

Online Supplement for “Landscape-Aware Hybrid Metaheuristic for Cross-Dock Door Assignment”

1 Comparison of LNS and Exact Solver

Since the objective function of the IQAP contains the quadratic term $x_{ki}y_{lj}$, it can be linearized via continuous variables $z_{kilj} = x_{ki}y_{lj}$ for all k, i, l, j . Consequently, the IQAP can be reformulated as the following Mixed-Integer Linear Programming (MILP) model:

$$\text{Minimize } \sum_{k=1}^{|I|} \sum_{i=1}^{|I|} \sum_{l=1}^{|J|} \sum_{j=1}^{|J|} \hat{f}_{kl} d_{ij} z_{kilj} \quad (1)$$

$$\text{Subject to } \sum_{k=1}^{|I|} x_{ki} = 1, \quad i = 1, 2, \dots, |I| \quad (2)$$

$$\sum_{i=1}^{|I|} x_{ki} = 1, \quad k = 1, 2, \dots, |I| \quad (3)$$

$$\sum_{l=1}^{|J|} y_{lj} = 1, \quad j = 1, 2, \dots, |J| \quad (4)$$

$$\sum_{j=1}^{|J|} y_{lj} = 1, \quad l = 1, 2, \dots, |J| \quad (5)$$

$$z_{kilj} \leq x_{ki}, \quad k, i = 1, \dots, |I|; \quad l, j = 1, \dots, |J| \quad (6)$$

$$z_{kilj} \leq y_{lj}, \quad k, i = 1, \dots, |I|; \quad l, j = 1, \dots, |J| \quad (7)$$

$$z_{kilj} \geq x_{ki} + y_{lj} - 1, \quad k, i = 1, \dots, |I|; \quad l, j = 1, \dots, |J| \quad (8)$$

$$z_{kilj} \geq 0, \quad k, i = 1, \dots, |I|; \quad l, j = 1, \dots, |J| \quad (9)$$

$$x_{ki}, y_{lj} \in \{0, 1\} \quad k, i = 1, \dots, |I|; \quad l, j = 1, \dots, |J| \quad (10)$$

To validate the efficiency of the LNS procedure, we compared it against solving the linearized IQAP model using CPLEX. For each instance, a random initial solution was generated by solving models P1 and P2, and converted into an IQAP instance. The LNS procedure was executed without a time limit; in contrast, CPLEX was allotted 10 seconds per SetA instance and 200 seconds per SetB instance. Table OLS 1 presents the average objective value (column “Obj”) and average time (column “Time”) over 10 independent runs. The “Gap%” column indicates the optimality gap reported by CPLEX. The “RT” column indicates the reference time that LA-HM found the best objective value. Bold values indicate superior performance in terms of objective value and computation time.

Table OLS 1: Comparison of LNS vs. Linearized IQAP Model

SetA (Time Limit: 10 seconds)							SetB (Time Limit: 200 seconds)						
Instance	LNS		Linearized IQAP			RT	Instance	LNS		Linearized IQAP			RT
	Obj	Time	Obj	t(s)	Gap(%)			Obj	Time	Obj	Time	Gap(%)	
8×4S5	5227.6	0	5180.4	0.09	0	0	25×10S5	52513.6	0.001	53345.4	200	93.49	0.14
8×4S10	5335.3	0	5331.3	0.104	0	0	25×10S10	52222.7	0.003	53307.5	200	92.52	0.46
8×4S15	5349.2	0	5342.3	0.093	0	0.003	25×10S15	52456.8	0.001	53565.4	200	93.85	0.14
8×4S20	5269.7	0	5257.3	0.108	0	0	25×10S20	52105.6	0.004	53251.7	200	93.91	0.10
8×4S30	5297	0	5291.3	0.092	0	0	25×10S30	51463.1	0.003	52843.1	200	95.56	0.21
9×4S5	6130.2	0	6123.3	0.109	0	0	25×20S30	54400.4	0.015	61196.6	200	100	3.91
9×4S10	6137.0	0	6137.0	0.104	0	0.005	50×10S5	206271.8	0.003	208411.4	200	92.12	97.6
9×4S15	6171.2	0.001	6170.6	0.09	0	0	50×10S10	205205.0	0.001	207343.7	200	92.65	61.2
9×4S20	6118.9	0	6112.4	0.102	0	0	50×10S15	204570.3	0.001	207006.7	200	94.5	41.8
9×4S30	6154.4	0	6146.0	0.11	0	0	50×10S20	203181.4	0.001	205940.4	200	93.61	104.4
10×4S5	6594.3	0	6590.9	0.105	0	0.001	50×10S30	201915.8	0.004	205177.4	200	95.68	18.5
10×4S10	6600.7	0	6592.6	0.099	0	0	50×20S5	257381.1	0.019	273740.2	200	100	110.5
10×4S15	6575.3	0.001	6564.1	0.111	0	0	50×20S10	256521.4	0.014	269711.5	200	100	43.3
10×4S20	6579.6	0.001	6566.6	0.091	0	0	50×20S15	255309.7	0.020	268984.1	200	100	70.2
10×4S30	6567.1	0.001	6565.1	0.093	0	0.001	50×20S20	251940.3	0.020	265012.6	200	100	79.1
10×5S5	6724.9	0	6676.0	1.991	0	0.004	50×20S30	247820.6	0.021	263566.6	200	100	102.0
10×5S10	6691.9	0	6656.3	1.599	0	0	50×30S15	291015.3	0.054	323725.9	200	100	64.2
10×5S15	6652.9	0	6627.7	1.609	0.01	0	50×30S20	287367.3	0.062	318556.9	200	100	85.1
10×5S20	6648.5	0	6617.5	2.135	0.01	0	50×30S30	280385.1	0.063	310398.8	200	100	61.7
10×5S30	6674.9	0	6652.4	1.725	0.01	0	50×43S30	346062.4	0.167	397878.4	200	100	111.3
11×5S5	7952.8	0	7948.7	1.82	0	0.002	75×10S5	469944.1	0.001	472588.7	200	92.91	112.5
11×5S10	7848	0	7847.4	1.607	0	0.003	75×10S10	467786.1	0.003	471706.4	200	93.11	101.2
11×5S15	7902.8	0	7871.8	2.013	0	0.017	75×10S15	464311.6	0.004	469624.1	200	93.42	104.3
11×5S20	7885.1	0.001	7860.8	2.16	0	0	75×10S20	462860.2	0.004	467598	200	94.15	80.5
11×5S30	7879	0.001	7839.6	1.377	0	0	75×10S30	460751.9	0.003	466799.6	200	92.92	79.6
12×5S5	8381.9	0	8366.7	2.119	0	0.002	75×20S5	578934.6	0.019	597899.1	200	100	96.3
12×5S10	8407.9	0	8384.6	1.839	0.01	0	75×20S10	573572.8	0.017	593129	200	100	114.3
12×5S15	8390.7	0	8355.9	1.385	0	0	75×20S15	568166.6	0.020	590248	200	100	93.3
12×5S20	8425.3	0.001	8410.7	1.589	0	0.003	75×20S20	560790.9	0.019	585338.1	200	100	95.5
12×5S30	8333.9	0	8327.3	2.01	0.01	0.008	75×20S30	553834.1	0.021	589485.4	200	100	108.3
12×6S5	11074.3	0	11024.4	9.638	44.02	0.103	75×30S10	689774.5	0.060	730195.7	200	100	109.8
12×6S10	10924.8	0	10890.2	9.727	52.16	0.007	75×30S15	680950.0	0.067	721064.3	200	100	139.9
12×6S15	10923.6	0	10915.4	9.513	42.81	0.001	75×30S20	669551.4	0.062	710698.5	200	100	135.8
12×6S20	10878.9	0	10893.5	9.599	51.42	0.002	75×30S30	656675.3	0.067	710618.9	200	100	116.5
12×6S30	10864.3	0.001	10821.5	9.689	49.01	0.001	100×10S5	820325.1	0.006	825481.4	200	91.84	101.7
15×6S5	14589.4	0.001	14555.4	9.838	46.52	0.041	100×10S10	815125.5	0.004	821400.4	200	93.46	93.4
15×6S10	14642.4	0.001	14583.5	9.969	56.94	0.009	100×10S15	811113.7	0.002	817846.8	200	94.61	101.8
15×6S15	14633.0	0.002	14642.3	9.461	45.53	0.104	100×10S20	808696.6	0.005	815307.5	200	92.44	119.5
15×6S20	14595.1	0.001	14580.6	9.979	47.35	0.016	100×10S30	806522.0	0.001	813299.2	200	92.02	88.0
15×6S30	14565.0	0	14597.6	9.825	48.22	0.015	100×20S5	1048647.6	0.019	1073390.8	200	100	92.8
15×7S5	15547.4	0	15685.9	9.991	86.61	0.05	100×20S10	1038881.8	0.023	1067106.6	200	100	89.9
15×7S10	15579.6	0.002	15707.7	9.985	87.17	0.129	100×20S15	1029049.0	0.021	1063716.1	200	100	116.0
15×7S15	15482.3	0.002	15681.9	9.98	87.46	0.073	100×20S20	1017441.7	0.023	1061529.6	200	100	104.2
15×7S20	15430.9	0.002	15579.1	9.989	88.25	0.102	100×20S30	1005727.2	0.020	1067583.8	200	100	86.4
15×7S30	15401.6	0.001	15559.3	9.964	89.1	0.044	100×30S5	1262616.6	0.056	1313521.7	200	100	122.0
20×10S5	31346.2	0.003	32517.4	10	100	0.771	100×30S10	1250657.8	0.065	1301306.6	200	100	124.2
20×10S10	31319.8	0.005	32354.7	10	100	0.033	100×30S15	1229899.1	0.067	1279689	200	100	142.1
20×10S15	31410.2	0	32325.1	10	100	0.024	100×30S20	1215044.2	0.068	1281224.5	200	100	102.7
20×10S20	31133.9	0.005	32575.3	10	100	0.036	100×30S30	1195876.6	0.061	1288361	200	100	127.9
20×10S30	31102.6	0	32518	10	99.4	0.019	Average	551502.8	0.026	573892.3	200	97.3	84.8
Average	11327.1	0.0007	11448.5	4.51	28.4	0.033							

From Table OLS 1, it can be observed that for small SetA instances (8×4 to 12×5), CPLEX finds optimal solutions but is orders of magnitude slower than LNS. Specifically, for instance 10×5S5, solving the linearized IQAP with CPLEX takes ≈ 1.99 s, whereas LA-HM solves the original problem only in ≈ 0.0038 s. For all larger instances in both SetA and SetB, CPLEX fails to converge within the time limits (10s and 200s, respectively), yielding large optimality gaps (40%–100%) and worse solutions. In contrast, the LNS procedure consistently yields high-quality solutions in milliseconds (< 0.1 s). Given that the IQAP is solved iteratively within the heuristic framework, the efficiency of LNS is essential to the overall tractability of the algorithm.

2 Stability Analysis of LA-HM, LA-ITS and MLNS

Figure OLS 1 shows the boxplot of percentage gaps among LA-HM, LA-ITS and MLNS. The y-axis represents the best and average percentage gap of each algorithm relative to the overall best result, calculated as $gap_{Algo}^{Best} = (f_{Algo}^{Best} - \min f) / \min f \times 100\%$ and $gap_{Algo}^{Avg} = (f_{Algo}^{Avg} - \min f) / \min f \times 100\%$ where $\min f = \min(f_{LA-HM}^{Best}, f_{LA-ITS}^{Best}, f_{MLNS}^{Best})$. The average value of each measurement is marked by a red dot. From the boxplot, it can be observed that LA-HM exhibits a more concentrated distribution of percentage gaps for both the best and average objective values,

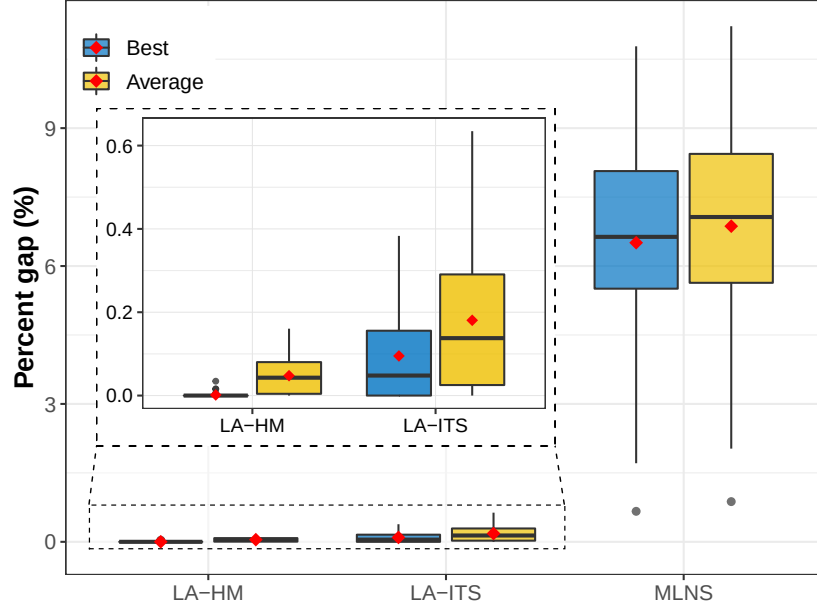


Figure OLS 1: Boxplot of percent gaps among LA-HM, LA-ITS and MLNS for best and average objective values

with lower mean and median values compared to LA-ITS and MLNS. This highlights LA-HM's superior stability across the SetB instances. In contrast, LA-ITS shows a higher mean than its median for both best and average gaps, indicating greater sensitivity to instance-specific variations. Finally, MLNS displays significantly higher percentage gaps and a wider distribution than the other two algorithms. This confirms that the LNS component alone is insufficient for finding high-quality solutions.