ETO Meets Scheduling: Learning Key Knowledge from Single-Objective Problems to Multi-Objective Problem

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Abstract—Evolutionary transfer optimization (ETO) serves as “a new frontier in evolutionary computation research”, which will avoid zero reuse of experience and knowledge from solved problems in traditional evolutionary computation. In schedule-ing applications via ETO, a highly competitive “meeting” framework between them could be constituted towards both intelligent scheduling and green scheduling, especially for carbon neutrality within the context of China.

To the best of our knowledge, our study on scheduling here, is the 1st work of ETO for complex optimization when multi-objective problem “meets” single-objective problems in combinatorial case (not multitasking optimization). More specifically, key knowledge like positional building blocks clustered, could be learned and transferred for permutation flow shop scheduling problem (PFSP). Empirical studies on well-studied benchmarks validate relatively firm effectiveness and great potential of our proposed ETO-PFSP framework.

Keywords—evolutionary transfer optimization, green scheduling, transfer learning, data analytics, system optimization, carbon neutrality

I. INTRODUCTION

A. Evolutionary transfer optimization (ETO) meets scheduling

Relation is ubiquitous, whereas, isolation is seldom, which is the philosophy for evolutionary transfer optimization (ETO), “a paradigm that integrates EA solvers with knowledge learning and transfer across related domains to achieve better optimization efficiency and performance”[3]. ETO, has emerged as a new frontier in evolutionary computation, which has connections with transfer learning[5], deep learning[4][15] and evolutionary algorithms.

In manufacturing and service industries, scheduling is a decision-making process that allocates resources to tasks in given periods to optimize one or more management objectives.

We hope to explore the relatively rare studied and new solution framework of ETO meeting scheduling, especially in production management[2] or system engineering towards intelligent scheduling[2] [16] and green scheduling[2].

B. ETO meets scheduling for complex optimization: from single-objective problems to multi-objective problem

According to types of problems solved, ETO can be categorized as follows in existing studies[3]: (1) ETO for Optimization in Uncertain Environment, (2) ETO for Multi-Task Optimization (MTO), (3) ETO for Multi-/Many-Objective Optimization, (4) ETO for Machine Learning Applications, (5) ETO for Complex Optimization.

When ETO meets scheduling, particularly, for complex optimization, we can narrow the setting of the problem pair as a scenario from single-objective problems to multi-objective problem[10].

Because single-objective problems (SOPs) are simpler and related problems for transferring knowledge into its corresponding multi-objective problem (MOP), which will greatly reduce computational complexity of scheduling, like permutation flow shop scheduling (PFSP), that often is a NP-hard problem.

C. Learning/Transferring specific key knowledge: building blocks between PFSPs

In this paper, we will focus on genetic algorithm (GA) based memetic algorithm (MA), Building block (BB) is the main object/role that is implicitly or explicitly manipulated for the success of GAs and MAs[7] [8]. The exploitation of BB, especially the tight one, is considered as the “holy grain to GA optimization”[8]. (From now on, “BB” and “block” are exchangeable in the paper.)

The definition of BBs or genetic linkage is tightly intertwined with crossover operator in [10] for both biological systems and GAs.

![Fig. 1. A example of building blocks in PFSP][9]

The BBs for machine scheduling, especially PFSP, have been identified by [9][13]. That is, engineering has proved the existence of blocks and the success manipulation via non-learning tools[9] on blocks. However, the manipulation via learning tools[13] on blocks is relatively rare (not only in machine/shop scheduling problems, but also in other combinatorial problems like travel salesman problems, vehicle routing problems and so on). Our recommended key knowledge for ETO and learning also tend to be the BBs between PFSPs.

D. Related works and main contributions

Related Works. The most related work to ours is [10]. To the best of their knowledge, their work is the first work to enhance evolutionary multi-objective optimization via trans-
erred knowledge from corresponding single-objective problems. Their problems are continuous, not combinatorial. For example, travel salesman problem(TSP), quadratic assignment problem(QAP), linear ordering problem(LOP), job shop scheduling problem(JSP) are combinatorial. In our work, we follow roughly the same basic framework in [10], like transferring experience by injection of external populations from source task of all single objective settings to the corresponding multi-objective problem as target task every G generations, where G is the gap. Fundamental differences between continuous and combinatorial cases prevent us from following their design of mapping/connection between populations in source task and target task directly via denoising autoencoder. The connection is lack of physical meaning for job permutation representation in PFSP. Instead, that connection in our work, is constructed as follow. We add the intra-task learning of clustering that is not applied in their work to choose potential elite solutions with good positional BBs, then inject the external population (may including those elites) from source task to target one.

In the following, we will present another four important related works. First one is ETO for multitask optimization in combinatorial case of TSP, QAP, LOP, and JSP. Multifactorial evolutionary algorithm has been designed to explore the potential power of evolutionary multitasking (EMT), which can serve as the engine to simultaneously optimize multiple permutation-based combinatorial optimization problems in supply chain networks[11]. To gain the adaptive ability, a unified representation design and selection operator are applied. Secondly, ETO for multitask optimization in combinatorial case of routing. In [12], a memetic computing paradigm is introduced, which can learn and evolve knowledge meme that traverses two different but related domains to enhance evolutionary search performance. For combinatorial case, a realization is studied on two NP-hard routing domains, i.e., capacitated vehicle routing problem and capacitated arc routing problem. Thirdly, machine learning based intelligent optimization(MA) for PFSP. In the work[13], machine learning base memetic algorithm is developed for PFSP with the setting of multi-objective. The algorithm of MA is called ML-MOMA, one of whose main features is improvement of local search via machine learning. In the algorithm, historical data during the optimization of PFSP is utilized. The clustering method is introduced to selected better solutions that are representative for refinement during local search phase. Duplicated searches thus are avoided effectively on similar individual solutions. Besides MA here, another method in the family of intelligent optimization, simulated annealing(SA) can also solve PFSP in the following. Lastly, residual learning based intelligent optimization(SA) for PFSP. To solve PFSP, [14] introduces an improved SA armed with residual learning. The neighborhood of the PFSP are defined and its key blocks are divided. Residual learning is applied to extract and train the features of those blocks, which belong to supervised learning style. Moreover, the trained/learned/fitted parameters are further stored in the SA for greater search efficiency.

Main contributions are as follow: 1. An ETO framework in scheduling application is proposed. To the best of our knowledge, it may be the first attempt to extend ETO for the complex optimization in scheduling cases (i.e., combinatorial cases) from single to multi-objective(not MTO). 2. A step towards green scheduling and carbon neutrality via a devotion to avoid the scheduling operations from scratch. 3. We develop a simple yet effective algorithm, MA for PFSP, as a powerful data analytics method for system optimization in smart industry [2].

II. PRELIMINARY: LOW DISCREPANCY, OPTIMIZATION OBJECTIVES, TRANSFERRED KNOWLEDGE

A. Low discrepancy: which problem pair

Firstly, the setting of which problem pair mainly concerns with similarity or discrepancy between them in nature. So the goal of low discrepancy motivates our setting here.

The SOPs “naturally share great similarity with the given MOP, which thus could yield useful traits for enhancing the problem-solving of the MOP”[10].

B. Optimization objectives: makespan objective dominates other objectives

Makespan(Cmax), the minimization of the maximum completion time, is the core and most powerful optimization objective /driving force among the objectives in multi-objective and single-objective scheduling problems.

It dominates total flow time(TFT), total tardiness, max imum lateness and so on. In other words, Cmax should be put forward first, better Cmax often is also correlated with other better objectives.

C. Transferred knowledge: positional BB dominates other BBs, for makespan

For combinatorial problems, especially shop scheduling or PFSP, those blocks remains unclear, and some clues may help us to figure out. Positional, precedent and adjacent information units are believed to exits in combinatorial problems. For TSP, adjacency structures dominates positional ones, while positional ones matters more than adjacency ones for optimization of Cmax in PFSP [1]. Based on the observations above, we propose our assumption that there may exit 3 kinds of BB, positional, precedent and adjacent ones. In later experiments, we focus on the 1st one.

Considering both B. and above, we could summarize that positional BBs help improve Cmax, and also inherently improve other objectives, therefore the significance of positional BB is highlighted here.

III. TEST PROBLEM: PFSP

PFSP is formulated as follow: each job/operation is to be processed sequentially on machines, given their processing time of the operation. Each machine in PFSP can process one job at most, and each job can be processed on one machine at most. The sequence of jobs is the same on each machine. In this literature, we choose both Cmax and TFT as objectives.

IV. THE FRAMEWORK ACROSS TASKS: ETO_PFSP

A. Three frameworks: transfer learning, transfer optimization, and our ETO_PFSP

Classical transfer learning[8] framework(F1), includes 2 learning tasks[5][6]. However, the framework(F2) of transfer optimization[3] (at least, the current definition) only emphasize the transfer action between two evolutionary tasks, the learning component in each evolutionary task is not
required. Our framework ETO_PFSP(F3) is between F1 and F2, and contains 2 evolutionary tasks, each of which apply intra-task learning components.

In other words, of cause, F3 is F2, furthermore, shares richer features with F1 which are lack in F2. We tend to believe that, F2 is an ongoing definition, with a lot room for theoretical refinement and practical enrichment.

B. Eight tasks, two groups: group 1, t1_wc(1.0, 1.1), t2_wc and t2e_wc; group 2, t1_nc(1.0, 1.1), t2_nc and t2e_nc

Overview (in Figure 2). In F3, we set two task groups.

Group 1 owns 4 tasks, namely, t1_wc including two sub tasks(t1_wc(1.0, 1.1), t2 wc and t2e wc, where “wc” means “with clustering and” “e” is “external” transferring from t1_wc, sharing the same toolkit of W-X-L (only probabilities vary in X, more is in V.A). All above is the same for group 2 of t1 nc(1.0, 1.1), t2 nc and t2e nc, except that no clustering(named “nc”) is in W.

W-X-L contains a special operator to chooses who to be parents(W), a special crossover(X) and local search(L) operator. It’s worth to mention that, task family above shares the same random initial(I) population for fair comparison.

Phase of selection(S) differs. In S, we use NSGA II, sort-ing methods by Cmax or TFT and so on.

Therefore, many shared parts above at both problem and algorithm levels are elaborately constituted as a harmony test bed towards a well-defined F3.

Fig. 2. Overview. From parent P_i to P_i+offspring, at generation i.

Details of W (in Figure 3). With C and S_7 in W, we choose who to be parents P_i. Density peak based clustering (DPBC)[6] is in C (in Figure 4). DPBC is based on the observation that centers of cluster are characterized by a relatively higher density than points in their neighborhoods and by a relatively long distance from points that have higher densities. We implement it via hamming distance, which is widely used in evolutionary computation. To our surprise, it also focus on the mining of the positional building block. Quite obviously and intuitively, measures of hamming distance (dissimilarity) and positional BB (similarity) work from opposite sides to the same characterization.

Details of XL (in Figure 5), especially X. More of X is in Figure 5. L is an ordinary insertion operator.

Details of SS in S (in Figure 6). t1_wc/nc and t2_wc/nc have no P_R, only t2e_wc/nc needs P_R every G generation. t_wc/nc 1.0 and 1.1 construct the selection pressure via single objective, and t2e_wc/nc and t2e_wc/nc consider both objectives via NSGA II.

Fig. 3. Details of W. Choose parents P_i. DPBC is in C.
V. EXPERIMENTAL STUDIES AND COMPARISONS

A. Experimental setting

To test the validation of F3, we carry out simulation on some instances in well-studied benchmarks, including ta101(20x5), ta142(50x10) and VFR100 20_1 (100x20), e.g., 20x5, is 20 jobs and 5 machines. In our simulation, F3 is coded in Python 3.7.0 (3.8.8 also OK), and is executed on servers.

The following parameters are set: N is 100, number of generation is 100. In t1_wc/nc 1.0 and 1.1, \(p_{c1}, p_{c2}\) are [0.3, 0.7] and [0.1, 0.9], respectively. For t2_wc/nc and t2e_wc/nc, it’s [0.2, 0.8]. For reference points, ta101 takes range (2500, 10000) to normalize Cmax, and (25000, 100000) to normalize TTF; ta142 uses (4200, 25000) and (120000, 80000); and instance 3 picks (10000, 50000) and (550000, 350000). The gap G is 2. The base-line size of \(P_2\) is 50, modified by a factor K1. For \(P_1\), the base-line size is 20+1H.

And 20 is also adapted by K2, H may be 0, 1, 2 or 3, depending on the solutions with equal distance at cutting distance.

Varying [K1, K2] from [1.0, 6], [0.6, 0.6] to [1.1] for each instance, we have 9 cases (in Figure 7), and each case calculates hamming distance from the 15th job to last job (test the distribution of positional BB) and owns 20 runs independently. In each run, we perform 8 tasks, namely, 2 task groups in IV.B.

B. Simulation results and comparisons

In each case/result, both t2_wc and t2e_wc perform with clustering, and both t2 nc and t2e nc work without clustering. And for each case, we evolve overall 100 (generations per task, seen at x axis) * 4 (4 tasks in a group) * 2 (wc/nc) * 20 (runs for average) = 16000 generations! Furthermore, the size of solution space is a factorial (e.g., 20x5, 20! solutions), imposing a great computational challenge to get those 9 cases.

Fig. 4. Details of C. A typical example of \(p\)-delta) graph in our simulation, where \(p\) is local density, and \(\delta\) is the minimum distance between one sample point and any other one with higher density.

Fig. 5. Details of X. M helps overcome premature convergence.

Fig. 6. Details of SS.
VI. DISCUSSION

A. Why t2\textsubscript{nc} and t2\textsubscript{e}\textsubscript{nc} are better than t2\textsubscript{wc} and t2\textsubscript{e}\textsubscript{wc}: philosophy behind K1 and K2

Why t2\textsubscript{nc} and t2\textsubscript{e}\textsubscript{nc} is better than t2\textsubscript{wc} and t2\textsubscript{e}\textsubscript{wc} in terms of hypervolume? In the paper [10], transferred task also is beaten by NSGA II on the test of DTLZ1 function. At times, there may exist some deceptive positional BB. When worse solutions dominate in P\textsubscript{b}, less confidence should be assigned or decrease K1, and vice versa. The common used injection of exact solutions sounds simple yet effective, with inherently robustness. So, controlling K2 seems valuable.

Mining and learning of positional BB should be improved in the future. Because building block is the “holy grail to GA optimization” [8], the nature of difficulty in mining and learning exists on our future road for improvement.

B. Transferring between four task 2

It’s should be highlighted that the knowledge/experience transferring between two tasks in F3, includes both negative and positive knowledge, both ordinary knowledge and specific knowledge of positional BB. Between t2\textsubscript{wc} and t2\textsubscript{e}\textsubscript{wc}, there is always obvious positive transferring in figure 7, which tends to validate the effectiveness part of our ETO\textsubscript{PFSP} (F3).

Whereas, as to t2\textsubscript{nc} and t2\textsubscript{e}\textsubscript{nc}, in cases 1 to 7, nearly no transferring exists, that is, both early and later stages
nearly overlap, and small negative transferring exists in middle stages. And for cases 8 and 9, slight negative transferring happens, which tends to validate the relative ineffectiveness part of our F3 (Also, many negative or nearly no transferring exist on continuous benchmark functions in [10]), left room for potential improvement.

VI. CONCLUSION AND FUTURE WORK

Our framework ETO_PFSP works as a common framework at macro level.

Considering the common property, it is similar to a common crossover operator, but those two are obviously different, in that at least the former is at macro level and the latter is at micro level.

Transferring from one task to another task, does not necessarily lead to the state of the art (SOTA) performance of the latter task (as usually observed in transfer learning community). Transfer optimization (TO) is new, and the shift to understand relationship between TO and SOTA is not easy. A solver that is already strong enough and armed with proper TO (like our framework) will be more likely to achieve SOTA. A (weak, or mild) optimization engine just equipped with TO, can’t guarantee SOTA. Again, we construct a framework, a new framework (for 1st time, in combinatorial case within single objectives to multi-objective setting, not MTO).

ETO_PFSP attempts to avoid scheduling production operations from scratch, not only contributing to “China’s industrial upgrading and transformation” [2][16], but also heading towards the pledge of the China’s carbon neutrality.

In the future, many directions are attractive and inspiring. First, extensive study of [K1,K2] may be helpful to the philosophy in VI.A and philosophy of ETO in 1.A. Then, extending to other problem in scheduling is also quite anticipated. For example, from a PFSP to a JSP. At last, to disentangle the kinds of different knowledge learned/ transferred (maybe via fitness landscape, local optima network, …) is also important, which somehow is like the disentanglement of different features/representations [5][15] in deep learning/transfer learning [5] towards interpretability [17][18][19][20][21] of AI.

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