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A hybrid systematic design for multiobjective market problems: a case study in crude oil markets

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Abstract

This paper studies an application of hybrid systematic design in multiobjective market problems. The target problem is suggested as unstructured real world problem such that the objectives cannot be expressed mathematically and only a set of historical data is utilized.

Obviously, traditional methods and even meta-heuristic methods are broken in such cases. Instead, a systematic design using the hybrid of intelligent systems, particularly fuzzy rule base and neural networks can guide the decision maker towards noninferior solutions. The system does not stay in search phase. It also supports the decision maker in selection phase (after the search) to analyze various noninferior points and select the best ones based on the desired goal levels. In addition, numerical examples of real crude oil markets are provided to clarify the accuracy and performance of the developed system.

Keywords: Multiobjective problems; Fuzzy rule-based system; Neural networks; Crude oil markets

1. Introduction

Market structures are fundamental to the analysis of marketing activities. The number and power of sellers/buyers, the nature of products and goals are among the important factors that dictate the structure of the market. For frequently purchased packaged goods and papers, there are numbers of different considerations conflicting with each other that influence the final purchasing decisions.

In order to find the best sell/buy orders in these multicriteria problems, it is necessary to make a tradeoff between these conflicting tangible and intangible goals (Zeleny, 1998). But finding the best tradeoff values of the goals is very difficult and also very different to the single objective optimization problems and is so called ‘‘multiobjective decision making’’ problems.

Although some mathematical methods (Gholamian and Fatemi Ghomi, 2004a) are developed to solve multiobjective problems; but generally the applications are restricted to small and medium size problems. In contrast, meta-heuristics, specially evolutionary algorithms have found a substantial growth (Jones et al., 2002). Popularity, parallel processing and flexibility of these methods are the main reasons of this extensive utilization (Jaszkiewicz, 2002). MOGA, HLGA, NPGA and VEGA (Zitzler and Thiele, 1998) are the most eminent of the first-generation multiobjective evolutionary algorithms (MOEA). But unfortunately, some of these methods such as MOGA and HLGA are progressive ones and others also need some initial factors such as tournament size, Pareto spread and sharing value (Zitzler et al., 2003). Table 1 illustrates the set of important MOEA methods

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Table 1
Classification of multiobjective evolutionary algorithms

MOEA	A priori (before)	Progressive (during)	A posteriori (after)
Plain aggregating approaches	Evolutionary weighting Evolutionary GP	HLGA	—
Population-based non-pareto approaches	Lexicographic selection	—	VEGA Non-generational GA
Pareto-based approaches	—	MOGA	NPGA, GRGA SPEA, SPEA2
		Evolutionary co-design	PAES, PESA, PESAII MOMGA, MOMGAII NSGA, Fast elitist NSGA

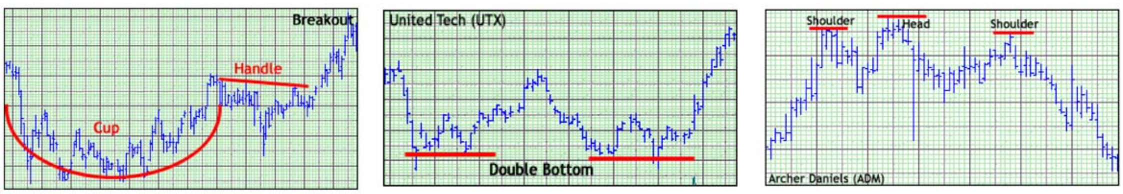

Fig. 1. Samples of market patterns.

classified by the stage of decision making (Tiwari et al., 2002).

Recently, the second generation methods such as PEAS II, MOMGA II, NSGA2 and SPEA2 try to improve MOEA with some additional techniques such as elitism, crowding measure, partially enumeration and second population (Zitzler et al., 2002), but the methods remain with the same complexity $O(m^2n)$ (where m is the population size and n is the number of objectives) (Coello et al., 2002).

In addition, MOEA methods are developed on deterministic decision making (i.e. mathematical structure) while generally in the market, the decisions are made based on inadequate information and under the pressure of time (Benton, 1991) in uncertain conditions. In fact, the market models are generally unstructured or semi-structured models that objectives or constraints may be difficult to express mathematically. In such cases, MOEA methods have found lack in application; because there are not quite the mathematical model to be used in MOEA algorithms (Gholamian and Fatemi Ghomi, 2004b).

Besides, mathematical models are very rigid and decision analysis even with MOEAs are entailed with high computational burden. It seems market decision making using the market entities (i.e. with mathematical models) is not simple at all.

Now, let us suppose the market as an integrated set and study the market with this new vision. It seems this unique set follows some trends. Sometimes, it is said that the market is backwardation or flat or contango. There are trends that explain the market situation. Bull and Bear markets are the resultant of these trends. When these trends are repeated sequentially, some structural patterns are shaped that the markets seem to be imitator of them. In other words, instead of paying attention to the market entities, the market behavior is achieved from the market totality as integrated set.

The patterns which represent the market behaviors are experientially extracted and employed by the market analyzers and brokers (Morphy, 1999). ‘‘Cup & Handle’’, ‘‘Double Bottom’’, ‘‘Head & Shoulder’’ and so on, are some of well-known patterns in the market context, as shown in Fig. 1.

Successful brokers and exchangers are those who recognize these patterns and know which patterns are activated and with which degree of truthness. In fact, the patterns act as rules of the market and knowledge base of market system is constituted with these rules (Martin, 2001). Then, instead of developing the mathematical models with all mentioned difficulties, a systematic design (Gholamian et al., 2004) can be generated with this knowledge base to make multicriteria decisions in market problems.

The resultant system developed in this paper, includes a knowledge base with the rules which are related to such market patterns. But as mentioned above, the market behaviors accompany with uncertainty; so fuzzy logic is used in knowledge base to support this nature. At the result, a knowledge base is designed with the fuzzy rules which are fired as a matter of degree of compatibility.

It is not the first time that the intelligent systems have found applications in the market problems, specially, in generating trading rules (Leigh et al., 2002). While the generation of trading rules is performed traditionally with stochastic and dynamic programming methods (random walk) (Li and Lam, 2002), some recent works are performed with intelligent agents (Skouras, 2001), neural networks (Fernandez-Rodrýguez et al., 2000), genetic algorithm (Allen and Karjalainen, 1999) and genetic programming (Potvin et al., 2004). Specially, neural networks are more attended (Jasic and Wood, 2003). But all mentioned methods are single objective, while in the real markets, various objectives such as maximizing profit and minimizing risk of loss are attended.

The aim of the paper is the development of an intelligent system (i.e. fuzzy rule-based system) for such multiobjective problems. The system is constructed on the noninferior region and maps the decision space (Z) into the solution space (X). In fact, the rules maps what the decision maker knows to what the decision maker wants. The following are samples of the linguistic interpretation of such rules:

IF Profit is Low AND Risk is High Then
Pos.1 = Medium Low AND Pos.2 = Low
AND Pos.3 = None,

IF Price is Medium AND Volume is Low
Then Pos.1 = High AND Pos.2 = Low
AND Pos.3 = Low.

The system supports the traders to make decisions based on the desired level of the goals and also analyze various solutions without any additional computation cost (Turban et al., 2004). The stages of the system generation will be described in the next sections after small description of the multiobjective concepts. The paper is convoyed with the real numerical examples of crude oil market, which the system is designed and applied on them and finally, recommendations for the future studies are devoted in the last section.

2. Basic definitions

Let $f_i(\mathbf{x},\mathbf{y})$ $(i = 1,\ldots,p)$: $\{\Omega,\Phi\} \to \Lambda$ be objective functions related to the goals, where $\mathbf{x} = [x_1, x_2, \ldots, x_n]$ and $\mathbf{y} = [y_1, y_2, \ldots, y_n]$ are respectively continuous and discrete solution vectors from some universes Ω and Φ (i.e. $\mathbf{x} \in \Omega \wedge \mathbf{y} \in \Phi$).

Then, the standard multiobjective problem is formulated as follows:

$$\begin{array}{ll} \text{Maximize} & \mathbf{F}(\mathbf{x},\mathbf{y}) = (f_1(\mathbf{x},\mathbf{y}),\ f_2(\mathbf{x},\mathbf{y})\ldots f_p(\mathbf{x},\mathbf{y}) \\ \text{Subject to} & g_i(\mathbf{x},\mathbf{y}) \leqslant 0 \quad i = 1,2,\ldots,m, \\ & \mathbf{x} \in \Re \ \&\ \mathbf{y} = -1,0,1. \end{array} \tag{1}$$

In general, there is no solution that maximizes all of the objective functions simultaneously. Thus, the trade-off solutions must be found to satisfy all of the objectives as well as the possible (Zeleny, 1998). These solutions are called noninferior points. In order to describe noninferiority, suppose the following definitions:

Definition 1. The solution $(\widehat{\mathbf{x}},\widehat{\mathbf{y}}) \in \{\Omega,\Phi\}$ is said to dominate $(\check{\mathbf{x}},\check{\mathbf{y}}) \in \{\Omega,\Phi\}$ iff $(\widehat{\mathbf{x}},\widehat{\mathbf{y}}) \succ (\check{\mathbf{x}},\check{\mathbf{y}}) \Leftrightarrow \forall i \exists j$: $f_i(\widehat{\mathbf{x}},\widehat{\mathbf{y}}) \geqslant f_i(\check{\mathbf{x}},\check{\mathbf{y}}) \wedge f_j(\widehat{\mathbf{x}},\widehat{\mathbf{y}}) > f_j(\check{\mathbf{x}},\check{\mathbf{y}})$ $i,j = 1,2,\ldots,p$.

Definition 2. The solution $(\hat{\mathbf{x}},\hat{\mathbf{y}}) \in \{\Omega,\Phi\}$ is said to be noninferior or nondominated if no solution $(\mathbf{x},\mathbf{y}) \in \{\Omega,\Phi\}$ can be found such that $(\mathbf{x},\mathbf{y}) \succ (\hat{\mathbf{x}},\hat{\mathbf{y}})$.

In fact, a point is said to be noninferior if, at that point any attempt of improvement in one of the objective functions from its current value would cause at least one of the other objective functions to deteriorate from its current value (Lai and Hwang, 1994). Naturally, in contrast with the optimization problems, the noninferior points are not single and there are sets of these points which constitute the noninferior regions. So, finding all of the solutions with traditional methods is very difficult. Instead, the fuzzy rule base is developed in this region and so, the decision maker can observe all noninferior solutions and their related objective values simply.

3. System development

As mentioned above, the hybrid decision support system must be built on the noninferior region. Following is the big picture of system construction stages (Fig. 2):

In the following subsections, each step of the "system construction" flowchart is described.

3.1. Set initial population

Since the knowledge base must be built on the noninferior region as the first step, an estimated subset of noninferior points should be provided. Since the market occurrences are not regular, globally the market objectives (i.e. $f_i(\mathbf{x},\mathbf{y})$ $(i = 1\ldots p)$) cannot be extracted with the stochastic and regression methods (Leigh et al., 2002); instead, only a set of historical data may be used as a subset of the real world information. Hence, a simple procedure is used in this historical data to generate such initial noninferior population. The outline procedure is brought as follows:

Parameters: n: Size of target population,
Ψ: Set of inferior population,
Υ: Set of noninferior population

Generate initial information:
$\mathbf{F} = [f_1(\mathbf{x},\mathbf{y}), f_2(\mathbf{x},\mathbf{y}), \ldots, f_p(\mathbf{x},\mathbf{y})] \in \Lambda \mid (\mathbf{x},\mathbf{y}) \in \{\Omega, \Phi\} \& |\mathbf{F}| = n$;
Set $\Psi = \varnothing$; $\Upsilon = [\mathbf{F},\mathbf{x},\mathbf{y}]$;

Noninferiority checking:
For each $F = [f_1 f_2, \ldots, f_p]$ from 1 to n–1,
If $F \notin \Psi$
For each $F' = [f'_1, f'_2, \ldots, f'_p]$ from $|F|$ to n
If $F' \notin \Psi$
If $f_1 <= f'_1$ & $f_2 <= f'_2$ &…& $f_p <= f'_p$
$\Upsilon = \Upsilon - \{F\}$; $\Psi = \Psi + \{F\}$;
Else if $f'_1 <= f_1$ & $f'_2 <= f_2$ &…& $f'_p <= f_p$
$\Upsilon = \Upsilon - \{F'\}$; $\Psi = \Psi + \{F'\}$;
end
end
end
end
end.

The procedure designed is very simple which produces noninferior population rapidly. It must be attended that this population produced with historical data, is an estimation of the real noninferior population which is used in construction of the fuzzy rule base.

3.2. Clustering

Now, a set of noninferior points is obtained; but because the points are scattered in the population, it is necessary that the points are clustered based on the distance parameters. In this study, specially designed "adaptive resonance theory" (ART) neural networks (Frank et al., 1998) is used for the clustering process. Fig. 3 illustrates the structure of the network.

The network inputs and outputs are defined as follows:

$$O_j = \begin{cases} I_{j^*}, & I_{j^*} = \min_{i=1}^{n} \{I_i\} \\ 0 & \text{else} \end{cases} \qquad I_i = \|[\mathbf{x},\mathbf{y}] - \mathbf{W}_i\|, \tag{2}$$

while the vigilance test determines the winner neuron as follows:

$$O_{j^*} = \|[\mathbf{x},\mathbf{y}] - \mathbf{W}_{j^*}\| < \rho$$

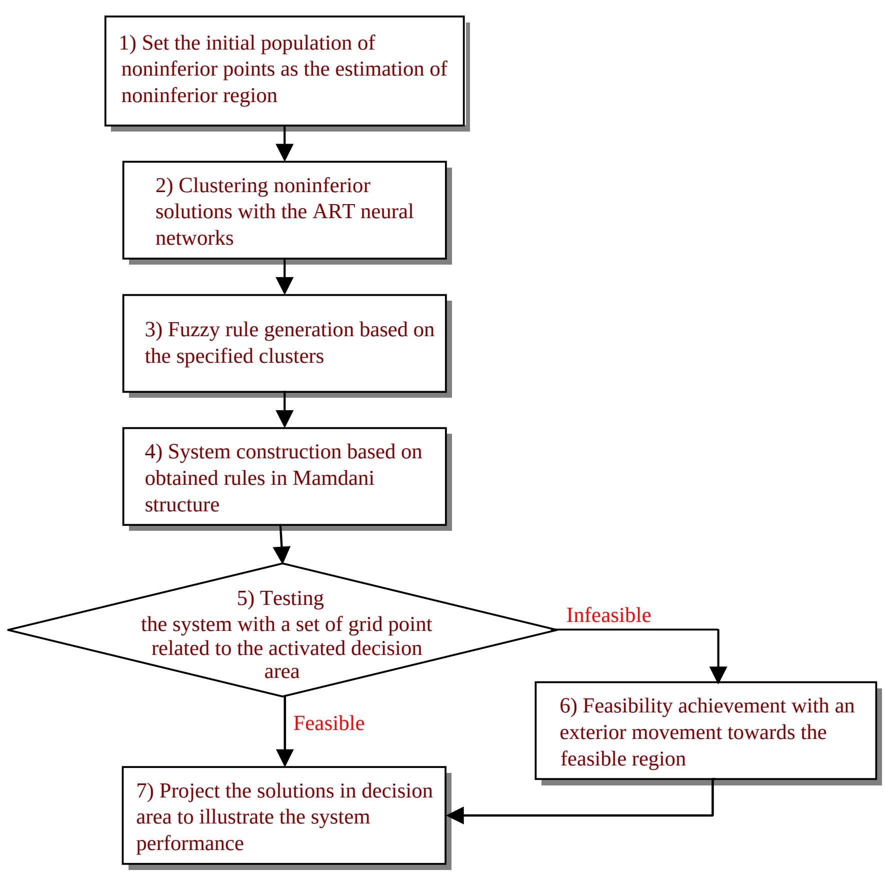

Fig. 2. The flowchart of system construction.

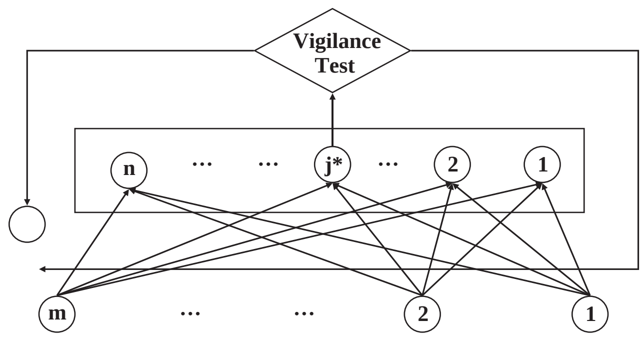

Fig. 3. ART network structure.

$$= \frac{1}{2n}\sum_{i=1}^{n}\sum_{\substack{j=1\\ i\neq j}}^{n} \|[x_i, y_i]\| \cdot \|[x_j, y_j]\| \cdot \cos\langle [x_i, y_i], [x_j, y_j]\rangle. \quad (3)$$

Consequently, the weights are updated as follows:

$$\mathbf{W}_{j^*} = \frac{[\mathbf{x}, \mathbf{y}] + \mathbf{W}_{j^*} * \mathrm{size}(\mathbf{W}_{j^*})}{1 + \mathrm{size}(\mathbf{W}_{j^*})}. \quad (4)$$

Obviously, $\mathbf{W}_{j^*}$ vectors are cluster centers which are updated with any new member. Finally, the network gives the cluster centers as the output of the network. The number of clusters is related to spread of the population and vigilance value (ρ).

3.3. Fuzzy rule generation

Now, the cluster centers are used to generate the fuzzy rules. In defining the fuzzy rules, various membership functions may be offered; but since in general cases, most of the membership functions are converged to typical smooth ones (i.e. sigmoid, Gaussian and π) (Durkin and Durkin, 1998) in this study, Gaussian membership functions are used as follows:

$$\mu_{ic}(x) = \exp\left(\frac{-(x - x_{ic})^2}{2\sigma_c^2}\right), \quad x \in \Omega,$$
$$i = 1, 2, \ldots, |x|, \quad c = 1, 2, \ldots, n_c, \quad (5)$$

where $x_{ic}\forall i, c$ are cluster centers and σ_c is defined as follows:

$$\sigma_c = \left(\frac{\sum_i x_{ic}^2 \mu_{ic}(x)}{n_c} - \left(\frac{\sum_i x_{ic}\mu_{ic}(x)}{n_c}\right)^2\right)^{1/2},$$
$$x_{ic} \in \Re_c = \left[\bigwedge_{i=1}^{n_c}(x_i), \bigvee_{i=1}^{n_c}(x_i)\right], \quad c = 1, 2, \ldots, n_c, \quad (6)$$

where n_c is the number of clusters.

Then, the fuzzy rules R: $A \to B$ are defined as follows (Zimmmermann, 1996):

$$A_j = \int_{f(\mathbf{x},\mathbf{y})\in \Lambda} (\mu_{jc}(f(\mathbf{x}, \mathbf{y}))|f(\mathbf{x}, \mathbf{y})) \quad j = 1, 2, \ldots, p, \quad (7)$$

$$B_i = \int_{\substack{\mathbf{x}\in\Omega\\ \mathbf{y}\in\Phi}} (\mu_{ic}(\mathbf{x}^{\to y})|\mathbf{x}^{\to y}) \quad i = 1, 2, \ldots, n, \quad (8)$$

where $x^{\to y}$ means x in the direction of y; which is related to market concepts that $\mathbf{y}$ is representative of sell or buy orders and $\mathbf{x}$ is the value of ordered trades.

3.4. System construction

In this stage, Mamdani inferencing system is used on developed rules to constitute the fuzzy rule base. Let $\mathbf{z}$ as the input vector of decision space, then the rule R_c is fired as follows:

$$\alpha_c = \bigwedge_{j=1}^{p} \mu_j^{c_j}(\mathbf{z})|A_j^{c_j};\ A_j^{c_j} = \left(\int_{z\in\Lambda} \mu_j^{c_j}(\mathbf{z})|\mathbf{z}\right) \subset A_j. \quad (9)$$

Then, the inferred consequences are obtained as follows:

$$\mu_c^{\mathrm{Cons}}(\mathbf{x}) = \alpha_c \wedge \mu_j^{c_j}(\mathbf{x})|B_i^{c_i};\ B_i^{c_i} = \left(\int_{x\in\Omega} \mu_i^{c_i}(\mathbf{x})|\mathbf{x}\right) \subset B_i. \quad (10)$$

Finally, the aggregation is performed as follows:

$$\mu^{\mathrm{Cons}}(\mathbf{x}) = \bigvee_{c=1}^{n_c} \mu_c^{\mathrm{Cons}}(\mathbf{x}). \quad (11)$$

The t-norm and t-conorm operators either may be simple, such as standard, product, drastic and bounded operators or may be parametric such as Yager class, Schweizer & Sklar classes, Hamacher class and Dubois class (Wang, 1997). As an alternative, neuro-fuzzy systems can be used to obtain slick operators and membership functions (Kosko, 1997); although the complexity cost should also be attended. It must be noted that the aim is not development of a controller but the social model is attended and so, the same complexity cost must be paid.

Finally, the solutions must be defuzzified to obtain crisp trading values. In this part also parametric and nonparametric methods can be used. Specially, SLIDE generalized defuzzification method (Yager and Zadeh, 1994) is applied as follows:

$$\mathbf{x}^* = \frac{(1-\beta)\int_{i\in L} x\mu^{\alpha}(x)\,\mathrm{d}x + \beta\int_{i\in H} x\mu^{\alpha}(x)\,\mathrm{d}x}{(1-\beta)\int_{i\in L} \mu^{\alpha}(x)\,\mathrm{d}x + \beta\int_{i\in H} \mu^{\alpha}(x)\,\mathrm{d}x}$$
$$\alpha \in [0, \mathrm{Height}[\mu(x_i)] \text{ and } \beta \in [0, 1], \quad (12)$$

where $L = \{i/\mu(x_i) < \alpha\}$ and $H = \{i/\mu(x_i) \geqslant \alpha\}$.

Similarly, **y**'s are determined based on the direction of related **x**'s. Now, the system is prepared to be used.

3.5. Testing

As mentioned in the previous section, the system supports the decision maker to analyze noninferior solutions. Simply, the decision maker can pick over the desired objective levels and observe related solutions in the noninferior region without any additional computation. To analyze various solutions, it is only sufficient to slide moving the goal levels. So, the system is derived as rapid and powerful analyzer of the market trading problems; similar to an oscillator (Gholamian and Fatemi Ghomi, 2004c).

In order to test the system, the activated area of the decision space is divided to the tiny grid points and then the ordered set points are given to the system. The results must be noninferior solutions.

The activated area can be obtained by optimization of each objective individually and then application of ranking methods (TOPSIS, ELECTRE and so on) on the resultant payoff table. But as mentioned in the first section, the market problems are suggested unstructured (i.e. without any mathematical objectives) and so, the range of noninferior historical data can be used as estimation of the activated area.

When grid points are given to the system, the system generates the noninferior (**x**, **y**) solutions. The solutions may be repetitive; so, an equality checking is performed to eliminate the repetitious solutions and save the nonrepetitive list.

Then, the feasibility of solutions are checked by replacing the solutions in the constraints. The solutions may or may not be feasible. In latter case, the following step must be performed to reach the feasible solutions.

3.6. Feasibility achievement

If the solutions are infeasible, they must be led to the boundaries of noninferior region with an exterior movement. In fact, opposite to all traditional methods which try to get the noninferior boundaries with an interior movement, in this system the boundaries are acquired with an exterior movement.

If the constraints are not so complex, simply the penalty function method can be used as follows:

$$\text{Min } L(\mathbf{g}(\mathbf{x},\mathbf{y})) = \sum_{i\in I}\{\max[0, g_i(\mathbf{x},\mathbf{y})]\}^2 + \sum_{j\in J} g_j^2(\mathbf{x},\mathbf{y}), \tag{13}$$

where $I = \{i/g_i(\mathbf{x},\mathbf{y})\leqslant 0\}$ and $J = \{j/g_j(\mathbf{x},\mathbf{y}) = 0\}$.

But if the constraints are sufficiently complex, mathematical methods cannot be used successfully. An offer may be application of multilayer feedforward neural network along with the penalty function method, such as shown in Fig. 4 (Gholamian and Fatemi Ghomi, 2004b):

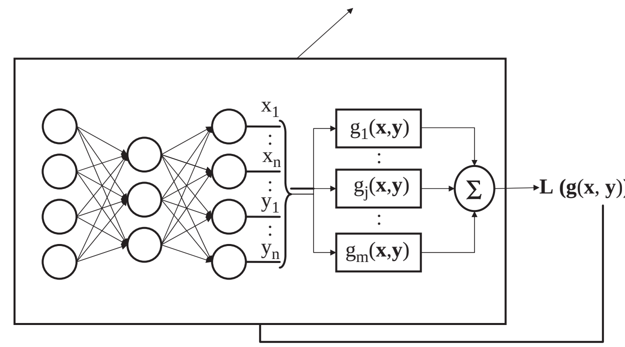

Fig. 4. Coupled neural network and penalty function method.

The network is designed with n (number of decision variables) output nodes which are concluded to the gates of penalty function. The target is satisfaction of the value of penalty function and the output is evaluated by the convergence test. If the convergence criterion is met, training will be stopped; since the feasible solution is obtained. Otherwise, the convergence error is back-propagated to the networks to modify the weights. The number of inputs and hidden layers are arbitrary, but the initial inputs and weights must be adjusted such that the initial infeasible solutions are generated in the output nodes. Finally, when the training is terminated constraints are satisfied and the feasible solutions are extracted from the network.

3.7. Projection

Now, the feasible solutions are obtained; directly or indirectly with exterior movement, which are claimed to be noninferior. This claim can be illustrated by projection of resultant solutions in the decision space.

If the objective functions are explained mathematically, this work is performed simply by replacing solutions in the objective functions. But in the unstructured cases, this operation is impossible. Instead again, neural networks are applied. Neural networks are very powerful in knowledge acquisition; specially neural networks are able to approximate noise-free functions with a high degree of accuracy (Smith, 1999). Hence, initially a supervised feedforward multilayer network is trained with a set of historical data. Fig. 5 illustrates such network structures; where the inputs (P_j) are the solution values and the outputs (a_i) are the objective values.

When the training is terminated, the network will play the role of objective functions and so giving the feasible noninferior points to the network, derives the projection values in the decision area. The obtained values are

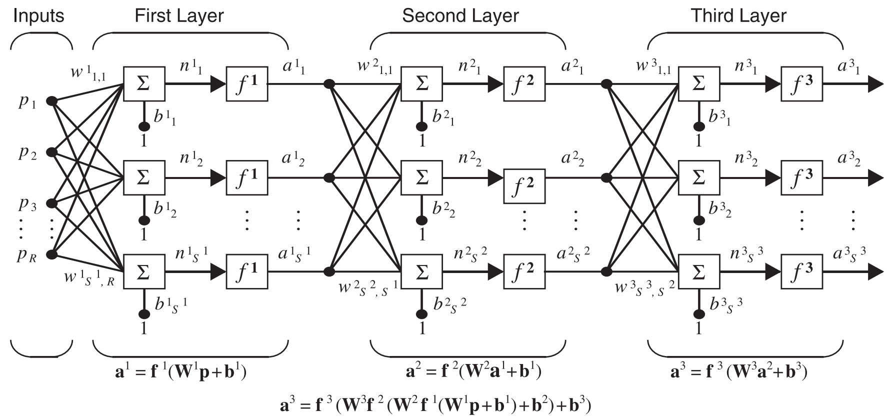

Fig. 5. Feedforward neural network for function approximation.

comparable with the other goal values which must be suited in the northeast–east part of the decision space.

4. Numerical examples

In this section, four real examples are provided to show the accuracy of the developed system. The examples are selected from the crude oil market and historical data included "the crude oil prices" and "current/future position prices" for each working day between June 2, 1998–November 30, 2000 and July 15, 1988–December 29, 2000, respectively. Consequently, for each set of historical data, two real problems are suggested and each problem encouraged with a systematic design. Then, the systems are tested to illustrate the performance of the system. Finally, the comparison discussions are provided for similar cases. The examples are developed by MATLAB$^{\text{Inc}}$ software used under Pentium IV personal computer (PC).

Problem F_1. Suppose the following multiobjective problem

$$\text{Max } Z^{\text{H}}_{\text{Iran}} = f_1(x_{\text{Dubai}}, x_{\text{Brent}}, x_{\text{WTI}}),$$

$$\text{Max } Z^{\text{L}}_{\text{Iran}} = f_2(x_{\text{Dubai}}, x_{\text{Brent}}, x_{\text{WTI}}),$$

subject to

$$x_{\text{Dubai}}, x_{\text{Brent}}, x_{\text{WTI}} \geqslant 30, \tag{14}$$

where $Z^{\text{H}}_{\text{Iran}}$ and $Z^{\text{L}}_{\text{Iran}}$ are respectively the prices of heavy and light crude oil of Iran and the variables are the index crude oil prices. The aim is to control maximum national crude oil prices, based on the regional and international prices in the paper trading markets.

The historical data contains 751 data points which are firstly evaluated with the noninferiority procedure to extract noninferior points. The process is performed at 0.01 s and 13 noninferior points are extracted.

Then, the points are clustered with ART2 network. ART2 network is specially designed for the continuous problems. The network is produced eight clusters with vigilance rate $\rho = 1.3$ after 50 iterations and in the time 0.07 s. Based on the range of noninferior solutions, the membership functions are distributed in the following activated areas:

$$28 \leqslant Z^{\text{H,L}}_{\text{Iran}} \leqslant 36, \quad 28 \leqslant x_{\text{Dubai}} \leqslant 35,$$
$$30 \leqslant x_{\text{Brent}} \leqslant 40, \quad 33 \leqslant x_{\text{WTI}} \leqslant 38.$$

The rules are defined based on these membership functions and noninferior points, in Mamdani system structure as shown in Fig. 6.

Now, in order to test the system, the activated area is divided to grid points with the rate 0.025 and all 103041 generated couple points are given to the system as an input vector. Simultaneously, the system produces solutions as an output vector. Obviously, most of the solutions may be repetitive; so, the solutions are compared with each other and the repetitious ones are eliminated. The equality checking is performed in 0.691 s and 100 nonrepetitive solutions are obtained. Then, the feasibility checking is performed and consequently, 97 (97%) solutions have been found feasible and others are discarded. The obtained solutions demonstrate high accuracy of the system when the resultant range is compared with the range of initial noninferior solutions. Following illustrates the absolute differences of these two ranges:

	x_{Brent}	x_{Dubai}	x_{WTI}
Min	0.03	0.01	0
Max	0.01	0.03	0.01

The solutions can be illustrated in decision space by projection process. A feedforward neural network with

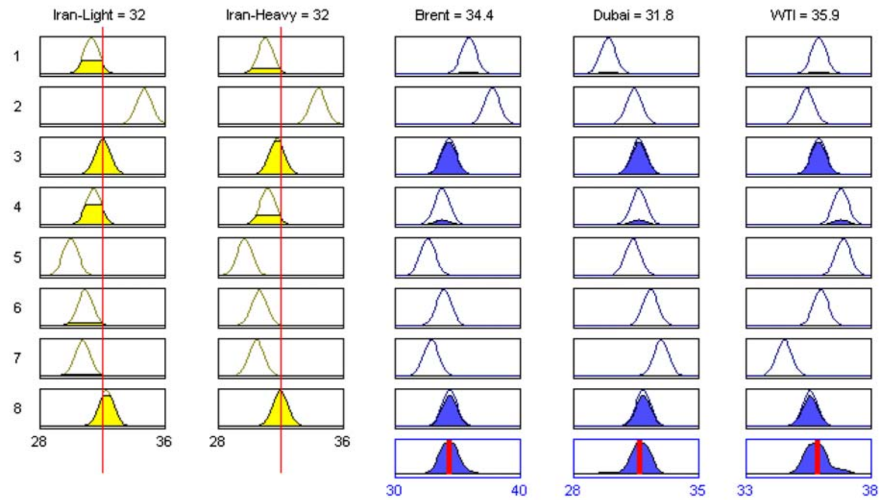

Fig. 6. Fuzzy rule base system of Problem F_1.

one hidden layer and 80 neurons is designed (Fig. 7) and then is trained with the set of feasible solutions as subset of historical data. Then, the solutions are given to the trained network and the projection values are obtained at 0.01 s.

The projected values are portrayed with historical data solutions. The result was wonderful as illustrated in Fig. 8. The upper chart of Fig. 8 shows the historical solutions of Problem F_1 whereas the lower chart indicates achieved noninferior solutions, which is located exactly in the noninferior region. This projection is achieved while the input was an area fragmented to set of the grid points.

As an overview to the Problem F_1, the numerical results are collected in Table 2.

Problem F_2. Previous example is designed with the same products (i.e. crude oil) while the prices are affected with the supplementary and even refinery products. Hence, in the following example a supplementary product (natural gas) and an oil product (gas oil) are used as solution variables:

$$\text{Max } Z^{\text{H}}_{\text{Iran}} = f_1(\text{NatGas, GasOil}),$$
$$\text{Max } Z^{\text{H}}_{\text{Iran}} = f_2(\text{NatGas, GasOil}),$$
subject to
$$\text{NatGas} \geqslant 20,$$
$$\text{GasOil} \geqslant 300, \quad (15)$$

where NatGas and GasOil are respectively the prices of natural gas and gas oil in IPE market.

Similar to the previous example, 751 data points are evaluated and 13 noninferior points are extracted at 0.01 s. Then, the points are clustered and six cluster points are generated with ART2 network.

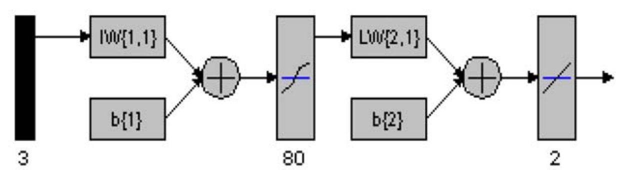

Fig. 7. The projection neural network of Problem F_1.

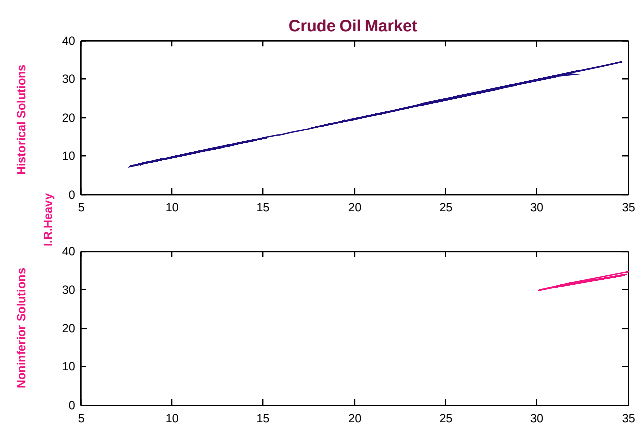

Fig. 8. The results of Problem F_1.

In the next stage, the membership functions are defined based on the cluster centers in the range $28 \leqslant Z^{\text{H,L}}_{\text{Iran}} \leqslant 36$, $15 \leqslant \text{NatGas} \leqslant 35$ and $300 \leqslant \text{GasOil} \leqslant 350$ and thereby, the above rule base is obtained (Fig. 9):

Similar to the previous example, the system is tested with the same grid points. The numerical results of Problem F_2 is given in Table 3:

Table 2
Numerical results of Problem F_1

	Reference	Initial noninferior	Clustering	Testing		Exterior method	Projection
				Equality	Feasibility		
Parameters	06/02/98 to 11/30/2000	—	$\rho = 1.3$ # Itr = 50	Grid. range: $[28–36]^2$ Grid. rate: 0.025 Grid. No: 103041		—	Net #hid.layer: 1
# Points	751	13	8	100	97 (97%)	—	Net #neuron: 80
CPU time (s)	—	0.01	0.07	0.691	≈ 0	—	0.03

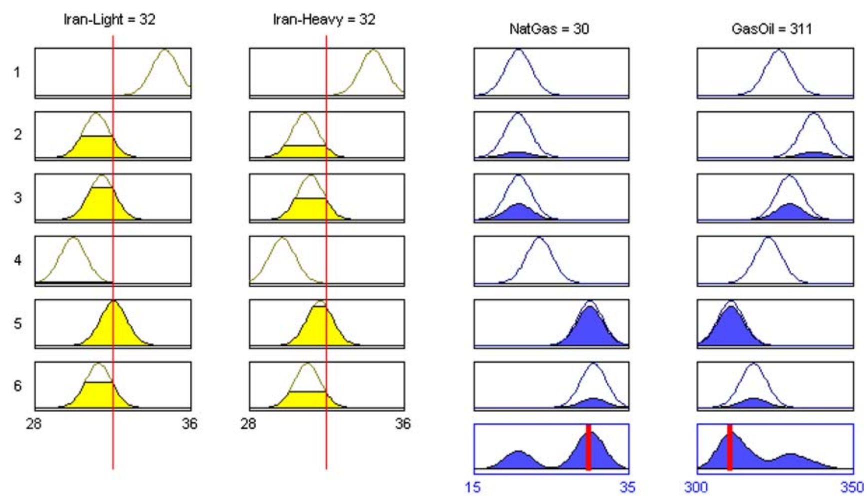

Fig. 9. Fuzzy rule base system of Problem F_2.

In comparison of the range of 69 obtained solutions and initial noninferior solutions, the following result (as absolute difference) is obtained.

	NatGas	GasOil
Min	0.079	0.0435
Max	0.087	0

Fig. 10 represents the projection of solutions in the decision space. The results indicate the system capability in mapping the solutions to noninferior region. This means that all noninferior solutions are in hand; as graphical user interface (Fig. 9) and the decision maker can analyze various points with only sliding red bars (Figs. 6 and 9) without any additional computation. The system supports the decision makers to select the desired objective price levels based on the national policies and then try to control the markets by moving towards the related solution price. It is important since in most cases the influence of traders and exchangers in crude oil markets is more than OPEC decisions. In addition, some national leverage such as natural gas and refinery products exist which can be used as invisible control methods.

As importance difference of systematic design and traditional methods is that the traditional methods have only found the noninferior solutions and do not help the decision maker in the selection phase; while as observed, the systematic design not only finds the noninferior solutions but also helps the decision maker in selection phase by providing an analytical device (Gholamian et al., 2004).

Comparison of the results of two examples demonstrates although both systems have provided describable results, Problem F_1 seems to be capable to present few better results. However, the results are not competitive and can be used together in the decisional analysis.

Problem F_3. The above examples are defined in the current date (position1) prices; while the financial markets are forward and future markets which trade in the future positions. This is the risky contract; because the actual prices may fall or rise. In the following example, the aim is to control maximum price

Table 3
Numerical results of Problem F_2

	Reference	Initial noninferior	Clustering	Testing		Exterior method	Projection
				Equality	Feasibility		
Parameters	06/02/98 to 11/30/2000	—	$\rho = 5$ # Itr = 21	Grid. range: $[28–36]^2$ Grid. rate: 0.025 Grid. No: 103041		—	Net # hid.layer: 1
# Points	751	13	6	69	69 (100%)	—	Net # neuron: 80
CPU time (s)	—	0.01	0.03	0.521	= 0	—	0.03

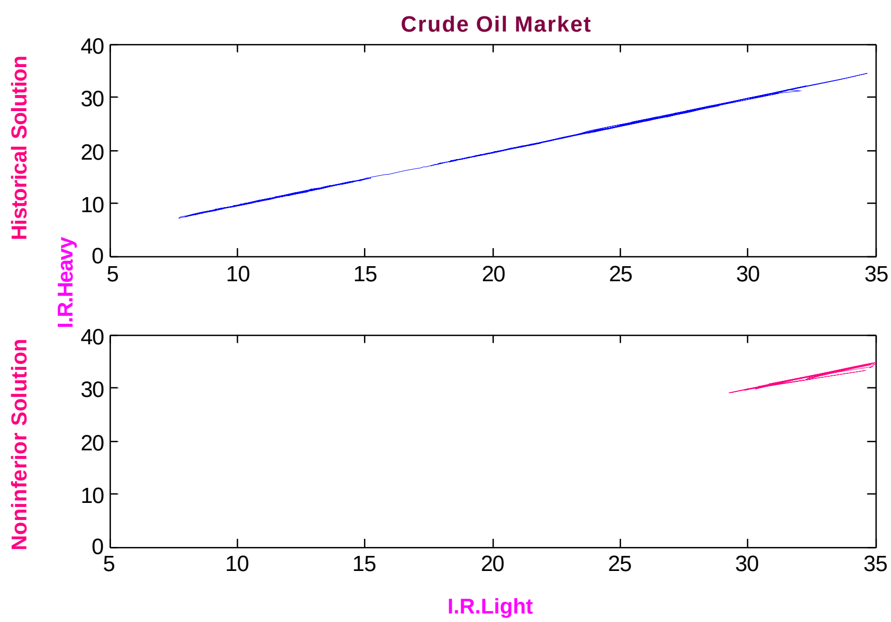

Fig. 10. The results of Problem F_2.

of the future positions based on the quadruple indices of current prices. The study is performed in "Brent North Sea" prices with a set of 12 year historical data. The problem is formulated as follows:

$$\text{Max } Z_B^{POS(2)} = f_1(x_{high}, x_{low}, x_{close}, x_{open}),$$
$$\text{Max } Z_B^{POS(3)} = f_2(x_{high}, x_{low}, x_{close}, x_{open}),$$
$$\text{Max } Z_B^{POS(4)} = f_3(x_{high}, x_{low}, x_{close}, x_{open}),$$

subject to

$$x_{close} \leqslant x_{low} + 3.5,$$
$$x_{high} \leqslant 1.07 x_{close},$$
$$0.94 \leqslant \frac{x_{close}}{x_{open}} \leqslant 1.01,$$
$$x_{high}, x_{low}, x_{close}, x_{open} \geqslant 30, \tag{16}$$

where $Z_B^{POS(k)}$ are the future prices and variables are the current high, low, close and open prices.

The historical data contains 2900 data points which are firstly evaluated by the noninferiority procedure in position values. The process is performed at 0.01 s and five noninferior points are extracted. The points are directly used in the rule generation process. The membership functions are defined based on the range of noninferior points in the following activated area:

$$30 \leqslant Z_B^{POS(k)} \leqslant 40 \quad k = 2, 3, 4$$
$$25 \leqslant x_s \leqslant 45 \quad S = \{\text{high, low, open, close}\}$$

Finally, the following rule base is generated in the noninferior region (Fig. 11):

Similar to the previous examples, a set of grid points are given to the system to test the efficiency of the system. Following Table illustrates the numerical results of Problem F_3.

Such as shown in Table 4, the number of infeasible points is not less (22.8%) and so an exterior method must be used to reach the feasible solutions. Since the constraints are not such complex, simply the penalty function method is used as follows:

$$\begin{aligned}\text{Min } L = & \sum_{i \in S} \{\max(0, 30 - x_i)\}^2 \\ & + \{\max(0, x_{\text{close}} - x_{\text{low}} - 3.5)\}^2 \\ & + \{\max(0, x_{\text{high}} - 1.07x_{\text{close}})\}^2 \\ & + \{\max(0, x_{\text{close}} - 1.1x_{\text{open}})\}^2 \\ & + \{\max(0, 0.94x_{\text{open}} - x_{\text{close}})\}^2. \quad (17)\end{aligned}$$

Specially, BFGS quasi-Newton method with a mixed quadratic and cubic line search procedure is used as penalty method. The vector of solutions is converged to the feasible region quickly in 2.133 s. As the range comparison of current solution and initial solution, the following absolute difference is obtained:

	x_{high}	x_{low}	x_{close}	x_{open}
Min	0.1	0.05	0.01	0.02
Max	0.1	0	0.12	0

Unfortunately, apart from two previous examples, the difference range is future observed in this example. Specially, x_{close} (as the index of position) and x_{open} have remarkable differences. These differences will affect the projection results. Although the projection results are not quite adjusted to the noninferior points, but the noninferior region is correctly and satisfactory recognized by the system. Fig. 12 illustrates the comparison of feasible and noninferior regions in the decision space:

Problem F_4. In the previous example, only the market prices are suggested for the future prices; while general market entities such as market volume of trades and market turnover also seems to have remarkable influence. In the following example, effects of such parameters in the future prices are studied:

$$\begin{aligned}&\text{Max } Z_B^{\text{POS}(2)} = f_1(x_V, x_{IO}),\\ &\text{Max } Z_B^{\text{POS}(3)} = f_2(x_V, x_{IO}),\\ &\text{Max } Z_B^{\text{POS}(4)} = f_3(x_V, x_{IO}),\\ &\text{subject to :}\\ &\quad 0.18x_{IO} \leqslant x_V \leqslant 0.26x_{IO},\\ &\quad 0.90x_{IO} \leqslant x_V \leqslant 0.95x_{IO}, \quad (18)\end{aligned}$$

where x_V and x_{IO} are respectively the volume of trades and the market input/output in the dimensions of 1000 units. Since the noninferiority is only made in the positions, the same process is performed and the following fuzzy rule base is obtained (see Fig. 13):

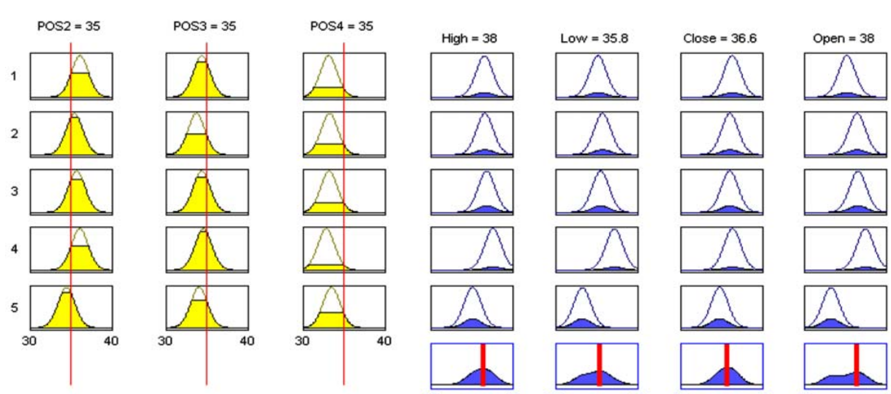

Fig. 11. Fuzzy rule base system of Problem F_3.

Table 4
Numerical results of Problem F_3

	Reference	Initial noninferior	Testing		Exterior method	Projection
			Equality	Feasibility		
Parameters	07/15/88 to 12/29/2000	—	Grid. range: $[30–40]^3$ Grid. rate: 0.25 Grid. No: 68921		Penalty function method	Net # hid.layer: 1
# Points	2900	5	1079	833 (72.2%)	246	Net # neuron: 100
CPU time (s)	—	0.01	2.844	0.01	2.133	0.06

The numerical results of problem are brought in Table 5:

Similar to the previous example, since 17.3% of the solutions are infeasible, the penalty function method is used as follows:

$$\text{Min } L = \begin{cases} \{\max(0, x_V - 0.26x_{IO})\}^2 + \{\max(0, 0.18x_{IO} - x_V)\}^2 \\ \quad \text{if } x_V < \frac{x_{IO}}{2}, \\ \{\max(0, x_V - 0.95x_{IO})\}^2 + \{\max(0, 0.90x_{IO} - x_V)\}^2 \\ \quad \text{if } x_V \geqslant \frac{x_{IO}}{2}. \end{cases} \tag{19}$$

All of the solutions converge to the feasible region only at 0.18 s; but in spite of the previous example, the comparison in the range of current and initial points seems to be more attainable:

	x_V	x_{IO}
Min	0.171	0.132
Max	0.096	0.062

However, the projection of obtained solutions is brought in Fig. 14:

As observed in the above two examples, the decision maker can set the future prices based on current market entities. Interestingly, all future positions are suggested which assure the interrelation effects; the subject which is not attended in optimization works.

On the other hand, while it is proved that "there is no way of making an expected profit by extrapolation past

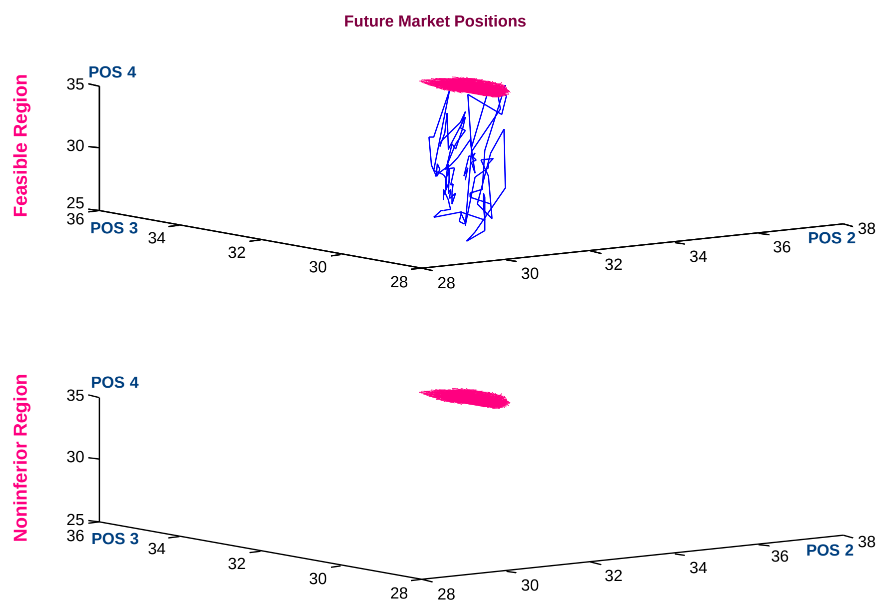

Fig. 12. The results of Problem F_3.

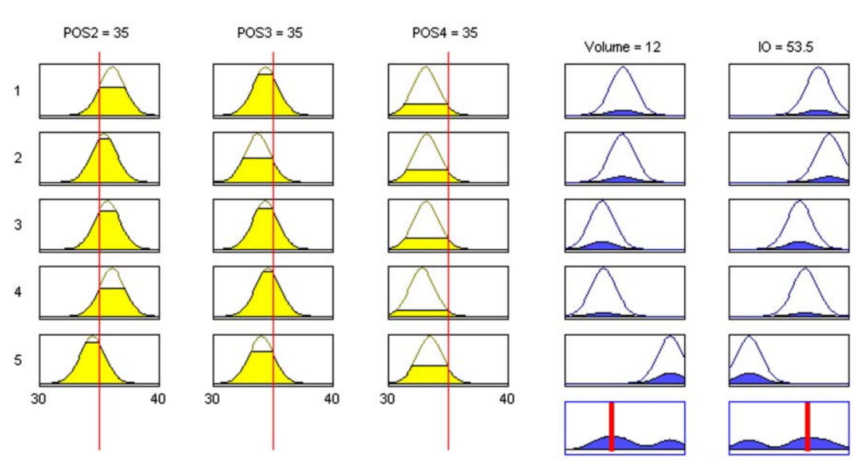

Fig. 13. Fuzzy rule base system of Problem F_4.

Table 5
Numerical results of Problem F_4

	Reference	Initial noninferior	Testing		Exterior method	Projection
			Equality	Feasibility		
Parameters	07/15/98 to 12/29/2000	—	Grid. range: $[30–40]^3$ Grid. rate: 0.25 Grid. No: 68921		Penalty function method	Net # hid.layer: 1
# Points	2900	5	185	153 (82.7%)	32	Net # neuron: 80
CPU time (s)	—	0.02	0.511	≈0	0.18	0.03

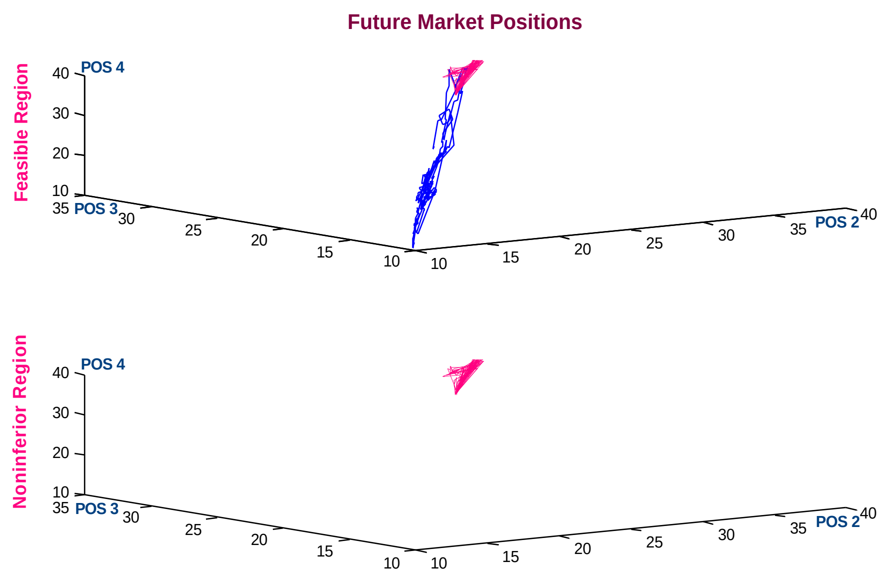

Fig. 14. The results of Problem F_4.

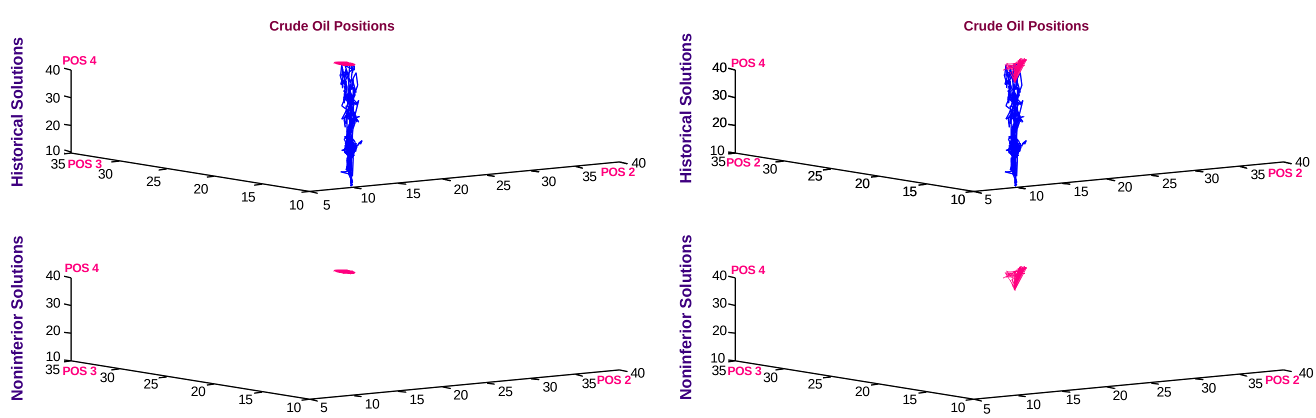

Fig. 15. The comparison of Problems F_3 (right) and F_4 (left).

changes in future prices by chart or any esoteric device of magic and mathematics'' (Leigh et al., 2002), the rule base can support the trader to make the best decisions in the future prices.

In addition, the rule bases can be used as mechanism of the market control; specially when the large contracts are suggested. The rule bases give information about the future prices which are controlled by the current prices and volume. Hence, the government trader with high contracts can adjust the market parameters so that the desired levels of the future prices are satisfied.

Although the systems can be used as complementary of each other, the performance comparisons indicates that F_3 has generated better results than Problem F_4. Fig. 15 illustrates this subject clearly.

Table 6
Fundamental factors of energy markets

Economic	Geographical	Political	Comparative	Background
Production/consumption	Pipeline/shipping	Cartel/trade agreements	Preference shift	Market developments
Storage availability/costs	Localized weather reports	Global events	Transaction costs	Types of oil and gas
Insurance costs	Seasonality	Taxation/trade tariffs	Alternative commodities	
Interest rates	Locality	Regulation/legislation	Production yields	
Transportation		Environmental pressures	Relative quality	
Currency rates				

5. Recommendations for future studies

The multiobjective market model can be expanded with the factors which fundamentally affects the market entities. The factors can be defined in various aspects such as shown in Table 6:

However, some of these factors are social and qualitative which would not be explained mathematically. But the fuzzy system can define these variables linguistically and accept a set of linguistic values as historical data and also generate the linguistic solutions.

As another remark for the future studies, the system can be developed in the other market problems such as option pricing, triggers, swaps, CfDs and EFPs.

On the other hand, the fuzzy rule based system can be developed using technical trading rules, charting patterns, trading strategies to produce buy and sell orders timely and quantitatively. In fact, the system instead of supporting the traders, works in place of the trader by generation of buy and sell signals and determination the best width of trading days.

Finally, case based systems can be used instead of rule based systems. The market behaviors can be recognized using specific features. Since the market transitions are repetitive, each market behavior could be saved as a case in knowledge base and then the decisions are made with an analogical deduction of current situation and historical cases.

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