Random Matrix Generators for Optimizing a Fuzzy Biofuel Supply Chain System

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1. Introduction

Industrial optimization often involves systems containing various complexities and uncertainties - thus requiring heavy computational effort when performing optimization. In such scenarios, metaheuristics play a prominent role (Ganesan et al.[25]; Ganesan et al.[26]; Yang [66]; Ganesan et al. [24]; Ganesan et al. [27]; Hong et al.[32]; Dong et al. [21]). Decision makers are globally facing various optimization challenges when optimizing supply chains - this is attributed to its large-scale and complex structure. Currently various state-of-the-art tools have been developed to overcome these challenges where they have been used to:

- Model these supply chains (Seuring [55]; Brandenburg et al. [12]; Ahi and Searcy [3])
- Efficiently optimize the decision making process (Ogunbanwo et al. [47]; Mastrocinque et al. [43])

Fuel supply chains have broad applications spanning across diverse industrial sectors. For instance in Lin et al. [38], the annual biomass-ethanol production cost in a fuel supply chain was minimized. In that work, the large-scale optimization

Abstract. Complex industrial systems often contain various uncertainties. Hence sophisticated fuzzy optimization (metaheuristics) techniques have become commonplace; and are currently indispensable for effective design, maintenance and operations of such systems. Unfortunately, such state-of-the-art techniques suffer several drawbacks when applied to large-scale problems. In line of improving the performance of metaheuristics in those, this work proposes the fuzzy random matrix theory (RMT) as an add-on to the cuckoo search (CS) technique for solving the fuzzy large-scale multiobjective (MO) optimization problem; biofuel supply chain. The fuzzy biofuel supply chain problem accounts for uncertainties resulting from fluctuations in the annual electricity generation output of the biomass power plant [kWh/year]. The details of these investigations are presented and analyzed.

Keywords
Random matrix theory, fuzzy framework, cuckoo search, biofuel supply chain, multiobjective (MO), large-scale optimization.
supply chain model consisted of: stacking, in-field preprocessing, transportation, transportation, biomass harvesting, packing/storage, ethanol production and ethanol distribution. Aiming to reduce the cost of production in a biorefinery (to approximately 62%), the researchers used the mixed integer programming technique. Another interesting work on a switchgrass-based bioethanol supply chain (located in North Dakota, U.S) was presented in the work of Zhang et al. [71]. In that work the supply chain system was modeled and optimized using mixed integer linear programming to attain the optimal utilization of marginal land for switchgrass production. The end goal for that work was to establish an economical and sustainable harvest of bioethanol. In Osmani and Zhang [49], a sustainable dual feedstock bioethanol supply chain (large-scale) was optimized in a stochastic environment. The optimization problem considered the following factors: biomass purchase and sales price; as well as biomass supply and demand. In addition to a mixed integer linear programming approach, the authors used a decomposition method: sample average approximation algorithm. A holistic review on metaheuristic techniques implemented to bioenergy supply chains could be seen in De Meyer et al. [20] and Castillo-Villar [14].

Due to uncertain variables in biofuel supply chains, recent works have integrated fuzzy formulations into these supply chain models. A very interesting fuzzy methodology for modeling supply chains was introduced in Kozarević, S. and Puška [35]. In that work the authors proposed a method for data processing and measurement of practices and performances of supply chains. This is done by conducting applying transformation of the obtained linguistic values (using appropriate fuzzy methods) into crisp values of research variable dimensions. A more practical work could be seen in Babazadeh [6]. In that work, the author developed a novel fuzzy framework for a bioenergy supply chain: the possibilistic programming model based on possibilistic mean and absolute deviation of fuzzy numbers. The model performance was evaluated by using data from a real-world case study and it was shown that the proposed method performed better than a pure possibilistic programming model. A similar work can be seen in Lin et al. [37]. In that work the uncertain factors considered were the demand of biomass energy (due to unstable price of fossil fuels) and the number of job offer opportunities springing up from the energy facilities. To account for these uncertainties the authors employed a fuzzy multiple objective linear programming to solve the problem. Another effective implementation of fuzzy framework for biofuel supply chains could be seen in the work of Balaman et al. [9]. In that work, a hybrid solution strategy combining fuzzy set theory and epsilon-constraint method was proposed. The proposed methodology was applied to handle system-specific uncertainties during the optimization of the supply chain and transportation network (entire West Midlands (WM) region of the UK). Fuzzy optimization has also been employed to model the design of renewable energy supply chains (integrated with district heating systems) (Balaman et al. [10]). In the work of Balaman et al. [10], the authors developed a novel decision model to obtain the optimal supply chain configuration and district heating system to meet the thermal demand of a certain locality. To this end, the authors formulated and validated a Fuzzy Mixed Integer Linear Programming (MILP) which consists of multiple types of biomass and systemic uncertainties.

Cuckoo search (CS) technique has been efficiently employed for optimizing real-world supply chains. A series of metaheuristics including CS was applied to a supply chain (consumer-packaged goods industry) (Mattos et al. [44]). The performance as well as the results generated by the techniques employed was presented in that work. Similar CS implementations on supply chains is given in Srivastav
and Agrawal [58] and Abdelsalam and Elssal [1]. Supply chains models often contain many variables (large-scale) - where these variables and expressions are interlinked in a complex way. The mathematical structure (universality) of such supply chains often resemble those observed in the nuclei of heavy atoms (e.g. gold, rhodium and platinum). Random matrices were developed to specifically model complex systems which contain universality - i.e. large and complex systems with highly interconnected components (Che [16]). Random Matrix Theory (RMT) has been utilized to model such systems in:

- Solid state physics (Verbaarschot [62]; Beenakker [11])
- Quantum information theory (Collins and Nechita [18])
- Quantum chromodynamics (Alemann [4])
- Transport optimization (Krbašek and Seba [36])
- Big Data (Qiu and Antonik [52])
- Finance

It is important to note that key characteristics of supply chain networks are highly similar to those mentioned complex systems. Hence the premise: that supply chains may naturally contain universality. Following this chain of thought, the RMT framework was utilized to improve the the conventional Cuckoo Search method (CS) in this work. This was carried out by performing certain modifications to the stochastic generator component of the algorithm. In this work the conventional Gaussian stochastic generator is replaced with a RMT-based generator.

This work targets to solve the complex MO fuzzy biofuel supply chain model. The previous approaches to solve this problem uses conventional linear and nonlinear programming approaches which do not account for the complexity of the large-scale problem at hand (Ghaderi et al. [30], Chávez et al. [15], Roni et al. [54], Bairamzadeh et al. [8]). Additionally current works and tackling this problem do not consider the uncertainty in the annual electricity generation output of the biomass power plant [kWh/year]. This work contributes to the field by addressing both concerns: (1) by reformulating the MO biofuel supply chain problem as a fuzzy problem to account for uncertainties arising from the annual electricity generation output of the biomass power plant [kWh/year]. (2) The complex MO fuzzy biofuel supply chain problem is solved by using the RMT-based method - which has been observed to be very effective for solving highly complex large-scale problems (Ganesan et al. [28]).

This paper is organized as follows: Section 2 presents the fuzzy formulation of the MO biofuel supply chain model. In Section 3 the conventional CS approach is presented while an overview of RMT and its role in the development of stochastic generators is described in Section 4. Section 5 presents the results and discussion followed by the final section; conclusions and potential directions for future work.

2. Biofuel supply chain: fuzzy formulation

The fuel supply chain formulation utilized in this work was developed in Tan et al. [61]. In that work only two objective functions were considered: profit (Pr) and social welfare (SW). The environmental benefits objective was incorporated into the SW function. In this work, the environmental benefits function was isolated from the SW function and taken as an independent objective function (denoted Env). Various factors influence electricity generation output of biomass power plants. For instance, plant system repairs, maintenance, inspections which involve turnaround periods and downtime influence the electricity generation output. Since biomass plant type considered in this model involves various types of fuel sources (e.g. sugarcane, wheat straw, bean straw, rice husk, corn cobs, branches, bark, and wood chips), the biomass plant would have to be frequently tuned to maintain robustness in the face of fuel heterogeneity. Such tuning would incur downtime which could heavily influence the power generation output. To account for these uncertain-
ties, the fuzzy formulation was employed - where the annual electricity generation output of the biomass power plant [kWh/year] is fuzzied with its respective constraint:

\[
\sum_t q_t \in [Q_{\text{min}}, Q_{\text{max}}] \rightarrow \sum_t \tilde{q}_t \in \tilde{Q}_{\min}, \tilde{Q}_{\max}
\]

where

\[
\tilde{Q}_{\min} = [1260000, 2340000], \\
\tilde{Q}_{\max} = [1714000, 3182000].
\]

where the uncertainty in the annual electricity generation output of the biomass power plant is assumed to contain a variation of approximately 30% from the mean. The optimization formulation of the biofuel supply chain problem is then redefined in the fuzzy environment with the elaborated structure as follows:

Minimize (objective functions: \( Pr, SW, Env \))

subject to fuzzy constraints:

\[
\sum_{j=1}^n a_{ij} x_j \leq \tilde{b}_i, \quad i = 1, 2, \ldots, m
\]

and Crisp (Non-fuzzy) constraints.

The left side of \( i \)-th fuzzy constraint in (2), \( \sum_{j=1}^n a_{ij} x_j \) is aggregated as a fuzzy set - utilizing Zadeh’s extension principle. Assuming a credibility level \( \varepsilon, (0 < \varepsilon < \frac{B}{1+C}) \) chosen by the decision maker, as a risk is taken and all the membership degrees smaller than \( \varepsilon \) levels are ignored (Rommelfanger et al. [33]). All fuzzy data \( \tilde{b}_i \equiv \hat{S}(b^a_i, b^b_i) \) comprise of fuzzy variables with the following logistic membership functions (Elamvazuthi et al. [22]),

\[
\mu_{\tilde{b}_i} = \begin{cases} 
1 & \text{if } b_i \leq b^a_i \\
\frac{B}{1 + Ce^\alpha \left( \frac{b_i - b^a_i}{b^b_i - b^a_i} \right)} & \text{if } b^a_i \leq b_i \leq b^b_i \\
0 & \text{if } b_i \geq b^b_i
\end{cases}
\]

where \( \alpha = d/j \).

The fuzzy coefficients \( B = 1, C = 0.1 \) and the \( \alpha \in (0, 1) \). The following points are considered when we replace a crisp system by a fuzzy system (Atanu et al. [73]):

(i) Specification of fuzzy inequality relations and methodology to obtain its crisp equivalents.

(ii) The interpretation ‘minimization’ in logistic type objective functions.

Therefore the fuzzy fuel supply chain model in this chapter consists of three objective functions to be maximized along with associated inequality constraints (see equation (9)). The objective functions are shown in equations (1)-(3):

\[
Pr = P(1 - EC) \times \sum_t q_t
\]

\[
\begin{aligned}
&FC_p \\
&+ \sum_t \left[ GC \cdot q_t + \sum_i \left( SC \cdot IQ_{i,t} + \sum_k SQ_{i,k,t} \cdot PP_i \right) \cdot Y_{1t} \cdot \text{extra}_1 + Y_{2t} \cdot \text{extra}_2 \right]
\end{aligned}
\]

\[
SW = ACS \cdot (1 - EC) \sum_t q_t + GT - GS \cdot (1 - EC) \sum_t q_t
\]

\[
Env = AC \cdot \left[ CET \cdot (1 - EC) \cdot \sum_t q_t \right] - (CEcb - CEtp)
\]

such that,

\[
CEcb = 2 \sum_{i,k} PQ_{i,k} \cdot \sum_{i,k} \left[ CEcb_{i,k} \cdot Dcb_{i,k} \right]
\]

\[
+ \left( \sum_{i,k} PQ_{i,k} \cdot \sum_{i,k} CEicb_{i,k} \cdot Dcb_{i,k} \right)
\]

\[
CEtp = 2 \sum_{i,k} SQ_{i,k} \cdot \sum_{i,k} \left[ CEnt_{i,k} \cdot Dtp_{i,k} \right]
\]

\[
+ \left( \sum_{i,k} PQ_{i,k} \cdot \sum_{i,k} CEicb_{i,k} \cdot Dcb_{i,k} \right)
\]
The crisp constraints for the biofuel supply chain model are given below:

\[ q_t \leq q_{\text{max}} \tag{10} \]
\[ IQ_{i,t} \geq S I b_i \tag{11} \]
\[ \sum_i IQ_{i,t} \leq IQ_{\text{max}} \tag{12} \]
\[ HV_{\text{min}} \leq \sum_i HV_i \cdot BR_{i,t} \leq HV_{\text{max}} \tag{13} \]
\[ \sum_i SQ_{i,k,t} \geq SQ_{\text{min},k} \tag{14} \]
\[ \sum_i PQ_{i,k,t} \leq PQ_{\text{max}} \tag{15} \]
\[ \sum_i PQ_{i,k,t} \leq AQ_{\text{max},i,t} \tag{16} \]
\[ WR_{i,k,t} \leq \left[ 1 - \frac{MC_{\text{ori},i,t}}{1 - MC_{\text{max},i,t}} \right] \tag{17} \]

\[ \sum_{i,t} SQ_{i,k,t} \cdot PP_{i,k,t} \geq [E_1 + E_2 + E_3] \cdot (1 + ER_k) \tag{18} \]

where

\[ E_1 := FC_{\text{b}k} \]
\[ E_2 := \sum_{i,t} SQ_{i,k,t} \cdot \left( \frac{AP_{i,k,t} + TC_{\text{c}b_i,k} \cdot D_{\text{c}b_{ik}}}{LC_{\text{c}b_{ik}}} \right) \frac{1}{WR_{i,k,t}} \]
\[ E_3 := \sum_{i,t} SQ_{i,k,t} \cdot \frac{T C_{\text{p}i,k} \cdot D_{\text{p}k}}{L C_{\text{p}i,k}} \]

such that,

\[ i \in [1,2], k \in [1,10], t \in [1,12] \tag{19} \]

The decision parameters are: \( q_t, IQ_{i,t}, SQ_{i,k,t}, PQ_{i,k,t} \) and \( BR_{i,t} \). Details on the parameter settings of the biofuel supply chain model used in this work could be obtained in Tan et al. [61].

### Tab. 1: CS Settings

| Parameters | Values |
|------------|--------|
| Total Number of Eggs (N) | 20 |
| Number of nests, nests | 4 |
| Lévy flight step-size, \( \lambda \) | 1.5 |
| Relaxation factor, \( \beta \) | 0.8 |
| Maximum number iteration, \( T_{\text{max}} \) | 300 |

### 3. Cuckoo search

CS is a population-based stochastic search and optimization algorithm (Mareli and Twala [41]; Joshi et al. [33]). It was initially inspired by brood parasitism which was often found among certain species of cuckoo birds. This parasitism occurs when the cuckoo birds lay their eggs in the nests of other bird species (non-cuckoo birds). The heavy-tailed random walk probability distribution, Lévy flights was used as a stochastic generator for the CS technique. The iterative expression at iteration, \( t \) for the candidate solution \( i \) for the CS technique is:

\[ y_{i}^{t+1} = y_{i}^{t} + \beta \cdot \text{Levy} (\lambda) \tag{20} \]

such that the Lévy distribution is given as follows:

\[ \text{Levy} (\lambda) = t^{-\lambda} \tag{21} \]

where \( t \) is the random variable, \( \beta > 0 \) is the relaxation factor (which is modified based on the problem at hand) and \( \lambda \in (1,3] \) is the Lévy flight step-size. With \( t \geq 1 \), \( \lambda \) is related to the fractal dimension and the Lévy distribution becomes a specific sort of Pareto distribution. The CS algorithm is based on a few fundamental philosophies. For instance each cuckoo bird lays a single egg at one time and randomly places the egg in a selected nest. The second being: via fitness screening, the best egg (candidate solution) is carried forward into the next iteration. The worst solutions are discarded from further iterations. The nests represent the objective space (or the optimization problem landscape). The parameter setting for the CS technique used in this work is shown in Tab. 1 while its respective algorithm is given in Algorithm 1:
Algorithm 1: Cuckoo Search (CS)

Step 1: Initialize algorithmic parameters; \( y_i, \beta, \lambda, N \)

Step 2: Define parameters in the constraints and decision variable

Step 3: Via Lévy flights randomly lay a cuckoo egg in a nest

Step 4: Define fitness function based on solution selection criteria

Step 5: Screen eggs and evaluate candidate solution

IF: fitness criteria is satisfied

Select candidate solution (egg) to be considered in the next iteration, \( n + 1 \)

ELSE: fitness criteria is not satisfied

Discard candidate solution (egg) from further iterations

Step 6: Rank the best solutions obtained during fitness screening

Step 7: If the fitness criterion is satisfied and \( t = T_{\text{max}} \) halt and print solutions, else proceed to Step 3.

4. Random matrix theory & stochastic generators

Random Matrix Theory (RMT) is a robust mathematical framework which is very effective for describing behavior of complex systems. RMT is known to exhibit universality – a property of global symmetries shared by many systems within a certain symmetry class. Details on the application of RMT on a non-fuzzy (crisp) biofuel supply chain model could be seen in Ganesan et al. [28]. In RMT there exists two probability distributions describing: the random matrix entries and the eigenvalue spread. The nearest neighbor spacing probability distribution of eigenvalues is given by Wigner’s Surmise:

\[ P(s) = A_i s^i \exp(-B_i s^2) \]  

(22)

where \( s \) is the eigenvalue spacing, \( A_i \) and \( B_i \) are constant parameters. The normalized spacing, \( s \) and the mean spacing \( \langle s \rangle \) is as follows:

\[ s = \frac{\lambda_{n+1} - \lambda_n}{\langle s \rangle} \]  

(23)

such that \( \langle s \rangle = \langle \lambda_{n+1} - \lambda_n \rangle \), where \( \lambda_n \) is the \( n^{th} \) eigenvalue sequentially such that \( \lambda_1 < ... < \lambda_n < \lambda_{n+1} \). The first type of random matrices are those that are modeled based on complex quantum systems (which have chaotic classical counterparts). RMT consists of four major ensembles to determine the spacing distributions of the eigenvalues: the Gaussian Orthogonal Ensemble (GOE), Gaussian Unitary Ensemble (GUE) and Gaussian Symplectic Ensemble (GSE). In this work, the GUE distribution is considered:

\[ P(s) = \frac{32}{\pi^2} s^2 \exp\left(-\frac{4}{\pi} s^2\right) \]  

(24)

These ensembles describe the probability density functions governing the random matrix entries. The constants, \( A_i \) and \( B_i \) are selected such that the following averaging properties are respected:

\[ \int_0^\infty ds P(s) = 1 \quad \text{and} \quad \int_0^\infty ds P(s)s = 1 \]  

(25)

Metaheuristics are equipped with stochastic generators called the random generator - which randomly initializes the search operation of the metaheuristic. This is done by positioning the starting point of the search operation prior to exploring the objective space. In the works of Ganesan et al. [25], Ganesan et al. [26] and Ganesan et al.[27], it was seen that variations in the type of stochastic generators have an influence on the optimization results. Therefore in this work the RMT is employed as the stochastic generator to solve the fuzzy biofuel supply chain problem. Essentially RMT deals with systems with a complex network of many interlinked and interacting components - which are often encountered in real-world settings. The proposed algorithmic framework for developing a random matrix generator is as follows:

Algorithm 2: Random Matrix Generator

Step 1: Generate random eigenvalue spacings, \( s \) from a GUE

Step 2: Determine the average eigenvalue spacing, \( \Delta \lambda \)

Step 3: Set initial eigenvalue, \( \lambda_0 \)
Step 4: Set initial \( n \times n \) matrix, \( H_{ij} \)

Step 5: Determine consequent eigenvalues

\[
\lambda_{i+1} = \lambda_i + \Delta \lambda
\]

Step 6: Determine \( n \times 1 \) eigenvector, \( E_i \):

\[
E_i = \sum_j H_{ij} + \lambda_i
\]

Step 7: Generate random variables from a Gaussian probability distribution function endowed eigenvector as the variance, \( \sigma^2 = E_i \):

\[
P_i(x) = \frac{1}{\sqrt{2\pi}E_i^2} \exp\left(-\frac{(x - \mu)^2}{2E_i^2}\right)
\]

5. Results and discussion

The following frameworks have been introduced in the past for tackling MO optimization problems: Strength Pareto Evolutionary Algorithm (SPEA-2) (Zhao et al.[69]), Weighted sum approach (Naidu et al. [46]), Normal-Boundary Intersection (NBI) (Ahmadi et al.[2]; Ganesan et al.[23]) and Non-Dominated Sorting Genetic Algorithm (NSGA-II) (Mousavi et al.[45]). Scalarization and NBI approaches involve the aggregation of multiple target objectives. Effectively transforming the MO problem into a single objective one reduces its complexity to a high degree - making it easier to solve. In this work, the objective functions of the fuzzy MO biofuel supply chain problem was combined into a single function using the weighted sum approach (Kalita et al.[34]). This procedure effectively transforms the fuzzy MO problem into a single-objective optimization problem which can be solved for different weight values. The computational experiments employed in this work was done using the C++ programming language on a computer using a 64-bit Win 10 platform with an Intel Core i5-7200U CPU (2.50 GHz).

Due to the stochastic nature of the algorithms employed in this work, the computational technique was executed multiple times (3 executions) and the best solution was taken. 28 solutions were obtained for a variation of weights. These solutions were then used to construct the Pareto frontier. - at which the individual solutions were classified as best, worst and median. The measured solutions were ranked using the hypervolume indicator (HVI) (Bringmann and Friedrich [13]). Applying the HVI, the level of solution dominance for the fuzzy MO optimization problem could be measured. A Nadir point is usually employed as a basis (or a baseline value) while measurement using the HVI. In this work, the nadir point for the HVI is computed as follows:

\[
HVI = \left[\frac{(z_1 - 10^6)(z_2 - 10^4)(z_3 - 10^2)}{10^{16}}\right]^{(26)}
\]
where \( z_1, z_2 \) and \( z_3 \) are individual candidate solutions. The ranked weighted individual solutions obtained using the fuzzy CS approach with random matrix generators (fuzzy RMT-CS) is given in Tab. 2. The entire Pareto frontier constructed using the fuzzy RMT-CS technique is shown in Fig. 1. In this analysis (Tab. 2 and Fig. 1), the values for the fuzzy membership function in equation (3) is fixed: \( d = 0.2 \) and \( j = 0.2 \).

The HVI value for the entire Pareto frontier is 27,957.73 and the total computational time taken for construction was 33.128 seconds. To observe the variation of the objective function with respect to the membership functions, the weights are fixed to \((PR, SW, Env) = (0.4, 0.2, 0.4)\) which is the best individual solution obtained (see Tab. 2).

In Fig. 1, some prevalent trends could be observed in the distribution of the solution points in the objective space. One of these trends is the high concentration of solution points in specific regions of the objective space: \( PR \in (3.0 \times 10^8, 3.8 \times 10^8) \), \( SW \in (1,004,400,1,004,800) \) and \( Env \in (0.8 \times 10^4) \). This high concentration could be attributed to the technique iteratively reaching the most optimal (local or near optimal) region of the objective space. Despite those high concentrations, some solution points could be observed to exist beyond those optimal regions. This shows that the proposed technique generates a sparse distribution of solutions and hence has good exploration capabilities - where the fuzzy RMT-CS approach explores regions in the objective space in search of other local optima.

The variation of the objective function, \( PR \) with respect to the parameters in the fuzzy membership function is given in Fig. 2:

In Fig. 2, the maximum value of \( PR \) is 365,021,000 obtained at \( d = 0.4 \) and \( j = 4 \) which corresponds to \( \mu = 0.1 \) (see equation) The median value of \( PR \) is 327,626,500 and it falls between \( \mu = 0.05 \) and \( \mu = 0.1 \). The minimum value of \( PR \) (259,954,000) is obtained at \( \mu = 0.0667 \). The objective function, \( SW \) plotted with respect to the parameters in the fuzzy membership function is given in Fig. 3:

The maximum and minimum value of the SW objective function shown in Fig. 3 were 1,005,660 and 1,004,490 with the membership value of \( \mu = 0.0667 \) and \( \mu = 0.1 \). The median value obtained was 1,004,650 which was in between \( \mu = 0.033 \) and \( \mu = 0.05 \). The objective function, \( Env \) with relative to the membership function is presented in Fig. 4:

| Description | Best | Median | Worst |
|-------------|------|--------|-------|
| weights \( w_1 \) | 0.4  | 0.2    | 0.1   |
| weights \( w_2 \) | 0.2  | 0.4    | 0.3   |
| weights \( w_3 \) | 0.4  | 0.4    | 0.6   |
| Objective functions | | | |
| \( PR \) | 246831000 | 352010000 | 342717000 |
| \( SW \) | 1005810 | 1004490 | 1004550 |
| \( Env \) | 242631 | 10598.1 | 124.342 |
| Iterations | \( t \) | 100 | 78 | 67 |
| Metric | HVI | 5937.18 | 366.46 | 0.83 |

The variation of the objective function, \( PR \) with respect to the parameters in the fuzzy membership function is given in Fig. 2:
Figure 3 shows that the objective function, $SW$ with respect to the parameters $d$ and $j$ in the logistic membership function.

Figure 4 shows that the objective function, $Env$ with respect to the parameters $d$ and $j$ in the logistic membership function.

Figure 4 shows that the objective function, $Env$ has a maximum of 266,045 at $\mu = 0.05$ and minimum of 5,326.36 at $\mu = 0.1$. The median of 22,092.65 was obtained between the membership values of $\mu = 0.075$ and $\mu = 0.3$.

The fuzzy RMT-CS approach produced feasible solutions; where the constraints in the fuzzy biofuel supply chain model was not broken. The computations performed during the numerical experiments were stable and the algorithm achieved convergence every time during execution. In terms of robustness, the fuzzy RMT-CS method performed stable computations and converged towards a feasible solution during each variation of the fuzzy membership function. The random matrix segment successfully complemented the CS technique to navigate through the objective space of the complex and multivariate biofuel supply chain problem.

Nevertheless the proposed technique does have some disadvantages. The first is the algorithmic complexity - where the addition of the RMT segment into the CS technique significantly increases the complexity of the algorithm. This in effect may considerably impact the computational time of the optimization process. Additionally, this technique only considers the GUE ensemble distribution and not the GOE as well as the GSE distributions for the RMT. This may adversely impact the performance of the proposed technique. Finally this work considers the uncertainty in the annual electricity generation output of the biomass power plant [kWh/year] to be of type-1 fuzzy uncertainty. It is high possible that fluctuations in the monthly/weekly electricity generation output of the biomass power plant may more precisely capture the mentioned uncertainties - making the model more realistic.

6. Conclusion and recommendations

In this work, the proposed MO biofuel supply chain problem was reformulated by taking into account fluctuations in the annual electricity generation output of the biomass power plant [kWh/year]. This effectively converts the problem into a fuzzy MO problem; which is nonlinear, nonconvex and multivariate. To deal with this MO problem the CS technique was retrofitted with the RMT approach to boost its performance when faced with high levels of complexity. The proposed approach was effectively applied and Pareto efficient solutions were attained. The dominance of these solutions were gauged using the HVI.

Further computational tests could be done by using the GSE and GOE ensembles for the RMT segment in the proposed approach. In addition, RMT - based generators could also be employed to complement other metaheuristic techniques such as PSO (Mousavi et al. [45]), differential evolution (Ganesan et al. [24]) as well as other computational approaches (Ganesan et al.[25]). The accuracy of the fuzzy formulation proposed in this work could be further improved by ac-
counting for monthly/weekly fluctuations; by re-formulating the MO biofuel supply chain problem by utilizing a type-2 fuzzy framework. This work can also be extended by exploring other approaches for handling uncertainty such as: robust optimization, (Bairamzadeh et al. [7]; Kara et al.[31]), stochastic optimal control (Vinod et al. [63]) and chance constraint optimization (Cheng et al. [17]). This extension could include emerging areas of applications such as complex networks in alternative energy systems (Syahputra et al. [60]; Lotfi et al. [39]), social networks, gene networks (Youseph et al. [67]) and pharmaceutical supply chain networks (Zahiri et al. [68]).

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Nomenclature and abbreviations

**Biofuel Supply Chain Parameters**

- **AC** abatement cost of carbon dioxide [yuan/kg]
- **CEicb\(_{ik}\)** increment of carbon dioxide emissions with loading each additional ton of biomass fuel per kilometer when broker \(k\) collects biomass fuel \(i\) with no-load conveyance [kg/t and km]
- **AQmax\(_{i,t}\)** maximum available quantity of local biomass fuel \(i\) in month \(t\) [t/month]
- **ACS** average electricity consumer surplus [yuan/kWh]
- **CEitp\(_{k}\)** increment of carbon dioxide emissions with loading each additional ton of fuel per kilometer when broker \(k\) transports biomass fuel to biomass power plant [kg/t and km]
- **CEncb\(_{ik}\)** carbon dioxide emissions per kilometer when broker \(k\) collects biomass fuel \(i\) with no-load conveyance [kg/km]
- **CEntp\(_{k}\)** carbon dioxide emissions per kilometer when broker \(k\) transports biomass fuel to biomass power plant with no load conveyance [kg/km]
- **CET** carbon dioxide emissions of thermal power plant for unit power generation [kg/kWh]
| Symbol | Description |
|--------|-------------|
| Dcb<sub>ik</sub> | average transport distance when broker <i>k</i> collecting biomass fuel <i>i</i> [km] |
| Dtp<sub>k</sub> | transport distance between broker <i>k</i> and biomass power plant [km] |
| E | efficiency of biomass power plant [decimal fraction] |
| EC | electricity consumption rate of biomass power plant [decimal fraction] |
| extraY1 | first extra cost of excessive biomass power plant fuel inventory [yuan/month] |
| extraY2 | second extra cost of excessive biomass power plant fuel inventory [yuan/month] |
| ERk | expected return of broker <i>k</i> [decimal fraction mass/year] |
| FCb<sub>k</sub> | fixed cost of broker <i>k</i> [yuan/year] |
| FCp | fixed cost of biomass power plant [yuan/year] |
| GC | unit generation cost of biomass power plant [yuan/kWh] |
| GS | government subsidies to biomass power generation [yuan/kWh] |
| GT | government tax revenues from biomass power plant [yuan/year] |
| HV<sub>i</sub> | heat value of biomass fuel <i>i</i> [kJ/kg] |
| HVe | heat value of electricity [kJ/kWh] |
| HV<sub>max</sub> | maximum heat value of mixed fuel [kJ/kg] |
| HV<sub>min</sub> | minimum heat value of mixed fuel [kJ/kg] |
| IQ<sub>i,0</sub> | inventory quantity of biomass fuel <i>i</i> at the beginning of month 1 [tonnes] |
| CEcb | carbon dioxide emissions during collecting biomass fuel [kg] |
| CEtp | carbon dioxide emissions during transporting biomass fuel to biomass power plant [kg] |
| EIC | extra inventory cost of biomass power plant [yuan] |
| IQ<sub>i,t</sub> | inventory quantity of biomass fuel <i>i</i> at the end of month <i>t</i> [tonnes] |
| PP<sub>i</sub> | purchase price of biomass fuel <i>i</i> from brokers [yuan/t] |
| PQ<sub>ik,t</sub> | purchase quantity of biomass fuel <i>i</i> by broker <i>k</i> in month <i>t</i> [t] |
| qt | electricity generation of biomass power plant in month <i>t</i> [kWh/month] |
| R<sub>t</sub> | conversion rate from biomass fuel to electricity in month <i>t</i> [kg/kWh] |
| IQ<sub>max</sub> | maximum inventory quantity of biomass power plant [t] |
| IL | rate of inventory loss [decimal fraction/month] |
| LCcb<sub>ik</sub> | load capacity of conveyance when broker <i>k</i> collects biomass fuel <i>i</i> [t] |
| Symbol | Description |
|--------|-------------|
| LCtp<sub>ik</sub> | Load capacity of conveyance when broker <i>k</i> transports biomass fuel <i>i</i> to biomass power plant [t] |
| MC<sub>max</sub><sub>i</sub> | Maximum moisture content of biomass fuel <i>i</i> required by biomass power plant [decimal fraction mass] |
| MC<sub>ori</sub><sub>ii</sub><sub>_t</sub> | Original moisture content of biomass fuel <i>i</i> in month <i>t</i> [decimal fraction mass] |
| MC<sub>aft</sub><sub>_ik</sub> | Moisture content of biomass fuel <i>i</i> after processing by broker <i>k</i> [decimal fraction mass] |
| P | On-grid price of biomass power plant [yuan/kWh] |
| PQ<sub>max</sub><sub>_k</sub> | Maximum purchasing quantity of biomass fuel by broker <i>k</i> [t/month] |
| q<sub>max</sub> | Maximum monthly electricity generation quantity of biomass power plant [kWh/month] |
| Q<sub>max</sub> | Maximum annual electricity generation quantity of biomass power plant [kWh/year] |
| Q<sub>min</sub> | Minimum annual electricity generation of biomass power plant [kWh/year] |
| Ū<sub>max</sub> | Fuzzy maximum monthly electricity generation quantity of biomass power plant [kWh/month] |
| Ū<sub>max</sub> | Fuzzy maximum annual electricity generation quantity of biomass power plant [kWh/year] |
| Ū<sub>min</sub> | Fuzzy minimum annual electricity generation of biomass power plant [kWh/year] |
| RI<sub>ub1</sub> | First upper bound of reasonable fuel inventory [t] |
| RI<sub>ub2</sub> | Second upper bound of reasonable fuel inventory [t] |
| SI<sub>lb</sub><sub>_i</sub> | Lower bound of safety inventory for biomass fuel <i>i</i> [t] |
| SC | Unit storage cost of biomass power plant [yuan/month] |
| SQ<sub>min</sub><sub>_ik</sub> | Minimum supply quantity of biomass fuel <i>i</i> from broker |
| TC<sub>cb</sub><sub>_ik</sub> | Average unit transportation cost of broker <i>k</i> when collecting biomass fuel <i>i</i> [yuan/km] |
| TC<sub>tp</sub><sub>_ik</sub> | Average unit transportation cost of broker <i>k</i> when transporting biomass fuel <i>i</i> to biomass power plant [yuan/km] |
| WR<sub>_ik</sub><sub>_t</sub> | Ratio of the weight of biomass fuel <i>i</i> after processing to the weight before processing by broker <i>k</i> in month <i>t</i> [decimal fraction mass] |
| AP<sub>_ik</sub><sub>_t</sub> | Average price of broker <i>k</i> buying biomass fuel <i>i</i> in month <i>t</i> [yuan/t] |
\(BC_{i,t}\) biomass fuel \(i\) consumption in month \(t\) [t]

\(BR_{i,t}\) blending ratio of biomass fuel \(i\) in mixed fuel in month \(t\) [decimal fraction mass]

CER carbon dioxide emissions reduction [kg]

\(CET_{eq}\) carbon dioxide emissions of thermal power plant for power generation equal to biomass power plant [kg]

CEB carbon dioxide emissions of biomass power plant [kg]

\(SQ_{ik,t}\) supply quantity of biomass fuel \(i\) by broker \(k\) in month \(t\) [t]

\(VCp\) total variable cost of biomass power plant [yuan/year]

\(Y_{1t}\) binary variable to determine whether the inventory is over \(R_{1ub1}\) at the end of month \(t\)

\(Y_{2t}\) binary variable to determine whether the inventory is over \(R_{1ub2}\) at the end of month \(t\)

\(B, C\) fuzzy coefficients

\(\alpha\) fuzzy membership function

\(d, j\) fuzzy membership values

\(\varepsilon\) credibility level

\(a_{ij}, \hat{b}_i\) fuzzy constraints

PR Profits (yuan)

SW Social Welfare (yuan)

Env Environmental Benefit (kg/power station)

\(P_1(s)\) Probabilistic Spacing Distribution for Gaussian Orthogonal Ensemble (GOE)

\(P_2(s)\) Probabilistic Spacing Distribution for Gaussian Unitary Ensemble (GUE)

\(P_3(s)\) Probabilistic Spacing Distribution for Gaussian Symplectic Ensemble (GSE)

\(P_0(s)\) Probabilistic Spacing Distribution for Poisson Distribution

\(s\) Eigenvalue Spacing distribution

\(\lambda\) Eigenvalue

\(\Delta \lambda\) Eigenvalue Interval

\(E_i\) Eigenvector

\(H_{ij}\) Initial Matrix

\(\sigma^2\) Statistical variance

\(\mu\) Statistical Mean

\(w_i\) Weights for the weighted sum method

\(T_{\text{max}}\) Maximum limit of function evaluations

\(m\) Maximum number of objective functions

\(HVI\) Hypervolume Indicator

\(\beta\) Relaxation factor

iter Number of algorithm iterations

\(t\) Random Variable

\(y^{t_i}\) Candidate solution

\(\text{Levy}(\lambda)\) Lévy Distribution

\(N\) Total Number of Eggs

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