2009 Ninth International Conference on Intelligent Systems Design and Applications

GA-Based Solutions Comparison for Storage Strategies Optimization for an Automated Warehouse

Valentina Colla, Gianluca Nastasi, Nicola Matarese
Scuola Superiore Sant'Anna, SSSA
Pisa, Italy
Email: colla {nastasi, n.matarese}@sssup.it

Leonardo M. Reyneri
Politecnico di Torino
Torino, Italy
Email: leonardo.reyneri@polito.it

***Abstract*—The paper analyses the issues behind strategies optimization of an existing automated warehouse for the steelmaking industry. Genetic Algorithms are employed to this purpose by deriving a custom chromosome structure as well as ad-hoc crossover and mutation operators. A comparison between three different solutions able to deal with multi-objective optimization are presented: the first approach is based on a common linear weighting function that combines different objectives; in the second, a fuzzy system is used to aggregate objective functions, while in the last the Strength Pareto Genetic Algorithm is applied in order to exploit a real multi-objective optimization. These three approaches are described and results are presented in order to highlight benefits and pitfalls of each technique.**

***Keywords*-genetic algorithms, multi-objective optimisation, logistic, warehouse**

I. INTRODUCTION

Automated warehouses [1] are a product of high integration of modern logistics, warehousing, automation and computer technologies. Despite their very relevant cost, major advantages of automated warehouse include high throughput, efficient use of space, high reliability and improvement of safety, as the human intervention is reduced at minimum. Furthermore, in order to improve customer service levels, they can be directly linked to the information system that handles customers orders, also via web through B2B (businness to businness) platforms.

Warehouses are included in the wider class of logistic systems. The efficiency of a logistic system is influenced by many factors; among the most important ones are the research of the best locations for distribution facilities and the research of optimized strategy to manage the distribution network in such a way that the customer demand can be satisfied at minimum cost and maximum profit [2], [3]. As a single warehouse is considered, its efficiency is mainly influenced by allocation and reordering methods, i.e. by procedures whose aim is, for example, to optimise space utilisation, items throughput and store and retrieval operations [4], [5].

This paper is focused on the study of an automated warehouse for the primary steel making industry, that allows to store several typologies of tubes with rectangular section in an automatic way. The first automated warehouse for steel tube storage was built in Japan at the end of '90s [6], but now they spread also allover USA and Europe.

The paper is organized as follows: Sec. II briefly describes the automated warehouse; Sec. III presents the optimisation problem and some Key Performance Indicators. A brief state-of-the-art survey is presented in Sec. IV, while is Sec. V the structure of the Genetic Algorithm model employed is illustrated. Three different solutions based on Genetic Algorithm are described in Sec. VI; In Sec. VII simulation results are presented and discussed, while some concluding remarks are given in Sec. VIII.

II. PLANT DESCRIPTION

The plant is composed by a *production area*, a *storage area* and a *shipping area*, as depicted in Fig. 1.

In the production area the tubes are manufactured and packaged. Each tube is characterized by a *typology*, which in turn is defined by means of tube length (6 or 12 meters), section shape and sizes (rectangular or squared) and steel quality: more then 1000 different typologies are currently produced. Each pack contains tubes of the same typology and for each typology, pack dimensions are predefined. Once a pack of tubes is ready at the end of one of the production lines, it is carried to the storage area by means of an automated material handling system, composed by 43 automated cranes, called *trolleys*, which are able to move through a suspended railway system and that are equipped with electromagnets that can be lowered and raised in order to grasp a pack of tubes. The storage area is about 50×90 meters and it is divided in 9 aisles: each aisle is composed by dynamically allocated mono-typology compartments, which in turn are composed by a certain number of stacks of packs, depending on the production order. Each compartment is identified by the aisle in which it lies and by its distance, expressed in centimetres, from the beginning of the aisle itself and it is characterized by a width (expressed in number of stacks) and by the tube typology it can contain. Compartments positions and size are assigned by the management system as soon as production orders are received by means of an *allocation strategy*.

978-0-7695-3872-3/09 $26.00 © 2009 IEEE
DOI 10.1109/ISDA.2009.201

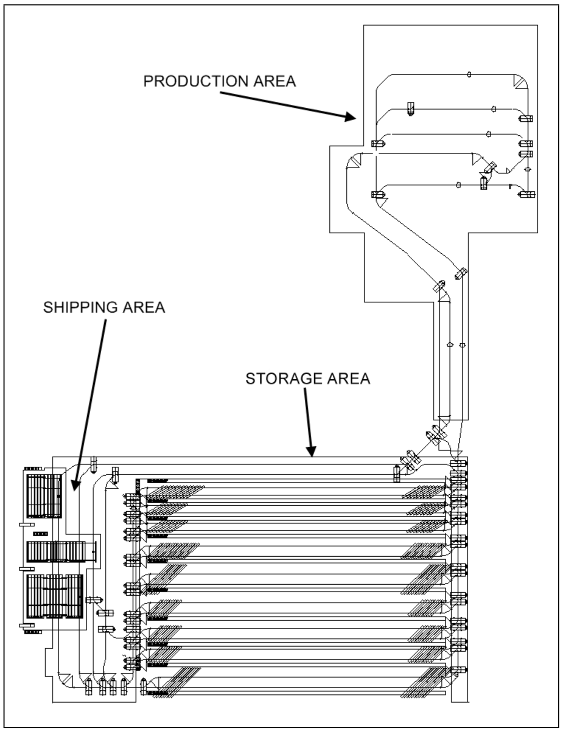

Figure 1: Map of the plant

Tube packs remain in the warehouse until they are acquired by customers through an information system directly linked to the automated warehouse management system. Finally, for the delivery, the tubes pack are carried to the dispatching area, where they are loaded on trucks that will deliver them to customers.

Current storage strategies as well as constraints they must satisfy - such as minimum distance between adjacent compartments, maximum stacks height, minimum number of stacks in a compartment, etc. - are described in deeper details in [7].

III. Problem statement

In the analysed warehouse, despite of the high level of automation, the algorithms that currently rule allocation and reordering strategies of tubes packs are merely based on heuristics and simple rules, so probably leaving room for large performance improvements. The limit of both strategies is due to the fact that a complete search on all available empty spaces or compartments is not performed. For example, as the compartment allocation procedure is concerned, empty spaces are examined in order, beginning from the first empty space of the first aisle on. When an empty space in which the new compartment fits and that satisfies predefined characteristics and rules is found, the search is stopped, sometimes ignoring other possible and maybe better storage sites. Thus, from a strict point of view, both allocation and reordering strategies are not optimized, i.e. are not guided by objective functions.

Unfortunately the employment of such procedures can sometimes lead the warehouse to a false saturation status: as a matter of fact, it can happen that, although existing compartments are almost empty, there is not enough room for the allocation of new compartments for tube typologies not currently present, thus forcing to perform a manual storage operation in another non-automated warehouse, which is slower, less efficient and less safe.

Let us define some Key Performance Indicators (KPIs) that will be used both to derive objective functions for new strategies and to compare them with the performances of the current procedures [8].

Total Stored Material. *It identifies how many items are stored in the warehouse. It can be measured as weight or items number, depending on the typology of merceology. The equation for the* Total Stored Weight *is*

$$TSW = \sum_{k=1}^{N_C} \sum_{j=1}^{N_i(k)} w_{kj} \tag{1}$$

where N_C is the number of allocated compartments, $N_i(k)$ is the number of items of the kth compartment and w_{kj} is the weight of a single item. This KPI should be maximised.

Empty Space. *It is the sum, expressed in centimetres, of the amount of empty space presents in the aisles.*

$$ES = \sum_{k=1}^{N_S} l_k \tag{2}$$

where N_S is the number of empty spaces that are in the warehouse and l_k is the individual length. This indicator should be maximised also.

Fragmentation. *It measures how much the empty spaces are broken in small slots rather then big ones. A value near to* 1 *means that in the warehouse there are a lot of small empty spaces, if it is near to* 0 *or less vice versa. The equation for the computation of the fragmentation is*

$$F(t) = 1 - \frac{N_S(0)}{N_S(t)} \tag{3}$$

where $N_S(0)$ is the total number of empty spaces present when no compartment is allocated (e.g. the analysed warehouse is divided in 9 aisles, each one divided in 3 section, thus $N_S(0) = 27$), while $N_S(t)$ is the number of empty spaces counted at the time of the measurement. By minimizing this indicator, bigger and less fragmented empty space are obtained.

Throughput. *It measures the amount of items in input in a given time lapse:*

$$T_{IN} = NI_{IN}/\Delta t \tag{4}$$

where NI_{IN} is the number of items inserted in the warehouse in the time lapse of Δt. This KPI needs to be maximised in order to boost warehouse performance.

The objective would be to optimise all these conflicting KPIs in one shot only, respecting all constraints. Let us define X as the representation of position and stacks configuration that a compartment can assume within the warehouse: consequently each KPI becomes a function of X. Let's define $\vec{Z}$ as the vector of KPIs to maximise (note that F has a minus sign because it needs to be minimised)

$$\vec{Z} = \{\mathrm{TSW}(X), \mathrm{ES}(X), -\mathrm{F}(X), \mathrm{T_{IN}}(X)\} \tag{5}$$

$$\max_{X \in D} \vec{Z} \tag{6}$$

where D is the domain of X representing the set of constraints on the position of the compartment to allocate. Finding the solution to this optimization problem is very difficult or even not possible by means of traditional optimization techniques. In fact the warehouse model is too complex to be represented in mathematical terms in an effective manner [9]. The layout, the type of material handling system, the shapes and properties of packages, storage and order picking polices, etc. introduce several constraint that are difficult to be translated into equations.

IV. State of the art

The issue of warehouse optimization is quite common in literature. The analysed issues and approaches differ a lot, depending on the peculiar nature of each warehouse. A comprehensive review of decision support model and solution algorithms based on "traditional" operational research is given in [10]. Warehouse operations are divided in three main groups: receiving and shipping, storage and order picking. For each operation a list of solutions found in literature is given.

One of the biggest issue with such solutions is that they require a large amount of computational time whilst decisions need to be made frequently and responsively and, moreover, typical warehouse optimization problems often have a multi-objective nature. This encourages the use of heuristics [10] that, if not carefully tuned, can lead to a non-optimal exploitation of the warehouse, as it is observed in the analysed plant.

In the last years research attention has focused on *Evolutionary Algorithms* (EAs) [11], [12], [13], which, in fact, provide different advantages: they can explore complex solution spaces, some EAs paradigms support multi-objective optimization [14], they are rather fast, multiple stop conditions can be set, etc.

In [15] a method based on EAs and a simulation model for the optimization of a manufacturing system is presented. Furthermore, the multi-criteria optimization issue is dealt in [5] where a method based on Pareto-optimal GA is analysed and applied to warehouse optimization.

Moreover [16], [17], [18] demonstrate how EAs have been successfully applied to a wide range of optimization problems, especially to those where objective functions are not well-behaved (not-differentiable, discontinuous or that don't have an analytical formulation) [9].

As multi-objective optimization (MOO) is concerned, two are the major approaches in literature [19], [20]: in the first one individual objective functions are combined into a single composite function transforming a MOO in a single-objective optimization (SOO), while in the second approach an entire Pareto optimal solution set is determined. Both these approaches present advantages and some drawbacks.

In the first case the greater advantage lies in the simple formulation of the fitness function, in opposition to the second solution, which, instead, requires an extension to the classic GA model. On the other side, the disadvantage lies both in the impossibility sometimes to combine all objective functions into a single function and in the proper selection of weights or utility functions characterising decision-makers preferences. Moreover, solutions found by means of a weighted function strongly depend on how good is the choice of the weights themselves [9].

By adopting the second solution instead, an entire set of Pareto-optimal solutions can be obtained with a single run of the algorithm, so leaving the possibility to the decision-maker to select the preferred solution. The main drawback of this solution is that with the increase in the number of objective functions, the definition of Parto-optimality begins to lose effectiveness [21].

V. Genetic Algorithm structure

In order to adapt the problem to the GA model, an appropriate *encoding function* has been defined. This function is responsible of translating a solution X, representing position and stacks configuration of one or more compartments (see. Sec. III), into a chromosome (Fig. 2) where the first part encodes stacks configurations, and the second contains positions assigned to compartments defined in the first part.

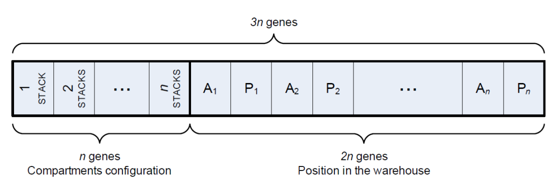

Figure 2: Chromosome structure

The initial population is created by a *creation function* which randomly generates a certain number of allowed solutions. GA enters in the main loop where *selection*, *mutation*, and *crossover* operators (which have been redefined too in order to reflect chromosome encoding) are iteratively executed until at least one of the following stop conditions is met: max number of iterations, fitness threshold, stall of the fitness value for a certain number of iterations.

At each iteration (called *generation*), population is divided into three groups: selected, mutated and recombined phenotypes. The first ones are chosen among population leaders (individuals with best fitness) while the others are randomly separated by means of a roulette-wheel algorithm.

When at least one of the stop conditions is met, GA returns the chromosome with the best fitness value among all generations or the *Pareto-front* (i.e. the set of Pareto-optimal solutions) depending on the particular GA paradigm employed.

Fitness functions will be discussed in the next section, where three different definitions will be illustrated.

VI. Proposed solutions

Three different solutions dealing with the multi-criteria warehouse optimization issue presented in Sec. III have been developed and tested: the approach of the first two is to aggregate the objective functions into one by means of a weighting function or a fuzzy system in order to transform a multi-objective optimization problem into a single-objective one; the last solution employs the *Strength Pareto Genetic Algorithm* paradigm, which extends GA model by allowing a real multi-objective optimization.

A. Linear weight aggregation (linWGA)

In this solution the fitness function evaluates selected KPIs for each chromosome in the current population. The values so obtained are then aggregate by means of the following function

$$F_k = \sum_i^N w_i \ \mathrm{KPI}_i(X_k) \text{ with } w_i \geq 0,\ \sum_i^N w_i = 1 \qquad (7)$$

where F_k is the fitness value of the kth chromosome, N is the number of selected KPIs, w_i is the weight associated with the ith KPI and $\mathrm{KPI}_i(X_k)$ is the value of ith KPI evaluated for the kth chromosome X_k.

B. Fuzzy aggregation (fuzzyGA)

In this approach a Mamdani fuzzy system [22] was developed in order to aggregate the values of the different KPIs.

Appropriate *fuzzy sets* relating to the various KPIs. have been defined as a first step towards the design of the fuzzy system. Membership functions have triangular or trapezoidal shapes. The parameters of each membership function have been heuristically chosen by exploiting the expertise of the technical personnel and afterwards fine-tuned during the test phase. The fuzzy output variable (chromosome fitness) has been defined in the same way by using three fuzzy sets characterized by triangular membership functions.

A set of rules has been defined upon the previously defined sets with the help of the technical personnel and a typical centroid method has been employed for defuzzification.

The fuzzy aggregation method, with respect to linear weight aggregation illustrated in the previous paragraph, gives to decision-makers more degrees of freedom in the customisation and tuning of the optimization by leaving the possibility to extend, modify and better control the fitness value assigned to each chromosome by simply modifying fuzzy rules or sets parameters.

C. Strength Pareto Genetic Algorithm (SPGA)

Strength Pareto Genetic Algorithm (SPGA) [23], [24] is an extension of standard GA paradigm that allows to obtain, from a single run of the algorithm, a set of Pareto-optimal solutions that represent different trade-offs between KPIs. A set of *non-dominated* solutions is externally stored and updated at each generation with new *non-dominated* solutions generated by the GA: this set is used to assign fitness values to chromosomes in the current population and its elements participate to selection in order to build the new mating pool. The diversity problem is not resolved by means of fitness sharing, but it uses Pareto-dominance in order to maintain different stable niches by assigning a *strength* value to each solution in the set proportionally to the number of covered individuals in the population.

This approach allows to exploit a real multi-objective optimization and to obtain a set of different trade-offs among which decision-makers can choose the preferred one, so leaving to them choice on the best trade-off.

This paradigm has been chosen because of its good performances in multi-objective optimisation [25] and because it does not change the standard GA model internally, but it is an external extension that can be simply developed and added to already existing software without much effort.

VII. Results

Proposed solutions have been tested on the warehouse simulator developed in a previous work [7]. Inputs are composed by data extracted directly from the information system of the analysed plant, which allow a more precise and realistic simulation, directly verifiable and comparable against the real system. The results in terms of KPIs have been then compared with current strategies, which are based on heuristics and simple rules (as depicted in Sec. III) and which had been already simulated and verified in [7]. Different runs of simulation as been done for each proposed solution and results ahve than been averaged. In Tab. I a summary of average KPIs results is shown: for each selected KPI the average value over a year of production and its percentual increment with respect to current strategies are shown.

The most important KPIs are TSM and $\mathrm{T_{IN}}$, whose optimization is the real goal on the long period. As illustrated, both of them are largely increased by proposed algorithms (e.g. SPGA improves TSM by 16.33% and $\mathrm{T_{IN}}$ by 13.4%), demonstrating that a strategy optimization could

Table I: Average KPIs results for current strategies, fuzzyGA, linWGA and SPGA over a year of production.

KPI	**Curr**	**FuzzyGA**	**LinWGA**	**SPGA**
TSM (tons)	7715	8430(+9.3%)	8914(+15.5%)	8975(+16.33%)
ES (m)	95.4	73(−23.5%)	74(−22.4%)	69.9(−26.7%)
F (%)	89.7%	89%(−0.8%)	90.5%(+0.8%)	89.9%(+0.2%)
T_{in}(TubeNum/day)	124.05	130(+4.8%)	138.8(+11.9%)	140.7(+13.4%)

allow the storage of more items without modifying the physical structure of the warehouse. The other two KPIs are, on the other side, necessary for choosing the best location for compartments, but only at allocation time: in fact these indicators worsen (ES) or remain steady (F). The reason is that ES and F guide the algorithm towards the choice of an allocation space where the compartment fits in the best way possible, i.e. without leaving unusable small spaces between compartments, but rather compacting them. A so high decrease of ES is then positive, because it means that the available space has been better exploited.

Of the three proposed solutions, the best one is without any doubt SPGA. It can increase the average receptivity of the warehouse of about 1260 tons. On the other side, fuzzyGA have the lowest performance, even if it is able to increase the average TSM of about 715 tons. Nevertheless, this solution aloows a Unexpectedly linWGA performances are near to those of SPGA, although it is not a real multi-objective optimisation, its performances vary with the choice of weights and the algorithm returns only a single solution (see Sec. VI-C).

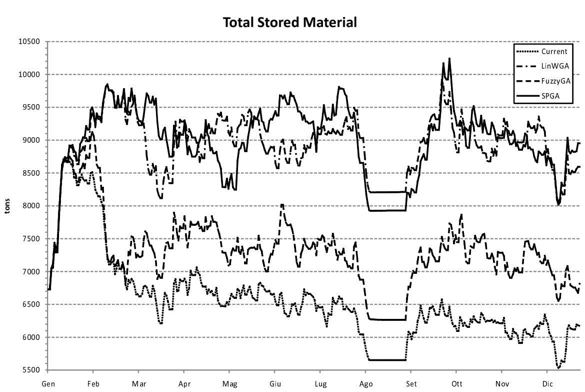

Figure 3: Comparison of TSM over a year of production

In fig. 3 the TSM trend is compared between current and proposed strategies over a year of production. The negative peak is due the stop of the production during the month of august. As already highlighted, linWGA trend is similar to SPGA and sometimes linWGA also overcomes it, while fuzzyGA stands in the middle. From this figure it is clear how SPGA and linWGA are able to push the saturation threshold of the warehouse higher, by allowing storing many more items in the same conditions. The highest score is obtained by SPGA at the end of September with a TSM of 10240 tons, 3770 tons more than current strategies, equal to an increase of almost 2000 items stored in the warehouse.

These improvements are due to a better space management, confirmed by a decrease of ES, which means that the available space has been better exploited with a consequent increase of the throughput T_{IN}, i.e. the number of items transiting through the warehouse.

VIII. Conclusions

In this paper three different solutions based on GAs to the multi-criteria optimisation of storage strategies of a real warehouse have been presented and their results compared and analysed. Two solutions make use of aggregation to transform a multi-objective problem in a single-objective one, whilst the other employs SPGA, an extension to the standard GA paradigm that allows it dealing with multiple goals. All presented solutions provide good results by allowing an increment between 9.3% and 16.33% of the average receptivity of the warehouse without afflicting any physical structure.

All methodologies exposed in this paper may be applicable also to warehouses with different layouts, as well as to other similar topics where space allocation optimisation is involved.

Acknowledgments

The authors thank Dr. Ing. Claudio Bisio and Dr. Silvano Mattiolo from the ILVA plant in Racconigi (Cuneo, Italy) for their precious support and the fruitful discussions which led to successful completion of the present work.

References

[1] J. van den Berg and W. Zijm, "Models for warehouse management: Classification and examples," *Internationa Journal of Production Economics*, vol. 59, pp. 519–528.

[2] M. Pang, G. He, and L. Xie, "Optimal number and sites of regional logistics centers by genetic algorithm and fuzzy c-mean clustering," *International Conference on Service Systems and Service Management*, 2007.

[3] L. Taoshen and W. Jingli, "An improved genetic algorithm on logistics delivery in e-business," in *Proceedings of the Third International Conference on Natural Computation*, 2007, pp. 765–769.

[4] L. Meijuan, C. Xuebo, and Z. Meifeng, "Optimal scheduling approach of storage/retrieval equipments based on genetic algorithm," *IEEE Intelligent Control and Automation*, vol. 1, pp. 3345–3348, 2006.

[5] P. Poulos, G. Rigatos, S. Tzafestas, and A. Koukos, "A pareto-optimal genetic algorithm for warehouse multi-objective optimization," *Engineering Applications of Artificial Intelligence*, vol. 14, pp. 737–749, 2001.

[6] T. Imai, "Production and technology of iron and steel in japan during 1998," *ISIJ International*, vol. 39, pp. 509–523, 1999.

[7] V. Colla, G. Nastasi, N. Matarese, and A. Ucci, "Simulation of an automated warehouse for steel tubes," in *Proceedings of the 10th International Conference on Computer Modeling and Simulation*. Los Alamitos, CA, USA: IEEE Computer Society, 2008, pp. 150–155.

[8] E. Krauth, H. Moonen, V. Popova, and M. Schut, "Key performance indicators in logistics service provision - a literature review and framework," in *Proceedings of the European Operations Management Association International Conference on Operations and Global Competitiveness*. EUROMA2005, 2005.

[9] P. Ngatchou, A. Zarei, and M. El-Sharkawi, "Pareto multi objective optimization," in *Intelligent Systems Application to Power Systems, 2005. Proceedings of the 13th International Conference on*, Nov. 2005, pp. 84–91.

[10] J. Gu, M. Goetschalckx, and L. McGinnis, "Research on warehouse operation: A comprehensive review," *European Journal of Operational Research*, vol. 177, pp. 1–21, 2007.

[11] J. Holland, "Adaptation in natural and artificial systems," *MIT Press*, 1975.

[12] H. Aytug, M. Khouja, and F. E. Vergara, "Use of genetic algorithms to solve production and operations management problems: a review," *International Journal of Production Research*, vol. 41, no. 17, pp. 3955 – 4009, November 2003.

[13] B. Can, A. Beham, and C. Heavey, "A comparative study of genetic algorithm components in simulation-based optimisation," in *Proceedings of the 40th Conference on Winter Simulation*, 2008, pp. 1829–1837.

[14] C. M. Fonseca and P. J. Fleming, "Genetic algorithms for multiobjective optimization: Formulation, discussion and generalization," in *Genetic Algorithms: Proceedings of the Fifth International Conference*. Morgan Kaufmann, 1993, pp. 416–423.

[15] H. Pierreval and L. Tautou, "Using evolutionary algorithms and simulation for the optimization of manufacturing systems," *IIE Transactions*, vol. 29, no. 3, pp. 181–189, 1997.

[16] E. Zitzler, K. Deb, and L. Thiele, "Multiobjective evolutionary algorithms; empirical results," *Evolutionary Computation*, vol. 8, no. 2, pp. 149–172, 2000.

[17] D. Jones, S. Mirrazavi, and M. Tamiz, "Multi-objective meta-heuristics - an overview of the current state-of-the-art," *European Journal of Operational Research*, vol. 137, no. 1, pp. 1–9, Feb. 2002.

[18] C. A. C. Coello, "A comprehensive survey of evolutionary-based multiobjective optimization techniques," *Knowledge and Information Systems*, vol. 1, pp. 269–308, 1998.

[19] A. Konak, D. W. Coit, and A. E. Smith, "Multi-objective optimization using genetic algorithms: A tutorial," *Reliability Engineering & System Safety*, vol. 91, no. 9, pp. 992–1007, September 2006.

[20] C. M. Fonseca and P. J. Fleming, "An overview of evolutionary algorithms in multiobjective optimization," *Evolutionary Computation*, vol. 3, pp. 1–16, 1995.

[21] M. Farina and P. Amato, *Fuzzy optimality and evolutionary multiobjective optimization*, ser. Lecture Notes in Computer Science. Springer, 2003, vol. 2632.

[22] L. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, pp. 338–353, 1965.

[23] E. Zitzler and L. Thiele, "An evolutionary algorithm for multiobjective optimization: The strength pareto approach," 1998.

[24] ——, "Multiobjective evolutionary algorithms: A comparative case study and the strength pareto approach," 1999.

[25] M. Abido, "Environmental/economic power dispatch using multiobjective evolutionary algorithms," *Power Systems, IEEE Transactions on*, vol. 18, no. 4, pp. 1529–1537, Nov. 2003.