A Hybrid Decision Model for Improving Warehouse Efficiency in a Process-oriented View

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1. Introduction

The Concept of Supply Chain Management (SCM) has been paid much more attention over the past decades. As one of the essential components of a supply chain, warehousing is valued because of the following major functions: smoothening the material flow; accomadating variability influenced by factors such as product seasonality or transportation scheduling; ensuring proper inventory level by product consolidation; guaranteeing the operation within high tolerances of speed, accuracy and lack of damage (Frazelle, 2002; Christopher, 2005; Harrison & van Hoek, 2005; Baker, 2007; Gu et al., 2007).
According to (Bernardy & Scherff, 1998), all the activities involved in a warehouse can be described by processes and are characterized by entailing a large number of differing, but interdependent sub-processes and many complex influential factors. Since there are diverse functional processes within which different combinations of influencing factors exist, the throughput capacity of the warehouse may be strongly affected, especially when the staffs at the operation level always keep different views upon process parameter settings based on their personal experiences. Hence it is essential to find out the optimal factor settings for the compound functional processes regarding the experts' knowledge so as to make the right strategy, and finally obtain satisfying warehouse operation.
World has witnessed the soaring use of Artificial Intelligence (AI) for operations management (OM) with the purpose of decision support (Kobbacy et al., 2007). Hybrid architecture has become a new field of AI research, in light of the development of the next generation of intelligent systems. Current research in this field mainly concentrates on the marriage of Genetic Algorithms (GA) and Fuzzy Logic (Feng & Huang, 2005; Lau et al., 2009). Exploring the similarities of the essential structures of these two knowledge manipulation methods is where intelligent decision support systems can possibly play an important role. However, such hybrid systems have not shown great significance in the warehousing sector.
This chapter aims to develop a Fuzzy-GA capacity decision model (FGCDM) to enhance rack efficiency in a One-Warehouse, N-Supplier warehouse by taking into consideration the performance metrics and various driving factors of the related processes. The hybrid framework is proposed to enable decision makers to formulate nearly optimal sets of knowledge-based fuzzy rules so as to identify better solutions for fully utilizing the warehouse capacity.

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2. Research background

2.1 Performance measurement

The supply chain encompasses a complex set of activities which require a collection of metrics to adequately measure performance (Caplice & Sheffi, 1995; Tompkins & Smith, 1998). (Bowersox & Closs, 1996) states three objectives for developing and implementing performance measurement systems: to monitor historical system performance for reporting, to control ongoing performance so that abnormal processes may be prevented, and to direct the personnel's activities. A conceptual framework for measuring the strategic, tactical and operational level performance in a supply chain is proposed in (Gunasekaran et al., 2001), in which performance measures on warehousing and inventory in a SCM was emphasized. An activity-based approach for mapping and analyzing the practically complex supply chain network is identified in (Chan & Qi, 2003), which can be regarded as a primary step on measuring the performance of processes. (Lohman et al., 2004) points out that by means of local key performance indicators (KPIs), The measurement scheme should be developing at a organization-wide scale. The interplay between organizational experiences and new performance measurement initiatives is highlighted (Wouters & Sportel, 2005). Furthermore, the research work in (Angerhofer & Angelides, 2006) shows how the key parameters and performance indicators are modelled through a case study which illustrates how the decision support environment could be used to improve the performance of a collaborative supply chain. (Niemi, 2009) optimizes the warehousing processes and assesses the related management attributes, realizing the objective of improving the warehousing practices and adopting more sophisticated warehousing techniques supported by knowledge sharing.

In addition, trade-off phenomenon on variable settings is a crucial aspect in the process-oriented supply chain. Leung and Spiring (Leung & Spiring, 2002) have introduced the concept of the Inverted Beta Loss Function (IBLF), which is a further deduction of the Taguchi Loss Function (Taguchi, 1986) in the industrial domain, helping to balance the possible loss resulting from trade-offs generated from different combinations of performance measures involved.

2.2 AI-based decision support system

Much work has been conducted in machine learning for classification, whereas the motivation is to attain a discovery of high-level prediction. Artificial intelligence (AI) has been widely used in knowledge discovery by considering both cognitive and psychological factors. Genetic Algorithm (GA), one of the significant AI search algorithms, is widely used to perform a global search in the problem space based on the mechanics of natural selection and natural genetics (Holland, 1992; Gen & Cheng, 2000; Freitas, 2001).

GA is regarded as a genetic optimization technique for global optimization, constrained optimization, combinatorial optimization and multi-objective optimization. GA has been used to enhance industrial engineering for achieving high throughput with quality guaranteed (Santos et al., 2002; Li et al., 2003; Al-Kuzee et al., 2004). There is a variety of evolutionary techniques and approaches of GA optimization, discussed in the research work by (Lopes et al., 1999; Ishibuchi & Yamamoto, 2002; Golez et al., 2002; de la Iglesia et al., 2003; Zhu & Guan, 2004; Goplan et al., 2006). Recently GA is also considered to be an essential tool in optimizing the inventory management (Radhakrishnan et al., 2009).

On the other hand, the fundamental concept of fuzzy logic is that it is characterized by a qualitative, subjective nature and linguistically expressed values (Milfelner et al., 2005).

Fuzzy rule sets, together with the associated membership functions, have been proven of great potential in their integration into GA to formulate a compound knowledge processing decision support system (Mendes et al., 2001; Leung et al., 2003; Ishibuchi & Yamamoto, 2004). Studies on applying fuzzy logics to systems for different sectors have been extensively undertaken (Cordon et al., 1998; Teng et al., 2004; Hasanzadeh et al., 2004; Chen & Linkens, 2004; Chiang et al., 2007; Tang & Lau, 2008).

2.3 Summary

Inspiring from all above, a Fuzzy-GA Decision Capacity Model is proposed for decision-makers to better select the proper warehousing strategies in terms of the corresponding performance metrics. The capacity will be evaluated by the rack utilization of the designated warehouse.

3. The proposed hybrid decision model

The proposed decision-supoort approach consists of two major processes: knowledge representation and knowledge assimilation, which are shown in Fig.1. In the first stage, the

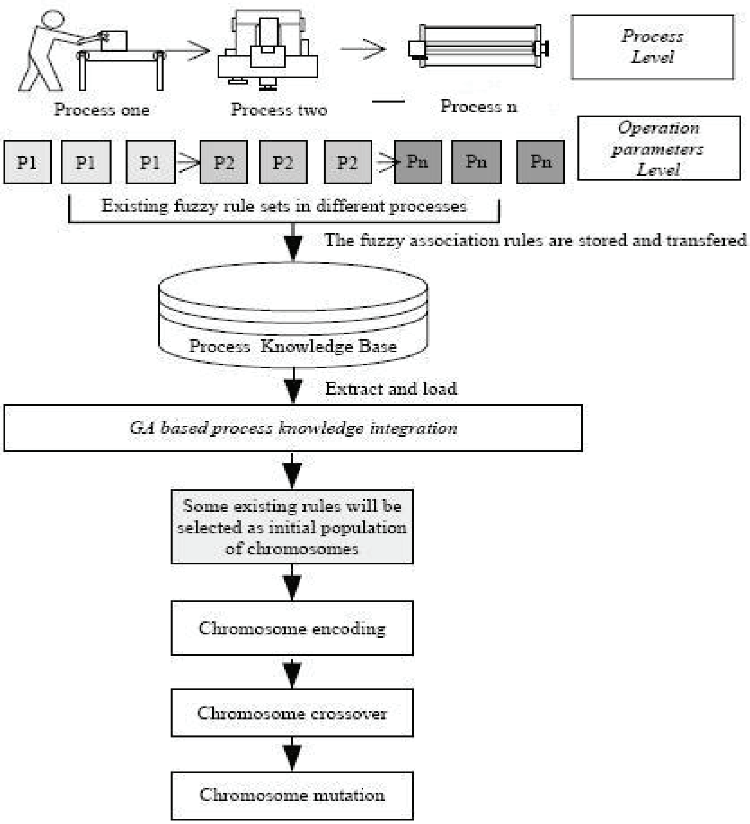

Fig. 1. The proposed decision-support framework

expertise of factor setting, which is represented by IF-THEN rules, is encoded as a string with fuzzy rule sets and the associated fuzzy membership function. The historical process data are also included into the strings mentioned above, contributing to the formulation of an initial knowledge population. Then in knowledge assimilation, GA is used to generate an optimal or nearly optimal fuzzy set and membership functions for the entitled performance indicators. Accordingly, it is necessary to set relative weights for them to aggregate the measurement results since there naturally contains essential fuzziness and ambiguity in human judgments.

Fig. 1 depicts the overview of the entire proposed knowledge-based framework, while the initial rules extracted from process knowledge base are used to form the initial population of the GA. Fig. 2 illustrates the data flow of the proposed capacity-optimizing model, indicating how the iterations envelop fuzzy rule mining, improving the quality of generated rule sets and streamlining the various functional processes in a single warehouse.

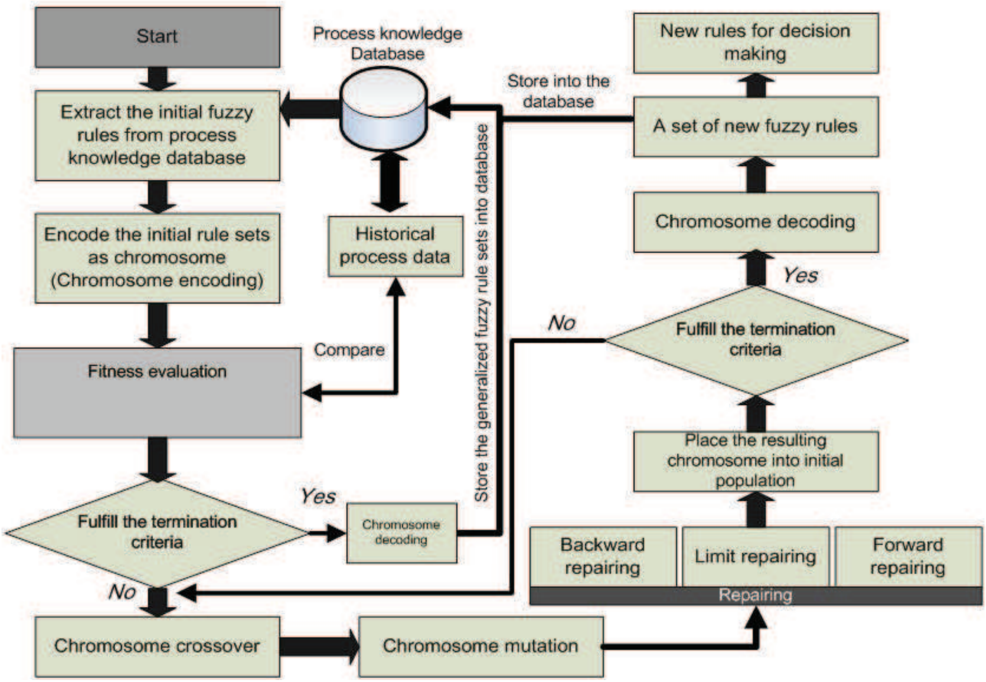

Fig. 2. Information flow of the proposed algorithm (Reference: Ho et al., 2008)

3.1 Problem formulation

Fuzzy-encorporated GA is proposed for capturing domain knowledge from an enormous amount of data. The proposed approach is to represent the knowledge with a fuzzy rule set and encode those rules together with the associated membership into a chromosome. A population of chromosomes comes from the past historical data and an individual chromosome represents the fuzzy rule and the related problem. A binary tournament, using roulette wheel selection, is used for picking out the best chromosome when a pair of chromosomes is drawn. The fitness value of each individual is calculated using the fitness function by considering the accuracy and the trade-off of the resulting performance measure setting, where the fitter one will remain in the population pool for further mating. After crossover and mutation, the offspring will be evaluated by the fitness function and the optimized solution will then be obtained.

The practitioners could freely select the specifically influential performance measures from a large pool of the candidate performance metrics based on the unique condition of the warehouse, leading to the optimized warehousing rack efficiency amongst all by comparing the weights.

3.2 Nomenclature

	Nomenclature
P_p	Total number of process parameters
D_r	Total number of defects
P	Index set of process parameters, $P = \{1,2,\ldots, P_p\}$
D	Index set of defects, $D = \{1,2,\ldots, D_r\}$
A	Index set of membership functions of process parameters, $A = \{1,2,\ldots, 6P_p\}$
B	Index set of membership functions of defects, $B = \{1,2,\ldots, 6D_r\}$
y_j	Parametrical value of the generated rules represented in chromosomes
y_j'	Parametrical value of the test objects
w_j	The weight of the j^{th} parameter
n	The total number of test objects selected for comparison
$c_{p_{iv}}$	Center abscissa of the membership function $\tilde{F}_{p_{iv}}$ for process parameter
$c_{d_{ix}}$	Center abscissa of the membership function $\tilde{F}_{d_{ix}}$ for defect
$w_{p_{iv}}$	Half the spread of the membership function $\tilde{F}_{p_{iv}}$ for process parameter
$w_{d_{ix}}$	Half the spread of the membership function $\tilde{F}_{d_{ix}}$ for defect
l_{P_p}	Lower bound of process parameter
u_{P_p}	Upper bound of process parameter
l_{D_r}	Lower bound of defect rate
u_{D_r}	Upper bound of defect rate

Table 1. Nomenclature of the proposed algorithm

Table. 1 above indicates the notations of the mathematical expressions involved in the proposed decision-support algorithm.

3.3 Chromosome encoding

Fuzzy concept is used to map the above linguistic decision rules into genes for GA optimization.

Definition 1: $C_h = \{1,2,\ldots,M\}$ represents the index set of chromosomes where M is the total number of chromosomes in the population.

Definition 2: $G_{m\times t}$ represents a gene matrix generated for the population where

$$G_{m\times w}=\left[\begin{array}{cccc|cccc|cccc|cccc} p_{11} & p_{12} & \cdots & p_{1a} & d_{11} & d_{12} & \cdots & d_{1b} & k_{11} & k_{12} & \cdots & k_{1c} & q_{11} & q_{12} & \cdots & q_{1d} \\ p_{21} & p_{22} & \cdots & p_{2a} & d_{21} & d_{22} & \cdots & d_{2b} & k_{21} & k_{22} & \cdots & k_{2c} & q_{21} & q_{22} & \cdots & q_{2d} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{ma} & d_{m1} & d_{m2} & \cdots & d_{mb} & k_{m1} & k_{m2} & \cdots & k_{mc} & q_{m1} & q_{m2} & \cdots & q_{md} \end{array}\right]$$

$$=\left((p_{iu})_{m\times a}(d_{ix})_{m\times b}(k_{iy})_{m\times c}(q_{iv})_{m\times z}\right)$$

$$p_{iv}=random\left[l_{P_p},u_{P_p}\right],d_{ix}=random\left[l_{D_r},u_{D_r}\right],$$
$$k_{i,\tau}=c_{piv},k_{i,\lambda}=w_{p_{iv}},q_{i,\tau}=c_{dix},q_{i,\lambda}=w_{dix}$$

$$\forall i\in C_h,\forall v\in P,\forall x\in D,\forall y\in A,\forall z\in B,\tau=1,3,5,......;$$
$$\lambda=2,4,6,......;m=M,a=P_p,b=D_r,c=6P_p,d=6D_r$$

Note that the decoding method of an element in the first sub-matrix $(p_{iv})_{m\times b}$ or second sub-matrix $(d_{ix})_{m\times s}$ of $G_{m\times w}$ to a linguistic variable is given by:
(i) 0: ignore, (ii) 1: low, (iii) 2: medium, and (iv) 3: high. For any row of the third sub-matrix $(k_{iy})_{m\times e}$ of $G_{m\times w}$, a group of six consecutive values $k_{i(6\rho-5)},k_{i(6\rho-4)},k_{i(6\rho-3)},k_{i(6\rho-2)},k_{i(6\rho-1)},k_{i(6\rho)}$ in the matrix forms a single set $\tilde{F}_{p_{iv}}=\left\{c_{p_{iv}}-w_{p_{iv}},w_{p_{iv}},c_{p_{iv}},w_{p_{iv}},c_{p_{iv}}+w_{p_{iv}},w_{p_{iv}}\right\}$ for process parameter pv where $\rho=1,2,3,......$. Also, for any row of the fourth sub-matrix $(q_{iz})_{m\times n}$ of $G_{m\times w}$, a group of six consecutive values $q_{i(6\rho-5)},q_{i(6\rho-4)},q_{i(6\rho-3)},q_{i(6\rho-2)},q_{i(6\rho-1)},q_{i(6\rho)}$ in the matrix forms a single set $\tilde{F}_{d_{ix}}=\left\{c_{d_{ix}}-w_{d_{ix}},w_{d_{ix}},c_{d_{ix}},w_{d_{ix}},c_{d_{ix}}+w_{d_{ix}},w_{d_{ix}}\right\}$ for defect rate dx where $\rho=1,2,3,......$. For both two cases, there are totally 6 genes in the sets of membership functions shown in Fig. 3.

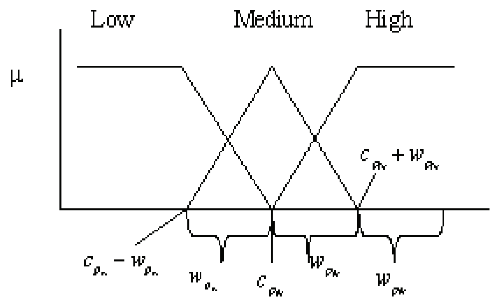

Fig. 3. Fuzzy membership functions of the influencing factors

$\tilde{F}_{p_{iv}}$ consists of aggregated membership functions which relate to a fuzzy rule set is assumed to be isosceles-triangle functions.

$c_{p_{iv}}$ is the center abscissa of $\tilde{F}_{p_{iv}}$; $w_{p_{iv}}$ represents half the spread of $\tilde{F}_{p_{iv}}$.

In " $c_{p_{iv}}$ ", "p_{iv}" indicates that the v-th feature test is included, while i specifies the order of all the condition levels of each feature test. For instance, $c_{p_{i1}}$ stands for the center abscissa of the 1st process test, within the whole membership function matrix.
Definition 3: $B_{m\times 1}$ denotes a random number matrix generated for selection and crossover where

$$Bm \times 1 = (bi)_{m \times 1}$$

$$b_i = random[0,1], \forall i \in C_h, m = M \ .$$

Definition 4: $C_{h\_c} = \{1,2,.....,S\}$ denotes the index set of the chosen chromosomes in the crossover where S is the total number of chosen chromosomes
Definition 5: $G'_{m\times w}$ indicates the gene matrix in which the Q chromosomes chosen in crossover are stored where

$$G'_{m\times w} = \left((p'_{iu})_{m\times a}(d'_{ix})_{m\times b}(k'_{iy})_{m\times c}(q'_{iv})_{m\times z}\right)$$

3.4 Fitness evaluation

To have a good set of process parameters, the genetic algorithm selects the best chromosome for mating according to the fitness function suggested below.

$$\text{Fitness Funtion} = \text{accuracy with error rate}$$

$$Accuracy = \frac{\text{objects correctly matched within error range}}{\text{total number of objects}}$$

$$\text{Error rate } (\varepsilon) = \sum_{j=1}^{m} w_j \frac{(y_j - y_j')^2}{2n}$$

Each chromosome is evaluated by calculating its mean-square error for the error measurement. As each chromosome is represented as the fuzzy rule, the quality of the chromosome is then validated by comparing its defuzzified output with the actual output of the test samples. The centre of gravity (COG) is used as the defuzzification method to obtain the crisp values of the finished quality level.

3.5 Chromosome crossover

Crossover is a genetic operation aiming at producing new and better offspring from the selected parents, while the selection is determined by a crossover rate. The current crossover methods include single-point crossover, two-point crossover, multi-point crossover, uniform crossover, random crossover, etc. Uniform crossover is selected in this research.

3.6 Chromosome mutation

Mutation is intended to prevent all solutions in the population from falling into the local minima. It does this by preventing the population of chromosomes from becoming too similar to each other, which might slow down or even stop evolution. Mutation operation randomly changes the offspring resulting from crossover, given that the value of the mutation rate must range within 0 and 1. In our paper a bit-flip mutation is used.

3.7 Chromosome repairing

After the mutation and crossover in the two regions, some violations in the chromosome may occur. If the membership function is not in ascending order, the new offspring should be modified by exchanging the gene order in accordance with the definition of $\tilde{F}_{p_{iv}} = \left\{c_{p_{iv}} - w_{p_{iv}}, w_{p_{iv}}, c_{p_{iv}}, w_{p_{iv}}, c_{p_{iv}} + w_{p_{iv}}, w_{p_{iv}}\right\}$.

The repairing is divided into two categories which are: the forward and backward repairing as illustrated in Fig.4(a) and Fig. 4(b).

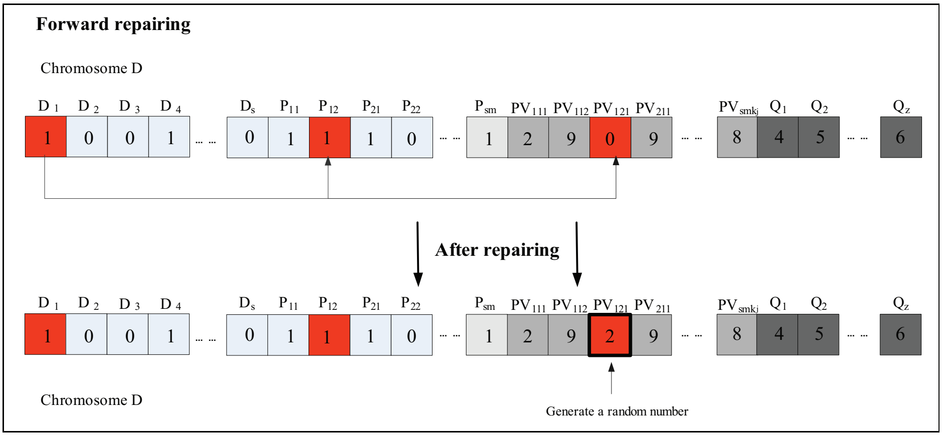

Fig. 4(a). Sample chromosome of forward repairing

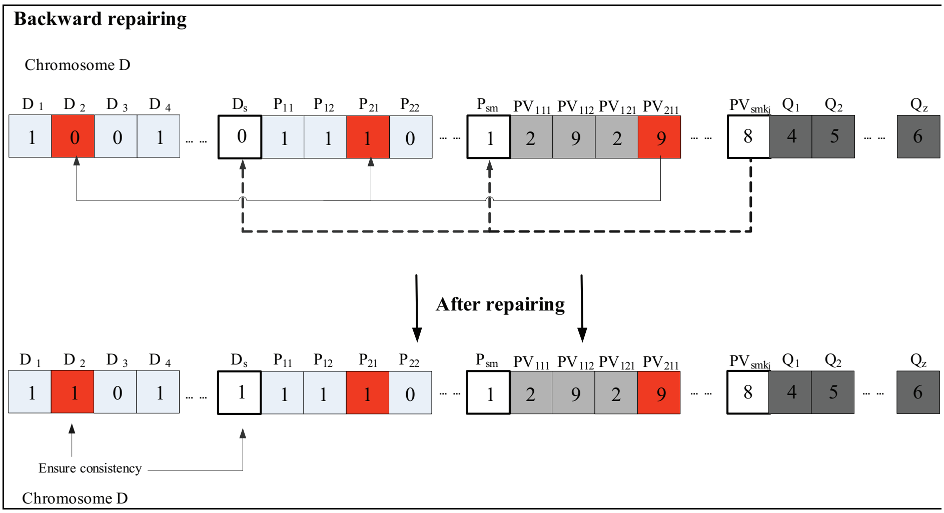

Fig. 4(b). Sample chromosome of backward repairing

3.8 Chromosome decoding

Once the termination criterion is fulfilled, the decoding process will be implemented on the whole set of optimum chromosomes (Fig. 5). The optimum chromosomes decode into a series of linguistic fuzzy rule sets as shown in Table 2 and their associated membership functions which are stored in the repository for further investigation.

Condition part <IF> *(Warehousing Influencing Factors)*	***Consequent part <THEN>*** *(Rack Utilization)*
Rule 1: *Process1*.Inventory cost is adjusted to medium AND *Process2*.Backorder cost is adjusted to medium AND *Process3*.Maintenance cost is adjusted to high … … AND *ProcessN*.	Rack utilization of Drive-in is extremely low AND Rack utilization of APR is high AND Rack utilization of Double-deep is medium AND ...
Rule 2: *Process1*.Inventory cost is adjusted to low AND *Process4*.Backorder cost is adjusted to high AND … … AND *ProcessN*+1.	Rack utilization of Drive-in is medium AND Rack utilization of Double-deep is extremely high

Table 2. Sample of generalized fuzzy rules obtained in the FGCDM

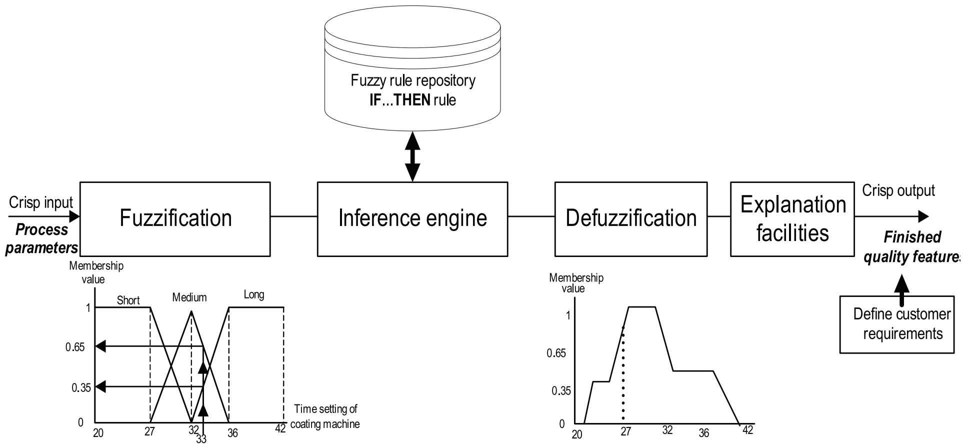

Fig. 5. Sample of generalized fuzzy rules obtained in the FGCDM

3.9 De-fuzzification

Once the termination criterion is fulfilled, the decoding process will be implemented on the whole set of optimum chromosomes. The optimum chromosomes decode into a series of fuzzy rule sets and their associated membership functions which are stored in the repository for further investigation.

4. Discussion and experiment results

The warehousing background for the simulation is of medium volumes (300 pallets/day throughput) and with 90 SKUs to be placed into the storage. The existing rack system include Block-stack, Drive-in, APR, Double deep and VNA. The evaluation criterion of the warehouse performance is mainly based on the utilization of the above racks.

In order to verify the proposed Fuzzy-GA capacity decision model (FGCDM), simulations on searching ability were carried out. Two different stochastic-based search methods, Simulated Annealing (SA) and Tabu Search (TS), were used for comparison with the proposed FGCDM approach. In this experiment, the historical data for supporting the warehousing operation and 30 performance indicators were used for the simulation. The results reported are all averaged over 10 independent runs. In each data set, the best (minimum) fitness value among the 10 simulation runs was documented for the comparison of each search technique mentioned above.

Number of runs	**SA**	**TS**	**FGCDM**
1	0.822	0.89	0.913
2	0.87	0.923	0.892
3	0.91	0.887	0.93
4	0.762	0.781	0.795
5	0.863	0.871	0.88
6	0.836	0.82	0.933
7	0.816	0.848	0.853
8	0.902	0.833	0.892
9	0.827	0.911	0.958
10	0.842	0.892	0.884
Average	0.845	0.866	0.893

Table 3. Best (Minimum) fitness values obtained by FGCDM, SA & TS

	Rack Utilizations (%)	
Warehouse Rack Type	Model Result	Observed
Block-stack	91.8%	88.2%
Drive-in	91.2%	75.7%
APR	95.5%	96.1%
Double deep	89.7%	77.3%
VNA	93.1%	92.8%

Table 4. Rack Utilization of Observed and Model Results

Table 3 presents that ten independent runs of fitness values acquired by various search techniques using 30 performance indicators. According to the experiment, SA was the worst performer in all 10 independent runs and the proposed FGA approach achieved the smallest average object value at 0.893 in the maximization of rack utilization over the interval 0 to 1. Compared with the observed test data which are half-extracted from the historical records, our approach shows an overall better result in Table 4.

5. Conclusion

In this research, the design and implementation of a GA based process knowledge model, which embraces the fuzzy theory and genetic algorithm to achieve warehouse capacity

improvement, has been introduced. Implementing the proposed methodology in the aspect of warehouse management through simulation has been successful. By incorporating the error measurement and complexity of process change into the fitness evaluation, the generalized fuzzy rule sets can be of less complexity and higher accuracy. An extension of different measures can also be included in order to improve the generalized rules. In the matter of generation of new fuzzy rules, the membership functions are assumed to be static and known. The proposed intelligent model can help the decision makers in the development and selection of the best warehouse design for the given application.
Other fuzzy learning methods should be considered to dynamically adjust the membership functions of various parameters to enhance the model accuracy. Future contribution of this endeavour goes to validation of the decision model to be launched in case companies.

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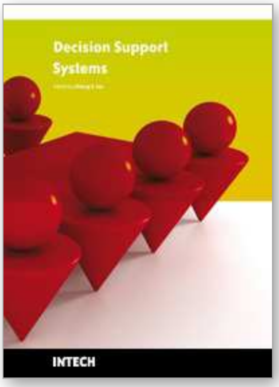

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Decision support systems (DSS) have evolved over the past four decades from theoretical concepts into real world computerized applications. DSS architecture contains three key components: knowledge base, computerized model, and user interface. DSS simulate cognitive decision-making functions of humans based on artificial intelligence methodologies (including expert systems, data mining, machine learning, connectionism, logistical reasoning, etc.) in order to perform decision support functions. The applications of DSS cover many domains, ranging from aviation monitoring, transportation safety, clinical diagnosis, weather forecast, business management to internet search strategy. By combining knowledge bases with inference rules, DSS are able to provide suggestions to end users to improve decisions and outcomes. This book is written as a textbook so that it can be used in formal courses examining decision support systems. It may be used by both undergraduate and graduate students from diverse computer-related fields. It will also be of value to established professionals as a text for self-study or for reference.

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