上海交通大學
SHANGHAI JIAO TONG UNIVERSITY

# Data-Driven Operation of Seaport Energy-Logistic System

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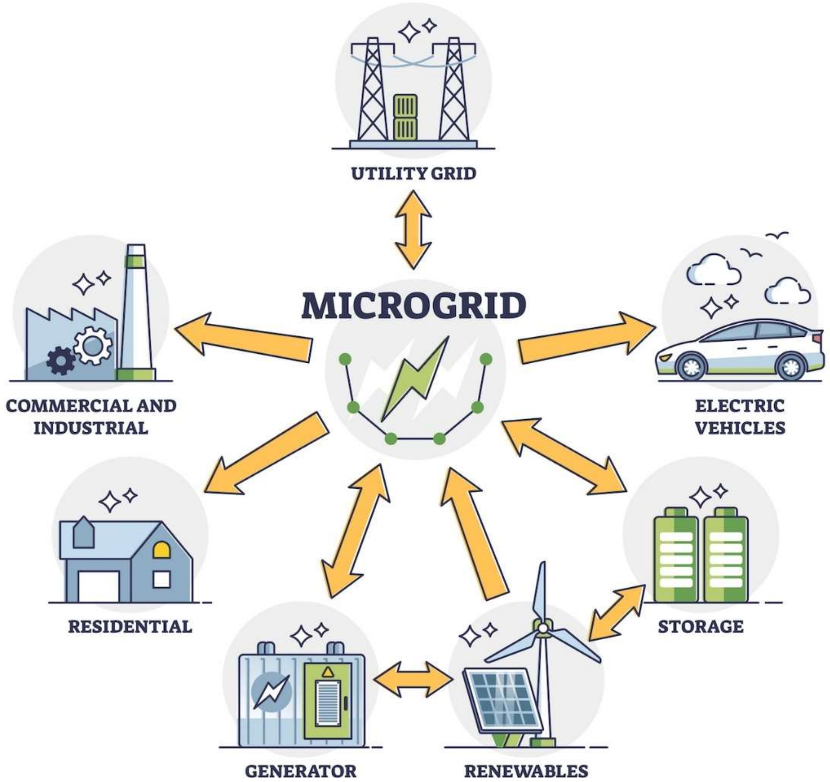
# Content |



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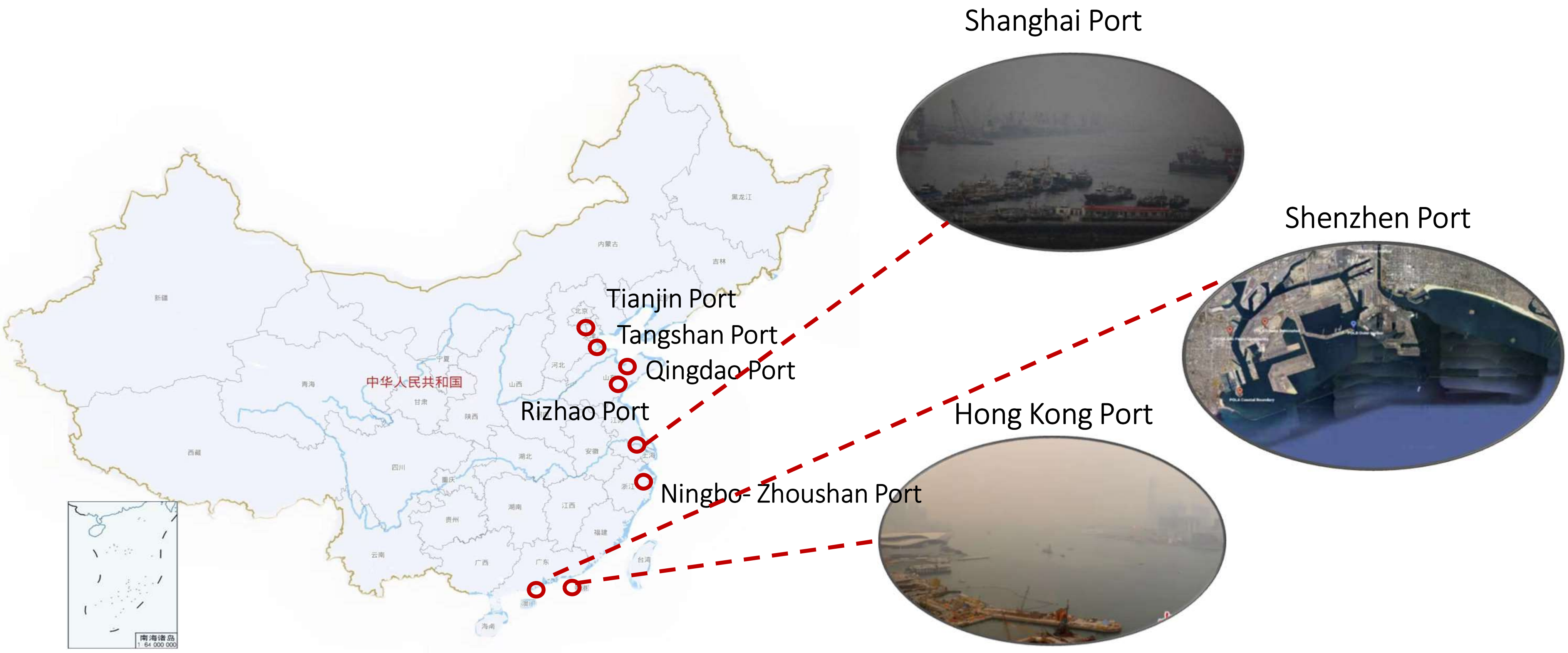
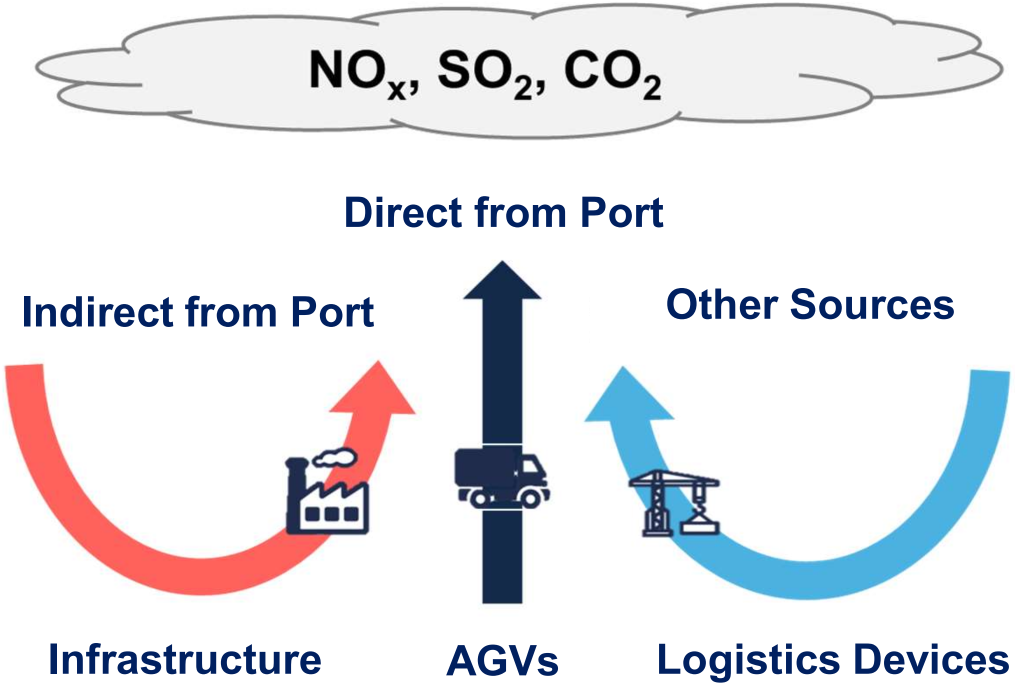
# Research Background

- **Seaports are strategic fulcrums and important hubs for international trade and marine development**
- **29 of the world's top 50 ports are in China, accounting for about 68% of port throughput.**

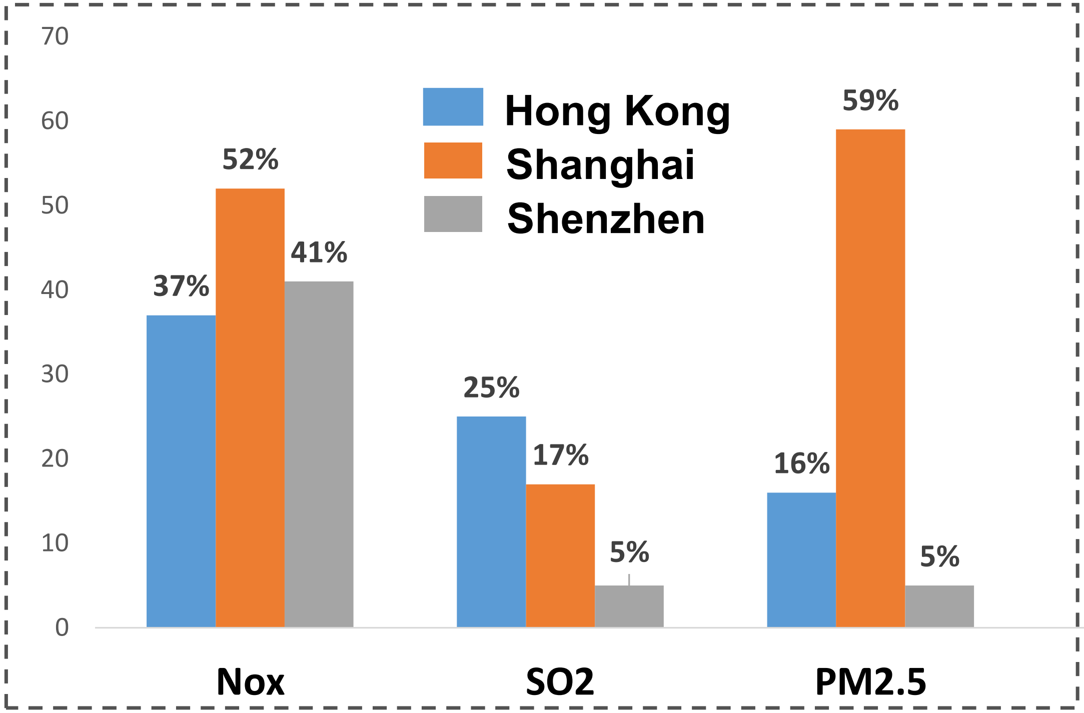


# Research Background

- Large seaports around the world handle nearly 90% of global trade.
- The continuous growth in port throughput and scale has become a major cause of energy consumption and high carbon emissions.



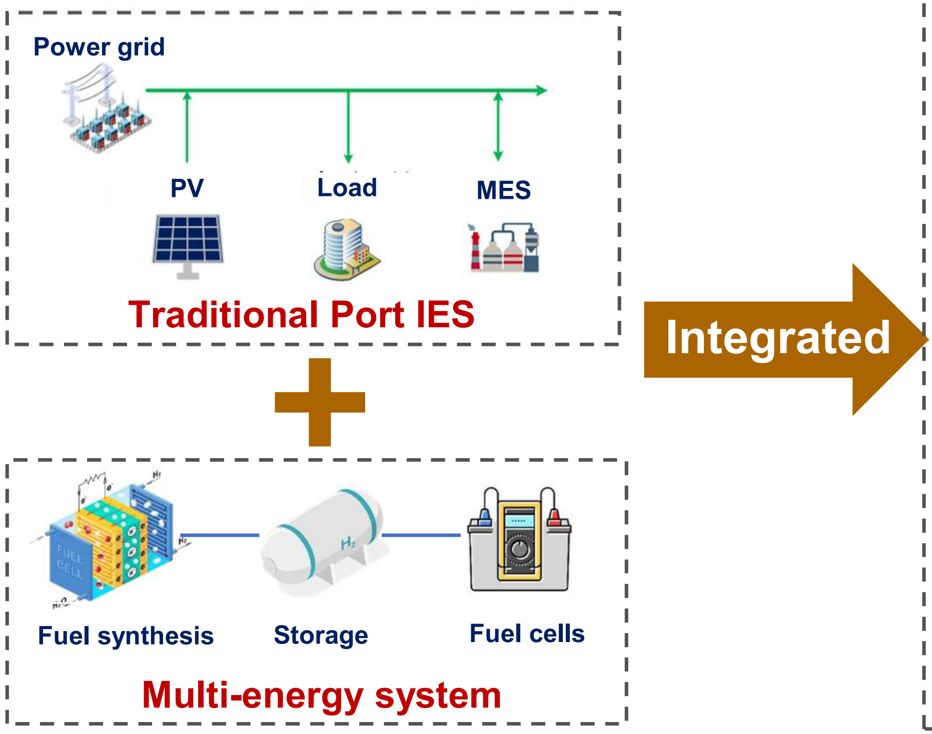

The contribution of shipping to air pollution in major port cities

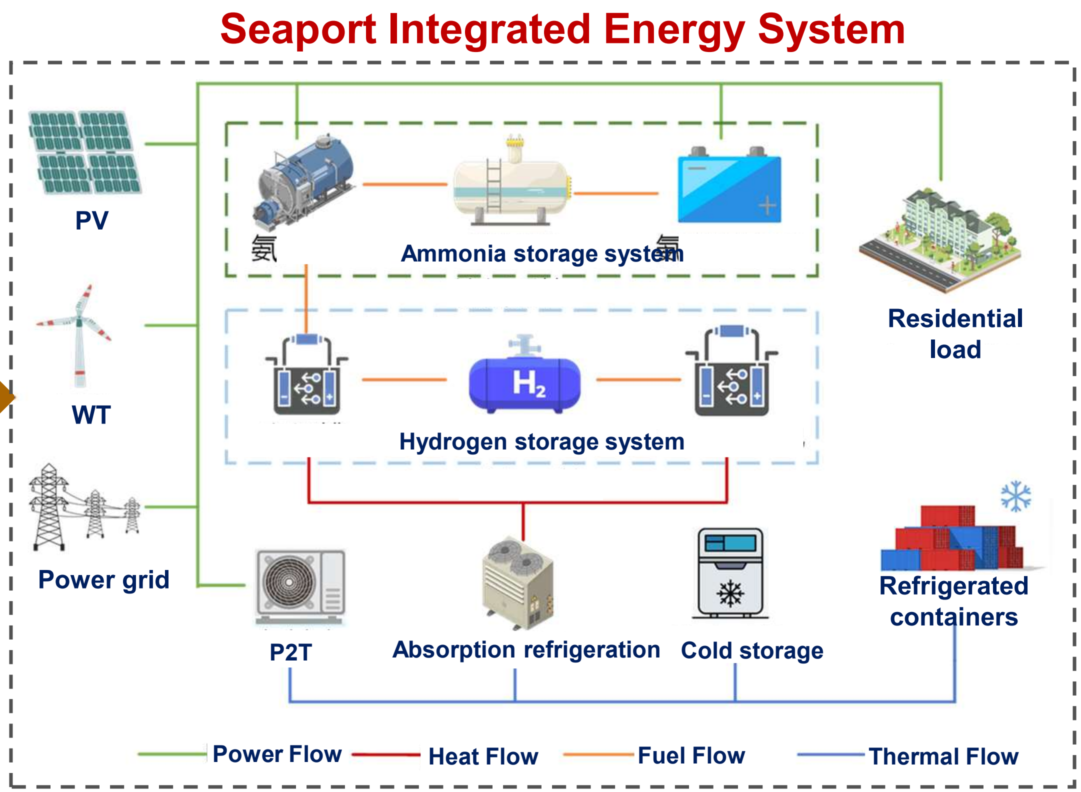


# ■ Research Background

- **Multi-energy integration & green substitution**
  Driving the transformation of traditional port energy systems

- **Benefits of integrated port energy systems**
  Reduce carbon emissions; Improve energy efficiency

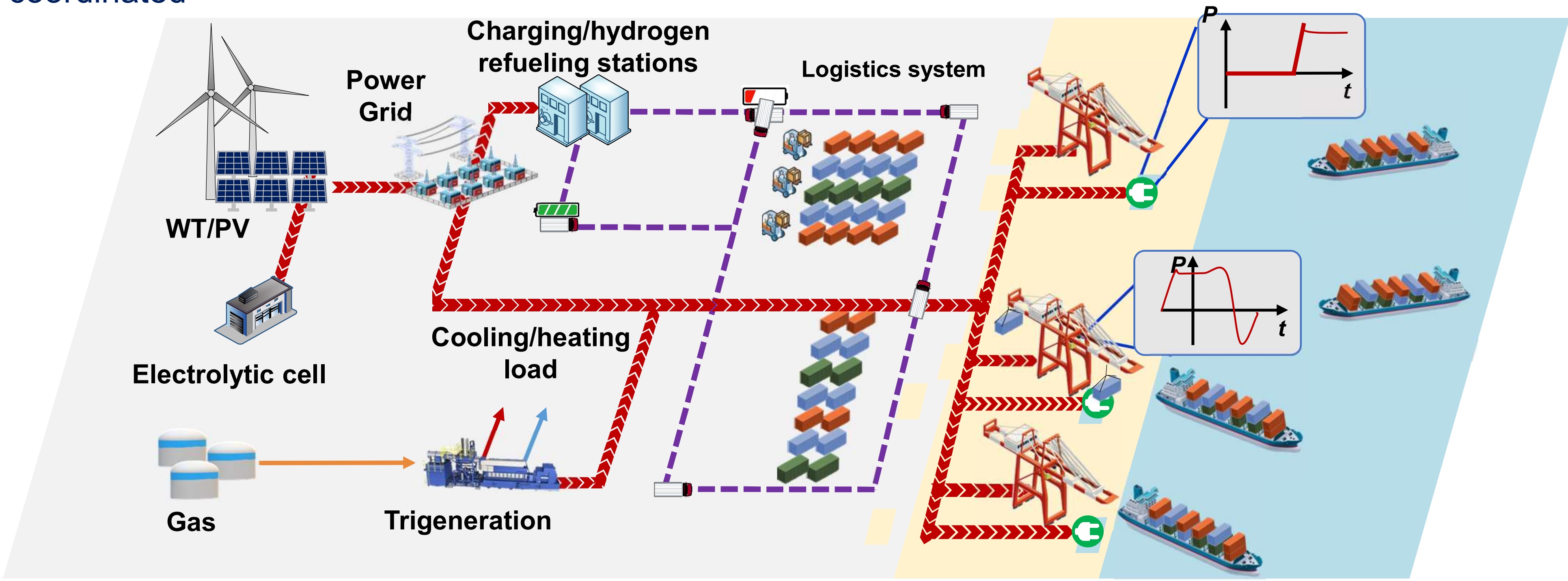


# ■ Research Background

- **Port Electrified Logistics System :** composed of vessels (ship), terminal equipment (shore), and energy–logistics devices (port)

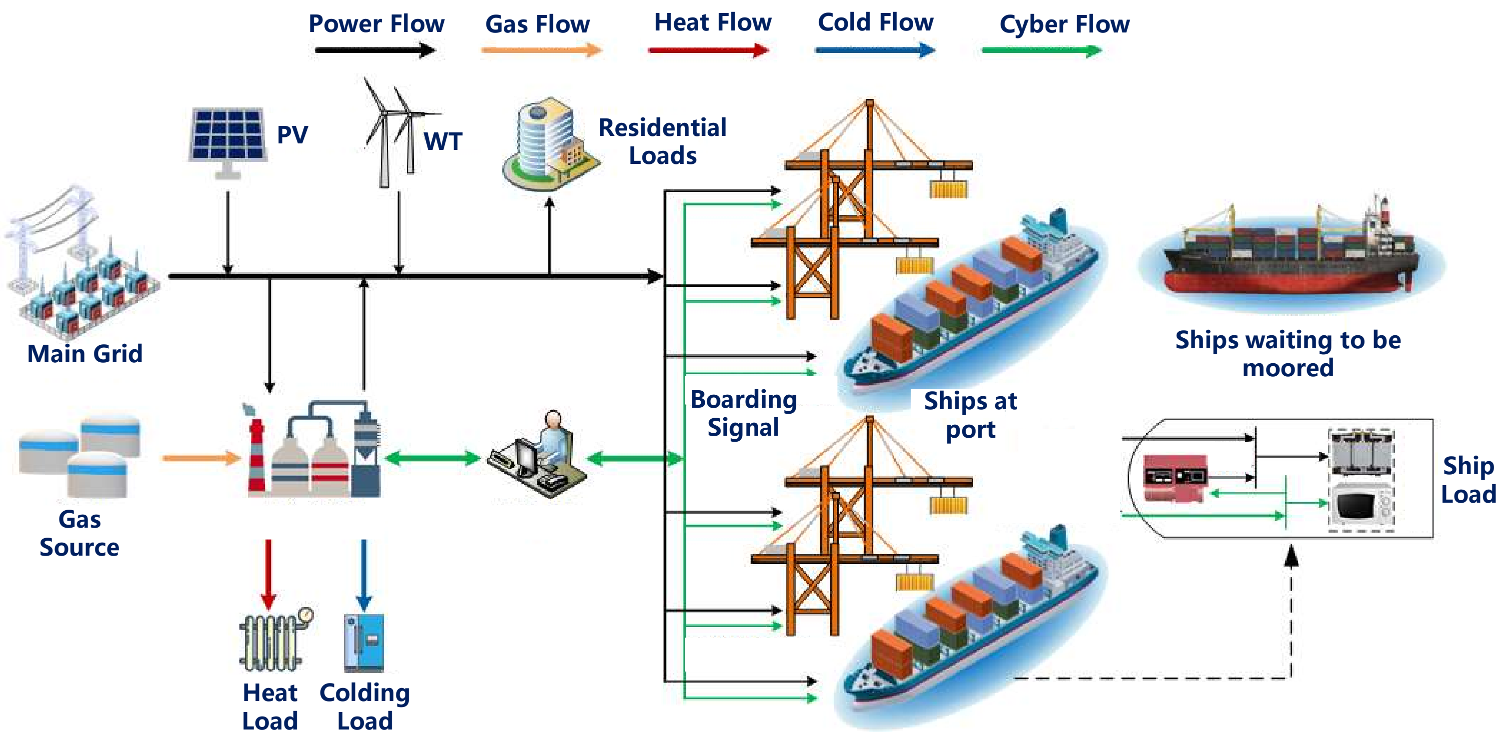
- **Flexible Scheduling:** vessel arrivals/departures and logistics workload can be dynamically coordinated




**Port:** **IES, Logistics system** **Shore:** **Loading Equips** **Ships:** **Containers**

# ■ Research Background

- ☐ **Logistics-driven Load:** Port energy demand is shaped by logistics operations
- ☐ **Impact on Energy Use:** Scheduling affects consumption of shore power, reefers, EVs, and quay cranes
- ☐ **Coordination is Key:** Joint optimization of logistics and energy systems ensures efficient operation



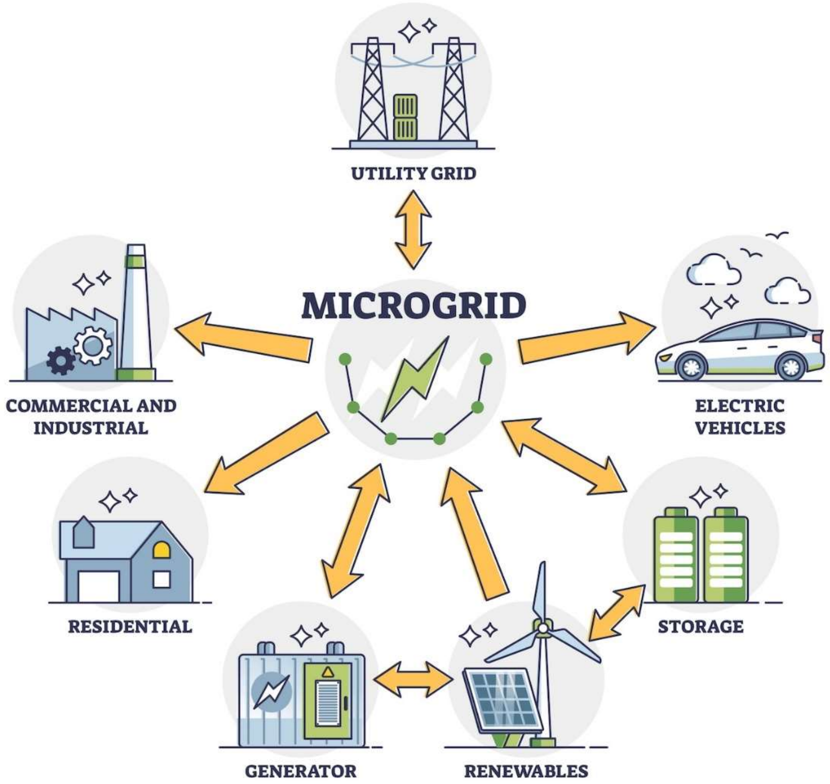

**Logistics:**

- ☐ Vessels
- ☐ Quay Cranes
- ☐ EVs

**IES:**

- ☐ Logistics Load
- ☐ Multi-Energy Scheduling
- ☐ RES

# Content |



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# ■ Operational Modeling of Seaport ELS

## Key Elements of the Operation Model

- □ **Objective Function: minimize total cost (power purchase, cost of devices, emission cost)**
- □ **Decision Variables: energy dispatch of devices, power purchase, logistics operations**
- □ **Constraints: physical limits of devices, power balance, logistics constraints**

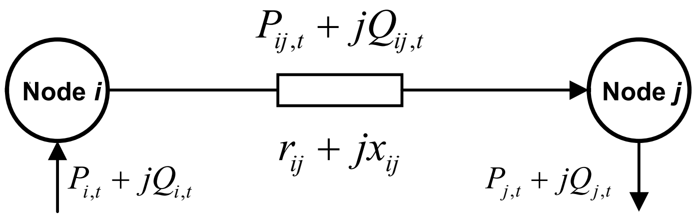
## General Formulation:

$$\min_{\mathbf{x}} \quad f(\mathbf{x}; \hat{\boldsymbol{\lambda}}, \hat{\mathbf{p}})$$

$$\text{s.t.} \quad \mathbf{x} \in \mathcal{X}(\hat{\mathbf{p}}, \mathbf{I}_{\mathrm{s}}, \mathbf{I}_{\mathrm{d}}), \quad \mathbf{x} \in \mathbb{R}^{s+d}$$

# Operational Modeling of Seaport PLS

## Power Flow




### Active power balance

$$P_{j,t} = \sum_{k:j\to k} P_{jk,t} - \sum_{i:i\to j}\left(P_{ij,t} - r_{ij}\left|I_{ij,t}\right|^2\right),\ \forall ijk,t$$

### Reactive power balance

$$Q_{j,t} = \sum_{k:j\to k} Q_{jk,t} - \sum_{i:i\to j}\left(Q_{ij,t} - x_{ij}\left|I_{ij,t}\right|^2\right),\ \forall ijk,t$$

### Ohm's Law for Line Voltage

$$V_{i,t} - V_{j,t} = (r_{ij} + jx_{ij})I_{ij,t},\ \forall ij,t$$

### Line power flow (complex calculation)

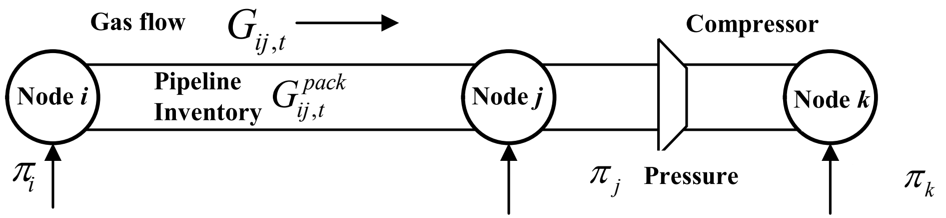
$$P_{ij,t} + jQ_{ij,t} = V_{i,t} I^*_{ij,t},\ \forall ij,t$$

### Voltage and current constraints

$$\left|I_{ij,t}\right| \leqslant \overline{I}_{ij},\ \forall ij,t \qquad \underline{V}_i \leqslant \left|V_{i,t}\right| \leqslant \overline{V}_i,\ \forall i,t$$

# ■ Operational Modeling of Seaport PLS

## Gas Flow




**The gas network pipeline flow equation is constructed based on the gas network flow, node gas pressure, pipeline storage, and compressor input and output:**

$$G_{j,t} - \sum_{z\in\Omega_C} \eta^C_{zj} G^C_{zj,t} = \sum_{k:j\to k} G_{jk,t} + \sum_{i:i\to j} G_{ji,t} + \sum_{z\in\Omega_C} G^C_{zj,t},\ \forall ijk \in \Omega_G, t$$

$$G^{ave}_{ij,t} = 0.5\left(G_{ij,t} - G_{ji,t}\right),\ \forall ij \in \Omega_G, t$$

$$\left(G^{ave}_{ij,t}\right)^2 = W_{ij}\left(\pi^2_{i,t} - \pi^2_{j,t}\right),\ \forall ij \in \Omega_G, t$$

$$G^{pack}_{ij,t} = 0.5K^{pack}_{ij}\left(\pi_{i,t} + \pi_{j,t}\right),\ \forall ij \in \Omega_G, t$$

$$\left(G_{ij,t} + G_{ji,t}\right)\Delta t = G^{pack}_{ij,t} - G^{pack}_{ij,t-1},\ \forall ij \in \Omega_G, t$$

$$\underline{\pi}_i \leqslant \pi_{i,t} \leqslant \overline{\pi}_i,\ \forall i \in \Omega_G, t$$

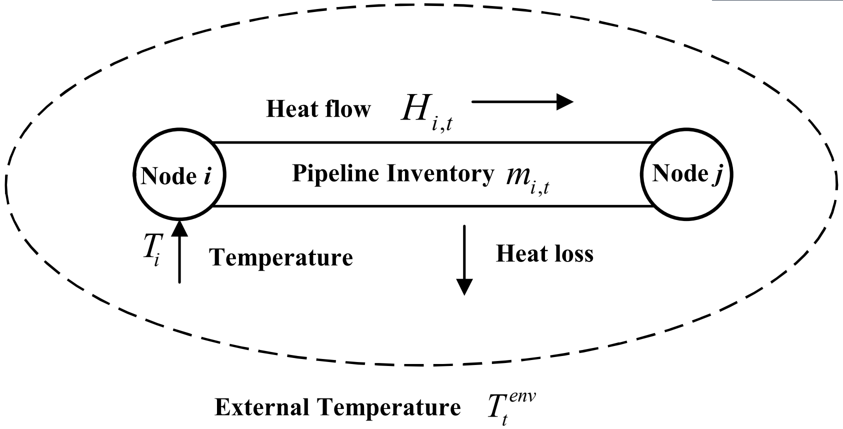
$$0 \leqslant G_{ij,t} \leqslant \overline{G}_{ij},\ \forall ij \in \Omega_G, t$$

$$\underline{\kappa}\pi_{i,t} \leqslant \pi_{j,t} \leqslant \overline{\kappa}\pi_{i,t}, \forall ij \in \Omega_C, t$$

$$0 \leqslant G^C_{ij,t} \leqslant \overline{G}^C_{ij},\ \forall ij \in \Omega_C, t$$

# Operational Modeling of Seaport PLS

## Heat Power Flow




**The heat network power flow equation is constructed based on the heat load power equation, the temperature drop equation, and the nodal power conservation equation**

### Heat Load Power

$$H_{i,t} = HC_w m_{i,t}(T_{i,t}^r - T_{i,t}^s),\ \forall i \in \Omega_H, t$$

### Pipe temperature drop equation

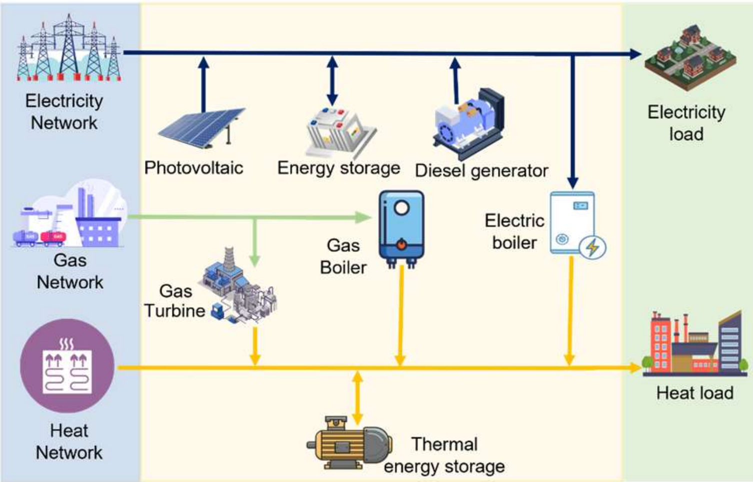
$$T_{j,t} = (T_{i,t} - T_t^{env})e^{-\frac{\gamma_{ij}L_{ij}}{HC_w m_{ij,t}}} + T_t^{env}, \forall i \to j \in \Omega_H, t$$

### Nodal power conservation equation

$$H_{j,t} + \sum_{i:i\to j} m_{ij,t}T_j^{in} = \sum_{k:j\to k} m_{jk,t}T_j^{out},\ \forall ijk \in \Omega_H, t$$

# ■ Operational Modeling of Seaport PLS

## Multi-Energy Devices




### Multi-Energy Balance

$$0 \le P_{G,t} \le \overline{P_G} \quad \forall t$$

$$0 \le G_{G,t} \le \overline{G_G} \quad \forall t$$

$$P_{G,t} + P_{PV,t} + P_{GT,t} + P_{ESS,t}^{dch} = P_{ESS,t}^{ch} + P_{EB,t} + P_{SR,t} + P_{QC,t} + \hat{P}_{L,t} \quad \forall t$$

$$H_{GT,t} + H_{GB,t} + H_{EB,t} = \hat{H}_{L,t} \quad \forall t$$

$$G_{G,t} = G_{GT,t} + G_{GB,t} + \hat{G}_{L,t} \quad \forall t$$

### Gas Turbine

$$P_{GT}(t) = \eta_{GT} \cdot Q_{fuel}(t) \qquad P_{GT}(t) \le P_{GT}(t-1) + R_{up} \cdot \Delta t$$

$$Q_{min} \le Q_{fuel}(t) \le Q_{max} \qquad P_{GT}(t) \ge P_{GT}(t-1) - R_{down} \cdot \Delta t$$

### Gas Boiler

$$Q_{GB}(t) = \eta_{GB} \cdot Q_{fuel,\,GB}(t)$$

$$Q_{GB}(t) \le Q_{GB}(t-1) + R_{GB,\,up} \cdot \Delta t$$

$$Q_{GB}(t) \ge Q_{GB}(t-1) - R_{GB,\,down} \cdot \Delta t$$

# Operational Modeling of Seaport PLS

**Berth scheduling**

$$T_{arr,s} \le t_{ber,s} \le t_{lea,s}$$

$$t_{ber,s} + \frac{t_{ber,s}}{C_{QC}} \le t_{lea,s} \le \overline{T_{lea,s}}$$

Decision vars

$$B_{i,s,t} = \begin{cases} 0 & t \in [1, t_{ber,s} - 1] \\ 1 & t \in [t_{ber,s}, t_{lea,s} - 1] \\ 0 & t \in [t_{lea,s}, T] \end{cases}$$

Decision vars

$$b_{i,s} = \begin{cases} 1 & \sum_{t=1}^{T} B_{i,s,t} \ge 0 \\ 0 & \sum_{t=1}^{T} B_{i,s,t} = 0 \end{cases}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I}(B_{i,s,t}\sum_{q=1}^{Q} C_{QC,i,q,t}) = N_s$$

$$\sum_{i=1}^{I} B_{i,s,t} \le 1, \sum_{j=1}^{J} B_{i,s,t} \le 1$$

$$P_{SH,i,t} = P_{shore}\sum_{s}^{S}\sum_{i=1}^{I} B_{i,s,t}$$

Introduce **auxiliary variables** u, v, w

Big-M Method

$$\sum_{i=1}^{I} B_{i,s,t} \le Mu_{s,t}$$

$$\sum_{i=1}^{I} B_{i,s,t} \ge -Mu_{s,t}$$

$$t - t_{ber,s} \le Mu_{s,t} - 0.01$$

$$t - t_{ber,s} \ge -M(1 - u_{s,t})$$

$$\sum_{i=1}^{I} B_{i,s,t} \le Mv_{s,t}$$

$$\sum_{i=1}^{I} B_{i,s,t} \ge -Mv_{s,t}$$

$$t - t_{lea,s} \le M(1 - v_{s,t}) - 0.01$$

$$t - t_{lea,s} \ge -M(1 - v_{s,t})$$

$$\left.\begin{aligned} &\sum_{t=1}^{T} B_{i,s,t} - (t_{lea,s} - t_{ber,s}) \le Mw_{i,s} \\ &w_{i,s} \le M(1 - b_{i,s}) \\ &w_{i,s} \ge -M(1 - b_{i,s}) \end{aligned}\right\}$$

The sum of the **time dimensions of the berthing state variables** is equal to the **berthing time**

# Operational Modeling of Seaport PLS

$$T_{arr,s} \le t_{ber,s} \le t_{lea,s}$$

$$t_{ber,s} + \frac{t_{ber,s}}{C_{QC}} \le t_{lea,s} \le \overline{T_{lea,s}}$$

$$B_{i,s,t} = \begin{cases} 0 & t \in [1, t_{ber,s} - 1] \\ 1 & t \in [t_{ber,s}, t_{lea,s} - 1] \\ 0 & t \in [t_{lea,s}, T] \end{cases}$$

$$b_{i,s} = \begin{cases} 1 & \sum_{t=1}^{T} B_{i,s,t} \ge 0 \\ 0 & \sum_{t=1}^{T} B_{i,s,t} = 0 \end{cases}$$

Decision vars

Decision vars

$$\sum_{t=1}^{T}\sum_{i=1}^{I}(B_{i,s,t}\sum_{q=1}^{Q} C_{QC,i,q,t}) = N_s$$

$$\sum_{i=1}^{I} B_{i,s,t} \le 1, \sum_{j=1}^{J} B_{i,s,t} \le 1$$

$$P_{SH,i,t} = P_{shore}\sum_{s}^{S}\sum_{i=1}^{I} B_{i,s,t}$$

**Introduce auxiliary variables z**

**Big-M Method**

$$\sum_{t=1}^{T} B_{i,s,t} = 0.01 - M(1 - b_{i,s})$$

$$\sum_{i=1}^{I} b_{i,s} = 1$$

**Determine which berth the ship is moored at**

$$z_{i,s,t} \le \sum_{q=1}^{Q} C_{QC,i,q,t}$$

$$z_{i,s,t} \ge 0$$

$$z_{i,s,t} \ge \sum_{q=1}^{Q} C_{QC,i,q,t} - M(1 - B_{i,s,t})$$

$$z_{i,s,t} \le MB_{i,s,t}$$

$$\sum_{i=1}^{I}\sum_{t=1}^{T} z_{i,s,t} = N_s$$

**The total number of containers loaded and unloaded by the quay crane during the ship's berth is equal to the number of containers transported by the ship**

## Operational Modeling of Seaport PLS

**Loading and unloading equipment model**

**Logistics Cascade Constraints**

$$\sum_{q=1}^{Q} C_{QC,i,q,t} = \sum_{q=1}^{Q} C_{YC,i,q,t}$$

$$0 \le C_{QC,i,q,t} \le \overline{C_{QC}}$$

$$0 \le C_{YC,i,q,t} \le \overline{C_{YC}}$$

$$P_{QC,i,q,t} = C_{QC,i,q,t} E_C^{qc}$$

$$P_{YC,i,q,t} = C_{YC,i,q,t} E_C^{yc}$$

**Electric container truck**

$$E_{EV,v,t+1} = E_{EV,v,t} + \eta_{EV}^{ch} P_{EV,v,t}^{ch} \Delta t - \frac{P_{EV,v,t}^{tp}}{\eta_{EV}^{tp}} \Delta t$$

$$\underline{S_{EV}}\, \overline{E_{EV}} \le E_{EV,v,t} \le \overline{S_{EV}}\, \overline{E_{EV}}$$

$$0 \le P_{EV,v,t}^{ch} \le \overline{P_{EV}^{ch}}, 0 \le P_{EV,v,t}^{tp} \le \overline{P_{EV}^{tp}}$$

Decision vars

$$r_{EV,v,t}^{ch} + r_{EV,v,t}^{tp} + r_{EV,v,t}^{rt} = 1$$

$$\sum_{v=1}^{V} r_{EV,i,v,t} P_{EV,v,t}^{tp} = \sum_{q=1}^{Q} C_{QC,i,q,t}$$

Decision vars

$$\sum_{i=1}^{I} r_{EV,i,v,t} \le 1$$

**Dimensional Reconstruction**

$$\sum_{i=1}^{I} P_{EV,i,v,t} = P_{EV,v,t}^{tp}$$

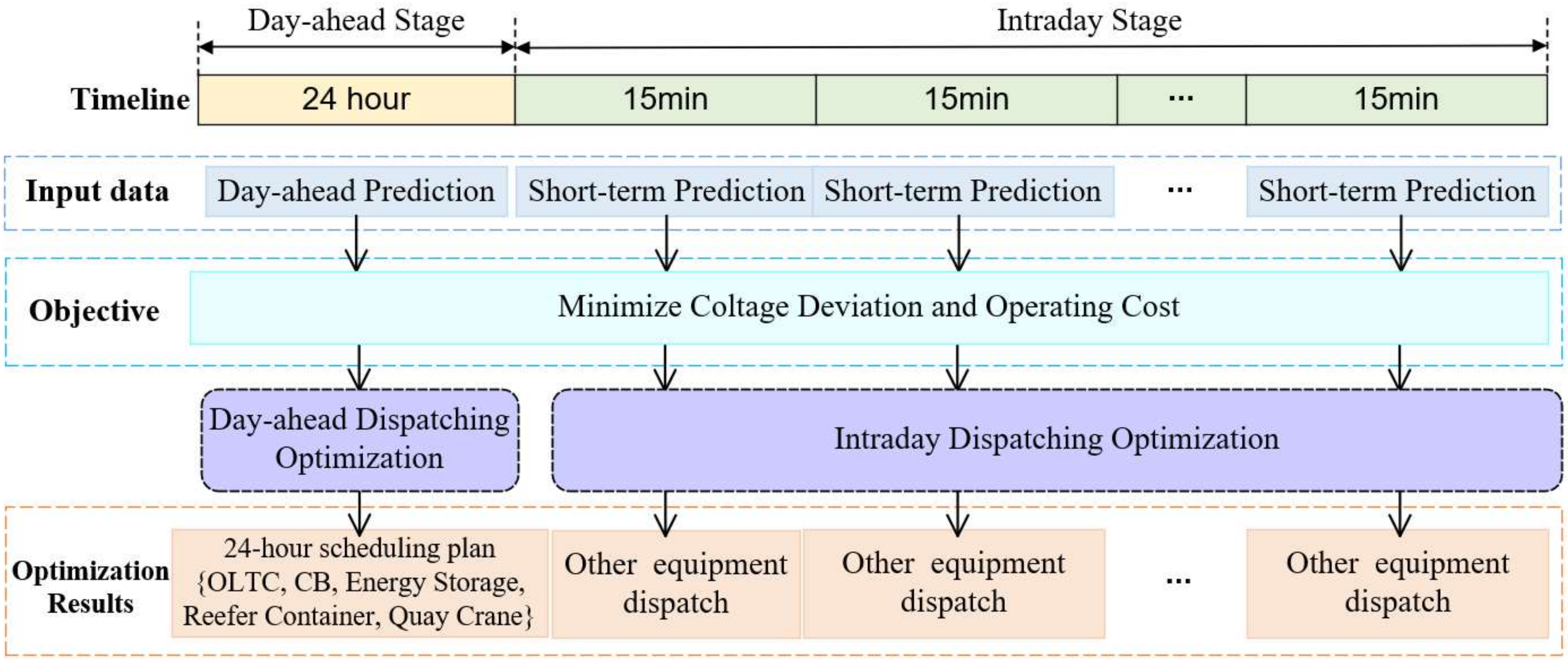
$$\frac{P_{EV,i,v,t} \Delta t}{E_C^{ev}} \le r_{EV,i,v,t} \overline{N_i}$$

$$\frac{\sum_{k=1}^{K} P_{EV,i,v,t} \Delta t}{E_C^{ev}} = \sum_{q=1}^{Q} C_{QC,i,q,t}$$

**Use the logistics route dimension as a new dimension to construct a high-dimensional variable**

# ■ Operational Modeling of Seaport PLS

- **Day-ahead dispatching-hourly dispatching:** energy storage equipment, quay cranes, berth allocations …
- **Intraday dispatching-15-minute dispatching:** photovoltaic inverters, gas turbines, gas boilers, electric boilers …



## ■ Operational Modeling of Seaport PLS

**Due to the uncertainty of source load, the model is expressed as a two-stage stochastic optimization model. The first stage optimization model is the day-ahead scheduling model:**

$$\min_{x,y} \left\{ F(x) + E\left[ G\left( y, \xi \right) \right] \right\}$$

$$E\left[ G\left( y, \xi \right) \right] = \sum_{s \in S} \rho_s G\left( y_s, \xi_s \right)$$

$$x = \left\{ \alpha_{u,t}, \beta_{i,t}, P_{i,t}^{es,ch}, P_{i,t}^{es,dch}, CR_{i,m,t}, I_{i,m,t}^{ship}, P_{i,n,t}^{rf} \right\}$$

$$\xi = \left\{ P_{i,t}^{pv,pre}, P_{i,t}^{load}, Q_{i,t}^{load}, G_{i,t}^{load}, H_{i,t}^{load}, T_t^{env}, P_{i.m,t}^{ship} \right\}$$

**Among them, F(x) is the day-ahead scheduling optimization subproblem; G(y, ξ) is the intraday scheduling optimization subproblem; x is the day-ahead scheduling decision variable, y is the intraday scheduling decision variable, and ξ is a random variable**

## ■ Operational Modeling of Seaport PLS

**The second stage optimization model is an intraday scheduling model. After the optimization results of the decision variables in the first stage are determined, the second stage will optimize the output of various energy supply equipment based on the short-term forecast value of the random variable within the day.**

$$\min_{y} \quad G\left(x, y, \xi^{\mathrm{in}}\right)$$

$$y = \left\{ \begin{array}{l} P_{i,t}^{pv}, P_{i,t}^{gt,out} P_{i,t}^{logi}, P_{i,t}^{grid}, Q_{i,t}^{pv}, Q_{i,t}^{grid}, V_{i,t}, \\ H_{i,t}^{gt,out}, H_{i,t}^{gb,out}, H_{i,t}^{eb,out}, m_{ij,t}, \\ G_{i,t}^{grid}, G_{ij,t}^{C}, \pi_{i,t} \end{array} \right\}$$

**Among them, F(x) is the day-ahead scheduling optimization subproblem; G(y, ξ) is the intraday scheduling optimization subproblem; x is the day-ahead scheduling decision variable, y is the intraday scheduling decision variable, and ξ is a random variable**

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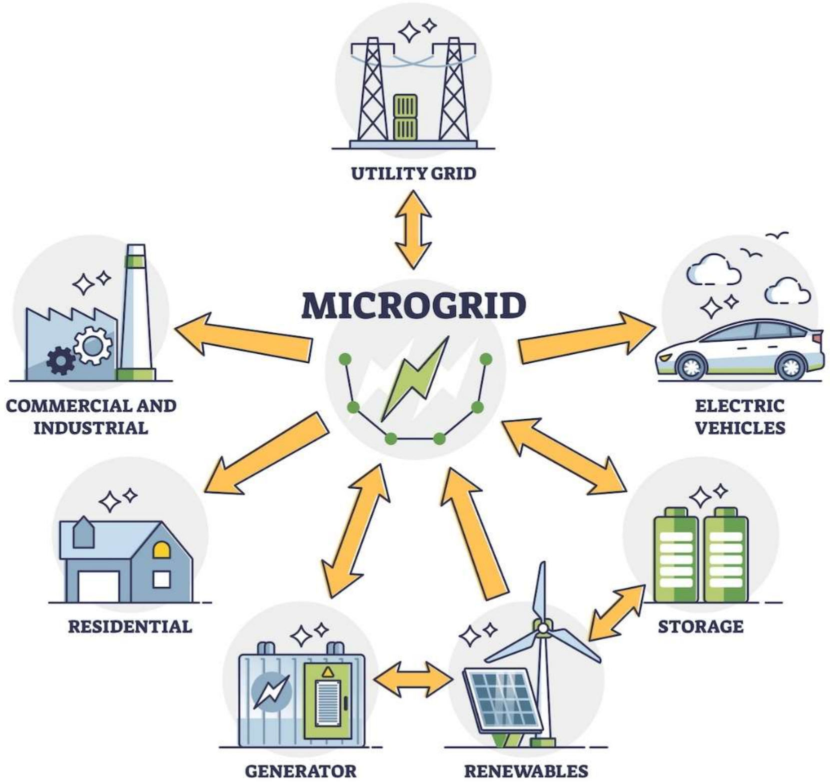
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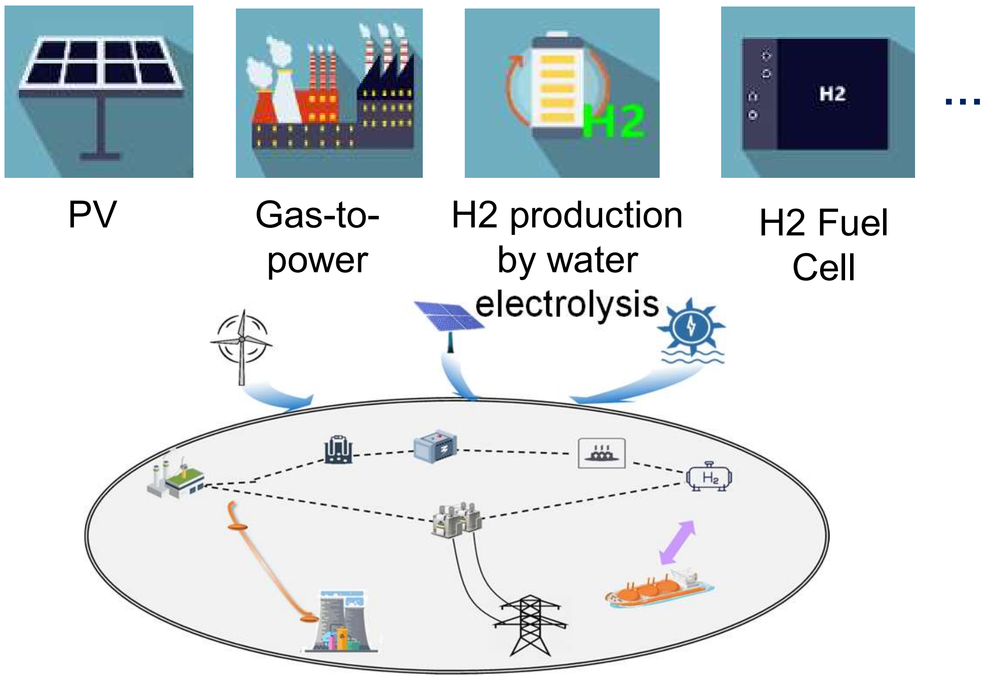
# ■ Data-Driven Operation of Seaport PLS

## What's the motivation?

□ A **wide range of distributed** equipment of **various energy types** needs to be considered




**MG Scheduling Problem**

$$\min_{x,y} \left\{F(x)+E\left[G(y,\xi)\right]\right\}$$

$$E\left[G(y,\xi)\right]=\sum_{s\in S}\rho_s G(y_s,\xi_s)$$

$$x=\left\{\alpha_{u,t},\beta_{i,t},P_{i,t}^{es,ch},P_{i,t}^{es,dch},CR_{i,m,t},I_{i,m,t}^{ship},P_{i,n,t}^{rf}\right\}$$

$$\xi=\left\{P_{i,t}^{pv,pre},P_{i,t}^{load},Q_{i,t}^{load},G_{i,t}^{load},H_{i,t}^{load},T_{t}^{env},P_{i.m,t}^{ship}\right\}$$

# ■ Data-Driven Operation of Seaport PLS

## What’s the motivation?

**MG Scheduling Problem**

$$\min_{x,y} \ \{F(x)+E[G(y,\xi)]\}$$

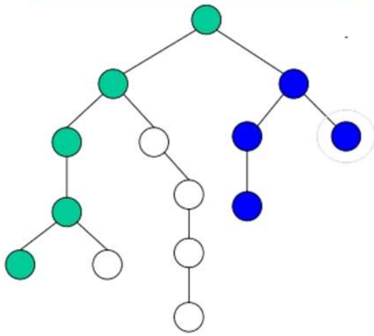
$$E[G(y,\xi)]=\sum_{s\in S}\rho_s G(y_s,\xi_s)$$

$$x=\{\alpha_{u,t},\beta_{i,t},P^{es,ch}_{i,t},P^{es,dch}_{i,t},CR_{i,m,t},I^{ship}_{i,m,t},P^{rf}_{i,n,t}\}$$

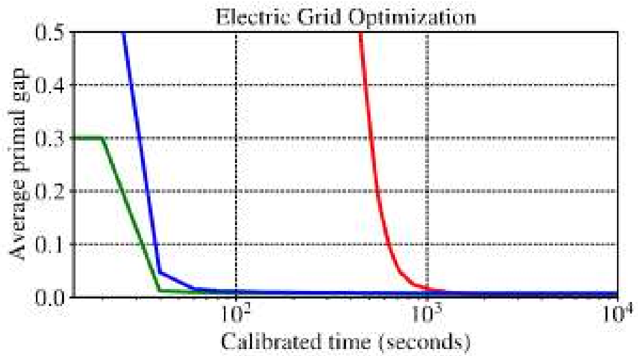
$$\xi=\{P^{pv,pre}_{i,t},P^{load}_{i,t},Q^{load}_{i,t},G^{load}_{i,t},H^{load}_{i,t},T^{env}_{t},P^{ship}_{i.m,t}\}$$

**Optimizer**

**Branch & Bround**



**Time consuming!**



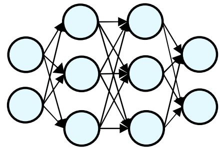

**Computationally expensive!**

# ■ Data-Driven Operation of Seaport PLS

**The Data-driven Operation Workflow**

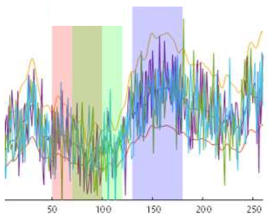
**Offline Learning**

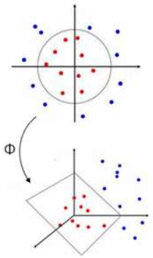
**Historical Scenario Parameters** + **Historical Optimal Decisions** →



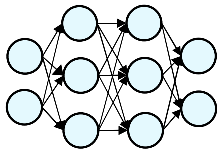
**Decision-Agent Training**

**Online Learning**

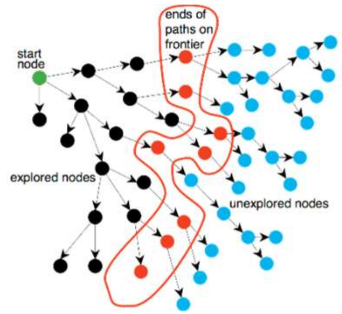



**Scenario Parameters**



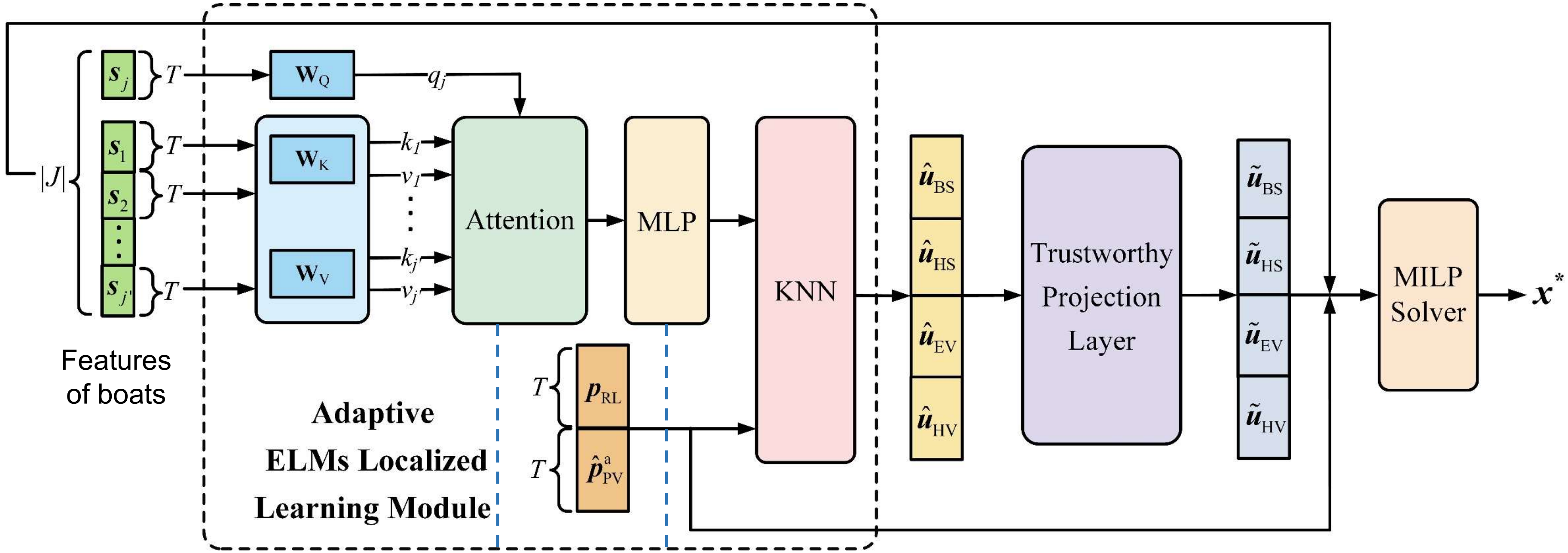
**Decision-Agent**


**Local optimal variable prediction and B&B for subproblems**

## ■ Adaptive Trustworthy L2O For Smart Microgrids

- **Attention mechanism** is incorporated into the L2O model due to its ability to focus on the most relevant features and **flexibly handle inputs of variable lengths**.




$$\mathbf{Q} = s_j \mathbf{W}_Q, \quad \mathbf{K} = \mathbf{W}_K \mathbf{S}_{j'}, \quad \mathbf{V} = \mathbf{W}_V \mathbf{S}_{j'}$$

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}}\right)\mathbf{V}$$

$$h^{(0)} = \text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V})$$

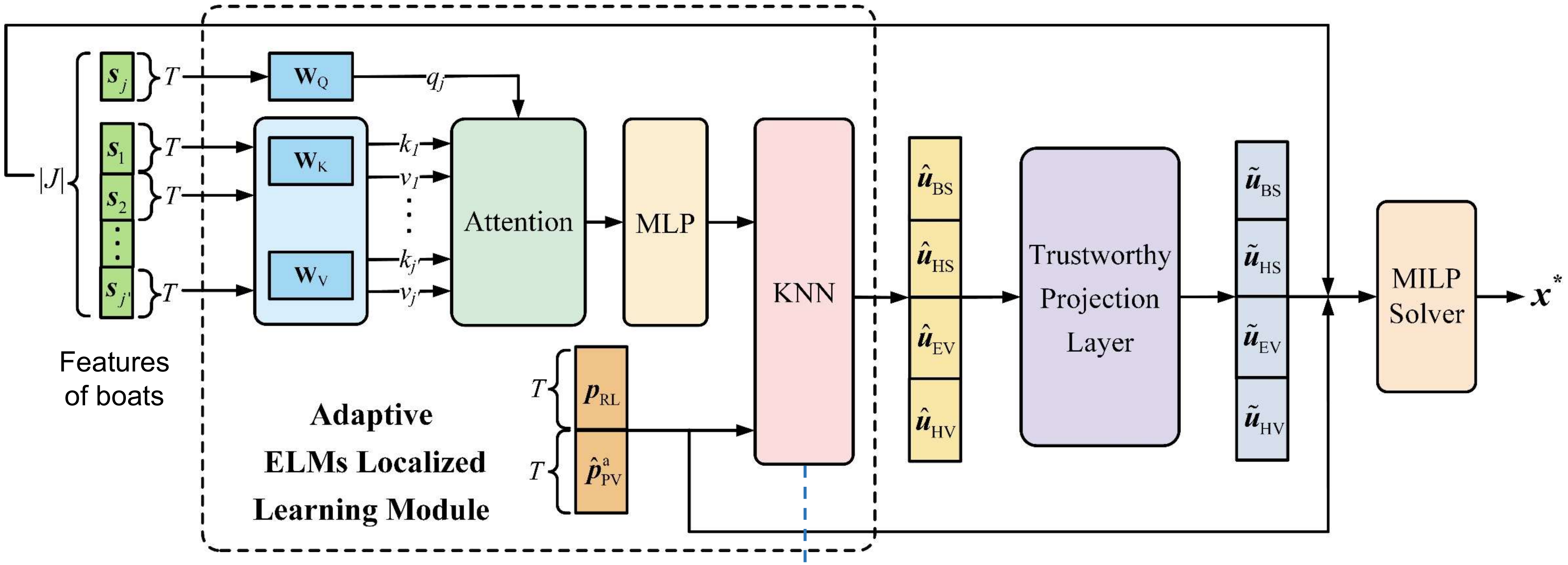
$$h^{(l)} = \sigma\left(\mathbf{W}^{(l)} h^{(l-1)} + b^{(l)}\right), \quad l = 1, \ldots, L-1$$

$$y = \mathbf{W}^{(L)} h^{(L-1)} + b^{(L)}$$

**The output of the attention network is fed into an MLP network to further extract features.**

## ■ Adaptive Trustworthy L2O For Smart Microgrids

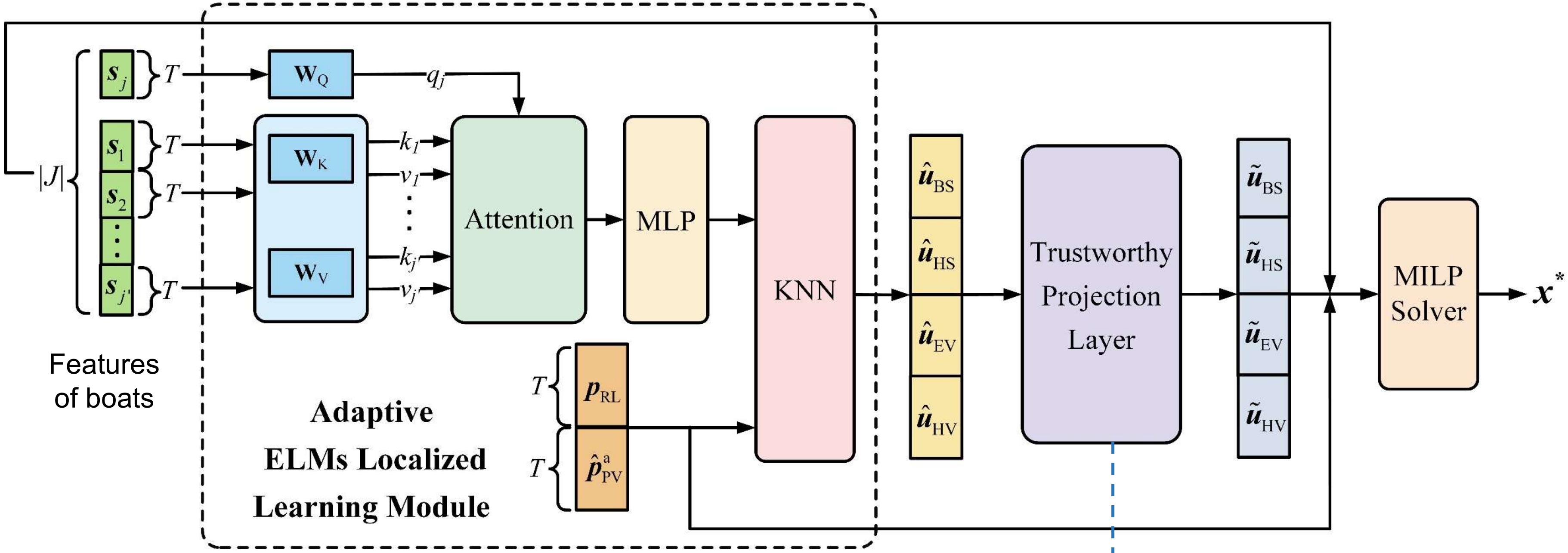
- **A parameter-free KNN module is embedded into the pipeline, computing the final prediction as a weighted average of the target labels from the k nearest neighbors.**




$$d_i = \|\boldsymbol{f} - \boldsymbol{f}_i\|_2, \quad \forall i = 1, \ldots, N_{\mathrm{H}}. \qquad w_j = \frac{\exp(-d_j/\tau)}{\sum_{j' \in \mathcal{N}_k(\boldsymbol{x})} \exp(-d_{j'}/\tau)}, \quad \forall j \in \mathcal{N}_k(\boldsymbol{f}) \qquad \hat{\boldsymbol{u}} = \sum_{j \in \mathcal{N}_k(\boldsymbol{f})} w_j \boldsymbol{u}_j$$

# ■ Adaptive Trustworthy L2O For Smart Microgrids

- The binary variable prediction network is followed by the **mechanism-aware projection layer**, which rectifies infeasible predictions by **mapping them onto the feasible region** based on the operational rules of the system.




$$\tilde{\boldsymbol{u}} = \Pi_{\Omega}^{\text{logic}}(\hat{\boldsymbol{u}})$$

## ■ Parameter Settings & Model evaluations

TABLE I
PARAMETER SETTINGS

| Parameter | Value | Parameter | Value |
|---|---|---|---|
| $\mu_{\mathrm{BS}}^{\mathrm{mt}}$ (\$/day) | 20 | $\overline{P_{\mathrm{TL}}}$ (kW) | 7000 |
| $\mu_{\mathrm{HS}}^{\mathrm{mt}}$ (\$/day) | 24.11 | $\overline{C_{\mathrm{QC}}}, \overline{C_{\mathrm{YC}}}$ | 110, 110 |
| $\mu_{\mathrm{BS}}^{\mathrm{cy}}$ (\$/kWh) | 0.008 | $\overline{C_{\mathrm{BZ}}}$ | 20 |
| $\mu_{\mathrm{HE}}^{\mathrm{on}}, \mu_{\mathrm{HFC}}^{\mathrm{on}}$ (\$) | 0.15, 0.012 | $E_{\mathrm{q}}, E_{\mathrm{y}}$ (kWh) | 6.5, 2.0 |
| $\mu_{\mathrm{HE}}^{\mathrm{off}}, \mu_{\mathrm{HFC}}^{\mathrm{off}}$ (\$) | 7.5e-3, 6.5e-3 | $E_{\mathrm{v}}$ (kWh) | 5.0 |
| $\mu_{\mathrm{HE}}^{\mathrm{fl}}$ (\$/kW) | 40.14 | $\underline{S_{\mathrm{BS}}}, \overline{S_{\mathrm{BS}}}$ | 0, 1 |
| $\mu_{\mathrm{HFC}}^{\mathrm{fl}}$ (\$/kW) | 10.23 | $\underline{S_{\mathrm{HS}}}, \overline{S_{\mathrm{HS}}}$ | 0.2, 0.8 |
| $\mu_{\mathrm{CU}}$ (\$/kWh) | 0.1 | $\eta_{\mathrm{HE}}, \eta_{\mathrm{HFC}}$ | 0.77, 0.6 |
| $\overline{E_{\mathrm{HS}}}$ (kWh) | 1800 | $\eta_{\mathrm{BS}}^{\mathrm{ch}}, \eta_{\mathrm{BS}}^{\mathrm{dch}}$ | 0.92, 0.92 |
| $\overline{E_{\mathrm{BS}}}$ (kWh) | 1600 | $\overline{I}, K$ | 3, 10 |
| $\overline{E_{\lambda,k}}$ (kWh) | 270 | $\overline{N_i}$ | 110 |
| $\overline{P_{\mathrm{HE}}}$ (kW) | 800 | $\Delta T_{\mathrm{HE}}^{\mathrm{on}}$ (h) | 2.0 |
| $\overline{P_{\mathrm{HFC}}}$ (kW) | 800 | $\Delta T_{\mathrm{HE}}^{\mathrm{off}}$ (h) | 2.0 |
| $\overline{P_{\mathrm{BS}}^{\mathrm{ch}}}$ (kW) | 750 | $\Delta T_{\mathrm{HFC}}^{\mathrm{on}}$ (h) | 2.0 |
| $\overline{P_{\mathrm{BS}}^{\mathrm{dch}}}$ (kW) | 750 | $\Delta T_{\mathrm{HFC}}^{\mathrm{off}}$ (h) | 2.0 |

**Parameter Settings**

TABLE II
ARRIVAL PLAN OF SHIPS

| Ship Id | Arrival Time | Max Leave Time | Cargo Volume |
|---|---|---|---|
| 1 | 1:00 | 7:00 | 270 |
| 2 | 3:00 | 9:00 | 252 |
| 3 | 5:30 | 15:00 | 208 |
| 4 | 7:00 | 17:00 | 321 |
| 5 | 9:30 | 16:30 | 264 |
| 6 | 10:30 | 17:30 | 257 |
| 7 | 15:00 | 22:00 | 325 |
| 8 | 16:30 | 24:00 | 266 |
| 9 | 19:00 | 24:00 | 301 |

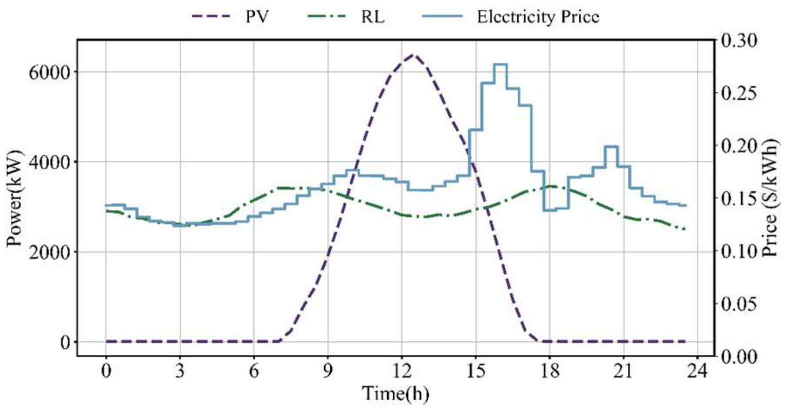
**Arrival Plans of Ships**

TABLE III
AVERAGE PERFORMANCE COMPARISON AMONG THE FOUR METHODS

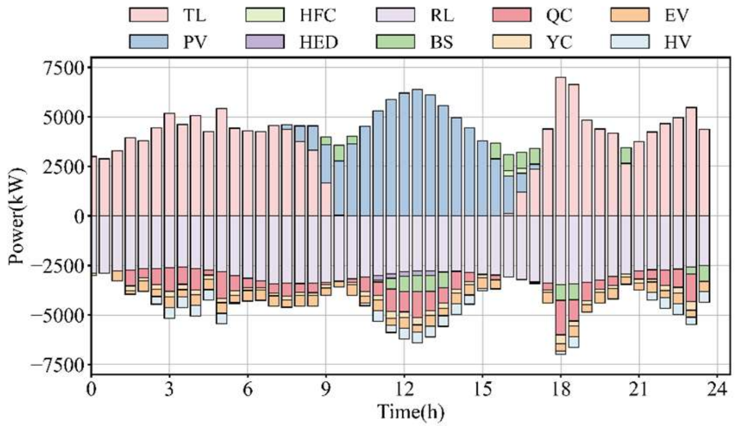
| Method | $\|J\| = 8$ | | | $\|J\| = 9$ | | | $\|J\| = 10$ | | | Feasibility Rate |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean Totalcost (\$) | Mean Time (s) | Number of Infeasible Cases | Mean Totalcost (\$) | Mean Time (s) | Number of Infeasible Cases | Mean Totalcost (\$) | Mean Time (s) | Number of Infeasible Cases | |
| Benchmark | 10032.69 | 452.92 | 0 | 10603.07 | 940.51 | 0 | 11433.42 | 1078.30 | 0 | 100% |
| Mean-KNN | 10043.81 | 222.03 | 3 | 10625.92 | 540.33 | 2 | 11227.42 | 857.13 | 6 | 63% |
| Adaptive L20 | 9998.17 | 131.03 | 0 | 10663.61 | 569.47 | 0 | 11437.62 | 878.20 | 6 | 80% |
| Adaptive L20* | 9998.17 | 131.03 | 0 | 10663.61 | 569.47 | 0 | 11412.66 | 828.28 | 2 | 93% |

**Model evaluations**

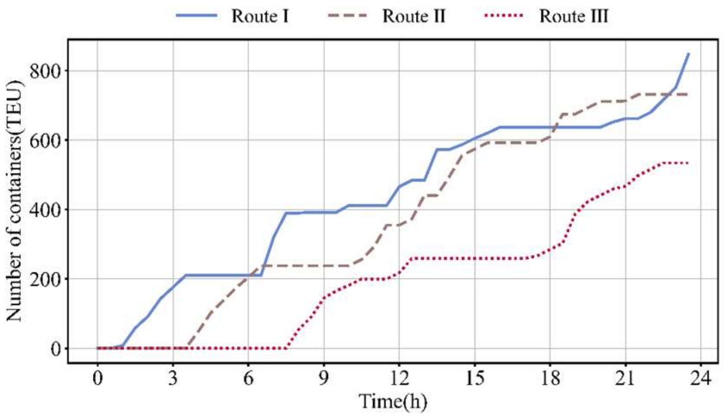
# ■ Operation Results



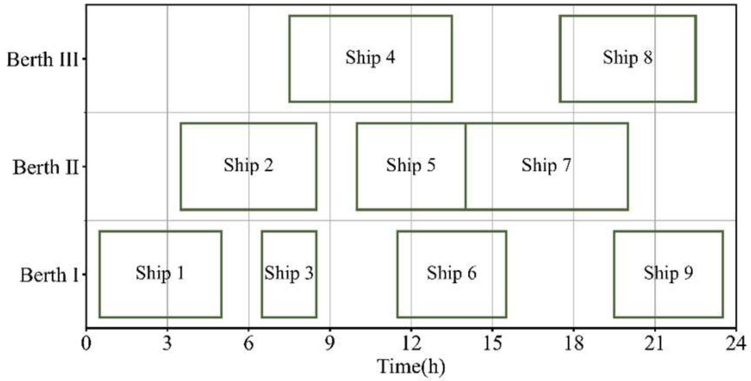

**Predictions of PVs, RLs, and electricity price**




**Electrical energy allocation results**

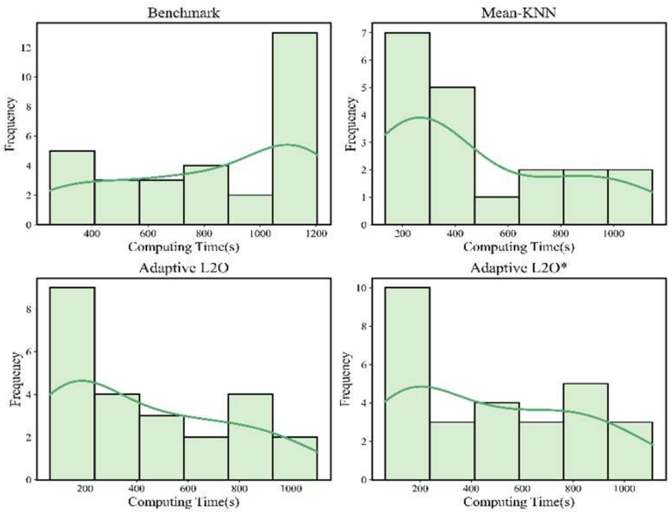



**Number of containers transported on three routes**

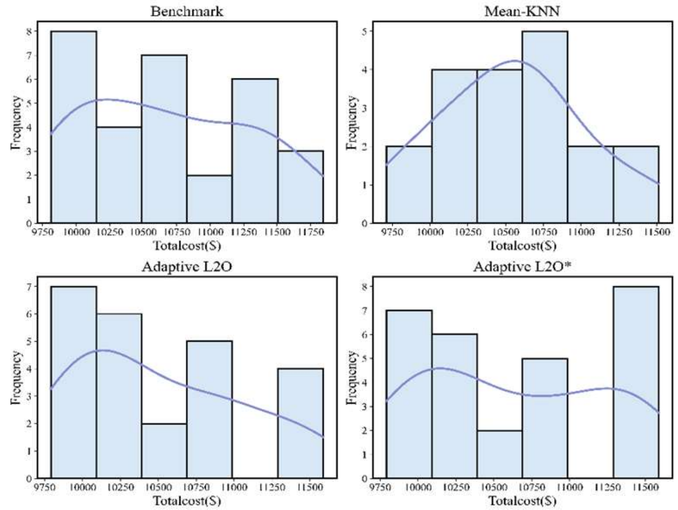



**Berth allocation results**

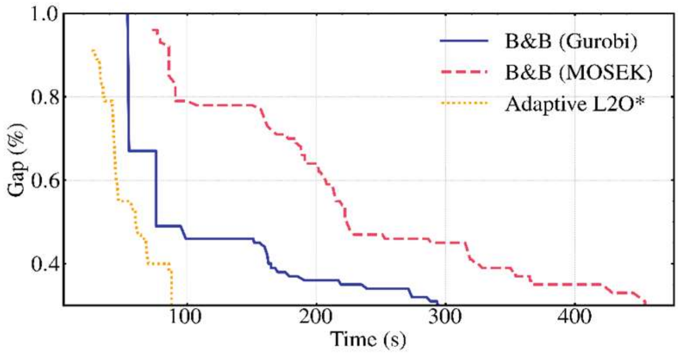
# ■ Comparative Analysis



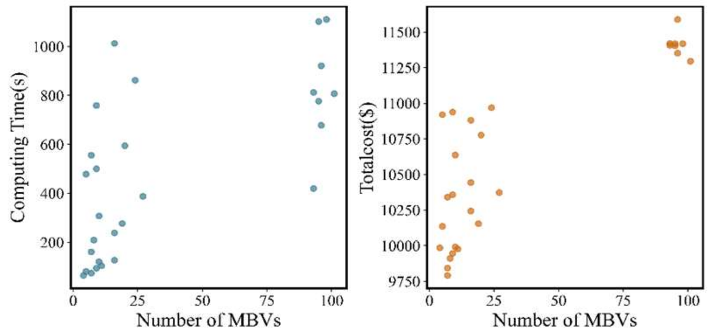

**Computing Time Distribution**




**Total Cost Distribution**

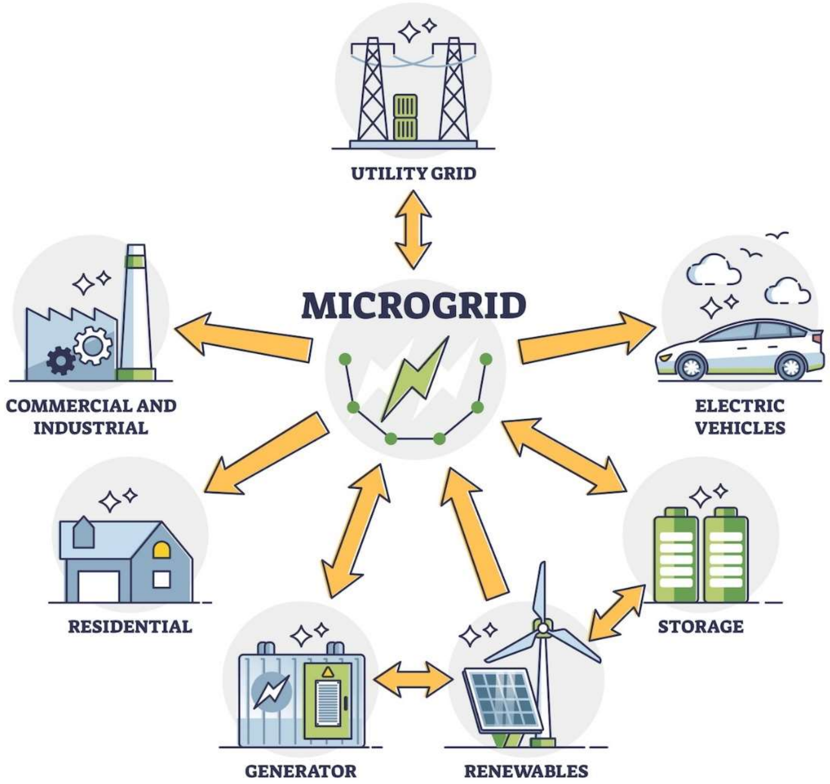



**Convergence curves of different methods**




**Robustness under Prediction Errors**

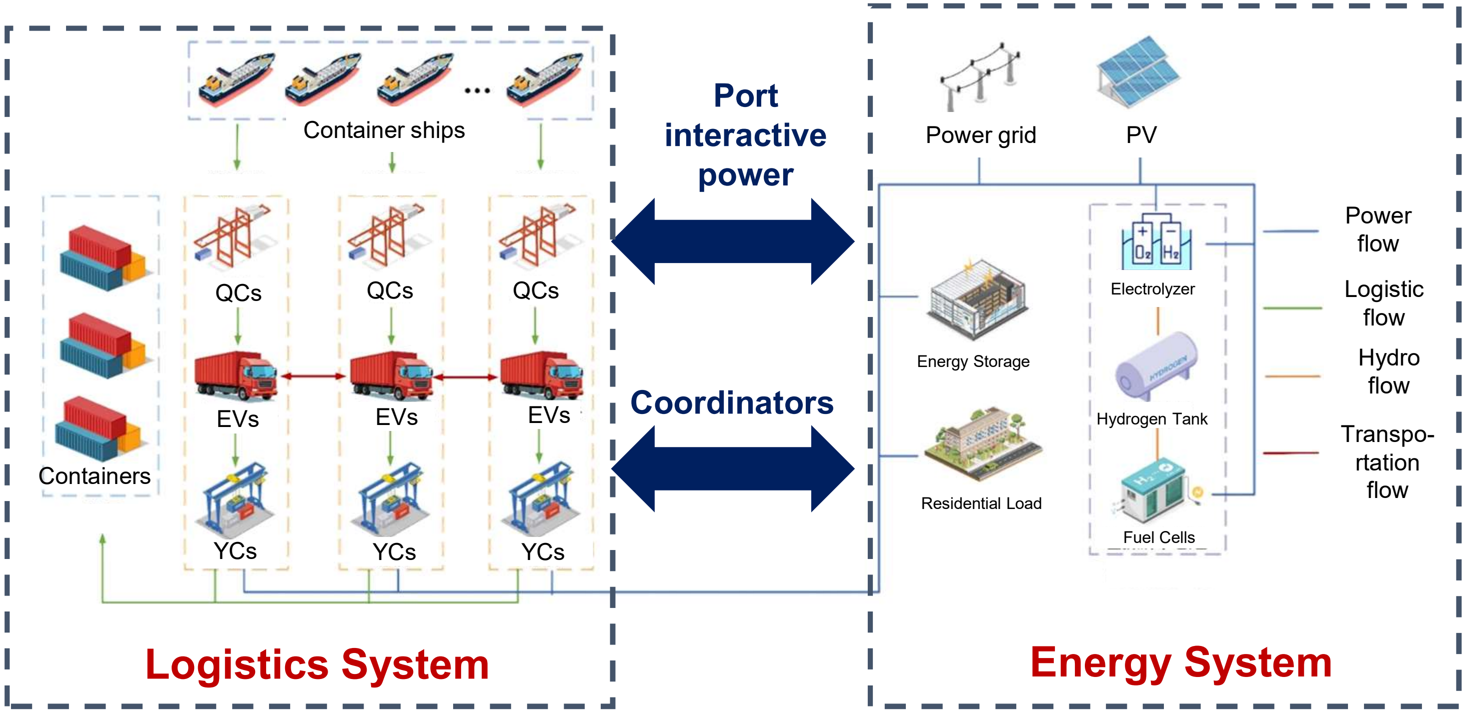
# Content |



UTILITY GRID
MICROGRID
COMMERCIAL AND INDUSTRIAL
ELECTRIC VEHICLES
RESIDENTIAL
STORAGE
GENERATOR
RENEWABLES

# ■ Integrated Data-Driven and Model-Based Operation

- ☐ The data platforms of the logistics system and energy system are deployed separately, with limited data sharing and independent decision-making authority
- ☐ Decentralized distributed scheduling is an effective way to coordinate the operation of logistic-coupled microgrids



# The Background of Distributed Optimization

## Logistics-Energy Distributed Optimization Problem

$$\min F_{LS}(\psi_{LS}) + F_{ES}(\psi_{ES})$$

## Objective Function of Energy system

$$F_{ES}(\psi_{ES}) = \sum_{t=1}^{T}(C_{buy,t} + C_{BS,t} + C_{\lambda,t}^{on} + C_{\lambda,t}^{off} + C_{cur,t} + C_{\lambda,t}^{mt} + C_{\lambda,t}^{fl})$$

## Objective Function of Logistics System

$$F_{LS}(\psi_{LS}) = \mu_{buy} \sum_{t=1}^{T}(\sum_{i=1}^{I} P_{SH,i,t} + \sum_{q=1}^{Q}\sum_{i=1}^{I} P_{QC,i,q,t} + \sum_{y=1}^{Y}\sum_{i=1}^{I} P_{YC,i,q,t} + \sum_{v=1}^{V} P_{EV,i,t})\Delta t$$

## Constructing the augmented Lagrangian function

$$L_{\rho}(\psi_{LS} + \psi_{ES}) = F_{LS}(\psi_{LS}) + F_{ES}(\psi_{ES}) + \lambda^{T} f(\psi_{LS}, \psi_{ES}) + \frac{\rho}{2}\left\| f(\psi_{LS}, \psi_{ES}) \right\|^{2}$$

**Common constraints of sub-problems:**

**Power balance constraints of nodes connected to logistics equipment**

## Update strategy

$$\begin{cases} \psi_{LS}^{k+1} = \arg\min_{\psi_{LS}} L_{\rho}(\psi_{LS}, \psi_{ES}^{k}, \lambda^{k}) \\ \psi_{ES}^{k+1} = \arg\min_{\psi_{ES}} L_{\rho}(\psi_{LS}^{k+1}, \psi_{ES}, \lambda^{k}) \end{cases}$$

**Global variable update**

$$\lambda^{k+1} = \lambda^{k} + \rho f(\psi_{LS}^{k+1}, \psi_{ES}^{k+1})$$

# ■ What's the Motivation ?

☐ **The logistics-energy collaborative operation problem embeds large-scale integer decision variables, and distributed optimization is difficult to converge and is computational expensive**

**Energy Sub-Problem**

- **Mostly continuous power decisions, few integer decisions**
- **SOCP Problem**

$$O(2^{n_{ES}}) \times poly(n_{ES})$$

**Expensive**

$n_{ES} \ll n_{LS}$

**Alternating Iterations**

**Cheap**

**Logistics Sub-Problem**

- **Mostly non-continuous state decisions, with many integer branches**
- **MIQP Problem, mostly NP-hard**

$$O(2^{n_{LS}}) \times poly(n_{LS})$$

## ■ What's the Motivation ?

- ☐ 1. High-frequency problem solving with similar parameter structures leads to repeated daily computations and cumulative waste of computing resources.

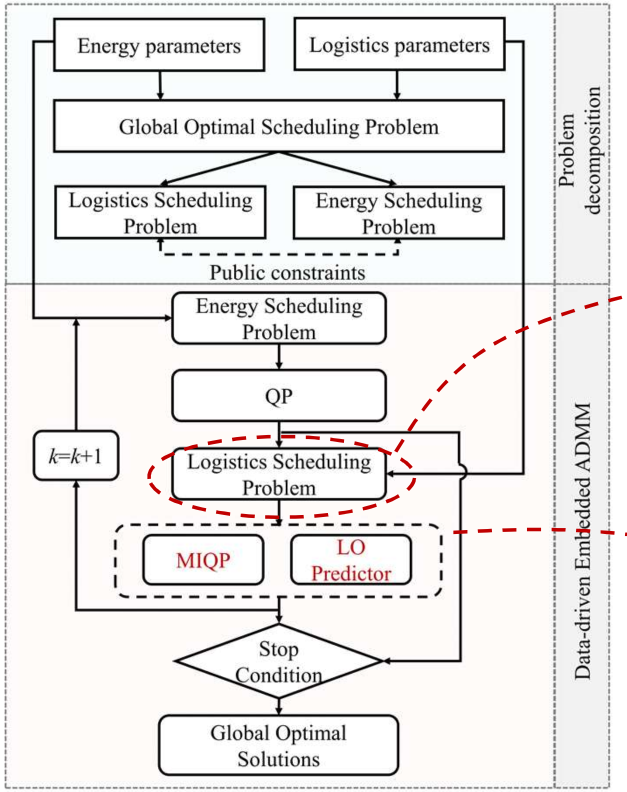
- ☐ 2. ADMM incurs higher computational cost in early iterations than in later optimization stages.

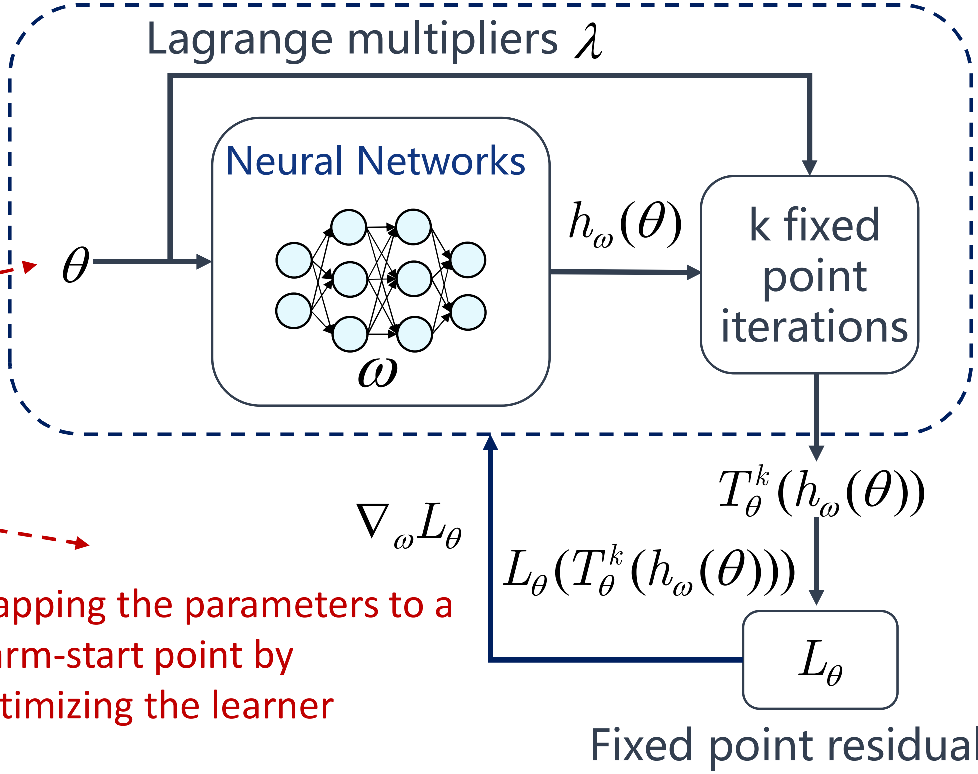
- ☐ 3. Non-continuous decisions are concentrated in the logistics subproblem, whose solving time far exceeds that of the energy subproblem, creating a bottleneck effect.

**How to use the above characteristics to accelerate the distributed optimization?**

## ■ The Solution Framework

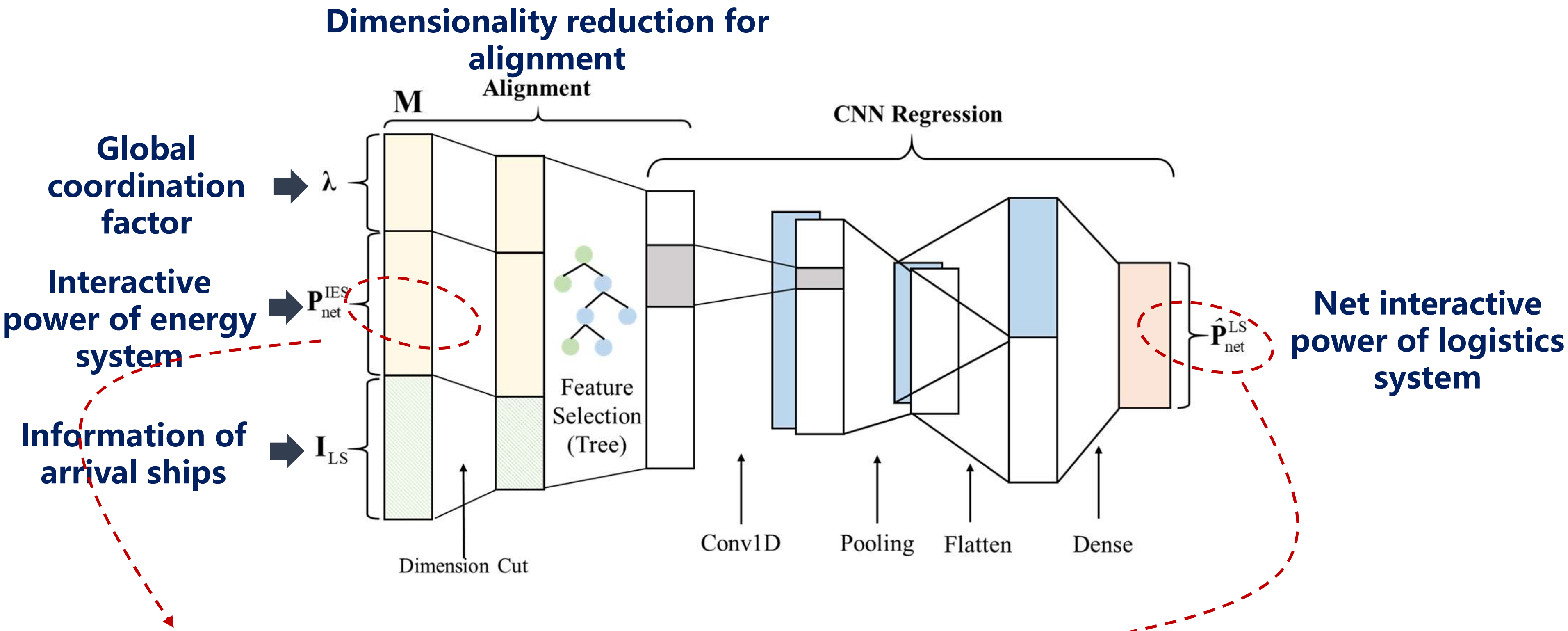
- ☐ **Neural networks predicts port-level logistics subproblems**
- ☐ **Warm-start Fixed-Point Iterations**
- ☐ **Branch-and-bound ensures optimality**




Mapping the parameters to a warm-start point by optimizing the learner

# ■ Integrated Data-Driven and Model-Based Operation




## ■ Defining the net interaction power of energy systems

$$\boldsymbol{P}_{\mathrm{ES},n} = [P_{\mathrm{G},n,s,t} + P_{\mathrm{PV},n,s,t} + P_{\mathrm{GT},n,s,t} + P_{\mathrm{ESS},n,s,t}^{dch'} - P_{\mathrm{ESS},n,s,t}^{ch'} - P_{\mathrm{EB},n,s,t} - P_{\mathrm{SR},n,s,t} - P_{\mathrm{L},\hat{b},s,t}]^{(S\times T)}$$

## ■ Defining the net interaction power of the logistics system

$$\boldsymbol{P}_{\mathrm{LS},n} = [\underbrace{P_{\mathrm{QC},n,s,t}}_{\text{Quay crane power}} + \underbrace{P_{\mathrm{SR},n,s,t}}_{\text{Shore power}}]^{(S\times T)}$$

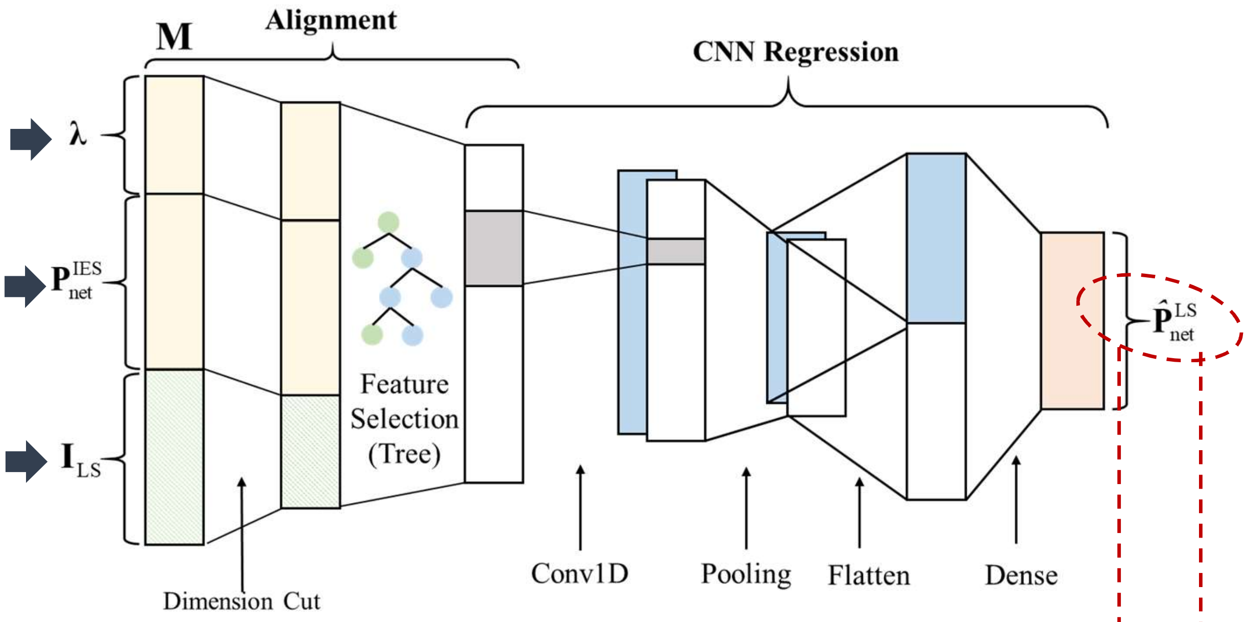
# ■ Integrated Data-Driven and Model-Based Operation

- **Use predicted logistic net power as warm-starts for the first $k$ iterations of distributed optimization.**

**Global coordination factor**

**Interactive power of energy system**

**Information of arrival ships**




**Net interactive power of logistics system**

**Warm-Start**

$$\varPhi_{\text{ES}}^{k+1} = \arg\min_{\varPhi_{\text{ES}}} L_\rho(\varPhi_{\text{LS}}^{k+1}, \varPhi_{\text{ES}}, \boldsymbol{\lambda}^k)$$

$$\lambda_s^{k+1} = \lambda_s^k + \rho f(\varPhi_{\text{LS}}^{k+1}, \varPhi_{\text{ES},s}^{k+1})$$

**After k iterations**

$$\varPhi_{\text{LS}}^{k+1} = \arg\min_{\varPhi_{\text{LS}}} L_\rho(\varPhi_{\text{LS}}, \varPhi_{\text{ES}}^k, \boldsymbol{\lambda}^k)$$

$$\varPhi_{\text{ES}}^{k+1} = \arg\min_{\varPhi_{\text{ES}}} L_\rho(\varPhi_{\text{LS}}^{k+1}, \varPhi_{\text{ES}}, \boldsymbol{\lambda}^k)$$

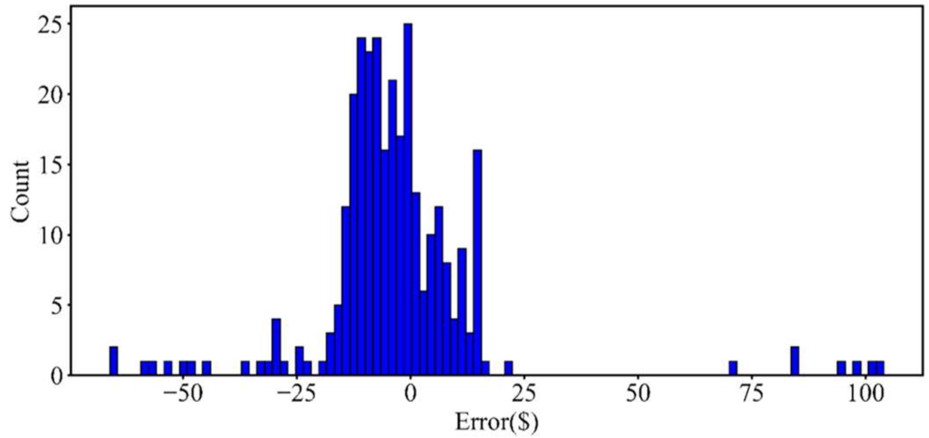
**Model-based solutions**

## ■ Case Study

- Compared to pre-warm-start solving time, traditional branch-and-bound takes around 30 minutes, while learning-based methods solve in seconds.

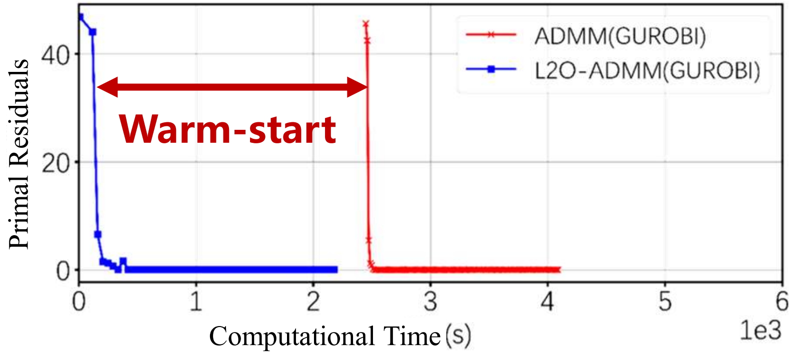
| Method | Energy System | Logistics System |
|---|---|---|
| GUROBI (MIP gap=1e-4) | 4.87s | 2544.9s |
| MOSEK (MIP gap=1e-4) | 3.62s | 1512.0s |
| GUROBI (MIP gap=1e-3) | 3.84s | 1823.6s |
| L2O predictor | / | 2.2s |

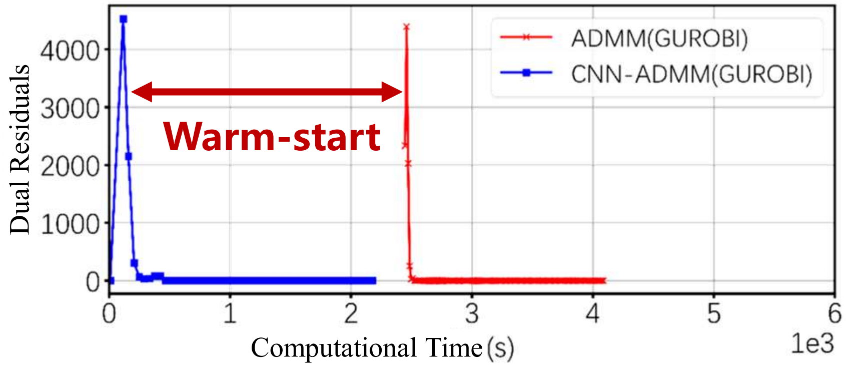
- Logistic net power prediction errors are centered around zero, with a maximum deviation below $120.



## ■ Case Study

☐ **Compared to GUROBI's branch-and-bound, ADMM reduces total convergence time by 50.7%.**




☐ **The system cost under distributed and centralized collaborative optimization is nearly identical, verifying convergence to the optimal solution.**

| Method | Cost (Energy) | Cost (Logistics) | Cost (Total) |
|---|---|---|---|
| **DCO** | **22907.41** | **5033.38** | **27940.49** |
| CCO | 22907.47 | 5033.45 | 27940.92 |
| DIO | 23183.38 | 12862.02 | 36045.70 |

# Thanks

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**Shanghai Jiao Tong University**