CHAPTER II

LITERATURE REVIEW

2.1 Evolutionary algorithms

Evolutionary algorithms (EA) have been recognized to be particularly suitable to solve multi-objective optimization problems because they deal simultaneously with a set of possible solutions which allows an entire set of Pareto-optimal solutions to be evolved in a single run of the algorithm, instead of having to perform a series of separate runs as in the case of traditional mathematical programming techniques. Moreover, EAs are less susceptible to the shape or continuity of the Pareto front (Coello, 1999). This has led to the development of many successful evolutionary multi-objective optimization algorithms over the past decade. Multi-objective genetic algorithms are typically divided into two groups: *non-Pareto* and *Pareto* based approaches.

Non-Pareto based approaches: These approaches do not incorporate directly the concept of Pareto optimality. The first GA proposed for multi-objective optimization was VEGA (Schaffer, 1985). This is a non-Pareto based approach based on the selection of several relevant groups of individuals, each group being associated to a given objective. It is reported that the method tends to crowd results at extremes of the solution space, often yielding poor convergence of the Pareto front. Fourman (1985) presented a genetic algorithm using binary tournaments, randomly choosing one objective to decide each tournament. A more recent algorithm, based on scalarization with a weighted sum function, is proposed in Ishibuchi and Murata (1998) where the weights are chosen at random. Coello and Christiansen (1999) proposed two different methods based on aggregated functions and min–max optimization.

Pareto based approaches: These methods use the concept of Pareto optimality explicitly. Many successful evolutionary multi-objective optimization algorithms were developed based on the two ideas suggested by Goldberg (1989): Pareto dominance and niching. Pareto dominance is used to exploit the search space in the direction of the Pareto front and niching technique explores the search space along the front to keep diversity. The well-known algorithms in this category include Multi-objective Genetic Algorithm: MOGA (Fonseca and Flemming, 1993), Niched Pareto Genetic Algorithm: NPGA (Horn et al., 1994), Non-dominated Sorting Genetic Algorithm: NSGA (Srinivas and Deb, 1995), Strength Pareto Evolutionary Algorithm: SPEA (Zitzler and Thiele, 1999), Multi-objective Evolutionary Algorithm: MOEA (Tan et al., 2001), etc. The idea behind Goldberg's Pareto-based assignment is to assign equal probability of reproduction to all non-dominated individuals in the population. Basically, it consists of assigning rank 1 to the non-dominated individuals and removing them temporarily from contention, then finding a new set of non-dominated individuals, ranked 2, and so forth. Pareto-based ranking correctly assigns all non-dominated individuals the same fitness. However, this does not guarantee that the Pareto set is uniformly sampled. In order to avoid such a problem, Goldberg and Richardson (1987) proposed the additional use of fitness sharing. The main idea behind this is that individuals in a particular niche have to share the available resources. The more individuals are located in the neighborhood of a certain individual, the more its fitness value is degraded. Coello (1999) and Deb (2001) provide excellent review on the state of the art in the field.

2.2 Applications of multi-objective evolutionary algorithm for Chemical Engineer

Many studies have been reported in the literature on the multi-objective evolutionary algorithm applied in industrial process modeling, optimal design and operation. Rahul B. Kasat & Santosh K. Gupta(2003) designed the two objective functions are the maximization of the yield of gasoline (economic reasons) and the minimization of the coke formed on the catalyst during the cracking of heavy compounds (to minimize catalyst decay and so to reduce the production of CO) for fluidized-bed catalytic cracking unit. S.R. Anderson, et al (2004) developed a supervisory level optimization tool for a waste incineration plant, which utilizes a multi-objective genetic algorithm (MOGA). Specifically, the tool enables controllable parameters to be adjusted for maximum throughput, whilst minimizing emissions and keeping within operational constraints. Shengjing Mu, et al (2004) presented study, a scalable multi-objective optimization strategy of industrial purified terephthalic acid (PTA) oxidation process is proposed to improve the industrial operation efficiency, in order to be better applied in different industrial operation cases, a four level scalable operation strategy is proposed in the steady multi-objective optimization problem. Wen-Cheng Lee & Cheng-Liang Chen(2004), a multi-product, multi-stage, and multi-period scheduling model is proposed in this study to deal with multiple incommensurable goals for a multi-echelon supply chain network with uncertain market demands and product prices and application of it to a numerical example, proved effective in providing a compromised solution in an uncertain multi-echelon supply chain network. Urmila M. Diwekar, et al(2004) presented the optimal trade-off design solutions or the Pareto set for this hybrid power plant through a multi-objective optimization framework and synthesis of any power plant under uncertainties. Fangyu Han, et al (2005) presents a methodology for multi-objective modeling and optimization with environmental impacts and economics aspects simultaneously in the context of cleaner production. Cheng-Liang Chen & Ping-Sung Hung (2005) presented a multi-criteria synthesis strategy for heat-exchanger networks (HENs) simultaneously considering minimum utility consumption, maximum source-stream temperature flexibility, and even minimum number of matches is proposed. A. Tarafder, et al (2005) Application multi-objective optimization for designed industrial styrene reactor, the objectives were to maximizing the styrene flow rate and selectivity and minimizing the total heat duty required by the manufacturing process.