AN INTEGRATION OF MULTI-OBJECTIVE GENETIC ALGORITHM AND FUZZY LOGIC FOR OPTIMIZATION OF AGROINDUSTRIAL SUPPLY CHAIN DESIGN

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ABSTRACT

Technological innovation and competition in agroindustry in today's manufacturing economy have led to the improvements in supply chain management for agricultural products. Agroindustry is defined as an enterprise that transforms agricultural products (plant, marine and aquatic, livestock, and forestry) into industrial products in order to gain their added value. Each different step in the entire production process, from the farming of basic raw materials to delivery of final products to consumer, is viewed as link in the chain of agroindustrial systems. Agroindustrial Supply Chain Management (Agro-SCM), therefore, represents the management of the entire set of production, manufacturing/transformations, distribution and marketing activities by which a consumer is supplied with a desired product.

The objective of this research is to develop an integrated decision support system consisting of a new multi-objective genetic algorithm and fuzzy logic for optimization of supply chain of bio-diesel industry, an important agroindustry in Indonesia. Supply chain improvements will reduce inventories, waste and costs, and thus increase efficiency within the bio-diesel industry and the market channel.

The mathematical model for supply chain management developed in this research attempts to capture the dynamics of a single product being produced from coconut or palm oil. There are *j* coconut or palm oil farming (suppliers), *k* bio-diesel industry and *l* customer demands. Coconut or palm oil can be supplied by any of the *j* farming. This raw material can be shipped to any of the *k* bio-diesel industry where the product is made. Then they are shipped to customers based on demands.

The multiple objectives used in this research are minimizing Total Supply Chain Cost (TSCC) and minimizing Expected Number of Deteriorated Product (ENDP). The second objective is essential for agroindustry. The variables to be optimized are the amount of coconut or palm oil from suppliers to plants, the amount of bio-diesel shipped from plants to customer zone and the inventories in the plants. The numerical result indicated that the genetic algorithm developed and fuzzy logic introduced in this work are robust and reliable as they can produce promising results.
Keywords: Genetic Algorithm, Fuzzy Logic, Supply Chain Management, Multiobjective optimization

1. INTRODUCTION

There are at least three strategic areas that will shape our business and society today and in the near future: (1) Information and Communication Technology, (2) Food and social safety and security, and (3) The use of agricultural products and renewable resources for manufacturing industry and for producing new energy. The last one leads to the development of agroindustry. Agroindustry is defined as agricultural products processing industry as well as other business-oriented activities to: (1) increase added value of agricultural products, and (2) make more environmental-friendly manufactured goods by using agricultural products as inputs (Austin, 1992; Brown, 1994). Some examples of agroindustry are pulp and paper, sugar cane, crude palm oil, bioplastics, bio-lubricants, bio-energy, feed, natural medicine and food industry, to mention only a few.

A supply chain is an integrated process where raw materials are acquired, converted into products and delivered to the consumer (Shapiro, 2001). In agroindustry, each different step in the entire production process, from the farming of basic raw materials to delivery of final products to consumer, is viewed as link in the supply chain. Therefore, Agroindustrial Supply Chain Management (Agro-SCM) represents the management of the entire set of production, transformations/processing, distribution and marketing activities in agroindustry by which a consumer is supplied with a desired product. Furthermore, unlike in manufacturing industry, a supply chain management of agroindustry is characterized in some special properties such as (1) the agricultural products are perishable, (2) the planting, growing and harvesting process depend on climate and season, (3) various sizes and shapes of products, (4) bulky, i.e. products are difficult to carry or manage because of size, shape and complexity of the products (Austin, 1992; Brown, 1994). These four factors should be considered in the design and optimization of Agro-SCM and thus, as a consequence, Agro-SCM becomes more difficult and complicated than general manufacturing SCM.

In addition, the existing research works in agricultural systems and agroindustry management have been using single objective instead of multi-objective models. For example Apaiah and Hendrix (2004) presented their work on the design of supply chain network with a single objective to manufacture a pea-based novel-protein food (NPF) as cheaply as possible. Similarly, Milan et.al. (2005) worked on the application of mixed integer linear programming model to solve the problem of cost minimization of sugar cane removal and its transport from the fields to the sugar mill at operational level. In another study Tarantilis and Kiranoudis (2001) developed a meta-heuristic algorithm for the efficient distribution of perishable foods with the objective is to minimize the distance of delivery routes for a fleet of vehicles located at the distribution centre of a producer for serving his traders. In a recent study, Widodo et.al. (2004) constructed a basic model of agricultural fresh products by formulating the plant growing process and the loss process of fresh products in mathematical forms. This model was then solved analytically to maximize the demand level.

In fact, many problems in agroindustry are multi-objective in nature that is several conflicting-objectives have to be optimized simultaneously, as indicated by Matthews et.al. (2005). Despite a few researchers have also applied multi-objective models in their projects, they still used conventional optimization tools such as goal programming, weighting methods ad ε-constraint methods, which have many limitations. For this reason, non-conventional optimization methods such as genetic algorithms are developed to solve multi-objective Agro-SCM in this work. Genetic algorithms are robust and adaptive optimization methods based on genetics and natural selection that can find an optimum solution to linear and nonlinear problems by simultaneously exploring multiple regions of the solution space (Goldberg, 1989; Gen and Cheng, 1997). Moreover, genetic algorithms also become good candidates for tackling multiobjective problems as they use population based or multiple points search strategy (Deb 2001; Coello, 2002).

Furthermore, the other drawback of the existing research works in multi-objective optimization is that they are only dedicated to find Pareto-optimum solutions. In fact, the user is now in a dilemma. Which of these optimal solutions must one choose? This is not an easy question to answer. It involves the consideration of higher-level information which is non-technical, qualitative and experience-driven. Thus, as suggested by Deb (2001) in a multi-objective optimization, ideally the effort must be made in finding the set of trade-off optimal solutions by considering all objective to be important. After a set of such trade-off solutions are found, a user can then use higher-level qualitative considerations to choose one of them for implementation. One good approach to process such higher level and qualitative information for choosing the most preferred solution is to use expert systems (Turban, 2000), and that is what is used in this research for agroindustrial supply chain design problems.

The remainder of the paper is organized as follows. Section 2 gives a comprehensive literature review on multi-objective genetic algorithms and then places this research in its respective place. Section 3 formulates the agroindustrial supply chain management problems into a decent mathematical model. Section 4 explains the development process of an intelligent DSS for Agro-SCM. Section 5 gives a numerical example to demonstrate the capability of the intelligent DSS to solve a non-trivial Agro-SCM problem. Section 6 concludes this research and gives direction for further research.

2. LITERATURE REVIEW ON MULTI-OBJECTIVE GENETIC ALGORITHMS

2.1 Multi-objective optimization

Many real-world system design or decision making problems involve simultaneous optimization of multiple objectives. There have been many research works that use multi-objective models in their optimization problems, such as reported by Gupta and Gupta (1999), Garg and Gupta (1999), Silva et.al (2004) and Vera et. al (2003). The principle of multi-objective optimization is different from that in a single-objective optimization. In single-objective optimization, the goal is to find the best design solution, which corresponds to the minimum or maximum value of the objective function. On the contrary, in a multi-objective optimization with conflicting objectives, there is no single optimal solution. The interaction among different objectives gives rise to a set of compromised solutions, largely known as the Pareto-optimal solutions (Deb, 2001 and Coello, 2002). Since none of these Pareto-optimal solutions can be identified as better than others without any further consideration, the goal in a multi-objective optimization is to find as many Pareto-optimal solutions as possible. The general form of multi-objective optimization is as follow.

$$
\begin{array}{ll}
\text{Minimize/Maximize : } \mathrm{f}_m(x), & m = 1, 2, \ldots, M; \\
\text{Subject to : } \mathrm{g}_j(x) \geq 0, & j = 1, 2, \ldots, J; \\
\qquad \mathrm{h}_k(x) = 0 & k = 1, 2, \ldots, K; \\
\qquad x_i^{(\mathrm{L})} \leq x_i \leq x_i^{(\mathrm{U})} & i = 1, 2, \ldots\ldots, n;
\end{array}
$$

The last set of constraints are called variable bounds, restricting each decision variable x_i to take a value within a lower bound $x_i^{(\mathrm{L})}$ and an upper bound $x_i^{(\mathrm{U})}$.

Besides having multiple objectives, there are three fundamental differences between single-objective and multi-objective optimization (Deb 2001). Firstly, multi-objective optimization has two goals, instead of one. In single objective optimization, there is one goal – the search for an optimum solution. In a single-objective optimization algorithm, as long as a new solution has a better objective function value than an old solution, the new solution can be accepted. However, in multi-objective optimization, there are clearly two goals. Progressing towards the Pareto-optimal front is certainly an important goal. However, maintaining a diverse set of solutions in the non-dominated front is also essential. Since both goals are important, an efficient multi-objective optimization algorithm must work on satisfying both of them.

Secondly, multi-objective optimization involves two search spaces, instead of one. Here, in addition to the decision variable space, there also exists the objective or criterion space. Although these two spaces are related by an unique mapping between them, often the mapping is non-linear and the properties of the two search spaces are not similar. For example, a proximity of two solutions in one space does not mean a proximity in the other space. Thus, while achieving the second task of maintaining diversity in the obtained set of solutions, it is important to decide the space in which the diversity must be achieved.

Thirdly, multi-objective optimization for finding multiple Pareto-optimal solutions eliminates all artificial fix-ups, such as in weighted sum approach and ε-constraint method, and can, in principle, find a set of optimal solutions corresponding to different weight and ε-vector in one single simulation run.

2.2 Multi-objective genetic algorithms: State of the art

One successful approach to finding sets of non-dominated solutions defining the trade-off between objectives is to use multi-objective genetic algorithms (Deb, 2001; Coello, 2002). Multi-objective genetic algorithms are an extension to a class of search and optimization algorithms based on the mechanics of natural selection. Research in multi-objective genetic algorithms came about with the development of Vector Evaluated Genetic Algorithm or VEGA (Schaffer, 1985). VEGA modifies the selection operator by performing proportional (roulette) wheel selection using each objective to select a number of sub-populations. For example, if there are two objectives, half of the population will be selected using f_1 and the other half using f_2. Then the sub-populations are shuffled together to form a new population. This is very simple an efficient, but solutions generated are what called locally non-dominated but not necessarily globally non-dominated. Individuals excel only along one objective. The frontier created will be mainly cluster near the ends of the frontier, as if we only optimized one objective.

Then, a number of researchers across the globe have developed different implementations of multi-objective genetic and evolutionary algorithms, such as Non-dominated Sorting Genetic Algorithm or NSGA (Srinivas and Deb, 1994), Elitist and Non-dominated Sorting Genetic Algorithms or ENGA (Bagchi, 1999), Niched Pareto Genetic Algorithm or NPGA (Horn *et.al.*, 1994), to mention only a few.

The most recent implementation of multi-objective genetic algorithm is Non-dominated Sorting Genetic Algorithm-II or NSGA-II (Deb *et.al.* ,2002) that is known as one of the best methods for generating the Pareto-frontier. The NSGA-II algorithm ranks the individuals based on dominance. It also calculates the crowding distance for each individual in the new population. Crowding distance gives the GA the ability to distinguish individuals that have the same rank (i.e. those that reside in the same frontier set). This forces the GA to uniformly cover the frontier rather than bunching up at several good points by trying to keep population diversity. A new comparison operator is used by NSGA-II to sort the population for selection purposes. Individuals that are in a lower frontier set are considered better than those in higher sets. If they are in the same frontier, then individuals which is the farthest from other individuals is considered better.

The successful application of multi-objective genetic algorithms in broad areas has been reported in recent publications. For example, Ishibuchi and Murata (1998); Garen (2004) and Bagchi (1999) used multi-objective genetic algorithms for shop scheduling. The objectives of their optimization models are to minimize make-span, mean flow-time and tardiness simultaneously. In fact, each of them developed a different variant of multi-objective genetic algorithms, but they all conclude that the application of multi-objective genetic algorithm in shop scheduling is very promising.

In another study, Zhou et.al, (2003) successfully developed a multi-objective genetic algorithm for optimizing the allocation of customers to warehouses of a manufacturing company by considering two conflicting objectives, i.e. transit time versus shipping cost. In a more recent study, Matthews et.al. (2005) reported their work on combining deliberative and computer-based methods for multi-objective lad-use planning. Their land-use planning tools are based on multi-objective genetic algorithms and designed to generate a range of alternative plans that define the structure of the trade-off between objectives. They concluded that the use of multi-objective genetic algorithms to solve land-use planning problem is satisfactory.

Given the proven success of genetic algorithms to multi-objective problems, we believe that genetic algorithm is suitable for solving agroindustrial supply chain management problems. However, the existing multi-objective genetic algorithms need to be improved in term of their population diversity. This important issue will be discussed in the following section.

3. PROBLEM FORMULATION

3.1 Mathematical Model

The mathematical model for supply chain management developed in this research is formulated based on several references (Shapiro 2001, Apaiah and Hendrix 2004, Bredstorm et.al 2004, Glenn, Kilmer and Stevens 2002, Sarker, Jamal and Wang 2000, Yao and Huang 2004) and presented in Figure 1.

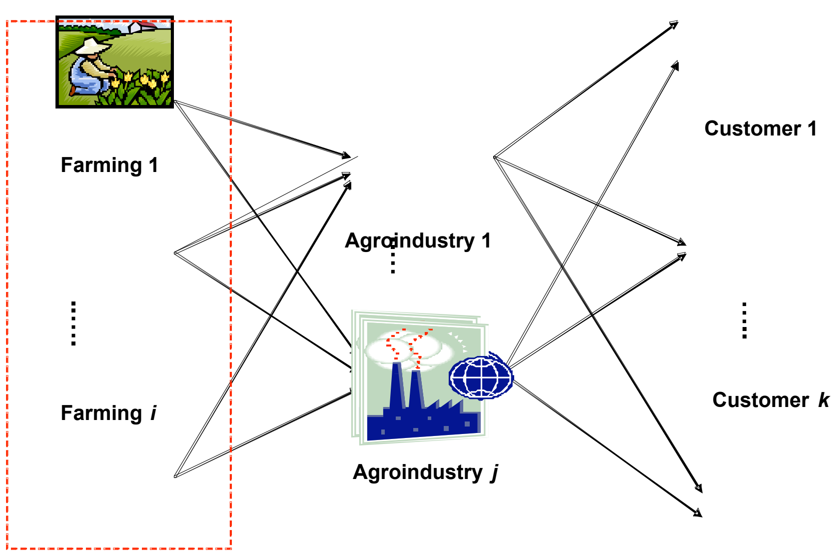

Figure 1. Supply Chain Model for Agroindustry

There are i farming (suppliers), j agroindustries and k customers. Raw materials can be supplied by any of the i farming. These raw materials can be shipped to any of the j agroindustries where the product is made. Then products are shipped to customers based on demand. The optimization model for this particular agroindustrial supply chain is presented below.

$$Min: \quad TSCC = \sum_{j=1}^{J}\sum_{k=1}^{K} CB_{jk} Y_{jk} + \sum_{i=1}^{I}\sum_{j=1}^{J} CA_{ij} X_{ij} + \sum_{j=1}^{J} CIP_j I_j$$

$$Min: \quad ENDP = \sum_{j=1}^{J}\sum_{k=1}^{K} PB_{jk} Y_{jk} + \sum_{i=1}^{I}\sum_{j=1}^{J} PA_{ij} X_{ij} + \sum_{j=1}^{J} PIP_j I_j$$

Subject to the following constraints:

$$\sum_{j=1}^{J} Y_{jk} = D_k \quad \forall_k \qquad (1)$$

$$\sum_{k=1}^{K} Y_{jk} \le Cap_j \quad \forall_j \qquad (2)$$

$$\sum_{j=1}^{J} X_{ij} \le S_i \quad \forall_i \qquad (3)$$

$$\sum_{i=1}^{I} X_{ij} = \left(\sum_{k=1}^{K} Y_{jk}\right) + I_j \quad \forall_j \qquad (4)$$

4. SYSTEM DEVELOPMENT

In order to solve the agroindustrial supply chain optimization with multiple and conflicting objectives as described before, an Intelligent Decision Support System which consists of a combination of a multi-objective genetic algorithm and fuzzy logic is developed in this work. The structure of this Intelligent DSS is presented in Figure 2.

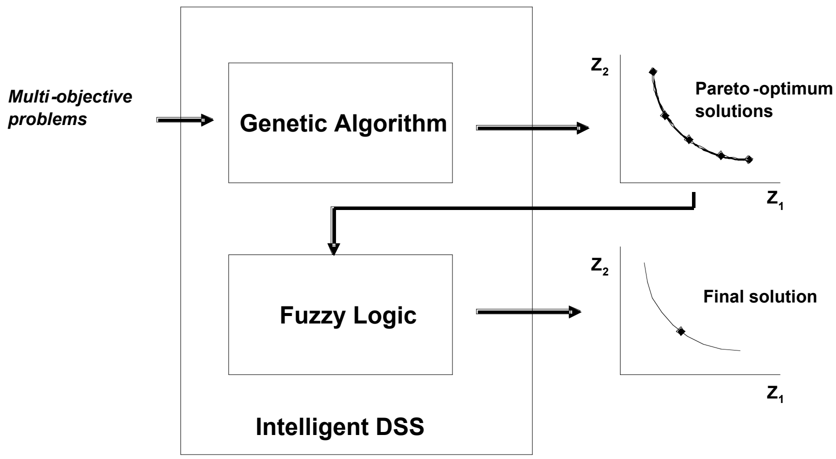

Figure 2. Configuration of Intelligent DSS

Figure 2 shows that at first a genetic algorithm is used to create a Pareto-front that consists of non-dominated solutions. A fuzzy logic is then proposed to be used to select the most preferred solution or final solution for implementation from these non-dominated solutions. The details of the development of genetic algorithm and fuzzy logic are described in the following sections.

4.1 Multi-objective Genetic Algorithm

As presented in the previous section, in the last few years there has been a number of research works conducted in the area of multi-objective optimization using genetic algorithms including VEGA, NSGA, ENGA, PAES and NSGA-II. Despite their success, there are rooms for improving the performance of the existing genetic algorithms. The main weakness of the existing multi-objective genetic algorithms is that they allow identical chromosomes or individuals in the population. This drawback leads to slow convergence to the true Pareto-optimum front and poor diversity of optimum solutions. For this reason, this research aims to develop a new genetic algorithm that has an additional module to preventing unintended identical chromosomes in the population. This additional module is called "Additional Diversity Module" (ADM) and inserted into a widely-used multi-objective genetic algorithm, namely NSGA-II developed by Deb et.al. (2002). More precisely, the genetic algorithm developed in this work is similar to NSGA-II, except that it use fully heterogeneous population in each iteration. This new genetic algorithm is called h-MGA stands for heterogeneous Multi-objective Genetic Algorithm. The procedure of h-MGA is presented in Algorithm 1 below.

Algorithm 1:

Step 1. Create initial population (Old-Pop) consists of ***N*** individuals (solutions) randomly
Step 2. Perform non-dominated sorting and fitness assignment for Old-Pop and put solutions into different levels (from the first to the last level) based on their non-domination ranking (fitness value)
Step 3. Calculate Crowding Distance (CD) value for all solutions in each level of Old-Pop
Step 4. Check whether solutions in Old-Pop violate constraints or not. If too many solutions violate constraints, recreate initial population; otherwise go to the next step.
Step 5. Select individuals from Old-Pop for reproduction by using Binary Tournament Selection (based on level and CD value)
Step 6. Perform crossover and mutation to form a new population (New-Pop)
Step 7. Check whether solutions in New-Pop violate constraints or not. If yes give penalty to this solution by assigning very big values for objective 1 and objective 2.
Step 8. Combine New-Pop and Old-Pop to form Uni-Pop with size 2***N***
Step 9. Perform non-dominated sorting and fitness assignment for Uni-Pop and separate solutions into different levels (from the first to the last level)
Step 10. Calculate Crowding Distance (CD) value for all solutions in each level of Uni-Pop
Step 11. Sort this new population based on its level and CD value to form New-Pop2
Step 12. Form a new and heterogeneous population of New-Pop3 with size ***N*** based on New-Pop2 using Additional Diversity Module (ADM)
Step 13. If stopping criteria met then Stop and New-Pop3 becomes the Pareto-optimum solutions; otherwise replace the value of Old-Pop with New-Pop3 and then go to Step 5.

It should be noted that in Step 12 above, an ADM is employed to detect and manipulate identical chromosomes in new population. The usefulness of ADM has been shown in the recent publication of the first and last author of this paper in solving flowshop scheduling problems (Yandra and Tamura, 2007). In order to be able to solve Agro-SCM problem in this research, some features of h-MGA developed in our previous research has been modified. The main modifications are in chromosome structure (integer instead of string representation), crossover method (simple instead of partially matched crossover), and mutation (simple instead of swap mutation). The other features and procedures are similar.

4.2 Fuzzy Logic

The genetic algorithm in general uses objectives and constrains value as well as fitness function fitting that are represented by using single exact value. The single-point representation and computation can be expanded further into fuzzy sets representation and computation. The fuzzy representation and computation allow the values used in the genetic algorithm represented in range value with membership function embedded on it.

The strict threshold valued computational models can be changed into fuzzy computational models on labels represented in various representation methods, such as TFN (triangular fuzzy numbers) or gaussian representation method. It allows for the use of fuzzy members and it preserves the nature of values and accuracy during computational processes.

The other possibility is that the fuzzy logic can be used to select the most preferred solution or final solution for implementation from these non-dominated solutions as suggested by the genetic algorithm. The non-dominated solution alternatives are compared in a pair, which is represented by using fuzzy preference relation. The solution is then derived from the pair-wise preference relation matrix by using direct approach. A fuzzy support concept, which is similar to the fuzzy core concept, is used to identify the alternatives, which are supported by the decision makers (Marimin et al, 1998).

5. AN APPLICATION DEMONSTRATION

In this section, the application of new developed genetic algorithm to solve agroindustrial supply chain problems is demonstrated by using a case study, i.e. optimization of coco-diesel supply chain. We are interested to use h-MGA to solve this problem and then come up with a set good and well diversed Pareto-optimum solutions. The output of genetic algorithm is then fed to fuzzy logic for further analysis.

For numerical experiment, a 4-farming, 3-factory and 5-customer network is used in this work. The transportation, inventory cost and probability of deterioration matrices are presented in Table 1,2,3 and 4 respectively. It should be noted that the dimension for transportation and inventory cost used in this research is monetary unit (m.u) per unit.

Table 1. Transportation cost from farming to agroindustry and then to customer (CB_{jk} and CA_{ij})

		TO: Agroindustry		
		A	B	C
FROM: Farming	P	12	16	14
	Q	11	7	16
	R	10	13	8
	S	8	9	7

		TO: Customer				
		1	2	3	4	5
FROM: Agroindustry	A	10	12	8	11	6
	B	5	15	9	11	8
	C	7	13	4	9	7

Tabel 2. Inventory cost (CIP_j)

Agroindustry	Inventory Cost
A	11
B	8
C	10

Table 3. Probability of deterioration in transportation from farming to agroindustry and then to customer or PB_{jk} and PA_{ij} (%)

		TO: Agroindustry		
		A	B	C
FROM: Farming	P	2	12	11
	Q	4	3	9
	R	8	2	3
	S	9	11	6

		TO: Customer				
		1	2	3	4	5
FROM: Agroindustry	A	5	1	3	9	11
	B	2	6	3	1	8
	C	15	9	12	1	7

Table 4. Probability of deterioration at inventory or PIP_j (%)

Agroindustry	Probability of deterioration
A	8
B	11
C	12

The heterogeneous multi-objective genetic algorithm was run with the following parameters: (1) Crossover probability or P_c = 0.9, 0.8 and 0.7, (2) Mutation probability or P_m = 0.05, 0.01 and 0, (3) Population size = 40 and (4) Number of replication for each combination of P_c and P_m was 5. The best Pareto-optimum solutions obtained are presented in Figure 3 and 4.

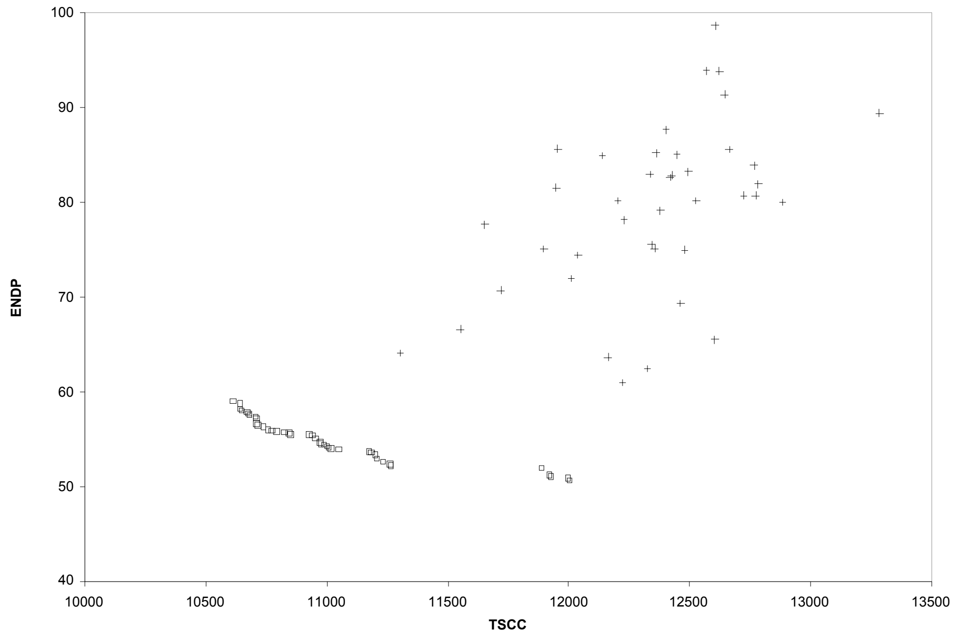

Figure 3. Pareto-optimum and initial solutions from h-MGA

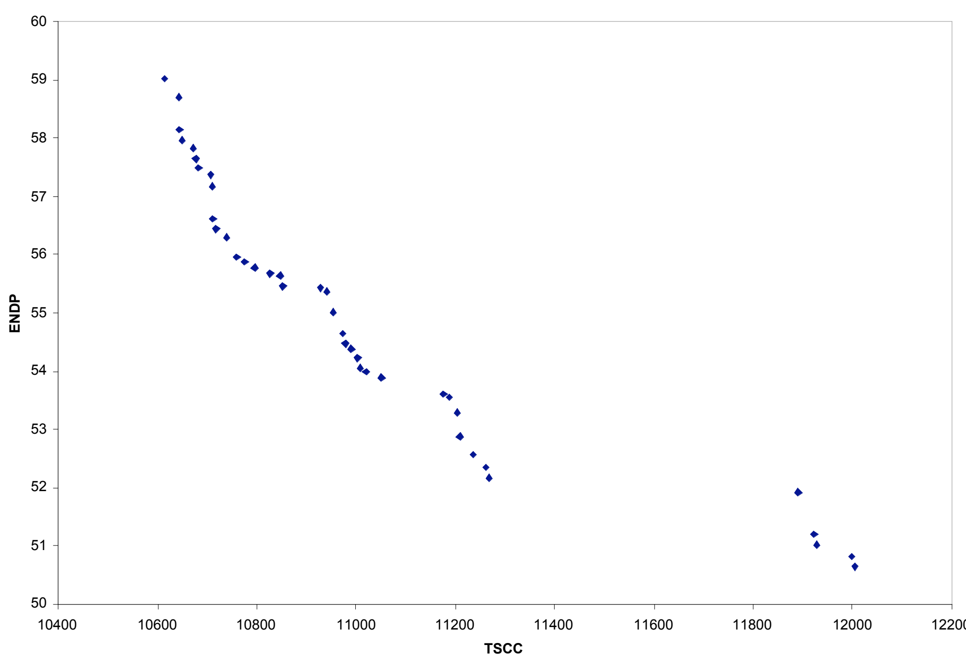

Figure 4. Diversity of Pareto optimum solutions

Figure 3 shows that a Pareto-optimum front can be found by GA in a reasonable number of generations. These Pareto-optimum solutions (_) are shown with a set of random initial solutions (+) for comparison purpose. In addition, Figure 4 shows that the Pareto optimum solutions of h-MGA have good diversity.

The Pareto-optimum solutions found by genetic algorithm then can be fed to fuzzy logic for selecting the most preferred solution. It should be noted here that at the time of writing this paper fuzzy logic module is still in the development process. However, our literature review, previous publication and preliminary research conclude that the use of fuzzy logic in selecting the most preferred solution will be very promising.

This numerical example shows that the integration of multi-objective genetic algorithm and fuzzy logic proposed in this work can be used to solve a difficult supply chain management problem in agroindustry successfully.

6. CONCLUSIONS

This paper has presented the development of an integrated methodology for optimization of multiobjective supply chain network in agroindustry based on artificial intelligence techniques: (1) heterogeneous multi-objective genetic algorithm, and (2) fuzzy logic. The new genetic algorithm developed in this work has been used successfully to solve a non-trivial agroindustry supply chain problem. A fuzzy logic has also been introduced to select the most preferred solution based on the input given by genetic algorithm. This research concludes that the intelligent system developed in this research is robust and reliable, so it can be used to tackle the other agroindustry supply chain optimization problems only with minor modifications.

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