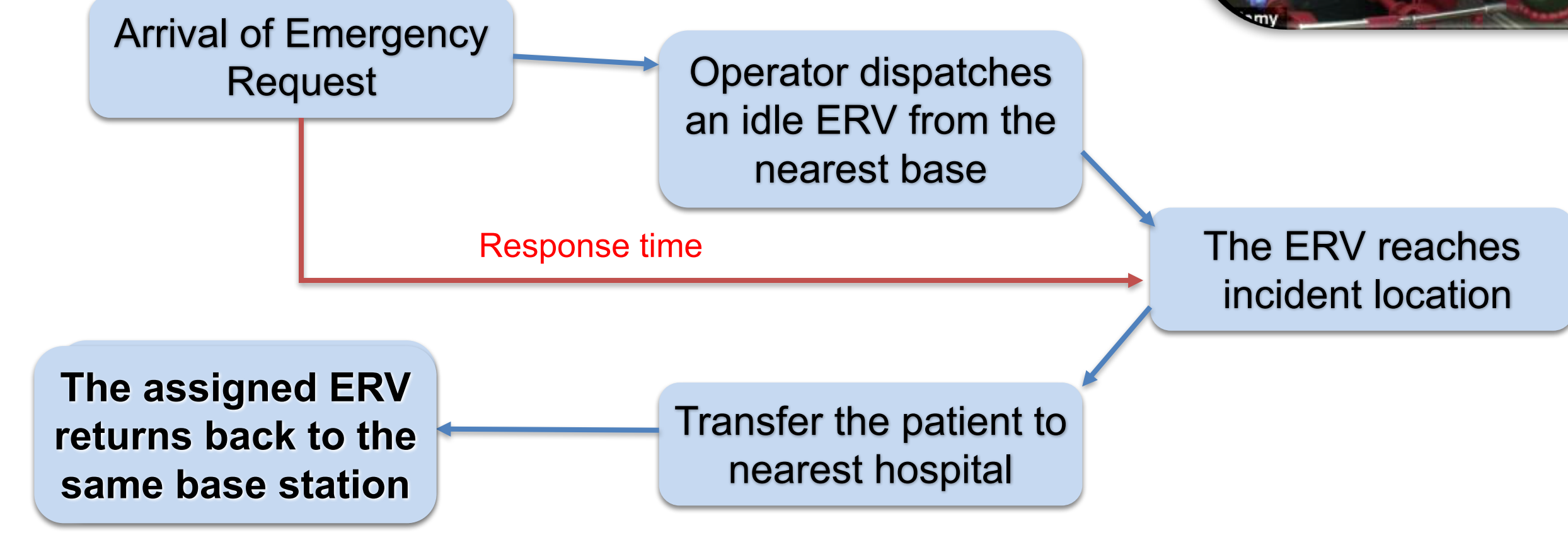


Motivation

- + Emergency Response Systems:
 - + E.g., Medical, Fire or Criminal management.
 - + Important for public safety and security.
 - + Response times for Emergency Response Vehicles (ERVs) are crucial.



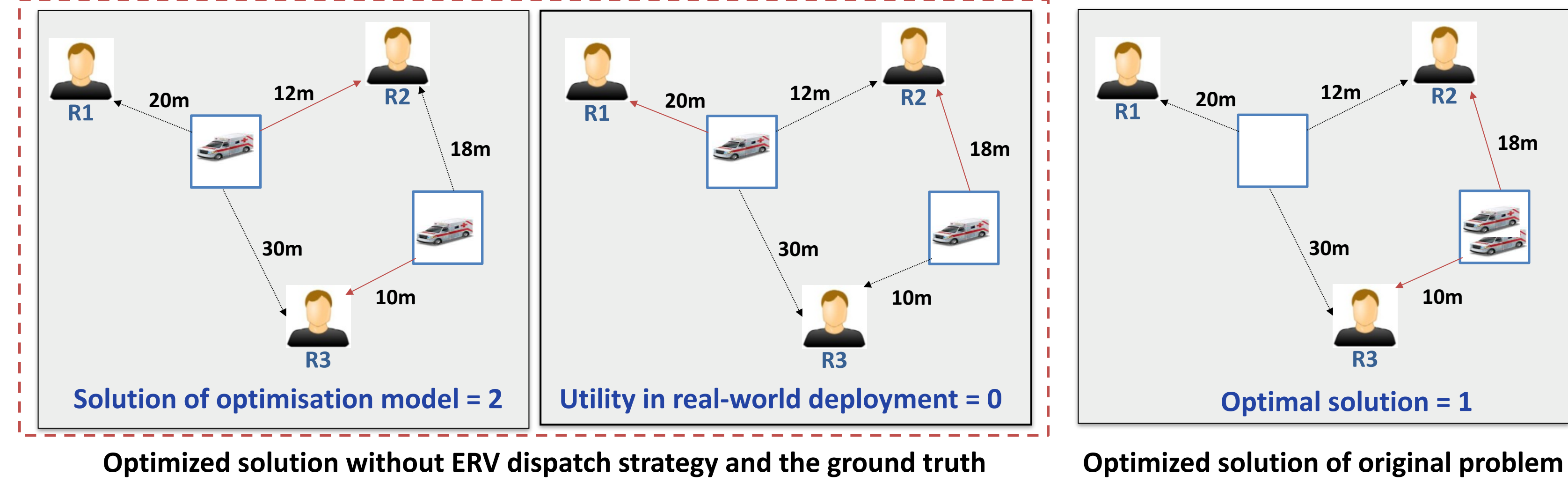
Challenges & Contributions

Goal: Find efficient allocation for an entire fleet of ERVs to a given set of bases so as to optimise **Bounded time response** (e.g., **maximise the number of requests served** within a threshold time bound) metric.

Existing Approaches:

- + Greedy approach (Yue *et al.*, 2012):
 - + Iteratively allocate one ERV at a time with highest marginal gain value.
 - + **Greedy solutions might be far away from optimal as ERV allocation problem is non-submodular.**
- + Optimisation approach (Saisubramanian *et al.*, 2015):
 - + Minimise response times for fixed percentage of requests.
 - + **Optimisation model does not incorporate nearest available ERV dispatch rules.**

Illustrative example: 3 requests, 2 bases and 2 ERVs, threshold time bound is 15 min

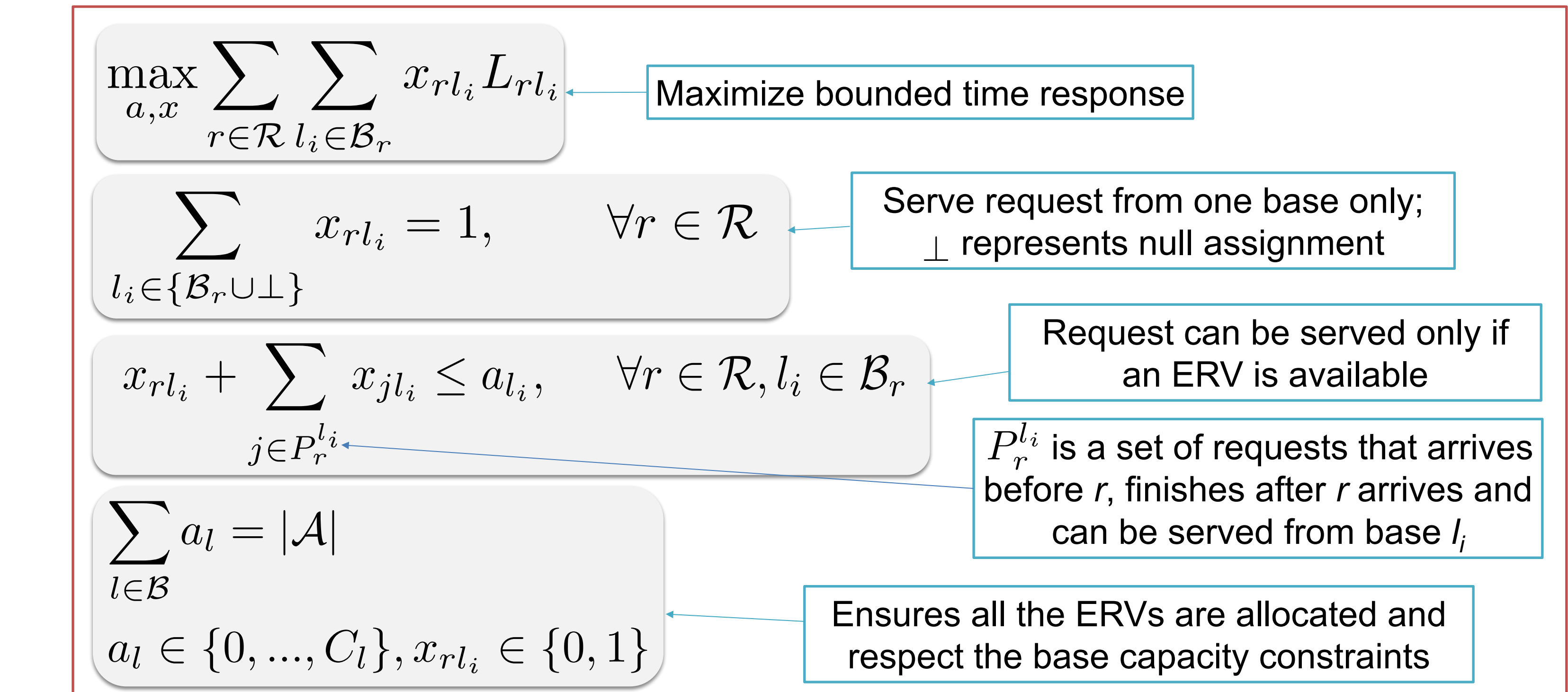


Our contributions:

- + A novel Integer Linear Programming (ILP) model for dynamic allocation of ERVs.
 - + Incorporates real-world ERV dispatch strategies as linear constraints.
 - + Exactly imitates the real dynamics of EMS when optimizing the allocation.
- + Two novel heuristic approaches for efficiently solving large-scale problems
 - + A relaxation based heuristic approach
 - + Two-stage hierarchical optimisation approach.
- + Evaluate solutions on an event-driven simulator build on two real-world datasets.

Optimization Model for ERV Allocation

- + Inputs: ERV allocation problem are defined using tuple: $\langle \mathcal{B}, \mathcal{A}, \mathcal{R}, \mathbf{T}, \mathbf{C}, L \rangle$
 - \mathcal{B} : set of bases, \mathcal{A} : Fleet of ERVs, \mathcal{R} : Set of requests, \mathbf{C} : Capacity of bases.
 - \mathbf{T} : A 2-D matrix that provides travel time between any two base locations
- $L_{rl} = \begin{cases} 1 & \text{if } T_{l,r.source} \leq \Delta \text{ minutes} \\ 0 & \text{Otherwise} \end{cases}$ Bounded time response objective
- + Outputs: Number of ambulances, a_l allocated to each bases $l \in \mathcal{B}$
- + Objective: Maximize number of requests served within threshold time bound.
- + Assignment decision variables: $x_{rl} = \begin{cases} 1 & \text{if request } r \text{ is served from base } l \\ 0 & \text{Otherwise} \end{cases}$
- + \mathcal{B}_r denotes set of feasible bases for request r , sorted based on their response time. i.e., if $\mathcal{B}_r = \{l_1, l_2, \dots, l_n\}$, then $T_{l_1,r.source} \leq T_{l_{i+1},r.source}$
- + Integer Linear Programming (ILP) formulation (without dispatch constraints):



Representation of Dispatch Constraints

- + Non-linear dispatch constraints: assign **nearest available** ERV to a request

$$\sum_{k \leq i} x_{rl_k} \geq 1 \quad \text{if} \quad \underbrace{a_{l_i} - \sum_{j \in P_r^{l_i}} x_{jl_i}}_{\text{\#ERV available at base } l_i} \geq 1, \quad \forall r \in \mathcal{R}, l_i \in \mathcal{B}_r$$

Dispatch from base l_i Base l_i is not empty when request r arrives in the system.
- + Linearization of complex dispatch constraints:

$$\sum_{k \leq i} x_{rl_k} \geq \frac{1}{C_{l_i}} [a_{l_i} - \sum_{j \in P_r^{l_i}} x_{jl_i}], \quad \forall r \in \mathcal{R}, l_i \in \mathcal{B}_r$$

Capacity of base l_i

Heuristic 1: Relaxation

- + Solve the global IP as MILP with continuous assignment variables.
 - + Integer allocation, but continuous assignment, i.e., $a_l \in \{0, \dots, C_l\}, x_{rl_i} \in [0, 1]$
 - + Provides relaxed solution, but a valid allocation of ERVs.
 - + Finally, we execute the resulted allocation on a real-world event-driven simulator (from Yue *et al.*, 2012) to obtain the actual utility.

Observation 1: If all the base stations have single capacity, then **Relaxation** approach provides an optimal and integral solution.

Heuristic 2: Two-stage Optimisation

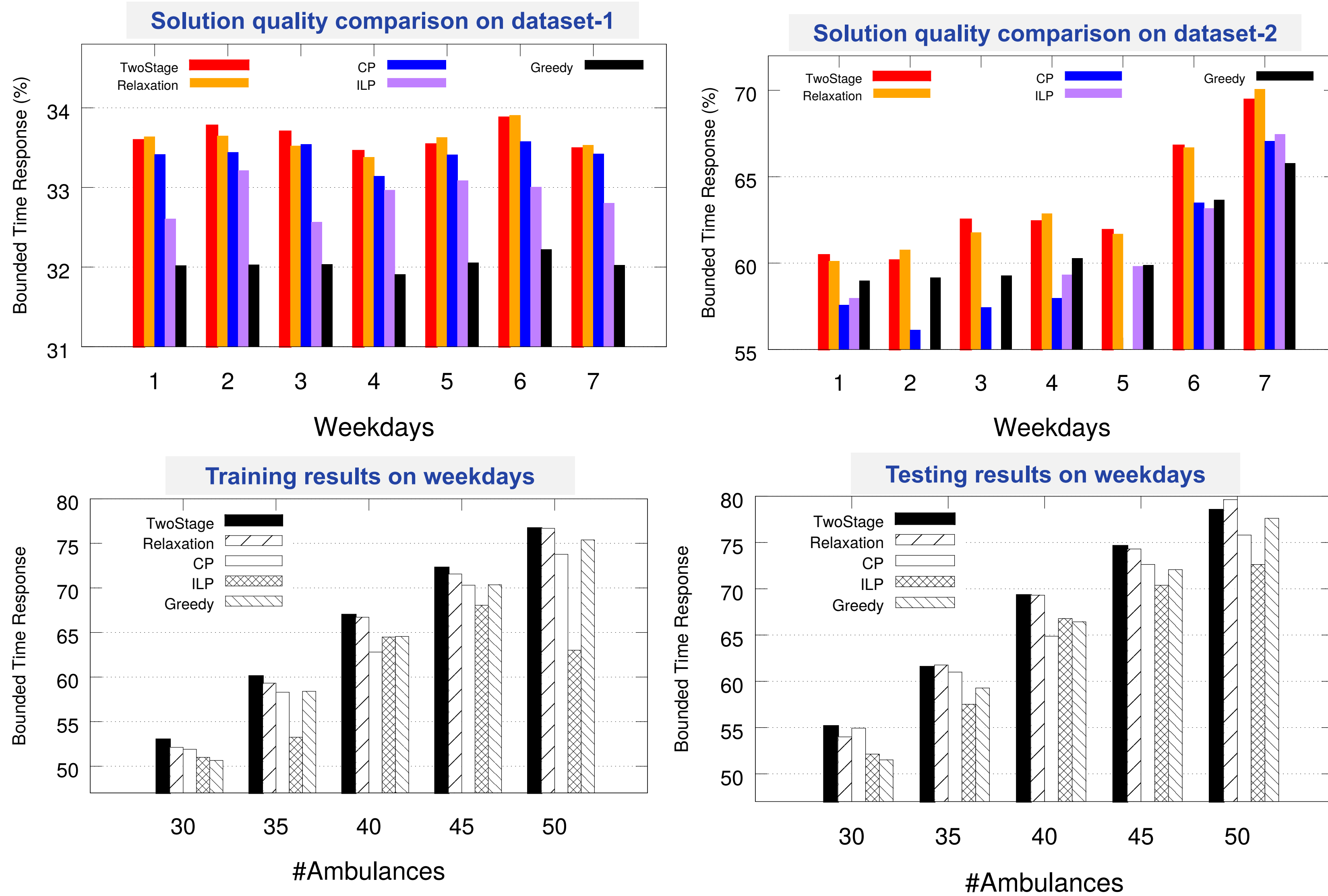
- + **First stage:** Solve the global MILP as LP relaxation.
 - + Round down the fractional allocation, \hat{a} to integral one, \bar{a} .
$$\bar{a}_l = \begin{cases} \lceil \hat{a}_l \rceil & \text{if } \hat{a}_l - \lfloor \hat{a}_l \rfloor \geq 0.95 \\ \lfloor \hat{a}_l \rfloor & \text{Otherwise} \end{cases}$$
- + **Second stage:** Solve the global MILP with following additional set of constraints
 - + A fixed allocation for a *subset of ERVs*, \bar{a} (1st stage solution).

$$a_l \geq \bar{a}_l, \quad \forall l \in \mathcal{B}$$

Ensure a lower bound on the number of ERVs at base l

Experimental Results

- + **Data sets:** Two real EMS data sets from large Asian cities.
 - + **Dataset-1:** 58 bases, 58 ambulances (threshold time bound is 15 minutes).
 - + 1500 weeks of request samples – divided into training, validation and test set.
 - + **Dataset-2:** 35 bases and 35 ambulances (threshold time bound is 8 minutes).
 - + 6 months of request samples – 3 months of training and 3 months of testing set.
- + **Approaches**
 - + Baseline – **Greedy** approach for optimising Bounded Time Response (Yue *et al.*, 2012)
 - + Global Integer Linear Program (**ILP**) – terminated after 2 hours.
 - + Constraint Programming (**CP**) model of the ILP – terminated after 2 hours.
 - + **Relaxation** – Our first heuristic approach.
 - + **TwoStage** – Our second heuristic approach using two stage optimisation.
- + All the approaches are evaluated on a data-driven simulator (Yue *et al.*, 2012)



- + Heuristic approaches serves 2.4% additional requests within 15 minutes over the existing greedy approach (Yue *et al.*, 2012) on *dataset-1*.
- + TwoStage optimization serves 2.5% extra requests within 8 minutes on *dataset-2*.
- + Performance of our heuristics improves for tight resource constraint and therefore, suitable for EMSs with limited number of ambulances.

Summary

- + We propose a complete optimisation model for ERV allocation in EMS.
- + Two efficient heuristic approaches are provided for solving large-scale problems.
- + Observation 1 can be exploited to further improve solution using classical SAT solver.