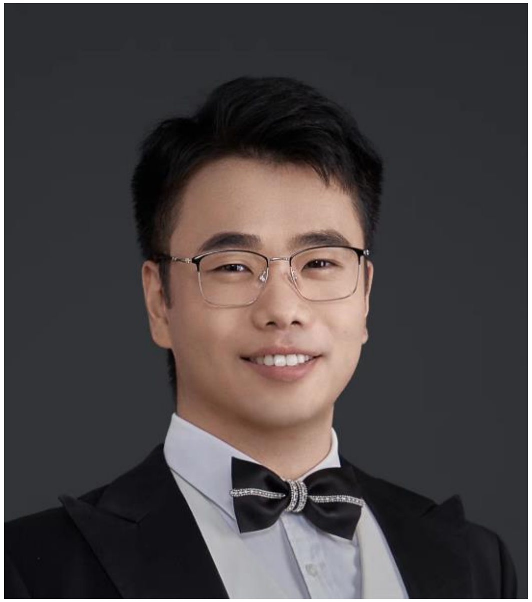
Artificial Intelligence in Smart Cities (EV Load Prediction and V2G Decision Making)

Yitong SHANG

Research Assistant Professor
The Hong Kong University of Science and Technology

11.2024

Personal profile



Education

Harbin Institute of Technology
PhD, Information Engineering, 2022

Southern University of Sci & Tech
Joint PhD, Excellent Graduate of Dept.

China Agricultural University
Bachelor, Electrical engineering, 2017

Awards & Honors

DAAD (Germany)
AInet Fellow, 2023

SPPIES (Conference)
Best Paper, 2022

Tencent Technology
Rhino Bird Elite, 2022

Positions

Hong Kong University of Sci & Tech
Postdoc Researcher, 01.2023-07.2024
Research Assistant Prof., 07.2024-now

Technical University of Munich
Visiting Scholar, 09.2023

Tencent Technology
Internship, 05.2022-08.2022

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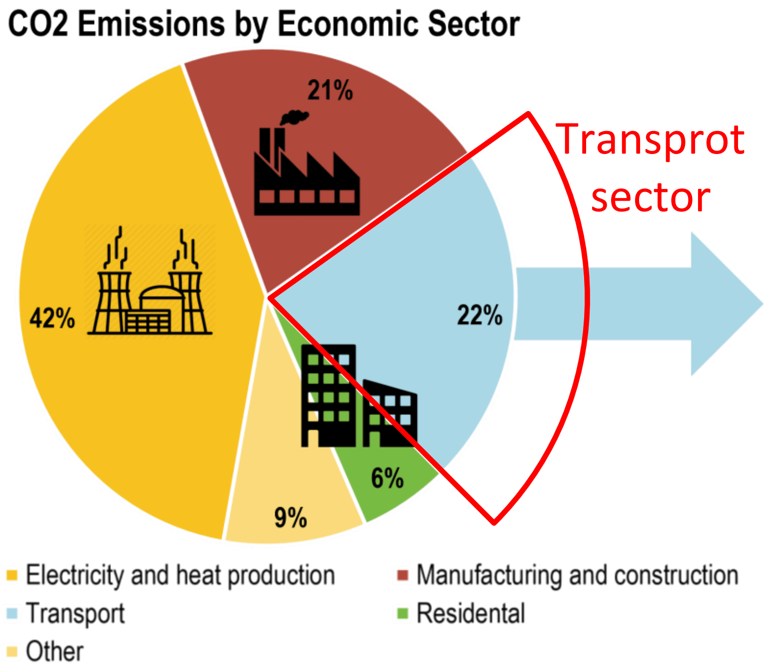
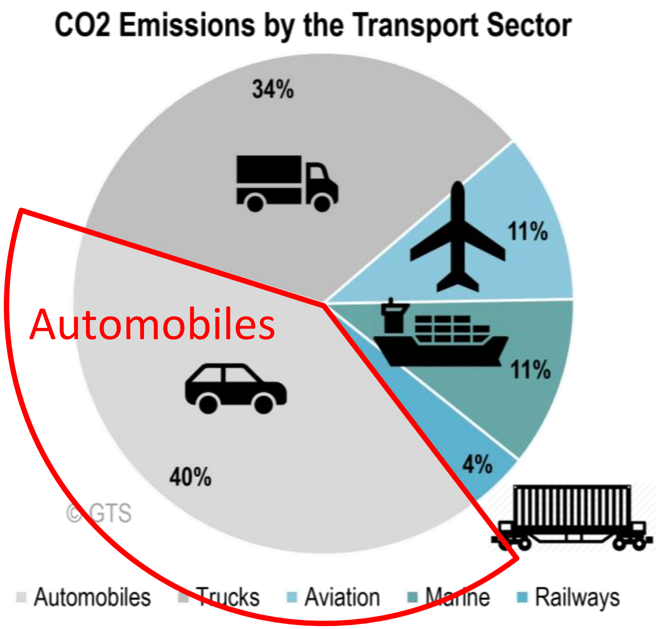
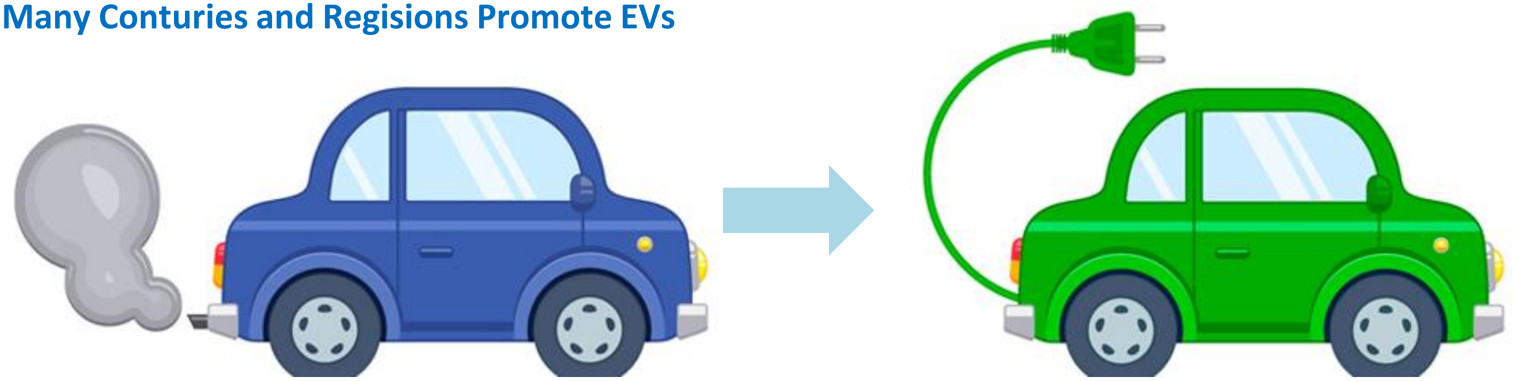
CO2 Emissions of Automobiles is Very Huge





Many Conturies and Regisions Promote EVs



The Development of EV in Hong Kong has 3 Milestones

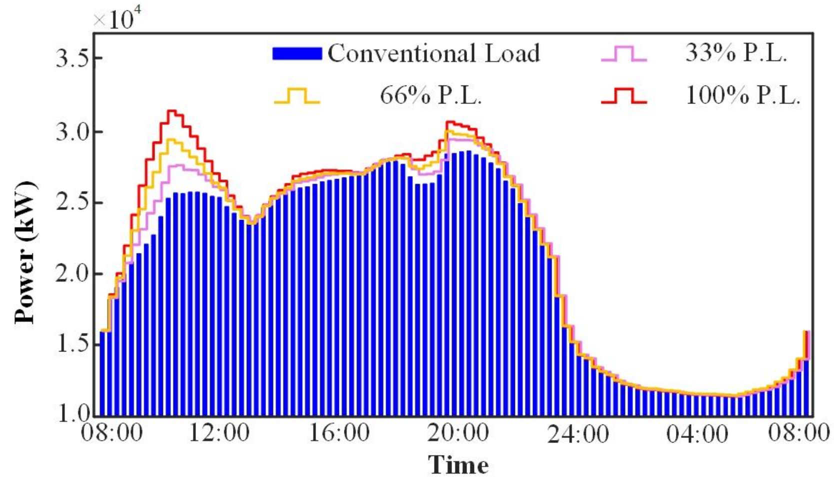
Private Charging Facilities

≥150 000

Public Charging Facilities

≥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

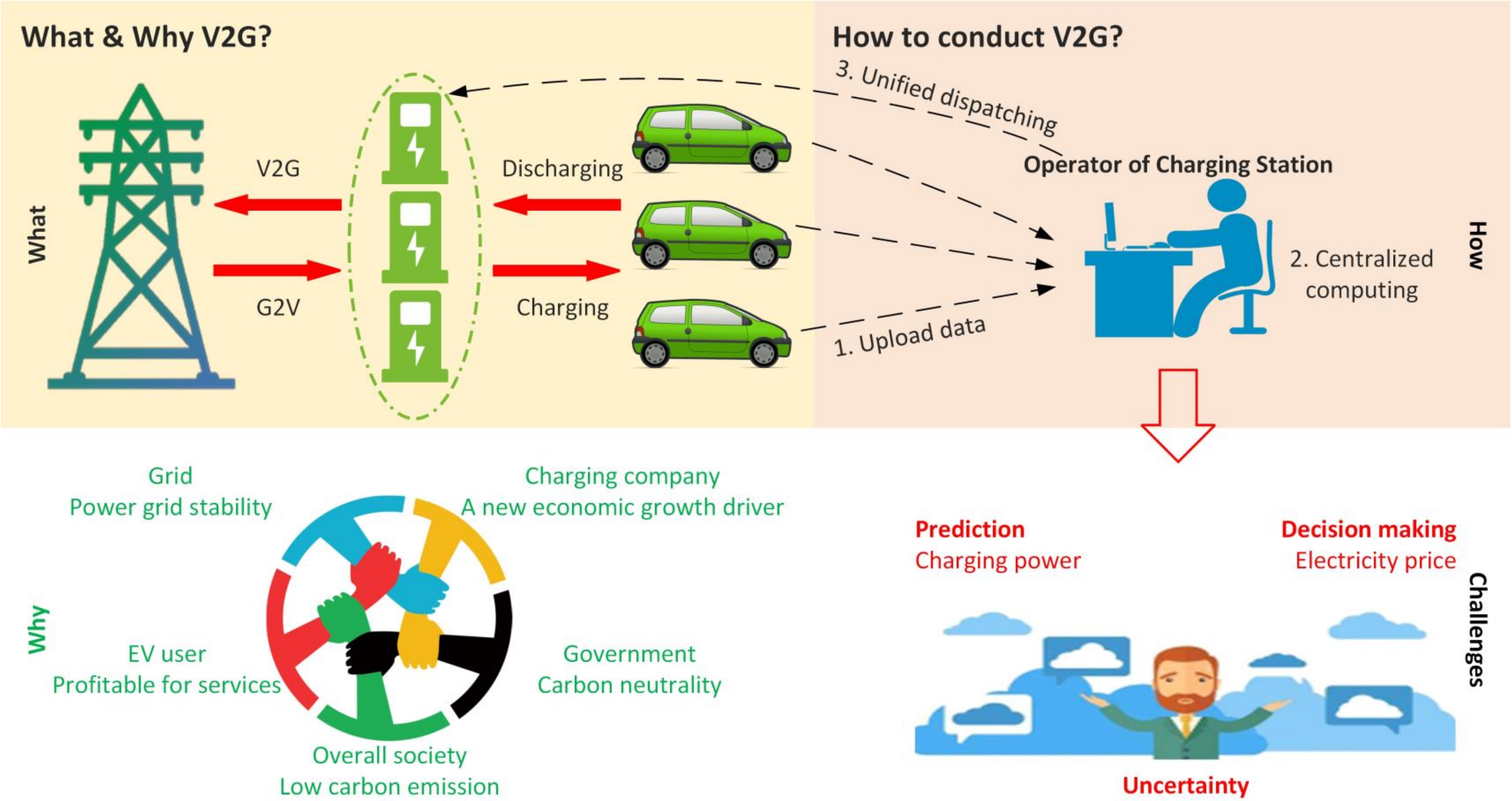
Calculation of load peak with unmanaged charging

- **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



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

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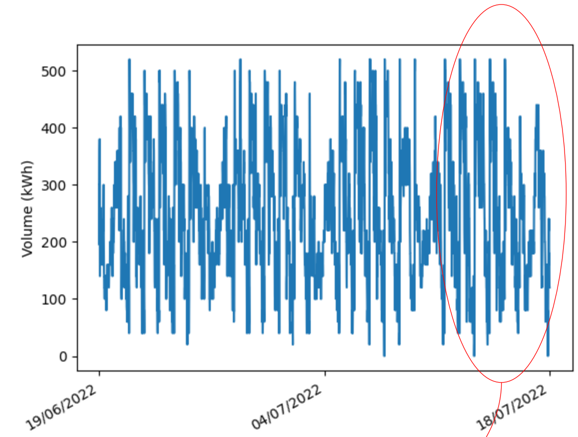
Why should AI be applied in EV load prediction?



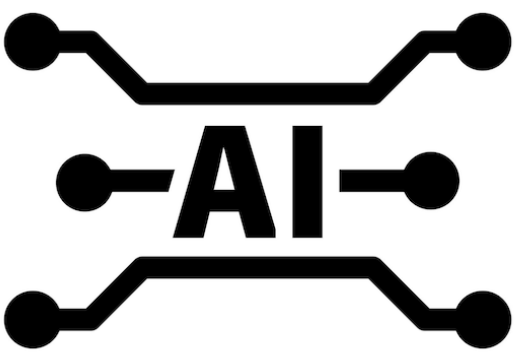
How should AI be applied in EV load prediction? - Dataset

Input features

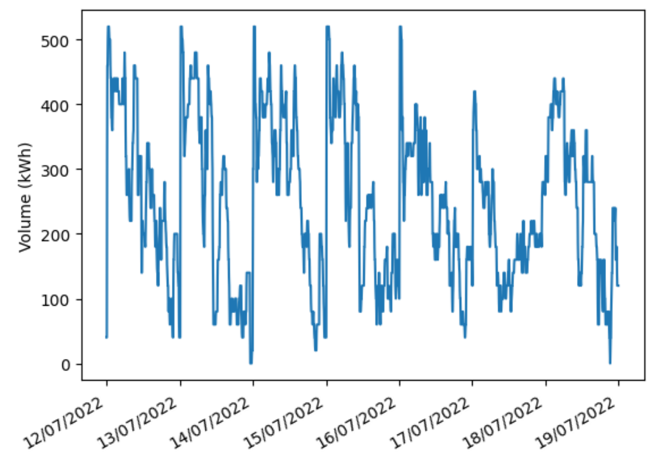
maybe included:

- privious EV load
- weathers
- weekday or weekend
- privious occupancy
- and so on.

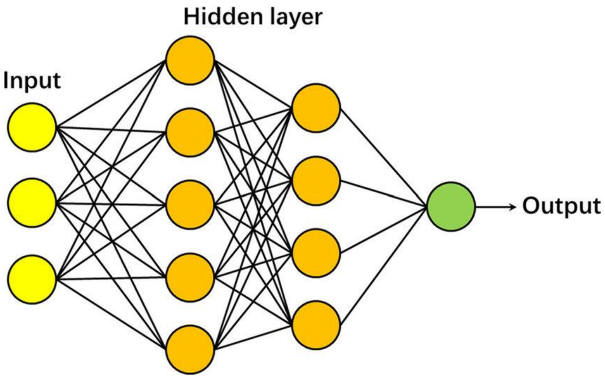
AI model

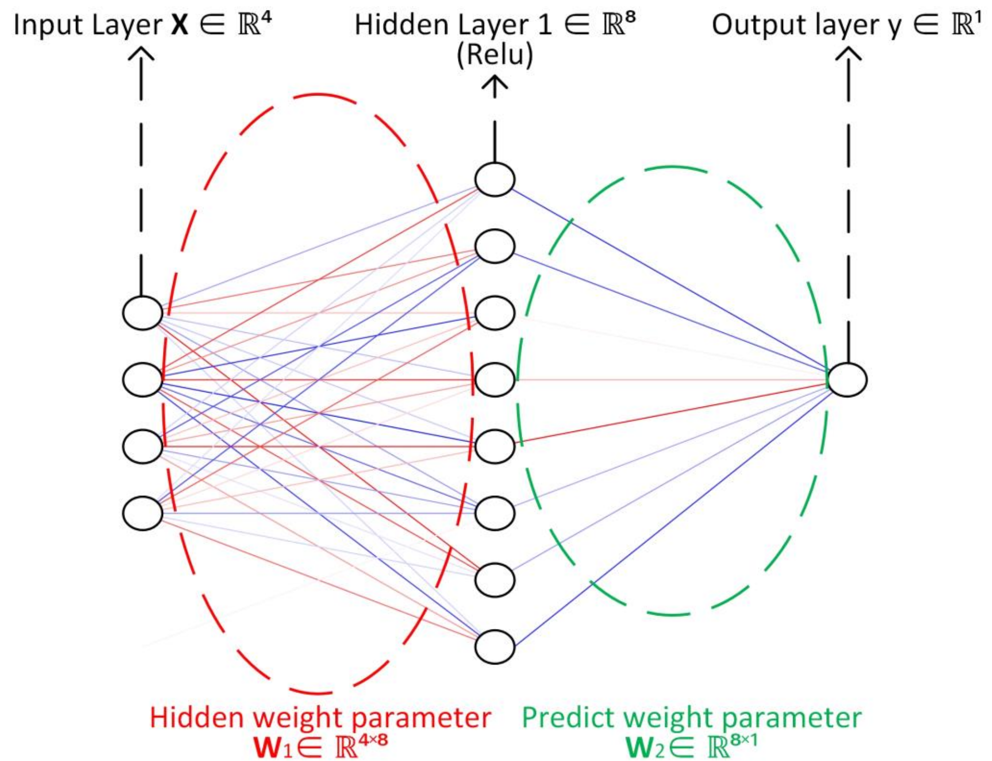


Output label: futher EV load



How should AI be applied in EV load prediction? - AI Model

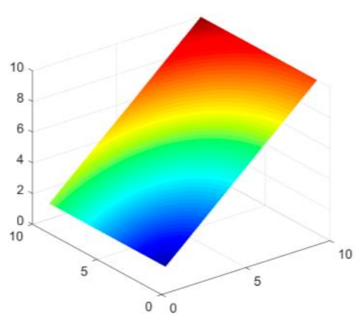


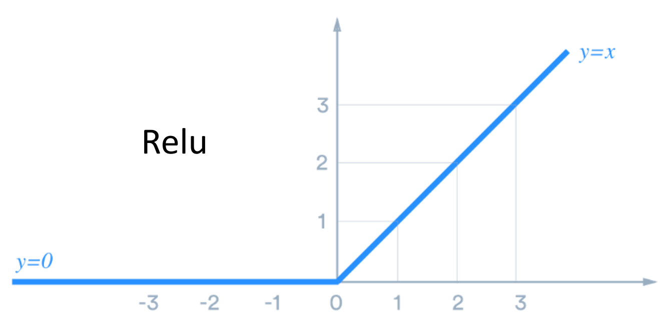


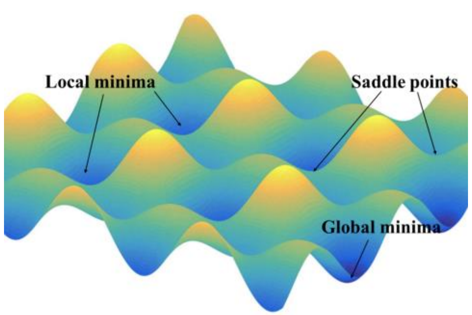
$$\underset{1\times1}{y} = (\underset{1\times4}{\mathbf{X}} \times \underset{4\times8}{\mathbf{W}_1}) \times \underset{8\times1}{\mathbf{W}_2}$$

$$y = \mathrm{Relu}(\mathbf{X} \times \mathbf{W}_1) \times \mathbf{W}_2$$

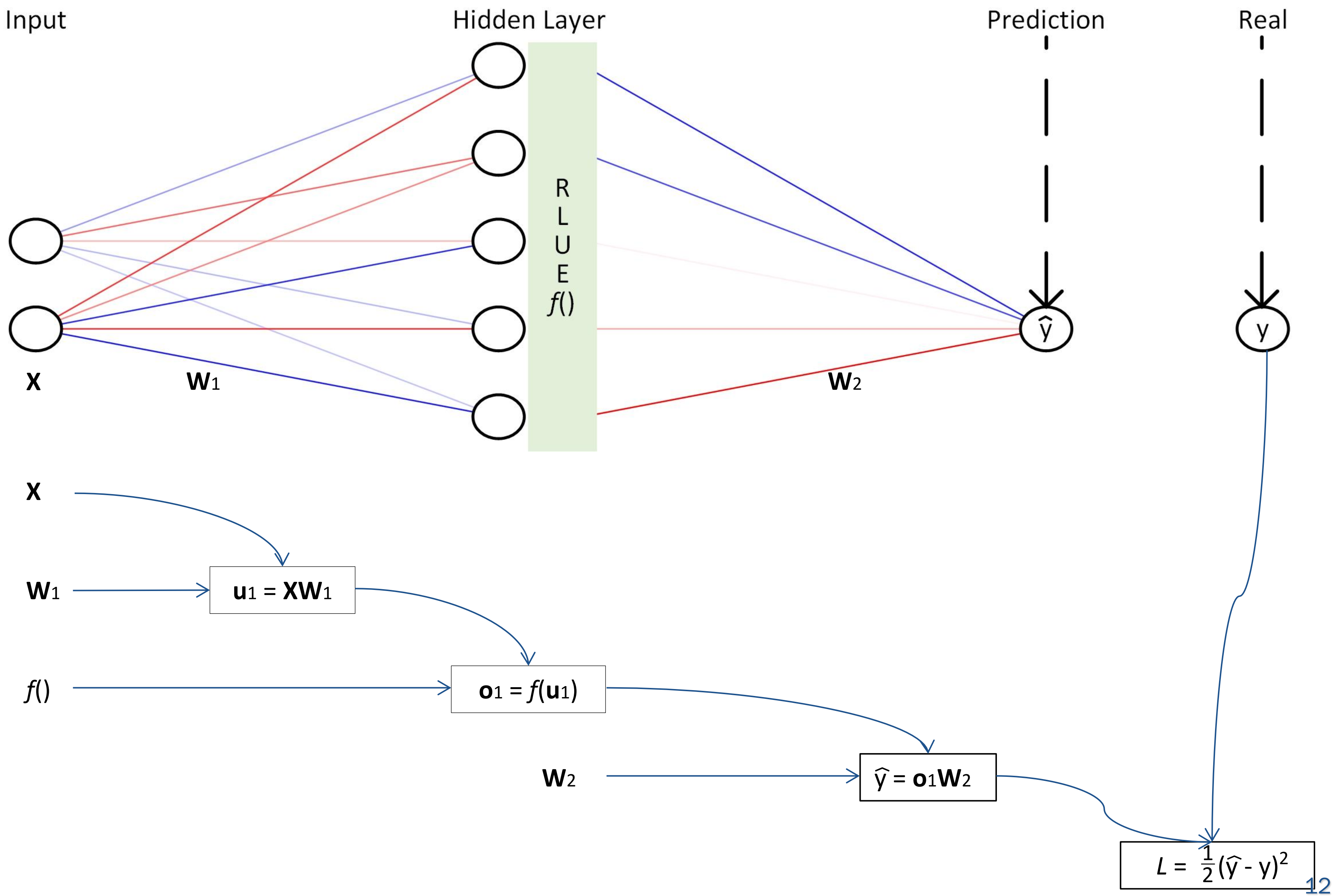
$$\cancel{y = \mathrm{Relu}(\mathbf{X} \times \mathbf{W}_1 + \mathbf{b}_1) \times \mathbf{W}_2 + \mathbf{b}_1}$$



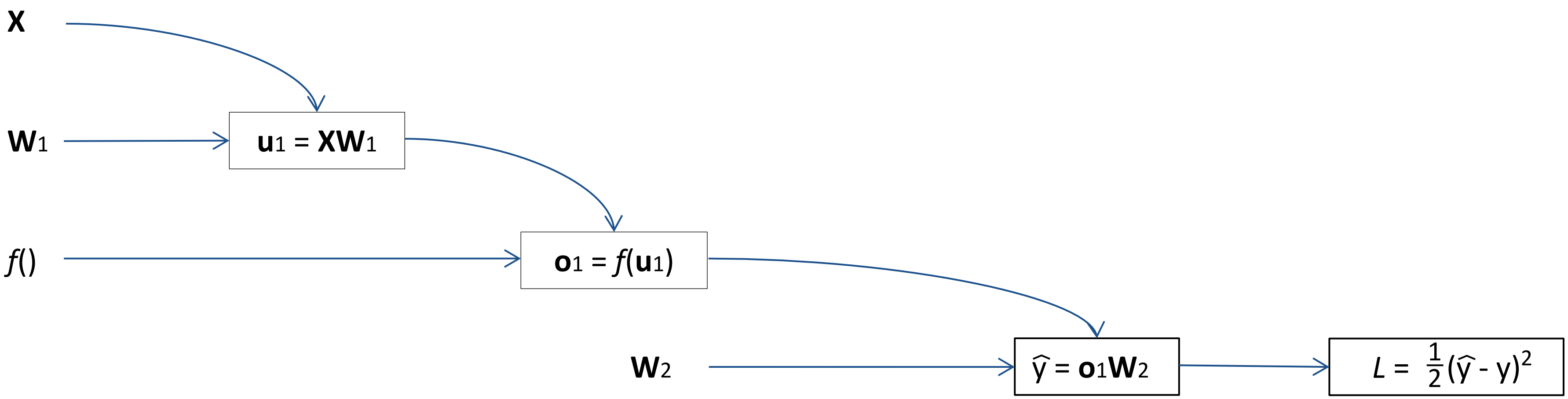


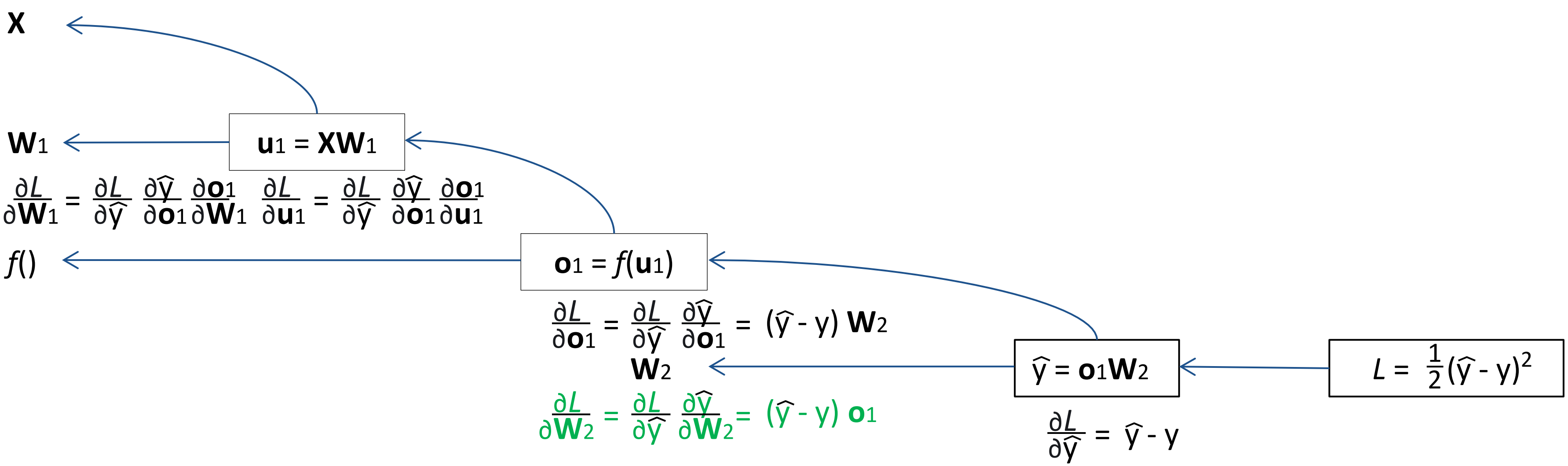


How should AI be applied in EV load prediction? - Loss Function/Forward Propagation



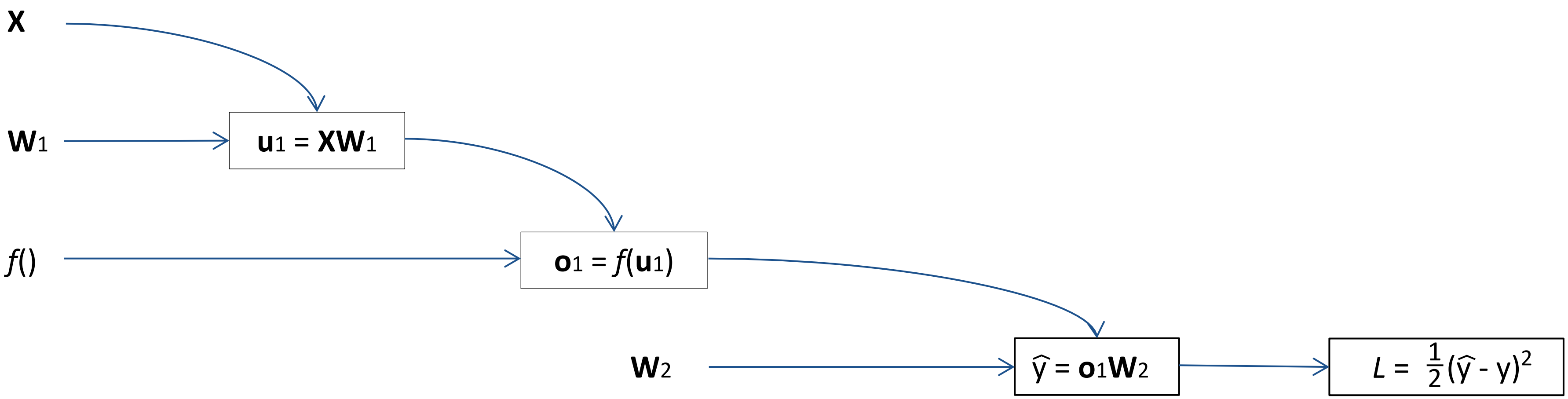
How should AI be applied in EV load prediction? - Backword Propagation

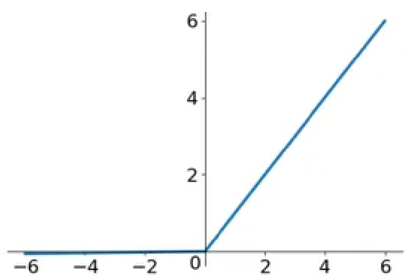


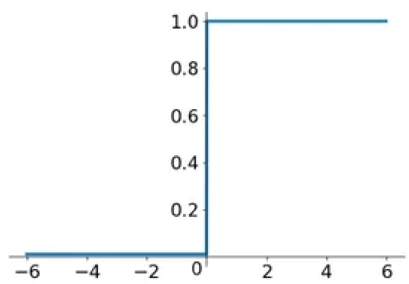


AI Application in EV Load Prediction: MLP

How should AI be applied in EV load prediction? - Backword Propagation







$\mathbf{X}$

$\mathbf{W}_1$ ← $\mathbf{u}_1 = \mathbf{X}\mathbf{W}_1$

$$\frac{\partial L}{\partial \mathbf{W}_1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{o}_1} \frac{\partial \mathbf{o}_1}{\partial \mathbf{W}_1} = (\hat{y} - y)\, \mathbf{W}_2\, \mathbf{X}\, f'(\mathbf{X}\mathbf{W}_1)$$

$\mathbf{o}_1 = f(\mathbf{u}_1)$

$$\frac{\partial L}{\partial \mathbf{o}_1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{o}_1} = (\hat{y} - y)\, \mathbf{W}_2$$

$\mathbf{W}_2$ ← $\hat{y} = \mathbf{o}_1\mathbf{W}_2$ ← $L = \frac{1}{2}(\hat{y} - y)^2$

$$\frac{\partial L}{\partial \mathbf{W}_2} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{W}_2} = (\hat{y} - y)\, \mathbf{o}_1 = (\hat{y} - y)\, f(\mathbf{X}\mathbf{W}_1)$$

$$\frac{\partial L}{\partial \hat{y}} = \hat{y} - y$$

How should AI be applied in EV load prediction? - Weight Parameter Updation

$\mathbf{X}$

$\mathbf{W}_1$

$\mathbf{u}_1 = \mathbf{X}\mathbf{W}_1$

$$\frac{\partial L}{\partial \mathbf{W}_1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{o}_1} \frac{\partial \mathbf{o}_1}{\partial \mathbf{W}_1} = (\hat{y} - y)\, \mathbf{W}_2\, \mathbf{X}\, f'(\mathbf{X}\mathbf{W}_1)$$

$\mathbf{o}_1 = f(\mathbf{u}_1)$

$$\frac{\partial L}{\partial \mathbf{o}_1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{o}_1} = (\hat{y} - y)\, \mathbf{W}_2$$

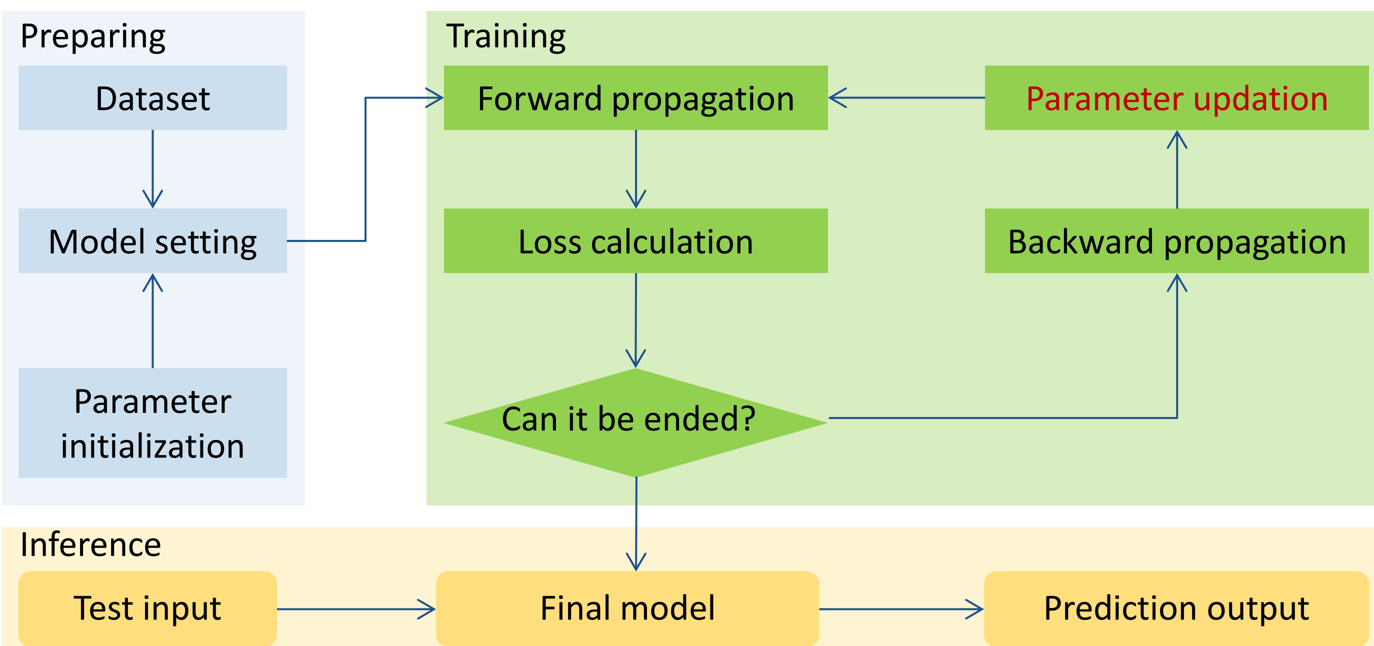
$\mathbf{W}_2$

$$\frac{\partial L}{\partial \mathbf{W}_2} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{W}_2} = (\hat{y} - y)\, \mathbf{o}_1 = (\hat{y} - y)\, f(\mathbf{X}\mathbf{W}_1)$$

$\hat{y} = \mathbf{o}_1\mathbf{W}_2$

$$\frac{\partial L}{\partial \hat{y}} = \hat{y} - y$$

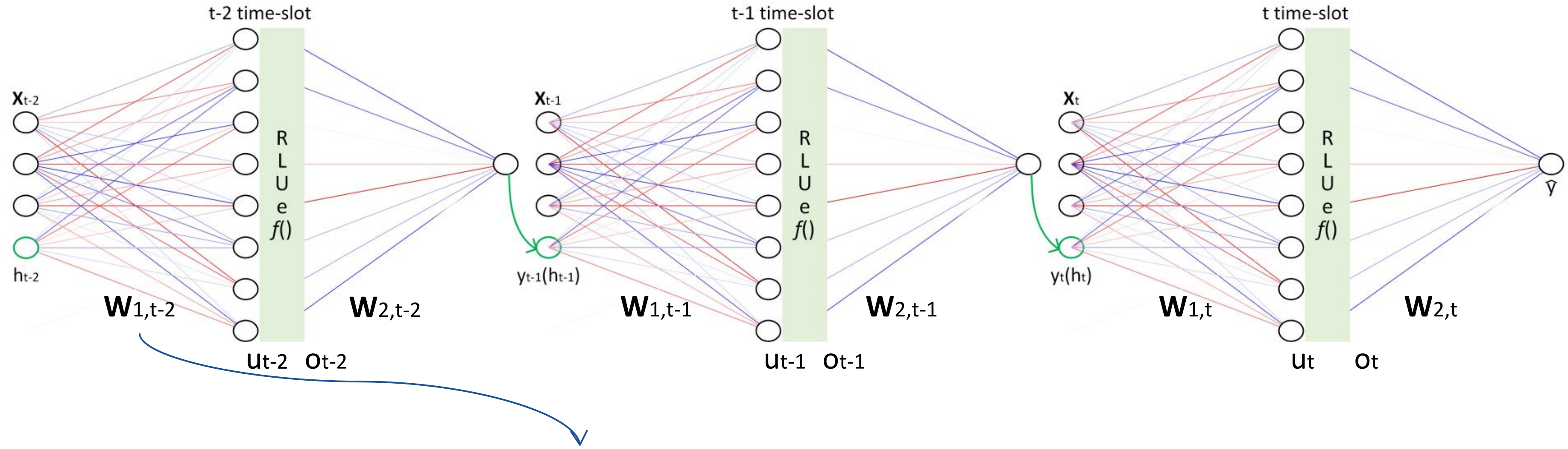
$$L = \frac{1}{2}(\hat{y} - y)^2$$



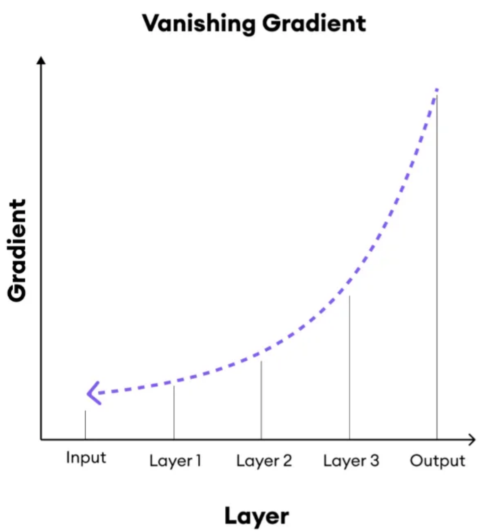
$$\mathbf{W}_1 = \mathbf{W}_1 - \eta_1 \frac{\partial L}{\partial \mathbf{W}_1}$$

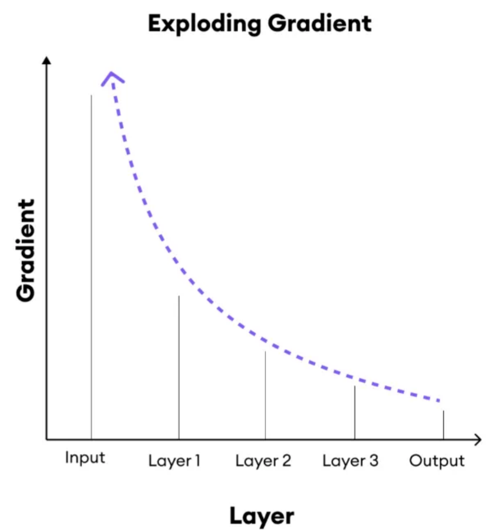
$$\mathbf{W}_2 = \mathbf{W}_2 - \eta_2 \frac{\partial L}{\partial \mathbf{W}_2}$$

Motivation of time-sequence data and Issue

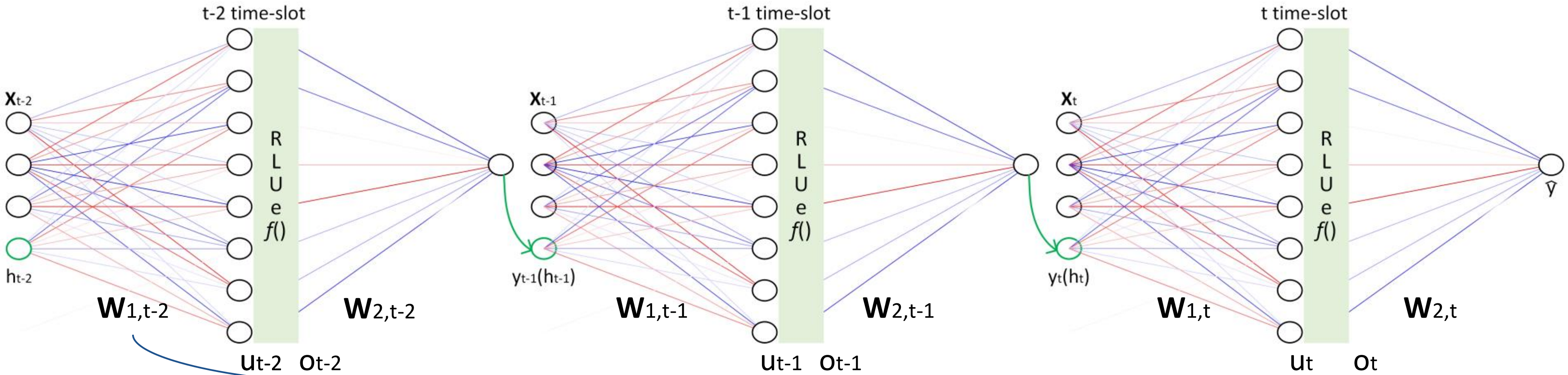


Gradients Vanishing and Exploding: $\frac{\partial L}{\partial \mathbf{W}_{1,t-2}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial y_t}{\partial \mathbf{o}_t} \frac{\partial \mathbf{o}_t}{\partial \mathbf{u}_t} \frac{\partial \mathbf{u}_t}{\partial y_t} \frac{\partial y_t}{\partial \mathbf{o}_{t-1}} \frac{\partial \mathbf{o}_{t-1}}{\partial \mathbf{u}_{t-1}} \frac{\partial \mathbf{u}_{t-1}}{\partial y_{t-1}} \frac{\partial y_{t-1}}{\partial \mathbf{o}_{t-2}} \frac{\partial \mathbf{o}_{t-2}}{\partial \mathbf{u}_{t-2}} \frac{\partial \mathbf{u}_{t-2}}{\partial \mathbf{W}_{w,t-2}}$





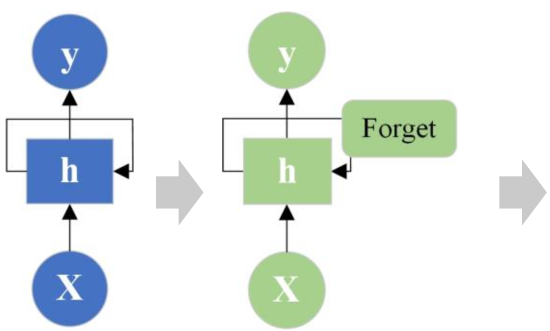
How to utilize time-sequence data



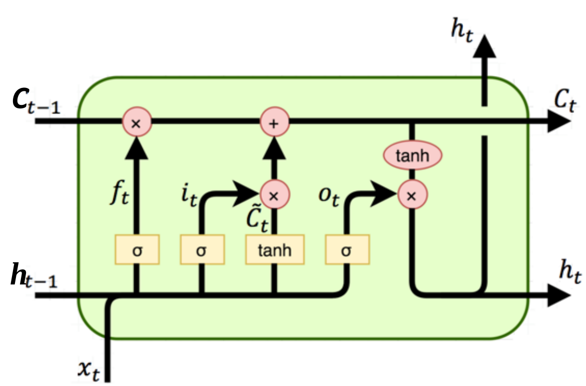
Gradients Vanishing and Exploding:

$$\frac{\partial L}{\partial \mathbf{W}_{1,t-2}} = \frac{\partial L}{\partial \hat{y}} \frac{\partial y_t}{\partial \mathbf{o}_t} \frac{\partial \mathbf{o}_t}{\partial \mathbf{u}_t} \frac{\partial \mathbf{u}_t}{\partial y_t} \frac{\partial y_t}{\partial \mathbf{o}_{t-1}} \frac{\partial \mathbf{o}_{t-1}}{\partial \mathbf{u}_{t-1}} \frac{\partial \mathbf{u}_{t-1}}{\partial y_{t-1}} \frac{\partial y_{t-1}}{\partial \mathbf{o}_{t-2}} \frac{\partial \mathbf{o}_{t-2}}{\partial \mathbf{u}_{t-2}} \frac{\partial \mathbf{u}_{t-2}}{\partial \mathbf{W}_{w,t-2}}$$

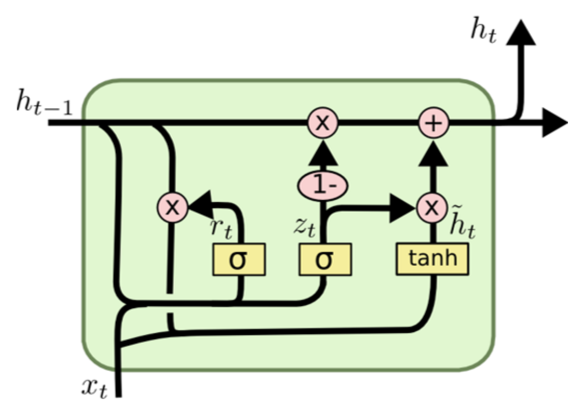
RNN Improved RNN



LSTM

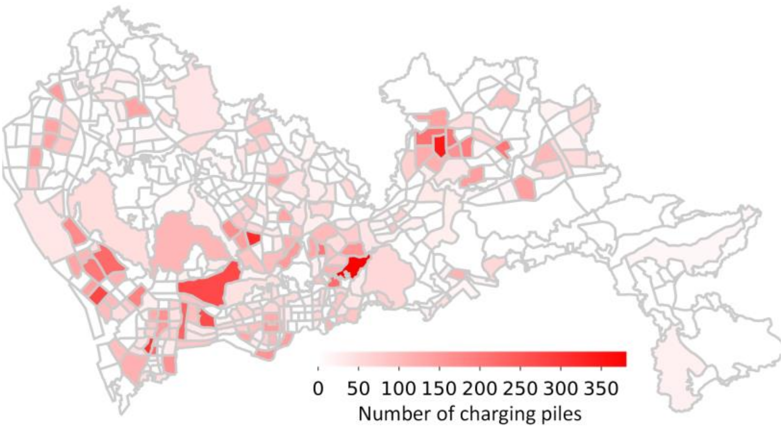


GRU

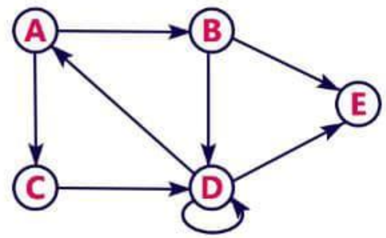


AI Application in EV Load Prediction: GCN

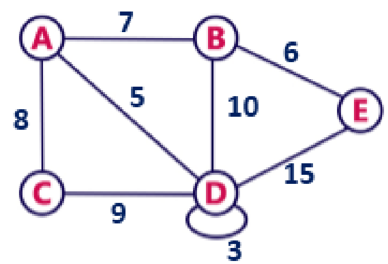
Motivation of spatial data



Graph input - adjacent matrix



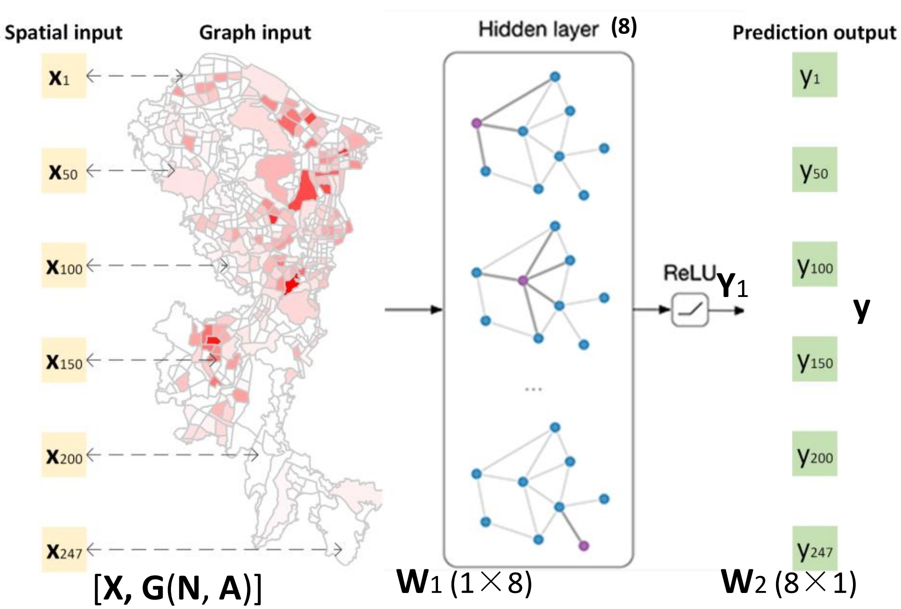
$$\begin{array}{c} \\ A \\ B \\ C \\ D \\ E \end{array}\begin{array}{c} \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{pmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$



$$\begin{array}{c} A \\ B \\ C \\ D \\ E \end{array}\begin{pmatrix} 0 & 7 & 8 & 5 & 0 \\ 7 & 0 & 0 & 10 & 6 \\ 8 & 0 & 0 & 9 & 0 \\ 5 & 10 & 9 & 3 & 15 \\ 0 & 6 & 0 & 15 & 0 \end{pmatrix}$$

G(N, A)

GCN model forward propogation



Input layer to hidden layer

$\mathbf{Y}_1 = f([\mathbf{X}, \mathbf{G}(\mathbf{N}, \mathbf{A})]; \mathbf{W}_1)$

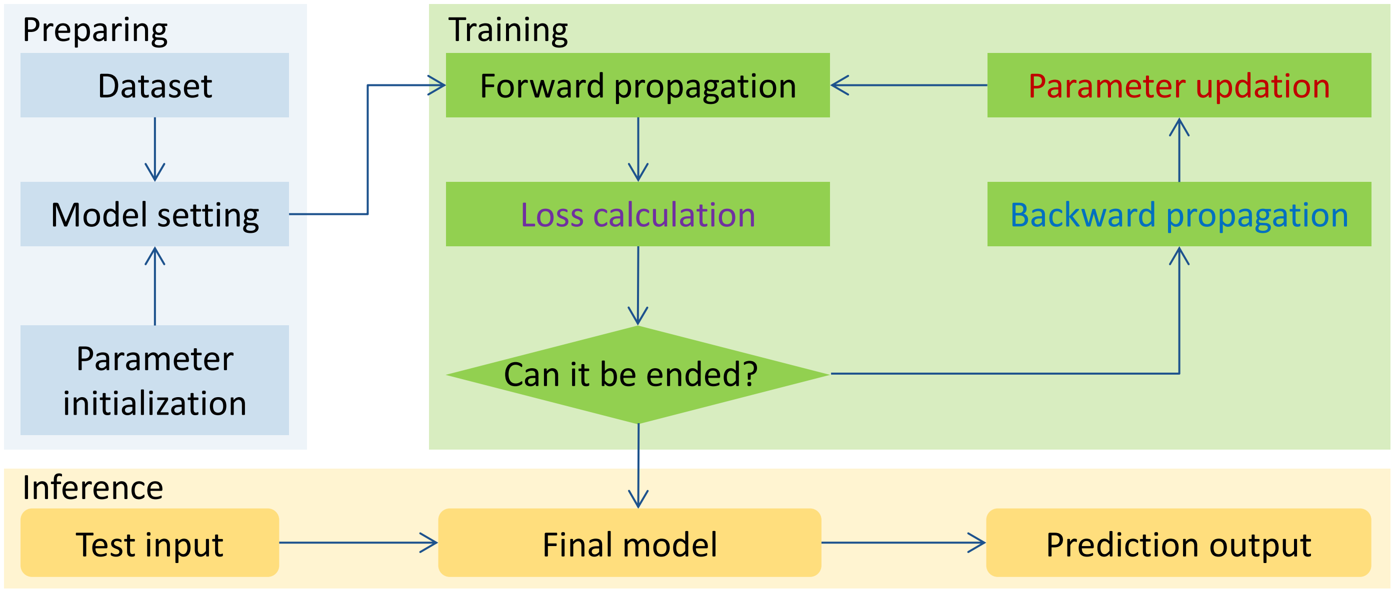
$= f(\mathbf{AXW}_1)$ $(247\times247)\ (247\times1)\ (1\times8) = (247\times8)$

$= f(\mathbf{D}^{-1/2}\mathbf{AD}^{-1/2}\mathbf{XW}_1)$

Hidden layer to output layer

$\mathbf{y} = f(\mathbf{D}^{-1/2}\mathbf{AD}^{-1/2}\mathbf{Y}_1\mathbf{W}_2)$ $(247\times247)\ (247\times8)\ (8\times1) = (247\times1)$

Algorithm perspective



$$\mathbf{W}_1 = \mathbf{W}_1 - \eta_1 \frac{\partial L}{\partial \mathbf{W}_1}$$

$$\mathbf{W}_2 = \mathbf{W}_2 - \eta_2 \frac{\partial L}{\partial \mathbf{W}_2}$$

$$\frac{\partial L}{\partial \mathbf{W}_1} = \frac{\partial L}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial \mathbf{o}_1} \frac{\partial \mathbf{o}_1}{\partial \mathbf{W}_1}$$

$$L = \frac{1}{2}(y - y)^2$$

$$y = \mathrm{Relu}(\mathbf{X} \times \mathbf{W}_1) \times \mathbf{W}_2$$

Model perspective

Type	Method	Pons	Cons
N.A.	MLP		
Temporal (T)	RNN		
	LSTM		
	GRU		
Spatial (S)	GCN		
	CNN		
ST	**Transformer***		

Contents

Artificial Intelligence in V2G Decision Making: Motivation and Idea

V2G Problem of Minimizing Load Variance

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

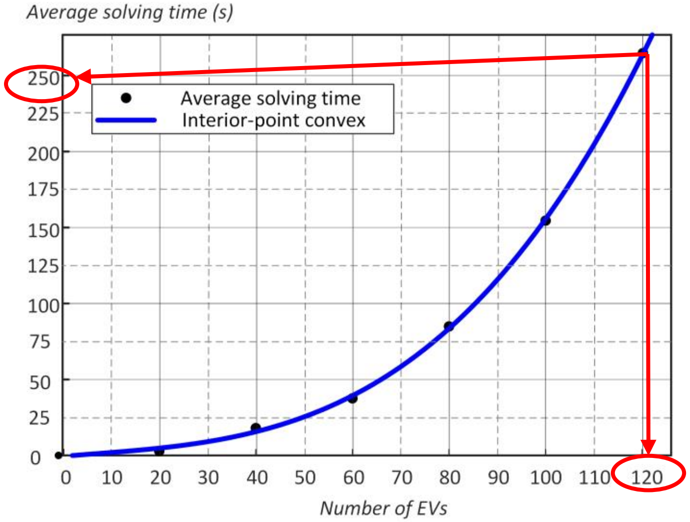
s.t.

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

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

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

Solving time of minimizing load variance (quadratic programming)

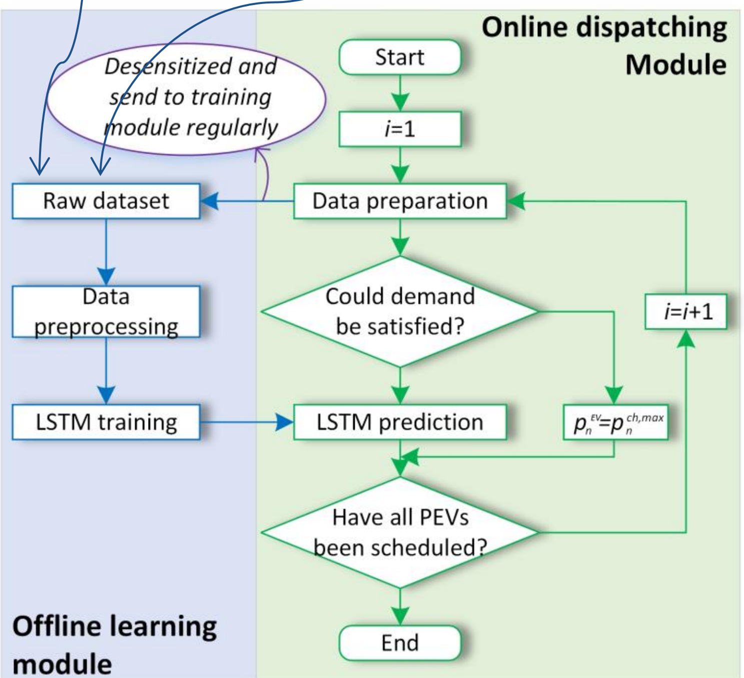


Offline Learning and Online Dispatching

t_{-96} *Privious* t_0 *Future* t_{96}

Input features
privious load (96)
privious PV output (96)
EV charging behivours
tempreture

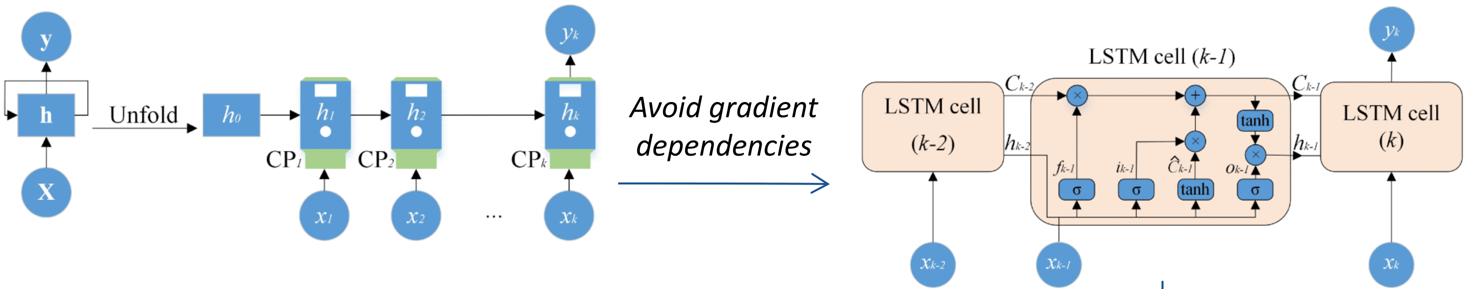
Output label
by optimization solver



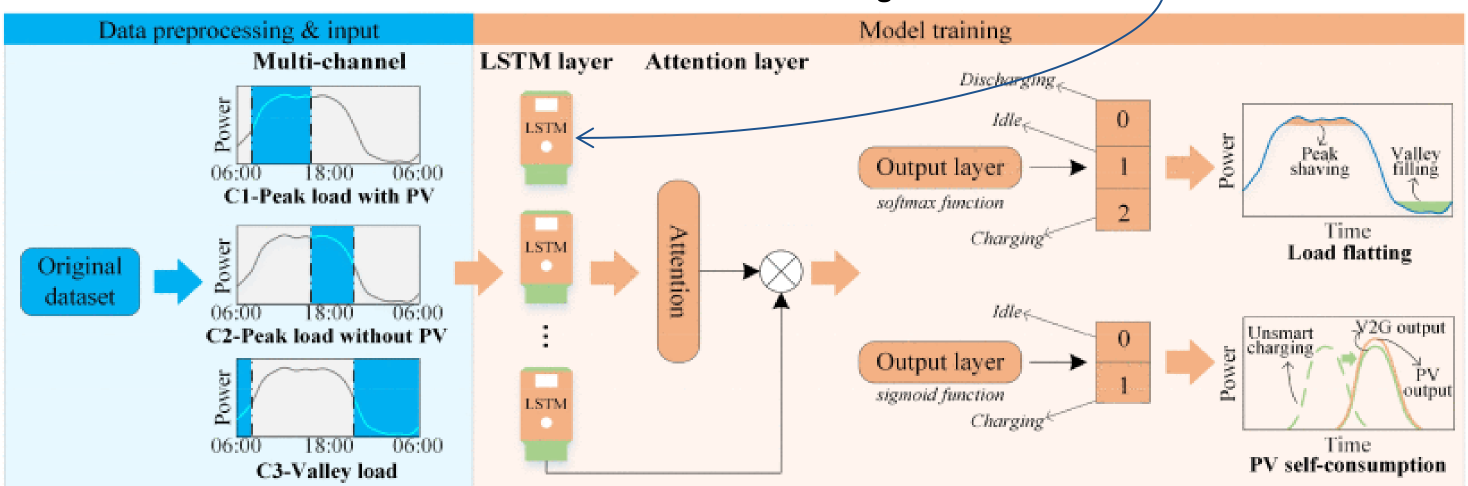
Shang, Yitong, et al. "Computational performance analysis for centralized coordinated charging methods of plug-in electric vehicles: From the grid operator perspective." *International Transactions on Electrical Energy Systems* 30.2 (2020): e12229.

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

Structure of RNN **Structure of LSTM**

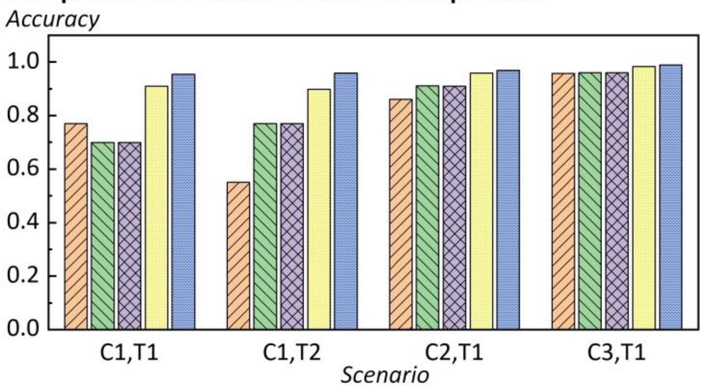


Overall network structure of the multichannel dual-task forecasting model.

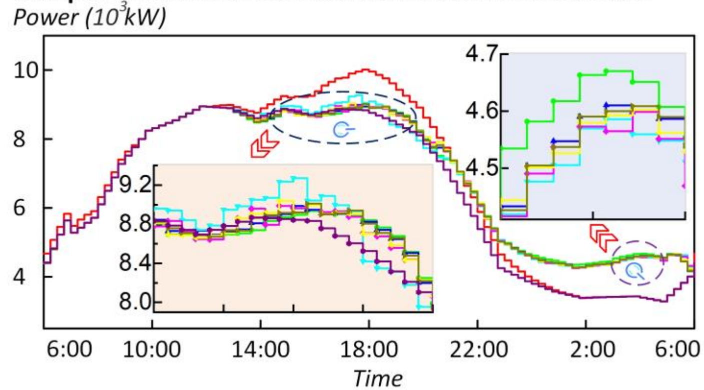


Artificial Intelligence in V2G Decision Making: Results

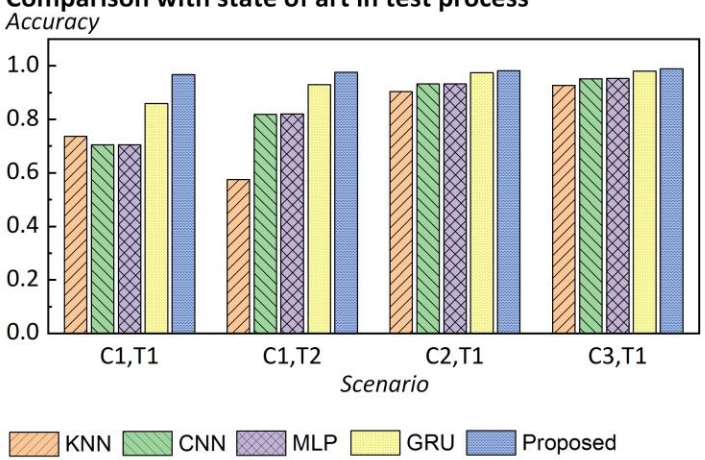
Comparison with state of art in train process



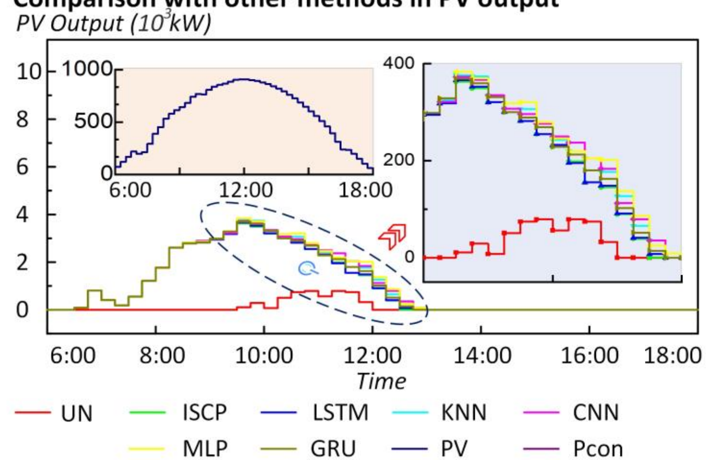
Comparison with other methods in conventional load



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.

Artificial Intelligence in V2G Decision Making: Extend and Brief Summary

Other method about learning to optimize

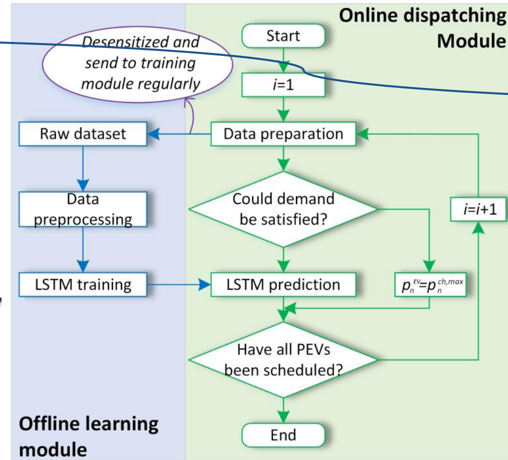
$$\min \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{n=1}^{N} p_{n,t}^{EV} + p_t^{con} - p^{ave}\right)^2$$

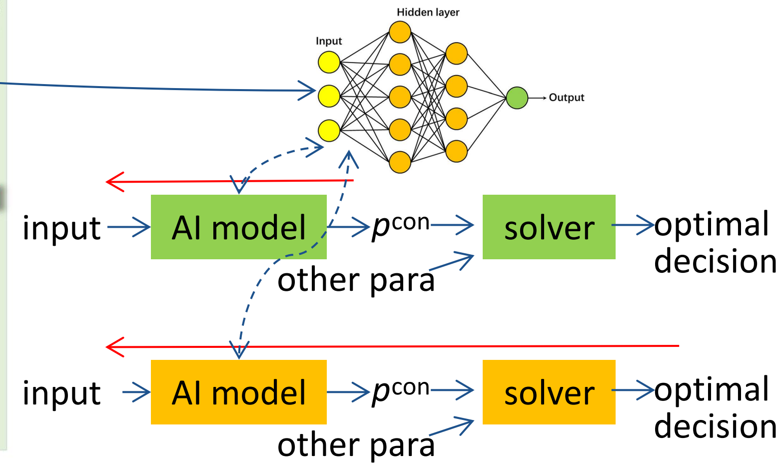
s.t.

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

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

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





Model perspective

Type	Method	Pons	Cons
Learning to Optimize	Imitation Learning		
	Two-Stage Predict-then-Optimize		
	End-to-End Predict-then-Optimize		
	Reinforcement Learning		

Contents

Thank You!

Yitong SHANG
ytshang@ust.hk

Q&A