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A NOVEL INTELLIGENT METHOD TO SUPPORT OPERATIONS MANAGEMENT IN CLUSTERS

Abstract: In this paper, the author proposed a novel intelligent method to support an integration of operating decision making in new structures of business. This approach focuses on interactions between the various firms within a cluster at operations management level in order to improve manufacturing processes. The author proposed a novel intelligent method for a collective scheduling in an industrial cluster. For this purpose, the genetic algorithm proposed by the author in previous work by Ławrynowicz [2008] is developed. The new genetic algorithm for the collective scheduling is based on operation codes, where each chromosome is a set of 4-positions genes. The proposed method is verification on some experiments. The analysis presented in the article shows that the new genetic algorithm proposed by the author can be used to improve a detailed scheduling in the cluster. Moreover, the proposed genetic algorithm may aid planners in transport orders planning. It can be applied in a dynamic setting when rescheduling is initiated by unexpected changes.

Keywords: cluster, operations management, genetic algorithm.

1. Introduction

The supply chain network optimization is a difficult problem to solve in the context of distributed (information across different members) and dynamic (changes in the structure and content of the information) environment with multidisciplinary decisions [Sheremetov, Rocha-Mier 2008]. Therefore, enterprises from industry are supported by evolution in the IT, the evolution of the global market and new concepts in strategic alliances among companies. The various types of supply networks can be formed by different classes of firms to respond to new market challenge. Generally, based on distance criterion between firms within network, two types of supply networks may be recognized: the global supply network and the local supply network. From the viewpoint of type of relationships, two basis structure of supply networks may be recognized: the supply network with a dominant enterprise and the supply network based on a partnership. The global supply network with one dominant enterprise is also named “global supply chain” [Morya, Dwivedi 2009, pp. 49-59], “global factory” [Buckley 2009], or “Multinational Enterprises” (MNEs) [Buckley 2009]. A global supply chain setup normally incorporates a focal firm that produces the main product, number of suppliers of raw materials and services, hundreds of distributors and dealers, and the end customers [Morya, Dwivedi 2009]. MNEs operate on a gigantic scale. Orientation of Multinational Enterprises is long term. Structurally, MNEs are huge and comprise numbers of subsidiaries and partnership firms across the globe.

The local supply network based on partnership is also known as “cluster”. Clusters (and similar forms of interorganizational structures) create the environment for innovation and technological advancement. A cluster, sometimes termed an industrial district, can be also defined as a geographical, shred-focus, and sectoral concentration and combination of firms [Niu 2009]. In literature the term “industrial cluster” is also widely used. An “industrial cluster” is defined as a geographical and sectoral concentration and combination of firms [Niu 2009].

Summarizing, the author places emphasis on the following differences of supply network structures. The structure dominated by one enterprise is characteristic for the global supply networks. A global supply network is usually characterized by a long time of transport operations, large number of tasks, and large scale of operations. Therefore, it is not possible to create one common system for planning and scheduling in the global supply network. In this network, each node (i.e. enterprise) applies an autonomous method for operations management, and detailed production scheduling is performed individually for each plant. A local supply network bases usually on a partnership. In the industrial cluster, there are transport operations with relatively short time, smaller number of tasks, and a relatively smaller number of operations. In this suplly network, the operations management can be executed together. Considering the aspects, the author suggests below a new genetic algorithm to solving the scheduling problem in the industrial cluster.

The paper is divided into the following sections. In section 2, a brief review of the literature on genetic algorithms is presented. Section 3 describes the background scheduling problem in an industrial cluster. In section 4, the optimization methodology of proposed new genetic algorithm is introduced. Some experiments are run and discussed in section 5 for the verification of the reliability of the new genetic algorithm, and section 6 contains conclusion.

2. Genetic algorithm

The main purpose of this research is to improve the traditional scheduling methods based on a priority rule and explore a more effective and efficient approach to solving the same problem with the genetic algorithm.

In order to make good decision within a SCN, a manufacturer needs to coordinate local activities with those of upstream suppliers and downstream customers under uncertainty and imprecision in very dynamic environment [Sheremetov, Rocha-Mier 2008]. Today, the efficient management of the new form of business needs new tools. Managers know that through a Business Intelligence solution they can have superior possibilities to business processes control. Business Intelligence uses a set of concepts, methods and technologies to improve the process of conversion of data into information, information into decisions and decisions into actions. Therefore, the author proposes novel intelligent methods for a description scheduling in an industrial cluster using genetic algorithms.

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 has evolved, over generations, to produce better solution to the problem. The process of reproduction, evaluation, and selection is repeated until termination criterion is reached. The evolutionary approach has proved particularly successful in problems that are difficult to formalize mathematically. Therefore, 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, Chung and Chan [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 of 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 shop problems [Ruiz, Maroto 2006], [França et al. 2005] where there are many constraints.

Currently, there is a research trend in 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 work by Zobolas, Tarantilis and Ioannou [2009]. The trends have been presented by Kobbacy, Vadera and Rasmy [2007] in very interesting survey of applications of artificial intelligence techniques for operation management. A modern hybrid approach 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 any factory of a global 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 **A**dvanced **Pr**oduction **M**anagement APRM model that minimizes the makespan by considering alternative machines, alternative sequences of operations with precedence constraints, and outsourcing.

Summarizing, advances in genetic algorithms create new prospects for interorganizational cooperation.

3. Description of the scheduling problem in an industrial cluster

Today, a corporate management depends on the effective use of resources and an aggressive automation of manufacturing processes in order to meet business goals. Many different approaches have been proposed for planning and 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, Chung, Chan 2005]. In the industrial cluster, multiple factories can be selected to manufacture the products. The factories may be located in distributed geographically location, 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 use some 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 makespan of the industrial cluster. The important criterion is also the computational time.

The following notation is used for optimization of scheduling in the industrial cluster:

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 a considered system includes three factories then the sources of transport orders 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.

4. The proposed methodology

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 using the genetic algorithm, critical issue is developing a representation scheme to represent a feasible solution. Particularly, in the industrial cluster where jobs will be dispatched to many factories, the encoding of the production plan plays an important role to implement effective supply network management methods. In the scheduling problem, the popular encoding method is operation-based method [Cheng, Gen, Tsujimura 1996]. In new approach, the genetic algorithm proposed by Ławrynowicz [2008], which adopts the operation-based encoding method is applied. This representation encodes a schedule as a sequence of operations and each gene stands for one operation. One natural way to name each operation is using a natural number. A schedule is decoded from a chromosome with the following decoding procedure [Cheng, Gen, Tsujimura 1996]: (a) firstly translate the chromosome to a list of ordered operations; (b) then generate the schedule by a one-pass heuristic based on the list. The first operation in the list is scheduled first, then the second operation, and so on. Each operation is allocated in the best available time for the corresponding machine the operation requires. The process is repeated until all operations are scheduled. As an example, consider the 3-job 3-machine problem given in Table 1 [Ławrynowicz 2008].

Table 1. Example of 3-jobs and 3-machines

Job	1			2			3		
Operation	1	2	3	1	2	3	1	2	3
Processing time	2	5	3	4	3	2	2	3	4
Machine	1	2	1	3	1	2	2	3	3

Source: [Ławrynowicz 2008, p. 459].

Suppose a chromosome is given as [3 1 1 2 2 3 1 3 2]. Each gene uniquely indicates an operation, and can be determined according to the order of occurrence in the sequence (Figure 1).

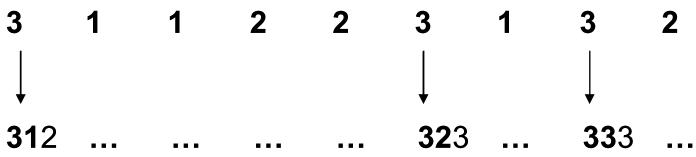

Figure 1. Operation-based representation

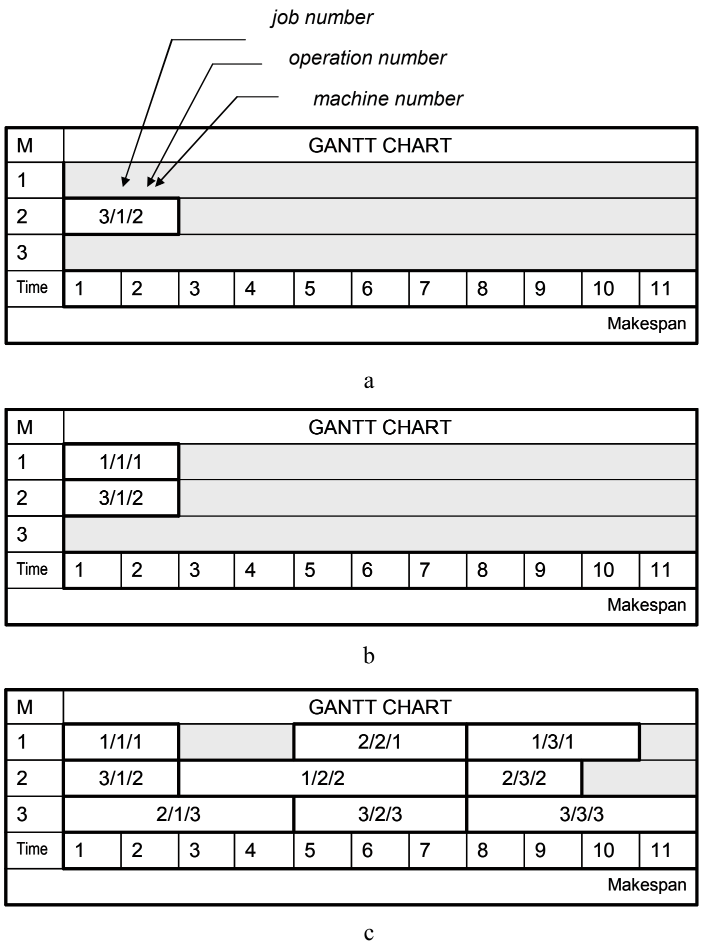

Figure 2. Decoded active schedule

Let o_{jim} denote the i-th operation of job j on machine m. The chromosome can be translated into a unique list of ordered operations of [o_{312} o_{111} o_{122} o_{213} o_{221} o_{323} o_{131} o_{333} o_{232}]. Operation o_{312} has the highest priority and is scheduled first (Figure 2a), then o_{111} (Figure 2b), and so on. The resulting active schedule is shown in Figure 2c.

According to previous ideas, 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 the 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 consists of a series of 4-positions gene. The chromosome structure can be represented as shown in Figure 3.

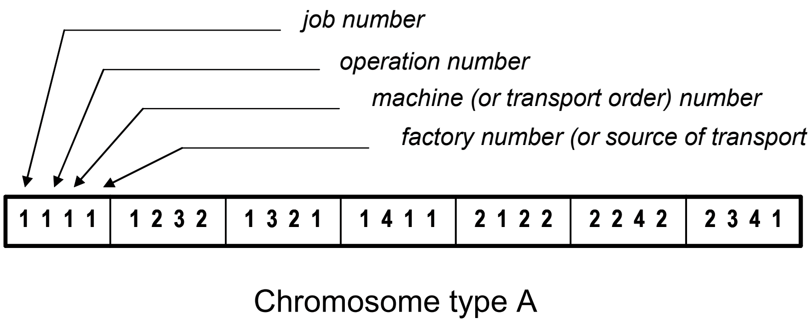

Figure 3. Example of a chromosome type A

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 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 chromosome A into the gene of 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 contains a unique number of the resource. Figure 4 shows the way of the translation.

The initial population is created from the chromosome type B. Each generation of the algorithm creates an entirely new population of chromosome type B. Based on this chromosome representation, the genetic algorithm by Ławrynowicz [2008] is used in search of schedules resulting. In the genetic algorithm proposed by Ławrynowicz [2006, 2007, 2008], the well-known roulette wheel selector was used. The genetic operators used for performing evaluation are crossover and mutation

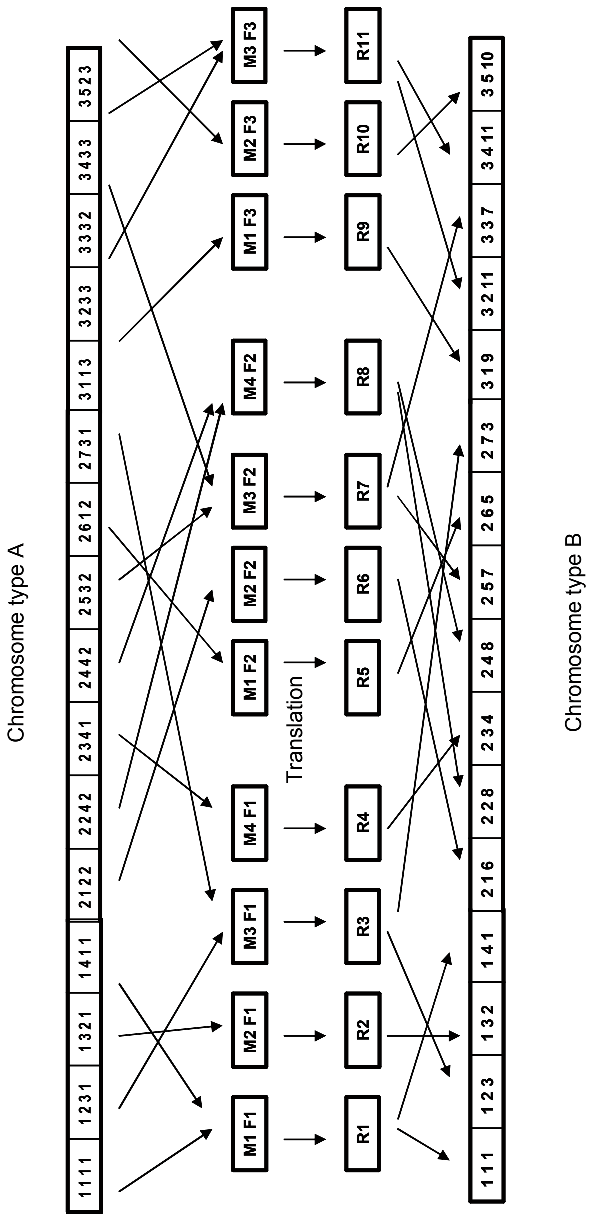

Figure 4. Example of translation

operators. The next population is created from the mating pool using the partial match crossover (PMX). Partial-mapped crossover was proposed by Goldberg and Lingle [1985]. It can be viewed as a variation of two-cut-point crossover by incorporating with a special repairing procedure to resolve possible illegitimacy. PMX has the following major steps:

1. Select two cut-points along the string at random. The substrings defined by the two cut-points are called the mapping sections.
2. Exchange two substrings between parents to produce proto-children.
3. Determine the mapping relationship between two mapping sections.
4. Legalize offspring with the mapping relationship.

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 works by Ławrynowicz [2006, 2008]. The study shows that this genetic algorithm is effective in solving scheduling problems. The research based on 10 different manufacturing systems indicates also that for the scheduling problem, the concept using genetic algorithm yields better results (average 20.95%) than using the methods based on dispatching rules.

5. Experiments, analysis and discussion

This section describes the computational tests which are used to evaluate the effectiveness and efficiency of the proposed genetic algorithm in finding good quality schedules. For this purpose, the author tests two production plans for industrial clusters.

In the application of genetic algorithm, one from among important tasks is how to determine the appropriate values of parameters such as the crossover probability, the mutation probability and so forth. In work by Ławrynowicz [2008], the adjustment of the proposed genetic algorithm is demonstrated by results of numerical simulations. The results of experiments are shown also in Ławrynowicz [2006, 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, probability crossover 1, and probability of mutation 0.05. The earlier results obtained by using the proposed genetic algorithm showed that the solutions are stable after 160 generations [Ławrynowicz 2006], and the genetic algorithm with initial population equal to 200 yields better makespan than genetic algorithm with initial population 20 or 40. But the results of the proposed genetic algorithm with initial population equal to 20 was more efficient than with initial population 40 or 200 in terms of computational time and population size. Therefore, the proposed new genetic algorithm was verification on two production plans. In the first experiment, the author uses the production plan that includes 3 jobs for 3 factories. Figure 5 depicts a model of relationships among the jobs, resources, and factories for a production plan 1.

As showed in Figure 5, the job shop scheduling problem for the industrial cluster is very complicated problem and difficult to solve using traditional methods. The detailed scheduling problem is given in Table 2, where T_{ji} denotes the operation time for operation i of the job j in hours. As it is shown in Table 2, the production plan 1 includes 15 operations executed on 8 machines.

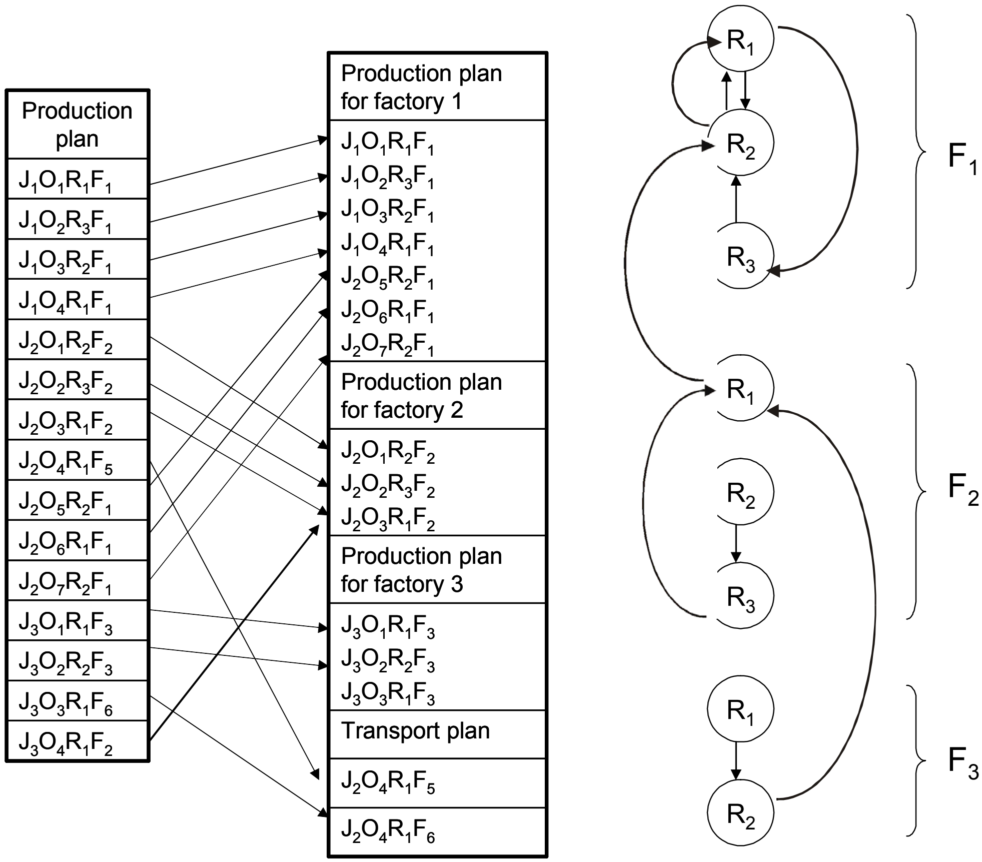

Figure 5. Model of relationships among jobs, resources, and factories for a production plan 1

In this experiment, the factory 1 consists of 3 resources, similarly, the factory 2 consists of 3 resources, and the factory 3 has 2 resources. As showed in Figure 4, there are two transport operations. The source of the first transport operation is the job 2. This operation is the flow of material from the resource 1 of the factory 2 to the resource 2 of the factory 1. The source of the second transport operation is the job 3. In this case, the flow of material is from the resource 2 of the factory 3 to the

Table 2. Production plan 1

Job	Operation 1	Operation 2	Operation 3	Operation 4	Operation 5	Operation 6	Operation 7
1	T(2) R_1F_1	T(3) R_3F_1	T(2) R_2F_1	T(3) R_1F_1	–	–	–
2	T(1) R_2F_2	T(2) R_3F_2	T(3) R_1F_2	T(4) P_1S_5	T(2) R_2F_1	T(1) R_1F_1	T(2) R_2F_1
3	T(4) R_1F_3	T(3) R_2F_3	T(4) P_1S_6	T(2) R_1F_2	–	–	–

resource 1 of the factory 2. The transportation times between factories are as follows: 5 hours from the factory 2 to the factory 1, and 4 hours from the factory 3 to the factory 2.

The chromosome A for production plan 1 can be as follows:

[1111 1231 1321 1411 2122 2232 2312 2415 2521 2611 2721 3113 3223 3316 3412].

In this encoding method, the chromosome A is translated into the chromosome B:

[1 1 1 1 2 3 1 3 2 1 4 1 2 1 5 2 2 6 2 3 4 2 4 9 2 5 2 2 6 1 2 7 2 3 1 7 3 2 8 3 3 10 3 4 4].

According to the traditional operation-based representation, above-mentioned chromosome B is given also as:

[1 1 1 1 2 2 2 2 2 2 2 3 3 3 3].

In this study, the roulette wheel selector method and aforementioned operators are used. Table 3 presents the results of simulations using the proposed genetic algorithm with the parameter as follows: number of generations 200 and 500, probability of crossover 1, probability of mutation 0.05 and the size of initial population 50, 100, 200, and 500.

The best chromosome (before decoding) obtained using the proposed genetic algorithm for the production plan 1 with initial population 200 and number of generation 200 was as follows (test 3):

[1 2 1 3 2 3 3 1 2 2 2 2 2 3 1].

Table 3. Comparison of CPU time and makespan – production plan 1

Test	Initial population	Generation number	CPU time in minutes	Makespan in hours	The best chromosome (before decoding)
1	50	200	0.80	15	2 1 1 3 2 3 2 1 1 2 2 3 3 2 2
2	100	200	1.13	15	1 2 1 2 1 1 3 2 2 2 2 3 3 2 3
3	200	200	3.08	15	1 2 1 3 2 3 3 1 2 2 2 2 2 3 1
4	500	200	7.78	15	1 2 1 3 2 3 3 1 2 2 2 2 2 3 1
5	500	500	19.40	15	1 2 1 3 2 3 3 1 2 2 2 2 2 3 1

According to the proposed decoding methods the chromosome B is:

[111 215 123 317 226 328 3310 132 234 249 252 261 272 344 141].

Finally, after translation the chromosome A is as follows:

[1111 2122 1231 3113 2232 3223 3316 1321 2312 2415 2521 2611 2721 3412 1411].

The Gantt chart for production plan given in Table 2 – for the chromosome [1 2 1 3 2 3 3 1 2 2 2 2 2 3 1] – presents Figure 6. The makespan for manufacturing all the jobs is 15 hours. As shown in Figure 6, the makespan equal to 15 is the best result of the optimization, because the sum of times of all operations for job 2 is 15. But, as showed in Table 3, the proposed genetic algorithm gives 2 optimal results.

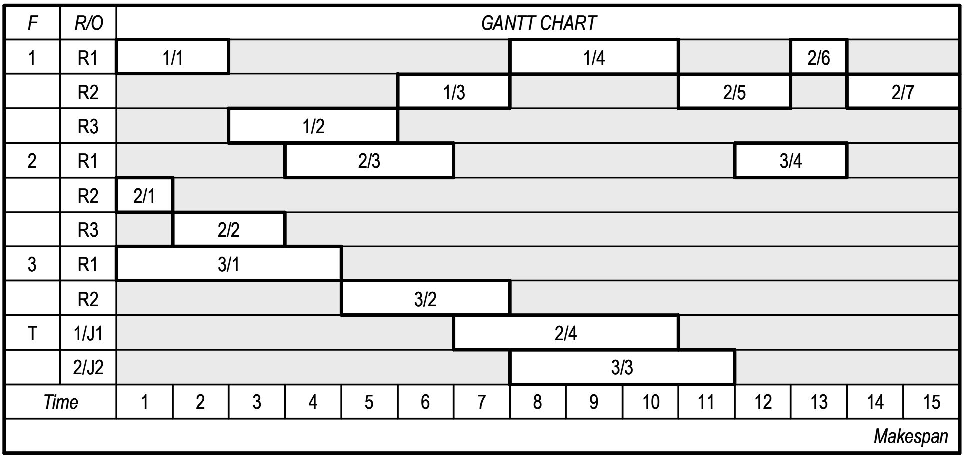

Figure 6. Gantt chart

In the second experiment, the new genetic algorithm was used for a more complicated problem. In this case, the production plan 2 presented in Table 4 is tested. This production plan includes 71 operations of 17 jobs executed on 11 machines in 3 factories.

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 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 this experiment, the roulette wheel selector method was used, and the same genetic operators as mentioned above experiment. Table 5 presents the results of simulations using the proposed genetic algorithm with the parameter as follows: number of generations 200 and 500, probability of crossover 1, probability of mutation 0.05 and the size of initial population 50, 100, 200, and 500.

Table 4. Production plan 2

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) P_1S_4	T(2) R_3F_2
2	T(4) R_2F_2	T(2) R_3F_2	T(2) P_1S_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	–	–
1	2	3	4	5	6	
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) P_1S_{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) P_1S_{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	–	–	–

Table 5. Comparison of CPU time and makespan – production plan 2

Test	Initial population	Generation number	CPU time in minutes	Makespan in hours	The best chromosome (before decoding)
1	50	200	0.90	24	10 11 1 16 13 9 8 9 3 1 15 16 16 9 17 3 11 3 8 6 2 3 1 17 7 6 2 6 4 5 7 4 15 5 8 5 2 1 2 10 4 5 10 10 11 17 1 11 13 12 1 12 12 14 13 13 8 7 14 5 6 15 15 4 14 8 12 2 10 14 11
2	100	200	1.80	24	1 13 1 4 1 11 10 2 2 14 5 3 12 11 3 4 4 4 17 1 16 10 5 8 6 15 10 6 8 7 12 7 2 8 15 14 9 12 9 16 5 10 8 10 11 5 17 16 11 8 3 1 9 2 13 13 15 3 7 1 14 6 15 13 2 6 14 5 12 17 11
3	200	200	3.57	23	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
4	500	200	8.86	23	1 7 3 8 3 10 10 5 10 2 15 11 10 7 11 13 7 11 16 4 8 3 5 3 17 4 1 10 4 13 17 6 16 11 5 14 6 9 1 8 1 4 5 13 11 1 9 6 2 5 15 12 8 2 12 13 2 12 1 14 14 15 12 2 14 9 8 16 17 15 6
5	500	500	22.25	23	1 7 3 8 3 10 10 5 10 2 15 11 10 7 11 13 7 11 16 4 8 3 5 3 17 4 1 10 4 13 17 6 16 11 5 14 6 9 1 8 1 4 5 13 11 1 9 6 2 5 15 12 8 2 12 13 2 12 1 14 14 15 12 2 14 9 8 16 17 15 6

The Gantt chart for the production plan 2 given in Table 2 – for the best chromosome [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] – is presented in Figure 7.

In this instance, the makespan was 23 time units. As shown in Figure 7, the proposed genetic algorithm gives very good results, because the machine 1 of factory 1 and the machine 1 of the factory 3 are bottlenecks.

The results of the experiments prove that the proposed new genetic algorithm is a very effective algorithm, because the computational time was only 3.57 minutes. The proposed method has been successfully implemented using the system Microsoft Windows XP Professional. The proposed algorithm was run on a PC that has a Pentium (R) M processor 1400 MHz, 585 MHz with 512 MB RAM. In other experiments, the new genetic algorithm was successfully used for a more complicated problem [Ławrynowicz 2009].

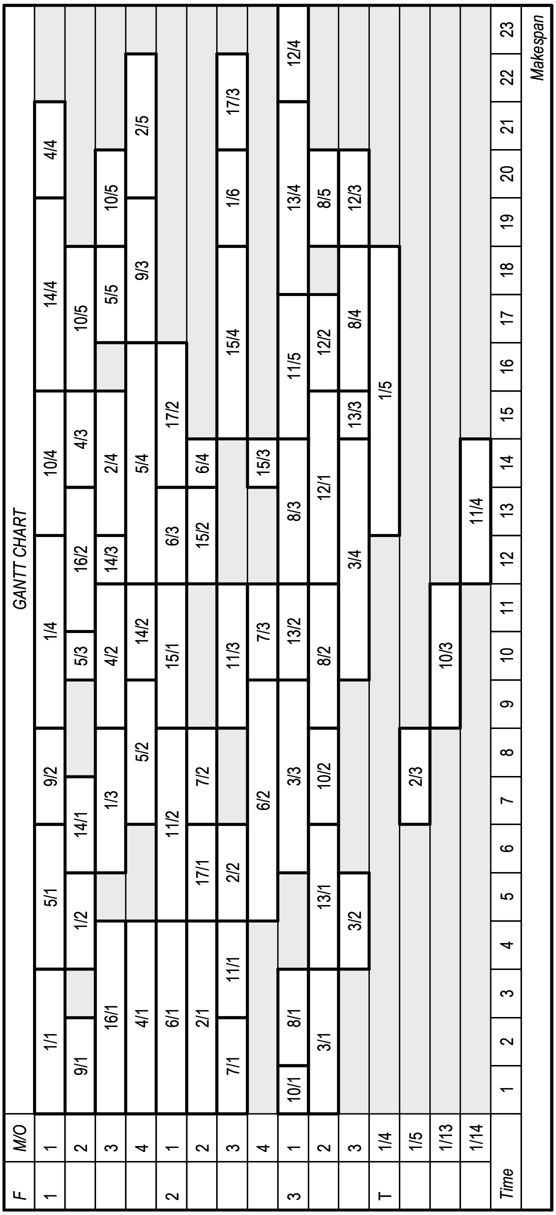

Figure 7. Gantt chart with external transport

By common access to the schedule generated by proposed genetic algorithm, managers can track and analyze the important operations of their production plans. Additionally, on the basis of the schedule, the planner may suggest orders for subcontracting or may adjust own capacities to expected orders. Moreover, the proposed genetic algorithm aided planners in transport orders planning. The advantage of the new genetic algorithm is very significant for Small and Medium-sized Enterprises (SMEs), because the firms use usually means of external transport and popular computers. The proposed genetic algorithm can be applied when there is a need to re-scheduling. It is common knowledge that in the industrial cluster there happen disruptions in production or needed mean of transport is sometimes not available. In such situations, the new genetic algorithm executes re-scheduling very quickly.

6. Conclusions

This paper demonstrates how an intelligent method known as the genetic algorithm can be used to optimize schedules for an industrial cluster. The research studies an application of new genetic algorithms for scheduling problems with makespan as the criterion. This approach adopts traditional operation-based method. On the basis of this method, the author creates a new genetic algorithm based on operation codes, where each chromosome is a set of 4-positions genes. This encoding method includes manufacture operations and transport operations. 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 transport order number, and the last value − the factory number or the source of the transport order number. The proposed method was verification on different experiments. The results of the experiments prove that the proposed new genetic algorithm is a very efficient and effective algorithm, because computational time for 71 operations was only 3.57 minutes on a popular computer. Therefore, it can be applied in a dynamic setting when re-scheduling is initiated by disruptions and other unexpected changes. The results from the cases study indicate that the model is not only practicable but also beneficial for the transport decision making. By collective access to the schedule for industrial cluster, managers can track and analyze the important activities of their production. Moreover, the proposed genetic algorithm aided planners in transport orders planning. The advantage of the new genetic algorithm is very important for SMEs, because the firms use usually means of external transport and popular computers.

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NOWATORSKA INTELIGENTNA METODA WSPOMAGAJĄCA ZARZĄDZANIE OPERACYJNE W KLASTRACH

Streszczenie: w artykule autorka proponuje inteligentną metodę wspomagającą zintegrowane podejmowanie decyzji operacyjnych w nowych strukturach biznesu. Podejście koncentruje się na interakcjach pomiędzy różnymi firmami klastra, na poziomie zarządzania operacyjnego, w celu ulepszenia procesów wytwarzania. Autorka zaproponowała nowatorską metodę do zespołowego harmonogramowania w klastrze przemysłowym. Do tego celu jest rozbudowywany algorytm genetyczny zaproponowany przez autorkę w 2008 r. Nowy algorytm genetyczny do zespołowego harmonogramowania jest oparty na kodowaniu operacji, gdzie każdy chromosom jest zbiorem 4-pozycyjnych genów. Zaproponowana metoda jest weryfikowana eksperymentalnie. Zaprezentowana w artykule analiza pokazuje, że nowy algorytm genetyczny zaproponowany przez autorkę może być wykorzystany do udoskonalenia szczegółowego harmonogramowania w klastrach. Ponadto zaproponowany algorytm genetyczny może wspomagać planistów w planowaniu zleceń transportu. To podejście może być zastosowane w dynamicznym środowisku, w którym ponowne harmonogramowanie jest inicjowane przez nieoczekiwane zmiany.