An Exploratory Study of Computational Challenges in Industrial Grouping Problems

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***Abstract*—Grouping problems are hard combinatorial problems concerned with partitioning or grouping items into categories, based on a given set of decision criteria. Complex industrial problems such as home healthcare scheduling, vehicle routing problem, task assignment, and team formation fall into this class of problems. These grouping problems are characterized with complex features, posing several computational challenges to decision makers in various disciplines. This study is concerned with investigation of common challenges inherent in grouping problems across industry disciplines. Based on recent case studies in the literature, the paper investigates common challenges and complicating features in real-world grouping problems. These features are classified into model abstraction, presence of multiple constraints, fuzzy management goals, and computational complexity. Further analysis of the case examples revealed four types of the complicating features. Insights into the general grouping problem and the inadequacies of solution methods are presented. Suitable approaches are then suggested. Thus, the study recommends solution approaches that make use of multi-criteria, flexible, interactive approaches that incorporate fuzzy set theory, fuzzy logic, multi-criteria decision, and expert systems.**

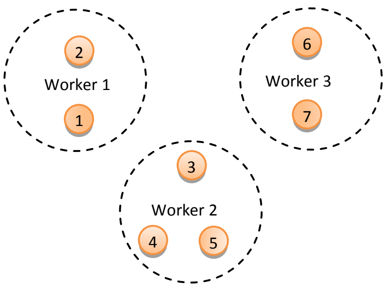
***Index Terms*— exploratory study, grouping problems, grouping genetic algorithms, computational challenges**

I. Introduction

GROUPING problems are concerned with classification or partitioning of entities into efficient categories based on a set of decision criteria [1]. For example, the task assignment problem consists in allocating a set of tasks to a team of workers in a cost effective manner [2]. Fig. 1 shows an assignment of groups of tasks {1,2}, {3,4,5}, and {6,7} are assigned to workers 1, 2, and 3, respectively, which is represented by a group encoding scheme as shown. Furthermore, in manufacturing group technology, it is often required to group together parts with similar characteristics that can be produced using specific sets of processes. Such problems are commonplace across several industrial disciplines. Several other problems and their variants are found in industry, including, homecare worker scheduling [1], group maintenance planning [3], team formation problems [4], modular product design [5], estimation of discretion accruals [6], customer grouping [7], order batching [8], and timetabling [9]. Due to many possibilities of combinations in forming groups, and several constraints, grouping problems are usually complex and NP-hard. In recent years, researchers have faced difficult challenges in addressing these problems.

Recent influx of articles in the literature on the subject matter shows that researchers continue to discover more grouping problems. Most of these newly discovered problems are large-scale real-world cases, with more complex characteristics. Given the ever-increasing global competition, decision makers need to come up with ne efficient and effective business processes. In logistics and supply chain management, decision makers are often faced with the challenge of optimizing their logistics operations in a cost-effective way. This will ensure improved quality of service and service delivery. Without that, business losses are inevitable in the long term.

Recent studies have also shown that, as customers increasingly become aware of the best services they deserve, they continue to expect more quality of service. For instance, nowadays, customers are on the lookout for products and processes that are friendly to the environment, the society, the economy, and energy. This has necessitated research in green modular product design, home healthcare scheduling, green vehicle routing, customer grouping, and economies of scale, among others. As this is of common occurrence across several other industrial disciplines, it is important to develop efficient decision support tools that can solve complex grouping problems. Further assessments in the literature show that grouping problems are highly combinatorial and



Tasks	1,2	3,4,5	6,7
Worker	1	2	3

Fig.1. Task assignment problem and its grouping encoding scheme

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NP-hard in nature [10] [11]. As such, it is useful to derive from real-world case studies in the literature, the common challenges that contribute to their computational complexity. Moreover, it will be interesting to learn from past studies, how to develop effective and reliable solution approaches to the problems.

Challenges experienced in solving grouping problems have stimulated intensive search for efficient approximate methods that can address these problems and provide near-optimal solutions. These approaches include heuristics derived for solving specific problem categories, general-purpose metaheuristics that can solve complex problems. Examples of such methods are simulated annealing [8], particle swam optimization [1] [12] genetic algorithms [1] [2] [13] [14], tabu search [15], ant colony optimization [16], simulated metamorphosis [17], and other evolutionary algorithms [18] [19] [20] [21] [22] [23] [24].

Notable work in grouping genetic algorithm and related applications were presented in [10] [11]. The author developed a grouping genetic algorithm specifically for solving grouping problems. The algorithm was motivated by the realization of the inadequacies of conventional genetic algorithms and other related algorithms. For instance, when solving grouping problems, conventional genetic algorithms are faced with three major limitations:

1) Conventional chromosome encoding tends to have significant redundant space;
2) It is not easy to generate good offspring through standard reproduction mechanism such as Roulette wheel; and,
3) Conventional genetic operators (crossover and mutation) tend to spoil the quality of offspring population.

However, since the inception of the grouping genetic algorithm, more challenges continue to come up as more challenging grouping problems arise in industry. Consequently, further research on grouping genetic algorithm and its variants is imperative. Therefore, the purpose of this study is to further explore the common challenging features inherent in industrial grouping problems. Specific objectives associated with this study are as follows:

1) To explore extant real-world cases of industrial grouping problems in the literature;
2) To identify common complex challenges associated with the grouping problems; and,
3) To evaluate and recommend suitable solution approaches to grouping problems.

The rest of the paper is structured as follows: The next section presents the research methodology, which focuses on literature search survey of extant case studies in the literature. Section III presents the research findings. Section IV discusses the complex challenges inherent in grouping problems. Suggested solution approaches are presented in Section V. Finally, Section VI concludes the paper.

II. Research Methodology

Fig. 1 provides a summary of the research methodology followed in this study. In the first phase of the study, a wide literature search survey was conducted, exploring recent case studies of industrial grouping problems since year 2000. Case studies, rather than hypothetical problems, were selected because they provide better understanding of the nature and characteristics of grouping problems from a practical perspective. Major sources of articles were searched and compiled from online literature sources and databases, including such sources as ScienceDirect, EBSCO Inspec, ISI Web of Science, and Ei Compendex, among others. In the second phase, closely pertinent articles were selected. To guide and limit the search process to relevant studies, key words specific to the area of study were used, for instance, “grouping algorithm,” “grouping problem,” “clustering problem,” “grouping algorithm” and “group technology”, and “group allocation.” As a result, articles that whose major focus was not related to grouping problems were eliminated. In the third phase, articles with real-world case studies were then selected for meta-analysis.

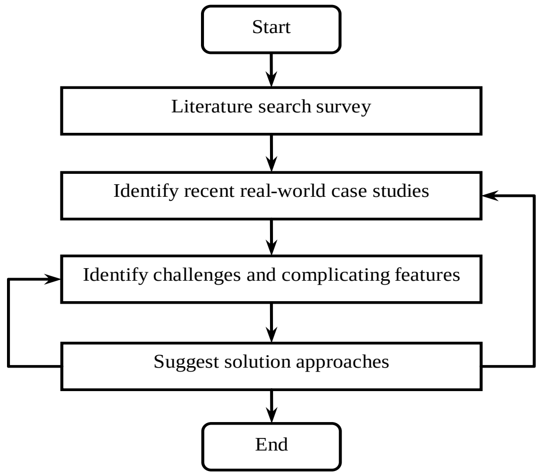

Fig. 1. Research methodology

III. Findings and Results

Most cases studies found in the literature were from the year 2000. As such, the articles were found appropriate as they contained the current state-of-the-art information from which relevant conclusions can be drawn. Surprisingly, case studies obtained were from a wide range of industry disciplines. This helped to extend our analysis over a pool of case studies from which credible conclusions can be drawn.

Table I presents a summary of the results of our literature search survey, giving details of the nature of the grouping problem, the country where it was solved, the solution approach, and the respective reference. A total of 19 selected recent empirical studies were obtained from various industry disciplines. Interestingly, a wide variety of real-world grouping problems were addressed in various places, such as UK, USA, China, Canada, Taiwan, Australia, Spain, Thailand, Iran, South Korea, and Nigeria. This clearly shows the intensity and the spread of research in grouping problems all over the globe.

It is also interesting to see that all the problems were addressed using metaheuristics. This is likely due to the complexity the grouping problem. About 72 % utilize genetic algorithm based approaches, which shows the

TABLE I
SELECTED RECENT CASE STUDIES

No.	Grouping Problem	Place of Country	Solution Approach	References
1	Modular product design of a family of three General Aviation Aircraft	USA	Genetic algorithm	[25]
2	Modular product design for an electrical consumer product provided by an Original Design Manufacturer	Taiwan	Grouping genetic Algorithm	[5]
3	Customer grouping for resource allocation at a window curtain manufacturer based in China	China	Genetic Algorithm-based k-means clustering technique	[7])
4	Estimating discretionary accruals using genetic algorithms	USA	Grouping genetic algorithm	[6]
5	Facility location modelling for Agricultural logistics sector	Thailand	Grouping genetic algorithm in GIS	[26]
6	Group maintenance for a company contracted to maintain engines in the aerospace industry	Canada	Network tree formulation; depth depth-first shortest path algorithm	[3]
7	Flexible job scheduling for a weapon production factory in Taiwan	Taiwan	Genetic algorithm, Grouping genetic algorithm	[27])
9	Heterogeneous student grouping for Bangkok University	Bangkok	Genetic Algorithm for Heterogeneous Grouping	[28]
10	Intelligent 3D container loading for automotive container engineering	South Korea	Intelligent packing algorithm	[29]
11	Team formation based on group technology with real application in a Spanish University	Spain	Group technology, hybrid grouping genetic algorithm	[4]
12	Reviewer group construction for National Science Foundation of China (NSFC)	China	Hybrid grouping genetic algorithm	[30]
13	Order batching for precedence constrained orders for a large order picking warehouse	Finland	Simulated annealing	[8]
14	Timetabling for 13 real-world problems – Carter Benchmarks	Canada	Informed genetic algorithm	[31]
15	Maintenance grouping model for an industrial case study	Australia	A modified genetic algorithm	[32]
16	Homecare worker scheduling for community care service	UK	Particle swarm optimization algorithm	[21]
17	Timetabling for a University of Agriculture	Nigeria	Genetic algorithm	[9]
18	Vehicle (homogenous) routing with prioritized time windows for a distribution company	Iran	Cooperative co-evolutionary multi-objective quantum-genetic algorithm	[33]
19	Subcontractor selection for construction industry	Turkey	Genetic algorithms	[34]

potential of genetic algorithm-based solution methods.

In addition to the above findings, it is interesting to see that grouping problems found in the literature had a number of common computational challenges arising from common complicating characteristics inherent in the problems. Fig. 2 presents an analysis of four categories of challenges and complicating factors behind industrial grouping problems, namely,

1) Model conceptualization or abstraction;
2) Presence of myriad constraints;
3) Fuzzy management goals; and,
4) Computational challenges.

The four challenges are closely related together, and the influence the computational complexity of grouping problems.

IV. Challenging Features

In order to obtain in-depth understanding of the challenges and complicating features of grouping problems, we discuss the four categories in this section.

A. Model Conceptualization

Model abstraction is the first step in solving industrial grouping problems. Oftentimes, it is difficult to conceptualize an industrial grouping problem from the perspective of a grouping problem. The level of abstraction of the problem is further influenced by the presence of imprecise management goals, complex cost functions, the nature of grouping, constraints between the groupings, and constraints within each group. When modelling the problem based on metaheuristics such as genetic algorithms, the encoding scheme should contain the requisite information while allowing for computational efficiency and effectiveness. This is because genetic operators such as selection, crossover ad mutation are significantly influenced by the encoding scheme, which in itself is a direct product of model conceptualization.

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Most encoding schemes algorithms are prone to the disadvantage of degeneracy, where multiple chromosomes represent the same solution [35]. In addition, most encoding schemes suffer redundancy problems, which is the amount of excess information in the chromosome. Degeneracy leads to inefficient exploration of the solution space as the same configuration of groups are repeatedly explored. As such, it is essential to have effective model conceptualization, which is crucial for minimizing of degeneracy. In turn, this is very crucial for an efficient algorithm.

B. Myriad of Constraints

Grouping problems in various disciplines are usually inundated with a myriad of constraints. In most cases, not all possible groupings are permitted; group formations must satisfy a number of constraints. In the presence of multiple constraints, it is highly difficult to model, and let alone solve the problems in polynomial time. The effect of such situations is that the problem becomes too restricted and computationally complex to handle. Constraints come in two basic forms, as follows:

1) Hard constraints, which should be always be satisfied, e.g., a worker capacity constraints, vehicle loading constraints, or statutory regulations; and,
2) Soft constraints, which may be violated, but at a cost (or pseudo cost), for ex-ample, violation of preferences and wishes.

Soft constraints can be imprecise (or fuzzy) in nature. By learning from the case studies, the identified constraints can be discussed in the following perspectives.

1) Intra-group Relationship

Intra-group related constraints are concerned with restrictions on the sequencing or the order of items in a group. If problem encoding is order dependent, the order of the items will affect the fitness of the candidate solutions [36]. For example, the sequence in a group may depict the order in which customers a visited, or the order by which tasks are executed by a worker. Therefore, the de-pendency between group members or items will influence the complexity of the problem. However, for an order independent grouping problem, the order does not influence constraints and fitness of the candidate solutions, for example, the team formation problem may not be order dependent. Therefore, the presence of these intra-group constraints will always influence the complexity of the problem significantly.

2) Inter-group Relationship

The relationship between groups may lead to complex restrictions, which adds to more complexity of the grouping problem. For instance, in team formation, it may be required that two members in two different groups should occasionally cooperate in accomplishing a task, or should share their expertise. On the other hand, due to some working conditions, some workers may not be allowed to work in the same group, adding to the restrictiveness of the problem. In the presence of such constraints, the model becomes too restrictive and can prolong the solution process.

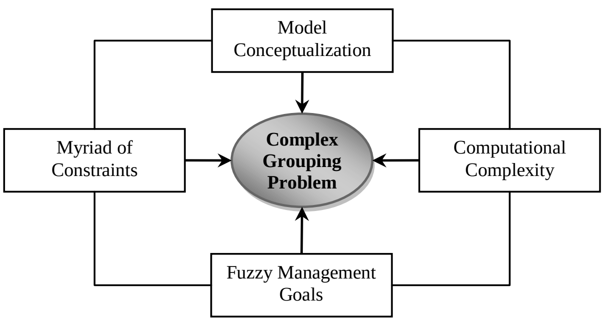

Fig. 2. Challenging features of complex grouping problems

3) Group Size Limit

The limitation on the allowable number of members in a group is another crucial piece of information that influences the complexity of grouping problems. In this respect, grouping problems can have uniform or non-uniform groups. Uniform groups tend to be easier to handle than non-uniform groups, since non-uniformity will result in more constraints and influence the fitness of the candidate solutions. For example, the non-identical parallel machines scheduling problem consists of machines with different operational characteristics and the group of jobs that may be assigned to each machine will differ. Therefore, the group size limits will influence the complexity of the grouping problem.

4) Grouping Limit

This refers to the maximum allowable number of groups that may be constructed in a given problem setting. In this respect, grouping problems can be classified as constant grouping problems and variable grouping problems (e.g., bin packing problem). The number of groups may be limited to problem-specific reasons, for example, due to limited number of available healthcare workers and the number of available vehicles. In such cases, the grouping problem becomes more restricted and complex.

C. Fuzzy or Imprecise Management Goals

Decision makers in the modern dynamic business world make decisions under fuzziness or imprecision. In attempting to make optimal decisions it is often realized that goals, constraints and aspirations tend to be imprecise. This is worsened by the fact that most of the available information and problem parameters are difficult to determine precisely. Such imprecise information usually arises from three sources, namely:

1) Fuzzy wishes and expectations of the customer in regards to the desired time windows, service delivery, service quality;
2) Fuzzy preferences worker, e.g., in terms of schedules, tasks assigned and the related choices; and,
3) Fuzzy management goals and targets upon which management aspirations are built.

For example, in vehicle routing, customers' time windows for delivery may be expressed in an imprecise manner, which may be difficult to model mathematically, let alone to solve. The same applies to home healthcare service providers. In addition, workers in such environments may be allowed to express their desires in regards to their work schedules.

To improve service delivery and service quality, it is important to satisfy fuzzy desires and management goals to the highest degree possible. Management goals can be expressed in terms of aspiration levels and evaluated using

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fuzzy evaluation techniques. In the presence of fuzzy multiple goals and constraints, multi-criteria evaluation methods may be used.

D. Computational Complexity

Computational complexity is highly influenced by the curse of dimensionality, usually with increasing problem sizes; grouping problems are highly combinatorial in nature. The presence of a myriad of constraints adds to the complexity of the problems. The application of classical metaheuristic algorithms such as genetic algorithms, particle swarm optimization and the related evolutionary algorithms, their operators and representation schemes tend to be highly redundant. This is due to the fact that the operators tend to be object-oriented rather than group-oriented, which often results in reckless breakup of the building blocks that were supposed to be promoted and improved.

In [10] [11], Falkenauer (1994) suggested an encoding scheme for grouping genetic algorithm problems, and affirming that the resulting genetic operators should be designed in a way that will allow propagation of groupings of objects, rather than objects, since the groupings are the inherent building blocks of the problem. It can also be argued that, working on the particular positions of any one object on its own also adds to the combinatorial complexity of the problem. In view of the above, the following add to the complexity of grouping problems:

1) The presence of a myriad of constraints and variables which makes the problem highly combinatorial;
2) The need to maintain group structure, and therefore prevent loss of key information;
3) The need for repair mechanisms whenever the group structure is disrupted during metaheuristic operations; and,
4) The need for problem specific constructive heuristics.

Effective techniques and heuristics should be built into metaheuristic algorithms in order to enable such approaches to address the aforementioned complexities. The next section suggests the most suitable solution approaches to industrial grouping problems.

V. Suggested Solution Approaches

In general, combinatorial optimization problems have a finite number of feasible solutions. However, in practice, the solution process for real-world grouping problems can be time consuming and tedious. As a result, the overall time and cost incurred in getting accurate and acceptable results can be quite significant. As problem complexity and size increase, the effectiveness and efficiency of the current methods is limited, especially when solving modern grouping problems whose complexity continue to grow.

As realized in the selected case studies in the literature, piecemeal solution approaches have been suggested on various problem instances, including manual or basic heuristic methods, mathematical programming, metaheuristic methods and artificial intelligence. In view of the inadequacies and shortcomings mentioned in the past approaches, the use of fuzzy multi-criteria grouping metaheuristic is highly recommended.

Intelligent fuzzy multi-criteria approaches should make use of techniques such fuzzy theory, fuzzy logic, multi-criteria decision making, and artificial intelligences. By so doing, fuzzy expert knowledge, fuzzy intuitions, fuzzy goals and preferences can be incorporated conveniently into the modeling process.

VI. Conclusions and Further Research

Due to a number of complicating features, industrial grouping problems are generally NP-hard and computationally difficult to comprehend and model. Based on recent case studies, this chapter identified characteristic complicating features that pose challenges to decision makers concerned with grouping problems. These features were classified into model abstraction, presence of multiple constraints, fuzzy management goals, and computational complexity.

Results of an in-depth taxonomic study of 18 case studies in the literature revealed a number of complicating features within the four categories. Among the methods that have been applied in these case studies, genetic algorithm is the most widely used. This indicated the great potential of the algorithm to solve a wide range of grouping problems. Realizing the inadequacies of solution methods applied, the study suggested the use of flexible, fuzzy multi-criteria grouping algorithms that hybridize fuzzy theory, fuzzy logic, grouping genetic algorithms, and intelligence. It is hoped that advances and applications of grouping genetic algorithm based on these techniques will yield remarkable progress in developing decision support tools for industrial grouping problems.

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