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A NOVEL INTELLIGENT METHOD FOR TASK SCHEDULING IN INDUSTRIAL CLUSTER

Abstract: In this paper the author proposes a new genetic algorithm (NGA) for a scheduling problem in a local supply network (in other words industrial cluster – IC). The new genetic algorithm enables not only a manufacturing scheduling in IC. Additionally, NGA aids planners in transport orders planning. New genetic algorithm employs two steps to encode the scheduling problem in IC. In the first step, each chromosome type A represents a potential optimal solution of a problem being optimized. Chromosome type A is a set of 4-positions genes. The value of the first position represents the job, the value of the second position – the operation number, the next value – the resource number or the order transport, and the last value – the factory number or the source of the transport order. The second step is to copy the first and the second position from the gene of the chromosome A into the gene of the chromosome B, and to translate the last two positions from the gene of the chromosome A into one position of the gene of the chromosome B.

The cases study shows that proposed by the author new genetic algorithm is effective in solving the scheduling problems in local supply networks.

1. Introduction

The manufacturing supply chain tries to optimize the total system to cope with global manufacturing. Increasingly, enterprises are being organized as multiple plant chains of different units. For that reason, planning and scheduling activities are very complex, and across the entire supply chain in order to achieve high quality products at lower cost, lower inventory and high levels of performance [Moon et al. 2006].

Genetic algorithms (GAs) are probabilistic search algorithms which mimic biological evolution to produce gradually better offspring solution [Ying-Hua, Young-Chang 2008]. Each solution to a given problem is encoded by a string that represents an individual in a population. The population is evolved, over generations, to produce better solution to the problem. The process of reproduction, evaluation, and selection is repeated until termination criterion is reached.

Genetic algorithms have been successfully implemented to find good solutions to the various planning and scheduling problems. For example, Moon et al. [2006]

developed an adaptive genetic algorithm for advanced planning in manufacturing supply chain. The objective of the advanced planning and scheduling problem was to determine an optimal schedule with resource selection for assignments, operation sequences, and allocations of variable transfer batches. Chen and Ji [2007] proposed a genetic algorithm for dynamic advanced planning and scheduling with frozen interval.

Genetic algorithms have been also applied for job scheduling in distribution manufacturing systems. Chan et al. [2005] proposed an optimization algorithm named Genetic Algorithm with Dominates Genes (GADG) to solve distributed production scheduling problems with alternative production routings. GADG implements the idea of adaptive strategy. Jia et al. [2007] proposed integration of genetic algorithm and Gantt chart for job shop scheduling in distributed manufacturing systems.

Recently, many genetic algorithms have been developed for the multi-objective problem. For example, Arroyo and Armentano [2005] developed a genetic algorithm for multi-objective flow shop scheduling problems.

A huge amount of literature on scheduling, including the approach with genetic algorithms, has been published within the last years. Nevertheless, many researches on scheduling often ignore the division of jobs and the relationship between the scheduling operations on the machines and the external transport. In most cases, the researchers study small-scale problems [Gao et al. 2007] or only flow problems [Ruiz, Maroto 2006; França et al. 2005] where there are many constraints.

Currently, the trend of researches is the adaptation of hybrid approaches which combine different concepts or components of various techniques. For example, a hybrid evolutionary algorithm for the job shop scheduling problem is presented in the work by Zobolas et al. [2009]. The trends have been presented by Kobbacy et al. [2007] in very interesting survey of applications of artificial intelligence techniques for operation management. Modern hybrid approaches for control problem in supply net has been published by Ławrynowicz [2008]. The author proposes a methodology that uses an expert system and a genetic algorithm to support production planning and scheduling in a focused factory of a supply network. In this approach, the production planning problem is first solved, and then the scheduling problem is considered within the constraints of the solution. It does not only offer short-term production planning and scheduling to meet changing market requirements that can better utilise the available capacity of manufacturing systems, but also provides a support for control. The main objectives of this approach were to produce an APRM model that minimizes the make-span by considering alternative machines, alternative sequences of operations with precedence constrains, and outsourcing.

The paper is divided into the following sections. In Section 2 the background problem is described. In Section 3 the optimization methodology of the proposed NGA is introduced. Some experiments are run and discussed in Section 4 for the verification of the reliability of the proposed NGA, and Section 5 contains conclusions.

2. Description of the scheduling problem in an industrial cluster

Many different approaches have been proposed for scheduling problems in multi-factory environment. Generally, distributed scheduling problems deal with the assignment of jobs to suitable factories and determine their production scheduling accordingly [Chan et al. 2005]. In the local supply network, multiple factories can be selected to manufacture the products. The factories may be located in different geographical locations, but in one region. In this research, a typical local supply network, which has J different tasks (products) (1, 2, ..., m) for F factories (1, 2, …, r) is considered. Each factory has R resources (1, 2, ..., q). All tasks (jobs) are loaded, according to the predetermined technological sequence given in processing plans. The routes for the jobs are such that a job may use some resources and transportation more than once. There are several constraints on jobs and resources: (1) there are no precedence constraints among operations of different jobs; (2) operations cannot be interrupted and each resource can handle only one job at a time; (3) each job can be performed only on one resource at a time. In this approach, the processing plans of jobs include also external transport orders. The problem in this network is to determine the production scheduling in each factory and external transport orders scheduling. The objective is to minimize the total make-span of the network.

The following notation is used for optimization of scheduling in the local supply network:

m – number of jobs,
p – number of operations,
q – number of resources,
r – number of factories,
J_j – the j-th job, where $j = 1, …, m$,
O_i – the i-th operation, where $i = 1, …, p$,
R_n – the n-th resource, where $n = 1, …, q$,
F_k – the k-th factory, where $k = 1, …, r$,
P_o – the o-th transport order, where $o = 1, …,$ q – 2 and $o > 2$,
S_t – the t-th source of transport order o, where $t = r + 1, …, r + m$,
T_{ji} – the time of operation i of job j.

In this approach, the source of the transport order is the job. If considered system includes three factories then the sources of transport order are denoted as follows: for the first job the source of transport orders is denoted by S_{3+1}, i.e. S_4, for the second job the source of transport orders is denoted by S_5, for the third job the source of transport orders is denoted by S_6, etc.

3. The proposed methodology

In this approach, the genetic algorithm proposed by Ławrynowicz [2008], which adopts operation-based encoding method, is applied. In this genetic algorithm, the well-known roulette wheel selector was used. The genetic operators used for performing evaluation are crossover and mutation operators. The next population is created from the mating pool using the partial match crossover (PMX). Mutation is a random interchange of values in two positions. In this GA, the number of generations is used as a stopping measure. The genetic algorithm has been tested using data from real factories. The detailed description adjustment of GA may be found in the work by Ławrynowicz [2008]. The study shows that this genetic algorithm is effective in solving scheduling problems.

Genetic algorithms work with a population of potential solution to a problem. A population is composed of chromosomes (i.e. a string), where each chromosome represents one potential solution. In ordering problem with the use of a genetic algorithm, critical issue is developing a representation scheme to represent a feasible solution. Particularly, in IC where jobs will be dispatched to many factories, the encoding of the scheduling problems plays an important role to implement effective supply network management methods. In the scheduling problem, the popular encoding is operation-based method [Cheng et al. 1996]. By this idea, the author proposed new encoding method for a scheduling problem. In this approach, new genetic algorithm employs two steps to encode the scheduling problem in industrial cluster. According to the step, two different types of chromosomes are designed. In the first step, each chromosome type A represents a potential optimal solution of a problem being optimized. Chromosome type A is a set of 4-positions genes. The chromosome structure can be represented as shown in Figure 1.

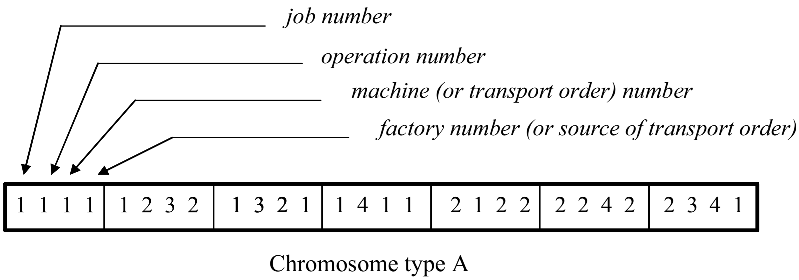

Figure 1. Example of a chromosome type A

Source: [Ławrynowicz 2009, p. 105].

The value of the first position represents the job, the value of the second position – the operation number, the next value the resource number, e.g. machine number – M or the transport order, and the last value – the factory number or the source of the transport order.

The second step is to copy the first and the second position from the gene of the chromosome A into the gene of the chromosome B, and to translate the last two positions from the gene of the chromosome A into one position gene of the chromosome B. Chromosome type B is designed as follows. Similarly as chromosome type A, the first position represents the job, and the second the operation number, but the last position represents a unique number of the resource. Figure 2 shows the way of the translation.

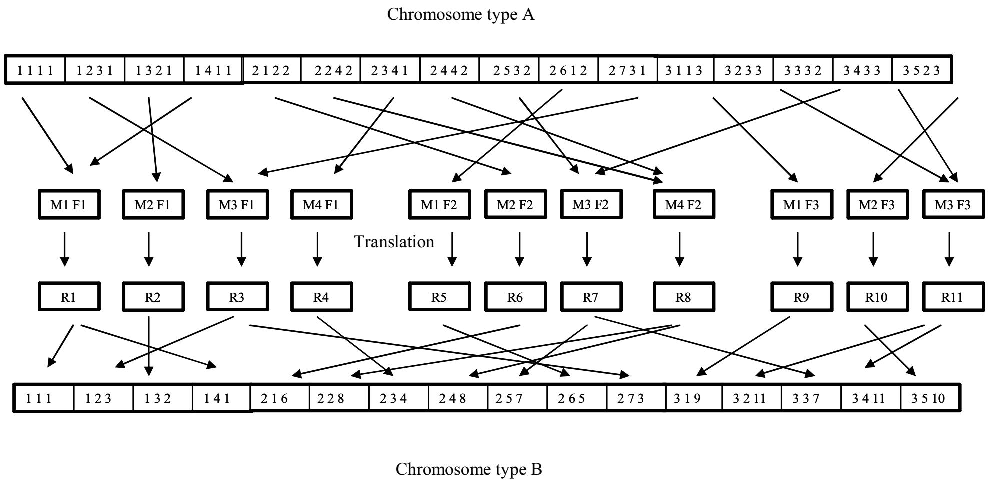

Figure 2. Example of translation

Source: own study.

The initial population is created from the chromosome type B. Based on this chromosome representation, the genetic algorithm by Ławrynowicz [2007, 2008] is used to search for schedules resulting.

Optimization takes place through series of selection, crossover and mutation operations applied to successive generation of candidate schedules. Each generation of the algorithm creates an entirely new population of chromosome type B. After the last iteration, the best found chromosome type B is translated to the chromosome type A.

4. Experiments, analysis and discussion

In this paper, an experiment has been established. Table 1 shows an example of the production plan for job shop scheduling in an industrial cluster. The production plan includes 3 factories, 17 jobs, 11 machines, and 71 operations. In this plan, the operation 5 of the job 1, the operation 3 of the job 2, the operation 3 of the job 10, and the operation 4 of the job 11 are external transport operations.

The job 1 is the source of one order of external transport for the operation 5, the job 2 is the source of one order of external transport for the operation 2, the job 10 is

Table 1. Production plan

Job	Operation 1	Operation 2	Operation 3	Operation 4	Operation 5	Operation 6
1	$T(3)$ R_1F_1	$T(2)$ R_2F_1	$T(3)$ R_3F_1	$T(4)$ R_1F_1	$T(6)$ R_1F_4	$T(2)$ R_3F_2
2	$T(4)$ R_2F_2	$T(2)$ R_3F_2	$T(2)$ R_1F_5	$T(3)$ R_3F_1	$T(3)$ R_4F_1	–
3	$T(3)$ R_2F_3	$T(2)$ R_3F_3	$T(4)$ R_1F_3	$T(5)$ R_3F_3	–	–
4	$T(4)$ R_4F_1	$T(3)$ R_3F_1	$T(2)$ R_2F_1	$T(2)$ R_1F_1	–	–
5	$T(3)$ R_1F_1	$T(3)$ R_4F_1	$T(1)$ R_2F_1	$T(5)$ R_4F_1	$T(2)$ R_3F_1	–
6	$T(4)$ R_1F_2	$T(5)$ R_4F_2	$T(2)$ R_1F_2	$T(1)$ R_2F_2	–	–
7	$T(2)$ R_3F_2	$T(2)$ R_2F_2	$T(2)$ R_4F_2	–	–	–
8	$T(2)$ R_1F_3	$T(3)$ R_2F_3	$T(3)$ R_1F_3	$T(3)$ R_3F_3	$T(2)$ R_2F_3	–
9	$T(2)$ R_2F_1	$T(2)$ R_1F_1	$T(3)$ R_4F_1	–	–	–
10	$T(1)$ R_1F_3	$T(2)$ R_2F_3	$T(3)$ R_1F_{13}	$T(3)$ R_1F_1	$T(3)$ R_2F_1	–
11	$T(2)$ R_3F_2	$T(4)$ R_1F_2	$T(3)$ R_3F_2	$T(3)$ R_1F_{14}	$T(3)$ R_1F_3	–
12	$T(4)$ R_2F_3	$T(2)$ R_2F_3	$T(2)$ R_3F_3	$T(2)$ R_1F_3	–	–
13	$T(3)$ R_2F_3	$T(2)$ R_1F_3	$T(1)$ R_3F_3	$T(4)$ R_1F_3	–	–
14	$T(2)$ R_2F_1	$T(2)$ R_4F_1	$T(1)$ R_3F_1	$T(4)$ R_1F_1	–	–
15	$T(3)$ R_1F_2	$T(2)$ R_2F_2	$T(1)$ R_4F_2	$T(4)$ R_3F_2	–	–
16	$T(4)$ R_3F_1	$T(3)$ R_2F_1	$T(2)$ R_3F_1	–	–	–
17	$T(2)$ R_2F_2	$T(3)$ R_1F_2	$T(2)$ R_3F_2	–	–	–

Source: own study.

the source of one order of external transport for the operation 3, and the job 11 is the source of one order of external transport for the operation 4.

In the work by Ławrynowicz [2008], the adjustment of the proposed genetic algorithm is demonstrated by result of numerical simulation. The results of experiments are shown also in [Ławrynowicz 2007]. The research indicated that from among different selection methods the roulette wheel selector gives the best result. The results obtained by using different crossover operators showed that the best operator is PMX. Next solutions obtained by experiments indicate that remaining parameters of proposed genetic algorithms can be as follows: the initial population 200, generation number 160, probability crossover 1, and probability of mutation 0.05. In this experiment, the genetic algorithm developed for job shop scheduling in distributed manufacturing system has an initial population 200 chromosomes, generation number 200, probability crossover 1, and probability of mutation 0.05.

The best chromosome type B obtained using the genetic algorithm proposed for the production plan of Table 1 was as follows:

1 6 6 3 3 5 5 7 11 9 4 5 10 3 13 2 9 1 11 10 10 16 14 8 11 15 15 15 11 13 6 14 1 16 4 17 1 1 2 3 7 8 4 5 5 11 1 10 17 13 8 14 2 2 14 12 13 6 4 8 9 10 2 15 12 7 16 12 17 12 8.

In this case, the make-span was 23 time units. The computational time was 6 minutes. The obtained final schedule from the new genetic algorithm is shown in Figure 3.

On the basis of the schedules, the planner may suggest orders for subcontracting or may adjust own capacities to expected orders.

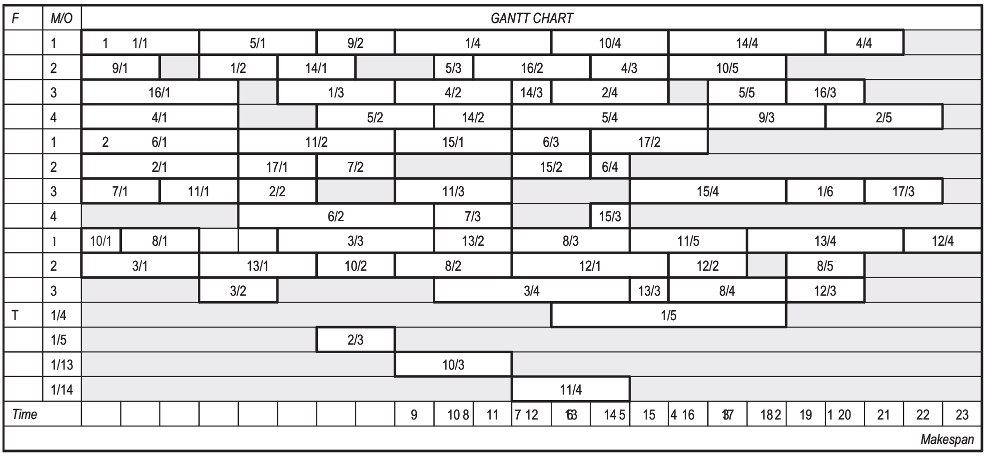

Figure 3. Gantt chart with external transport

Source: own work.

The results of the experiments prove that the proposed new genetic algorithm is a very effective algorithm, because computational time was only 5 minutes. In other experiments, the NGA was used for a more complicated problem [Ławrynowicz 2009].

The proposed genetic algorithm can be applied when there is a need to do re-scheduling. It is common knowledge that in the local supply network there are often disruptions in production or needed mean of transport is not available. In such situations, the new genetic algorithm executes re-scheduling very quickly.

5. Conclusions

This paper depicts the framework and functional details of new genetic algorithm to enhance the agility of job shop scheduling in an industrial cluster. In this paper, the author proposes new encoding method based on an operation representation to improve the scheduling method in a multi-factory environment. The author develops the new genetic algorithm based on operation codes, where each chromosome is a set of 4-positions genes. The value of the first position of the gene represents the job, the value of the second position – the operation number, the next value – the resource number or the number of transport order, and the last value – the factory number or the source of the transport order.

In this paper, the experiment with production plan has been established. The results of the experiments provide that the proposed modified genetic algorithm is a very effective algorithm, because computational time of the NGA was only 5 minutes. The proposed new genetic algorithm can be applied in a dynamic setting when re-scheduling is initiated by disruptions and other unexpected changes. The advantage of new genetic algorithm is very important for small and medium-sized enterprises, because the firms use usually means of external transport.

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