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A Multi-criteria Fuzzy Random Crop Planning Problem using Evolutionary Optimization

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***Abstract*—In this paper, we deal with fuzzy random objectives in a multi-criteria crop planning problem considered as a multi-objective linear programming problem. These fuzzy random factors are related to decision making processes in practice, especially the uncertainty and synthesized objectives of experts. The problem is transformed into a multi-objective nonlinear programming problem by a step of evaluating expectation value. Instead of using classical methods, we use a multi-objective evolutionary algorithms called NSGA-II to solve the equivalent problem. This helps finding many approximate solutions concurrently with a low time consumption. In computational experiments, we create a specific fuzzy random crop planning problem with the data synthesized from government's reports and show convergence of the algorithm for proposed model.**

***Index Terms*—Fuzzy random coefficients, Crop planning problem, Multi-objective programming, Evolutionary algorithms**

I. Introduction

IN PRACTICAL optimization problems, the unknown and uncertain factors are inevitable. They present the errors in measuring processes, the randomness or vagueness of data or expert's knowledge, the approximation or uncertainty in decision making and inference processes,... These factors affect the parameters of both objective functions and constraints in programming problems. There are some approaches for single objective problem of stochastic programming, for instance probabilistic programming (Vajda [18]), fuzzy programming (Sakawa [13]), fuzzy random programming (Luhandjula and Gupta [9]). Then these studies are extended for multi-objective stochastic programming problem (see Sakawa [13], Katagiri et al. [8], Yano et al. [21], [22] and references therein). In these works, the authors consider the multi-objective linear programming problem including fuzzy/ random or both fuzzy random coefficients. The stochastic problems are transformed by probabilistic models or fuzzy models to the deterministic variants. These problems are usually nonlinear and nonconvex problems. They are solved by deterministic optimization algorithms in interactive approaches to find some efficient solutions. In this research, we also consider multi-objective fuzzy random linear programming modeled by the expectation model [8] and solve it by efficient multi-objective evolutionary algorithms.

Crop planning problem is a very popular and highly concerned in agricultural countries. Besides regularly maximizing the net revenue, the managers may deal with other objectives like gross revenue, water consumption, erosion, labor,... with restrictions of land, labor, min-max yield requirement. A wide survey of optimization techniques for crop planning was studied by Jain et al. [7] and provides views on previous research about this problem. Derived from reality, its coefficients are hard to be specified exactly, therefore fuzzy approaches including fuzzy goals are usually engaged [10], [14] and also fuzzy random approaches [17], [21], [22]. Our stochastic model for crop planning problem has some differences from the models of Yano et al. [21] and Toyonaga et al. [17]. While these models dealt with possibility measure directly, our main focus is discrete randomness of random fuzzy variables. It comes from the decision making process of experts in practice which is presented specifically in Section 2.2.

Due to the advantages of parallel computing as well as compatibility with various types of objectives and constraints, multi-objective evolutionary algorithms (MOEA) which are based on evolutionary algorithms have been advanced for decades [6], [19] to deal with multi-objective optimization problems. The essential attribute of these algorithms is population-based nature, which grants the ability to generate many non-dominated solutions simultaneously, therefore they can gradually converge toward Pareto solutions and present an approximate Pareto front at each iteration loop if well-established. With the significant performance when compared to later algorithms [4], NSGA-II [2] has been a standard algorithm used to evaluate new methods. For that reason, we choose NSGA-II represented for MOEA to solve our crop planning problem, which is different from the deterministic methods in [17], [21].

The paper content is summed up as follows: Section 2 formulates our crop planning problem in form of a fuzzy random multi-objective linear programming which is transferred to an equivalent form of degree of possibility. An expectation model is defined in Section 3 as a means to handle the stochastic problem. The algorithm NSGA-II is presented in fourth section with the aim of solving the expectation model. Computational experiments are shown in the next one and the last one presents a conclusion.

II. Crop planning as a fuzzy random multi-objective linear programming problem

A. Crop planning problem

Crop planning problem (CPP) is a problem of considering what kind of crops should be planned on a predetermined cultivated area in order to archive optimal benefits of predefined objectives. Suppose that n is the number of disparate crops whose planned areas denoted by $x_i,\ i = 1,\dots,n$. In practice, agricultural managers often determine several essential objectives like revenue, time consumption, labor, water consumption, erosion [7], we assume that k is the number of objectives. Then the problem is formulated as follows

$$\begin{aligned} &\text{Min } \ Cx = (c_1x,\dots,c_kx) \\ &\text{s.t. } \ x \in X \end{aligned} \tag{1}$$

where $x = (x_1,\dots,x_n)^T$ and $c_i = (c_{i1},\dots,c_{in}), i = 1,\dots,k$ are the coefficients of i^{th} objective function. The feasible set X may contain constraints that are relevant to cultivation like land, labor, water, min-max yield,...

B. Crop Planning Problem with fuzzy random coefficients

We formulate crop planning problem in the same way likes Yano et al. [20] with the random and fuzzy transformation processes dealing with practical needs. Specifically, in an expert-based decision system, we need to quantify reliability of each expert after gathering estimated coefficients in optimization model. Also, we have to evaluate modeling error as well, therefore it is essential to associate both random and fuzzy approaches in order to similarly fit the actual model.

We assume that there is not only one set of values for coefficients vectors of objective functions but an expert group's decision with their own distinct reliability. Denoting E_i as the number of experts who specify coefficients vector of i^{th} objective function, p_{ie} $(e \in \{1,2,...,E_i\})$ is the quantified reliability of expert e which satisfies

$$\sum_{e=1}^{E_i} p_{ie} = 1, \quad i = 1,2,...,k. \tag{2}$$

Subsequently, by denoting that random attribute by symbol "−", linear programming problem (1) becomes

$$\begin{aligned} &\text{Min } \ \overline{C}x = (\bar{c}_1x,\dots,\bar{c}_kx) \\ &\text{s.t. } \ x \in X, \end{aligned} \tag{3}$$

where $\bar{c}_i = (\bar{c}_{i1},\dots,\bar{c}_{in})$, are estimated by expert $E_i, i = 1,2,...,k$. Each the value $\bar{c}_{ij}$ has its own values c_{ije} evaluated by expert e $(e \in \{1,2,...,E_i\})$ with the reliability p_{ie}.

By examining each estimated c_{ije} $(e \in \{1,2,...,E_i\})$ values's bias caused by miscalculation of human, we regard estimated coefficients by each expert as symmetric triangular fuzzy variables with membership function in form

$$\mu_{\tilde{c}_{ije}}(t) = \max\left\{0, 1 - \frac{|t - c_{ije}|}{\gamma_{ij}}\right\}, \tag{4}$$

where $\tilde{c}_{ije}$ are fuzzy extension variables of c_{ije}, γ_{ij} are positive constant which denote the spread of fuzzy numbers. With implementation of Zadeh's extension principle, each objective function becomes fuzzy random variable and has membership function as follows

$$\mu_{\tilde{\bar{c}}_ix}(y) = \max\left\{0, 1 - \frac{|y - \bar{c}_ix|}{\gamma_ix}\right\}, \quad i = 1,2,...,k, \tag{5}$$

where $\gamma_i = (\gamma_{i1}, \gamma_{i2}, ..., \gamma_{in}) > 0$. Therefore, problem (3) transforms into

$$\begin{aligned} &\text{Min } \ \tilde{\overline{C}}x = (\tilde{\bar{c}}_1x,\dots,\tilde{\bar{c}}_kx) \\ &\text{s.t. } \ x \in X, \end{aligned} \tag{6}$$

where $\tilde{\bar{c}}_i = (\tilde{\bar{c}}_{i1},\dots,\tilde{\bar{c}}_{in}), i = 1,\dots,k$ and $\tilde{\bar{c}}_{ij}$ is a fuzzy random variable with its own fuzzy numbers set which represents expert estimation.

Furthermore, decision makers often expect objective functions to reach desired values as close as possible in practice. Consequently, we can define a set of fuzzy goal functions corresponding to objective functions to assess the quality of each solution, the formula is expressed by

$$\mu_{\tilde{G}_i}(y) = \begin{cases} 1 & y < \delta_i^1 \\ \frac{y-\delta_i^0}{\delta_i^1-\delta_i^0} & \delta_i^1 \le y \le \delta_i^0 \\ 0 & y > \delta_i^0, \end{cases} \tag{7}$$

where δ_i^0 is the maximum acceptable value that i^{th} objective function are not expected to exceed and δ_i^1 is the upper bound of most effective range that i^{th} objective function is required to reach. By utilizing the notion of degree of possibility, the level that objective function $\tilde{\bar{c}}_ix$ satisfies the fuzzy goal $\tilde{G}_i$ is presented as

$$\Pi_{\tilde{\bar{c}}_ix}\left(\tilde{G}_i\right) = \sup_y \min\left\{\mu_{\tilde{\bar{c}}_ix}(y), \mu_{\tilde{G}_i}(y)\right\}, i = 1,...,k. \tag{8}$$

In consequence, problem (6) can be regarded as

$$\begin{aligned} &\text{Max } \ \Pi_{\tilde{\bar{c}}_ix}\left(\tilde{G}_i\right), \quad i = 1,\dots,k \\ &\text{s.t. } \ x \in X \end{aligned} \tag{9}$$

III. Expectation model

To deal with problem (9), Katagiri et al. [8] introduced E-model which maximizes the expectation of possibility measure. Considering the i^{th} objective function estimation of expert e $(e \in \{1,2,...,E_i\})$ in (5) and fuzzy goal (7), possibility measure of (8) in that scenario becomes

$$\Pi_{\tilde{c}_{ie}x}\left(\tilde{G}_i\right) = \frac{(\gamma_i - c_{ie})\,x + \delta_i^0}{\gamma_ix - \delta_i^1 + \delta_i^0}, \quad i = 1,2,...,k \tag{10}$$

Thus, the expectation evaluation of (8) is calculated as follows

$$E\left[\Pi_{\tilde{\tilde{c}}_i x}\left(\tilde{G}_i\right)\right] = \sum_{e=1}^{E_i} p_{ie}\Pi_{\tilde{c}_{ie}x}\left(\tilde{G}_i\right) = \frac{\left(\gamma_i - \sum_{e=1}^{E_i} p_{ie}c_{ie}\right)x + \delta_i^0}{\gamma_i x - \delta_i^1 + \delta_i^0}. \quad (11)$$

By notating $Q_i^E = E\left[\Pi_{\tilde{\tilde{c}}_i x}\left(\tilde{G}_i\right)\right]$, we examine problem (9) by an expectation maximizing model as follows

$$\begin{aligned} \text{Max} \ & Q_i^E(x), \quad i = 1, \ldots, k, \\ \text{s.t.} \ & x \in X. \end{aligned} \quad (12)$$

IV. The Multi-Objective Evolutionary Algorithm Solving Crop Planning Problem

In this section, we use the evolutionary algorithm (EA) approach NSGA-II [2] (Non-dominated sorting genetic algorithm II) to deal with the equivalent crop planning problem as a multi-objective programming problem (12), instead of using the deterministic algorithms (see [15], [16] and references therein) or interactive methods (see [17], [21]). The reason is that EAs simultaneously find many approximate solutions (see [1], [11]) without analysis of objective functions and have speedy performance when compared with classical methods. Decision makers can easily choose the optimal solution from this approximated solution set, for instance, by adding a sub-criteria as optimizing a function over the finite set of approximated solutions. And NSGA-II has been one of the state-of-the-art evolutionary algorithms for years. The NSGA-II's principal idea is presented briefly as follows

After initializing a random solution set which is a N sized parent population P_0, the algorithm launches into a iterations loop with t^{th} parent population P_t as input. Firstly, P_t creates a same size offspring population Q_t by implementing genetic operators: selection, crossover, mutation. Next, P_t and Q_t are merged to construct the $2N$ sized population R_t in order to maintain the elitism of populations. A procedure to classify R_t into a set of ranked non-dominated fronts $\mathcal{F}$ is performed afterwards, before the second one selects N best solutions from $\mathcal{F}$ as the next generation population P_{t+1} due to low-rank priority and proposed crowding distances measurement which partly produces solutions diversity in objective space. This iteration loop ends when termination conditions are met.

V. Computational Experiments

In this section, implementation of NSGA-II is illustrated in a particular example of crop planning problem.

TABLE I
MIN-MAX QUANTITY LIMITS IN 4 KINDS OF CULTIVATED FARMS.

Type	Min quantity(tons)	Max quantity(tons)
Rice	22,000,000	∞
Vegetable	6,000,000	12,000,000
Rice	3,872,000	7,000,000
Shrimp	850,000	6,000,000

TABLE II
PARAMETERS OF OBJECTIVE FUNCTIONS.

	$e=1$	$e=2$	$e=3$	γ_{ij}
c_{11e}	-66	-63	-64	5
c_{12e}	-180	-185	-177	4
c_{13e}	-294	-300	-295	5
c_{14e}	-384	-386	-380	3
p_{1e}	0.5	0.3	0.2	
c_{21e}	83	88	85	3
c_{22e}	231	225	234	4
c_{23e}	65	64	68	3
c_{24e}	127	125	125	3
p_{2e}	0.6	0.2	0.2	

In Mekong Delta of Vietnam, there are many types of cultivate farms, but for a concise example we only consider four main kinds including rice, vegetable, fruit and shrimp farm. By denoting their farming land areas as $x = (x_1, x_2, x_3, x_4)^T$, we deal with an multi-objective optimization problem modeled in form of (6) with two objectives: revenue and labor. With 2019 data collected from Vietnam MARD[1]'s reports, we convert restriction of land areas and min-max quantity limits described in Table I to problem's constraints also the coefficients of objective functions after dividing them by same numbers in order to get small values without changing the ratios. Therefore, the crop planning problem is represented as follows

$$\begin{array}{lrcl} \min & \tilde{\tilde{c}}_1 x = \tilde{\tilde{c}}_{11}x_1 + \tilde{\tilde{c}}_{12}x_2 + \tilde{\tilde{c}}_{13}x_3 + \tilde{\tilde{c}}_{14}x_4 \\ \min & \tilde{\tilde{c}}_2 x = \tilde{\tilde{c}}_{21}x_1 + \tilde{\tilde{c}}_{22}x_2 + \tilde{\tilde{c}}_{23}x_3 + \tilde{\tilde{c}}_{24}x_4 \\ \text{s.t.} & x_1, x_2, x_3, x_4 \in \mathbb{R}, \\ & x_1 + x_2 + x_3 + x_4 & \leq & 35000, \\ & -6.11x_1 & \leq & -22000, \\ & -1.42x_2 & \leq & -6000, \\ & 1.42x_2 & \leq & 12000, \\ & -1.06x_3 & \leq & -3872, \\ & 1.06x_3 & \leq & 7000, \\ & -0.12x_4 & \leq & -850, \\ & 0.12x_4 & \leq & 6000, \end{array} \quad (13)$$

where $\tilde{\tilde{c}}_{ij}\,(i = 1, 2; j = 1, 2, 3, 4)$ are fuzzy random coefficients specified by three experts with corresponding possibility, spread values given in Table II and the parameters of fuzzy goal functions are shown in Table III. With denoting feasible set in (13) as X for short, we transform (13) into an E-model described in (12)

$$\begin{aligned} \text{Min} \ & \left(-Q_1^E(x), -Q_2^E(x)\right) \\ \text{s.t.} \ & x \in X. \end{aligned} \quad (14)$$

For solving multi-objective optimization problem (14) by NSGA-II, we initialize genetic parameters including: crossover probability is 0.5, mutation probability is 0.5, population size is 100, simulated binary crossover, random reset mutation, max iteration is 200. To observe improvement of NSGA-II, we collect populations of 4 iterations and visualize their objective values in Fig. 1, owing to the convergence of population that can't get better after iteration 200. We can

[1]Ministry of Agriculture and Rural Development: https://mard.gov.vn/.

TABLE III
PARAMETERS OF FUZZY GOAL FUNCTIONS.

	δ_i^0	δ_i^1
$i = 1$	-5000000	-11000000
$i = 2$	5000000	2000000

TABLE IV
HYPERVOLUME OF POPULATIONS.

Iteration	Hypervolume
25	0.1499
50	0.1649
100	0.1976
200	0.2293

notice that after converging to Pareto optimal front at iteration 100, NSGA-II enhances diversity of population and eventually creates last population marked by black pentagram in large range distribution which provides wide range strategies for making decisions with different circumstances. We also use the hypervolume metric [12] to quantify the result which shown in Table IV. The algorithm is deployed in MATLAB and consumed 68.6 seconds for 200 iterations on Intel Core i7-5600U which is a bit slow cause of recreation of feasible solutions in genetic phases.

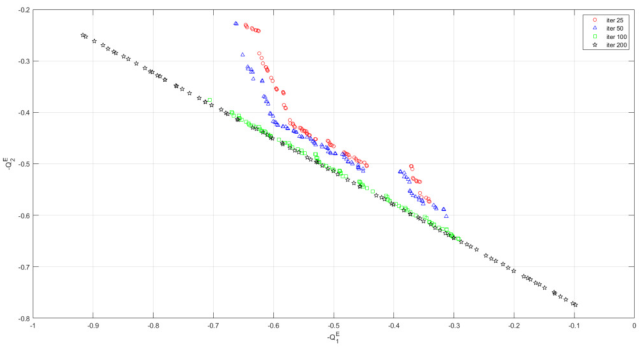

Fig. 1. NSGA-II generations on the proposed crop planning problem.

VI. CONCLUSION

In this paper, we use a multi-objective evolutionary algorithms - NSGA-II to solve the fuzzy random crop planning problem with the data analysed from ministry's reports. We construct a crop planning problem based on uncertainty of experts for collecting data, synthesizing objective suggestions and making decisions. The final result presents the convergence of the algorithm and the diversity's improvement afterwards giving decision makers multiple plans to choose while balancing examined objectives. Based on considering the stochastic factors, the cropping arrangement is more flexible in different conditions. In future, we shall model the fuzzy random multi-objective linear programming problem by other stochastic models for example variance or probability one, as well as establish more efficient algorithms to solve.

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