Review Article

Multiobjective Fuzzy Stochastic Linear Programming Problems in the 21st Century

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Abstract: The focus of this paper is a survey of various kinds of multiobjective linear programming problems, where fuzziness and/or randomness in objective and/or in constraints are discussed comprehensively including full fuzzy stochastic in both the objective functions and constraints. This paper also studied the multiobjective fuzzy stochastic linear programming problems, and what relatives to them chronologically in this century, such formulation, and the various research methodology that has been used in transforming them to their corresponding equivalent deterministic linear programming problems. Optimal solution for the original problem has been discussed too.
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1. Introduction

Since the emergence of multiobjective optimization problems at the beginning of the second decade of the last century, it has become a necessary requirement and has an important role to all areas and fields in the real world. From its early stages, it evolved systematically and scientifically through the genius of scientists and professionals in this field. It had passed has through several stages, and it has branched more into various specialized disciplines in the real world.

The necessity proved that the entry of both of randomness and fuzziness (Chou et al., 2009; Bector and Chandra, 2005; Katagiri and Ishii, 2000; Hop, 2007c) into multiobjective programming problems, fitness, goals and requirement, was because the real world is constantly changing, and its components in constant motion and unstable, and the waves of those components are continually superimposed. Some scientists and researchers tried to explore the multiobjective optimization problems to go through its depths, thereby exploring its profundity. They came out with various concepts of multiobjective optimization problems such as multiobjective stochastic programming (Li et al., 2008; Ben Abdelaziz and Masri, 2009; Mu˜noz and Ruiz, 2009; Aouni and T orre, 2010; Adeyefa and Luhandjula, 2011), multiobjective fuzzy programming (Lotfi et al., 2009; Li and Hu, 2009; Zhang et al., 2010) and receiving data with the uncertainty of information on how to deal, address and treat such kind of the problems and data.

With the passage of time and the growing humanitarian needs in real life, numerous realistic optimization problems need to take into account the various multiple objectives, on the one hand, and various types of uncertainties, on the other hand. Thus there is a need to integrate the previous concepts of multiobjective optimization modeling systems to be used in multiple life problems (Iskander, 2003; Iskander, 2001; Hop, 2007c; Hop, 2007b; Rommelfanger, 2007), seeking to achieve different conflicting objectives, and to find approximate and satisfactory solution in uncertainty with fuzzy random circumstances(Yoshida et al., 2000; Kato and Sakawa, 2011). Since the aim and purpose of the multiobjective optimization programming and its types is to confront the real problems modeled or formulated in the scientific and systematic manner, and find appropriate solutions for them, from here emerged the concept of the best or efficient.

Solution to the multiobjective optimization programming. Furthermore, there is no absolute and fixed in the real world since everything is relative in nature, thus the concept of the best solution is another relative characteristics from one to another(Mu˜noz and Ben Abdelaziz, 2012; Ben Abdelaziz and Masri, 2010; Sakawa et al., 2012b; Sakawa et al., 2012a). So it was found out that certain solution may be optimized for a specific problem and not to be optimized for the same problem formulated by another decision-maker in different environments. Thus, studies and researches have been done by researchers and scholars to formulate the original basic problem in the multiobjective optimization model. They found various methods and approaches for this purpose and optimal solutions relative to them. On the other hand they looked for a Pareto solution (Ben Abdelaziz, 2012; Turgut and Murat, 2011; Laumanns and Zenklusen, 2011) and defined new specific definitions to this concept. It is in this light that this paper presents to study the Multiobjective Fuzzy Stochastic Linear Programming Problems, and discuss the concepts related to them historically, especially in this century.

This study has surveyed various studies, journal articles, and publications to provide a better understanding of the multiobjective fuzzy stochastic linear programming concept. This study is organized as follows: section two describes milestones and historical stages of multiobjective stochastic linear programming problems since the beginning of the century up to the present; section three is the conclusion, followed acknowledgment, and the references.

2. Historical stages of Multiobjective Fuzzy Stochastic Linear Programming Problems

Inuiguchi and Ramik (2000) have reviewed some fuzzy linear programming problems and solution techniques. They discusses the general history, the introduction of approaches for fuzzy linear programming, and showed how real world modeling with ambiguity on parameters, and vagueness of aspiration, and preferences can represented by fuzzy models in two phases: the first phase is fuzzy model for fuzzy mathematical programming problem converted to fuzzy environment to interpret the problem which is the formulation or transformation to a usual mathematical model, while in the second phase uses optimization technique to find a solution for the usual mathematical model in the real life. The difference between fuzzy mathematical models and the conventional mathematical models were also discussed which were associated with fuzzy mathematical model, and its solution using post optimization technique by answering the following question: is the solution valid? If not, the decision maker must rebuild fuzzy model, and improve the interpretation and re-finding a solution for the model. The second fuzzy mathematical approach compared with stochastic programming, showed the advantage, and the disadvantage of the fuzzy mathematical programming.

The study by Cadenas and Verdegay (2000) multiobjective mathematical programming (MMP) problems or vector optimization problem (VOP) and fuzzy multiobjective optimization (FMO) problem showed how these problems are transformed into uniobjective mathematical programming using either the weighting approach or the constant approach ($k^{th} - objective, \lambda - constraint\, problem$) to find the set of non-inferior solutions. Parallel to this FMO problem were studied which is an extensions of VOP in the fuzzy environment in its cases. Fuzziness in the constraints in two different methods of fuzzification in the right hand side of the constraints, the other of both coefficients of the technological matrix, including the right hand side. Also in the second case, fuzziness in the objective functions was developed, and stated as follows:

$$\min\,[c_1^f \mathrm{x}, \dots, c_n^f \mathrm{x}]$$
$$s.t.$$
$$Ax \le b$$
$$x \ge 0$$

where each $c_j^f, \mathrm{j} = 1, \dots, \mathrm{n}$ is an N-vector of fuzzy numbers. On the other side the existence of the fuzzy goals assumed, and defined as:

$$Find\ x \in R^N$$
$$s.t.$$
$$c_j \le_g Z_j, j = 1, \dots, n$$
$$Ax \le_g b, x \ge 0$$

where $\le_g$ meaning that there is a membership functions $\mu_i: R \to [0.1]$, express that for all $x \in R^N$ accomplishment degree of the i^{th} constraint to obtain the formal problem as follows:

$$\min\,[c_1 x, \dots, c_n x]$$
$$s.t.$$
$$Ax \le \mu^{-1}(\alpha)$$
$$x \ge 0, \alpha \in [0,1]$$

where μ^{-1} is an m-vector constraint inverse of the membership functions $\mu_i, i = 1, \dots, m$ for each α ∈ [0, 1], and this VOM can be solved elegantly. In addition to obtaining VOM the index of Adomo or thats of Yagar can be recourse as evident in the study.

During the waning years of the century and the beginning of Buckley and Feuring (2000), they first defined the fully fuzzified linear programming (FFLP) problem and suggested a solution for it. They have considered the parameters, so as the variables that are fuzzy numbers in the maximizing fuzzy model and has proven that the fuzzy flexible programming can be used to explore the set of all un-dominated solutions to the multiobjective fuzzy linear programming problem through an evolutionary algorithm. So in their study, the FFLP problem is defined as:

$$\max \bar{Z} = \overline{C_1}\,\overline{X_1} + \dots + \overline{C_n}\,\overline{X_n}$$
$$s.t.$$
$$\overline{A_{\iota 1}}\,\overline{X_1} + \dots + \overline{A_{\iota n}}\,\overline{X_n} \le \overline{B_\iota}, i = 1, \dots, m$$
$$\overline{X_\iota} \ge 0, \forall i$$
$$s.t.$$

where the $\overline{C_\iota}, \overline{A_{\iota 1}}, and\ \overline{B_\iota}$ are the triangular fuzzy numbers, so as $\overline{X_n}$, and code to the FFLP problem as:

$$\max \bar{Z} = \bar{C}\bar{X}$$
$$s.t.$$
$$\bar{A}\bar{X} \le \bar{B}$$
$$\bar{X} \ge 0$$

where $\bar{C} = (\overline{C_1}, \dots, \overline{C_n})$, $\overline{X^t} = (\overline{X_1}, \dots, \overline{X_n})$, $\overline{B^t} = (\overline{B_1}, \dots, \overline{B_n})$, $\bar{A} = [\overline{A_{\iota\jmath}}]$ as m×n matrix of fuzzy numbers. They explained that a bar over a capital letter denoting a fuzzy subset of the real numbers.

They used the fuzzy properties, mathematical analysis, and mathematical logics to explain the meaning of maximization $\bar{Z}$, including inequalities of the both sides of the constrained programming model, and handled the program and searched for the optimal $\bar{X}$. They found out the un-dominated set of solution to the program, i.e. approximate unbounded solution, employed the evolutionary algorithm, using fuzzy triangular properties, and the combined mathematical analysis and logics. They also used concepts like supremum, infimum, maximizing fuzzy number and its membership function value, big the area and small area under the triangular-shaped fuzzy numbers.

They changed the programming problem in the case of maximizing fuzzy number, the value of the objective function into a multiobjective fuzzy linear programming problem, and to a single objective programming problem in order to find the un-dominated solution. The solution algorithm of their evolutionary algorithm is changing the maximum value of the objective into multiple objective functions, and has looked for un-dominated set of solutions for the fully fuzzified programming.

The advantage of the method is obvious since some or all parameters and variables may be extended to the trapezoidal fuzzy number. On the difficulty of showing $\bar{Z}$ can add extra constraints to the feasible region in the closed intervals to overcome this issue. The proposal approach can be extended to other kinds of the fuzzy programming like non-linear fuzzy programming.

Few years before the beginning of this century, fuzzy programming for multi-level linear programming problems was of interest to researchers. Some has developed this kind of the problems and have been constructed and modeled (Y.J. Lai, Hierarchical optimization: a satisfactory solution, Fuzzy Sets and Systems 77 (1996) 321-335, and H.S. Shih, Y.J. Lai, E.S. Lee, Fuzzy approach for multilevel programming problems, Comput. Oper. Res. 23 (1996) 73-91.). The fuzzy goals of these models were determined by both the objective function and decision variables at the upper level, and when the fuzzy goals are inconsistent, the undesirable solutions are obtained and the production of these solutions, depends on Stackelberg solution to solve fuzzy multi-level programming problem which there are three categories; the vertex enumeration approach of Kuhn-Tucker, and the penalty function approach. These approaches lead to a solution to an undesirable one due to its inconsistency as mentioned above between determining the fuzzy objective goals and the decision variables.

To overcome this issue, Sakawa et al. (2000b) proposes an interactive fuzzy programming for multi-level linear programming problems with fuzzy parameters. This interactive method was proposed after eliminating the fuzzy goals for decision variables and determining the fuzzy goals of the decision maker at all of the levels. A satisfactory solution can be derived by updating the degrees of satisfaction on the decision maker who considers the balance among whole levels of the problem, and the feasibility of the method has been proved in the paper.

Ringuest et al. (2012) presented a paper proposed a sampling-based method for generating nondominated solutions in stochastic multiobjective mathematical programming (MOMP) problems which is applicable to both cases of continuous and discrete. Supposed that the objective function coefficients are random with known probability distribution or can be approximated, the method can generals the nondominated solution, and all the approach programming to solve MOMP problems can be applicable in this proposed method, exception PROTRADE method can be applying for this method if the probability distribution acceptable or agreeable to formulating as a chance constraints.

The method is extension of Sobol's method (Sobol, I.M., 1992a. A global search for multicriteria problems. In: Goicoechea, A., Duckstein, L. and Zionts, S. (Eds.), Proceedings of the Ninth International Conference. Springer, New York, pp. 401-412, Sobol, I.M., 1992b. An efficient approach to multicriteria optimum design problems. Survey of Mathematics for Industry 1, 259-281.) for stochastic and deterministic that modeled the parameter space investigation (PSI), and can solves the $0-1$ problems for more than ten variables.

Dhillon and Kothari (2000) attempted to solve no inferior surface of the multiobjective thermal power dispatch problem and employed the surrogate worth trade off method to choose the best solution. Hota et al. (2000) formulated F_i-objective fuzzy functions and how finding the best value optimal solution for it by the scale value of the membership function in the interval (0, 1) by giving minimax of it, as follows:

$$\text{Max}\,\{Min\left[\mu(F_j)^k; j = 1, \ldots, L\right]; k = 1, \ldots, 2^{L-1} + 1\}$$

where 2^{L-1} is the number of vertex points of $(L - 1) -$ dimensional hypercube.

Yoshida et al. (2000) discussed the fuzzy random variables in the multiobjective stochastic programming, and its optimal fuzzy stopping. The multiobjective programming approach with chance constraints and its right hand sides are normal random variables where the constraints have a combined probability distributions has been modeled and assumed by Sinha (2003). On the other hand, the special kind of fuzzy mathematical programming (FMP) approach, which is multilevel programing (MLP) problems with

N levels, namely, bi-level programming (BLP) problems considered and solved by Sinha and Biswal (2000).

Dubois et al. (2000) outlined of the likeness between multi-criteria decision making problems, and uncertainty decisions, and emphases of the discussed examples for each usually separate and, independent examples that various and different solution techniques may be applicable for each kind of problems. Ringuest et al. (2012)provided three different technique solution to solve deterministic multicriteria optimization problems can be selected as a favorites method by the decision maker are; the prior, progressive, and posterior articulation.

An interactive process contains STEM which is the type of Progressive articulation method presented by Sun et al. (2000) Stam to help the decision maker to avoid evaluate utility function. An interactive fuzzy satisficing method based on optimal expected model for multiobjective linear programming problems with random variable coefficients was studied and modeled by Sakawa et al. (2000b).

The result of the fuzzy transformation is the optimization programming problem called stochastic linear programming with linear partial information on the probability distribution (SPI), the equivalent deterministic is the standard linear programming (LP) problems when the stochastic transformation on the SPI has been ran out by using a chance constrained approach and a recourse approach Ben Abdelaziz and Masri (2000).

In many conditions, crisp data are undetermined to model real-life states. Since human requirements including vague and cannot approximation his preference with an exact numerical value. So in this circumstance a more realistic approach may be to use linguistic valuations instead of numerical values (Chen, 2000; Herrera and Herrera-Viedama, 2000), thus the fuzziness in decision data collection decision-making process were considered by Chen (2000), and he used linguistic variables to measure the weights of all criteria, and assessments of each alternative with respect to each criteria.

Mohammed (2000) has provided similarities and differences in dealing with hard stochastic programming problems through simple and related fuzzy so asSinha and Biswal (2000) in the same time.

In portfolio selection with the application of multiobjective stochastic programming problems, Ogryczak (2000) has extended Markowitzs method (Markowitz, H., 1952. Portfolio selection. The Journal of Finance 7, 77-91.), and developed a multi-criteria linear goal programming. The fully fuzzy linear programming problem with all fuzzy numbers in its parameters and variables has been studied by Buckley and Feuring (2000) and converted the problem into multiobjective fuzzy linear programming problem. They have proposed the supple programming method which is appropriate to discover undominated set to the multiobjective programming, and suggested further with an evolutionary algorithm to deal the supple programming method.

The modality measures in fuzzy optimization problems have been used by Inuiguchi et al. (2001) which combines fuzzy goals and fuzzy decision space.

Based on his pre-study (H. Katagiri, H. Ishii, T. Itoh, Fuzzy random linear programming problem, in: Proceedings of Second European Workshop on Fuzzy Decision Analysis and Neural Networks for Management, Planning and Optimization, 1997, pp. 107-115), Katagiri and Ishii (2000) have extended the fuzzy random programming (FRP) model which considers the coefficients of an objective function of a linear programming problem as fuzzy random variables based on possibilistic programming (PP) model separation and F-model. Mandal and Maiti (2000) considered a market place as important as it has its vital role for business, and have considered the multi-item inventory models in the marketplace in crisp and fuzziness situations.

Kouwenberg (2001) has developed and tested the scenario generation methods for asset liability management which is considered a financial planning problem of a large Dutch pension fund. Considered both were the randomly sampled event trees, and trees that fit the mean, and covariance of the undertaking distribution in each node.

Comparing the average cost and the risk of the stochastic programming policy has resulted into a simple fixed model and showed that the performance of the multistage programming problems can be improved strictly by choosing a suitable scenario. On the other hand, developed and tested methods in constructing even trees for ALM models that are rolling horizon simulations, indicate that the random sampling method could lead to excessive asset mix switching, and spurious profits.

Mohan and Nguyen (2001) came up with a method called Preference Level Interactive Method (PRELIME) for solving multiobjective fuzzy-stochastic programming (MOFSP) problems, and considered MOFSP problem as: Consider MOFSPP of the type:

1. $Max\ \widetilde{c_{j1}}\ y_1(X) \oplus \ldots \oplus \widetilde{c_{jn}}\ y_n(X), j = 1, \ldots, m,$
2. $Max\ \widehat{c_{k1}}\ y_1(X) + \cdots, +\widehat{c_{kn}}\ y_n(X), k = 1, \ldots, q, X = (x_1, \ldots, x_p), s.t.$
3. $\widetilde{a_{\acute{j}1}}\ y_1(X) \oplus \ldots \oplus \widetilde{a_{\acute{j}\acute{n}}}\ y_n(X)(X) \leq \widetilde{b_{\acute{j}}}, \grave{j} = 1, \ldots, \grave{m},$

4. $\widehat{a_{k_1}} y_1(X) + \cdots + \widehat{a_{k_n}} y_n(X) \leq \widehat{b_{k}}, k` = 1, \ldots, q`$,

5. $a_i \leq x_i \leq b_i, i = 1, \ldots, p$

where $y_k(X) \forall k$, are linear/nonlinear functions of $x_1, \ldots, x_p$ in crisp environment. Superscript $\sim$ and $\wedge$ stands for fuzziness and randomness respectively. Symbol $\oplus$ denotes extended addition in fuzzy environment (In case no misunderstanding, instead of $\oplus$ symbol + may be used).

In their study, a fuzzing method was presented to solve multiobjective fuzzy programming (MOFP) and multiobjective stochastic programming (MOSP); the first real-life modeling of multiobjective optimization problems in fuzzy environment, and the source of uncertainties is fuzziness, while the second problem in a stochastic environment with types of uncertainties related to randomness. The PRELIME method for solving MOFSP problems can be applied to linear as well as nonlinear problems with real/integer variables having three mechanisms:

1. Interpretation and treatment of fuzziness, randomness and collection of fuzzy goals are derived,
2. Interactive phase to help the DM choose his/her preference levels and modifying these step by step looking at Pareto optimal solution, and
3. Computational algorithm for solving the resulting single-objective programming problem in crisp environment occurring in each interactive phase duration.

In PRELIME, fuzzifing has been proposed for the treatment of stochastic objectives/ constraints. The stochastic objectives are treated on the basis of extended E-method, and the stochastic constraints on the basis of fuzzified chance constrains. Both the stochastic objectives and stochastic constraints can be treated in a fuzzy environment providing an opportunity for trade-off of fuzzy and stochastic objective functions, and constraint functions. The method is simple but effective in supporting the DM.

Some programming problems application have been applied (Tilmant et al., 2001a; Tilmant et al., 2001b) with fuzzy stochastic dynamic programming (FSDP) model to the reservoir process problems. Stanciulescu (2001) applied some real life applications, especially the optimal viable heating system for a certain house.

The network flow problem presented by Ragsdale (2001) describes the recycling operation of used office papers. Chen and Tsai (2001a) suggested the additive approach for the deterministic crisp model with preemptive priority structure where the decision maker can consider priority for the purpose constraints in any environment system, and the additive structure can be used to obtain the maximum value of the membership function.

Further, they presented an important overview of fuzzy goal programming. Based on some previous studies (M.L. Hussein, An iterative-approach to fuzzy chance-constrained parametric goal programming, The Journal of Fuzzy Mathematics 5 (1997) 793803, R.H. Mohamed, A chance constrained fuzzy goal program, Fuzzy Sets and Systems 47 (1992)183– 186), Iskander (2001) has made some contributions in the fuzzy stochastic multiobjective programming (FSMP) problems.

Caballero et al. (2001) found the efficiency concept solution associated with prime stochastic optimization problem, and the strong relationship between them. This is based on pre-study which provides that there is a core relationship between these two concepts when they are stated and proved by some theorems which are corollary to Caballero et al. (2000). Based on utility function and mean-variance model, a model of stochastic goal programming (SGP) was proposed by Ballestero (2001).

Lately, dealing with fuzzy programming problems and solving it, has been the concern and has attracted great attention (Chanas and Zielinski, 2000; Chiang, 2001; Maleki et al., 2000; Jamison and Lodwick, 2001). Many studies faced great challenges while converting the original problem into its equivalent standard LP problems. For example, the signed distance method can convert the fuzzy linear programming (FLP) problem into a conformist deterministic linear programming LP problem as the method of ordinary fuzzy numbers used by Chiang (2001), and the expected mid- point approach which was proposed by Jamison and Lodwick (2001).

Yao and Wu (2001) in their signed distance method, used defuzzifing method to obtain results between fuzzy numbers and fuzzy stochastic variables using the absolute relationship between changed points of fuzzy numbers. The big challenge was the expected mid-point of fuzzy numbers which was proposed as the method of ordinary numbers to convert the fuzzy linear programming (FLP) problem into conformist deterministic linear programming LP problem and finding an optimal solution for it(Jamison and Lodwick, 2001).

Kofler (2001) showed that in general cases, the statistical tools failed and has not enable to provide an exact or deterministic evolution of the different probability distributions. By focusing only on probability and possibility at the same time, a fuzzy random chance constrained programming formulation was proposed (Liu, 2001a; Liu, 2001b).

Brar et al. (2002) introduced an interactive method to establish a compromise with non-inferior solution to optimization problem, which contains more than one objective function such as cost and emission using a weighted technique. The method employed the evolutionary optimization technique which performs search weight age pattern to get the best or optimal solution in non-inferior domain.

They pointed three major improvements in problem solving and showed two titles broadly grouped in the multiobjective programming problems solution methods: the non-interactive methods and the interactive methods. On the other hand, it has determined three properties of the interactive method such, (i) find a non-inferior solution, (ii) interact with DM to get and obtain his/her response to the solution, and (iii) repeating previous steps (i) and (ii) to satisfy an optimal solution. It showed that the interactive methods are mostly used to find non-inferior solutions, and proved that the noninferior solution of multiobjective mathematical problems is one when improvement of one objective function is to be achieved if the expense on the other has occurred.

The intent of Brar et al. (2002) is to solve multiobjective thermal power dispatch problem with more than two objective functions like the economy and the impact to environment due to SO2 and some others. The multiobjective programming problems are transformed into a single programming problem using weighted method. Implied fuzzy decision making theories deals with vagueness or fuzziness is intrinsic in constraints and objectives. Thus fuzzy methodology has been put up for solving a mathematical problem containing or involving multipurpose objectives and selecting the best compromise solution for the problem.

To reduce the enormous amount of computational time, the evolutionary optimization approach proposes to look for the optimal weight pattern in the domain of non-inferior solution by forming hypercube of weight combination around the initial searching point. On the other hand, the continuity of the interactive steps or process employing another hypercube around the relatively preferred point was compared with the previous one; this process is repeated continually until the best compromise solution is attained.

It has been proven in the study that the optimal solution for the multiobjective problem was obtained by looking for the optimal weightage pattern of objective functions, with the evolutionary optimization technique and the optimal non-inferior solution with the maximum satisfaction level which was obtained from the membership function.

Tilmant et al. (2002) presented a fuzzy stochastic dynamic programming (FSDP) approach to derive steady-state multipurpose reservoir operating policies. The methodology under the FSDP problems has four steps:

1. Construct membership functions,
2. run several FSDP models at the same time with different parameters,
3. Identify selection criteria, and
4. Perform a sensitivity analysis to determine the optimal compensation parameter by running continuous re-optimization programming models with membership functions which was developed in step 2.

The general optimization programming method for deriving efficient reservoir operating has these assumptions: (i) the operating objectives as flexible constraints, (ii) hydrologic conditions, and (iii) the planning period should be the unbounded. The flexibility of the operating objectives allows researchers to capture decision makers preferences on the solution, thus the feasible solutions could be examined partially. It shows that the stochastic dynamic programming (SDP) is a powerful approach for optimizing reservoir operation problems.

Also, SDP can be fuzzified to capture the imprecise nature of the objectives and/or constraints. Fuzzy logic and fuzzy set theory provide the frameworks for explaining the vagueness of the objectives, and the reasoning approximation by implementing the basic two concepts: (i) utilization of fuzzy-rule based on the If-Then principle, and (ii) the reliance on fuzzified traditional optimization techniques like linear programming (LP) and the dynamic programming (DP).

The study, as pointed out in the beginning having a methodology of four steps, has operating objectives which is considered as flexible constraints of a stochastic optimization problem over unbounded programming. The fuzzy DP equation has been generalized by: (i) directly incorporating the probability distribution of the hydrologic inputs, (ii) the unboundedness of the planning horizon clearly considered, and (iii) allowing compensatory connectives to modeling multiobjective decision-making. Thus the reservoir operating problem is analyzed as infinite sequences of decisions, implies that current and future decisions may impact any other.

Moreover, the study pointed out that the traditional framework for the fuzzy decision-making is based on max/min optimization problem unsatisfactory system, and it addresses the issue when implementing FSDP algorithm like compensation, required, time, and systems study by considering the levels of both the independence of the systems status and time-invariant. Hence, the level itself ought to be determined by sensitivity analysis comparable to the system using criteria, like reliability, and resiliency of simulated system optimization.

The fuzzy linear programming duality has been studied by Nishizaki and Sakawa (2001) and Bector and Chandra (2002). Fuzzy stochastic linear programming (FSLP) problems was converted into a standard LP problem by defuzzifing and derandomizing fuzzy random variables at the same time or simultaneously in the Random fuzzy dependent-chance programming method(Liu, 2002a).

The maximization of linear programming problems considered by some researchers (Caballero et al., 2001; Chen et al., 2002; Dupacov´a, 2002) emphasized that in real life, the researcher often encounters the difficulty to determine all the parameters in the objectives, matrix coefficients of the constraints, and RHS of the matrix constraints.

It offers two different paths to modeling; the first is the imprecision of some data that may be modeled by probability distribution, where SLP follows uncertain parameters which are probability distribution of maximized SLP problems through random variable parameters only in the constraints coefficients, and objective functions coefficients which are random variable parameters. The second is the imprecision of some data modeled as fuzzy sets where FLP problems follow the uncertain parameters fuzzy sets provided that both sides of the constraints have the same fuzzy numbers or fuzzy intervals.

Yoshida (2003) presented a multiobjective fuzzy stopping model of the fuzzy stochastic systems. The author discussed the multiobjective fuzzy stopping problem, evaluated the randomness by probabilistic expectation, and fuzziness by linear ranking functions. Also discussed is the optimization problem by fuzzy stopping times. On other hand, Pareto optimal fuzzy stopping times for multiobjective provides the introduction of the notion of λ−optimal stopping times.

For his part, Iskander (2003) introduced and transformed stochastic fuzzy linear programming problem using fuzzy weighted objective function. In a stochastic fuzzy linear multiobjective problem, it considered the right-hand sides of the constraints as independent random variables with known distribution function. First, to obtain the equivalent deterministic fuzzy linear programming model, the constraints in the model must be transformed using triangular/ trapezoidal fuzzy numbers, utilizing the chance constraint approach, while the left-hand side coefficients, including the objective function coefficients are considered fuzzy numbers.

Three criteria used in the comparison are the dominance possibility, strict dominance possibility, and strict dominance relation. Weights and coefficients in the fuzzy objective function are considered as fuzzy numbers with similar or different membership functions. The approach allows the DM to determine the value of θ, and α in choosing the most suitable dominant criterion. The author showed that this approach is applicable in different fields like economics, industrial engineering, management...etc.

Stanciulescu et al. (2003) defines multiobjective fuzzy linear programming problem with fuzzy decision variables which sums up to a constant as follows:

$$min_x = \widetilde{f_i}(x) = min_x = \widetilde{c_i}(x)$$
$$= min_x \sum_{k=1}^{n} \widetilde{c_{ik}} x_k , i = 1, \dots , q$$
$$s.t.$$
$$\widetilde{a_j}(x) = \sum_{k=1}^{n} \widetilde{a_{jk}} x_k \le \widetilde{b_j}, j = 1, \dots, m$$
$$\sum_{k=1}^{n} x_k = K$$
$$x_k \ge 0, x_k \in R, k = 1, \dots, n$$

where$x = (x_1, \dots, x_n)$, the n− dimension vector of the crisp decision variables: $\widetilde{f_1}(x), \dots, \widetilde{f_q}(x)$ the fuzzy linear objective functions: $\widetilde{c_j} = (\widetilde{c_{j1}}, \dots, \widetilde{c_{jn}})$,, the fuzzy coefficients of the objective functions, $\widetilde{a_j} = (\widetilde{a_{j1}}, \dots, \widetilde{a_{jn}})$ the fuzzy coefficients of the left side of the fuzzy linear constraints, $\widetilde{b_j}$ the fuzzy coefficients of the right side of the fuzzy linear constraints, K is a real positive constant.

Stanciulescu et al. (2003) proposed a method using fuzzy decision variables with joint membership function instead of crisp decision variables, considering lower-bounded fuzzy decision variables that setup the lower bounded decision variables, and the generalizing to lower-upper bounded fuzzy decision variables that setup the upper bounded decision variables too.

Besides the optimal solutions, the method supplies the decision-maker regions containing potential satisfactory solutions around the optimal solutions. The results of the optimal solution are closely related to the special kind of the problems they are coping with. The method assists the choice of crisp decisions among the fuzzy solutions. The objectives of the multiobjective fuzzy linear programming was defuzzified by means of the compensation method, and the constraints have been defuzzified by a worst case by an interactive method and multi-attribute utility theory (MAUT). On the other hand, it described the fuzzy coefficients of the optimization problem by flat fuzzy numbers (fuzzy intervals).

Sinha (2003) assumed a multi-level linear programming problem, and fuzzy mathematical programming (FMP) approach applied to solve the system. The FMP method was for the objective functions minimizing linear the use of membership functions.

The modified method provides a sufficient solution which is approximated to the ideal solution for all individual DM. The method is a higher order multi-level programming problems (MLPP) applicable to pragmatic and logical in calculating the upper/lower bounds in max/min objective functions. This method takes successive lower lever at any iteration. In the study, the value of λ reduces when more levels are accounted. It is observed that the FMP is simple to implement, interactive, and applicable to MLPP, as well as to multi-level decentralized programming problem (MLDPP).

It is also noted that through the decision-making process from the top to the bottom level, the last level become important. This is due to the decision vector under the control of the latest/lower level tolerance limits not given by the DM. Hence, the decision vector remained unchanged or approximates its value in its solution. At a higher level, some tolerance were given by the decision vectors so they are free to move in the tolerance limitations, and these tolerance levels can assumed as variables, while the system can be optimizing.

Novak and Ragsdale (2003) introduced a decision support methodology for identifying linear programming (LP) problems robust solutions involving stochastic parameters and multi-criteria. The aim of the study is to develop clearly understood methodology for solving LP problems with stochastic parameters and multiple criteria in spreadsheets.

The study shows three approaches to solving stochastic programming. The first approach deals with probabilistic or chance constraint that constrained the probability of infeasibility to be no bigger than pre-specified value. The second method provides modeling future response or recourse which consists of information about a process after the observation of some random event, and the third is solving stochastic programming problems containing scenario-based analysis.

It also shows that the advantages and the disadvantages of these three approaches. On the other hand, there are three techniques for solving deterministic multi-criteria optimization problems from the perspective of stochastic programming; these are the prior articulation methods, progressive articulation methods, and posterior articulation methods. Finally, over their proposed methodology, they introduced that Excel software could be a stochastic programming tool.

Sakawa et al. (2003) have focused on multiobjective linear programming (MLP) problems with random variable coefficients in objective functions and constraints. It employs stochastic programming based on probability theory and fuzzy programming representing the ambiguity based on fuzzy concepts. An interactive fuzzy satisficing method for the expectation model was introduced after fuzzy goals of the decision maker for the objective functions have been incorporated. The optimal solution has been obtained based on M-Pareto optimal solution set, and investigated the feasibility of the method demonstrated.

In the fuzzy and stochastic environment which consist of cooperation between fuzzy stochastic systems with sequences of fuzzy random variables, Yoshida (2003) proposed multiobjective fuzzy stopping model applicable to the notion of fuzzy stopping times based on pre-study (Y. Yoshida, M. Yssuda, J. Nakagami and M. Kurano, Optimal stopping problems in a stochastic and fuzzy system, J. Math. Analy., and Appl. 246, 135–149, (2000)).

The authors analyzed the multiobjective stopping model for fuzzy stochastic systems as extension results of the classical stochastic systems (J.P. Aubin, Mathematical Methods of Game and Economic Theory, North-Holland, Amsterdam, (1979), and Y. Ohtsubo, Multi-objective stopping problem for a monotone case, Mem. Fac. Sci. Kochi Univ. Ser. A 18,99–104, (1997)), and gave Pareto optimal fuzzy stopping time for the multiobjective fuzzy stochastic model depended on notion of $\lambda-$ optimal stopping time.

On the other hand, Inuiguchi et al. (2003) studied the fuzzy inequalities of the type $\tilde{A}x \lesssim \tilde{b}$, and suggested an approach to analyzing the system which consists such kinds of inequalities based on other studies (M. Inuiguchi, H. Ichihashi, Y. Kume, Relationship between modality constrained programming problems and various fuzzy mathematical programming problems, Fuzzy Sets and Systems 49 (1992) 243–259, M. Inuiguchi, H. Ichihashi, Y. Kume, Some properties of ex- tended fuzzy preference relations using modalities, Inform. Sci. 61 (1992) 187–209, M. Inuiguchi, H. Ichihashi, Y. Kume, Modality constrained programming problems: a uniEed approach to fuzzy mathematical programming problems in the setting of possibility theory, Inform. Sci. 67 (1993)93–126) which are extends directly from another approach to study these inequalities of the fuzzy system (D. Dubois, H. Prade, Ranking fuzzy numbers in the setting of possibility theory, Inform. Sci.30 (1983) 183–224).

There are attempts by Liu to obtain the standard LP problems and solving it from the fuzzy stochastic programming problems by performing the defuzzify and derandomize, especially calculating the expected value of fuzzy random variables but they are too complex and time consuming(Liu, 2001a; Liu, 2001b; Liu and Liu, 2002; Liu and Liu, 2003).

Iskander (2004a) presented and solve certain structure by utilizing the chance constrained approach and additive criterion. The probabilistic fuzzy constraints are presented and the stochastic constraints have been transformed into equivalent deterministic form by utilizing the chance constrained approach. The decision-makers levels of satisfaction are expressed in the concept of fuzzy relation with three cases: when the decision-maker is fully satisfied, when the decision-maker is almost satisfied, and when the decision-maker is not satisfied.

On the other hand, an additive approach has been suggested to know if the preemptive priority structure is determined or not. Thus the idea of the deterministic-crisp model within/without preemptive priority structure was presented. In the first case, the decision-maker can set priority ranks for the goal constraints in any system constraints, and the concept of the additive model is to maximize the membership function for every goal constraint; while in the second case is when the decision-maker does not able to precisely determine the preemptive priority structure, then the fuzzy weighted either as trapezoidal or as triangular fuzzy numbers should be assigned for the achievement degrees of the various goal constraints.

Finally, the approach allows the decision-maker to determine a fuzzy relative for any goal with respect to the other goals and helps him/her to avoid infeasible solutions which may happened if the model with preemptive priority structure was used.

Meanwhile, Iskander (2004b) studied, defined, and solved stochastic fuzzy multiobjective linear fractional programs by suggesting the possibility of programming approach. Considered programs are fuzzy linear fractional objectives and stochastic fuzzy constraints. The coefficients and scalars in both numerator and denominator in the objective functions are fuzzy numbers that can either be trapezoidal or triangular, so as to the fuzzy coefficients in the left hand side of the constraints, while the right hand side of the constraints were considered independent random variables with known distribution functions.

The approach used to transform the program into crisp deterministic was mixed using chance constrained approach and the possibility programming method, as well as employing the prior method in the case of exceedance possibility or another strict exceedance possibility. In the study, two propositions were stated and employed for crisp constraints that represent the decision space, and the other is for the solution infeasibility of the model to the case of strict exceedance possibility. It showed that the suggested approach is applicable efficiently in small/large problems in the case of single objective or multiobjective functions. The probability maximization model presented by Sakawa et al. (2004) was aimed to study multi- objective linear programming problems with random variable coefficients in objective functions and/or constraints. This is the method used to maximum probability that each objective function becomes a determined value with chance constraints conditions.

The method is focused on multiobjective linear programming problems with uncertainty in both the objectives and the constraints in order to transform the stochastic programming problems into deterministic ones. This approach considers the decision maker has a fuzzy aim for any one of the objective functions and has determined the fuzzy purpose. An interactive fuzzy satisficing method was presented and reference membership levels were updated to derive a satisficing solution for the decision maker. The method implemented in several steps is to obtain M-Pareto optimal solution and trade-off rates among membership functions by using the Lagrange function and the Kuhn-Tucker necessary theorem.

Urli and Nadeau (2004) presented a paper studying multiobjective stochastic linear programming with partial uncertainty. The proposed a scenario approach is the called PROMISE/ scenarios. The study deals with situations which are modeled by a universal scenario approach without assigning probabilities of those scenarios by DM. The researchers suggested methods were based on scenarios on multiobjective stochastic linear programming problems under partial uncertainty considering that the probabilities of those scenarios are known. The study's new pragmatic method PROMISE/scenarios deals with partial uncertainty, and has supposed that the probabilities of those scenarios are incompletely known.

The algorithm of the proposed method has two main phases: the modeling phase has the multiobjective stochastic linear programming problems with partial uncertainty, the transformation of each stochastic objective functions, and stochastic constraints to obtain an equivalent deterministic multiobjective programming problem. The second phase begins with the interactive procedure by building the pay-off table to obtain the first compromise solution by decision to satisfactory compromise if it has been obtained or not. If the DM gets and affirmative answer then the problem was solved. Otherwise s(h)e attempts to obtain another compromise by improving objective/scenarios, and then s(h)e tries to relax the constraints/scenarios or obtain another compromise solution by mixing those two procedures. This method is derived from the STEM method which was developed by Benayoun et. al. (1971) which is appropriate for problems with small dimensions. It also deals with the case of global scenarios on objective functions and constraints that can be modified to deal with the case of partial scenarios.

Caballero et al. (2004) tried to obtain efficient solutions by using two different approaches: stochastic approach and multiobjective approach. The authors have focused on obtaining efficient solutions for optimization problems with constraints random variables affecting the objective functions since the feasible set of the problem considered has been transformed into its equivalent deterministic. In the study, they considered the application of the weighting method to the initial problem in the stochastic approach because it is one of the more widely used, and has carried out techniques in deterministic multiobjective programming problems. The study was organized according to the type of stochastic criterion which was applied to get the deterministic problem. For each criterion compared, the optimal solutions for the weighted optimization problem, corresponding to the stochastic approach, the efficient solutions have been obtained with the multiobjective approach. The study was focused on the efficient solution results of the multiobjective programming in:

1. Expected value efficient solution,
2. Minimum variance efficient solution,
3. Expected value standard deviation efficient solution,
4. Minimum risk efficient solution for fix a priori an aspiration level, and
5. Kataokas criterion or efficient solutions with fix a probability.

Comparing these solutions to their corresponding in the stochastic approach, i.e. stochastic approach versus multiobjective approach, it obtained efficient solutions in stochastic multiobjective programming problems. The work has carried out (i) the achievement of efficient solution in the problems of multiobjective stochastic programming problems through a double transformation techniques of the problem, or a combination of the techniques of both of stochastic programming approach and multiobjective programming approach, (ii) the achievement of efficient solutions of stochastic multiobjective programming problems by the stochastic approach using the weighted method which is strictly related to problem resolved by the multiobjective approach, and (iii) the dependency between random variables taking into account the stochastic approach even partially, in terms of covariance.

In this sense, it is given in real cases that there exist stochastic dependences among objective functions. The existence of these dependences in stochastic approach is more appropriate achievement of efficient solutions than the multiobjective approach because determines a certain interval of stochastic/multiobjective landscape of the real problem.

Yang and Li (2002) and Chen and Tsai (2001b) studied fuzzy linear programming using goal programming to transform multiobjective linear programming approach to its standard LP problems. After the transformation, the entire objective functions have a scalar criterion by weights as conventional strategy formulation. These weights additive model can be specified by the DM as coefficients of the individual terms into easy additive fuzzy achievement function to reflect the relative importance for the different weights.

There are some weighted min-max approaches as emphasized by Lin (2004) and Yang and Li (2002). On the other hand, Li et al. (2004) studied the satisfying optimization method on goal programming for fuzzy multiple objective optimization problem. They used varying-domain optimization method to solve multiobjective optimization problem with preemptive priorities determined by DM. In addition, the relative importance between objectives and the desirable achievement degree for each objective was distinguished by Chen and Tsai (2001b) stating that the more important of the objectives, the higher the desirable achievement degree is obtained. Adding the inequity about membership function and desirable achievement degree of all objectives to the model formulation is considered as a new constraint in a clear manner.

Bector and Chandra (2002) and Bector et al. (2004b) have considered duality in fuzzy linear programming problems establishing a two person zero-sum matrix game with fuzzy goals. It showed that there exist equivalence between two person zero-sum matrix game with fuzzy goals and a pair of primal-dual fuzzy linear programming problems. They have proven that there is no strong duality between pair of fuzzy linear programming problems in the general.

Bector et al. (2004a) introduced duality for linear programming problems with fuzzy parameters. According to Bector and Chandra (2002) there is an equivalence between two person sum zero matrix game with fuzzy pay-offs and primal-dual pair of this kind of fuzzy linear programming problems.

Luhandjula (2003) introduced linear programming with fuzzy random variable (frv) in the case of inclusive constrained, and modeled as follows:

$$\begin{gathered} \max cx \\ s.t. \\ a_{i1}x_1 + \cdots + a_{in}x_n \subseteq b_1; i = 1, \dots, m \\ x_j \geq 0; j = 1, \dots, n \end{gathered}$$

where c_i, a_{ij} and b_i are frvs on (Ω, F, P).Considered to solve this problem should be reformulating as following:

$$\begin{gathered} \min t \\ s.t. \\ cx \subseteq t \\ a_{i1}x_1 + \cdots + a_{in}x_n \subseteq b_1; i = 1, \dots, m \\ x_j \geq 0; j = 1, \dots, n \end{gathered}$$

where t is a maximal tolerance for the objective function. It is recommended that the last formula can be set in the form of semi-infinite program, and under mild considerations can be transformed it into standard LP problems to solve it, and eventually finding the optimal solution. On the other hand, Luhandjula (2004) found some potential choices like simplicity, efficiency, and effectiveness of frv.

Some applications have been done to fuzzy stochastic linear programming (FSLP) problems and converted it toward multistage programming problems (Weber and Zhaohao, 2000b; Weber and Zhaohao, 2000a; Weber and Cromme, 2004). Shahinidis (2004) applied stochastic in several various fields like energy investment, production planning, water management, and finance.

Recently, studding optimization problems combined with both fuzzy optimization programming problems and stochastic optimization programming problems, has been of interest to researcher. Many have studied on how to convert the original problem into standard LP problem. They found two main strategies: the first is to de-fuzzify and (or) derandomize in sequential manner, and second is to run both two action at the same time.

Luhandjula (2004) chose the first one and converted the fuzzy stochastic optimization problem to its equivalent LP problems by defuzzifing first followed by derandomizing. However, discretizing the fuzzy set via α−levels has inserted too many extra constraints to the original constraints.

Nehi and Mashinchi (2004) have considered fuzzy linear programming (FLP) problems and used a comparison concept of fuzzy numbers to solve it by using ranking functions to suit their requirement under an assumption. Generally, there are accepted measures for application of the ranking functions, hence they have obtained an equivalent crisp model to FLP problems, and then used it to obtain optimal solution for FLP problem.

Rommelfanger (2007) considered the FLP problems as followed:

$$Max\ \widetilde{Z}\,(x) = \tilde{C}_1 x_1 + \cdots + \tilde{C}_n x_n$$
$$s.t.$$
$$\tilde{A}_{i1}x_1 + \cdots + \tilde{A}_{in}x_n \le \tilde{B}_i, i = 1, \dots, m$$
$$x_j \ge 0, j = 1, \dots, n$$

where $\tilde{C}_i, \tilde{A}_{ij}, and\ \tilde{B}_i$ are fuzzy sets on R. Provided that some data modeled by fuzzy sets, and both sides of the constraints have the same fuzzy numbers or fuzzy intervals, and proposed a procedure for solve it. On the other hand Sakawa et al. (2004) considered the following SLP problems:

$$Max\ \tilde{Z}_k(x) = \tilde{C}_1(w_k)x_1 + \cdots + \tilde{C}_n(w_k)x_n$$
$$s.t.$$
$$\tilde{A}_{i1}(w_k)x_1 + \cdots + \tilde{A}_{in}(w_k)x_n \le \tilde{B}_i(w_k), i = 1, \dots, m$$
$$x_j \ge 0, j = 1, \dots, n$$

Sakawa et al. (2004) used the mean value of the objective functions combined with the fat solution to solve the multiobjective problem of K fuzzy linear programs, and known probabilities $p(w_k)$, his result was as follows:

$$MaxE\left(\tilde{Z}_k(x)\right) = \sum_{j=1}^{n}[\sum_{k=1}^{K}\tilde{C}_j\ (w_k).p(w_k)]x_j$$
$$s.t.$$
$$\tilde{A}_{i1}(w_k)x_1 + \cdots + \tilde{A}_{in}(w_k)x_n \le \tilde{B}_i(w_k), i = 1, \dots, m$$
$$x_j \ge 0, j = 1, \dots, n$$

Multistage integer programming (MSIP) models deal with size extension subjects under stochastic conditions through expansion of multistage stochastic integer programming (MSIP) models (Chen et al., 2002; Ahmed et al., 2003; Lulli and Sen, 2004) These studies of MSIP models the independent uncertainties in the left-hand of constraints hardly considered, especially Ahmed et al. (2003) which considers the optimization problem as a multistage size expansion problem with doubt/ uncertainty in demands, cost parameters, and scale in expansion costs.

Iskander (2005) suggested an approach for solving a stochastic fuzzy linear programming problems utilizing two possibilities and two necessity dominance indices based on Dubois and Prode (D. Dubois, H. Prode, Ranking Fuzzy numbers in the setting of possibility theory, Information Sciences 30(1983):183-224). In the stochastic fuzzy linear programming problem, the stochastic fuzzy constraints were transformed to deterministic fuzzy constraints by incorporating fuzzy tolerance measures using the chance constrained approach. Thus, the equivalent fuzzy objective function subject to the deterministic fuzzy constraints was made to become fuzzy linear programming problem. Hence, the program obtained can be transform to its crisp equivalent program, and the transformation is applicable for different fuzzy numbers trapezoidal/ triangular.

The transformation of the problem was done in both the objective function, as well as that of the constraints by assuming the fuzzy coefficients of the objective and constraints are trapezoidal numbers and by utilizing the α – cut approach. On the other hand, transforming the constraints should be formulated according to each dominance index such as the (Possibility of Dominance (P D), Possibility of Strict Dominance (P SD), Necessity of Dominance (ND), and Necessity of Strict Dominance (NSD)).

It was also the suggested approach for formulating crisp set constraints that depends on utilizing the α − cut approach for membership functions of fuzzy coefficients of the constraints and the fuzzy tolerance measures for using the chance constrained approach. Therefore, for each of the four dominance indices, the deterministic-crisp linear programming problem can be solved by giving values to the α in the closed interval [0, 1].

According to the suggested approach for comparing closed crisp intervals, the approximation that may exist due using another approach can be avoid, and in general comparison among for dominant indices, the value of objective function Z pointed that;

ZNSD ≤ ZP SD ≤ ZP D,and ZNSD ≤ ZND ≤ ZP D; where ZP D,ZP SD,ZND, and ZNSD are the value of objective functions; P D,P SD, ND, and NSD respectively.

Multiobjective inventory models for stochastically deteriorating items under a single management, and limited storage space formulated by Mahapatra and Maiti (2005), assumes the demand capacities of the people in developing countries like India, Nepal, Bangladesh,...etc., that the price of goods and commodity determines the demand. The demand of commodity depends on the time, selling price, stock level, quality of the item, and so on. The deterioration of commodities depends on the quality level and the duration of storage time. A two parameter Weibull distribution in time t was followed with the time-related function for deterioration. The quality level of items changes inversely with production rate and the unit production is dependent upon the production rate. In addition, the cost is also quality dependent which is considered over the production cost. It assumed that the items were produced separately by companies under individual ownership and stored in single items capacity warehouse.

Under these assumptions, the inventory system involves n items, the planning horizon is finite, and the lead time is negligible, and there is no replacement of deteriorated units. The maximum profit objectives are formulated and derived for all items as to the multiobjective inventory problems. By using the developed goal programming (GP) method, the problem was solved and the compromise solution was obtained for the model. The results were derived without shortage and partially back logged shortages. The results of the compromise solution have been obtained as a single objective, and eventually, the multiobjective problems were compared.

The paper presents an interactive approach for production-inventory objectives general man/machine interaction with membership functions (linear membership functions, quadratic membership functions, and exponential membership functions) for the objective goals. Finally, Pareto optimal and satisficing solutions tested the model to the interactive fuzzy satisficing method (IFSM) which has been used by the DM.

The existence of stochastic goal programming (SGP) problems examined by Aouni et al. (2005) and the goal programming (GP) problems, has been developed in the probabilistic situation, taking into account the DMs preferences and explicated it by using the concept of satisfactory function based on pre-studies (Martel, J.-M., Aouni, B., 1990. Incorporating the decision makers preferences in the goal programming model. Journal of the Operational Research Society 41 (12), 11211132, Roy, B., Bouyssou, D., 1993. Aide multicritre la dcision:Mthodes et cas. Economica, Paris.). Based on his previous study (Zmeskel, 2001) Zmeskel (2005) applications of portfolio selection in fuzzy stochastic environments, and the use of fuzzy stochastic methods and approaches in the field.

Ben Abdelaziz and Masri (2005a) studied the goal programming based on (Ben Abdelaziz, F., Lang, P., Nadeau, R., 1995. Distributional efficiency in multiobjective stochastic linear programming. European Journal of Operational Research 85, 399415, Ben Abdelaziz, F., Lang, P., Nadeau, R., 1999. Efficiency in multiple criteria under uncertainty. Theory and Decision 47, 191211), saw that the multiobjective stochastic programming (MSP) can be challenged and can face difficulties.

Aouni et al. (2005) showed the decision maker can establish some parameters or values, especially in the portfolio selection problems where the values are stochastic. Zmeskel (2005) presented the fuzzy stochastic optimization problems arising from several situations in the real world, and there is a difficulty to determine the goals, objectives, constraints, and coefficients for the problems because they depend on varying factors. Liu and Liu (2005) proposed fuzzy random programming with equilibrium chance constraints by converting the problem into standard LP problem through defuzzifing and derandomizing fuzzy random variables simultaneously. Based on previous study (Bector et al., 2004a) Bector and Chandra (2005) on fuzzy matrix game proved that it is equivalent to primal programming problems and its dual programming problem.

The fuzzy field with random variables is patentable for applications of different decision making issues and problems.Dutta et al. (2005) proposed a model with fuzzy random variable, while an interactive method was presented (Katagiri and Sakawa, 2004; Katagiri et al., 2005) and the stochastic programming approach to fuzzy random MST problem. This is also to value at risk methodology for index portfolio which was proposed by Zmeskel (2005) under soft situations as a fuzzy-stochastic method. A class of FLP problems was considered and discussed based on a new concept of duality and fuzzy relationships and some feeble and robust theorems were inferred (Ramik, 2003; Ramik, 2005).

Some applications on fuzzy stochastic linear programming (FSLP) problems have been done (Nguyen, 2005b; Nguyen, 2005a) and FSLP problems have been extended toward multiobjective linear/nonlinear programming problems. A stochastic programming with fuzzy linear partial information on probability distribution by Ben Abdelaziz and Masri (2005b), has defined the probability distribution by crisp or fuzzy inequality on the probability of the different natures states. Both stochastic linear program with linear partial information and stochastic linear program with fuzzy linear partial information on probability distribution has been defined and stated. It showed that in stochastic linear program with fuzzy linear partial information on probability distribution where probability distribution P is known, it became a stochastic linear program.

The paper presented a strategy for both of the fuzzy/stochastic programs in two steps: the fuzzy transformation and the stochastic transformation. In fuzzy transformation, the fuzziness on the stochastic linear programming with fuzzy linear partial information was addressed, and α−cut technique on triangular membership function was used to defuzzify the fuzzy inequalities on the probability distribution using DMs credibility. The second step has two main approaches namely: the chance constraints approach and the recourse approach in order to obtain an equivalent deterministic linear programming problem, followed by using a modified L−shaped algorithm to solve the obtained deterministic programming problem.

The paper also presented a proposition with proof on minimization of the upper expected value on the recourse approach, and some notations in the modified L − shaped method. It asserts on the convergence to an optimal solution by using modified L − shaped method by inserting a theorem with proof. A study by Abbas and Bellahcene (2006) deals with the kind of problem incorporating integer variables in the constraints of a multiobjective stochastic linear programming (MOSLP) problem and assumed that:

$$\min Z_k = C_k(\xi)x, k = 1, \dots, K$$
$$s.t.$$
$$Ax = b$$
$$\tau(\xi)x = h(\xi)$$
$$x \geq 0, x\ interer$$

where Ck, τ, h are random matrices with dimensions $(1 \times n), (m_o \times n), and\ (m_o \times 1)$ respectively, defined over some probability space (Ω, E, P); $A, and\ b$ are deterministic matrices of dimensions $(m \times n), and\ (m \times 1)$ respectively. The study considered a joint finite discrete probability distribution $(\xi^r, p^r), r = 1, \dots, R$ of the random data, and for each realization ξ^r of ξ associated a criterion $Z_{kr} = C_k(\xi^r)$ the matrix $\tau\ (\xi^r)$ and the vector $h\ (\xi^r)$) taken into account the different scenarios affecting the K objective functions, and the stochastic constraints.

On the other hand, the idea of recourse function using single-criterion stochastic programming was back. In addition, it defined each of the concepts of feasibility, optimality, efficiency of a solution, and dominated of an integer feasible point solution.

The study proposes an algorithm combining the cutting plane technique and the L-shaped de- composition method by getting integer efficient solution to the multiple stochastic integer linear programming and after representing uncertain aspirations of the DM by converting the original problem into its equivalent deterministic multiobjective integer linear programming (MOILP), leaving the MD to choose his/her efficient solution according to the depended preferences. The method is to generate all the efficient solutions of the feasibility cuts optimization problem by solving sequences of problem of progressively more constrained single objective integer linear programming problems, and the additional constraints at each iteration generated efficient points, and ensure that it obtained new generated solutions that are efficient, and consists of repeating several steps, proving that the procedure to find all efficient solutions of the stochastic integer converges into a finite number of steps, depending on finitely feasible bases from the recourse matrix, and repeated applications of cutting plane by application Gomorys cuts.

The approach has the advantage giving the DM too information. The efficient solutions and optimal cost values of the random constraint violates of the efficient solutions. The approach is appropriate for problems with small number of scenarios since only one objective problem is solved at each iteration, hence the approach could be applicable for large number of objectives, and on the other hand, the feasibility cuts cancel some parts of the first-stage decision set, thus a new iteration numbers is needs to obtain the efficient solutions.

To deal with the supplier selection problem in supply chain system (Chen et al., 2006), it explained that the determination of suitable suppliers in the supply chain is a key strategic consideration, and the decisions of the field is complicated complex, unstructured, and factors such as: quality, price, flexibility, and delivery performance should be assumed to determine appropriate suppliers. In the paper, the concept of Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) proposes a methodology for solving supplier selection problems in fuzzy environment, assuming that the decision data and group decision-making process vague, and estimated with un-exact numerical values or considering the fuzziness of them. Also, linguistic variable have been used to assess the weights of criteria and ratings.

To deal with the TOPSIS, concepts and definitions were used in the paper such as: positive ideal solution (PIS), negative ideal solution (NIS), fuzzy sets, fuzzy numbers, normalized fuzzy number, convex set, universe fuzzy number, α−cut of the fuzzy number, a positive trapezoidal fuzzy number(PTFN), fuzzy matrix, linguistic variable, and the identical of fuzzy numbers. In the paper extended that; supplier selection in supply chain system is a group multi-criteria decision-making (GMCDM) problem, and consisting of the main four sets:

1. A set of K decision-makers say; $E = \{D_1, \dots, D_k\}$;
2. A set of m possible suppliers say, $A = \{A_1, \dots, A_m\}$;
3. A set of n criteria say, $C = \{C_1, \dots, C_m\}$; with which supplier performances are measurable;
4. A set of performance ratings of Ai $(i = 1, 2, \dots, m)$ with respect to criteria $Cj\ (j =$

$1, 2, \ldots, n$), say, $X = \{x_{ij}, i = 1, 2, \ldots, m; j = 1, 2, \ldots n\}$.

Finally, the authors concluded that TOPSIS method can deal with the ratings quantitatively, qualitatively, and select the appropriate supplier effectively and can be a useful tool the supplier selection problems in supply chain management system. It can also be used in determine ranking order as well as the evaluation of all possible suppliers.

Luhandjula (2006) reviewed papers on fuzzy stochastic linear programming and showed that the researchers have combined the information which are both fuzzily imprecise, and probabilistically uncertain in many real-life problems based decision on i.e. combining possibilistic and probabilistic uncertainties, more clear modeling, and problem solving issues in situations where randomness of parameters, fuzziness of coefficients, and numbers co-occur in a linear optimization problems namely fuzzy stochastic linear programming problems.

As known linear programming (LP) problems which are operationally applicable nowadays are simplex method, ellipsoid method, and the interior point methods to solve LP problems with certainty. But in the real world, we face concrete problems with some level of uncertainty related values to various parameters, and some of the components of the problem. The rationality model builder states the optimization programming problems in the real life involving probabilistic description of unknown elements. These undertakings lead to stochastic linear programming, or problem consisting of informational imprecision which leads to deal with fuzzy linear problems. On the other hand, DM may deal with probabilistic problem and possibilistic uncertainty which leads to fuzzy stochastic linear programming (FSLP) or grappling with the optimization problem in hybrid situations.

Luhandjulas study deals with FSLP problems in the following sides: the tools for combining fuzziness and randomness to state FSLP problems, and its mathematical form, problem statement, and unified methodological approach, as well as the solution approaches for FSLP problems. Thus, the re- searcher studied FSLP problems of these three aforementioned aspects: first, to deal with logic mathematically with situations of FSLP problems taking both fuzziness, as well as randomness in the problem. It needs to deal with ideas of probability and fuzzy sets theories. In other words, defining and dealing with the following notions and concepts like:

- Probability of a fuzzy event,
- Probabilistic set,
- Fuzzy random variable (frv),
- Random fuzzy variable (rfv), and
- Linguistic probabilities

The author deals with the first three concepts and defined it resourcing by some of references he used. He recommended to interested researcher to find them at references he used. The study deals with the issues by taking it in its two sides: problem statement, and unified methodological approach for FSLP problems. For the problem statement, the paper pointed out that FSLP problems are different and may be distinguished by any manner, or a number of aspects which each one leads to varied model. The aspects include the kind of uncertainty level which enters into the linear programming problem based on the most famous and most studied FSLP problems as follows:

1. Flexible stochastic linear.
2. Inclusive-constrained linear programming with frv coefficients.
3. Inequality-constrained linear programming with frv coefficients.
4. Linear programming with random variables, and fuzzy numbers.

It should be noted that although each type of these problems differ on research methodology to a solution, the DM can governed them by a common set of principles dealing with the problem effectively and efficiently.

For the unified methodological approach for FSLP problems and its optimal solution, the paper explained a general procedure for solving a FSLP problems with three main steps: the first step contains the program statement and program with fuzzy and random data, while the second step consists of uncertainty processing like the minimum uncertainty, the maximum uncertainty, and the uncertainty invariance principles to obtain an equivalent deterministic problem, and the last step consists of solving the obtained resulting deterministic problem by a software program or by the emergence metaheuristics. But in the third side solution of the approach for FSLP models, the paper dealt with the in two sides:

- Flexible SLP.
- LP with frv coefficients.

What related to Flexible SLP there are:

1. Problem formulation; considered LP of the form:

$$(P_F)\begin{cases} \widetilde{min}\, C(w)x \\ A_i(w)x \lesssim b_i(w);\, i = 1, \ldots, m \\ x \in X = \{x \in R^n | x \geq 0\} \end{cases}$$

2. Symmetrical approaches for (P_F).
3. Asymmetrical approaches for (P_F).

These above approaches are some steps for solving (P_F). While for LP with frv coefficients, there are the following methods associated with each one with solution steps:

1. Inclusive constrained case.
2. Inequality-constrained case.
3. LP with random variables, and fuzzy numbers.

Finally, in the paper pointed out that extension of FSLP problems may be carried out toward (MOL/N) P problems, so as multistage problems, and it has rich potential applications in many fields like air pollution regulation, production scheduling, network location, and others. In the study of fuzzy multiobjective linear model for supplier selection in supply chain(Amid et al., 2006), a fuzzy multiobjective linear model was developed with vagueness, imprecision of the goals, constraints, and parameters, and the decision-making was complicated. It tries to overcome the vagueness of the information because the supplier selection is a multiple criteria (cost, quality, delivery time, serves...) decision-making (MCDM) problem, and a purchasing manager should analyze the trade-off among the several criteria where input information is not precisely known. Based on basic concepts like the theory of fuzzy sets, α−cut, fuzzy decisions, and symmetric/asymmetric fuzzy decision-making, the fuzzy supplier selection model has been formulated as:

$$Z_k = \sum_{i=1}^{n} C_{ki} x_i, i = 1, \dots, p,$$

$$Z_l = \sum_{i=1}^{n} C_{li} x_i, l = p+1, \dots, q,$$

$$s.t.$$

$$x \in X_d, X_d = \{x/g(x) = \sum_{i=1}^{n} a_{ri} x_i \le b_r, r = 1, \dots, m; x \ge 0\}$$

Where $C_{ki,} C_{li,} b_r$ are crisp or fuzzy values. The previous problem has been solved by using fuzzy linear programming employing the max-min operator as used by Zimmerman (1987, 1993). The convex (weighted additive) operator, which enables the DM to assign different weights to several criteria, summarizes the step solutions in a model algorithm of supplier selection problems to the fuzzy multiobjective programming. As previously pointed in the real world, many input data are not exactly known for the DM. Hence, a fuzzy multiobjective model should be developed for supplier selection to assign different weights to different (various) criteria. The fuzzy model helps the DM to find out suitable ordering from each supplier which helps purchasing manager to arrange the performance on cost, quality, quantity, delivery time... etc. On the other hand, transforming the fuzzy multiobjective supplier selection problem into an equivalent convex fuzzy programming model, as well as into crisp single objective linear programming, reduces the dimension of the model system, and makes the application of the fuzzy approach easier, and less computational.

The study concluded that in the real world, the proposed model has vector optimization problem by using a single utility function to preference of DM because the values of objective criteria and the constraints expressed are vague that have no equality importance.

Li et al. (2006) discussed a kind of multiobjective programming problem with fuzzy random coefficients.

The portfolio selection problem of Ben Abdelaziz et al. (2007) presents a multi-objective stochastic programming where the parameters in the objectives are random, has normal distribution, and has transformed multi-objective stochastic programming into its equivalent deterministic by combining the chance constrained compromise programming model, and constrained programming model.

The basic idea of portfolio selection theory by Markowitz (1952), considers several conflicting objectives like; rate of return, liquidity, and risk, and collected them as multi-objective programming problems. The main objectives of portfolio problems are: corporal validity objectives, the stocks acceptability by the investors, and the financial objectives. Hence, in many decision-making it is able to state some values of parameters either as goal programming or as compromise programming; thus by developing multi criteria linear goal programming, the multi-objective stochastic programming has been extended.

The purpose of the paper is to deal with portfolio selection with some random parameters with normal distribution. Chance constrained compromise programming allows the DM to use conflicting objective functions, and eventually collecting them in multi-objective stochastic programming, which was illustrated in the portfolio selection from the Tunisian stock exchange market.

In the paper, goal programming and compromise programming models are used, and the multi-objective stochastic programming was formulated. It proposed deterministic equivalent program by using chance constrained programming and chance programming approaches, and has called the resulting approach chance constrained compromise programming in the random constrained. While the random objectives depended on statistic concepts such as mean, variance, and standard deviation. Thus the chance constrained compromise programming allows conflicting objectives and random parameters in multiobjective stochastic programming to find a compromise solution to its equivalent deterministic program.

The fuzzy stochastic goal programming by Hop (2007a) measures to attain the value of fuzzy stochastic goals. The new approach was used to defuzzify and derandomize the fuzzy stochastic goal programming problems in order to obtain standard linear program.

In recent years, solving fuzzy optimization problems, as well as stochastic optimization problems has attracted attention by researchers. Stochastic and fuzzy aspects were combined by researchers to provide an efficient tool to treat and describe real world problems when faced by uncertainty and imprecision information of optimization problems. The researchers have been challenging the fuzzy stochastic optimization problems to find efficient solution to convert the problem into its equivalent deterministic optimization problem.

Hops method to solve the fuzzy stochastic goal programming problems of uncertainty and imprecision consists of goals, objectives, constraints, and parameters which are related to goals are random variables.

The method is a new approach to attain the values of fuzzy random variables to convert the problem into standard form of linear programming which was the extension of Luhandjulas work (Luhandjula, M.K.1996. Fuzziness and randomness in an optimization framework.Fuzzy Sets and Systems 155,89–102), and Luhandjula (2006)based on some important concepts like: fuzzy random variable, random interval, the necessary and efficient condition relation between random variable and random interval, lower-side attainment of random variable, both-side attainment of random variable, average lower-side attainment of two random variables, average both-side attainment of two random variables, and fuzzy stochastic goal programming.

The advantage of this method is it streamlines by developing different approach which are more efficient than those exists compared with Liu and Liu (2003) model having small number of constraints and variables compared with Luhandjulas linear programming model.

In the portfolio selection problem, Ben Abdelaziz et al. (2007) present multiobjective stochastic programming which considered that the parameters in the objectives as random and normally distributed. It transformed multiobjective stochastic programming into its equivalent deterministic by combining the chance constrained compromise programming model and constrained programming model.

As mentioned earlier, Markowitz (1952) theory of portfolio selection also deals with some parameters that are random with normal distribution with chance constrained compromise programming (CCCP) combined together with chance compromise programming(CCP) based on compromise programming (CP). This was as pointed previously to allow the DM to use conflicting objective functions, and collecting them in as multiobjective stochastic programming as illustrated by portfolio selection problem from the Tunisian stock exchange.

In the paper, GP and CP models are used and the multiobjective stochastic programming was formulated. Moreover, it proposed deterministic equivalent program by using CCP and CP approach, hence CCCP approach; first in random constraints, and consequently in random objectives, depending on the statistic concepts like mean, variance, and standard deviation. Thus, it is considered that CCCP approach allows conflicting objectives and random parameters in multiobjective stochastic programming to find a compromise solution to its corresponding equivalent deterministic program.

It is observed that the new deterministic formulation is found to be multiobjective stochastic program since the computation of transformation, the best/ideal values for each assumed objective combined with CP and CCP approaches, gets a deterministic programming from multiobjective stochastic program.

In the measure, the attained values of fuzzy numbers and/or fuzzy stochastic variables, Hop (2007c) presents a model to convert the fuzzy linear program/fuzzy stochastic linear programming problems to its corresponding deterministic linear programming problems, and to find solution to it. The author based on his another paper Hop (2007a) defined some important concepts and formulated the fuzzy linear programming as follows:

$$\begin{gathered} max\ cx \\ s.t. \\ \sum_{i=1}^{n} (\tilde{a}_{ij}) x_j \leq \tilde{b}_i; i = 1, \dots, m \\ x_j \geq 0 \end{gathered}$$

where c is a $1 \times n$ matrix and $A, b\ are\ m \times n, m \times 1$ matrices of fuzzy variable constraint coefficients. He obtained the following standard LP problem after applied upper-side attainment index to the constraints:

$$\begin{gathered} max\ cx - \sum_{i=1}^{m} \lambda_i \\ s.t. \\ \overline{D}\ ((\tilde{b}_i), \sum_{j=1}^{n} (\tilde{a}_{ij}) x_j) = \lambda_i;\ i = 1, \dots, m \\ x_j, \lambda_i \geq 0 \end{gathered}$$

The solution of this LP gives better results in terms of objective values compared to those solved in traditional methods. This is because the method compares fuzzy numbers based on their relative relationships among them that made the constraints relaxes, and then larger spreads of the fuzzy numbers. Thus, overlapping areas between the fuzzy numbers increases and the results are better. In the traditional methods, the fuzzy numbers are converted into corresponding deterministic and do not adjust the values of deterministic constraints, so as it to the deterministic case.

On the other hand, the fuzzy stochastic linear program defined and formulated as follows:

$$\max cx$$
$$s.t.$$
$$\sum_{j=1}^{n}(\tilde{a}_{ij})_w x_j \leq (\tilde{b}_i)_w; i = 1, \dots, m$$
$$x_j \geq 0, w \in \Omega, k = 1, \dots, l$$

where c is $1 \times n$ matrix and A, b are $m \times n, m \times 1$ matrices of fuzzy random variable constraint coefficients defined on a probability space (Ω, F, P). After applying the lower-side attainment index to minimize achievement between LHS and RHS the problem become:

$$\max cx - \sum_{i=1}^{m} \lambda_i$$
$$s.t.$$
$$\overline{D}\ (\textstyle\sum_{j=1}^{n}(\tilde{a}_{ij})_w x_j, (\tilde{b}_i)_w) = \lambda_i(w);\ i = 1, \dots, m$$
$$x_j, \lambda_i \geq 0,, w \in \Omega$$

Finally, by using stochastic programming techniques to de-randomizing the problem, the corresponding deterministic problem is obtained as follows:

$$\max cx + E[\textstyle\sum_{i=1}^{m} \lambda_i]$$
$$s.t.$$
$$\overline{D}\ (\textstyle\sum_{j=1}^{n}(\tilde{a}_{ij})_w x_j, (\tilde{b}_i)_w) = \lambda_i(w);\ i = 1, \dots, m$$
$$x_j, \lambda_i \geq 0,, w \in \Omega$$

where E is the mathematical expectation. When the author solved the last deterministic programming problem and compared the results with Luhandjulas model (M.K. Luhandjula, fuzziness and randomness in an optimization framework, Fuzzy Sets and Systems 77 (1996) 291-297), he found out that the objective value was less than exited in Luhandjula's result. However, since the program problem was minimized, hence he has a better result; in addition his model has fewer constraints compared with that result, and for larger problems, the computation of his model relatively is better.

Hop (2007b) continued on studying fuzzy/stochastic linear programming problems. He presented another model to solve such types of optimization problems by using superiority and inferiority measures. This model was to convert fuzzy/stochastic linear programming problems to its corresponding conventional deterministic linear programming problems to find an optimal solution to it.

In the study, the author tried to find an efficient solution for the fuzzy/stochastic linear programming problems that he presented a new model to measure the superiority and inferiority of the triangular fuzzy numbers/fuzzy stochastic variables. The model takes the triangular fuzzy numbers/ fuzzy random variable because of their important properties, and holding most of the information about fuzzy numbers like the lower/upper bounds of numbers and most of its possible value. Thus, based on his available, the study (Hop, 2007a; Hop, 2007c), also defined and developed a set of triangle fuzzy numbers (T -numbers) as follows:

$$\tilde{T} = \{\tilde{\delta} = (\delta, a.b), a, b \geq 0\}$$

and

$$\mu_{\tilde{\delta}}(x) = \begin{cases} \max\left(0{,}1 - \dfrac{\delta - x}{a}\right), if\ x \leq \delta, a > 0 \\ 1, if\ a = 0, and/or\ b = 0 \\ \max\left(0{,}1 - \dfrac{x - \delta}{b}\right), if\ x > \delta, b > 0 \\ 0, otherwise \end{cases}$$

where the scalars $a, b \in R^+$ are called the left and the right spreads respectively, Also defined superiority/inferiority of the fuzzy numbers as: if $\tilde{P}$ and $\tilde{Q}$ are fuzzy numbers, then the superiority and inferiority of $\tilde{P}$ over $\tilde{Q}$ is defined as:

$S(\tilde{P}, \tilde{Q}) = \int_0^1 \max\{0, \sup\{s: \mu_{\tilde{P}}(s) \geq \alpha\} - \sup\{t: \mu_{\tilde{Q}}(t) \geq \alpha\}\} d\alpha,$

$I(\tilde{P}, \tilde{Q}) = \int_0^1 \max\{0, \inf\{s: \mu_{\tilde{P}}(s) \geq \alpha\} - \inf\{t: \mu_{\tilde{Q}}(t) \geq \alpha\}\} d\alpha$ for all $\alpha \in (0,1)$. So he considered the two fuzzy numbers:

$\tilde{P} = (u, a, b), \tilde{Q} = (v, c, d) \in \tilde{T}, and\ \tilde{P} \leq \tilde{Q}$ then the superiority of $\tilde{Q}$ over $\tilde{P}$ is:

$S(\tilde{Q}, \tilde{P}) = v - u + \frac{d-b}{2}$, and inferiority of $\tilde{P}$ to $\tilde{Q}$ is: $I(\tilde{P}, \tilde{Q}) = v - u + \frac{c-a}{2}$

Similarity, the superiority/inferiority between two fuzzy random variables $P^{\simeq}$ and $Q^{\simeq}$ defined as:

$S(Q^{\simeq}, P^{\simeq}) = v(w) - u(w) + \frac{d(w)-b(w)}{2}$,

$I(P^{\simeq}, Q^{\simeq}) = v(w) - u(w) + \frac{c(w)-a(w)}{2}$

In solving fuzzy/stochastic linear programming problems, the difference among developed methods is the manner to defuzzify and/or derandomize fuzzy number/fuzzy stochastic variables. There are two main manners to convert the fuzzy linear program so as to fuzzy stochastic linear programming problems into conventional deterministic linear program through sequential manner and simultaneous manner. In the sequential manner, the defuzzifing process is performed first and derandomizing process is done second. If done simultaneously, both defuzzifing and derandomizing process is done at the same time, and each has its advantage and disadvantage.

The author selected the first one to solve the problem, thus he restricted the idea and optimization concepts (Hop, 2007a; Hop, 2007c) to solve fuzzy/stochastic linear programming problems by using superiority and inferiority measures as:

1. Fuzzy linear programming

1.1 Fuzzy linear programming with fuzzy constraints, considered:

$$max\ cx$$
$$s.t.$$
$$\sum_{i=1}^{n}(\tilde{a}_{ij})x_j \leq \tilde{b}_i; i = 1, \dots, m$$
$$x_j \geq 0$$

Maximized the objective subject to superiority of right-hand sides over left-hand sides, and inferiority of left-hand sides to the right-hand sides of constraints, and with paying a penalty for any violation of superiority and inferiority, so the model can be converted to corresponding equivalent deterministic problem as:

$$\max\ cx - [p_i S_i\left(\sum_{j=1}^{n}(\tilde{a}_{ij})x_j, \tilde{b}_i\right)$$
$$+q_i I_i\left(\tilde{b}_i, \sum_{j=1}^{n}(\tilde{a}_{ij})x_j\right)]$$
$$x_j \geq 0, j = 1, \dots, n$$

Where p_i, q_i are penalty coefficients, determined without any rule, and can find the optimal solution of it easily.

1.2 Fuzzy linear programming with fuzzy constraints and objective function.

He extended his consideration to more general case as:

$$max \sum_{j=1}^{n} \tilde{c}_j x_j$$
$$s.t.$$
$$\sum_{j=1}^{n}(\tilde{a}_{ij})x_j \leq \tilde{b}_i, i = 1, \dots, m$$
$$x_j \geq 0, j = 1, \dots, n$$

The converted equivalent problem is:

$$Max\ \theta$$
$$s.t.$$
$$max \sum_{j=1}^{n} \tilde{c}_j x_j \geq 0$$
$$\sum_{j=1}^{n}(\tilde{a}_{ij})x_j \leq \tilde{b}_i, i = 1, \dots, m$$
$$x_j \geq 0, j = 1, \dots, n$$

Then,

$$Max\theta - p_o\left(\theta, \sum_{j=1}^{n}\tilde{c}_j x_j\right) - q_o I\left(\sum_{j=1}^{n}\tilde{c}_j x_j, \theta\right)$$
$$-p_i S\left(\sum_{j=1}^{n}(\tilde{a}_{ij})x_j, \tilde{b}_i\right) - q_i S\left(\tilde{b}_i, \sum_{j=1}^{n}(\tilde{a}_{ij})x_j\right)$$, thus,
$$s.t.$$
$$x_j \geq 0, j = 1, \dots, n$$

the formulation is the standard linear programming if crisp value θ fuzzified as (θ, 0, 0), and solving it.

2. Fuzzy stochastic linear programming problems.

The fuzzy stochastic linear programming problems were considered as follows:

$$max\ cx$$
$$s.t.$$
$$\sum_{j=1}^{n}(\tilde{a}_{ij})_w x_j \leq \left(\tilde{b}_i\right)_w; i = 1, \dots, m$$
$$x_j \geq 0, w \in \Omega, j = 1, \dots, n$$

where c, A, b are $1 \times n, m \times n, m \times 1$ matrices of fuzzy random variable constraints respectively, and defined on a probability space (Ω, F, P).

By the same manner which is used to convert fuzzy linear programming problem, the formula can be converted into corresponding deterministic standard linear programming problem as:

$$\max cx - p_i E\left[\sum_{i=1}^{m}\lambda_i(w)\right] - q_i E\left[\sum_{i=m+1}^{2m}\lambda_i(w)\right]$$
$$S_i(\sum_{j=1}^{n}\left(\tilde{a}_{ij}\right)_w x_j, (\tilde{b}_i)_w = \lambda_i(w), i = 1, \dots, m$$
$$I_i\left(\left(\tilde{b}_i\right)_w\right) = \lambda_i(w), \sum_{j=1}^{n}\left(\tilde{a}_{ij}\right)_w x_j$$
$$= \lambda_i(w), i = m + 1, \dots, 2m$$
$$x_j, \lambda_i(w) \geq 0, w \in \Omega$$

where E is the expected value. The researcher showed illustrative numerical example of his proposed model to solve these types of optimization problems better than others especially that of Luhandjulas method because of:

• The proposed method gives better solution than Luhandjula's method,
• The proposed method considering the amount of calculations and complexities embedded in Luhandjula's method,
• The proposed method is with a few number of constraints, and more simplicity of conversion,
• The proposed method has taken the comparison of fuzzy stochastic variables based on their membership function relationships, and
• The proposed method abolishes wholly or fully properties to maximize the objective function.

Since the fuzzy variable linear programming problems have been explored, and various formulations have been developed, especially linear programming with triangular as well as trapezoidal fuzzy variables, have attracted some interest recently. Many researchers have employed the triangular fuzzy variables in their studies. On the other hand, linear programming with trapezoidal variables has also been an interest and attracted researchers in the last few years ago. Mahdavi-Amiri and Nasseri (2007) presented fuzzy linear programming problems applied to linear ranking function to present trapezoidal fuzzy numbers. After proposing the method in the formulation of dual problem in linear programming problem with trapezoidal fuzzy variables, they got some results of duality.

The authors proved that the auxiliary problem is another type of the linear programming problem with trapezoidal fuzzy variables, and in the other words, the dual of it is the auxiliary problem. After they established the dual program, the crisp data results was used and developed into a dual algorithm for solving the linear programming problem with trapezoidal fuzzy variables, and showed that the algorithm may be useful for post optimality/sensitivity analysis.

It is noticed that their main contributions is the establishment of duality and complementary slackness. In addition, the use of certain linear ranking function to inserting trapezoidal fuzzy numbers, and using the results to develop a dual simplex algorithm, and using it directly to primal simplex tablue. In the paper, necessary notations and definitions of fuzzy set theory were given discussing fuzzy numbers and the properties, so as linear ranking function. After that they defined the linear programming problems with trapezoidal fuzzy variables, fuzzy basic feasible solution, formulation of the dual problem with trapezoidal fuzzy variables, and dual simple method with trapezoidal fuzzy variables. They showed that a numerical example can be used in a dual simplex algorithm for solving the primal/dual directly. In solving multicriteria programming problems with imprecise data and information, researchers offered two different methods: the use of probability distribution or the use of fuzzy sets. However, Rommelfanger (2007) presented a concept for solving multi-criteria linear programming problems with crisp, fuzzy or stochastic values, and suggested that the two solution concepts may be used in parallel/simultaneous or in combination depending on the real situation. He based his opinion on economic problems since the well-known probabilistic or fuzzy solutions are not suitable because the stochastic variables do not have simple traditional and classical distribution, while the fuzzy values are not intervals.

He proposed a new method which retained the original objective functions dependent on the different states and situations of nature, and studied the following linear programming problem:

$$Max\, Z(x) = c_1x_1 + \cdots + c_nx_n$$
$$s.t.$$
$$a_{i1}x_1 + \cdots + a_{in}x_n \leq b_i; i = 1, \ldots, m$$
$$x_j \geq 0, j = 1, \ldots, n$$

and he saw for modeling the problem may be in:

1. A stochastic linear program, the uncertain parameters or probability distribution as follows:

$$Max\, Z(x) = c_1(w)x_1 + \cdots + c_n(w)x_n$$
$$s.t.$$
$$a_{i1}(w)x_1 + \cdots + a_{in}(w)x_n \leq b_i(w); i = 1, \ldots, m$$
$$x_j \geq 0, j = 1, \ldots, n$$

where $c_j(w), a_{ij}(w), b_i(w)$ are random variables on probability space, and can be solved either by Fat solution, chance constraint programming, stochastic programming with recourse, and integrated chance constrained program if the coefficients of the constraints are random variable parameters.

Or, by optimization of the mean value $Max_x E(Z(x,w))$, minimization of the variance $Min_x\, Var(Z(x,w))$, and minimum risk problem $Max_x P\,(w|Z(x,w) \geq \gamma), \gamma$ is a certain aspiration level.

2. A fuzzy linear program as:

$$Max\, \tilde{Z}(x) = \tilde{C}_1x_1 + \cdots + \tilde{C}_nx_n$$
$$s.t.$$
$$\tilde{A}_{i1}x_1 + \cdots + \tilde{A}_{in}x_n \leq \tilde{B}_i; i = 1, \ldots, m$$
$$x_j \geq 0, j = 1, \ldots, n$$

where c_j, a_{ij}, b_i are fuzzy sets on R, and there are several methods for solving this model if both sides of each constraint have the same type of fuzzy numbers or fuzzy intervals, in addition this fuzzy linear program has some special cases like; some or all the parameters of the objective function crisp, some or all constraints are crisp, and some are or all constraints have the soft form, i.e.$\sum_{j=1}^{n} a_{ij} \precsim \tilde{B}_i; i = 1, \ldots, m$.

To transform stochastic linear programming problems into its corresponding equivalent standard form of linear programming system, it is possible to introduce the constraints and/or objectives in the fuzzy system as additional extra constraints, and solving the system with several objective kinds by crisp, fuzzy, or stochastic. Thus, the author suggested a new method to combine the fuzzy set theory and the probability concepts to solve multi-criteria linear programming problems with crisp, stochastic, or fuzzy values, where he sees it as complementing with each other. Hence, his proposal method is sufficient to use fuzzy numbers or fuzzy intervals for modeling the parameters if they are described imprecisely by fuzzy sets, and scenarios selected in the suitable manner. The presenter showed the advantages of the method because the process could be done interactively by changing the aspiration levels and/or the risk aversion. In addition, fuzzy linear programming based on aspiration levels which are used in the proposed method offers the possibility to use more flexibility in the left hand side of the extended extra constraints.

Peng and Liu (2007) introduced a new concept of birandom variables and exhibited the framework of birandom variables or the class of hybrid of uncertainties which consists of randomness and roughness; while Ak¨oz and Petrovic (2007) studied fuzzy iportant relations and defined three types in different linguistic terms:

- Slightly more important than,
- Moderately more important than, and

• Significantly more important than.

Many models like multistage stochastic programming (MSP) approach which is the extension of the two-stage stochastic programming (TSP) approach, multi-stage stochastic integer programming (MSIP) approach in the past decades have been presented by researchers who dealt with multilayered scenarios tree to address a multistage capacity expansion problem, economies of scale in costs, and water resources.

Previous methods did not deal (hardly) with independent uncertainties of the constraints in the left hand-side, so as cost coefficients, hence many real life world problems with inexact mathematical programming is effected to deal with the difficult real life problems that motivated Li et al. (2008) to present a study to deal with inexact, and presented a paper for water resources management under uncertainty to proposed in inexact multistage stochastic integer programming (IMSIP) method. They proved that the method is able to deal with uncertainty in probability distributions, so as discrete intervals, and has able to reflect the dynamics in the water resources management systems, balancing between drought and flooding, as well as maximized economic benefits and on the other side minimized system failure.

The authors showed the advantages of IMSIP over TSIP. It can deal with uncertainties in exit stream flow by generating scenarios in its future events. The proposed method reflects effectively the dynamic complexities in water resources management system in multistage context, and can deal with uncertainties presented as probabilities, so as intervals. IMSIP method can communicate uncertainties of all modeling parameters, so as interactions of the parameters into the optimization process.

Katagiri et al. (2008) considered the multiobjective fuzzy random programming (FRP) problem, and proposed to solve the model by combining both the possibilistic programming (PP) and stochastic programming (SP) approaches. This is due to the real-life world decision making problems that deals with multiobjectives/multiple criteria, and they are may be fuzzy, or random, fuzzy-random. Thus, the authors presented an interactive proposal method to solve multiobjective programming problem with fuzzy random coefficients, and gave a definition of random variable different from another researchers. It explained fuzzy random programming, stochastic programming, and possibilistic programming, and gave special attention to concepts: vagueness and ambiguity, where vagueness represents the fuzziness of which degree the element of the set belongs, while ambiguity is related to the fuzziness itself. The defined the problem formulation of the fuzzy random multiobjective linear programming problem as follows:

$$minimize\ C_i^{\approx} x, i = 1, \dots, k$$
$$s.t.$$
$$x \in X \triangleq \{x \in R^n | Ax \le b, x \ge 0\}$$

where denoted randomness and fuzziness of the objective coefficients by the" dash above", and" wave above" i.e." −" and" ∼" respectively, x is n −dimensional decision variable column vector, A is an $m \times n$ cofficient matrix, and b is an m−dimensional column vector, and $C_{ij}^{\approx}, j = 1, \dots, n$ of the vector $C_{ij}^{\approx} = (C_{i1}^{\approx}, \dots, C_{in}^{\approx})$ fuzzy random vectors, take fuzzy numbers with respect to occurrence of each event of w.

On the other hand, they defined Pareto optimal as weak solution to construct an interactive satisficing method and for fuzzy random multiobjective linear programming problems associated with algorithm and flowchart. They sing out their proposed method by conclusions: combining a program of the fuzzy programming approach with SP approach is complex as compared individually, but more realization to real-life world problems, and the deterministic minimax problem can be solved optimality by combining the bisection method and the first-phase of the two-phase simplex method of the standard LPP, and the obtained solution it is at least weak Pareto optimal solution.

In fuzzy linear programming problems, Wu (2008) suggested an optimality conditions for linear programming problems with fuzzy coefficients. He investigated the optimality conditions after introducing some basic properties and arithmetic of fuzzy numbers, and formulated two linear programming problems with fuzzy coefficients: first, a crisp/conventional and the other is the fuzzy linear constraints. The proposed two solutions for the two problems are through deriving the optimality conditions for the problems by introducing the multipliers properties.

The solution concepts were considered on the ordinary fuzzy numbers. The optimality conditions for the solution concepts/nondominated solution in the proposed approach of the multiobjective programming problem were naturally elicited.

Iskander (2008) proposed to utilize the possibility programming to transform the fuzzy multiobjective linear programming as modeled (D.S. Negi, E.S. Lee, Possibility programming by the comparison of fuzzy numbers, Computers and Mathematics with Applications 25 (1993) 4350) into its corresponding equivalent crisp programming according to the authors modifications (Iskander, 2004b; Iskander, 2002) and used the two main criteria with the same evaluation concept: the global criterion method and the distance functions method.

In the study, the possibility programming in the fuzzy multiobjective linear programming problems was modeled, and showed its two cases: the exceedance possibility and strict exceedance possibility. The proposed global criterion method and the distance functions method respectively as follows:

$$Minimize\ F_1 = \sum_{r=1}^{p}((Z_{or} - Z_r)/Z_{or})^q$$

$$Minimize\ F_2 = (\sum_{r=1}^{p}|Z_{or} - Z_r|^q)^{1/q}$$

where Z_{or} is the most desired predetermined value of the Z_r.

The proposed computational comparison recommended that in the case of exceedance possibility exponent q takes 1 is better, where if it takes 2, the global criterion method is more preferable. However, the decision-maker has to choose his level θ of the required possibility, and the study c onclused that in general, the case of strict exceedance possibility is preferable than the case of exceedance possibility. Li et al. (2008) emphasized that the solution of hybrid multiple-objective problems can be found by using of fuzzy set concepts specifically fuzzy linguistic variables. Allowing a hold of strong duality has been proven by an approach study in fuzzy linear programming problems under certain conditions (Inuiguchi et al., 2003; Wu, 2008).Based on the PP- model, E-model, V-model, and F-model (Katagiri et al., 2001; Katagiri et al., 2003b; Katagiri et al., 2003a) the probability distribution model was applied and converted into maximize probability measure (Katagiri et al., 2008).

The types of single and/or multiobjective LP problems where the variable of the RHS of constraints are fuzzy parameters have been studied, t and were considered by some researchers (Ganesan and Veeramani, 2006; Maleki, 2002; Nehi et al., 2002). Gil et al. (2006) considered the fuzzy random variables and presented the structure of fuzzy random variables and proved that a fuzzy number is a convex set, and helps others to various equivalent definitions of fuzzy random variable (Katagiri et al., 2008) class of hybrid. Xu and Yao (2009) based on Liu (2002b) introduction on the concepts of random rough variable and random rough expected value; the chance constrained multiobjective programming (CCMOP)

Model is presented by him as follows:

$$Max\{f_1, \dots, f_m\}$$
$$s.t.$$
$$Ch\{f_i(x,\xi) \geq f_i\}_{\gamma_i} \geq \delta_i, i = 1, \dots, m$$
$$Ch\{g_r(x,\xi) \geq f_i\}_{\eta_r} \leq \theta_r, r = 1, \dots, p$$
$$x \in X$$

where ζ is a random rough variable $\gamma_i, \delta_i, \eta_r, \theta_r$ are predetermined confidence levels, $i = 1,\dots, m,$and $r = 1,\dots, p$ dealing with uncertain optimization problems with randomness and roughness in the same time. Based on the chance measure of random rough variable which was defined by Liu (2004) considered the $t_r - p_r$ multiobjective programming model as follows:

$$Max\ \{c_1^{\simeq T}x, \dots, c_n^{\simeq T}x\}$$
$$s.t.$$
$$e_r^{\simeq T}x \leq b_r^{\simeq}, r = 1, \dots, p$$
$$x \geq 0$$

where $c_i^{\simeq} = (c_{i1}^{\simeq}, \dots, c_{in}^{\simeq})^T, e_r^{\simeq} = (e_{r1}^{\simeq}, \dots, e_{mn}^{\simeq})^T, b_r^{\simeq}$; are random rough vectors , $i = 1, \dots, m, r = 1, \dots, p.$

Xu and Yao (2009) turned the constructed random rough variables into crisp equivalent model and employed an interactive algorithm. Then a random rough simulation was applied to deal with general random rough objective functions and random rough constraints to convert the problem into crisp equivalent problem. Finally, a combination of random rough simulations with genetic algorithm was applied to find a compromise solution to the original problem. On the other hand, they have proven that this combination is more effective and efficient than the traditional algorithm for complex problems.

In an amendment article, a paper by Chou et al. (2009) which was noted by Hop (2007c), proposed a method in studying multiobjective linear programming problems in fuzziness and randomness environment. It has amended the paper of its method about how to convert the multiobjective optimization problems with fuzziness and/or randomness into its corresponding equivalent LP problems, where Hop employed the relative relationship between fuzzy numbers and fuzzy stochastic variables. The relative relationship which was obtained was called attainment values of degrees such lower side attainment index (both-side attainment index and average index). In Hops approach, the relationship and attainment values play the main role to convert of fuzzy and fuzzy stochastic linear programming problems into crisp or standard LP problems and then solving it.

The authors proved that the Hops proposal has failed or flawed and confound his proposal because it could not the find maximum/minimum values of desired objectives, and neglected some of the relevant and unavoidable theoretical essentials; hence, they emphasized that in their revisions:

• The intersection of two membership functions not always exist,

• The Hop's preposition is not general but special case that means the proposal which construct based on the preposition is not general but special case, and

• showed that by resolving the numerical examples were solved by his proposal method infeasibility solution.

On the other hand, it was discovered that there are some scholars who proposed the fuzzy environment based on Hops proposed method, have not noted that this method results to infeasibilities (Gao et al., 2008;

Qiu and Shu, 2008; Xu et al., 2008; Xu and Liu, 2008).

Ben Abdelaziz and Masri (2009) have extended their previous study (Ben Abdelaziz and Masri, 2005b), by introducing the multistage stochastic programming with fuzzy probability distribution for the first time. Their extended proposal was focused on fuzzy probability distribution defined by triangular fuzzy numbers. The proposal has two levels of uncertainty: randomness on the parameters and the fuzziness on the values of probability distribution. The strategy is the same with their pre-study on two-step fuzzy transformations: first, utilizing the α−cut technique to defuzzify the fuzzy probability distribution, while the in the second step of stochastic transformation, they considered the risk attitude of the decision maker to obtain the deterministic equivalent standard programming. And lastly, they used a modified nested decomposition method to get the solution for the original problem.

They relied their solution on two concerns that has considered the high level of uncertainty and the ambiguity of the problem being undertaken, and have supposed that DMs ability to estimate the credibility degree α on the information sources. On the other hand, the DMs pessimistic for future events to look for a robust solution. The advantage of the proposed solution is the nested decomposition algorithm that generates the optimal solution in countable steps. Hashemi et al. (2006) has considered the possibilities of mean value and variance of the fuzzy numbered which considered symmetric triangular fuzzy numbers.Lotfi et al. (2009) addressed a full fuzzy multiobjective linear programming (FMFLP) problems and considered all variables and parameters as fuzzy triangular asymmetric numbers with certain conditions.

They considered the defuzzification approach on the nearest symmetric triangular approximation. The concept of symmetric triangular fuzzy numbers used in addition to the concept of the nearest symmetric triangular approximation of fuzzy numbers or fuzzy quantity. After converting the full multiobjective fuzzy linear programming (FMFLP) problem into multiobjective linear programming (MOLP) problem with crisp numbers for parameters and variables, and on the other side, for solving FMFLP problems, the ranking of the constraints was also considered.

The advantage of the method is that it can be used even if the entries of the matrix constraints may be negative as well as for objective coefficients. The disadvantage of the method is the value of objective functions that may not satisfy the fuzzy production of two positive fuzzy asymmetric parameter numbers because of the fuzzy production properties.

Based on (Chen and Tsai, 2001b; Li et al., 2004), Li and Hu (2009) presented a paper to study multiple optimization problem, and introduced satisfying optimization method based on goal programming for solving fuzzy multiple objective optimization problem. The proposed method is adapted to solve the fuzzy optimization problems with the three different relations introduced by Ak¨oz and Petrovic (2007).The method follows the more important objective in achieving the higher desirable satisfying degrees, reformulated the fuzzy multiple objective optimization problem, and the new reformulated fuzzy optimization problem. Each of the desirable degrees of achievement, and the important difference maximized objective done by ranking the desirable satisfying degrees under the inter-working with DM.

The result consists of DMs satisfying his/her fuzzy preference because of the trade-off between satisfying optimization and the importance of the requirement which is taken into a count and was realized at the same time. The proposed method verifies the efficiency, flexibility and sensitivity. In the continuous optimization problem for stochastic multiobjective programming (SMOP) problems in order to cover an important gap in the scientific literature, Mu˜noz and Ruiz (2009) presented an interval stochastic multiobjective (ISTMO) programming problems, more clearly an interval reference point-based method for stochastic multiobjective programming problems. It is an extension of Urli and Nadeau (2004) and (Urli and Nadeau; 1990 in PROMISE, Teghem et al.; 1986 in STRANGE in discrete optimization problems) wherein the proposed interactive method refers to a combination of the concept of probability efficiency for stochastic problems, and the reference point for deterministic multiobjective problems. The main idea in this method is that the DM expresses his/her references by dividing the different range of all objectives into some special intervals like: very poor, poor, fair, good, very good that are acceptable to redviding and redefining during the process.

This interactive method helps the DM to verify the interactive procedure for solving SMOP problems, as well as understanding the stochastic nature of the problem. This is to discover the risk levels he/she is willing to accept on each objective function by trade-offs among the objective functions by considering:

- Efficiency analysis,
- Determination of satisfying solutions, and
- Compromise programming approach.

Thus, as emphasized by authors, the interactive method comes with three new contributions:

- The DM must find reasonably comfortable, and natural to give the information required by the method, to avoid throwing in consistent in formulations into the optimization problem,

• Based on the noted mentioned above informations, the method must get the solution in reasonable number iterations, and

• The method must aid the DM to understand the stochastic nurture of the problem, gives the DM the risk of levels associated with each iteration solution.

The method has relied on the probability efficiency (Kataoka, S., 1963. A stochastic programming model. Econometrica 31, 181196.) in order to adapt the reference point as the first step to choose an efficiency criterion. Although this method was basically introduced to solve and treat optimization problems with continuous random variables, the results described in Larsen et al. (2002) can be tackled together in this method to understand in the analyzing for the discrete case of the random variables.

Hu et al. (2009) introduced an interactive satisficing method based on alternative tolerance for fuzzy multiple objective optimization. This new tolerance of the dissatisficing objectives is based on (R. Benayoun, J. De Montagolfier, J. Tergny, O. Larichev, Linear programming with multiple objective functions: step method (STEM), Math. Program. 1 (3) (1971) 366375.), and the objective functions in attaining their aspiration levels are iteratively relaxed so that other objective functions are improved.

This procedure is continued until all the objective functions are satisficing. According to this method the new tolerance of dissatisficing objectives are generated by using an auxility programming problems. Moreover, according to this method, the membership functions may either be changed or added to the objective constraints.

Through changing the tolerance of objective functions, different membership functions are modeled and has removed the difference among objective functions which was determined by strict priority, and to overcome the unfeasibility if it appears that the attainable reference point method is referred which introduced by Wang et al. (2001). The paper suggests an efficient solution by lexicographic two-phase programming method (E.S. Lee, R.J. Li, Fuzzy multiple objective programming and compromise programming with Pareto optimum, Fuzzy Sets Syst. 53 (1993) 275288.), and if the objective values are lower than aspiration goals, adding the objective constraints about the goal values, then the solution is reduced into weak efficient solution.

The advantages of this method are: effectively in the optimization results which can be applied in nonlinear optimization problems in addition to linear optimization problems. This may be used to solve a general multiobjective optimization programming (MOOP) problems.

A special situation of multiple level programming problem (MLPP) includes two optimization problems called the bilevel programming problem (BLPP). This was considered and discussed (Deb and Sinha, 2009a; Deb and Sinha, 2009d; Deb and Sinha, 2009c) based on evolutionary multiobjective optimization (EMO) principles and on BLPP planned active and hybrid evolutionary-local-search constructed algorithm which offers a challenging test problem (Deb and Sinha, 2009b). The paper of Aouni and Torre (2010) showed how to get a stochastic solution of stochastic multiobjective (SMOP) problem by using goal programming (GP) model. The proposed approach contains two unit activities: first, a unit devoted to the introduction of corresponding deterministic equivalent problems when the feasible set is random and displayed how to solve these problems by using goal programming technique. In the second unit they tried and supposed SMOP to be a random variable. In the new approach, which deals with stochastic goal programming (SGP), they highlighted that there are different SGP formulations based on the solutions of the corresponding equivalent deterministic programming problems. Their approach has dealt with these two types of decision making solutions: the discrete and the continuous cases.

They showed that in the discrete situation, the best solution can be obtained by using the highest probability criterion, while in the other case, can estimate the mean and the variance of the unknown solution. These solutions become more and more accurate in increasing the number of observations. The proposed approach needs more computational time than the one that is based on deterministic equivalent problems. This is due to the fact that there is some optimization problems needed to be run and solved since this approach assumes that the SMOP solution is a random variable. Hence, according to the Central Limit Theorem (CLT) the larger number of observations, the more precise will be the approximation of the statistical moment of the SMOP solution.

Zeng et al. (2010) saw that some goals, coefficients and constraints of crop area planning could not be well-defined because the goals or constraints of the decision-making could not be expressed. This is precisely because the utility function may be not defined precisely due to uncertainty of natural and environment factors. This includes the limitation of human beings understanding in crop planning owing to parameters such as surface water withdrawal, crop, yield, price, irrigation volume are uncertainty.

So, they proposed the fuzzy multiobjective linear programming (FOMOLP) model and its corresponding fuzzy goal programming (FGP) problem to crisp which can be solved by the traditional or conventional programming methods, and applying the proposed method to crop area planning to Liang Zhou region, Gansu province of northwest China. Their crop planning problems have conditions where the coefficients of the objective functions, goals, and constraints are all ambiguous. The following objectives of the study are: FMOLP problem with fuzzy triangular numbers and its corresponding FGP problem are transformed to crisp one and then solving it through traditional method, where they applied the proposal method to northwest China.

The FMOLP model was developed and was used to solve thereby obtaining optimal crop area pattern under different water-saving levels. Compared to MOLP, the FMOLP model is more appropriate when the fuzzy characteristics in the coefficients, goals and constraints are involved in the decision-making. The FMOLP model presents a more stable approach as strategy in agriculture when goals, constraints and coefficients of objectives are presented by uncertainty. The FMOLP model and FGP problem can be applied in other management and decision-making fields.

In continuous optimization, Ben Abdelaziz and Masri (2010) forwarded the multiobjective stochastic linear programming under partial uncertainty, and solved the multiobjective stochastic linear program (MSLP) with partial known probability distribution. They studied the case on probability distribution defined by crisp inequalities. Further, they have proposed a chance constrained programming (CCP) approach and the compromise programming (CP) approach to transform MSLP with linear partial information on probability distribution (MSPLI) into corresponding equivalent standard LP problem and solved it using modified $L-$shaped method. First they addressed and defined MSPI as follows:

$$Min\ Z = C(w)x = [c_1(w)x, \dots, c_k(w)x]$$
$$s.t.$$
$$T(w)x - h(w) \geq 0$$
$$x \in X_o$$

where $X_o = \{x \in R^n : A_o x = b_o, x \geq 0\}$ is the set of deterministic constraints with A_o is $m_o \times n$ matrix and b_o is m_o vector; $C, T\ and\ h$ are random matrices of $k \times n, m \times n, and\ m \times 1$ respectively defined on some probability space $(\Omega, 2^{\Omega}, P)$ with $\Omega = \{w_1, \dots, w_N\}$ is a discrete set of events, 2^{Ω} is the power set of Ω and P is the partially known-probability distribution that signs to each $A \in 2^{\Omega}$ the probability of occurrence $P\ (A)$.

Second, they defined the polyhedral set of the gathering probability p_i as follows:

$$\pi = \{p = (p_1, \dots, p_N)^t : Ap \leq b, \sum_{i=1}^{N} p_i = 1, p_i \geq 0, i = 1, \dots, n\}$$

where $= a_{ij}$, and$b = b_i$ are respectively $s \times N$ and $s \times 1$ and fixed matrices.

Third, they employed the CCP approach, CP approach and the chance constrained compromise CCCP approach, and consequently, they used modified L−shaped method to obtain the compromise solution to the MSPI. Their method does not take into account on cases where the shortage occurs in constraints, and does not consider a recourse version of the compromise programming approach to MSPLI. In multiobjective stochastic integer programming (MSIP) problems, Kato et al. (2010) concentrated on multiobjective integer programming problems involving random variables coefficients in both of the multiobjective and constraints.

They projected an interactive fuzzy satisficing method based on fractal criterion optimization for MSIP problems, and verified their plan method in gradual environment, or introduced the chance constrained conditions into the problem, transformed and reformulated the problems into agreeing equivalent deterministic integer programming problems based on fractal criterion optimization, introduced fuzzy goals into the problem, employed and defined a new concept efficient solution, namely: $M - \theta -$ efficiency as follows: $x^* \in X$ is said to be a $M - \theta-$ efficient solution to:

$$minimize\ \mu_i(\zeta_l(x)), l = 1, \dots, k$$
$$s.t.$$
$$x \in X$$

if and only if there doesn't another $x \in X$ such that $\mu_l(\zeta_l(x)) \geq \mu_l(\zeta_l(x^*)), \forall l \in \{1, \dots, k\}$, and $\mu_j\left(\zeta_j(x)\right) > j\left(\zeta_j(x^*)\right), for\ at\ least\ j \in \{1, \dots, k\}$, for all the optimization model, where, $\mu_l(.)$ is a membership function to quantity a fuzzy goal for the l^{th} objective function in the optimization model.

They introduced the $M - \theta -$ efficiency as a combination of stochastic approaches and fuzzy ones. Finally, used a genetic algorithm (GA) of constructed an interactive satisficing method to develop satisficing approximation efficient solution $M - \theta-$ efficient by adapting the membership levels considered.

Zhang et al. (2010) proposed a fuzzy-robust stochastic multiobjective programming (FRSMOP) approach to integrate fuzzy-robust linear programming and stochastic linear programming into a general form of multiobjective programming problems. For reflecting the decision-makers preference can generate selected number of non-inferior or robust solutions. They have proven that the FRSMOP approach can deal with fuzziness and randomness effectively where the information of parameters were uncertain and can be expressed as a fuzzy membership functions or as probability distribution. On the other hand, FRSMOP method has been developed by the authors and has applied it to a case study of planning petroleum waste management successfully.

They concluded that the DM can generate the proposal approach by selecting a number of non-inferior desired solutions by trade-offs between conflicting environmental and economic objectives. Hence, the method is applicable to many other practical real life problems if there exist a trade-off among conflicting objectives.

On the Pareto sufficient solution, Bringmann and Friedrich (2010) suggested a fully polynomial randomized approximation scheme (FPRAS) for hyper volume, but with hardly computational step since it must be performed as search algorithm at each iteration of the Pareto sufficient solution procedure.

A capacity investment has been formulated and discussed as a kind of stochastic multiobjective integer programming (SMOIP) problems, and a local search metaheuristics has been proposed as a solution technique for it(Claro and Sousa, 2010).

Various kinds of fuzzy linear programming (FLP) problems have been considered (Ebrahimnejad et al., 2010; Ebrahimnejad and Nasseri, 2010; Ebrahimnejad et al., 2011; Nasseri and Ebrahimnejad, 2010b; Nasseri et al., 2010) and several research methodology using the concept of comparison of fuzzy numbers to solve these problems were proposed. Most suitable methods stated are based on the concept of comparison of fuzzy numbers using linear ranking functions. Zheng et al. (2011) studied BLPP and presented a new proposal method, namely a fuzzy inter-active method in BLPP, where the lower level/follower level is a multiobjective linear optimization problem as well as upper level/leader level. They formulated bilevel multiobjective programming problem (BMOP) as follows:

$$(x.y)^{Max_{F(x,y)}}$$
$$s.t.$$
$$A_1x + B_1y \le b_1$$
$$x \ge 0$$
$$where\ y\ solves$$
$$y^{Max_{C_y}}$$
$$s.t.$$
$$A_2x + B_2y \le b_2$$
$$y \ge 0$$

where $x \in R^{n_1}, y \in R^{n_2}$ the decision variables of BMOP are dividied into two classes; up level ble x and lower level variable y.

$F: R^{n_1} \times R^{n_2} \to R^{m_1}, F = (F_1, \dots, F_{m_1})$,
$C \in R^{m_2 \times n_2}, A_1, A_2, B_1, B_2, b_1, b_2$ are of appropriate dimensions.

The considered problem is solved through two steps: the first step was the transformation of the leader level into multiobjective optimization problem to achieve efficient solutions, while the other is a measurement function to check up the obtained solution if its efficient or not. The interactive method emphasizes that the final solution for the optimization problem is always efficient to the leader level, while the follower level examines all these efficient obtained solutions to help the measurement function until the acceptable solution is obtained.

Laumanns and Zenklusen (2011) examined the stochastic convergence of random search techniques of Pareto front approximations to achieve the random search techniques, equipped with Archive size bounded to store a limited aggregate solutions and other data, were able to get a good approximation to the Pareto. They recommended and analyze two archiving plans that allow to retain a series of groups out of the solution due to meet with one possibility to −Pareto set of a certain quality, under very mild assumptions on the process used for sampling new solutions.

The first algorithm uses hierarchical network for the definition of the family of dominance relations approximate to compare solutions and solution sets. The acceptance of the new solution is based on the potential function that calculates the number of employed boxes (at numerous levels), and thus keeps the progress monotonous accurately into a limit, which covers the Pareto front with non-overlapping funds in the best possible accuracy. The second scheme adapted is to modify the present value on the basis of information that has been collected during the previous period. In this way, it will be probable to achieve the convergence of the best (smaller enough) value and to solve a variety of solutions corresponding k − dominates all other solutions, which is probably the best likely result on the behavior of reducing research methods random or metaheuristics for approximate Pareto front.

Kato and Sakawa (2011) studied MSLP problems and proposed an interactive fuzzy satisficing method based on variance minimization under expectation constraints for MSLP problems. They attached the case where all the coefficients in the objective functions and the constraints in the optimization problem are random variables. The authors used the concept of chance constrained conditions to transform such MSLP problems into equivalent deterministic standard LP problems based on the variance minimization model in expectation constraints circumstances, after introducing fuzzy goals and aims to reflect the ambiguous expressions of the decision maker on objective functions. They verified that the interactive fuzzy saisficing method can easily be employed to solve the deterministic LP problems which were attained from the MSLP problems because since the deterministic optimization problems are convex. On the other hand, it is observed that if the DM studied the objective functions well, perhaps the ambiguity of the DMs judgments for the objective functions be less, and could obtain a robust compromise solution for the original optimization problem.

The multiobjective integer programming (MIP) problems with stochastic objective coefficients considered by Turgut and Murat (2011), proposed to generate a Pareto surface as a solution method for it. Although there are two main exact methods for solving stochastic multiobjective programming (SMOP) problems, namely: the multiobjective approach and stochastic approach in converting MOP problems into its equivalent deterministic programming problems. The authors preferred the second approach to achieve efficient solutions rather than the first one.

Thus, the multiobjective was converted to its equivalent deterministic one based on minimum expectation and variance efficiency concepts, followed by the Pareto method to generate all Pareto surface of MOIP problems.

After four years of linear programming with fuzzy parameters (Jimen´ez et al., 2007), a critical analysis of Hatami Marbini and Tavana (2011) proposed an amendment to the optimal crisp value which is imposed in Jimenezs method. They showed and examined the method given by counterexample that their proposed method is not to be generalized as it offers as an optimal solution under precise restrictive conditions. They could not confirm their claim that the method proposals DMs with reliable information to launch fuzzy goals and aims in real-world problems, thus emphasized that their method can be generalized to solve many real-world linear programming problems where all the coefficients are fuzzy numbers.

In Adeyefa and Luhandjula (2011), many papers have been reviewed and surveyed in multi-objective stochastic linear programming (MOSLP) problems from the second half of the last century to the first decade of this century.

The paper presents that the important ideas from optimization, probability theory, and multi criteria decision analysis, and concrete real life problems, may put the MOLP problem model as several objective functions conflicted, and random variable data under one roof in the optimization problem.

The authors showed that there are three main compromise solutions in the MOSLP problems, namely: hard, soft, and metaheuristics associated with researchers following each method for singling out the solution. On the other side, it explains each compromise solution that the original problem may be solved by one of the main methods: stochastic approach which reduces the problem to a single objective stochastic program, the multiobjective approach which converts the problem into a deterministic multiobjective program, and the hybrid approach which combines the appropriate manner of stochastic approach with multiobjective approach.

In addition the paper focuses on the hard compromise solution, and specific a section to comparison among different solution approaches, and showed the advantages and disadvantages for each approach, furthermore inserts applications for each one.

The paper concludes that the systematic approach to decision making and problem solving can be offered as efficient tools to deal with MOSLP problem, and could inserts some of its properties. In Katagiri and Sakawa (2011), they focused on multiobjective fuzzy random programming (MOFRP) problems which the objective function coefficients are fuzzy random variables, the concept $M - \alpha -$Pareto optimality definition has been extended and a new Pareto optimal solution named $P - M - \alpha -$Pareto optimal solution defined.

The study proposes an interactive method using the reference point method (A.P. Wierzbicki, The use of reference objectives in multiobjective optimization theoretical implications and practical experiences, WP-79-66, International Institute for Applied Systems Analysis, Laxenburg, Austria, 1979), to satisficing the new Pareto optimal solution.

The advantage of the proposed method is the use of a combination of the first stage of two-stage simplex method with the bisection method to obtain exact solution, as it is difficult to solve MOFRP problem and getting an exact solution for it, involving fuzzy random variables, or complex of the form mixture of fuzziness and randomness. Sakawa et al. (2000a) has modeled two-level linear programming involving fuzzy random variable. To deal with such kind of the problems, $\alpha -$ level sets of fuzzy random variables, and $\alpha-$ stochastic two level linear programming problems were defined and with the cooperative behavior of decision makers, solution methods for decision making problems have been considered in the hierarchical models in fuzzy random circumstances.

Stochastic two-level programming problem has been transformed and reduced into deterministic programming problem, and the interactive fuzzy was considered to satisficing obtained solution for the decision maker at the upper level of the cooperative relation between decision makers. The advantage of the proposed method is it can solve all problems by the simplex method.

Maleki et al. (2000) who proposed a crisp model equivalent to FLP problems, presented a new method for solving fuzzy number linear programming (FNLP) problem and using its solution to obtain fuzzy solution of fuzzy variable linear programming (FVLP) problems. Mahdavi-Amiri and Nasseri (2006) extended the concepts of duality in FNLP problems, while Nasseri and Ebrahimnejad (2010a) used this extension as a similar problem leading to the dual simplex procedure for solving FNLP problems.

On the other hand, Ebrahimnejad et al. (2010) proposed a primal-dual simplex procedure to obtain a fuzzy solution of FVLP problem as an efficient method. Furthermore, a fuzzy primal simplex method has been applied to solve flexible LP problem directly without needing to solve any auxiliary problem (Nasseri and Ebrahimnejad, 2010b).

Since the discovery that the dependence idea of Maleki et al. (2000) does not lead to an efficient solution when the decision variables bounded in FNLP problem, a new approaches have been proposed (Ebrahimnejad and Nasseri, 2010; Ebrahimnejad et al., 2011) to overcome this weakness and inefficiency of the dual and prime simplex method.

Ebrahimnejad (2011) presented a paper generalized the concept of sensitivity analysis in FNLP problems. Applied fuzzy simple algorithm and used the general linear ranking functions on fuzzy numbers to regulate changes in the optimal solution of FNLP problems as a result from data changes.

The author built his proposal by depending on sensitivity analysis on crisp linear programming parameters as highlighted by Bazaraa et al. (2005). Furthermore, he depended on if → then fuzzy concept in his paper, i.e. if the change affects the optimality, he performed primal pivots to attain optimality using fuzzy primal simplex method, otherwise if the change rescinds the optimal feasibility, he performed dual pivots to attain optimal feasibility using fuzzy dual simplex method. The researcher got out by the spelt conclusion that the fuzzy primal simplex algorithm and the fuzzy dual simplex algorithm stated by Mahdavi-Amiri et al. (2009) and Nasseri and Ebrahimnejad (2010a) respectively can be used on LP problem with fuzzy numbers for post optimality analysis.

Ben Abdelaziz (2012) considered the multiobjective stochastic programming (MOSP) problems and surveyed most solution approaches to the MOSP problems. The kinds of problems were considered that the random variables can be in the objectives as well as in the constraints. After the definition of the MOSP problems in its general form, and in its linear case, the author emphasized that the linear case of the problem has not been well-defined mathematically. He divided his paper into three main sections:

• Transforming of MOSP problems,
• Efficient solutions for the MOSP problems, and
• Real applications of the MOSP problems.

For the first section, in order to solve MOSP problem, it needs to be transformed into its equivalent deterministic form and finding an optimal solution for it.

Since the random variables exist in both the objectives and the constraints, therefore before transforming the multiobjective, the random constraints have to be addressed and transformed to obtain a deterministic feasible set. As soon as the random constraints have converted into feasible deterministic constraints, the multiobjective functions should be transformed either by multiobjective transformations or by stochastic transformations.

The first transformation eliminate the randomness of the problem in the first step, after that it must look for appropriate technique to solve the deterministic model and generally solved by interactive methods. Several proposed methods have been inserted to solving MOSP problem by multiobjective transformations. While in the second one, the multiobjective ought to be aggregated first to obtain a uniobjective stochastic program, then solving it by stochastic approach like weighted sum approach, and the obtained problem can be handled either by a recourse method or by a chance constrained method, by goal programming approach or compromise programming models. Also, several approaches were inserted for this transformation.

On efficient solutions for the MOSP problem, when the DM solving the deterministic transformed problem from the original problems, (he) must be concerned in the second step for the best solution, because it is natural to view the solution for the original problem as a non-dominated. To overcome this weakness, the DM must search the Pareto-efficient solutions, or to consider the probability distribution in order to define efficient solutions. The paper provides some general definitions for the efficient solutions for the MOSP problem. For real applications of the problem, several applications have been inserted in various fields like water resources management, management of stochastic farm resources, mineral blending, thermal power generation scheduling, human resource management, and financial applications. The paper concludes that understanding the situation of the problem by program modeler has its role and his/her contribution in the resolution process has also its role to get an optimal solution to the original problem, and depending on the decision situation and numerous meanings of efficient solutions can be measured.

In (Mu˜noz and Ben Abdelaziz, 2012), the stochastic multiobjective programming (SMOP) problems deals with the concepts of satisfactory solution for these kind of problems, different concepts of satisfactory solutions for SMOP problems have been introduced, and has defined a new concept of solution.

The paper shows the aims and purposes of the study; analyze the different concepts of disease solutions for SMOP problems through the application of fundamental criteria in conversion objective functions to deterministic ones through expected value, standard deviations, and probabilistic goals.

On the other hand, authors ideas and suggestions are displayed as follows: First, the DM must choose transformation criteria for all stochastic objectives individually and the specific corresponding aspiration levels. Second, the obtained aspiration levels must be analyzed according to the other transformation criterion for each stochastic objective, and supply the DM of various satisfactory sets which are included from his/her satisfactory solutions have been selected. Third, the DM can change the transformation criterion for some stochastic objectives during the transformations analysis.

In the study, two transformation criteria for stochastic objectives have been considered: expected value-standard deviation and the Kataoka criterion, where the authors defined three satisfactory solution concepts: $E\sigma, LP\ and\ 2LP$.On the other hand, the paper proposed some new propositions: a set of satisfactory solutions $E\sigma\ or\ 2LP$ and a set of satisfactory solutions $LP\ or\ 2LP$.

Sakawa et al. (2012b) studied fuzzy random two (bi)-level linear programming (BLP) problems with vagueness judgments of decision makers. He introduced fuzzy goals into formulated non-cooperative problem involving fuzzy random variables and has considered Stackelberg solutions for decision making problems in hierarchical optimizations in fuzzy random circumstances.

The authors considered that each objective function fulfills the possibility and necessity measuring fuzzy goal correspondingly through stochastic programming with fuzzy maximum probability (A. Charnes, W. W. Cooper, Deterministic equivalents for optimizing and satisficing under chance constraints, Oper. Res. 11(1963)1839), then proposed a new bilevel fuzzy random decision making models that fulfills maximum probabilities in which the degrees of each necessity and possibility is greater than or equal to pre-specific value.

They transformed the problem into its corresponding equivalent deterministic bilevel fractional programming (DBFP) problem by extending Stackelbergs concept solutions which can be obtained by combining the variable transformation method (Charnes A., Cooper W.W. (1962) Programming with linear fractional functionals. Nav Res Logist Q 9:181186), and K^{th} best algorithm (Bialas WF, Karwan MH (1984) Two-level linear programming. Manag Sci 30:10041020) and by introducing computational methods in getting the deterministic bilevel programming (DBP) problem. Finally, looking for an optimal solution for the obtained DBP problem and a compromise feasible solution can be obtained for the original problem. Sakawa et al. (2012a) continuously studied BLP problems, dealt with new decision making problems, and introduced several concepts like: hierarchical modeling and structures, fuzziness and randomness simultaneously, no cooperative relationships between two decision makers are taken into account in dealing with bilevel linear programming (BLP) problems, considering non-cooperation between decision makers, and assuming that both possibility and necessity measure is fulfilled by each objective function.

Considering the vague nature of decision making, fuzzy goal is introduced to minimize fuzzy random non-cooperative BLP problems, thereby transforming such model into stochastic bilevel programming (SBP) problem to maximize the degree of possibility and necessity; then transforming the SBP problem through expectation optimization in the stochastic programming by extending Stackelbergs concept solutions as pointed in their previous study, and to finally look for an optimal solution for the obtained DBP problem.

3. Conclusion

In this paper, we have surveyed the various types of multiobjective linear programming problems, the fuzziness and/or randomness in objective functions and/or in constraints and the full fuzzy stochastic linear programming problems. We have studied the multiobjective fuzzy stochastic linear programming problems chronologically from the beginning of the century up to the present, and what relatives to them, such; modeling, and how to transform them into their corresponding deterministic multi (uni) objective linear programming problems, and what research methodologies used to achieve this aim. On the one hand, how the deterministic problem has been solved, and on the other hand the optimal solution for the original has been discussed too.

Finally, we concluded that:

1. We have not examined all studies and publications for multiobjective fuzzy stochastic linear programming because this collective action and institutional, and we cannot,
2. each of multiobjective fuzzy/stochastic linear programming problems addresses and deals with real world problems partially, and neither meet the desired purpose nor achieve the desired aim of the problem,
3. with the increasing complexity and entanglements of the real world, facing the real life world problems requires multiobjective fuzzy stochastic non (linear) programming problems, and in the uncertainty circumstances and environments, and
4. Pareto optimal solution and solution efficiency are two relative concepts from DM to other.

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