



Data Article

Data for a meta-analysis of the adaptive layer in adaptive large neighborhood search



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ABSTRACT

Meta-analysis, a systematic statistical examination that combines the results of several independent studies, has the potential of obtaining problem- and implementation-independent knowledge and understanding of metaheuristic algorithms, but has not yet been applied in the domain of operations research. To illustrate the procedure, we carried out a meta-analysis of the adaptive layer in adaptive large neighborhood search (ALNS). Although ALNS has been widely used to solve a broad range of problems, it has not yet been established whether or not adaptiveness actually contributes to the performance of an ALNS algorithm. A total of 134 studies were identified through Google Scholar or personal e-mail correspondence with researchers in the domain, 63 of which fit a set of predefined eligibility criteria. The results for 25 different implementations of ALNS solving a variety of problems were collected and analyzed using a random effects model. This dataset contains a detailed comparison of ALNS with the non-adaptive variant per study and per instance, together with the meta-analysis summary results. The data enable to replicate the analysis, to evaluate the algorithms using other metrics, to revisit the importance of ALNS adaptive layer if results from more studies become available, or to simply consult the ready-to-use formulas in the summary file to carry out a meta-analysis of any research question. The individual studies, the meta-analysis and its results are described and interpreted in detail in Renata Turkeš, Kenneth Sörensen, Lars Magnus Hvattum, Meta-analysis of Metaheuristics: Quantifying the Effect of Adaptiveness in Adaptive Large Neighborhood Search, in the European Journal of Operational Research.

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Specifications Table

Subject	Management Science and Operations Research
Specific subject area	Analysis of metaheuristic algorithms
Type of data	Table
How data were acquired	For each individual study included in the meta-analysis, the ALNS and its non-adaptive variant (–A)LNS were run a number of times on a number of problem instances. These results from the individual studies were pre-processed and then analyzed with a random-effects model.
Data format	Raw Filtered Analyzed
Parameters for data collection	We performed a literature review of ALNS, restricting our search to articles that: • describe the weight adjustment mechanism used in sufficient detail, • employ a weight adjustment formula which includes a parameter, that could be set to a certain value so that the adaptive layer is switched off, and • employ a roulette wheel mechanism to choose between heuristics.
Description of data collection	The results of the comparison of ALNS and (–A)LNS for [1,2] are directly obtained from the respective articles. The results from the remaining individual studies were collected via e-mail. For every individual study S_k , we calculate the added value A_k of the ALNS adaptive layer, and the within-study variance V_k , which are then analyzed with a random effects model to obtain the summary importance A of adaptiveness across all included studies.
Data source location	Institution: University of Antwerp City/Town/Region: Antwerp Country: Belgium
Data accessibility	Repository name: Mendeley Data, Turkeš, Renata (2020), "Data for a meta-analysis of the adaptive layer in Adaptive Large Neighborhood Search" Data identification number: 10.17632/h4smx32r4t.3 Direct URL to data: https://doi.org/10.17632/h4smx32r4t.3
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Value of the Data

- Detailed per-instance comparison results of ALNS with its non-adaptive variant across a number of independent studies, i.e., implementations of ALNS to solve a broad range of different problems, helps to evaluate the importance of ALNS adaptive layer.
- The data are of greatest interest for researchers interested in Adaptive Large Neighborhood Search, and in particular its adaptive layer. Furthermore, the ready-to-use sheet with random effects model formulas can benefit those interested in carrying out a meta-analysis of any research question within operations research, or any domain.
- The data enable to replicate the analysis, to evaluate the algorithms using other metrics, to study the influence of different factors on the added value of ALNS adaptive layer, to revisit its importance if results from more studies become available, or to simply consult the summary file for a meta-analysis of any research question.

1. Data Description

In adaptive large neighborhood search (ALNS), a solution is iteratively destroyed and repaired through the application of several heuristics $h \in \mathcal{H}$. In order to select the heuristic to use, a weight is assigned to each destroy heuristic $h \in \mathcal{D}$ and each repair heuristic $h \in \mathcal{R}$. First, weights are set to some initial values, which are usually equal. An adaptive weight adjustment procedure updates these weights based on the performance of each heuristic. At the end of each segment

s (a number of iterations), the weight w_h^{s+1} of the heuristic h is calculated as follows:

$$w_h^{s+1} = (1 - r)w_h^s + r \frac{\pi_h}{\theta_h}, \tag{1}$$

where π_h is the score of heuristic which reflects its performance, θ_h is the number of times heuristic h was used during the last segment, and r is the reaction factor. The reaction factor r controls how quickly the weight adjustment procedure reacts to changes in the effectiveness of the heuristic, and if $r = 0$, the weights remain unchanged.

This dataset contains a detailed comparison of ALNS and its non-adaptive variant (–A)LNS, for ALNS implementations described in [1,2,4–22]. In other words, it lists the results of comparing ALNS with the value of the reaction factor r as chosen in each of the articles, and ALNS with $r = 0$ (without adaptiveness). The results from the individual studies are then processed, and analyzed with a random effects model. The dataset is structured into two folders and a summary file:

- data_individual_studies_raw.zip
- data_individual_studies_filtered.zip
- data_analyzed.xls

The folder `data_individual_studies_raw.zip` consists of the comparison of ALNS with the non-adaptive variant per study and per instance, in the format (.xlsx,xsl.csv,ods,xml or.html) summarized by the authors of the individual studies and e-mailed to Renata Turkeš, and is only added for the purpose of completeness and transparency.

The folder `data_individual_studies_filtered.zip` consists of the comparison of ALNS with the non-adaptive variant per study and per instance, and corresponds to the raw data from `data_individual_studies_raw.zip`, but pre-processed by Renata Turkeš. Each of the files corresponding to an individual study S_k is specified in the same format, the redundant data are removed, and some further information is calculated in order to summarize the impact of the ALNS adaptive layer for each study.

More precisely, a file corresponding to study S_k starts with the information about the article title and objective function f_k , with the main information summarized in a table. The first three table columns list instance names, and the average objective function value across a number of runs of the best solution found by ALNS and its non-adaptive variant, and are obtained from `data_individual_studies_raw.zip`. These objective function values are then used to calculate the next four columns, which evaluate the improvement in the objective function value with the adaptive layer, and whether ALNS outperforms (–A)LNS or not. Finally, from this table we calculate some summary values for the considered study: average, variance and 95% confidence interval for the added value of the ALNS adaptive layer, across problem instances. The calculation of the improvement A_k in the objective function value with adaptiveness in study S_k , and the within-study variance V_k is described in great detail in the next section on the experimental design. For example, the file `grimault2017adaptive.xlsx` corresponding to the ALNS introduced in [7] is summarized in Table 1.

The folder `data_individual_studies_filtered.zip` thus consists of 21 files in.xlsx format for each of the 21 individual studies included in the meta-analysis. A few of the files for some of the individual studies consist of a number of separate sheets, corresponding to the different ALNS versions considered, or for multiple instance classes.

Finally, these results from the individual studies are used for the meta-analysis of the ALNS adaptive layer, available in the table in `data_analyzed.xls`. The summary effect A reflecting the importance of the adaptive layer is the weighted average of effects A_k of individual studies. The study weights W_k are calculated using the within-study variance V_k and the variance T^2 across studies. Table 2 lists the features that are calculated for each study, as described in detail in the next section on the experimental design.

Table 1Example of a file in `data_individual_studies_filtered.zip`, summarizing the importance of the adaptive layer for a single individual study S_k .

Article title: An adaptive large neighborhood search for the full truckload pickup and delivery problem with resource synchronization						
Minimization problem (minimization of the sum of travel costs, costs of service times and vehicle utilization costs)						
instance I	objective function value (-A)LNS with reaction factor ($r = 0$), averaged across 10 runs $\bar{f}_k(x_0(I))$	objective function value ALNS with reaction factor ($r = r_k = 0.5$), averaged across 10 runs $\bar{f}_k(x_r(I))$	improvement A in objective function value with adaptiveness, averaged across 10 runs, $\frac{\bar{f}_k(x_k(I)) - \bar{f}_k(x_0(I))}{\bar{f}_k(x_0(I))}$ (%) (minimization problem)	ALNS better than (-A)LNS	ALNS worse than (-A)LNS	ALNS equal to (-A)LNS
OS22	2786.93	2797.92	-0.39	0	1	0
OS30	4840.30	4848.06	-0.16	0	1	0
OS49	6433.89	6414.43	0.30	1	0	0
		improvement A_k in objective function value with adaptiveness (%), averaged across runs and instances	-0.08	1	2	0
		standard deviation σ_k	0.35	% better:	% worse:	% equal:
		number of instances N_k	3	33.33	66.67	0
		within-study variance $V_k = \frac{\sigma_k^2}{N_k}$	0.04			
		standard error $\frac{\sigma_k}{\sqrt{N_k}}$	0.20			
		95% confidence interval lower bound	-0.48			
		95% confidence interval upper bound	0.32			

Table 2

The columns in `data_analyzed.xls` correspond to features obtained for each study, which are then used to calculate the importance of the adaptive layer across all studies.

article, i.e., study S_k	Data obtained from <code>data_individual_studies_filtered.zip</code> .
observed effect A_k	
within-study variance $V_k = \frac{\sigma_k^2}{N_k}$	
$\frac{1}{V_k}$	Auxiliary columns to calculate variance T^2 across studies.
$\frac{1}{V_k} A_k$	
$\frac{1}{V_k} A_k^2$	
$(\frac{1}{V_k})^2$	
between study variance T^2	
weight $W_k = \frac{1}{V_k + T^2}$	
normalized weight $\frac{W_k}{\sum_j W_j}$	
weighted effect $\frac{W_k}{\sum_j W_j} A_k$	

2. Experimental Design, Materials and Methods

The summary effect A reflecting the importance of the adaptive layer is the weighted average of effects A_k of individual studies S_k , $k \in \{1, 2, 3, \dots, K\}$.

Let us assume study S_k considers a maximization problem with the objective function f_k , and let $\mathcal{I}_k = \{I_1^k, I_2^k, \dots, I_{N_k}^k\}$ denote the set of available problem instances. We run ALNS introduced in study S_k , with the value of the reaction factor r_k chosen in the individual article, to find the solution $x_{r_k}^*(I)$ for problem instance $I \in \mathcal{I}_k$. The best solution found by the non-adaptive (-A)LNS with $r = \vec{0}$ for the same problem instance is denoted with $x_0^*(I)$. Since ALNS is not a deterministic algorithm, we run both algorithms several times on each problem instance, and calculate the average objective function values across a number of runs, $\bar{f}_k(x_{r_k}^*(I))$ and $\bar{f}_k(x_0^*(I))$. The added value of adaptiveness in study S_k is calculated as the improvement in the average objective function value yielded with the adaptive layer, across the set of available instances:

$$A_k = \frac{1}{N_k} \sum_{I \in \mathcal{I}_k} \frac{\bar{f}_k(x_{r_k}^*(I)) - \bar{f}_k(x_0^*(I))}{\bar{f}_k(x_0^*(I))}. \tag{2}$$

If we are considering a minimization problem, the average improvement in the objective function for study S_k is calculated as

$$A_k = -\frac{1}{N_k} \sum_{I \in \mathcal{I}_k} \frac{\bar{f}_k(x_{r_k}^*(I)) - \bar{f}_k(x_0^*(I))}{\bar{f}_k(x_0^*(I))}. \tag{3}$$

The weight W_k of study S_k is calculated as inverse variance. In a random effects model, variance is calculated as the sum of within-study variance and variance across studies. The within-study variance is estimated with the squared standard error:

$$V_k = \frac{\sigma_k^2}{N_k},$$

(σ_k is the standard deviation, and N_k is the number of problem instances in study S_k). It makes sense to weigh studies with the inverse variance: we assign more weight to the studies which include a greater number of instances, and for which the dispersion of the effect size across instances is small.

The between-study variance is estimated using the DerSimonian and Laird method:

$$T^2 = \frac{Q - df}{C},$$

where:

- Q is a sum of squares of the effect size estimates about their mean, weighted by the inverse of variance V_k ,

$$Q = \sum_k \frac{1}{V_k} \left(A_k - \frac{1}{\sum_j \frac{1}{V_j}} \sum_j \frac{1}{V_j} A_j \right)^2 = \sum_k \frac{1}{V_k} A_k^2 - \frac{1}{\sum_k \frac{1}{V_k}} \left(\sum_k \frac{1}{V_k} A_k \right)^2,$$

- df degrees of freedom, $df = K - 1$, where K is the number of studies included in the meta-analysis,
- C is simply a factor which puts the standardized variation between studies $Q - df$ back into the same metric that had been used to report the within-study variance,

$$C = \sum_k \frac{1}{V_k} - \frac{1}{\sum_k \frac{1}{V_k}} \sum_k \frac{1}{V_k^2}.$$

If T^2 is less than zero, it is set to zero, since variance cannot be negative.

The total variance under the random effects model is therefore $V_k + T^2$, so that the weight of study S_k is calculated as:

$$W_k = \frac{1}{V_k + T^2}.$$

In the remainder of this section, we illustrate the experimental design (i.e., all the calculations carried out in `data_individual_studies_filtered.zip` and `data_analyzed.xls`) with a small example of a meta-analysis with only two studies, with two and three considered problem instances, and two runs of the algorithms for each instance, summarized in Table 3. The information in the highlighted upper-left rectangle corresponds to data collected from a single study S_k : the objective function value of the best solution found by ALNS and the non-adaptive variant (–A)LNS, for a number of problem instances and algorithmic runs. This information is used to estimate the mean importance A_k of the adaptive layer, i.e., the average improvement of ALNS upon the non-adaptive algorithm, for a study S_k .

The weights W_k of the studies are then calculated as the sum of within-study variance V_k (square of standard error, which incorporates both the standard deviation σ_k across problem instances within a study, and a number of instances N_k) and between-study variance T^2 (estimated with poor precision when the number studies is very small). The summary effect A in this example is weighted more strongly towards A_1 than A_2 , since the weight of the study S_2 is very small: indeed, the adaptive layer improves the algorithmic performance by 0.64% for one instance, 5.71% for another instances, but by –0.33% for the last instance, and we are therefore less confident about the true effect of adaptiveness in this study (i.e., the standard deviation is large, and hence the weight is small, indicating that the estimate A_2 is less precise).

The summary effect A reflecting the importance of the adaptive layer for the two small studies S_1 and S_2 is the weighted average of effects A_1 and A_2 :

$$A = \frac{W_1}{W_1 + W_2} \times A_1 + \frac{W_2}{W_1 + W_2} \times A_2 = \frac{7.93}{7.93 + 0.28} \times 1.00\% + \frac{0.28}{7.93 + 0.28} \times 1.97\% = 1.03\%.$$

Author contributions

Renata Turkeš carried out the literature review, identified and selected the studies, communicated with the authors of eligible studies via e-mail, collected and pre-processed the raw data into `data_individual_studies_filtered.zip`, and wrote the manuscript. These results from individual studies were then analyzed by Renata Turkeš, Kenneth Sörensen and Lars Magnus Hvattum, and summarized in `data_analyzed.zip`. Eva Barrera, Hayet Chentli, Leandro Coelho, Iman Dayarian, Axel Grimault, Anders Gullhav, Çağatay Iris, Merve Keskin, Alexander Kiefer, Richard Lusby, Geraldo Mauri, Marcela Monroy-Licht, Sophie N. Parragh, Juan-Pablo Riquelme-Rodríguez, Alberto Santini, Vinicius Gandra Martins Santos and Charles Thomas carried out the experiments which compare an ALNS previously introduced in an individual study, with its non-adaptive variant, collected in `data_individual_studies_raw.zip`.

Table 3

A toy example of a step-by-step meta-analysis with two included studies.

Study S_k	Instance $I \in \mathcal{I}_k$	Run	$f_k(x_0^*(I))$	$f_k(x_{I_k}^*(I))$	$\bar{f}_k(x_0^*(I))$	$\tilde{f}_k(x_{I_k}^*(I))$	$\frac{\tilde{f}_k(x_{I_k}^*(I)) - \bar{f}_k(x_0^*(I))}{\bar{f}_k(x_0^*(I))}$ (%)	Effect A_k (%)	Standard deviation σ_k	Number of instances N_k	Within-study variance $V_k = \frac{\sigma_k^2}{N_k}$	Between-study variance T^2	Weight $W_k = \frac{1}{V_k + T^2}$
S_1	I_1^1	1	856.0	863.0	855.00	866.50	1.35		0.50	2	0.13	0	
		2	854.0	870.0									
	I_2^1	1	40.0	39.0	39.00	39.25	0.64						
		2	38.0	39.5				1.00					
S_2	I_1^2	1	1200.0	1208.0	1200.00	1206.5	0.64		3.26	3	3.55		
		2	1200.0	1205.0									
	I_2^2	1	10.0	10.5	10.5	11.1	5.71						
		2	11.0	11.7									
	I_3^2	1	301.0	299.0	300.5	299.5	-0.33						
		2	300.0	300.0				1.97					

Table A1

Important notation and acronyms.

	Acronyms
ALNS	adaptive large neighborhood search
(-A)LNS	ALNS without the adaptive layer
Notation	
\mathcal{H}	set of (destroy or repair) heuristics
\mathcal{D}	set of destroy heuristics
\mathcal{R}	set of repair heuristics
h	(destroy or repair) heuristic
s	segment, a number of consecutive iterations
π_h	total score of heuristic h at the end of the current segment
θ_h^s	number of times heuristic h has been called during the current segment
r	reaction factor, which controls the importance of heuristic performance in the last segment
w_h^s	weight of heuristic h updated after segment s (calculated as $(1-r)w_h^{s-1} + r\pi_h/\theta_h$)
K	number of studies in the meta-analysis
S_k	study S_k (an individual study in the meta-analysis)
f_k	objective function in study S_k
$\bar{f}_k(\cdot)$	average objective function value in study S_k across a number of runs
x_{rk}^*	best solution found by ALNS from study S_k , with reaction factor r_k
x_0^*	best solution found by non-adaptive (-A)LNS, with $r = 0$
I_i^k	instance I_i in study S_k
A_k	improvement with the adaptive layer in study S_k , averaged across instances and runs
N_k	number of instances in study S_k
σ_k	standard deviation in study S_k
V_k	variance within study S_k (calculated as σ_k^2/N_k)
T^2	variance across studies
W_k	weight of study S_k (calculated as inverse total variance $1/(V_k + T^2)$)
A	improvement with the adaptive layer, weighted across studies

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships which have, or could be perceived to have, influenced the work reported in this article.

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Appendix A

Table A.4 summarizes the notation.

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