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AUTOMATIC LEARNING OF FUZZY LOGIC WITH THE USE OF GENETIC ALGORITHMS

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S u m m a r y

This paper is concerned with building a rule base in the metod based on genetic fuzzy systems to control robotised manufacturing systems. The suggested method of building a rule base employs a genetic algorithm, or more pricisely, a chromosome coding algorithm. Widely used methods of chromosome coding have their faults, which make it necessary for the methods to extend their block diagrams of the genetic althorithm or make the methods labour intensive. The method, which is a compilation of well-known metchods, allows to use their advantages and eliminate the influence of their disadvantages. Therefore, it will be possible to efficently employ genetic fuzzy logic to automatically build a rule base of fuzzy logic.

Keywords: workpiece flow control, FMS, fuzzy logic, genetics algorythm

Automatyczne uczenie wnioskowania rozmytego z wykorzystaniem algorytmów genetycznych

S t r e s z c z e n i e

W pracy prowadzono analizę budowania bazy reguł w metodzie genetycznego wnioskowania rozmytego w zastosowaniu do sterowania pracą zrobotyzowanych systemów wytwarzania. Opracowano metodykę budowy bazy reguł z użyciem algorytmu genetycznego – algorytm kodowania chromosomu. Stosowane w praktyce metody kodowania chromosomu obarczone są wadami. Powodują one konieczność rozbudowy schematu blokowego algorytmu genetycznego. Wiążą się także ze znaczną pracochłonnością. Zaproponowano metodę będącą kompilacją dotychczas stosowanych metod i pozwalającą na zachowanie ich zalet, a jednocześnie niwelującą oddziaływanie ich wad. Umożliwia więc sprawne wykorzystanie genetycznego wnioskowania rozmytego do automatycznej budowy baz reguł wnioskowania rozmytego.

Słowa kluczowe: sterowanie przepływem materiałów, ESW, logika rozmyta, algorytmy genetyczne

1. Introduction

Flexible manufacturing systems (FMS) are expensive industrial facilities. Consequently, it is essential to use all the possibilities of the manufacturing potential of FMS in an optimal way. Therefore, it is crucial to carry out research

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to streamline the steering of flexible manufacturing systems. A great deal of research centres all over the world are involved in the research.

For many years, the Unit of Automated Manufacturing Systems at West Pomeranian University of Technology has been conducting research into the application of artificial intelligence methods to steer FMS, and particularly to use fuzzy logic based on knowledge bases prepared by an expert.

The fundamental premise to use fuzzy logic to steer the work of robotized flexible manufacturing system is a diversifed character of the relationship between components of a manufacturing system (in some places it is discreet, in other linear, nonlinear, and sometimes discontinuous), therefore, it is difficult to discribe by means of mathematical equations indeed.

A knowledge base of fuzzy logic, or more priecisely, a rule base of fuzzy logic is made by a man – an expert – on the basis of their knowledge about advances and relationships taking place in a real object. Making rule bases is relatively simple, when there are few rules, no more than a couple of dozens. However, when the number of rules exceeds few hundred it is complicated to make rule bases. Such a task is far beyond man's perceptual abilities. In every case, such a base is, to a large extent, intuitive. Although it is effective, it has all the hallmarks of subjectivity, and ocassionaly it bears the hallmark of contradiction. Additionaly, there are problems finding a right expert in some field, who would be able to comprehend the complexity of all the phenomena in the field.

That is why it is necessary to try to find effective methods which would facilitate the building of rule bases in the method of fuzzy logic to steer the work of FMS. It will allow to use flexible manufacturing systems and shorten the time necessary to prepare changes resulting from changing manufacturing orders.

2. Facing the Problem

In the last decade of the 20th century, attempts to automatically generate knowledge bases on the bases of data describing the phenomenon were started. Appeared systems linking fuzzy logic with evolutionary algorithms and artificial neural networks appeared. The works on "hybrid" systems were conducted in two directions:

- making and researching evolutionary fuzzy methods [1-5],
- using neuro fuzzy methods [6, 7].

Evolutionary methods, which are good global optimizers, always allow to obtain clear results, unlike artificial neural networks, which can give an uncertain answer (neither "YES", nor "NO"). Therefore, the evolutionary methods seem to be more suitable for building rule bases as well as adjusting working model parameters and for making a hybrid system [8].

That is why, genetic fuzzy logic (based on an evolutionary fuzzy system) to automatically generate rule bases used for scheduling the work of robotized tooling systems has been used.

Figure 1 depicts a block diagram of a classic genetic algorithm, often quoted in specialist literature dealing with genetic algorithms [9-11].

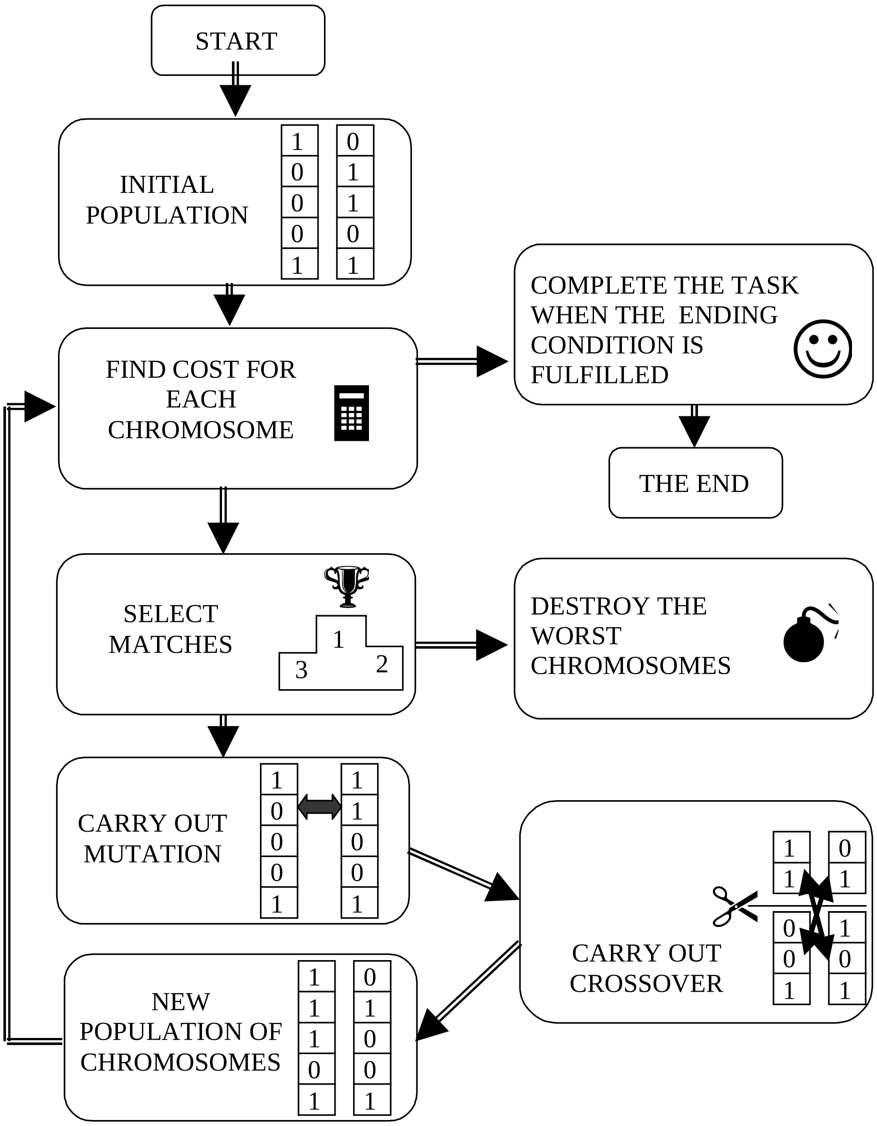


Fig. 1. Block diagram of genetics algorithm [own work]

The algorithm shown in Figure 1 is built only of one loop which has a single stopping criterion and several blocks alligned linearly. The algorithm can be seen as a base for different modifications indispensable for the realization of research objectives. The modifications of the algorithm can result from, for example, necessary initial coding of external parametres. Because of the modifications, different algorithms, which differ in consrtucion but have basic evolutionary features, can be found in literature [9]. In spite of some interference, the general skeleton of the agorithm remains intact and it will always be characterized by basic functional blocks indispensable for conducting evolution.

One of the most crucial elements of the work of genetic algorithm, which has not been presented in the block diagram, is chromosome coding. It is to comply with the two fundamental requirements:

- Be resistant to the operation of crossover (i.e. after the genetic material has been changed, new sequences should be decoded). The crossover operation is often adapted to the coding which was used.
- Reflect exact features of solutions. Consequently, inheriting parents' traits by children is quaranteed.

There are three basic coding methods [12]:

- classic, i.e. binary,
- based on integral numbers,
- based on floating point numbers.

3. Solving the Problem

3.1. The Pitts Method

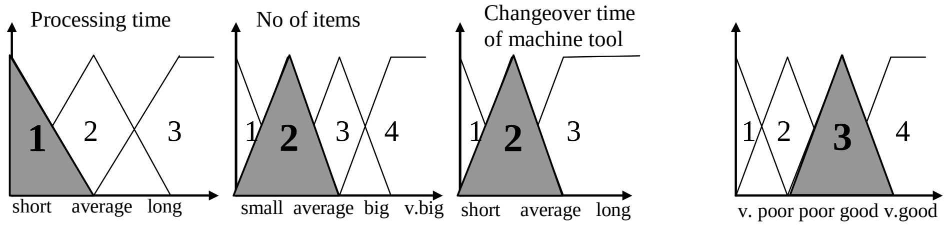
There are two binary coding methods of evolutionary algorithms for making knowledge bases for fuzzy logic:

- the Pitts method, in which a chromosome, from a point of view of a genetic algorithm, is a single rule [13],
- the Michigan method, in which a chromosome is a collection of all used rules; here the population consists of many rule collections [14].

Individual genes in this method denote the number of membership functions and conclusion used for making a knowledge base. Figure 2 shows an example of coding rule of a batch selection for processing on a tool machine. Dark fields show membership functions and conclusions covered by the knowledge base rule.

A serious drawback of the method is a necessity to conduct an additional analysis which is to specify the number of rules in a knowledge base, and consequently the size of the population.

If (Processing time = short) and (No of items = average) and (Changeover time of machine tool = average) then (order assessment = good)



Chromosome form: 1 2 2 3

Fig. 2. An example of coding knowledge base by means of the Pitts method

3.2. The Michigan Method

Coding in the Michigan method is binary coding, in which "1" means that a knowledge base rule will be in a knowledge base, whereas "0" means it will not be used. Figure 3 depicts an example of coding rule of a batch selection for processing on a tool machine by means of the Michigan method.

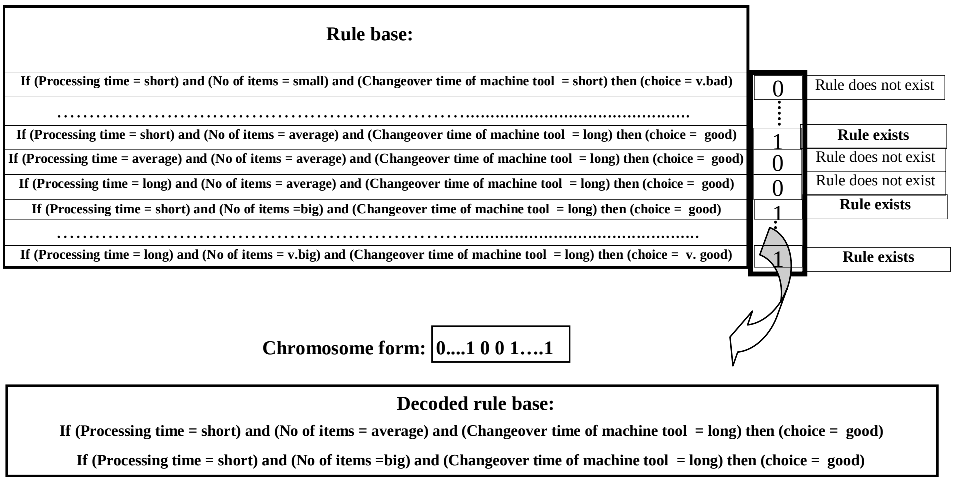


Fig. 3. An example of coding knowledge base by means of the Michigan method

The main advantage of the method is that all the rule base is coded, therefore, it is not necessary to do the quantitative analysis of indispensable rules to see if the method functions properly, because, unlike the Pitts method, all possible rules take part in the working time of genetic algorithm.

The considerable size of chromosome is a disadvantage. The length of the chromosome is dependent on the size of rule base and it increases exponentially depending on the number of used fuzzy sets or conclusion membership functions.

The work employs a type of coding which joins the above mentioned methods. It was supposed to reduce the size of a chromosome in relation to the Michigan method and simultanously solve the problem of the size of a rule base in the Pitt method. The way of coding a rule base used in this paper is shown in Fig. 4.

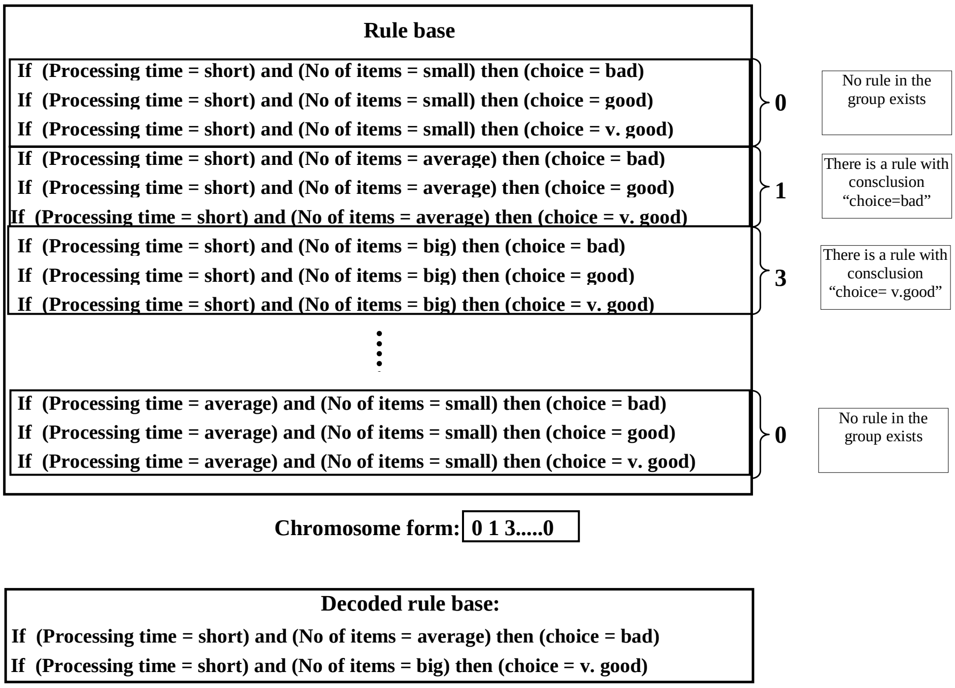


Fig. 4. Coding knowledge base used in the paper

The suggested coding is to group rules having identical premises but different conclusions. Therefore, the length of a chromosome is the number of functions of conclusion membership shorter than the length of a chromosome used in the Michigan method.

At the same time, all possible rules to be created, of a fuzzy logic rule base, take part in the work of a genetic algorithm.

4. Results

The efficiency of the suggested method has been checked in the scheduled work of a miniature robotized manufacturing system (Fig. 5), which was designed and constructed in the Unit of Automated Manufacturing Systems and Quality Engineering at West Pomeranian University of Technology [15].

Items to be processed and processed items are stored on carriers, in the form of transportation pallets in a rack store operated by a stacking machine. The pallets are transported to machining stands by means of an industrial car equipped with active manipulators.

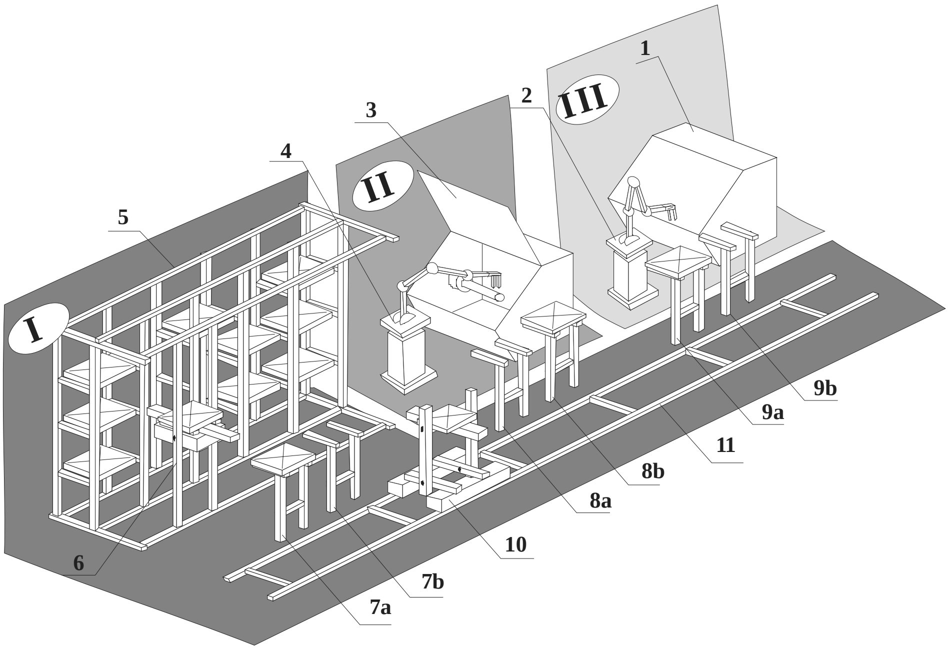


Fig. 5. Configuration of research flexible manufacturing system: 1 – turning lathe, 2 – lathe robot, 3 – milling-machine, 4 – milling-machine robot, 5 – rack store, 6 – stacking machine, 7a – input magazine – mag_in, 7b – output magazine – mag_out, 8a – lathe buffer magazine – mag_11, 8b – buffer magazine – mag_12, 9a – milling-machine buffer magazine mag_21, 9b – buffer magazine mag_22, 10 – industrial car, 11 – passable track

The subsystem topology of system steering has been based on a protocol tcp/ip computer network (Fig. 6). On the level of production planning and scheduling (PPS; the highest) a system operating schedule has been devised by means of eM-Plant software (which employs fuzzy logic), which is fundamental in generating steering procedures for element subsystems of FMS.

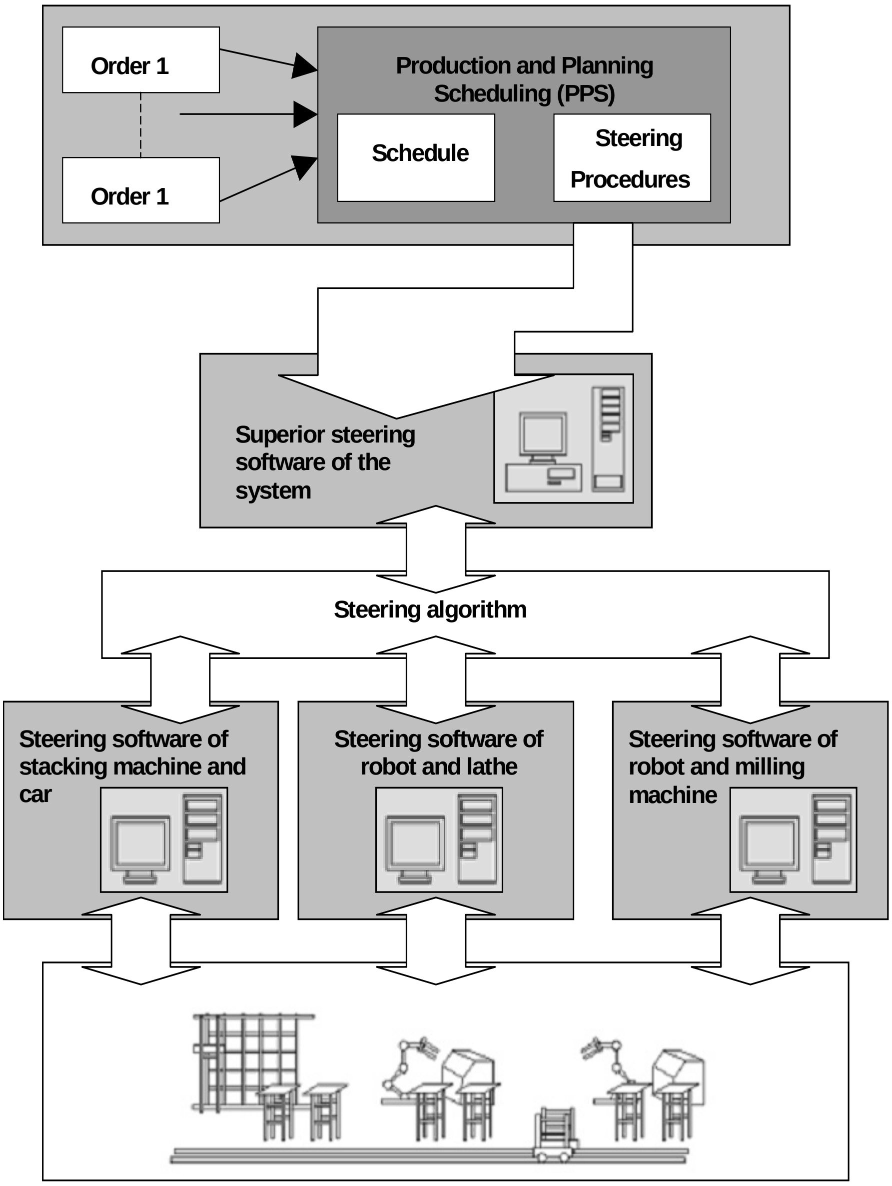


Fig. 6. Computer subsystem of research flexible manufacturing system

For the sake of comparison, three models, which have different steering strategies of store and transport subsystems, have been compared with the fourth model [16].

Model 1 **FIFO** – the work of the industrial car as well as the stacking machine followed the FIFO rule (First In First Out), which is often described as a queue processing rule.

Model 2 **Alg**. – taking pallets from the rack stack follows the algorithm which attributes some weight to the pallets.

Model 3 **FL** – the work of the industrial car as well as the stacking machine followed the FL rule (Fuzzy Logic), however, the rules have been devised by a man – an expert.

Model 4 **Gen-FL** – the work of the industrial car as well as the stacking machine followed the FL rule (Fuzzy Logic), however, the rules have been devised using a genetic algorithm on the basis of generally prepared learning data.

Table 1 contains sample input data of production orders to be realized in the system. Figure 7 depicts results of the simulation.

Table 1. Input data

Or-der	**Techno-logical route**	**No. of pallets**	**No of pieces on pallet**			**Machining time on machine M1 [h:m:s]**	**Machining time on machine M2 [h:m:s]**	**Changeover time of machine M1**	**Changeover time of machine M2**
			P 2.1	**P 2.2**	**P 2.3**				
Z1	MT1	8	1	2	3	00:03:20	00:03:52	Z1	MT1
Z2	MT2	7	1	2	3	00:03:01	00:03:56	Z2	MT2

5. Conclusions

Suggested method is a compilation of well-known methods. It allows to retain their advantages and eliminate their disadvantages; particularly owing to grouping rules having the same premises, the method makes it impossible to introduce mutually exclussive rules into a fuzzy logic rule base. It means that for a data rule only one conclusion will be chosen or the whole rule will be rejected because it does not affect the result of fuzzy logic.

The suggested coding encompasses all feasible fuzzy logic rules, even though a chromosome is much shorter in relation to the chromosome used in the Michigan method.

Retaining the location of a gene related to some rule in a chromosome guarantees a possibility of inheriting features by a genetic algorithm.

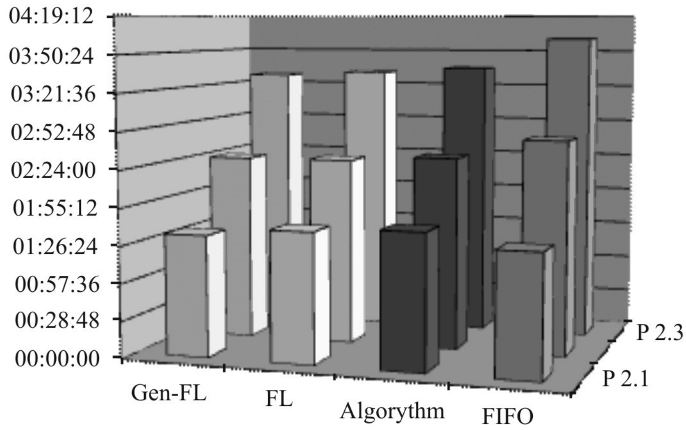


Fig. 7. Graphic representation of results for cases P 2.1, P 2.2, P 2.3 [12]

Using such coding will allow effective use of genetic fuzzy logic for the automated building of a fuzzy logic rule base.

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