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Towards a Conceptual Design of Intelligent Material Transport Using Artificial Intelligence

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Aksiomatska teorija projektiranja
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Reliable and efficient material transport is one of the basic requirements that affect productivity in industry. For that reason, in this paper two approaches are proposed for the task of intelligent material transport by using a mobile robot. The first approach is based on applying genetic algorithms for optimizing process plans. Optimized process plans are passed to the genetic algorithm for scheduling which generate an optimal job sequence by using minimal makespan as criteria. The second approach uses graph theory for generating paths and neural networks for learning generated paths. The Matlab© software package is used for developing genetic algorithms, manufacturing process simulation, implementing search algorithms and neural network training. The obtained paths are tested by means of the Khepera II mobile robot system within a static laboratory model of manufacturing environment. The experiment results clearly show that an intelligent mobile robot can follow paths generated by using genetic algorithms as well as learn and predict optimal material transport flows thanks to using neural networks. The achieved positioning error of the mobile robot indicates that the conceptual design approach based on the axiomatic design theory can be used for designing the material transport and handling tasks in intelligent manufacturing systems.

Koncepcijsko projektiranje inteligentnog unutarnjeg transporta materijala korištenjem umjetne inteligencije

Izvornoznanstveni članak

Pouzdan i efikasan transport materijala je jedan od ključnih zahtjeva koji utječe na povećanje produktivnosti u industriji. Iz tog razloga, u radu su predložena dva pristupa za inteligentan transport materijala korištenjem mobilnog robota. Prvi pristup se zasniva na primjeni genetskih algoritama za optimizaciju tehnoloških procesa. Optimalna putanja se dobiva korištenjem optimalnih tehnoloških procesa i genetskih algoritama za vremensko planiranje, uz minimalno vrijeme kao kriterij. Drugi pristup je temeljen na primjeni teorije grafova za generiranje putanja i neuronskih mreža za učenje generirane putanje. Matlab© softverski paket je korišten za razvoj genetskih algoritama, simulaciju tehnoloških procesa, implementaciju algoritama pretraživanja i obučavanje neuronskih mreža. Dobivene putanje su testirane pomoću Khepera II mobilnog robota u statičkom laboratorijskom modelu tehnološkog okruženja. Eksperimentalni rezultati pokazuju kako inteligentni mobilni robot prati putanje generirane korištenjem genetskih algoritama, kao i da uči i predviđa optimalne tokove materijala zahvaljujući neuronskim mrežama. Ostvarena pogreška pozicioniranja mobilnog robota ukazuje da se koncepcijski pristup baziran na aksiomatskoj teoriji projektiranja može koristiti u projektiranju transporta i manipulacije u inteligentnom tehnološkom sustavu.

1. Introduction

For the last thirty years manufacturing concepts have had several redefinitions. In the eighties and nineties, the concept of flexible manufacturing systems (FMS) was introduced. The manufacturing enterprises of the 21st century are in an environment where markets are frequently shifting, new technologies are continuously emerging, and competition is globally increasing. All these requirements indicate that we need a methodology for the technological migration [1] from flexible manufacturing systems (FMS) to intelligent manufacturing systems (IMS). Many design methodologies that can be used for this migration are developed and proposed in [2]. Some of them are the axiomatic design theory, design decision-making methods, TRIZ (Theory of Inventive Problem Solving), etc.

Symbols/ Oznake

FMS	- Flexible Manufacturing System - Fleksibilni tehnološki sustav	*TW*	- processing time of operation - vrijeme trajanja operacije
ITS	- Intelligent Manufacturing System - Inteligentni tehnološki sustav	*TT*	- transportation time - vrijeme transporta
GA	- Genetic Algorithm - Genetski algoritam	*TP*	- production time - proizvodno vrijeme
NN	- Neural Network - Neuronske mreže	*M*	- vector of machines - vektor strojeva
{FR}	- Functional Requirement Vector - vektor funkcionalnih zahtjeva	*J*	- vector of jobs - vektor tehnoloških zadataka
{DP}	- Design Parameter Vector - vektor parametara projektiranja	p_{ij}	- parameter in M_{JM} matrix - parametar u M_{JM} matrici
[A]	- design matrix - matrica projektiranja	*R*	- matrix of distances between machines - matrica udaljenosti između strojeva
p_c	- crossover probability - vjerojatnost križanja	A^*	- search algorithm - algoritam pretraživanja
p_m	- mutation probability - vjerojatnost mutacije	x_t	- state vector at time instant *t* - vektor stanja sustava u trenutku t
n	- number of jobs - broj tehnoloških zadataka	*x,y*	- position at time instant *t* - pozicija u trenutku *t*
q	- maximum number of operations - maksimalan broj operacija	θ	- angle orientation at time instant *t* - kut orijentacije u trenutku *t*
G	- total number of process plans - ukupan broj tehnoloških procesa	*x',y'*	- position at time instant *t'* - pozicija u trenutku *t'*
t	- 1, 2, 3, …, M generations - broj generacija	θ'	- angle orientation at time instant *t'* - kut orijentacije u trenutku *t'*
o	- operation - operacija	Δs	- incremental path lengths - pređeni put kotača
P	- number of operations in process plan - broj operacija u tehnološkom procesu	*MSE*	- Mean Square Error - srednja kvadratna pogreška

Design and optimization of intelligent material transport system within IMS are big challenges and they can be achieved by implementing artificial intelligence. According to the literature published by CIRP and other manufacturing periodicals during the past decade [3, 4], nearly 34 modern manufacturing systems and production modes have been proposed and 35 mathematical methods have been used for the development of intelligent systems. Some of the methods are: Genetic Algorithms (GAs), Neural Networks (NNs), Fuzzy Logic, Machine Learning, Graph Theory, Heuristic Search (HS), Multi Agent Systems (MAS), Simulated Annealing (SA), etc. Evolutionary computation (i.e. GAs [5], genetic programming (GP), evolutionary programming, and evolutionary strategies) and NN are among the most widespread [6].

The intelligent material transport implies solving a path generation problem and controlling the movement of an intelligent agent - a mobile robot. The path that a mobile robot tracks can be generated and optimized in many ways. Firstly, the path directly depends on process planning and scheduling. Because most jobs may have a large number of feasible process plans and optimality of scheduling depends on the result of process planning, many researches proposed integration of process planning and scheduling.

Some of them applied an agent-based approach for integrated process planning and scheduling. An agent-based approach presented in [7] has been developed to facilitate the integration of these two functions. In this approach, the two functions are carried out simultaneously and an optimization agent based on an evolutionary algorithm is used to manage the interactions and communications between agents. The development of an agent-based negotiation protocol for negotiations between the part agents and the machine agents is presented in [8], and online hybrid agent-based negotiation multi-agent system to integrate process planning with scheduling/rescheduling is given in [9].

Dynamic flexible job shop scheduling problem with alternative process plans essentially involves deciding the order or priority for the jobs waiting to be processed on each machine. The concept of multi-agent systems is also applied to integrate dynamic process planning and dynamic production scheduling [10, 11].

On the other hand, integration of process planning and scheduling can be done by using artificial intelligence techniques. Evolutionary algorithms (GAs, SA, and HS) have recently been employed to generate optimal or nearly optimal plans satisfying the constraints and objectives of process planning and scheduling simultaneously. In [12] GA based algorithm is developed to solve the integrated process planning and scheduling problem. Simulation based GAs approach to integrate process planning and scheduling is proposed in [13]. In order to simultaneously optimize the production plan and the schedule, an improved hybrid genetic algorithm (HGA) is given in [14]. The new coevolutionary algorithm, called symbiotic evolutionary algorithm, given in [15], can simultaneously deal with the two problems of process planning and job shop scheduling. In [16], a modified two-phase GA approach is used to optimize process planning and scheduling simultaneously. In the first step, considering production time as an objective, three to five nearly optimal process plans for each job are determined. Then, the scheduling problem (by using the selected process plans) is optimized. A unified representation model and a SA-based approach have been developed to facilitate the integration and optimization process [17].

Process planning and scheduling can be viewed as an integrated problem but they can be solved separately as well. Evolutionary algorithms (GAs [18-21], GP [22]) and other intelligent methods, such as the fuzzy, and NNs are also widely used for both the process planning and the job-shop scheduling process. Minimal production time and minimal production cost are the most widespread criteria for process plans optimization and the minimal makespan, mean tardiness, mean lateness, manufacturing cost, minimal mean flow time, the balanced level of machine utilization, etc. are used as job-shop scheduling criteria.

The imprecise or fuzzy nature of the data introduced in real-world job shop scheduling problems is modelled with fuzzy processing time [23], or with both fuzzy processing time and fuzzy due date [24, 25]. They put forward a GA for job shop scheduling problem with fuzzy processing time and fuzzy due-date. A fuzzy logic rule-based scheduler, proposed in [26], uses the prevailing conditions in the job shop to select dynamically the most appropriate dispatching rule from several candidate rules.

NN has also been used in modelling and solving scheduling problems. The development of NN scheduler for scheduling job-shops is presented in [27]. In this hybrid intelligent system, GA is used to generate optimal schedules to a known benchmark problem and NN is used to capture the predictive knowledge regarding the assignment of an operation's position in a sequence. A new adaptive neural network and heuristics hybrid approach for job-shop scheduling is presented in [28]. The adaptive NN has the property of adapting its connection weights and biases of neural units during the iterations while obtaining the feasible solution. In [29] the job-shop scheduling problem is translated in an integer linear programming format which facilitated translation in an adequate neural network structure. This NN is capable of solving deterministic scheduling problems and always generates feasible solutions. A hybrid approach involving combination of NNs with a GA is proposed in [30]. The GA is used for the optimization of a sequence and a NN is used for the optimization of operation start times with a fixed sequence.

After the job sequence generation in job-shop planning and scheduling phase, each job needs to be transported between machines by using single or multiple transport robots. The job shop scheduling problem with the consideration of transportation tasks performed by a single robot is given in [31, 32], where effective tabu HS procedures are developed. NN and simulation modelling (scheduling) of manufacturing systems are used for making control decisions in specific applications of rail-guided vehicle systems [33]. There are few papers which consider simultaneously scheduling of jobs and vehicles [34-36]. The problem of simultaneous scheduling of machines and automated guided vehicles (AGVs) is solved by using a disjunctive graph for modelling the joint scheduling problem and memetic algorithm for scheduling machines and AGVs [34]. In [35] a hybrid GA is presented for the integrated simultaneous scheduling of machines and AGVs, by using a makespan as a minimization objective. A hybrid multi-objective GA approach is proposed in [36].

This paper presents two approaches for conceptual design of intelligent material transport, both based on axiomatic design theory. In the first approach, optimal process plans and schedules are obtained by using a GA-based approach. The optimization objective for process planning is to minimize production time, while minimum makespan and balanced level of machine utilization are two objective functions used for scheduling. In the second approach, optimal process plans are generated by using GA and appropriate job sequences are further generated by using graph algorithms applying minimal distance criteria. NN are used for learning generated paths and online prediction of optimal material transport flows. A single mobile robot is used to track the generated trajectories as well as to transport parts (jobs) between machines in an experimental manufacturing environment.

The remainder of this paper is organized as follows. In Section 2, the axiomatic design methodology is presented. A GA for process plan optimization is described in Section 3. Both GA job shop scheduling and NN–graph based scheduling approach are explained in Section 4. Experimental results for the two experiments are reported in Section 5 and discussion is provided in Section 6, which is followed by the concluding remarks in Section 7.

2. Axiomatic design theory

Axiomatic design theory is an attempt at synthesis of the basic principles of design in various engineering fields and in all phases of design. This design methodology is based on identifying customer needs and their transformation into correspondent functional requirements in the physical domain. According to [37], going from one domain to another is called mapping and it happens in each design phase: the conceptual, the product and the process design phase, respectively. For each hierarchical level the design process is done through the iterative mapping between the functional requirements (FRs) in the functional domain, and the design parameters (DPs) in the physical domain (Figure 1). The relationship between the FRs and DPs is expressed as [37]:

$$\{FR\} = [A] \cdot \{DP\}, \tag{1}$$

where $\{FR\}$ denotes the functional requirement vector, $\{DP\}$ denotes the design parameter vector, and $[A]$ denotes the design matrix that characterizes the design process. The structure of the matrix $[A]$ defines the type of design being considered and for the three hierarchical levels particular design matrices $[A]$ are presented in Table 1. It can be concluded that $[A]$ matrices in both the second and the third hierarchical levels (Table 1) are diagonal and each of the FRs can be fulfilled independently by means of one DP. Such design is called an uncoupled design [37].

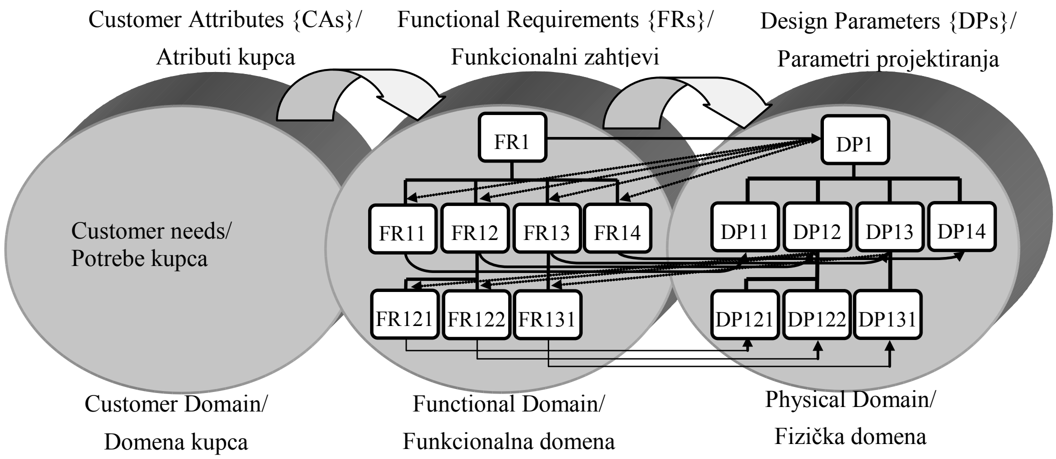

Figure 1. Concept of domain, mapping and axiomatic decomposition

Slika 1. Koncept domena, mapiranje i askiomatska dekompozicija

3. Genetic algorithms for process plans optimization

3.1. Representations for flexible process plans

In process planning, three types of flexibilities are given: operation, sequencing, and processing flexibility [19, 38]. Graphs, Petri net and networks are some of the numerous methods used to describe these types of flexibilities. In this paper, a network representation method is adopted. Generally, there are three node types in the network representation: the starting node, the intermediate node and the ending node. The starting and the ending node indicate the beginning and the end of the manufacturing process of a job and an intermediate node represents an operation. The intermediate node contains a set of alternative machines that are used to perform the operation and the processing time for the operation according to the machines. All nodes are connected with arrows that represent the precedence between them. For each job, every alternative path in the network starts with an OR-connector and ends with a join-connector. OR-links are used for making decisions as to which of the alternative manufacturing process procedures will be selected. All links that are not connected by OR-connectors must be visited [19, 38]. Figure 2 shows process plan networks for four alternative jobs.

3.2. Mathematical model of flexible process planning

In this paper the optimization objective of the flexible process planning problem is to minimize the production time which consists of processing time and transportation time. In accordance with the assumptions given in [19], the mathematical model of flexible process planning is described as follows:

n – total number of jobs;
G_i – total number of process plans of the i-th job;
t – 1, 2, 3,..., M generations;
o_{ijl} – j-th operation in the l-th process plan of the i-th job;
P_{il} – number of operations in the l-th process plan of the i-th job;
k – alternative machine corresponding to o_{ijl};
$TW(i,j,l,k)$ – processing time of operation o_{ijl} on the k-th alternative machine;
$TP(i,t)$ – production time of i-th job in the t-th generation;

$TT(i,l,(j,k_1),(j+1,k_2))$ – the transportation time between the k_1-th and the k_2-th alternative machine

The production time is calculated as shown in equation (2).

$$TP(i,t) = \sum_{j=1}^{P_{il}} TW(i,j,k,l) + \sum_{j=1}^{P_{il}-1} TT(i,l,(j,k_1),(j+1,k_2)),$$
$$i \in [1,n],\ j \in [1,P_{il}],\ l \in [1,G_i]. \qquad (2)$$

Two constraints given in [19] are also used. The first constraint is that each machine can handle only one job at a time and the second is that the operations of one job cannot be processed simultaneously. The objective function is given as follows:

$$\max f(i,t) = \frac{1}{TP(i,t)}, \qquad (3)$$

and it defines the alternative process plan with the minimum production time TP(i).

Table 1. List of the functional requirements, corresponding design parameters and [A] matrices

Tablica 1. Spisak funkcionalnih zahtjeva, korespodentnih parametara projektiranja i [A] matrice

X	Impact / Utjecaj
0	No impact / Nema utjecaja

	DP1: Intelligent mobile robot/ Inteligentni mobilni robot	DP11: GA for process plan optimization/ GA za optimizaciju tehnološkog procesa	DP12: Path planning module/ Modul za planiranje putanje	DP13: Control algorithm/ Algoritmi za upravljanje	DP14: Neural networks/ Neuronske mreže	DP121: Path planning algorithms/ Algoritmi za planiranje putanje	DP121: GA for scheduling/ GA za vremensko planiranje	DP121: Sensory information from encoders/ Senzorske informacije sa enkodera
FR1: Intelligent material transport/ Inteligentan transport materijala	X							
FR11: Process plan optimization/ Optimizacija tehnološkog procesa		X	0	0	0			
FR12: Path planning/ Planiranje putanje		0	X	0	0			
FR13: Path following/ Praćenje putanje		0	0	X	0			
FR14: Machine learning of material transport paths/ Strojno učenje transportnih tokova materijala		0	0	0	X			
FR121: Generating path nodes (criteria 1)/ Generiranje čvorova putanje (kriterij 1)						X	0	0
FR122: Generating path nodes (criteria 2)/ Generiranje čvorova putanje (kriterij 2)						0	X	0
FR131: Motion model (position and orientation)/ Model kretanja (pozicija i orijentacija)						0	0	X

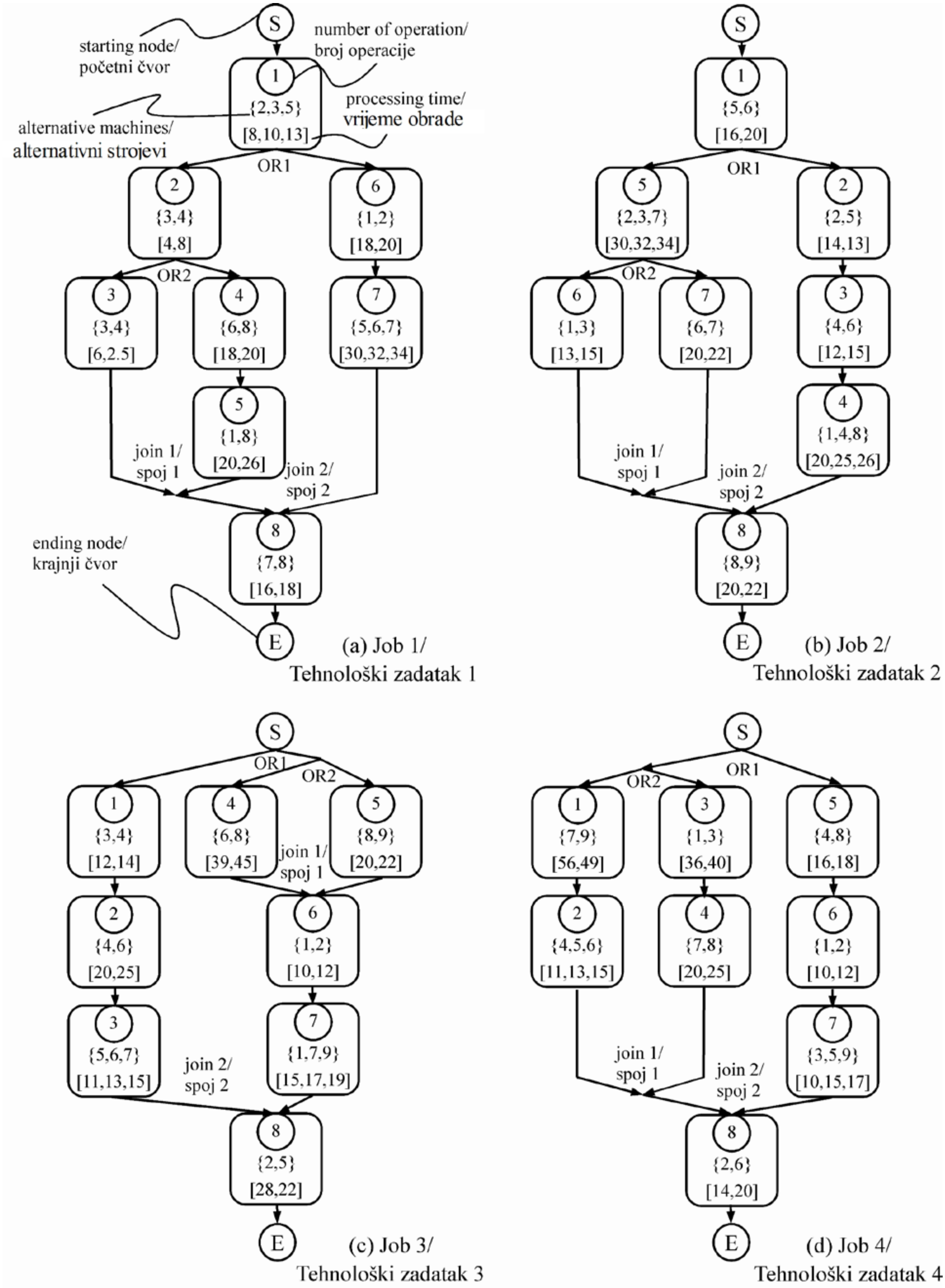

Figure 2. Process plans networks for four jobs

Slika 2. Mreže alternativnih tehnoloških procesa za četiri tehnološka zadatka

3.3. Genetic components for process planning

3.3.1. Encoding and decoding

Each chromosome in process planning population consists of two parts with different lengths (head substring and tail substring [38]), as shown in Figure 3. The first part of the chromosome is the process plan string [19]. It is made up of Genes and each Gene is a structure made up of two numbers. The first position in Gene defines number of an operation. It can represent all operations of one job, even those that may not be carried out due to alternative operation procedures. This can be resolved by using the tail substring. The tail encodes OR-connects as the binary numbers of 0 and 1. Zero denotes the right OR-link path and one denotes the left OR-link path. The second number in the Gene is the alternative machine on which the given operations are processed. Figure 3 shows an example of an individual for job 1. If we take the first Gene (1,2) for example, the operation number is 1 and 2 is the alternative machine that corresponds to operation 1. Process plan string shown in Figure 3 is made up of eight Genes and the OR string is made up of two discrimination values. The encoding is directly decoded. The selection of the OR-link paths defines which machining sequence will be chosen from the whole process plan substring. In the encoding example shown in Figure 3, the OR1-link takes value 1 which means that the left OR1-link path of the job1 is selected and the OR2-link takes value 0 (the right OR2-link path is selected). The Genes that belong to the unselected OR-link paths are first removed from the chromosome and the final result is the next operation-machine sequence (1,2)–(2,3)–(4,6)–(5,8)–(8,7).

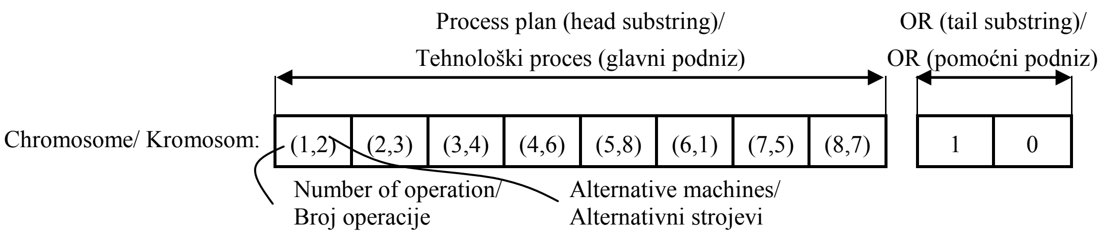

Figure 3. Chromosome encoding for process plan

Slika 3. Kodiranje kromosoma za tehnološki proces

3.3.2. Initial population

GA starts by randomly generating an initial population of chromosomes. When generating the individuals for an initial population, feasible operation sequence in a process plan is taken into account. Feasible operation-machine sequence means that the order of elements in the encoding does not break constraints on precedence relations of operations and machines in the network representation. After randomly assigning each operation-machine sequence in head substring, a tail substring of chromosome is initiated by randomly generating 0 or 1 for each component of the substring.

3.4. Genetic operators for process planning

3.4.1. Selection

After deciding on an encoding phase and generating an initial population, we need to a make decision how to choose individuals in the population that will create offspring for the next generation. This phase is called selection and it is a process of selecting two parents from the population for crossing. We adopted the fitness-proportional, roulette wheel selection, where the probability of selection is proportional to an individual's fitness.

3.4.2. Crossover

According to the defined crossover probability p_c, some individuals are picked out for crossover. For each pair of selected parent chromosomes, a single crossover point is randomly generated and applied for the recombination of process planning individuals. The first part of parent1 (the part left from the cutting-crossover point) is the same as the first part of offspring1. The second part of parent2 (the part right from the cutting-crossover point) is passed to the same position on offspring1. Analogously, the first part of parent2 is passed to the same position on offspring2 and the second part of parent1 is the same as the second part of offspring2. Figure 4 shows how two offspring are produced from a parent's pair in terms of the crossover operation. Traditional single point crossover is also applied to the tail substring of selected chromosomes.

3.4.2. Mutation

After the crossover the strings are subjected to mutation. According to the defined mutation probability p_m, some individuals are randomly selected to be mutated. For each selected chromosome a mutation point is randomly chosen and an appropriate operation-machine Gene is obtained. An offspring is generated when a selected machine in parent string Gene is replaced with one from all alternative machines for the selected operation. In the example illustrated in Figure 5, the Gene (7,5) is the one which is randomly selected and machine 5 can be replaced with machines 6 or 7, which are alternative machines for operation 7 of job 1 (see Figure 2). In the same way, one of the two OR-links' values in the tail string is chosen randomly and it is converted to the opposite value.

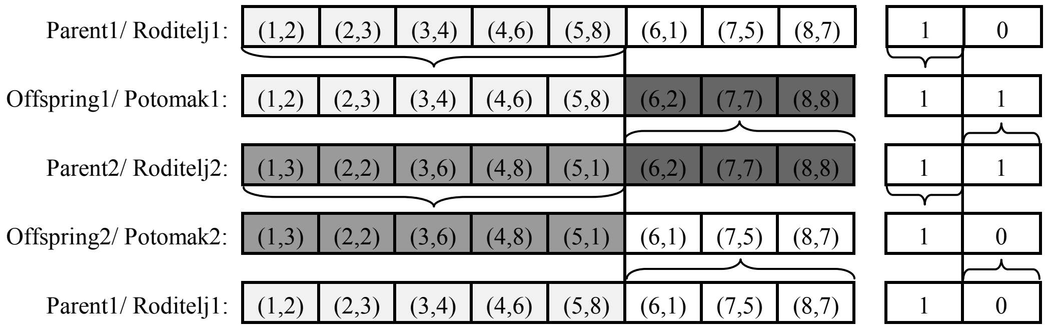

Figure 4. Crossover for process planning

Slika 4. Križanje kromosoma za tehnološki proces

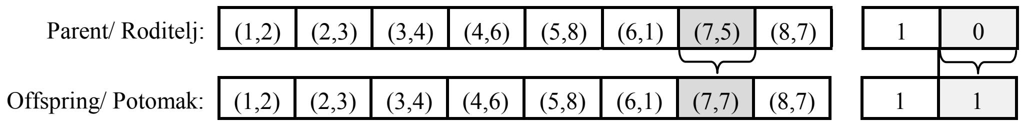

Figure 5. Mutation for process planning

Slika 5. Mutacija kromosoma za tehnološki proces

4. Modules for path planning, following and learning

To explain a mobile robot motion and actions in a manufacturing environment three modules are developed.

4.1. Path planning module

4.1.1. Genetic algorithm for scheduling (criteria 1)

The scheduling process determines the job (operation-machine) sequence and the processing time on the appropriate machines. Here, the GA based scheduling is the first way to generate optimal path that a mobile robot should follow. Considering the n job and the m machine problem (section 3), one process plan from three alternative process plans is randomly selected (Table 2). Using the methodology given in [19], genetic components for the scheduling process are determined. In this example, there are four jobs and nine machines (n=4 and m=9). The length of the scheduling plan chromosome is determined by the number of jobs and the maximum number of operations q. Parameter q is the maximum number of operations for all alternative process plans (i.e. q=4). Therefore, the scheduling plan string is made up of 16 ($n\times q$) elements and the process plan string is made up of four elements. For job 1, the process plan contains four operations and so four elements of scheduling plan string are equal to 1. Similarly, for job 4, the process plan consists of three operations and three elements of the scheduling plan are equal to 4. In the same way we generate elements for the second and the third job. Therefore, the scheduling plan string is made up of four 1s, four 2s, four 3s and three 4s. The other elements of this string are 0 and the number of 0s is equal to 1 (16−4−4−4−3=1). All these elements are arrayed randomly to generate a scheduling plan string, as shown in Figure 6.

Table 2. Selected alternative process plans for each job

Tablica 2. Odabrani tehnološki procesi za svaki tehnološki zadatak

Job/ Tehnološki zadatak	Selected process plans/ Odabrani tehnološki procesi
1	(1,3)-(2,3)-(3,3)-(8,8)
2	(1,5)-(5,3)-(6,3)-(8,9)
3	(1,3)-(2,6)-(3,5)-(8,5)
4	(1,9)-(2,5)-(8,6)

In this paper, two objective functions of the scheduling problem are calculated by using these equations:

$$object1 = \max(c_{ij})(c_{ij} \in T_d(s_{ij}, c_{ij})), \quad (4)$$

$$object2 = object1 + \sum_{a=1}^{m} \left| \sum p_{ij} - avgmt \right| (o_{ij} \in M_a), \quad (5)$$

where c_{ij} is the earliest completion time of operation o_{ij}, s_{ij} the earliest starting time of operation o_{ij}, $\sum p_{ij}$ is the total processing time for a machine and $avgmt$ is the average processing time of all machines [19]. The goal of minimizing objective functions *object1* and *object2* is lined on the synthetic consideration of the makespan and balanced level of machine utilization, respectively.

4.1.2. Genetic algorithm for scheduling

All steps of the crossover and mutation procedures for scheduling are extensively described in [19]. Here, we will give only examples of those operators characteristic for the aforementioned problem (*n*=4 and *m*=9). Firstly, the crossover phase is conducted. After selecting a pair of chromosomes (parent1 and parent2), we initialize two empty offspring. When the crossover procedure for the process string is carried out, the process plan string of parent1 is compared with the process plan string of parent2. The same elements in both strings are first detected and then saved. These elements in the process plan string of parent1 are copied to the same positions in offspring1, and in the same way the saved elements from the process plan string of parent2 are copied to offspring2. The remaining elements in parent1 are copied to offspring2, while the remaining elements in parent2 are copied to offspring1. In that way, we generate process plan strings for two offspring.

After process plan strings generation, the crossover procedure for the scheduling string is done. The saved elements of parent1 (2, 4 and 0) are appended to the same positions in offspring1 and these elements in parent2 are appended to the same positions in offspring2. In this example, the number of the remaining elements in the scheduling plan of parent1 is *n1*=0, and the number of the remaining elements in the scheduling plan of parent2 is *n2*=0. Knowing that *n1*=*n2* there is no empty positions in offspring 1 and offspring 2. Figure 7 shows the described crossover procedure for generating two offspring.

Two mutation operators are used for the mutation procedure. The first one is a two-point swapping mutation shown in Figure 8 and it is carried out in three steps. In step 1, a selection of one parent chromosome is done. Then, in step 2, we select two points in the scheduling plan string of the parent randomly and in the end, we generate a new chromosome offspring by interchanging these two elements. The second mutation is used for generating new offspring by changing one job's alternative process plan. After selecting one parent chromosome in step 1, one point in the process plan string of a parent is selected randomly. The next step changes the value of this selected element to another one in the selection range (for example: the first alternative process plan for job 4 is replaced with the third one, Table 5). In accordance with this change and because the number of operations of the third alternative process plans for job 4 is greater than the first one, the one 0 is selected randomly in the scheduling plan string and its value is changed to 4, as shown in Figure 9.

4.1.3. Graph algorithms for path planning (criteria 2)

Graph theory based algorithms were recognized as the alternative to generating optimal job scheduling sequence by using GA and minimizing total production time as criteria. The robot path planning optimization is very common in the field of robotics [39]. Here, the criteria are a reduction of energy consumption achieved by minimizing the total mobile robot transport paths. The first step in this approach is the analysis of material transport in a manufacturing environment. First of all, a job-shop layout is adopted. The process plans from Table 2 are chosen and the data about machines, jobs and the processing time of operations on the machine are adopted and analyzed. After that we need to define the quantitative relations between the adopted data. This dependence can be presented with matrix [M_{JM}], which is written by using vector [M] (vector of machines) and vector [J] (vector of jobs) [40, 41]. The time dependence between machines and jobs is described with matrix [T]. In the end, we define matrix [R] (matrix of distances between machines) by using the graph theory.

4.1.4. Path planning algorithms

Three algorithms are developed and implemented for the mobile robot path planning task. The first one is A* search algorithm [42, 43, 44] that is used for finding the shortest path between the start and goal points. It combines the *Dijkstra* algorithm and the *bread-first* search algorithm. Using the M_{JM} matrix, the second algorithm determinates the sequence of machines for each job and chooses a machine the robot should visit in accordance with the minimal distance criteria. Finally, the third algorithm is used to simulate the manufacturing process and to determine the sequence of machines in accordance with the simulated manufacturing process. This algorithm generates characteristic time parameters of the manufacturing process (the duration of the operation on the machine) and time parameters related to part transport to the machine (time needed for mobile robot part transport between machines).

4.2. Path following module

4.2.1. Motion model

The position of the mobile robot is determined by the system state vector x_t = (x, y, θ) and its evolution is given by simple odometry (6):

$$\begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \Delta s \cos(\theta + \Delta\theta / 2) \\ \Delta s \sin(\theta + \Delta\theta / 2) \\ \Delta\theta \end{bmatrix}, \quad (6)$$

where x', y' and θ' are the components of the state vector at time t', x, y and θ components at time t; Δs the incremental path lengths [43, 45].

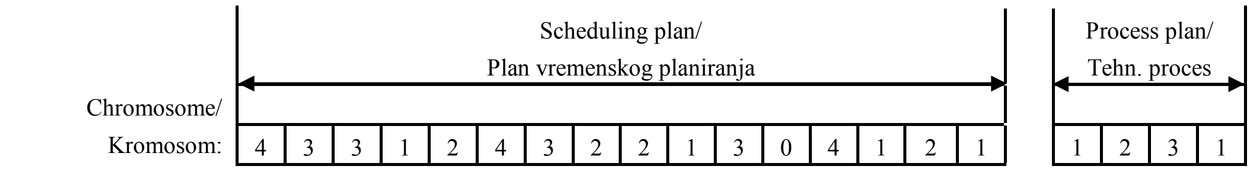

Figure 6. Chromosome of scheduling plan

Slika 6. Kromosom za plan vremenskog planiranja

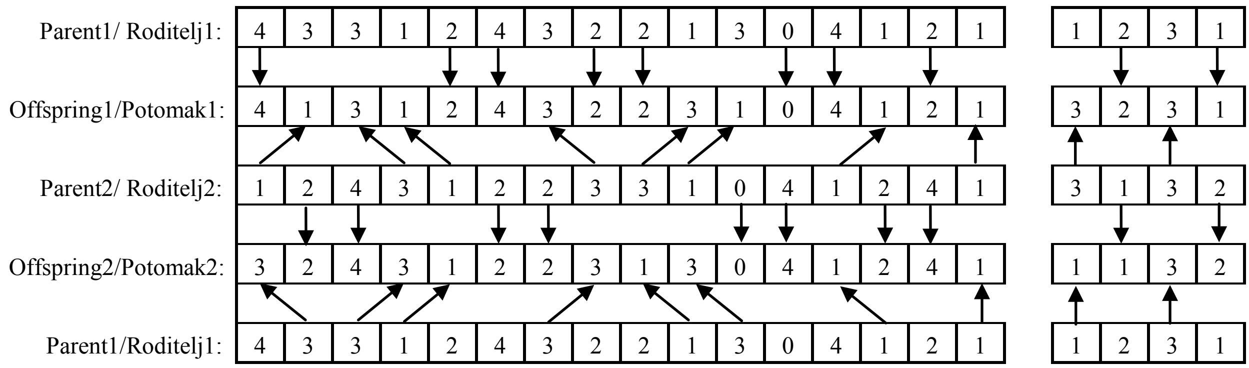

Figure 7. Crossover for scheduling

Slika 7. Križanje za vremensko planiranje

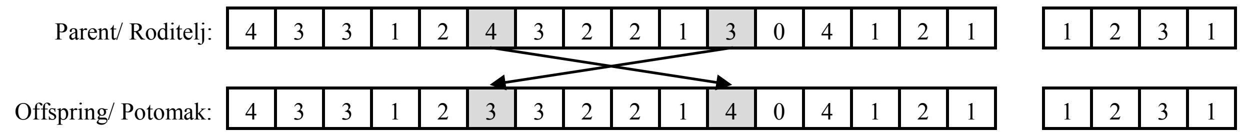

Figure 8. Mutation for scheduling

Slika 8. Mutacija za vremensko planiranje

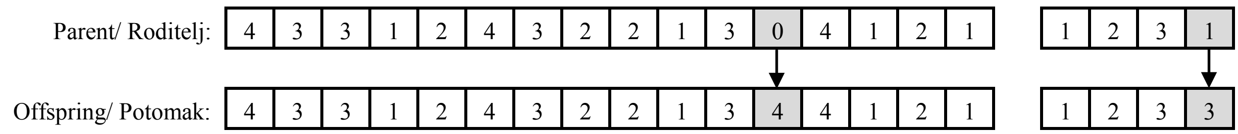

Figure 9. Mutation for scheduling

Slika 9. Mutacija za vremensko planiranje

4.3. Machine learning of material transport paths by using neural networks

Engineering processes generally do not have a deterministic nature. The processes that are important for the material transport task in terms of duration are the machining process and the process of robotized material transport between the defined nodes (machines). Considering the fact that these processes have stochastic nature, we can conclude that nominal time duration of operations, as well as time of transport from one node to another, are different for each job. For that reason, uniform distribution is chosen to model stochastic nature of the nominal time duration.

The NNs are powerful statistical tools used for classification, prediction and functional approximation [8]. Prediction of the next node (machine) in the path, where a robot needs to go and deliver the part, is based on past values of the system state and the current values of the system state. So, the previous robot pose, the time parameters of the process and the time of robot movement between the machines are the inputs of NN and the next node is the output of NN. For NN training the Matlab Neural Network Toolbox is used, with supervised learning algorithm (Levenberg-Marquardt) and the sigmoid activation function [46]. After a number of trials the best results were obtained with two layered architecture 4 $[8\text{-}4]_2$ 1 with an achieved error during optimization MSE=$7{,}04 \cdot 10^{-7}$.

5. Experimental results

In order to verify the proposed approach, two experiments are performed. The GA parameters used for optimization of process planning and scheduling are given in Table 3 and transportation time between machines is given in Table 4. Using these input parameters three alternative process plans for all jobs are generated according to an objective function given by equation (3). Generating three alternative process plans for all jobs by using GA approach is the same for both experiment 1 and experiment 2.

5.1. Experiment 1

The first experiment starts with randomly selecting one from the three alternative process plans for each job given in Table 5. GA for scheduling then generates a jobs-machine sequence in accordance with two objective functions: *object1* (Figure 11 (a)) and *object2* (Figure 11 (b)). In that way the path that a mobile robot follows is generated by using GA for scheduling with minimization of production time *TP* as criteria. Testing the accuracy of the mobile robot following a path is carried out in a static laboratory model of manufacturing environment, where positions of the machines are known *a priori*. Experimental model, the *Khepera II* mobile robot and parts of the whole path (3,3)-(1,3)-(4,9)-(1,3)-(1,3)-(3,6)-(2,5)-(3,6)-(3,6)-(4,6)-(3,5)-(2,3)-(2,3)-(1,8)-(0,/)-(2,9)-(4,6) are shown in Figure 12. While executing the transport task, the robot uses simple odometry, [43, 45, 47], to determine its pose and A* algorithm to optimizes the path between the machines. The mean position errors during the first experiment in x and y directions are Δx=0,53 [cm] and Δy=2,35 [cm].

5.2. Experiment 2

The best alternatives from all four jobs are selected and, by using graph algorithms in path folowing module as well as the minimal distance criteria, the nominal path job-machine sequence is generated (1,3)-(3,3)-(2,5)-(4,9)-(2,5)-(2,3)-(1,8)-(4,9)-(4,5)-(3,3)-(3,6)-(4,5)-(4,6)-(2,3)-(2,9)-(3,6)-(3,5). The experiment 2 starts but the coordinates of the goal point are not known at the beginning. This parameter depends on the time the robot needs to travel from one machine to another and the processing time of the operation on the machine. When the robot finishes the transport of the last part to the machine for the first operation, its current pose, previous pose, time parameters (total transportation time and total machining time) are passed to NN. Based on this information, NN predicts the nearest machine where the manufacturing operation is completed and generates information about future robot movement [43]. One predicted sequence is (1,3)-(3,3)-(2,5)-(4,9)-(1,3)-(1,8)-(2,5)-(3,3)-(3,6)-(4,9)-(4,5)-(3,6)-(3,5)-(2,3)-(2,9)-(4,5)-(4,6).

Table 3. GA parameters

Tablica 3. Parametri za GA

Parameters/ Parametri	Process planning / Tehnološki proces	Scheduling / Vremensko planiranje
The size of the population, S/ Veličina populacije	40	500
Total number of generation, M/ Ukupan broj generacija	30	100
Probability of crossover operation, p_c/ Vjerojatnost za križanje	0,60	0,80
Probability of mutation operation, p_m / Vjerojatnost za mutaciju	0,10	0,10

Table 4. Transportation time between machines

Tablica 4. Vrijeme transporta između strojeva

Machine / Stroj	1	2	3	4	5	6	7	8	9
1	0	50	79	36	99	106	130	116	102
2	50	0	31	16	51	56	78	67	54
3	79	31	0	47	20	27	63	48	26
4	36	16	47	0	67	70	90	84	70
5	99	51	20	67	0	7	55	40	22
6	106	56	27	70	7	0	62	47	29
7	130	78	63	90	55	62	0	15	37
8	116	67	48	84	40	47	15	0	22
9	102	54	26	70	22	29	37	22	0

Table 5. Experimental results of process planning

Tablica 5. Eksperimentalni rezultati tehnološkog procesa

Job/ Teh. zadatak	Alternative process plans/ Alternativni tehnološki procesi	Fitness/ Funkcija cilja	Production time/ Proizvodno vrijeme
1	(1,3)-(2,3)-(3,3)-(8,8)	0,0116	86
	(1,2)-(2,3)-(3,3)-(8,8)	0,0101	99
	(1,5)-(2,3)-(3,3)-(8,8)	0,0087	115
2	(1,5)-(5,3)-(6,3)-(8,9)	0,0076	131
	(1,6)-(5,3)-(6,3)-(8,9)	0,0070	142
	(1,5)-(5,3)-(6,3)-(8,8)	0,0066	151
3	(1,3)-(2,6)-(3,5)-(8,5)	0,0096	104
	(1,3)-(2,6)-(3,6)-(8,5)	0,0094	106
	(1,4)-(2,4)-(3,5)-(8,5)	0,0075	134
4	(1,9)-(2,5)-(8,6)	0,0090	111
	(1,9)-(2,6)-(8,6)	0,0088	113
	(5,4)-(6,2)-(7,3)-(8,2)	0,0077	130

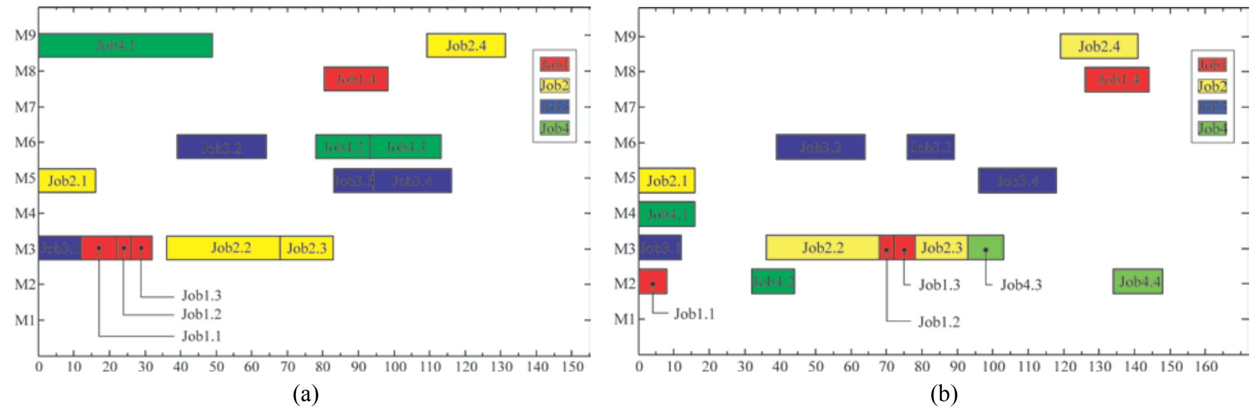

Figure 11. (a) Gantt chart of experiment 1 based on *object1* (Makespan=131); (b) Gantt chart of experiment 1 based on *object2* (Makespan=148)

Slika 11. (a) Gantov dijagram za eksperiment 1 na osnovu *object1* (Makespan=131); (b) Gantov dijagram za eksperiment 1 na osnovu *object2* (Makespan=148)

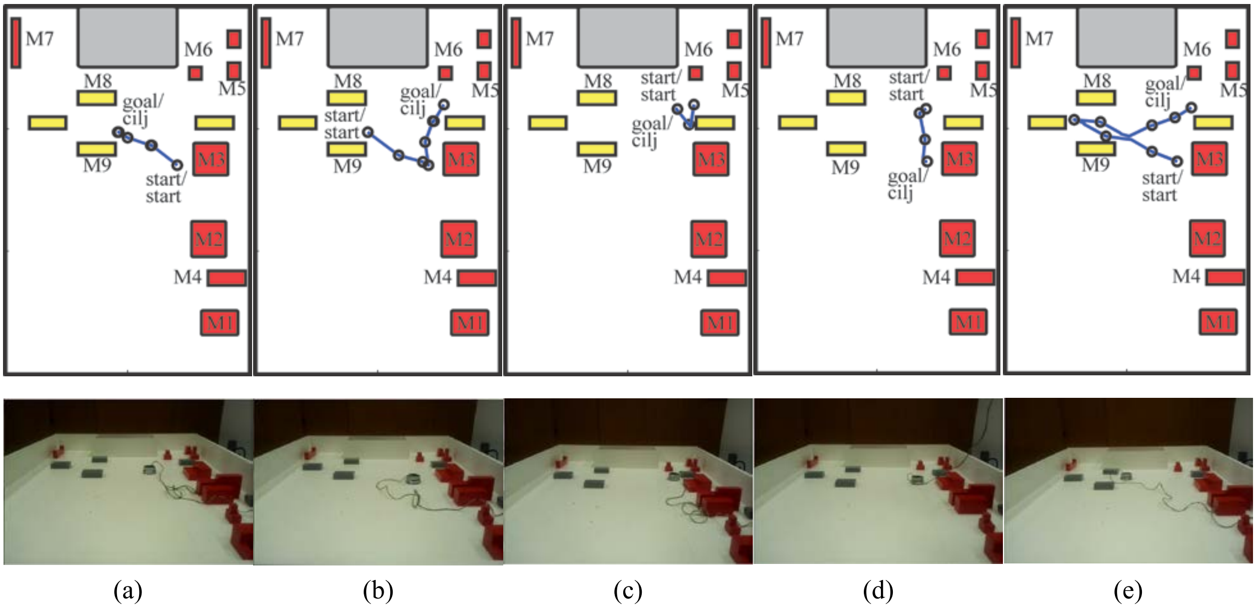

Figure 12. Parts of entire path and poses of the mobile robot. The path is given as the result of GA scheduling described in the text: (a) M3-M9; (b) M9-M3-M6; (c) M6-M5-M6-M5; (d) M5-M3; (e) M3-M8-M9-M6

Slika 12. Segmenti putanje i položaji mobilnog robota. Putanja predstavlja rezultate primjene GA opisane u tekstu: (a) M3-M9; (b) M9-M3-M6; (c) M6-M5-M6-M5; (d) M5-M3; (e) M3-M8-M9-M6

6. Discussions

On the whole, the experimental results indicate that the axiomatic design methodology can be used for conceptual design of intelligent material transport within IMS. This design methodology together with artificial intelligence techniques is an innovative concept in the domain of single robot scheduling in a job-shop environment.

In literature [7, 12, 14, 16, 17] it is quite common to find only simulation results for optimal process plans and schedules in the form of the Grant chart. Besides simulation results (Table 5 and Figure 11), we propose an additional experimental verification, where the job shop sequences obtained by using integrated approach are tested in an experimental environment. Satisfactory results in the path-following are obtained while a single mobile robot performs transportation tasks, Figure 12.

The NN model developed for learning optimized transport paths has proved to be effective in online prediction of material transport flows. One more advantage of this approach is that the NN is trained with the empirical time parameters of the real manufacturing process and stochastic nature of the process is modelled according to the uniform distribution. Time parameters (machining time and transportation time) obtained in real-world environments can be used for making decisions in mobile robot material transport tasks.

Minimal production time is used as criteria for process plans optimization. The adopted formulation given by equation (2) considers the machining and the transportation time. Transportation time between two machines depends on the distance between those two alternative machines for two successive operations. As a consequence of using this objective function, successive operations of a part (job) are assigned to the same machine tool, as long as it is an alternative machine for both operations. In this manner, the transportation time between these consecutive operations becomes zero and the completion time is further reduced. The potential quality problems due to re-fixing the part on different machine tools are reduced and total mobile robot transport paths are minimized. This approach has the following limitation: Process plans with the shortest processing times might cause bottlenecks, or similarly assigning the successive operations on one machine tool might cause a bottleneck machine. This problem can be solved by introducing a rescheduling stage in the scheduling module.

In case of a mobile robot path following in real-world environments, a motion model based only on the odometric information from encoders would not be sufficient for robot localization. Considering real world constrains and problems (such as friction or part manipulation), future research is directed towards developing advanced localization and map-building algorithms. Furthermore, an additional module for part (job) handling tasks needs to be integrated in an intelligent manufacturing system.

7. Conclusion

This paper presented a method for conceptual design of mobile robot material transport in an intelligent manufacturing system. An intelligent mobile robot, with *a priori* known static obstacles in the environment, has the ability to generate an optimal motion path in accordance with the requirements of the manufacturing process and priority servicing of machine tools. Two approaches were presented for optimal transport paths generating.

The first is based on optimization of process plans by using GA. Optimized process plans are then used as inputs in GA for scheduling. This algorithm generates a jobs-machine sequence in accordance with minimal makespan as criteria.

In the second approach a mobile robot learns the optimal transport paths and the sequence of manipulations by using a neural network [45]. The neural network was developed to predict the parameters of a manufacturing process and to learn characteristic time parameters of the process. For the purposes of simulation, we used nominal time parameters (estimated by using empirical data) of the manufacturing process, and its stochastic nature is modeled according to the uniform distribution [45]. All algorithms and neural network models are developed in the Matlab environment and implemented on the *Khepera II* mobile robot. The achieved positioning error of mobile robot indicates that conceptual design approach based on axiomatic design theory, GAs for process planing and scheduling, and neural networks can be used for material transport and handling tasks in intelligent manufacturing systems.

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