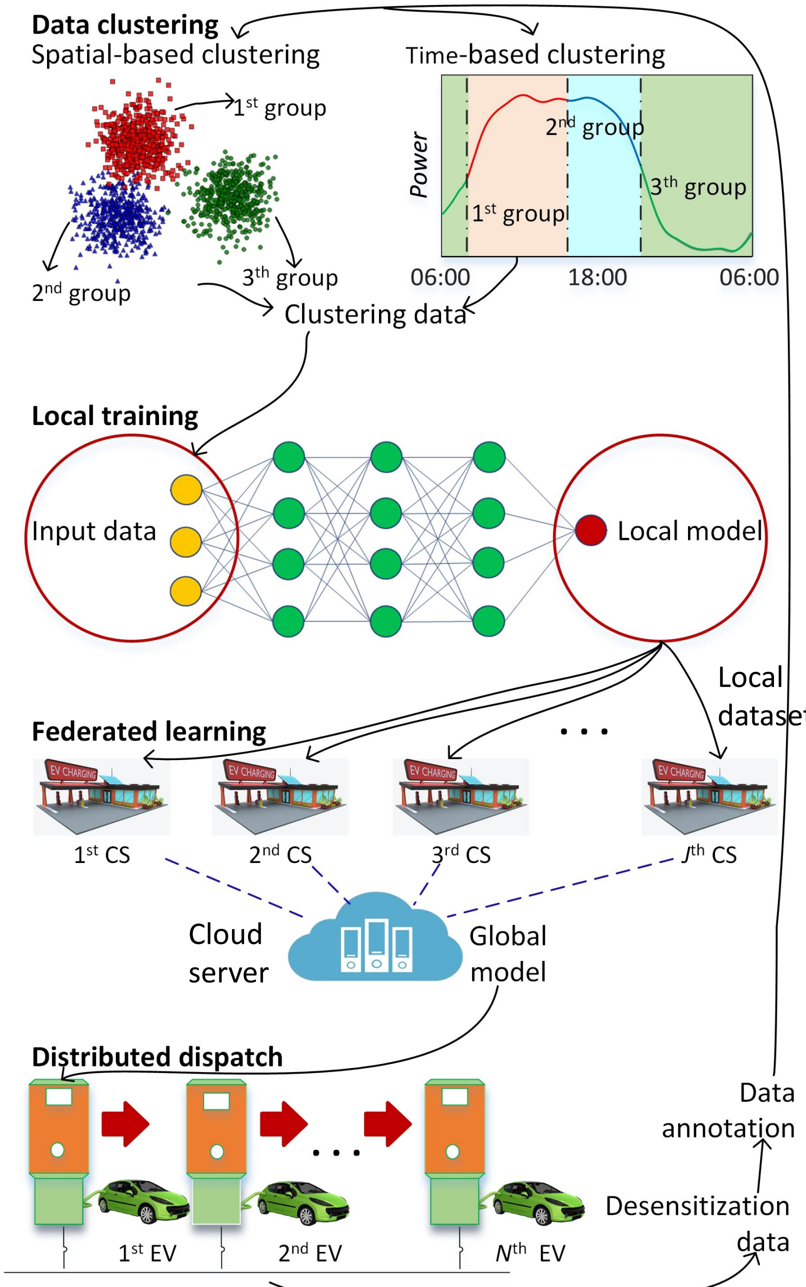


Past issue 2: uncertainties handling arising from unknown future parameters

Solution 2: data-driven method

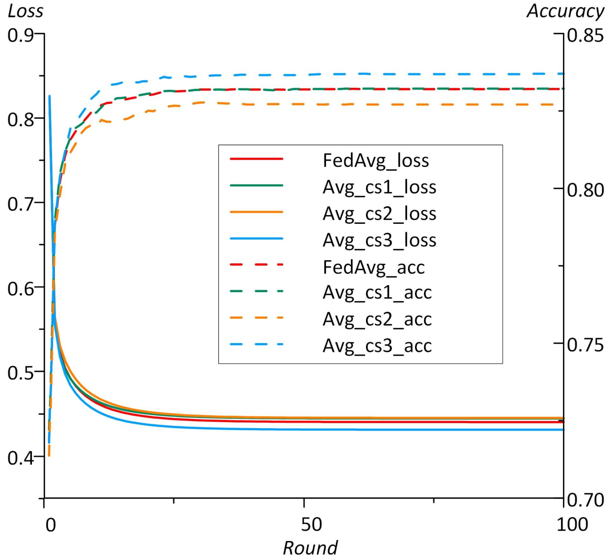


New issue: digital asset leakage due to restricted data at charging stations



High Information Security 2: Results of Federated Learning

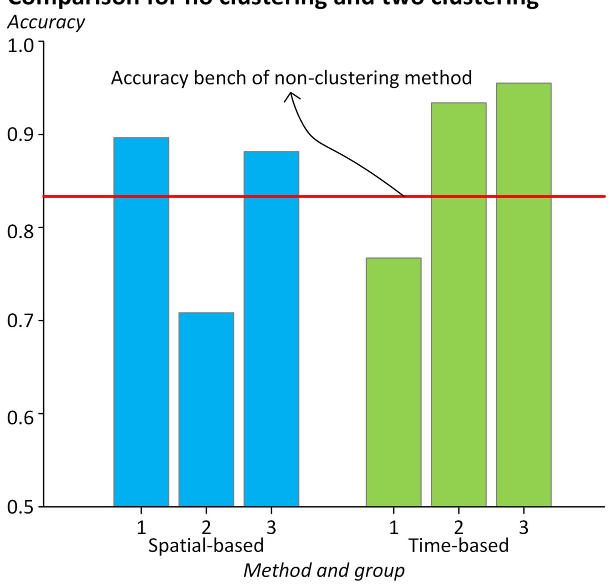
Trend curve of loss and accuracy for learning



Training results of federated and centralized learning

Type	model	Accuracy	Precision	Recall	F1-score
FedISCP	**FedAvg**	**0.83267**	**0.80052**	**0.83267**	**0.83008**
	Avg_cs1	0.83000	0.79093	0.83000	0.82739
	Avg_cs2	0.82900	0.80903	0.82900	0.82580
	Avg_cs3	0.83900	0.80160	0.83900	0.83705
CenISCP	**CenAgg**	**0.86300**	0.83322	0.86300	0.86198
	Cen_cs1	**0.81400**	0.77427	0.81400	0.80707
	Cen_cs2	**0.81800**	0.80201	0.81800	0.81414
	Cen_cs3	**0.82700**	0.77454	0.82700	0.82541

Comparison for no clustering and two clustering



Results with different clustering methods

Method	Group	Accuracy	Precision	Recall	F1-score
Non	**---**	0.83267	0.80052	0.83267	0.83008
Spatial based	**1**	0.89667	0.85772	0.89667	0.89567
	2	0.70833	0.53470	0.70833	0.69844
	3	0.88167	0.85188	0.88167	0.88157
Temporal based	**1**	0.76700	0.71523	0.76700	0.75144
	2	0.93400	0.82319	0.93400	0.93146
	3	0.95500	0.81908	0.95500	0.95163

High Information Security 2: Results of Federated Learning

Randomly Selecting Method can Guarantee the Training Performace and Decrease Training Time

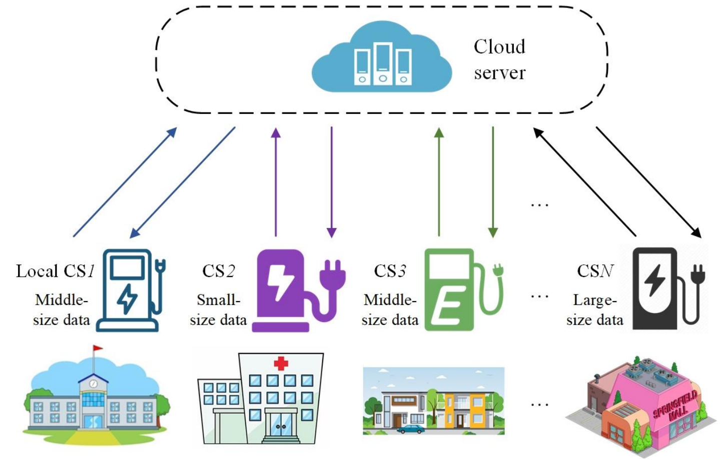
Training results for randomly selecting to participate in federated learning (20 CSs in total)

Method	Number	Accuracy	Precision	Recall	F1-score
Non-cluster	3	0.78760	0.59906	0.78760	0.74965
	5	0.79370	0.69613	0.79370	0.77434
	10	0.79970	0.71754	0.79970	0.77980
	15	0.79250	0.68735	0.79250	0.76929
	20	0.79130	0.64594	0.79130	0.76000
Time-based	3	**0.94880**	0.69503	0.94880	0.93962
	5	0.94820	0.69453	0.9482	0.93903
	10	0.94790	0.69430	0.94790	0.93974
	15	0.94820	0.69451	0.94820	0.93903
	20	0.94830	0.69468	0.94830	0.93913

Training time for randomly selecting to participate in federated learning (20 CSs in total)

Random number	3	5	10	15	20
Training time (s)	**7864**	12654	24714	36341	45216

Current work: federated learning for V2G scheduling with Non-IID Data



Problem 1: Different data sample size and differnert data distribution. Training results need to be improved.

Problem 2: Need therotical proof of convergence in federated learning

Shang, Y., et al. "Secure and Efficient V2G Scheme through Edge Computing and Federated Learning." *2022 4th International Conference on Smart Power & Internet Energy Systems (SPIES)*. IEEE, 2022. (Best Paper Award)
Shang, Y., et al. "FedPT-V2G: Security Enhanced Federated Transformer Learning for Real-time V2G Dispatch with Non-IID Data." *Applied Energy*. (In Second Round Review)
Shang, Y., et al. "An Information Security Solution for Vehicle-to-grid Scheduling by Distributed Edge Computing and Federated Deep Learning." *IEEE Transactions on Industrial Applications.* (In Second Round Review)

Brief Summary

1. Introduction

2. High Computational Performance Algorithm

3. High Information Security Method

4. High Stable Cyber-Physical-System Verification

Dataset
Real-world data

Handling uncertainties
LSTM+attention

Protected data asset
Federated learning

Next work
Cyber-physical-system verification

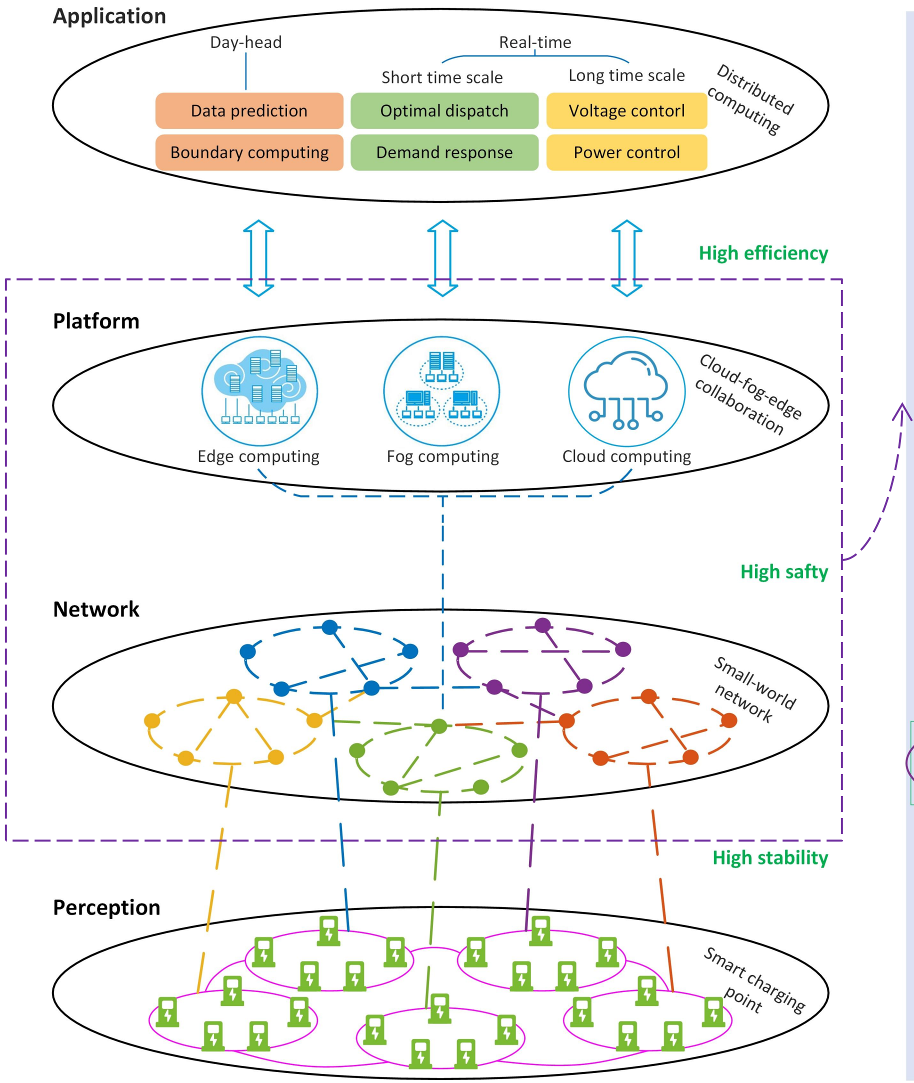
Contents

High Stable Cyber-Physical-System Verification: Architecture

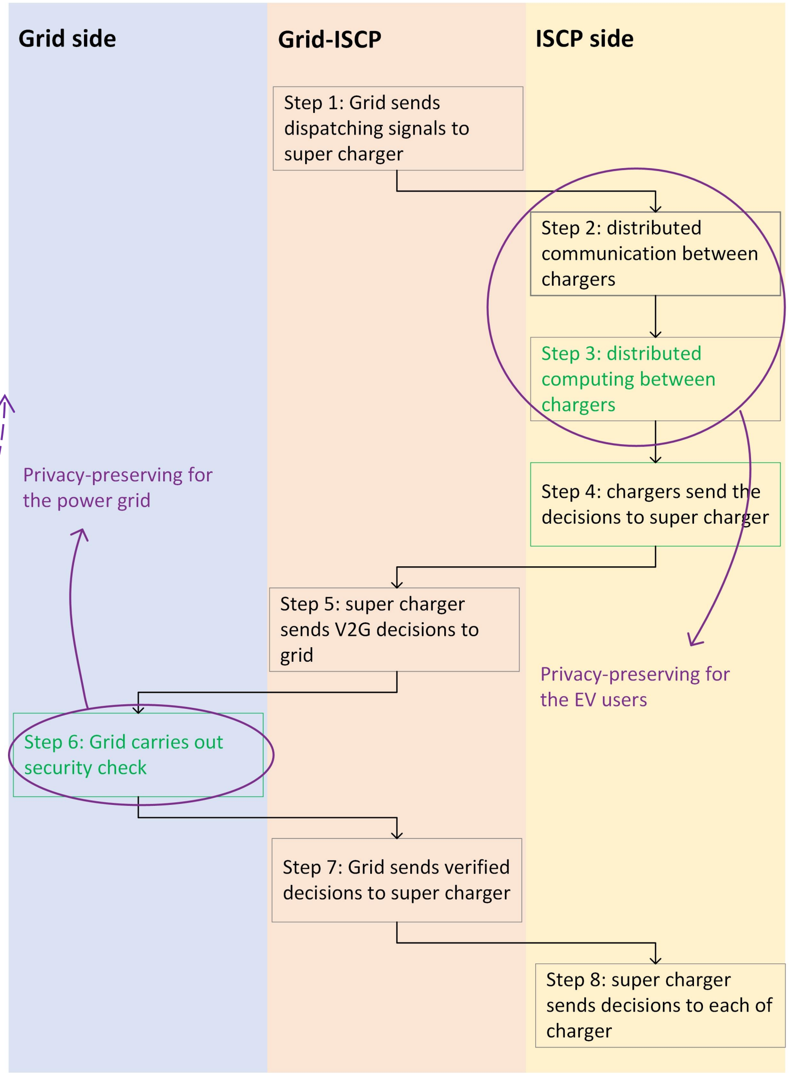
Analysing and Setting of Network Communication in ISCP, which Has Three Parts

- ✓ Distributed computing for Privacy-preserving of EV users
- ✓ Security checking of of power flow for Privacy-preserving of Grid

Cyber-physical-system of ISCP framework

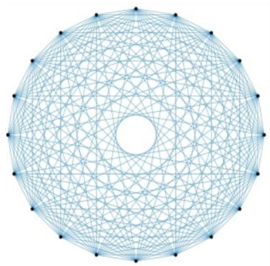
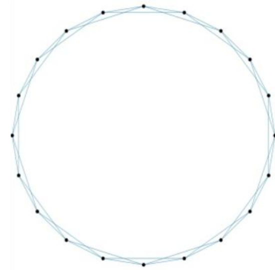
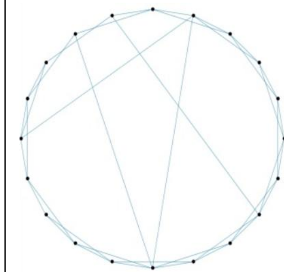


Data transmission and computational process in ISCP



High Stable Cyber-Physical-System Verification: Small-world Netork

Description for different networks

Name	Fully meshed	Lattice/regular	Small world
Typology			
Edge	*N(N-1)/2*	*NK/2*	*NK/2*
Wring cost	Large	Small	Small
Mean path length	Small	Large	Small
Latency	Small	Large	Small

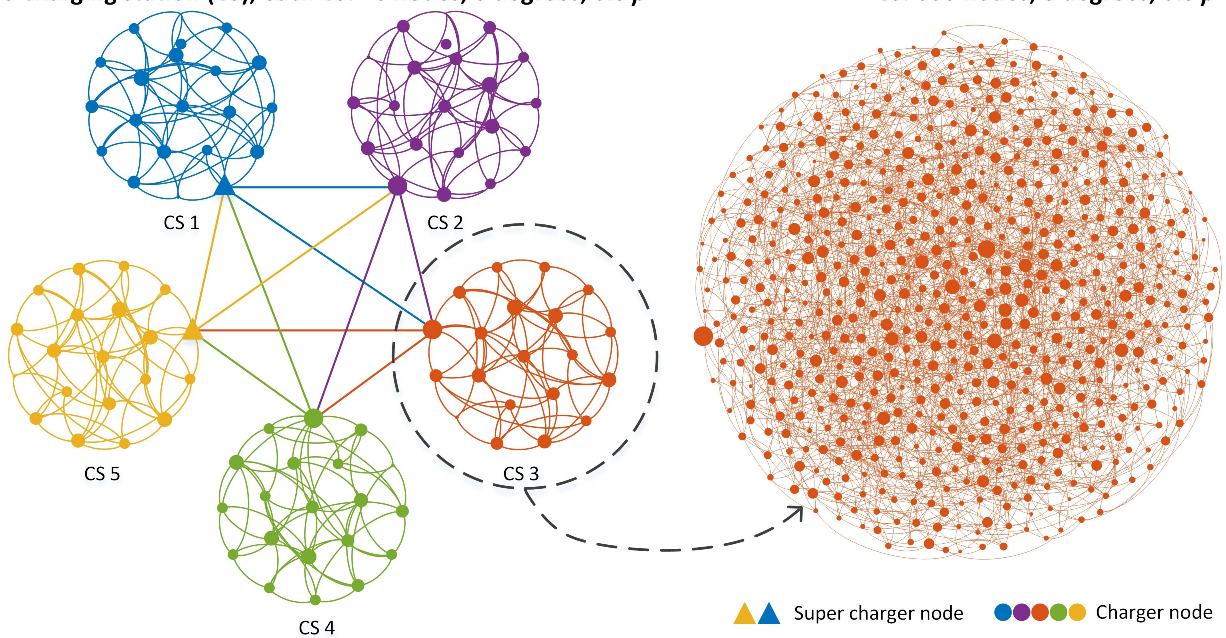
Small-world Network

- ✓ Based on 6 degree theroy
- ✓ Low wring cost
- ✓ Low latency

Network typology of ISCP utilizing smart-world network

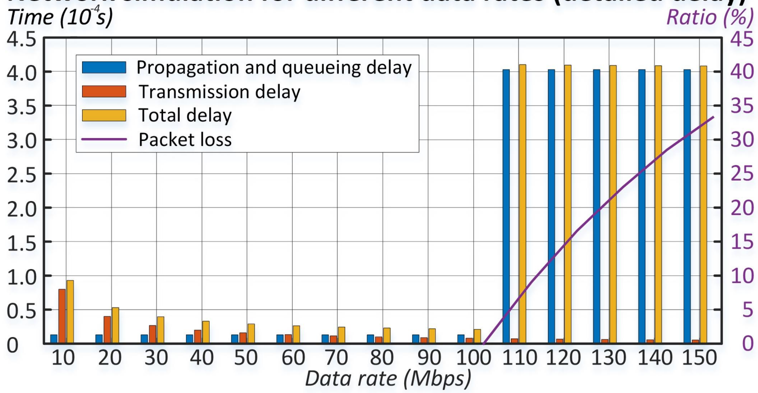
5 charging station (CS), each CS: 20 nodes, 6 degrees, 0.5 β

1 CS: 600 nodes, 6 degrees, 0.5 β

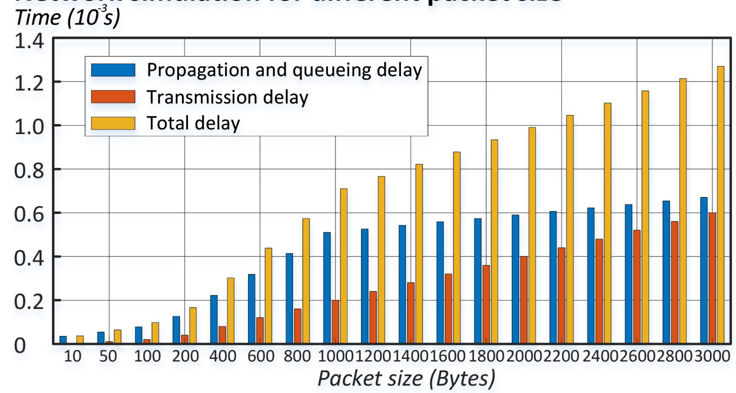


Analysing Different Scenirios, Find Suitable Parameters, and Simulate the Communication in ISCP

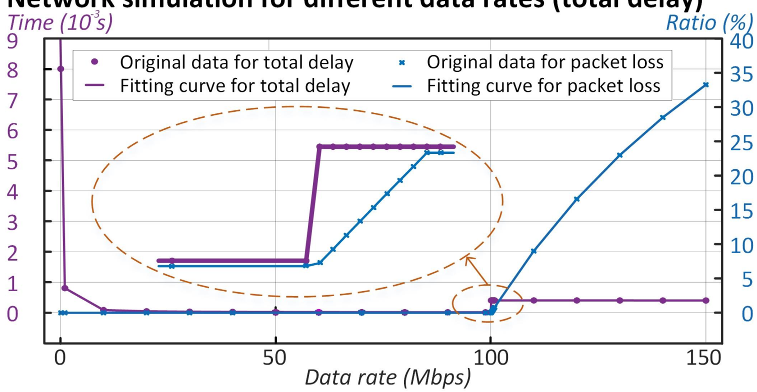
Network simulation for different data rates (detailed delay)



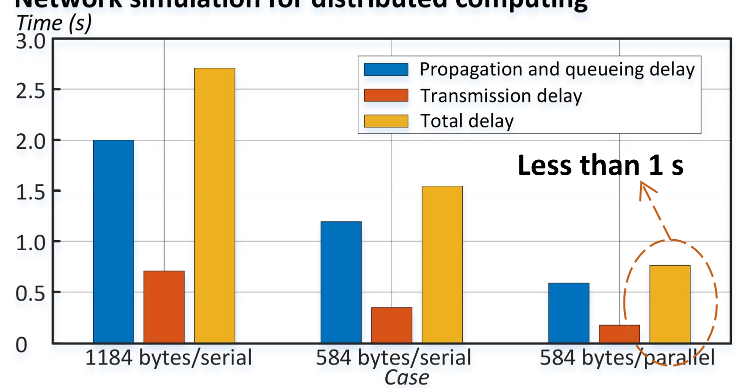
Network simulation for different packet size



Network simulation for different data rates (total delay)



Network simulation for distributed computing



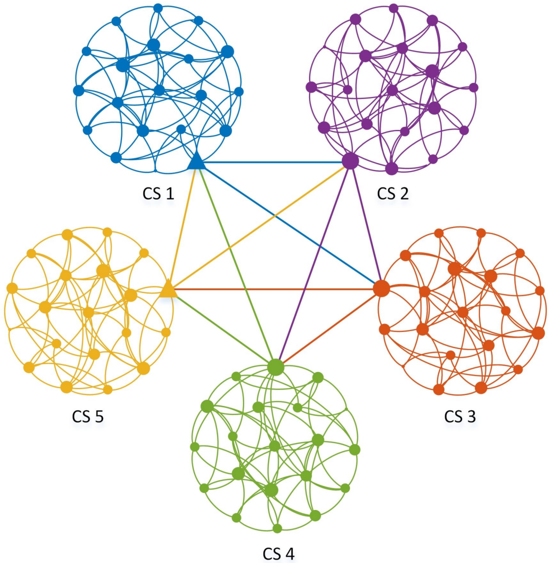
Comparison among different topologies concerning communication efficiency and wring cost

Network topology	Lattice (K=2)	Lattice (K=6)	Small world	Fully meshed
Delay (s)	53.7149	18.6315	**0.590653**	0.109501
Wring cost	3×10^3	9×10^3	$\mathbf{9\times10^3}$	4.4985×10^6

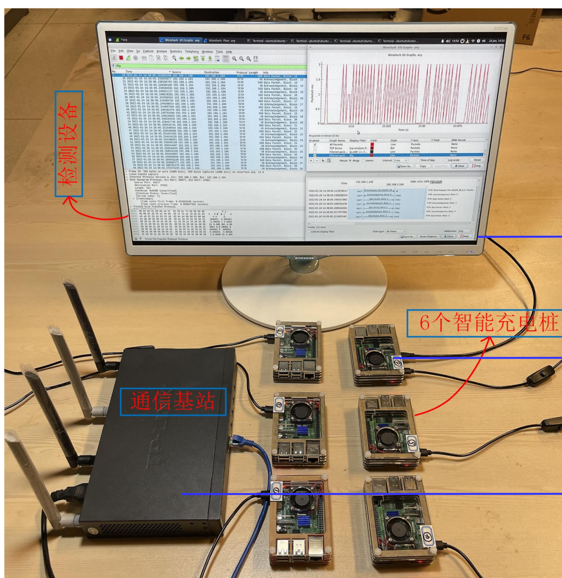
Shang, Y., et al. "Cyber-physical co-modeling and optimal energy dispatching within internet of smart charging points for vehicle-to-grid operation." *Applied Energy* 303 (2021): 117595.

High Stable Cyber-Physical-System Verification: Next Work

Current work: software verification for ISCP framework



Future work: scale-down hardware verification for ISCP

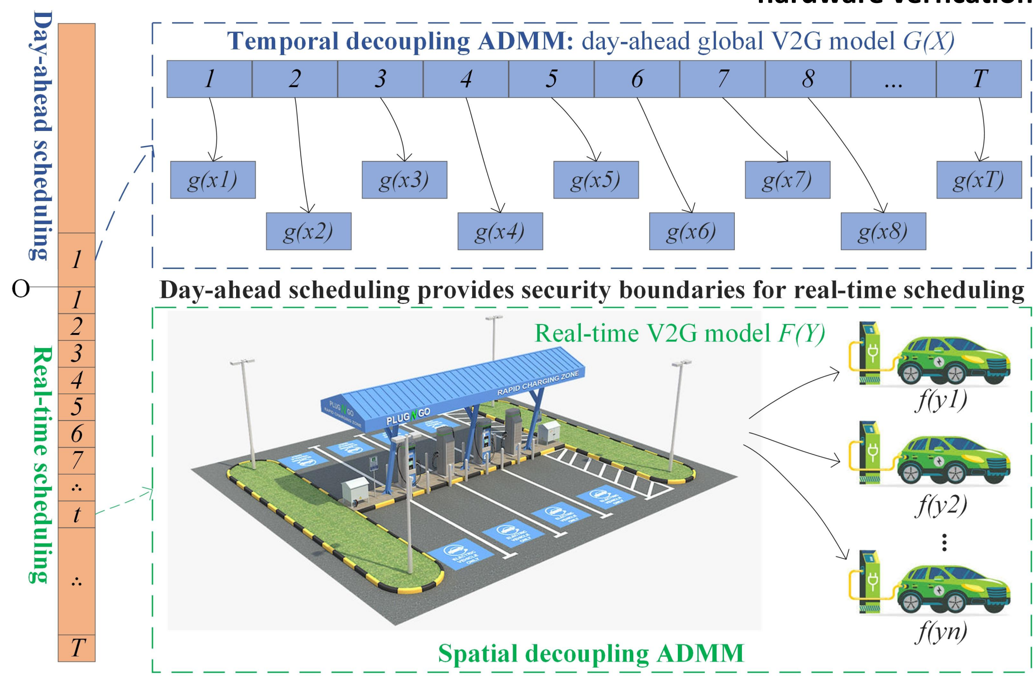


Dispaly screen

Six chargers

Communication station

Future work: Multi-block ADMM for distributed V2G based on scale-down hardware verfication



For more about ADMM, please refer to homepage of Prof. He Bingsheng http://maths.nju.edu.cn/~hebma/

Work summary

Internet of Smart Charging Point (ISCP)
Distributed edge computing, equality and decentralization

High Computational Performance
Distributed optimal algorithm, load flatting, PV self-consumption

High Information Security
Distributed data driven method, LSTM, federated learning

High Stable Cyber-physical-power System
Small-world network with simulation, network communication

CRC Press
Taylor & Francis Group

A book contact has been signed with ***CRC Press****,*
The following book is being prepared

Distributed Vehicle-to-grid Scheduling Strategy:
Computational Efficiency, Information Security and Multi-dimensional Verification

Looking Ahead

ISCP: from grid operator to Energy Market, particularly considering scalable and privacy-perserving

Previous work

Previous work		Challenge
High Computational Performance *Distributed optimal algorithm*	→	*Only grid but not including **users cost*** *Cannot guarantee **global convergence***
High Information Security *Distributed data driven method*	→	*Not including **interaction** among **EVs*** ***Non-iid data** in federated learning*
High Stable CPP System *Small-world network with NS2*	→	*Only simulation but **not hardware*** *More comprehensive joint verification*

Future work

Joint V2G prediction securely and effectually with **federated multi-task learning**
Real-time V2G **incentive pricing mechanism** with prediction model and **non cooperative game**

Privacy-preserving and **global convergence** optimal V2G dispatch with efficient **parallel ADMM**
Robust and secure data-driven V2G dispatch with **GCN** and **personalized federated learning**

Scale-down **hardware platform** for joint verification including energy, computation, and network
Choose the appropriate method according to the specific situation

Dissemination Plan: journal paper, conference activity, public engagement, digital platform, etc.

Thank You!

Yitong SHANG
ytshang@ust.hk

Sincere blessings to colleagues in MESPO group!