Comparative Analysis of Metaheuristics Techniques for Trade Data Harmonization

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Abstract: The harmonization of trade data from two datasets containing different and distinct categories poses a challenging real-world problem. To address this issue, we model it as an optimization problem and investigate the effectiveness of various metaheuristic techniques in achieving optimal or near-optimal solutions. Particularly, we analyze the performance of Genetic Algorithm (GA), Population-based Incremental Learning (PBIL), DEUM, and Simulated Annealing (SA) in terms of best fitness, scalability, and their respective strengths and weaknesses. We explore multiple instances of the trade data harmonisation problem of different sizes to assess the applicability of these techniques in mitigating trade volume disparities. By examining the outcomes, our research offers valuable insights into the suitability of metaheuristic techniques for this problem.

1 INTRODUCTION

International trade is pivotal for global economies, fostering growth, job creation, and diverse consumer choices (Lewrick et al., 2018) (Lewer and Berg, 2003). Trade relationships enable specialization, allowing countries to harness their strengths and allocate resources efficiently. International trade positively correlates with GDP growth and higher productivity (Lewrick et al., 2018) (Lewer and Berg, 2003). Trade liberalization and barrier removal, like tariffs and quotas, boost global trade (FULLER and SGRO, 1998). Yet, international trade dynamics are complex, shaped by political ties, economic policies, technology, and market demand. Understanding these intricacies is crucial for informed decisions by policymakers and businesses (WTO,).

Beyond economics, international trade secures vital strategic commodities for countries (HAMMOUDEH et al., 2009). Such resources, including energy, minerals, metals, and agriculture products, drive trade as nations aim to ensure growth, industrialization, and security (Harding and Harding, 2020). This competition motivates partnerships, favorable agreements, and infrastructure investments. By trading, countries diversify resource sources, bolstering reliability (Bernhofen, 2001).

Stability of strategic commodities influences policymaker decisions (Hansen and Prusa, 1997). Challenges arise from inconsistent trade data collected from different sources (Feenstra et al., 1999) (Ferrantino et al., 2012). Data harmonization addresses this, enhancing reliability (Torres-Espín and Ferguson, 2022). We model trade data harmonization as a subset sum problem (Martello and Toth, 1990) (Hartmanis, 1982), aiming to identify subsets that match another dataset. Leveraging metaheuristics like Genetic Algorithm (GA) (DE, 1989), Population-based Incremental Learning (PBIL) (Baluja, 1994), Distribution Estimation using MRF (DEUM) (Shakya and McCall, 2007), and Simulated Annealing (SA) (Kirkpatrick et al., 1983), we explore solutions for policy insights. Our goal is to reconstruct trade categories that compose the target at various scales. Formally it translates into finding a subset of numbers that matches the exact target sum or is the closest to it, as depicted in Fig. 1 showing traded rice volumes.

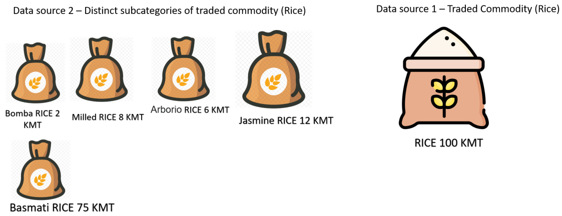

Figure 1: Trade vol. differences for a sample prod. category.

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The rest of the paper is structured as follows, Section 2 addresses the problem of trade data harmonization through a combinatorial optimization approach. It utilizes metaheuristic techniques, including GA, PBIL, DEUM, and SA, to optimize the process. Section 3 is dedicated to the experimental evaluation of the metaheuristic techniques. Section 4 summarizes the paper with brief concluding remarks.

2 MODELLING AND METHODOLOGY

Let $Product_1$ be a traded commodity present in dataset S1. Let P_{subc} be the set of subcategories present in another dataset S2 associated with $Product_1$. Such that,

$$P_{subc} = \{p_1, p_2, ...p_i\} \tag{1}$$

where $p_i \in P_{subc}$ is a subcategory of $Product_1$.

In this section, our primary goal is to model the trade data of commodities, such as $Product_1$ in S1, for a particular country, C_1, thus to achieve Trade Data Harmonization. This entails aligning the data with the goal of identifying relevant set of subcategories that accurately represent the traded volumes of any $Product_1$. This can be expressed mathematically as follows:

$$\exists \mathbb{P}_{subc} \subset P_{subc} : T_v(Product_1) = \sum_{\forall p_i \in \mathbb{P}_{subc}} T_v(p_i) \tag{2}$$

where T_v is the traded volume, and $\mathbb{P}_{subc} \subset P_{subc}$ and $p_i \in \mathbb{P}_{subc}$.

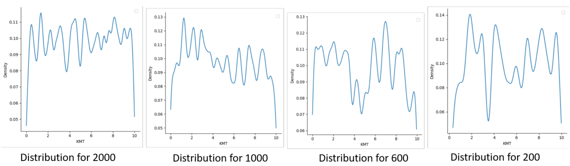


Figure 2: Distribution of data for sizes: 2k, 1k, 600 and 200.

2.1 Modelling

To conduct a thorough evaluation of the metaheuristic techniques, we consider four products within the dataset S1 that have comparable traded volumes. In addition, we increase the number of relevant subcategories in S2 associated with each of the products from S1 by a factor of $\sim$ ten. This deliberate expansion of the dataset allows us to demonstrate the suitability and relevance of the combinatorial optimization problem at hand. The resulting ten-fold increase in subcategories determines the problem size for the meta heuristic techniques. Mathematically:

$$N \approx 10 \cdot |P_{subc}| : \hat{P_{subc}} = \{p_1, p_2, ...p_N\} \tag{3}$$

where P_{subc} denote the set of subcategories associated with any $Product_i$ among the four selected products from dataset S1 and $\hat{P_{subc}}$ represent the set of newly simulated subcategories associated with $Product_i$.

To generate representative data for the problem size (N) related to any $Product_i$, we assigned random values between 0 and 10 (inclusive) representing trade volumes in Kilo Metric Tonne (KMT) for subcategories $p_i \in \hat{P_{subc}}$ associated with $Product_i$. This reflects the observed range of trade volumes for a typical month. That is:

$$p_i \in \hat{P_{subc}}; T_v(p_i) \in \mathbb{R}[0, 10] \tag{4}$$

where $\mathbb{R}[0, 10]$ represents the set of real numbers between 0 and 10, inclusive.

The initial range of subcategories observed for $Product_1$, $Product_2$, $Product_3$, and $Product_4$ in dataset S1 were 19, 54, 92, and 192, respectively. After scaling up by a factor of $\sim$ ten, the problem sizes for the metaheuristic techniques were adjusted to 200, 600, 1000, and 2000 subcategories, respectively. Figure 2 illustrates the distribution of the generated data as KDE (Kernel Density Estimation)

2.2 Fitness Evaluation

We utilize a fitness evaluation as a metric to assess the quality of identified subcategories, aiming to effectively harmonize the data and gain meaningful insights into the trade patterns of specific commodities.

Mathematically, let $X = \{x_1, x_2, x_3, ..., x_n\}$, where $n = N = |\hat{P_{subc}}|$ can take values of 200, 600, 1000, or 2000, $\hat{P_{subc}}$ is the set of associated subcategories of a product $Product_i$ among the four selected products from dataset S1, and $x_e \in X$ where x_e can take value of either 0 or 1. Then the fitness evaluation involves minimizing the cost $f(X)$ as:

$$\min_{X=\{x_1,x_2,x_3,...,x_n\}} f(X) = |target_i - \sum_{e,i=1}^{n} x_e.T_v(p_i)| \tag{5}$$

where $p_i \in \hat{P_{subc}}$. For the purpose of this paper, the value of the $target_i$ associated with $Product_i$ is calculated using the formula:

$$target_i = \frac{\sum_{i=1}^{n} T_v(p_i)}{k} \tag{6}$$

where $p_i \in \hat{P_{subc}}$ and $k \in \{2, 4, 8, 16, 32\}$.

We thus generated a series of realistic targets that align with the actual traded values for a commodity from S1. This approach not only ensures compatibility with the real trade data but also increases the complexity of the problem, making it more challenging to solve.

To enhance the evaluation process, two additional featured targets were incorporated, considering the uncertainty surrounding the generated targets and the absence of a guaranteed actual solution. These supplementary targets were selected based on their physical existence within the subset, enabling a comparison between the solutions generated by the meta-heuristic techniques and the actual solution within the dataset. The two additional targets are as follows:

- The subcategory with minimum traded volume within the subset, denoted as: $\min_{p_i \in P_{\hat{subc}}} T_v(p_i)$. This minimum value is unique in the dataset.
- The sum of the subcategories with the lowest traded volume belonging to subset $P_{\hat{subc}}$, obtained by considering the first 30% of the subcategories when sorted in ascending order on the traded volume.
  $\sum_{j=1}^{\lceil 0.3 \cdot |P_{\hat{subc}}| \rceil} \text{sorted}(P_{\hat{subc}})[j]$.

Where, $\lceil 0.3 \cdot |P_{\hat{subc}}| \rceil$ denotes the ceiling of 0.3 multiplied by the total number of elements in $P_{\hat{subc}}$. The function $\text{sorted}(P_{\hat{subc}})$ arranges the subcategories of the subset in ascending order of the traded volume.

2.3 Methodologies

We consider four different binary meta heuristic techniques for our comparative analysis, aiming to find the optimal or near-optimal solution for the Trade Data Harmonization problem. The length ‘n’ of the bit string representation of the solution for these binary metaheuristic techniques corresponds to problem sizes of 200, 600, 1000, and 2000, introducing varying levels of complexity and data volume. For instance, consider a scenario where a traded commodity from one data source is associated with seven subcategories (P1, P2, P3, P4, P5, P6, P7) from another data source. To select the desired subcategories P2 and P6 the binary solution generated by any meta-heuristic technique should resemble the representation shown in Figure 3.

P1	P2	P3	P4	P5	P6	P7
0	1	0	0	0	1	0

Figure 3: Illustration of Binary Representation of Solution.

Below, we provide brief description of each algorithm and its functionality.

The **Genetic Algorithm (GA)** optimizes potential solutions in a **population (pop)** through generations (**g**), employing crossover (**cOper**) and mutation (**mOper**) operators with probabilities (**cp** and **mp**). A **selection operator (sOper)** determines parent selection, letting GA explore the solution space and converge (DE, 1989).

Population-based incremental learning (PBIL) uses a probability distribution vector guided by **learning rate (λ)**, updating probabilities for elite solutions with **selection size (ss)**. It focuses on promising regions and prevents premature convergence, without considering variable interactions (Baluja, 1994).

DEUM (Distribution Estimation using MRF) estimates distribution through a Markov Random Field model (Shakya and McCall, 2007; Shakya et al., 2021). It selects top solutions based on **selection size**, creates equations for feature-fitness relationships, and uses an elitism strategy with **temperature coefficient (β)** for solution generation (Shakya and McCall, 2007; Shakya et al., 2021).

Simulated Annealing (SA) uses **temperature (τ)** to control search. Exploration turns selective with decreasing temperature. Cooling schedule balances exploration and exploitation (Kirkpatrick et al., 1983).

These algorithms offer different approaches to solving optimization problems, allowing for a comprehensive analysis of their performance in trade data harmonization.

2.4 Parameter Tuning

The parameter settings for GA, PBIL, DEUM, and SA in section 2.3 are chosen based on empirical analysis. Through extensive testing, the settings that yield near-optimal solutions are selected. These settings ensure that the average fitness of the population converges towards the best fitness, aligning with the target. This iterative process enables effective exploration of the solution space and progressive improvement of solution quality.

To achieve a final fitness of 10^{-6} or lower in at least one run (using equation 5), a focused effort is made to determine the optimal parameter settings for the techniques. This choice is justified in the context of trade volume in Kilo Metric Tonne (KMT). Each KMT represents 1000000 kg, and aiming for a fitness threshold of 10^{-6} aligns well with this precision level. It allows capturing subtle variations and nuances in the trade data, generating high-quality solutions that align with observed trade patterns. This precision level is crucial for informed decision-making and gaining valuable insights from the trade data, specifically in KMT units.

Table 1: Average Fitness and Standard Deviation from 15 runs - Realistic and Featured Targets (Highlighted Best Results).

SolLength	Algorithm	AVG ± SD k = 2	k = 4	k = 8	k =16	k =32	MIN	SUM_30_MIN
2000	GA	247.503 ± 302.577	190.745 ± 156.328	301.934 ± 280.071	304.582 ± 223	425.028 ± 349.095	0 ± 0	762.799 ± 845.525
	PBIL	549.865 ± 559.106	288.832 ± 355.716	270.04 ± 215.58	260.752 ± 324.334	**100.661 ± 80.754**	0 ± 0	252.921 ± 535.711
	DEUM	308.961 ± 330.477	272.149 ± 246.348	289.788 ± 261.37	911.875 ± 864.014	2101.574 ± 2394.943	0 ± 0	4476.757 ± 6768.286
	SA	**51.174 ± 42.241**	**106.707 ± 103.08**	**77.842 ± 58.548**	**79.278 ± 59.251**	116.625 ± 84.181	0 ± 0	**69.287 ± 65.339**
1000	GA	176.029 ± 152.513	185.178 ± 150.032	223.631 ± 173.918	285.453 ± 252.296	148.378 ± 145.338	0 ± 0	585.429 ± 657.632
	PBIL	129.629 ± 114.304	182.001 ± 182.649	172.319 ± 168.927	117.473 ± 104.579	121.545 ± 130.16	0 ± 0	179.282 ± 183.762
	DEUM	230.691 ± 163.507	531.331 ± 493.312	283.416 ± 338.082	336.497 ± 220.191	478.441 ± 387.516	0 ± 0	2901.839 ± 3267.291
	SA	**74.704 ± 36.943**	**56.512 ± 45.239**	**68.768 ± 55.052**	**63.661 ± 48.145**	**70.089 ± 87.497**	0 ± 0	**28.627 ± 22.527**
600	GA	149.838 ± 125.104	128.48 ± 104.796	87.198 ± 56.515	123.41 ± 124.291	136.593 ± 120.313	0 ± 0	520.315 ± 521.901
	PBIL	251.287 ± 199.581	245.762 ± 241.397	182.451 ± 178.345	165.272 ± 216.713	129.974 ± 84.304	0 ± 0	97.595 ± 89.376
	DEUM	265.162 ± 379.643	344.44 ± 454.093	284.993 ± 273.882	432.953 ± 709.581	443.619 ± 378.509	0 ± 0	2758.422 ± 2222.289
	SA	**40.16 ± 33.452**	**42.44 ± 28.299**	**61.179 ± 58.963**	**54.903 ± 58.029**	**40.411 ± 39.868**	0 ± 0	**27.11 ± 21.032**
200	GA	202.75 ± 135.094	237.11 ± 180.716	247.043 ± 160.83	145.538 ± 81.012	93.952 ± 48.443	0 ± 0	468.891 ± 715.54
	PBIL	221.472 ± 174.968	132.928 ± 115.464	186.006 ± 131.933	138.469 ± 102.778	126.516 ± 106.601	0 ± 0	**61.405 ± 47.872**
	DEUM	135.027 ± 145.172	163.385 ± 145.829	76.096 ± 134.074	210.697 ± 170.13	279.187 ± 190.763	0 ± 0	203.969 ± 270.355
	SA	**80.07 ± 101.947**	**40.554 ± 46.987**	**45.744 ± 42.094**	**104.517 ± 174.255**	**58.993 ± 93.325**	0 ± 0	73.204 ± 32.808

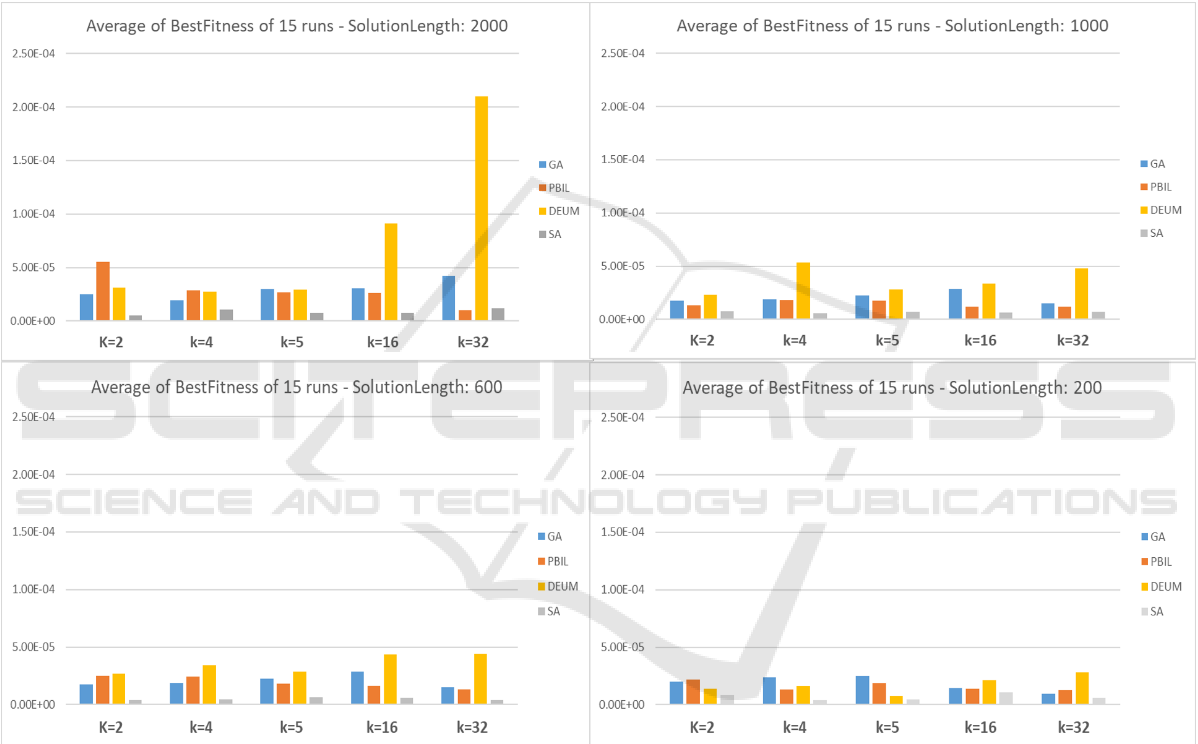


Figure 4: Analysis of result : Average Fitness for all the realistic targets.

3 EXPERIMENTS AND THE RESULTS

This section provides a detailed explanation of the experimental setup and presents the analysis of the obtained results.

3.1 Experiment Setup

Experiments were conducted on a workstation equipped with an 11th Gen Intel(R) Core(TM) i7-11800H @ 2.30GHz processor and 32 GB of RAM.

The datasets used in the experiments were obtained from Section 2.1 and consisted of four products with possible subcategories of 200, 600, 1000, and 2000. Seven targets were selected, as described in Section 2.2, including the five realistic targets derived from equation 6 with corresponding k values of 2, 4, 8, 16, and 32. Additionally, two featured targets, namely "MIN" (representing the minimum value within the subset) and "SUM_30_MIN" (representing the sum of the lowest 30% of elements sorted in ascending order), were included due to their practical significance within the dataset. For each product-target combination, each algorithm (GA, PBIL, DEUM, SA) was executed 15 times, resulting in a comprehensive set of experiments covering various solution lengths and targets. The performance of each algorithm was evaluated based on fitness values (lower fitness indicates better performance), as discussed in Section 2.2.

Parameter tuning experiments were conducted for GA, PBIL, DEUM, and SA to achieve a fitness value of 10^{-6} for different solution lengths and targets. GA, PBIL, and DEUM used population sizes of 400 and 4000 generations, with adjustments for smaller lengths. SA had specific generation counts based on the population and generation values of the other algorithms. The number of elite solutions was set to 2 for GA, PBIL, and DEUM. GA was evaluated using various selection operators (tournament, roulette wheel, truncation0.5, truncation0.3) and crossover operators ("simple one point", uniform with bit swapping probabilities of 0.5 (uniform0.5), 0.1 (uniform0.1), and 0.2 (uniform0.2)), accompanied by the mutation operator of one-bit flip mutation (Bäck et al., 1997).

Crossover operators in the GA experiment were selected based on target values: "uniform0.1" for k = 2 and 4, "uniform0.2" for k = 8, and "uniform0.5" for other combinations. The consistent mutation operator was "one bit mutation" with a fixed crossover probability of 0.7. Among the parameters, mutation probability had the most significant impact. For PBIL, the selection size ranged from 0.20 to 0.55 of the population size, and the learning rate ranged from 0.09 to 0.40. Empirical observations for the current problem indicated that higher selection size with a smaller learning rate yielded better results for PBIL. DEUM had a temperature coefficient of 0.05 to 0.5 and a selection size of 0.04 to 0.07. Empirically, for both PBIL and DEUM in the current problem, larger solution lengths demanded higher selection size. Simulated Annealing had a temperature coefficient ranging from 0.000002 to 0.000005 for various solution lengths and targets. For simulated annealing, the probability of accepting the new solution is calculated using the Metropolis-Hastings algorithm (Hitchcock, 2003).

3.2 Results and Analysis

Table 1 presents the average best fitness values (AVG) obtained from 15 independent runs of each algorithm, solution length, and target. The values are scaled by 10^7 for readability. Standard deviations (SD) indicate result variability. The analysis is divided into three subsections. The first evaluates algorithm performance across solution lengths for realistic targets. The second compares results for two featured targets. The third approximates the number of evaluations needed for a typical run, considering both realistic and featured targets.

3.2.1 Realistic Targets

Here, we analyse the results of table 1 related to the realistic targets. In figure 4 the trends in average best fitness values for realistic targets are examined. Simulated Annealing (SA) consistently outperforms other algorithms for all solution lengths and targets, except for a solution length of 2000 and $k = 32$ where PBIL outperforms SA. SA consistently achieves the lowest average best fitness values with lower standard deviations, indicating its effectiveness. Figure 5 shows the spread of average fitness values and standard deviations across all the realistic targets. SA is the most likely algorithm for superior fitness across solution lengths and realistic targets, followed by PBIL and GA, while DEUM is less likely to yield better results.

3.2.2 Featured Targets

We now analyse the results of table 1 related to the featured targets. Table 1 demonstrates that all algorithms achieved the exact solution for the "MIN" featured target at all solution lengths. However, for the "SUM_30_MIN" target, table 1 reveals that SA consistently outperforms the other algorithms (except for solution length of 200 when PBIL performed better), while DEUM performs the worst (except for a solution length of 200, where GA performs the worst).

The representation of the solution as binary BITs was earlier explained in section 2.3 using figure 3. Since the featured targets are already part of the dataset, we evaluated the ratio of differing bits in the solution generated by the best run for each algorithm and solution length compared to the actual solution. This ratio reflects the proportion of differing bits relative to the length of the solution.

For the "MIN" target since all the algorithms found the exact solution, the number of differing bits was zero. For "SUM_30_MIN", figure 6 explores the correlation between fitness value and the ratio of differing bits across solution lengths from the best run for each algorithm. The plot reveals that a higher ratio of bit difference corresponds to a greater deviation of fitness value from the actual solution, consistently observed across all algorithms.

3.2.3 Efficiency Analytics

Lastly, we compare the number of evaluations required to find optimal or near optimal solutions for

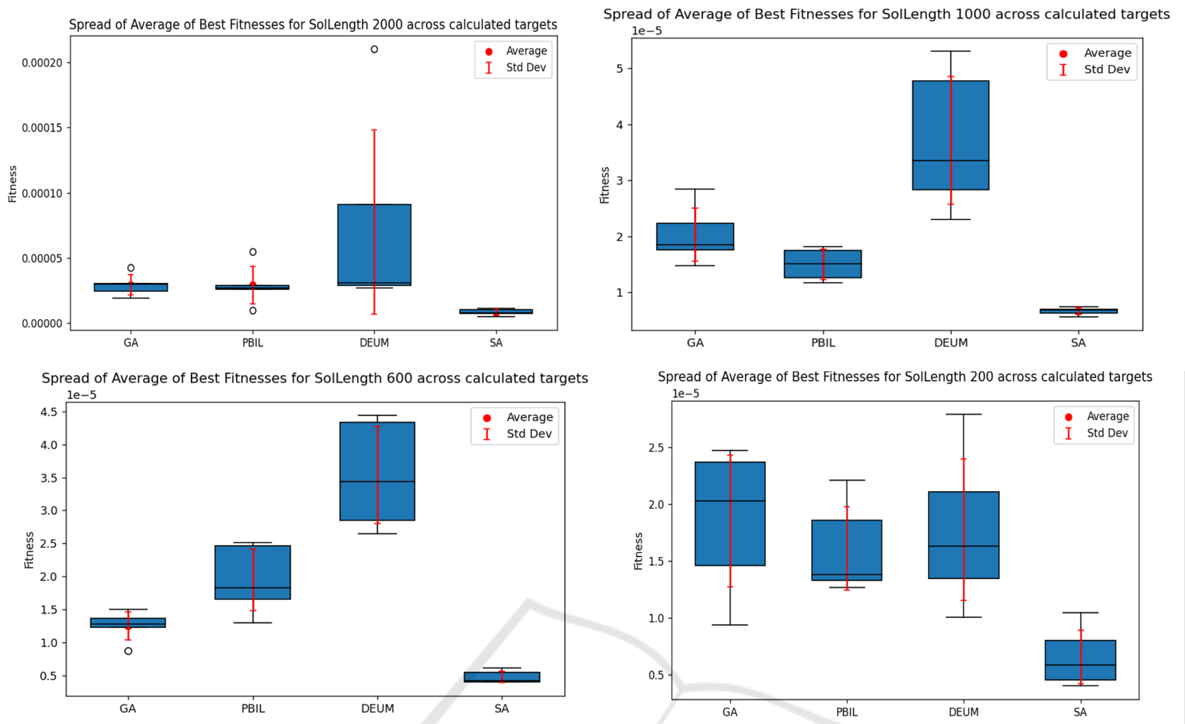


Figure 5: Analysis of result : Spread of average fitness across all realistic targets (k).

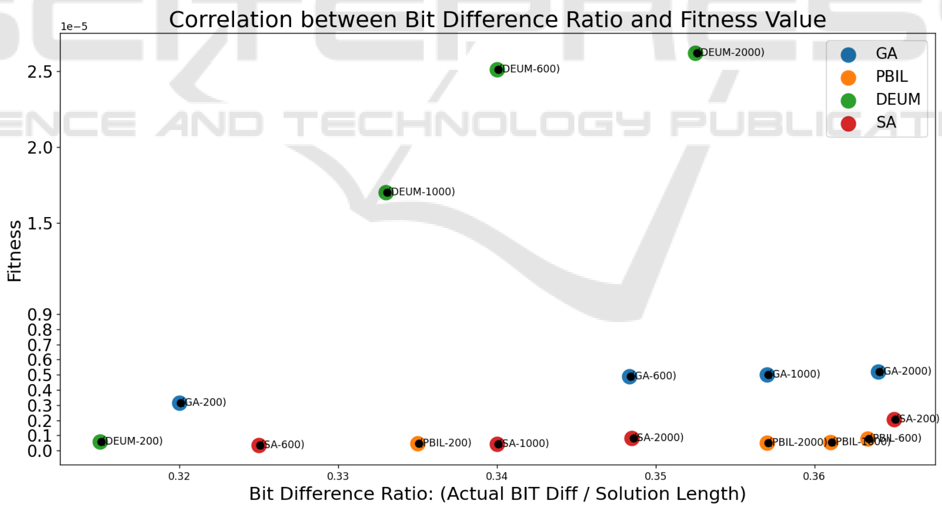
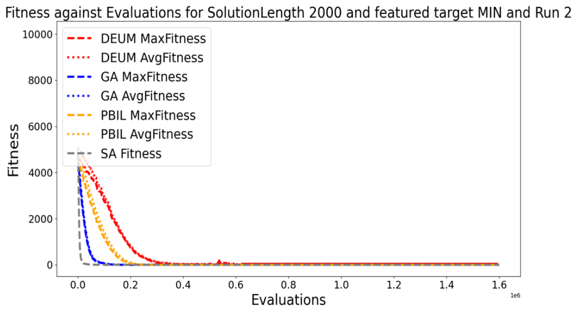


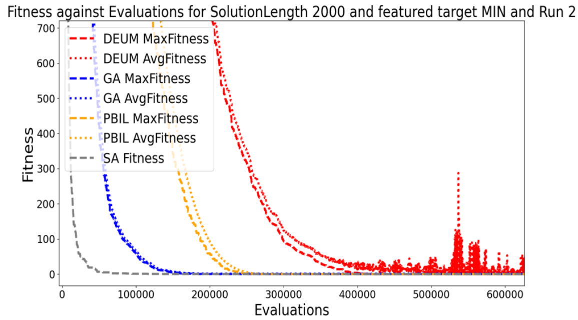
Figure 6: Analysis of result : Correlation of BIT difference ratio and Fitness value for target "SUM_30_MIN".

each algorithms. Figure 7 illustrates the evolutionary process and improvement of GA, PBIL, DEUM, and SA for a solution length of 2000, specifically focusing on the "MIN" target. Across multiple runs, all algorithms consistently achieved the exact solution with a fitness value of 0 for the "MIN" target. The analysis emphasizes run number 2 for fair comparison. Detailed zoom at different scale of fitness range in figure 7 depict the algorithms' progression, with the best fitness values converging towards 0 for the "MIN" target. SA achieves a fitness of 0 at around 150,000 evaluations, followed by GA at 175,000, PBIL at 260,000, and DEUM at approximately 440,000 evaluations.

Figure 8 examines the realistic target with k=4. In zoom level 1, figure 8(b), GA, DEUM, and PBIL demonstrate average fitness ranging from 40 to 20. Zoom level 2, figure 8(c) displays the best fitness values and their corresponding evaluation counts. SA

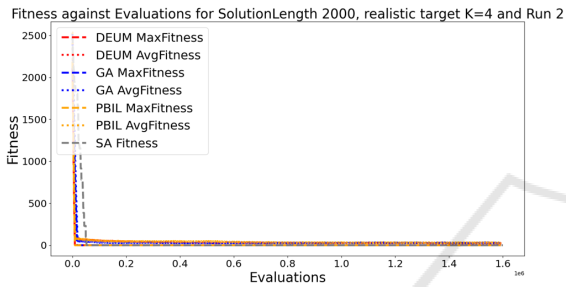


(a) Zoom 0

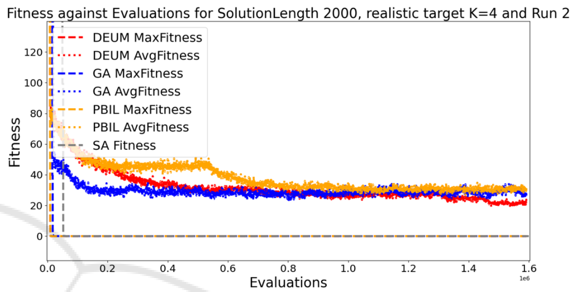


(b) Zoom 1 at fitness level 10^2

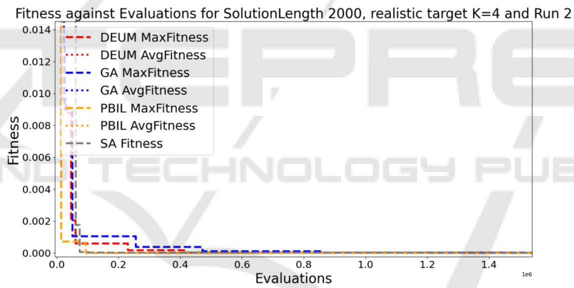
Figure 7: Evolution for solution length of 2000 for featured target "MIN".



(a) Zoom 0



(b) Zoom 1 at fitness level 10^1



(c) Zoom 2 at fitness level 10^{-3}

Figure 8: Evolution for solution length of 2000 for realistic target with k=4.

achieves the best fitness at around 100,000 evaluations for the realistic target, followed by PBIL, DEUM, and GA. These insights offer valuable information about algorithm performance and the evaluation range required for optimal fitness in different target scenarios.

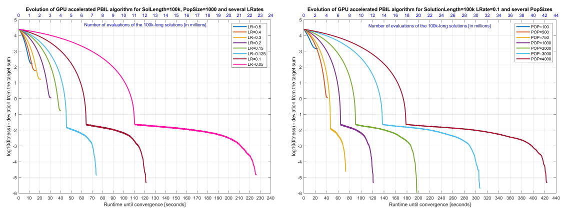
3.3 Deep Scalability Extensions

Deep scalability improvements beyond 100k components are possible with population-wide vectorization of critical operations combined with GPU deployment.

As an example we have adapted PBIL to sample from probability vector directly on the GPU using Philox 4x32 random number generator with all the subsequent algorithm operations vectorized on matrices and executed on the GPU.

Such optimized PBIL achieved 10k-times processing speedup (10sol/sec) tested on 100k and 1m-components problems with a similar accuracy.

Figure 9 illustrates discovered sensitivity of the final fitness and processing load to the learning rate and population size. The best sub 1e-5 fitness achieved after 2-3 minutes was observed for learning rate around 0.1 and population size of 1-2k, but more research is needed to study the parametric sensitivities and interesting performance profiles for very long solutions.



(a) Learning rates impact (b) Population size impact

Figure 9: Performance and processing pace of GPU accelerated PBIL for various learning rates and population sizes.

4 CONCLUSION

This paper presents a comparative analysis of four binary metaheuristic techniques in the context of trade data harmonization. The objective of this research was to assess the effectiveness of these techniques in achieving optimal or near-optimal solutions when reconciling disparate datasets.

To model the trade data harmonization problem, we adopt a subset sum approach, which involves identifying subcategories from a detailed dataset that correspond to specific categories in another dataset. Through an extensive experimental evaluation, we compare the performance of these techniques. Our findings indicate that Simulated Annealing (SA) shows great promise in consistently obtaining near-optimal solutions, even with empirically selected parameter settings and fewer evaluations compared to PBIL, DEUM, and GA.

In conclusion, our study provides valuable insights into the applicability of metaheuristic techniques for trade data harmonization. Additionally, our findings highlight the potential of GPU-accelerated computations, exemplified by the Deep Scalability Extension, which enables the harmonization of trade data on a larger scale. Future research can focus on enhancing existing techniques, exploring alternative approaches, and conducting real-world case studies to comprehensively address the challenges of trade data harmonization.

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