Online Supplement of the Paper “Optimizing Inspection Routes and Schedules for Infrastructure Systems under Stochastic Decision-dependent Failures”

1 Algorithms

Algorithm 1 Random coloring algorithm (Yu et al., 2022)

Network $G = (N, E)$, color coding ϕ, iteration budget maxIter, number of solutions to early stop nSol, evaluated solution set S, dual optimal solution π.
Initialization $T = \emptyset$ as candidate solution set, $k = 0$
while $k <$ maxIter or $|T| <$ nSol **do**
    Generate a random coloring function $\phi_k : N \to \{1, \dots, Q\}$
    Initialize $\Lambda_{\text{depot}} \leftarrow \{0 \dots, 0\}$
    for $i \in N$ **do**
        $\Lambda_i \leftarrow \emptyset$
    end for
    $B = \{\text{depot}\}$
    while $B \neq \emptyset$ **do**
        Sample $i \in B$
        if $i =$ depot **then**
            Add corresponding routes from Λ_{depot} with negative cost to T
        else
            for $j : (i, j) \in E$ **do**
                for $\lambda_i = (R_i, C_i) \in \Lambda_i$, with $R_i = (n_i, N_i^1, \dots, N_i^Q)$ **do**
                    if $N_i^{\phi(j)} = 0$ **then**
                        Extend λ_i to obtain λ_j
                        if $\lambda_j \notin S$ **then**
                            if λ_j is not dominated by any path in Λ_j **then**
                                Add λ_j to Λ_j and $B = B \cup \{j\}$
                                Remove any path in Λ_j that is dominated by λ_j
                            end if
                        end if
                    end if
                end for
            end for
        end if
        Remove i from B
    end while
    Add routes with negative cost to T
    $k = k + 1$
end while
Return T

Algorithm 2 Stochastic ALNS benchmark heuristic. Adapted from Liu et al. (2025)
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Instance $I = (N, A, depot, \Omega)$ with $depot$. scenarios Ω, vehicle types $\mathcal{T}$ with capacities Q_t and fleet sizes $|K_t|$.
Deterministic travel costs c_{ij}, failure penalties w_i, failure functions $F_i(\cdot)$ (as in the two-stage SMIP).
Parameters: maxAtt (attempts), maxIter (iterations), destroy fraction $\eta \in (0, 1)$, temperature factor $\gamma \in (0, 1)$.
Initialization: best solution $R^\star = \emptyset$, best cost $z^\star = +\infty$.
for $a = 1, \ldots, \text{maxAtt}$ **do**
  Initial solution construction
  Randomly assign customers to vehicles in $\mathcal{T}$ respecting capacities Q_t, following feasible arcs A, and close each route at the depot to obtain an initial route set $R^{(D)}$.
  Compute $z^{depot} \leftarrow \text{EvaluateCost}(R^{depot})$ using the sample-average two-stage objective.
  Set $R^{\text{curr}} \leftarrow R^{depot}$, $z^{\text{curr}} \leftarrow z^{depot}$, $R^{\text{loc}} \leftarrow R^{depot}$, $z^{\text{loc}} \leftarrow z^{depot}$.
  Set initial temperature $T_{depot} \leftarrow \gamma \cdot z^{depot}$, $T \leftarrow T_{depot}$.
  for $k = 1, \ldots, \text{maxIter}$ **do**
    Random destroy
    Collect all customer visits in R^{curr} and randomly remove a fraction η of them to obtain a partial solution $(\bar{R}, \mathcal{U})$, where $\mathcal{U}$ is the set of removed customers.
    Greedy repair
    Initialize $R^{\text{cand}} \leftarrow \bar{R}$.
    for each removed customer $i \in \mathcal{U}$ **do**
      For every feasible insertion position of i in every route of R^{cand} that respects vehicle capacity and arcs E, temporarily insert i and compute the resulting cost $\tilde{z} = \text{EvaluateCost}(\tilde{R})$.
      Choose the insertion with minimal $\tilde{z}$ and fix i at that position in R^{cand}.
    end for
    Compute $z^{\text{cand}} \leftarrow \text{EvaluateCost}(R^{\text{cand}})$.
    Simulated annealing acceptance
    Let $\Delta \leftarrow z^{\text{cand}} - z^{\text{curr}}$.
    if $\Delta \leq 0$ **then**
      Accept: $R^{\text{curr}} \leftarrow R^{\text{cand}}$, $z^{\text{curr}} \leftarrow z^{\text{cand}}$.
    else
      Draw $u \sim \text{Uniform}(0, 1)$.
      if $u < \exp(-\Delta/T)$ **then**
        Accept: $R^{\text{curr}} \leftarrow R^{\text{cand}}$, $z^{\text{curr}} \leftarrow z^{\text{cand}}$.
      end if
    end if
    if $z^{\text{curr}} < z^{\text{loc}}$ **then**
      Update local best: $R^{\text{loc}} \leftarrow R^{\text{curr}}$, $z^{\text{loc}} \leftarrow z^{\text{curr}}$.
    end if
    Cooling $T \leftarrow T_{depot} \cdot \left(1 - \frac{k}{\text{maxIter}}\right)$.
  end for
  Update global best
  if $z^{\text{loc}} < z^\star$ **then**
    $R^\star \leftarrow R^{\text{loc}}$, $z^\star \leftarrow z^{\text{loc}}$.
  end if
end for
Return best heuristic solution $R^\star$ and its cost $z^\star$.

2 Additional Computational Results

2.1 Computational Strenghtening

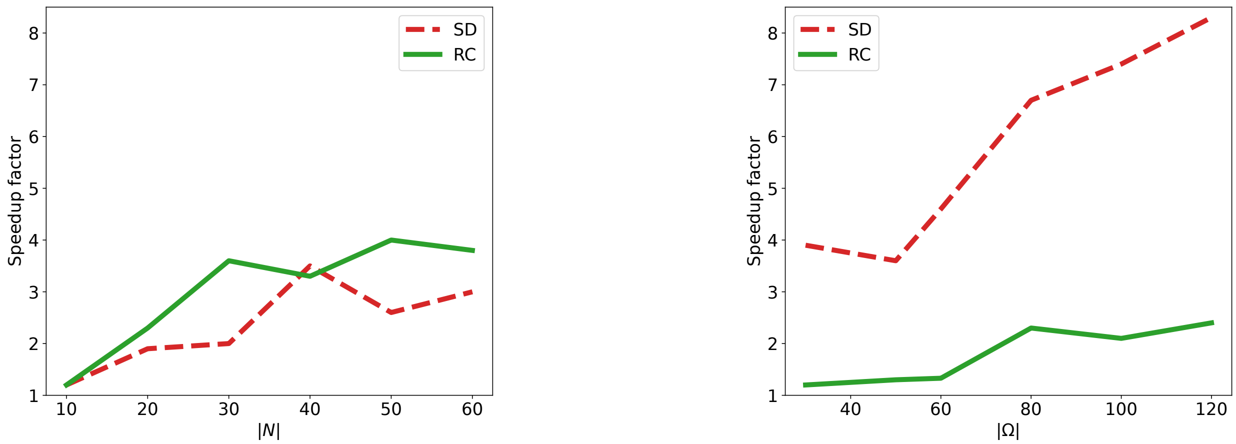
Based on insights from the sensitivity analysis, we propose initializing the restricted master problem with strategically generated routes that prioritize early visits to critical nodes. These routes are constructed using heuristic or local search techniques and are included in the initial pool $\bar{P}$.

Table 1 compares the runtime of the scenario decomposition algorithm with and without this initialization. Although not universally dominant, initializing with critical node-prioritized routes consistently reduces runtime in most configurations without adding significant overhead. We observe a benefit in initializing the set of columns as we observe a reduction in total time in most instances to find an optimal solution, and thus this procedure strengthens the initial set of candidate routes.

Table 1: Impact of column initialization on runtime in G-20-75.

Crit. (%)	$\|K\|$	Q	Baseline (s)	Initialized (s)
5	4	8	213	110
		9	266	243
		10	301	225
	5	6	156	94
		7	198	189
		8	178	180
	7	5	113	89
		6	129	119
		7	304	261
20	4	8	171	159
		9	289	232
		10	332	336
	5	6	150	105
		7	151	146
		8	170	180
	7	5	136	140
		6	144	152
		7	150	140
40	4	8	684	572
		9	753	732
		10	893	867
	5	6	170	191
		7	201	213
		8	256	246
	7	5	150	90
		6	150	160
		7	279	298

We conduct all experiments under a serial implementation. To further enhance scalability, we implement two levels of parallelization: (i) between scenario subproblems in the scenario decomposition algorithm, and (ii) between iterations of the random coloring acceleration within the column generation algorithm. Figure 1 shows the speedup factors using 12 CPU cores as a function of instance size and number of scenarios.



(a) Number of nodes in G-type instances

(b) Number of scenarios in G-20-75

Figure 1: Speedup from parallelizing scenario decomposition (SD) and random coloring (RC) in the computation of randomly generated instances. SD benefits more from increasing scenario count.

In Figure 1, we observe that the scenario-level parallelization offers the highest speedup as $|\Omega|$ grows. For smaller instances, the parallelization of random coloring provides meaningful gains. Coordination between workers is handled through a barrier synchronization step after solving each scenario, ensuring consistent pool updates and avoiding redundant evaluations (see, e.g., Deng et al., 2018).

2.2 Runtime Analysis

Table 2: Runtime and optimality gap comparison across solution approaches for G-type instances

				Gurobi		Scenario Decomposition		Stochastic ALNS	
Instance	Fleet	$\lvert K\rvert$	$\frac{Q\lvert K\rvert}{\lvert N\rvert}$	Time (s)	Gap (%)	Time (s)	Gap (%)	Time (s)	Gap (%)
G-10-30	S–S	1	1.0	13.2	–	16.2	0.03	4.1	1.27
	L–S	1	1.0	15.2	–	19.4	0.08	5.1	1.82
	L–L	1	1.0	17.8	–	22.7	0.13	6.2	2.39
	S–S	1	1.5	14.6	–	16.7	0.09	4.3	1.61
	L–S	1	1.5	16.8	–	20.0	0.14	5.4	2.04
	L–L	1	1.5	19.7	–	23.4	0.19	6.5	2.63
	S–S	2	1.0	31.2	–	28.3	0.02	7.4	1.94
	L–S	2	1.0	35.9	–	34.0	0.07	9.3	2.36
	L–L	2	1.0	42.1	–	39.6	0.12	11.1	2.91
	S–S	2	1.5	42.8	–	30.4	0.11	8.1	1.83
	L–S	2	1.5	49.2	–	36.5	0.17	10.1	2.29
	L–L	2	1.5	57.8	–	42.6	0.22	12.2	2.88
	S–S	3	1.0	71.7	–	38.2	0.10	10.4	2.07
	L–S	3	1.0	82.5	–	45.8	0.16	13.0	2.58
	L–L	3	1.0	96.8	–	53.5	0.21	15.6	3.11
	S–S	3	1.5	86.2	–	56.2	0.04	15.7	2.39
	L–S	3	1.5	99.1	–	67.4	0.10	19.6	2.97
	L–L	3	1.5	116.4	–	78.7	0.16	23.6	3.54
G-20-75	S–S	3	1.0	140.2	–	123.1	0.04	38.5	1.93
	L–S	3	1.0	161.2	–	147.7	0.09	48.1	2.41
	L–L	3	1.0	189.3	–	172.3	0.15	57.8	2.96
	S–S	3	1.5	141.1	–	170.2	0.03	52.1	2.31
	L–S	3	1.5	162.3	–	204.2	0.08	65.1	2.79
	L–L	3	1.5	190.5	–	238.3	0.14	78.2	3.33
	S–S	5	1.0	320.2	–	164.2	0.07	49.6	2.12
	L–S	5	1.0	368.2	–	197.0	0.13	62.0	2.63
	L–L	5	1.0	432.3	–	230.0	0.18	74.4	3.14
	S–S	5	1.5	372.5	–	241.5	0.16	76.8	2.74
	L–S	5	1.5	428.4	–	289.8	0.22	96.0	3.27
	L–L	5	1.5	503.9	–	338.1	0.28	115.2	3.81
	S–S	7	1.0	763.2	–	231.2	0.03	73.3	2.49
	L–S	7	1.0	877.7	–	277.4	0.09	91.6	3.02
	L–L	7	1.0	1030.3	–	323.7	0.15	110.0	3.55
	S–S	7	1.5	989.5	–	249.6	0.07	79.2	2.97
	L–S	7	1.5	1137.9	–	299.5	0.13	99.0	3.48
	L–L	7	1.5	1335.8	–	349.4	0.18	118.8	4.02

Table 3: Runtime and optimality gap comparison across solution approaches for IEEE instances

Instance	Fleet	$\|K\|$	$\frac{Q\|K\|}{\|N\|}$	Gurobi Time (s)	Gurobi Gap (%)	Scenario Decomposition Time (s)	Scenario Decomposition Gap (%)	Stochastic ALNS Time (s)	Stochastic ALNS Gap (%)
S–S	3	1.0	204.3	–	182.3	0.12	88.1	4.37	
	L–S	3	1.0	234.9	–	218.8	0.18	110.1	4.92
	L–L	3	1.0	275.8	–	255.2	0.23	132.1	5.41
	S–S	3	1.5	264.6	–	234.5	0.03	117.2	4.89
	L–S	3	1.5	304.3	–	281.4	0.09	146.5	5.36
	L–L	3	1.5	357.2	–	328.3	0.14	175.8	5.97
	S–S	5	1.0	523.1	–	243.2	0.01	121.6	5.23
	L–S	5	1.0	601.6	–	291.8	0.07	152.0	5.81
IEEE-33-136	L–L	5	1.0	706.2	–	340.5	0.12	182.4	6.28
	S–S	5	1.5	750.6	–	269.7	0.11	135.1	5.76
	L–S	5	1.5	863.2	–	323.6	0.17	168.9	6.34
	L–L	5	1.5	1013.3	–	377.6	0.22	202.7	6.91
	S–S	7	1.0	1829.1	–	310.3	0.10	161.4	6.21
	L–S	7	1.0	2103.5	–	372.4	0.16	201.8	6.73
	L–L	7	1.0	2469.3	–	434.4	0.21	242.1	7.19
	S–S	7	1.5	1968.1	–	359.8	0.12	190.7	6.87
	L–S	7	1.5	2263.3	–	431.8	0.18	238.4	7.43
	L–L	7	1.5	2656.9	–	503.7	0.23	286.1	7.96
S–S	3	1.0	540.9	–	420.3	1.96	210.2	6.53	
	L–S	3	1.0	622.0	–	504.4	2.02	262.7	7.08
	L–L	3	1.0	730.2	–	588.4	2.08	315.3	7.62
	S–S	3	1.5	640.9	–	422.8	0.89	215.0	7.02
	L–S	3	1.5	737.0	–	507.4	0.95	268.8	7.63
	L–L	3	1.5	865.2	–	591.9	1.01	322.5	8.11
	S–S	5	1.0	1203.2	–	502.8	0.75	256.4	7.58
	L–S	5	1.0	1383.7	–	603.4	0.81	320.5	8.17
IEEE-123-556	L–L	5	1.0	1624.3	–	703.9	0.86	384.6	8.69
	S–S	5	1.5	1255.2	–	596.6	2.49	314.2	8.32
	L–S	5	1.5	1443.5	–	715.9	2.55	392.8	8.91
	L–L	5	1.5	1694.5	–	835.2	2.61	471.3	9.37
	S–S	7	1.0	4302.9	–	720.4	0.37	388.9	9.18
	L–S	7	1.0	4948.3	–	864.5	0.43	486.1	9.71
	L–L	7	1.0	5808.9	–	1008.6	0.48	583.3	10.23
	S–S	7	1.5	4756.6	–	738.2	0.72	399.5	9.81
	L–S	7	1.5	5470.1	–	885.8	0.78	499.4	10.36
	L–L	7	1.5	6421.4	–	1033.5	0.83	599.2	10.87

Table 4: Runtime and optimality gap comparison across solution approaches for EPANET instances

Instance	Fleet	$\|K\|$	$\frac{Q\|K\|}{\|N\|}$	Gurobi Time (s)	Gurobi Gap (%)	Scenario Decomposition Time (s)	Scenario Decomposition Gap (%)	Stochastic ALNS Time (s)	Stochastic ALNS Gap (%)
EPANET-36-275	S–S	3	1.0	600.5	–	310.4	0.93	140.3	9.84
	L–S	3	1.0	690.6	–	372.5	0.99	175.4	10.37
	L–L	3	1.0	810.7	–	434.6	1.06	210.5	10.91
	S–S	3	1.5	720.8	–	365.2	1.21	165.7	10.48
	L–S	3	1.5	828.9	–	438.2	1.27	207.1	11.02
	L–L	3	1.5	973.1	–	511.3	1.33	248.5	11.57
	S–S	5	1.0	1420.7	–	512.9	1.42	210.4	11.28
	L–S	5	1.0	1633.8	–	615.5	1.49	263.0	11.83
	L–L	5	1.0	1917.9	–	718.1	1.55	315.6	12.36
	S–S	5	1.5	1685.9	–	648.3	1.83	262.7	12.15
	L–S	5	1.5	1938.8	–	778.0	1.89	328.4	12.67
	L–L	5	1.5	2276.0	–	907.6	1.95	394.0	13.19
	S–S	7	1.0	2890.3	–	835.6	2.04	328.9	13.08
	L–S	7	1.0	3323.8	–	1002.7	2.11	411.1	13.59
	L–L	7	1.0	3901.9	–	1169.8	2.18	493.3	14.12
	S–S	7	1.5	3156.4	–	972.1	2.35	379.2	14.19
	L–S	7	1.5	3629.9	–	1166.5	2.42	474.0	14.67
	L–L	7	1.5	4261.1	–	1361.0	2.48	568.8	15.21
EPANET-97-2013	S–S	3	1.0	1805.2	–	910.5	1.63	260.8	12.76
	L–S	3	1.0	2076.0	–	1092.6	1.69	326.0	13.31
	L–L	3	1.0	2437.0	–	1274.7	1.75	391.2	13.88
	S–S	3	1.5	2150.7	–	1048.9	2.03	305.3	13.72
	L–S	3	1.5	2473.3	–	1258.7	2.09	381.6	14.26
	L–L	3	1.5	2903.4	–	1468.5	2.15	457.9	14.79
	S–S	5	1.0	4525.9	–	1432.7	2.33	402.6	14.93
	L–S	5	1.0	5204.8	–	1719.2	2.39	503.2	15.48
	L–L	5	1.0	6110.0	–	2005.8	2.45	603.9	15.97
	S–S	5	1.5	5210.4	–	1765.8	2.71	485.1	15.84
	L–S	5	1.5	5992.0	–	2119.0	2.78	606.4	16.37
	L–L	5	1.5	7034.0	–	2472.1	2.84	727.7	16.92
	S–S	7	1.0	8923.6	–	2289.3	2.93	590.4	16.55
	L–S	7	1.0	10262.1	–	2747.2	3.01	738.0	17.06
	L–L	7	1.0	12046.9	–	3205.0	3.07	885.6	17.61
	S–S	7	1.5	9635.8	–	2620.7	3.22	672.9	17.39
	L–S	7	1.5	11081.2	–	3144.8	3.28	841.1	17.94
	L–L	7	1.5	13008.3	–	3669.0	3.34	1009.3	18.41

2.3 Solution Performance

Table 5: Solution quality and fleet utilization for SD and stochastic ALNS on G-type instances ($|\Omega| = 50$) under different coverage ratios.

				Scenario Decomposition (SD)					Stochastic ALNS				
Instance	Fleet	$\|K\|$	$\frac{Q\|K\|}{\|N\|}$	Obj.	Util.	Avg. len	Std. len	Fail. (%)	Obj.	Util.	Avg. len	Std. len	Fail. (%)
G-10-30	S–S	3	1.0	3141	0.79	4.3	0.8	6.4	3239	0.81	4.6	1.1	7.5
G-10-30	S–S	3	1.5	2986	0.57	5.2	1.0	4.5	3098	0.59	5.4	1.2	5.7
G-10-30	L–L	3	1.0	3199	0.76	5.0	1.2	6.7	3317	0.78	5.3	1.3	8.1
G-10-30	L–L	3	1.5	3046	0.54	6.1	1.3	4.8	3179	0.56	6.4	1.4	6.2
G-10-30	L–S	3	1.0	3083	0.97	4.5	1.0	5.8	3181	0.95	4.7	1.1	6.7
G-10-30	L–S	3	1.5	2952	0.89	4.9	1.1	4.1	3057	0.87	5.1	1.3	5.1
G-10-30	S–S	5	1.0	3067	0.73	3.3	0.9	5.9	3158	0.75	3.4	0.9	6.9
G-10-30	S–S	5	1.5	2921	0.52	4.4	1.1	4.2	3033	0.54	4.6	1.2	5.4
G-10-30	L–L	5	1.0	3121	0.71	4.1	1.0	6.1	3249	0.73	4.3	1.2	7.7
G-10-30	L–L	5	1.5	2983	0.49	5.1	1.3	4.6	3105	0.51	5.3	1.3	5.8
G-10-30	L–S	5	1.0	3022	0.95	3.6	0.9	5.3	3119	0.93	3.8	1.0	6.4
G-10-30	L–S	5	1.5	2891	0.87	4.1	1.1	4.0	3004	0.85	4.3	1.1	5.2
G-20-75	S–S	3	1.0	6264	0.79	6.0	1.1	9.4	6422	0.81	6.3	1.2	10.2
G-20-75	S–S	3	1.5	5951	0.55	7.9	1.5	6.8	6185	0.57	8.3	1.6	8.3
G-20-75	L–L	3	1.0	6396	0.75	7.7	1.4	9.7	6613	0.77	8.1	1.6	11.0
G-20-75	L–L	3	1.5	6085	0.51	9.9	1.9	7.3	6342	0.53	10.2	2.0	9.0
G-20-75	L–S	3	1.0	6151	0.97	6.8	1.2	8.8	6353	0.95	7.0	1.4	9.9
G-20-75	L–S	3	1.5	5874	0.88	8.3	1.6	6.4	6102	0.86	8.6	1.7	7.8
G-20-75	S–S	5	1.0	6098	0.81	4.8	0.9	8.9	6253	0.83	5.0	1.1	9.8
G-20-75	S–S	5	1.5	5824	0.53	6.6	1.3	6.5	6066	0.55	6.9	1.5	7.9
G-20-75	L–L	5	1.0	6207	0.77	6.3	1.2	9.2	6445	0.79	6.5	1.4	10.5
G-20-75	L–L	5	1.5	5921	0.49	8.4	1.7	7.0	6189	0.51	8.7	1.8	8.7
G-20-75	L–S	5	1.0	5993	0.99	5.4	1.0	8.4	6179	0.97	5.6	1.2	9.3
G-20-75	L–S	5	1.5	5751	0.89	7.0	1.4	6.1	5975	0.87	7.3	1.6	7.5

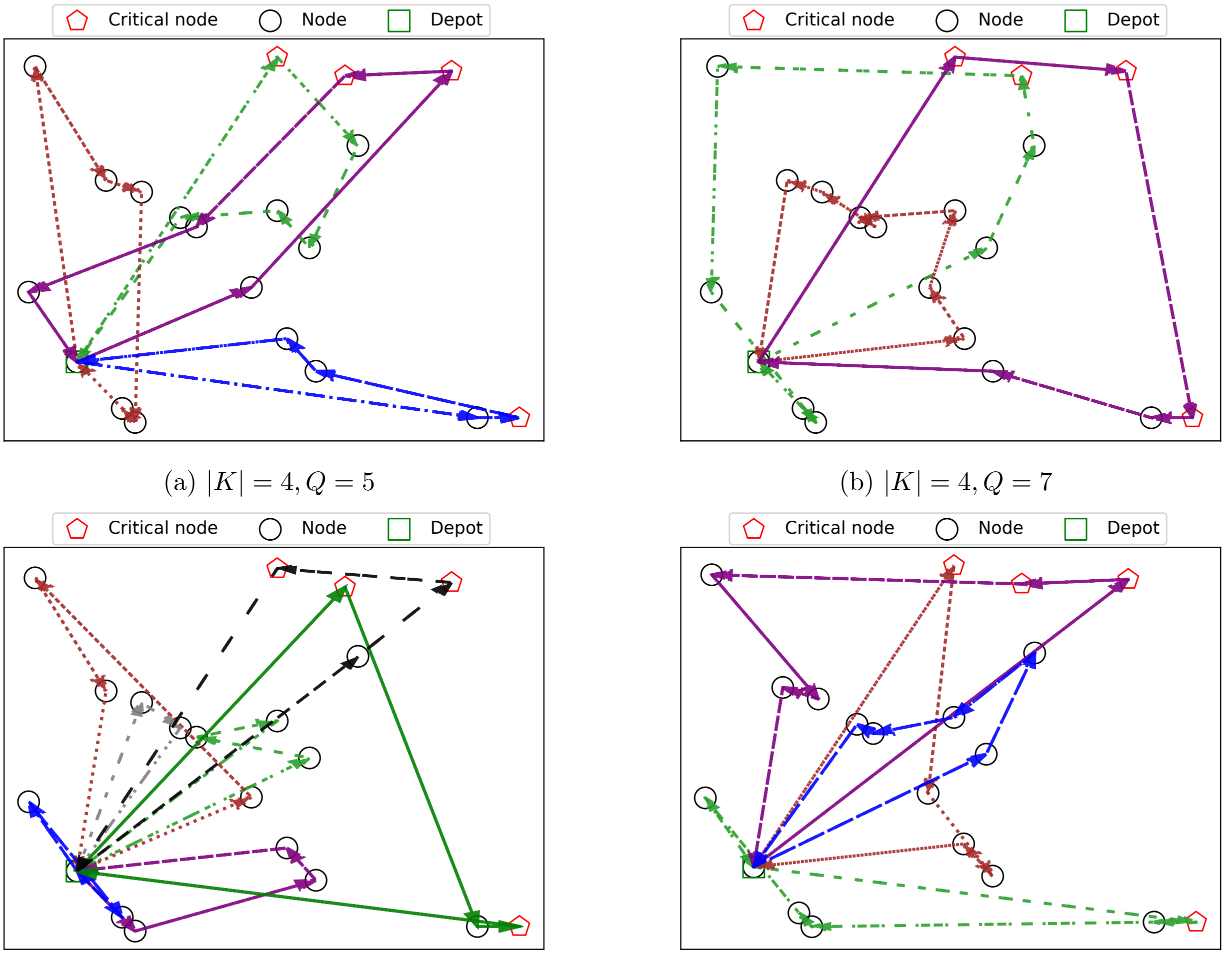
Table 6: Solution quality and fleet utilization for SD and stochastic ALNS on IEEE instances ($|\Omega| = 50$) under different coverage ratios.

				Scenario Decomposition (SD)					Stochastic ALNS				
Instance	Fleet	$\|K\|$	$\frac{Q\|K\|}{\|N\|}$	Obj.	Util.	Avg. len	Std. len	Fail. (%)	Obj.	Util.	Avg. len	Std. len	Fail. (%)
IEEE-33-136	S–S	3	1.0	10234	0.83	9.37	2.11	9.7	10621	0.80	9.91	2.34	12.5
IEEE-33-136	S–S	3	1.5	9738	0.59	12.84	2.63	7.1	10192	0.61	13.32	2.88	9.8
IEEE-33-136	L–L	3	1.0	10489	0.79	10.42	2.27	10.3	10873	0.77	10.96	2.55	13.2
IEEE-33-136	L–L	3	1.5	9924	0.56	14.23	2.81	7.6	10318	0.57	14.79	3.07	10.4
IEEE-33-136	L–S	3	1.0	10087	0.95	9.82	2.05	9.2	10473	0.92	10.29	2.28	12.0
IEEE-33-136	L–S	3	1.5	9629	0.88	13.21	2.54	6.8	10083	0.86	13.67	2.81	9.3
IEEE-33-136	S–S	5	1.0	9941	0.84	7.61	1.93	9.3	10312	0.82	8.07	2.15	12.1
IEEE-33-136	S–S	5	1.5	9527	0.61	10.94	2.39	6.9	9998	0.63	11.37	2.63	9.5
IEEE-33-136	L–L	5	1.0	10136	0.80	8.44	2.06	9.9	10584	0.78	8.93	2.29	12.8
IEEE-33-136	L–L	5	1.5	9703	0.58	11.89	2.55	7.3	10162	0.59	12.35	2.82	10.2
IEEE-33-136	L–S	5	1.0	9857	0.96	8.02	1.88	8.9	10291	0.94	8.49	2.10	11.7
IEEE-33-136	L–S	5	1.5	9446	0.89	11.37	2.32	6.5	9879	0.87	11.82	2.58	9.1
IEEE-123-556	S–S	3	1.0	21473	0.81	14.87	3.92	12.9	22416	0.78	15.41	4.23	16.4
IEEE-123-556	S–S	3	1.5	20368	0.57	20.16	4.51	9.5	21437	0.59	20.79	4.86	13.2
IEEE-123-556	L–L	3	1.0	21992	0.77	16.93	4.21	13.6	23081	0.74	17.48	4.56	17.1
IEEE-123-556	L–L	3	1.5	20789	0.55	22.34	4.83	10.1	21976	0.56	22.97	5.17	14.0
IEEE-123-556	L–S	3	1.0	21106	0.95	15.42	4.03	12.3	22097	0.92	15.96	4.32	15.8
IEEE-123-556	L–S	3	1.5	20087	0.88	21.01	4.59	9.1	21164	0.86	21.58	4.95	12.7
IEEE-123-556	S–S	5	1.0	20931	0.82	12.76	3.61	12.4	21879	0.80	13.29	3.94	16.0
IEEE-123-556	S–S	5	1.5	19924	0.60	17.38	4.18	9.2	20983	0.62	17.94	4.52	12.9
IEEE-123-556	L–L	5	1.0	21362	0.78	14.49	3.84	13.1	22397	0.76	15.01	4.13	16.7
IEEE-123-556	L–L	5	1.5	20311	0.57	19.62	4.39	9.8	21364	0.58	20.17	4.74	13.6
IEEE-123-556	L–S	5	1.0	20724	0.96	13.68	3.69	11.9	21703	0.94	14.17	3.99	15.4
IEEE-123-556	L–S	5	1.5	19782	0.89	18.41	4.24	8.8	20816	0.87	18.93	4.59	12.3

Table 7: Solution quality and fleet utilization for SD and stochastic ALNS on EPANET instances ($|\Omega| = 50$) under different coverage ratios.

				Scenario Decomposition (SD)					Stochastic ALNS				
Instance	Fleet	$\lvert K\rvert$	$\frac{Q\lvert K\rvert}{\lvert N\rvert}$	Obj.	Util.	Avg. len	Std. len	Fail. (%)	Obj.	Util.	Avg. len	Std. len	Fail. (%)
EPANET-36-275	S–S	3	1.0	12941	0.76	11.82	2.81	13.9	13784	0.72	12.51	3.19	16.8
EPANET-36-275	S–S	3	1.5	12296	0.54	15.89	3.26	10.6	13147	0.56	16.41	3.61	13.9
EPANET-36-275	L–L	3	1.0	13354	0.71	14.12	3.23	14.6	14293	0.69	14.83	3.57	18.1
EPANET-36-275	L–L	3	1.5	12637	0.50	18.39	3.67	11.4	13582	0.51	19.02	4.01	15.4
EPANET-36-275	L–S	3	1.0	12741	0.94	12.63	2.95	13.3	13596	0.91	13.18	3.23	16.4
EPANET-36-275	L–S	3	1.5	12047	0.86	16.58	3.35	10.1	12872	0.84	17.21	3.70	13.5
EPANET-36-275	S–S	5	1.0	12643	0.78	9.97	2.44	13.5	13418	0.75	10.62	2.78	16.6
EPANET-36-275	S–S	5	1.5	11978	0.57	13.92	2.94	10.3	12843	0.59	14.51	3.27	13.5
EPANET-36-275	L–L	5	1.0	12983	0.73	12.21	2.86	14.1	13876	0.70	12.79	3.17	17.5
EPANET-36-275	L–L	5	1.5	12264	0.52	16.85	3.51	11.1	13207	0.53	17.43	3.88	15.0
EPANET-36-275	L–S	5	1.0	12431	0.96	11.21	2.61	12.9	13264	0.94	11.77	2.93	16.0
EPANET-36-275	L–S	5	1.5	11732	0.88	15.12	3.17	9.7	12591	0.86	15.63	3.53	13.1
EPANET-97-2013	S–S	3	1.0	29281	0.80	20.13	4.53	16.1	31097	0.77	20.91	4.97	19.9
EPANET-97-2013	S–S	3	1.5	27643	0.57	27.04	5.46	12.5	29536	0.59	27.83	5.93	16.4
EPANET-97-2013	L–L	3	1.0	29974	0.75	23.72	5.07	16.9	31941	0.72	24.43	5.55	20.8
EPANET-97-2013	L–L	3	1.5	28324	0.54	31.67	6.03	13.5	30382	0.55	32.48	6.44	18.1
EPANET-97-2013	L–S	3	1.0	28641	0.96	21.78	4.87	15.6	30422	0.93	22.39	5.21	19.3
EPANET-97-2013	L–S	3	1.5	27234	0.88	28.76	5.66	12.0	29141	0.86	29.51	6.11	15.8
EPANET-97-2013	S–S	5	1.0	28391	0.82	17.09	4.19	15.7	30162	0.79	17.81	4.63	19.3
EPANET-97-2013	S–S	5	1.5	27046	0.60	23.31	4.99	12.2	28897	0.62	24.09	5.42	16.2
EPANET-97-2013	L–L	5	1.0	29071	0.77	20.51	4.71	16.3	31022	0.74	21.16	5.09	20.2
EPANET-97-2013	L–L	5	1.5	27839	0.56	27.86	5.66	13.1	29827	0.57	28.47	6.12	17.6
EPANET-97-2013	L–S	5	1.0	28053	0.97	18.89	4.39	15.1	29814	0.95	19.47	4.81	18.7
EPANET-97-2013	L–S	5	1.5	26741	0.89	24.26	5.22	11.7	28596	0.87	24.98	5.69	15.3

2.4 Solution Visualization Across Number of Critical Nodes in Network



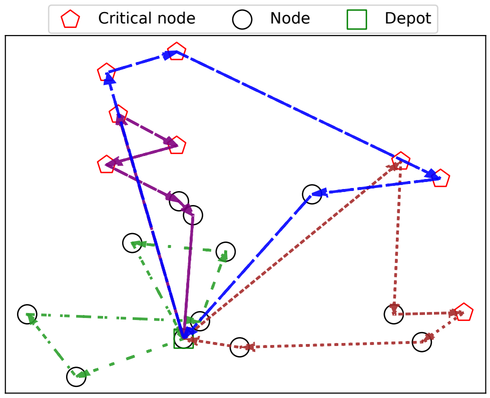
(a) $|K| = 4, Q = 5$

(b) $|K| = 4, Q = 7$

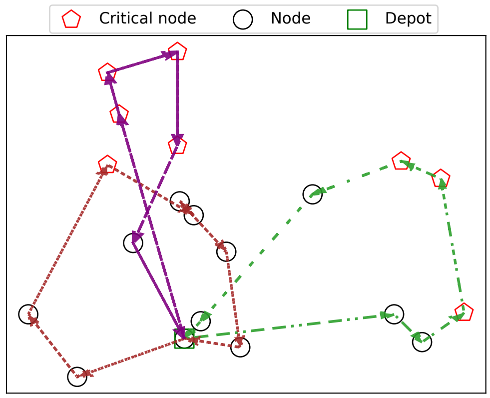
(c) $|K| = 7, Q = 3$

(d) $|K| = 7, Q = 5$

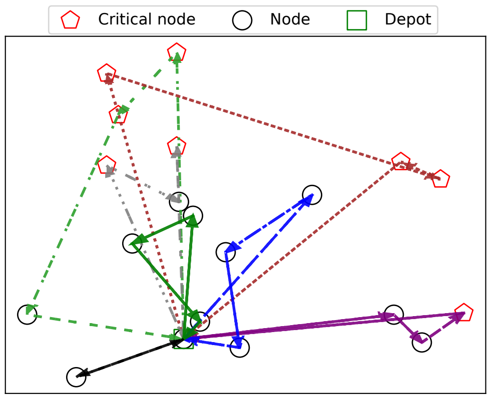
Figure 2: Routing solutions under varying fleet characteristics in G-20-75 with 20% of critical nodes



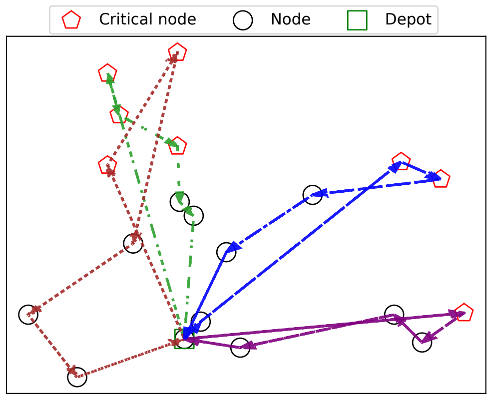
(a) $|K| = 4, Q = 5$



(b) $|K| = 4, Q = 7$



(c) $|K| = 7, Q = 3$



(d) $|K| = 7, Q = 5$

Figure 3: Routing solutions under varying fleet characteristics in G-20-75 with 40% of critical nodes

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