Faster Latency Constrained Service Placement in Edge Computing with Deep Reinforcement Learning[1]

Séminaire Clourd Optimization DVRC/ESILV

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Problem Statement

Smart Warehouse Usecase

From Orange

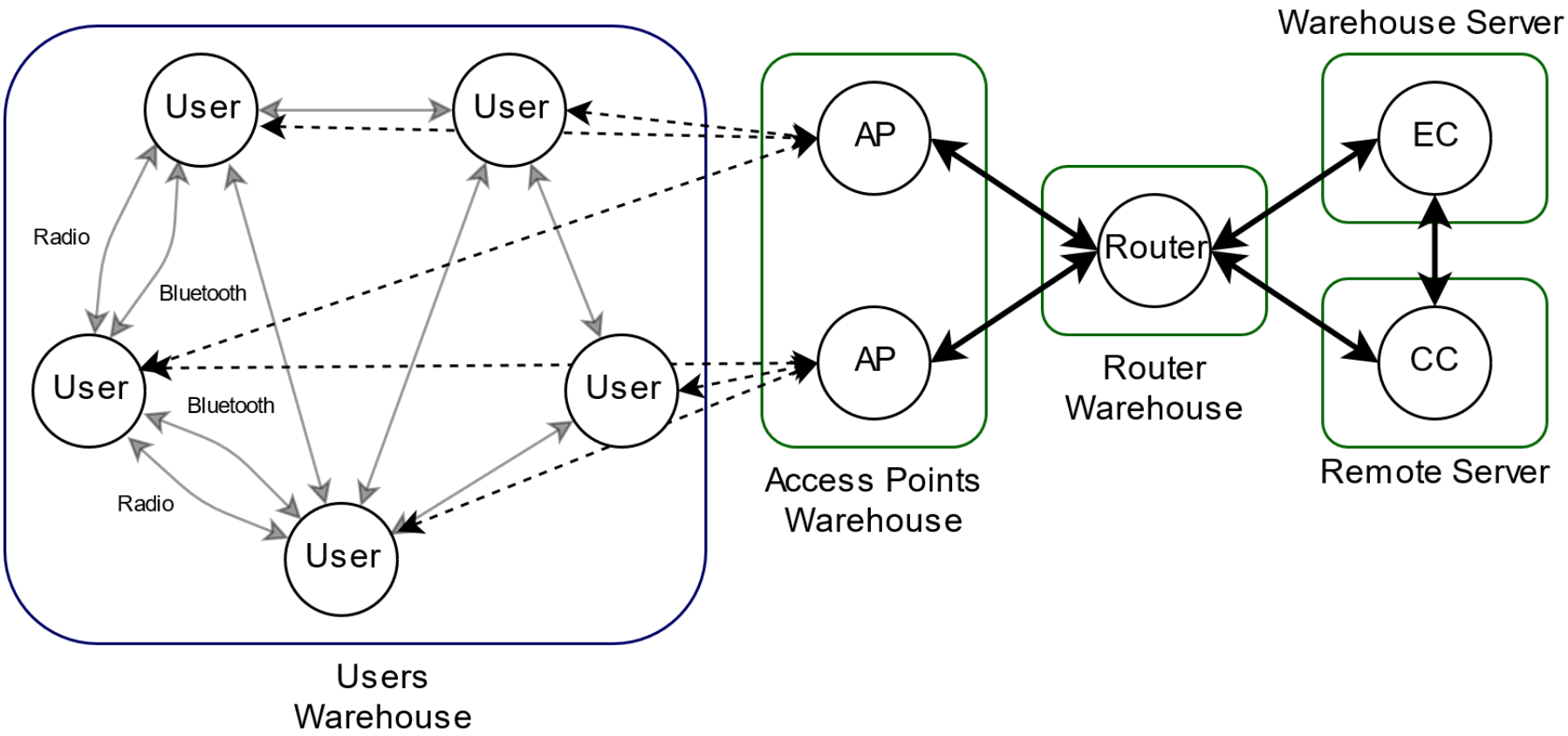

Figure 1: Smart Warehouse instance [11].

Problem Statement

Mobile Edge Computing (MEC)

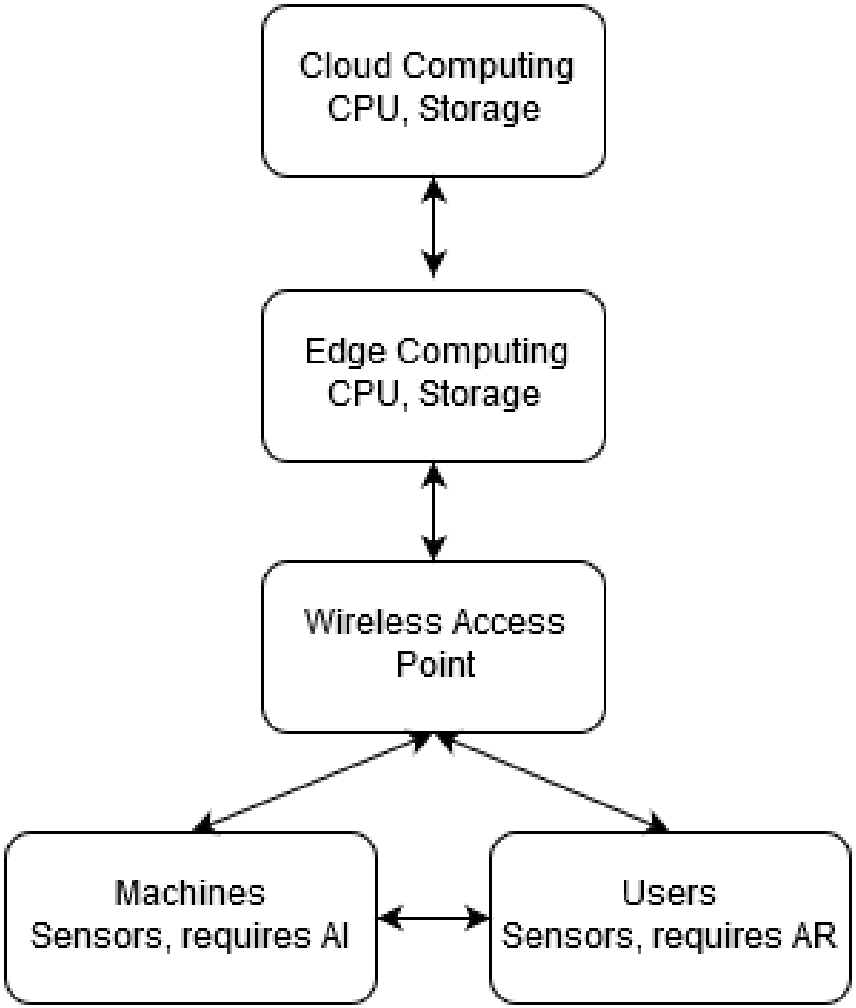

Figure 2: Smart warehouse in the global network.

Customer request:

- A service to deploy.

ISP's decision: Where to place the service?

1. Cloud (high power, high latency)
2. Edge (low latency, limited power)
3. Access Points (Tradeoff between latency and resources)

Optimize QoS for all services simultaneously and provide an **adapting and deployable** method.

Description of Services

A **service** S includes:

- Multiple **demands** with known origins and the same destination. (User data and server data meet at an intermediate point)

Each **demand** d of S is defined by:

- An (known) origin d_o and a variable destination;
- A maximum latency l_d (to decide);
- A QoS level $\mathbf{q}_d \in \{q_{d,\min}, \ldots, q_{d,\max}\}$;
- A path from origin to selected destination (to find).

Description of the Network

The network

An undirected graph $\mathcal{G} = (\mathcal{E}, \mathcal{A})$ with:

- $\text{res}^e \in \mathbb{N}$: available resources at node $e \in \mathcal{E}$ (e.g., CPU, storage);
- $\text{capa}^a \in \mathbb{N}^+$: capacity of edge $e \in \mathcal{E}$;
- lat^a: latency associated with edge e.

Latency model (linear approximation)

Using edge $e \in \mathcal{E}$ with bandwidth q_a induces a latency:

$$\text{lat}^a = \alpha^a \sum_{d \in \mathcal{D}} \mathbf{q}_a + \beta^a$$

- $\alpha^a \in \mathbb{R}^+$: latency increase per unit of traffic;
- $\beta^a \in \mathbb{R}^+$: base latency of edge e.

Orchestration Problem Description

Key subproblems:

- **Service placement:** Assign services to nodes with available resources (e.g., GPU, memory);
- **Routing:** Define paths from sources to destinations;
- **QoS management:** Allocate bandwidth to satisfy demand requirements.

This turn to be an Assignment problem coupled with multicommodity flow (NP Hard).

Core question: Can deep RL provide a scalable and deployable solution?

Literature Review

- **Use Cases:** [9, 11]
- **Service Assignment:** surveys [3, 10], RL [6]
- **Network Flows:** linear [4], nonlinear [2], multicommodity [5]
- **RL for Combinatorial Optimization:** original work [1], survey [8]
- **Deep RL for Multicommodity Flow:** CDN [13, 12]

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Decision Variables

Decision variables:

- **Service placement**:
  $y_S^e \in \{0, 1\}$ (1 if S is on node e, 0 otherwise)
- **Demands routing**:
  x_d^a (1 if request d uses edge e, 0 otherwise)
- **Quality of Service/Bandwidth**
  $q_d \in \{q_{d,min}, ..., q_{d,max}\}$ the quality of demand d.

Objective function :

$$\max \sum_d q_d$$

Integer Program

$$\max \sum_{S, d \in S} q_d \qquad \text{(Maximize quality)}$$

$$\text{s. t.} \sum_{f \in \delta(e)} \left(\mathbf{x}_d^{(e,f)} - \mathbf{x}_d^{(f,e)} \right) = \mathbf{1}_{e=d_o} - \mathbf{y}_S^e \,, \ \forall e, \forall d \in S, \forall S \quad \text{(routing)}$$

$$\sum_{S \in \mathcal{S}} \mathbf{y}_S^e r_S \leq \text{res}^e \,, \quad \forall e \in \mathcal{E} \qquad \text{(Resources on nodes)}$$

$$\sum_{S \in \mathcal{S}} \sum_{d \in S} \mathbf{q}_d \mathbf{x}_d^a \leq \text{capa}^a \,, \quad \forall a \in \mathcal{A} \qquad \text{(Edges capacities)}$$

$$\sum_{a \in \mathcal{A}} \mathbf{x}_d^a \left(\alpha^a \sum_{S' \in \mathcal{S}} \sum_{d' \in S'} \mathbf{q}_{d'} \mathbf{x}_{d'}^a + \beta^a \right) \leq l_d \,, \quad \forall d \in S, \forall S \in \mathcal{S}$$

(Demands latencies)

$$\sum_{e \in \mathcal{E}} \mathbf{y}_S^e \geq 1 \,, \quad \forall S \in \mathcal{S} \qquad \text{(Services placement)}$$

$$\mathbf{q}_d \in \{q_{d,\min}, \ldots, q_{d,\max}\}, \ \mathbf{y}_S^e \in \{0,1\}, \ \mathbf{x}_d^a \in \{0,1\}$$

Resolution of the Mathematical Program

This Integer Program:

- Can be linearized by introducing new variables;
- Can be finally solved using ILP exact solvers (e.g., CPLEX Optimizer).

Studied improvements:

- Path-Formulation,
- Continuous relaxation and rounding,
- Decomposition: Service placement (solved by local search) and Multi commodity flow (with Linear Progamming).

Possible Improvements: Dantzig Wolfe decomposition

Anyway ILP solvers are slow in practice. $\rightarrow$ **RL approach**.

Local search heuristic

Solution description

A solution is a vector (e_S, q_d, SP_d) where

- e_S describes the *service placement* for each service ($\in [1, |\mathcal{E}|]^S$).
- q_d describes the *quantity* for each demand ($\in [1, Q]^D$).
- SP_d describes the *shortest path* chosen (index of the path) by demand ($\in [1, MAXPCC]^D$).

Greedy Algorithm

We assume that there is a feasible solution.

- Find the feasible solution (minimal quantity and all services on cloud)
- Repeat while improvement exists
  - Increases the flows greedily
  - If possible decrases load of the most loaded arc (by changing path)
  - If possible change the placement of services

Local search heuristic

Solution description

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Metaheurisics

Here we consider Evolutionary approaches **Using CMAES**

Anyway Local Search and metaheuristics have poor performances. $\rightarrow$ **RL approach**.

Reinforcement Learning for Combinatorial Optimization

Markov Decision Process (MDP) Framework

- **State space:** the set of feasible solutions;
- **Action space:** modifications applicable to a solution;
- **Transition:** deterministic evolution to a new solution based on the selected action;
- **Reward:** a measure of improvement from the action.

Neural network: enables generalization of the policy to unseen solutions.

RL Model

Observation Space

Input to the neural network: $o = (\mathbf{x}, \mathbf{y}, \mathbf{q}, \mathcal{G}_{\text{des}}, \mathcal{S}_{\text{des}})$

- $\mathbf{x}, \mathbf{y}, \mathbf{q}$: Current solution represented as vectors;
- $\mathcal{G}_{\text{des}}$: Complete description of the graph (capacities, resources, edge usage, etc.);
- $\mathcal{S}_{\text{des}}$: Description of the instance requirements.

$\rightarrow$ **Integration of any relevant technical feature — the more, the better.**

RL Model

Action Space

For each service, **the action operates**:

- An explicit selection of the placement node;
- An explicit selection of the shortest path index;
- An adjustment of the QoS q_d by ± 1.

$\rightarrow$ Fine-grained action specification $\implies$ complex exploration.

RL Model

Reward Shaping

Reward function:

- Penalty for **infeasible actions**:

$$\begin{cases} -10 \text{ for service displacement} \\ -2 \text{ for demand routing} \\ -1 \text{ for QoS change} \end{cases}$$

- $\max(0, q_{\text{now}} - q_{\text{best}})$ otherwise.

where q_{best} denotes the maximum quantity achieved so far during the trajectory.

$\rightarrow$ Reward is related to an **exploration/exploitation trade-off.**

RL algorithm

Actor-critic method:

1. Policy parameterized by θ.
2. Optimization of θ by SGD following:

$$\nabla_\theta J(\pi_\theta) = \mathbf{E}_{\pi_\theta}\left(\sum_t \nabla_\theta \log \pi_\theta(a_t|s_t) G(s_t, a_t)\right)$$

with $G(s,a) = \sum_{t=t'}^{H} \gamma^{t-t'} r(s_t, a_t)$.

Two algorithms considered:

- **A2C**: Less stable, require tuning.
- **PPO**: Explore if reward is well shaped, stable, sample efficient;

$\rightarrow$ **PPO more efficient** in practice

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Instances description

Parameterization

Parameter	**Typical Value**
Maximum flow	1-100 Mbps
Resources	10 TB-10 PB
Base latency	1 ms
Induced latency	1 ms/Mbps
Required letency	10 ms

Table 1: Main graph parameters and variables [7].

Instances design

Tree-shaped graph

- Cloud and edge nodes;
- Close users are connected.

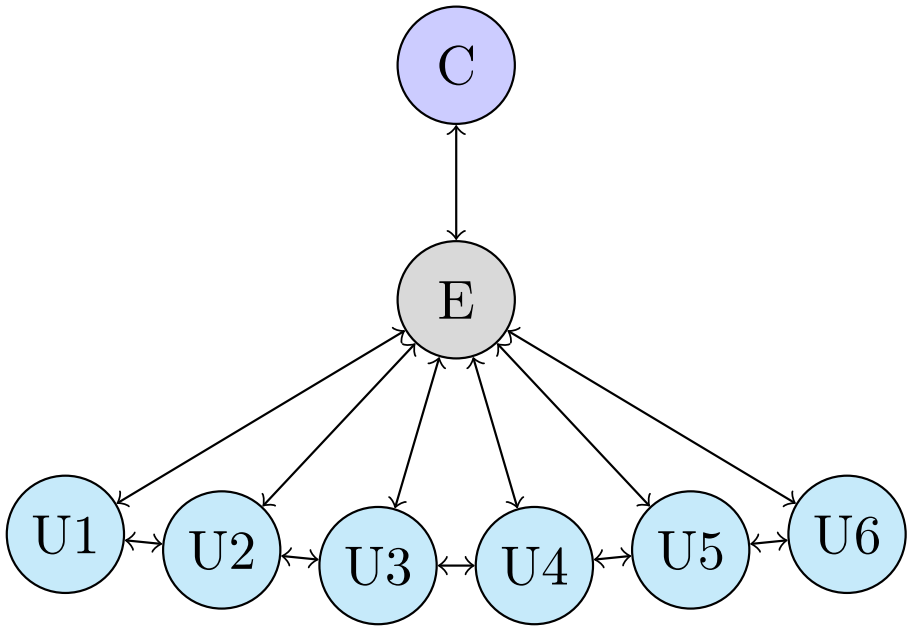


Figure 3: Tree-shaped graph

Solving Approaches

We selected:

- An **exact ILP-solving** approach using the CPLEX Optimizer;
- The previously proposed **RL method**;
- The previously proposed **heuristic placement and routing** approach based on traditional Multi-commodity Flow algorithms.

Runtime comparison for static tree instance

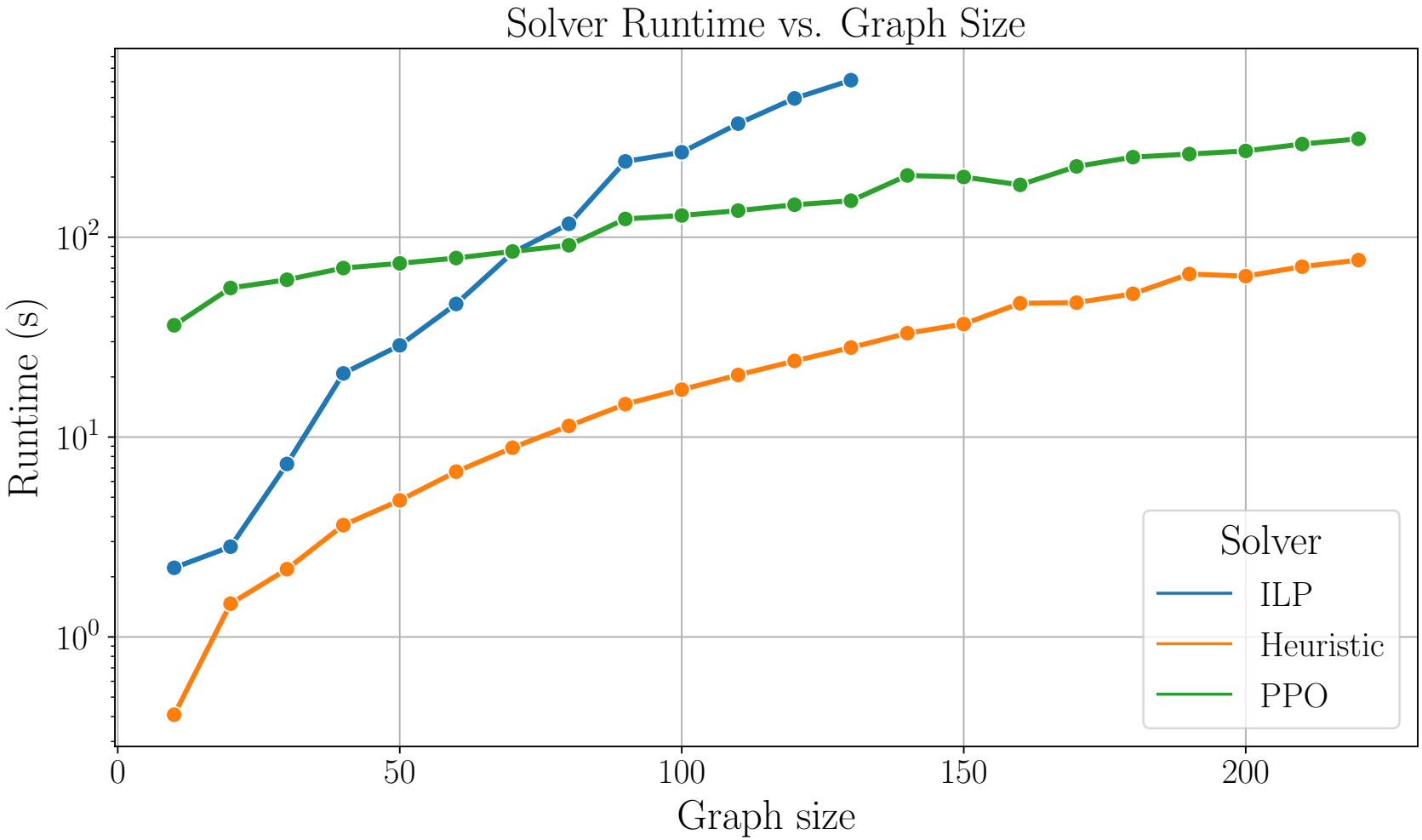


Figure 4: RL training is scalable considering both memory and runtime.

Performance comparison for static tree instance

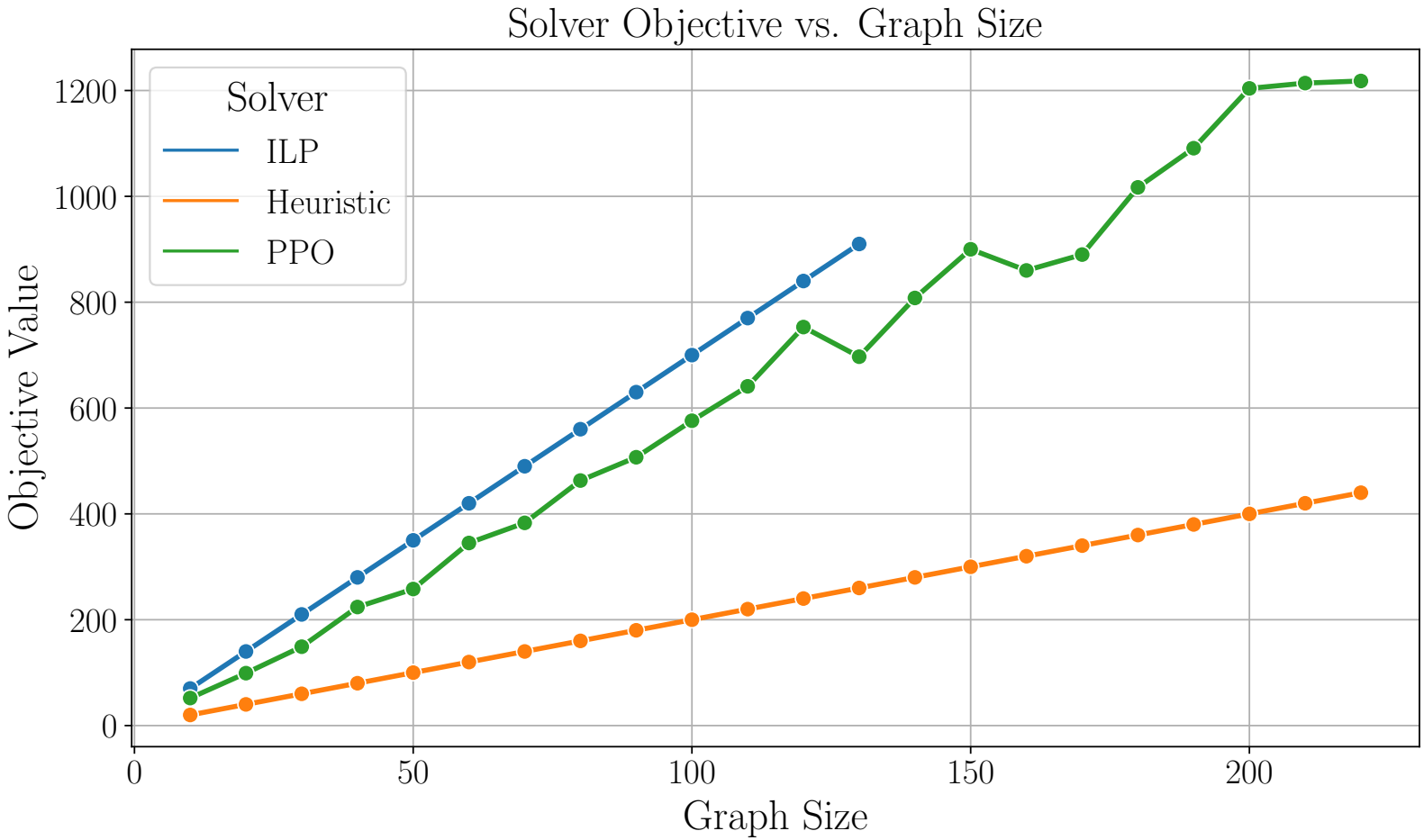
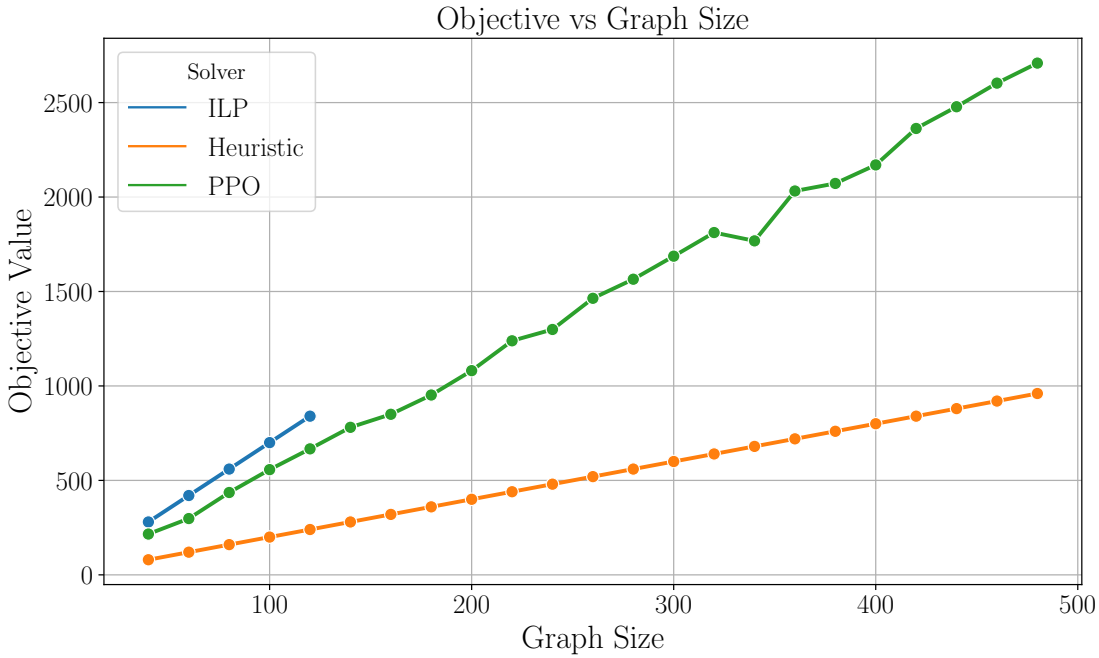
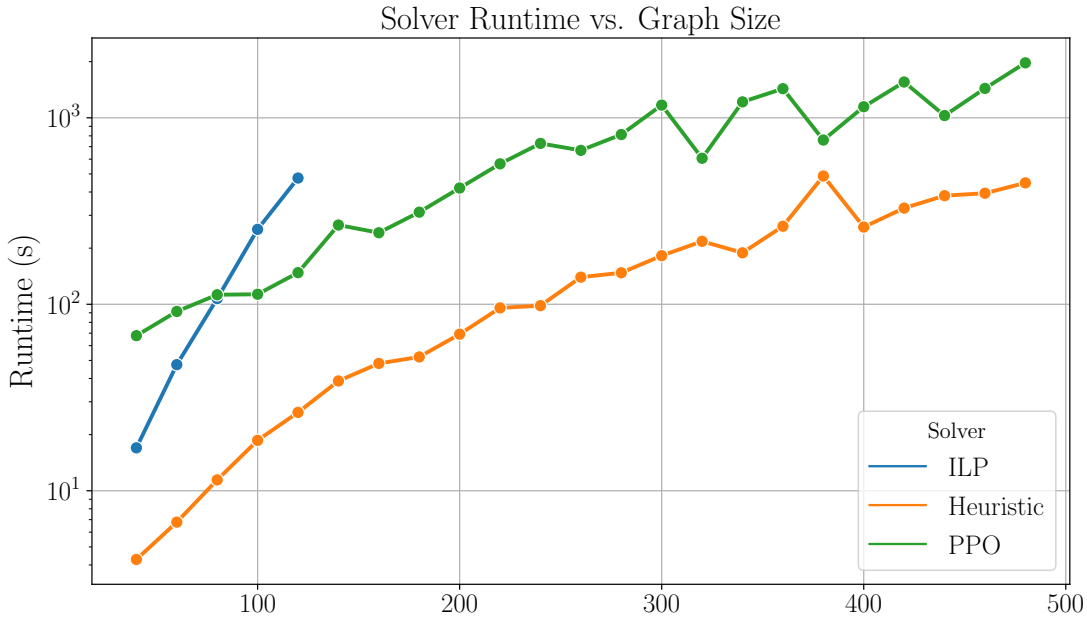


Figure 5: Tree instance: RL usually reaches a 20% optimality gap.

Performance comparison for static star instance





Dynamic Instances

RL takes advantage of learning ?

In industrial settings decision placement should be taken very often either **on the same graph** or **on a different graphs**.

We consider dynamics instances.

- Differents fixed instances close to each other on the same graphs.
- **NOT** the dynamic stochastic control problems where instances at each time step are interdependent through a stochastic evolution.

A new instance ask a new resolution of ILP (or a warm start).

Dynamic Instances – Performance and runtime

	Instance	Tree-50	Tree-100
Runtime (s)	**ILP**	80.2	266.0
	RL	**1.7**	**4.6**
Objective	**ILP**	370.0	700.0
	RL	278.5	582.7
Opt. Gap (%)	**RL**	24.7	16.8

Table 2: Average objective values and runtimes on Tree topologies.

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Conclusion

We presented:

- A Smart Warehouse model;
- Linear and RL solving methods with explicit features.

The RL approach:

- Scales to large instances;
- Achieves a consistent optimality gap between 15% and 25% in practice;
- Makes decisions in seconds, enabling transfer learning across instances.

Perspectives

- Improved implementations could enable deployable orchestration;
- Incorporating more technical features can reduce the optimality gap.

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