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A Bi-Objective Optimization Model to Design a Reliable Biomass Supply Chain Network under Uncertainty and Congestion Effect

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***Abstract** – This study proposes a bi-objective optimization model to design a reliable biomass-biofuel supply chain, in which loading and unloading hubs and biorefineries can be encountered with disruption. For this purpose, the first objective function minimizes the total costs, and the second one minimizes the total times of recovery of disrupted facilities. Furthermore, due to the uncertain essence of the biomass supply chain, two efficient approaches, including robust optimization and congestion effect, are considered to overcome this challenge. Finally, several test problems are investigated to demonstrate the validity of the suggested mathematical model.*

***Keywords**– biomass; supply chain; robust optimization; congestion effect; reliability.*

I. INTRODUCTION

One of the main streams of sustainable energy production during recent years is biofuels production attributed to cellulosic feedstock. In this regard, to achieve the production of 16 billion gallons of cellulosic ethanol in 2022 (EPA, 2010; Lan et al. 2020), which will be required to fulfill the customers' demands, nothing more than 200 million MG of biomass will be needed per annum with respect the conversion rate of them (Wyman, 2007; Humbird et al., 2011; Lin et al., 2014). Nevertheless, due to the deficiency of trustworthy resources and cost-effective technology, there are a finite number of commercial cellulosic ethanol facilities.

In a biomass supply chain, the significant proportions of production costs typically include bioprocessing at biorefineries and biomass procurement costs (Humbird et al., 2011; Lin et al., 2013). Also, in planning this given supply chain, there are a number of concerns, which are contained uncertainty, seasonality, and dispersed and palmate resources. Additionally, in a year, the mentioned feedstocks should be processed at concentrated biorefineries to make it economical, so biomass preparation in an effectual way can be considered a crucial measure for commercial biofuel production (Lin et al., 2014).

Similar to the other types of supply chain network, to manage and organize this kind of supply chain, the manager is encountered with operational, tactical, and strategic decisions (Vahdani et al., 2017; Salimi and Vahdani, 2018), although the main focus of this study is on the coordination between tactical and strategic decisions. The major strategic decisions are typically included facilities location and allocation them to the other members of the supply chain, capacity

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planning, and biomass resources evaluation; also, the leading tactical decisions are typically included planning or biomass production, inventory control, harvesting, transportation, delivery, scheduling operations, etc. (Quddus et al., 2018).

Practically, there are two types of calamities, including natural and man-made, which endanger facilities and the infrastructure of the supply chain at various disruption risks. In this situation, customers should either cede service or seek substitute ones more remote (Marufuzzaman et al., 2014). In both solutions, any kind of supply chain might face substantial losses. As a result, establishing a reliable supply chain to alleviate the implications of disruptions is one of the main actions, which has been gaining prestige among practitioners and scholars. In this regard, the primary purpose is to return to the normal state by applying appropriate approaches quickly to minimize the related imposed costs of disruption recovery measures. From this perspective, the recovery time of facilities and infrastructures is the central aspect, which can facilitate achieving this purpose (Vahdani et al., 2011; Mohammadi et al., 2014; Vahdani et al., 2018a; Hatefi et al., 2019).

Moreover, because of the increasing competence of the business environment with the short shelf life of merchandises, the performance of a biomass supply chain is very relevant to approximate the uncertain essence of parameters accurately, and ceding this matter can create unsuitable solutions (Vahdani and Naderi-Beni, 2014; Vahdani et al., 2015). In this regard, various parameters such as demand, facility capacity, budget, and cost considered in the literature in an uncertain environment (Vahdani, 2015; Mousavi and Vahdani, 2016; Foroozesh et al., 2018 a,b; Niakan et al., 2015; Vahdani et al., 2016; Veysmoradi et al., 2018; Davoudabadi et al., 2019; Birjandi and Mousavi; Mousavi et al., 15, 2019). What is more, in the course of the peak period of producing biomass, more biomass is expected to carry among different members of the biomass supply chain, so this situation leads to creating congestion at various facilities, and it can have some implications for the performance of this supply chain (Poudel et al., 2018).

Ekşioğlu et al. (2009) formulated a biomass- biorefinery supply chain network under an uncertain environment, where the objective function minimized the total costs. Different decisions such as facility location-allocation, shipping, inventory control, and capacities of facilities were ascertained. To consider several crucial decisions such as facility location-allocation and capacity planning to design a biomass supply chain network, two-stage stochastic programming was proposed by Kim et al. (2011), where the objective function maximized the profit of the investigated system. A multi-period mathematical model was considered by An et al. (2011) to design a lignocellulosic biofuel supply chain, in which different decisions such as facility location-allocation, shipping, and capacities of facilities were ascertained. The objective function of this study minimized the total profit under a specific condition. In order to determine the number of decisions such as the location of biorefineries, shipping planning, routing of vehicles, and capacity expansion of roadway in a biofuel supply chain, a mathematical model was proposed by Hajibabai and Ouyang (2013), where the objective function minimized the total costs. With the intention of reflecting the biomass shortage considerations in a biofuel supply chain, a mathematical model was proposed by Zhang and Hu (2013), where the objective function minimized the total costs.

Awudu and Zhang (2013) investigated a biofuel supply chain to formulate the biofuel logistics network under an uncertain environment, in which two significant parameters, including demand and price, were considered uncertain parameters. Also, to surmount these uncertainties, a stochastic programming method was utilized, where the objective function maximized the total expected profit. What is more, they proposed a hybrid solution method, including Monte Carlo simulation and benders decomposition to solve the proposed model. To render a reliable biofuel supply chain, a mathematical model proposed by Marufuzzaman et al. (2014), in which the probability of disruption is considered for the one type of facility. Also, a probabilistic model was offered to estimate the disruption probability.

Also, accelerated Benders decomposition was proposed to solve the proposed model. Ahn et al. (2015) investigated a microalgae biomass-biodiesel supply chain network and offered a mathematical model to formulate this problem, where the objective function minimized the total costs. What is more, they considered various resources, such as phosphorus, CO2, flocculant, H2O, flocculant, and nitrogen, to supply feedstocks. In order to formulate a forest biomass-biodiesel supply chain network, a multi-period mathematical model was proposed by Zhang et al. (2016), where the objective function minimized the total costs. More importantly, they considered two transportation modes for better planning of shipments in the investigated supply chain.

By considering the probability of disruption of facilities, a multi-period mathematical model was proposed by Maheshwari et al. (2017) to design a resilient biomass-biofuel supply chain, where the objective function minimized the total costs. In this study, the number of decisions, such as location-allocation of facilities, inventory control, and shipping planning, was determined. The considerations of facilities disruptions and congestion in biorefineries were reflected in a multi-period mathematical by Poudel et al. (2018). They utilized an M/M/1 queuing system to overcome the challenges of congestion. What is more, a heuristic algorithm was also offered to solve the proposed model. Salimi and Vahdani (2018) offered a mathematical model in which the facility and connection link among facilities can be encountered with disruption, simultaneously. The major decisions of this research were location-allocation of facilities and the improvement amount of reliability of connection links. Also, they conducted a risk-pooling method to surmount the challenges of uncertainty in demands.

Furthermore, they employed two meta-heuristic algorithms to solve the proposed model. Lee et al. (2019) rendered a multi-period mathematical model to formulate a biomass-biofuel supply chain problem, where the objective function maximized total profit. Hence, a new bi-objective optimization model is proposed to design a reliable biomass supply chain network. The first objective function minimizes the totals costs. The second one minimizes the total time of recovery of disrupted facilities, in which some decisions, including facilities location-allocation, recovery time, recover budget, number of containers, and production amount of biofuel, are determined.

The rest of this paper is organized as follows: The proposed model is described in Section 2. The solution approach is introduced in Section 3. The computational results are provided in Section 4. Finally, the conclusions are provided in Section 5.

II. PROBLEM DEFINITION

A three-echelon biomass supply chain is addressed, which is contained feedstock suppliers, loading and unloading hubs, and biorefineries. In order to reflect the calamity repercussions, the disruption possibility is two mentioned facilities considered for loading and unloading hubs and biorefineries. It is worth noted that the failure probabilities of the two mentioned facilities are independent. In this problem, feedstocks are supplied by suppliers and transported to the loading and unloading hubs; next, these raw materials are carried to the biorefineries by containers. Also, the storage capacities of loading and unloading hubs, containers, and biorefineries, and production capacities of biorefineries are restricted.

On the other side, to mitigate the repercussions of the peak period of harvesting biomass, such as increasing costs, the congestion effect at biorefineries is considered by utilizing an M/M/1 queuing system. Additionally, to return to the normal state after disruption in a minimum time quickly, the total time of recovery of disrupted facilities is minimized, although the recovery and outsourcing budgets are limited for this purpose. More importantly, there are two alternative ways to carry biomass from supplier to biorefineries; the first one is a straightforward way, and the second one is through loading and unloading hubs.

A. Sets and indices

I: Set of suppliers

J: Set of loading and unloading hubs

K: Set of biorefineries

L: Set of capacities

B. Parameters

$\tilde{w}_{lj}$: Opening cost for a loading and unloading hub with capacity l at location j

$\tilde{w}_{lk}$: Opening cost for a biorefinery with capacity l at location k

$\tilde{\delta}_{jk}$: Fixed cost of container for transporting biomass from multi-modal terminal j to biorefinery k

$\tilde{c}_{ik}$: Unit transportation cost for the biomass from supplier i to biorefinery k

$\tilde{c}_{ijk}$: Unit transportation cost for the biomass from supplier i through loading and unloading hub j to biorefinery k

$\widetilde{cp}_{lk}$: Unit cost of production of bio-fuel at biorefinery k with capacity l

$\tilde{s}_i$: Available amount of biomass at supplier i

$\tilde{d}_k$: Minimum amount of biofuel production in biorefinery k

cap_{jk}: Capacity to transport biomass containers from loading and unloading hub j to biorefinery k

ca_{lj}: Biomass storage capacity at loading and unloading hub j with capacity l

ca_{lk}: Biomass storage capacity at biorefinery k with capacity l

pca_{lk}: Biofuel production capacity at biorefinery k with capacity l

φ: Rate of conversion from biomass to biofuel

q_j: Probability of failure of loading and unloading hub j

q_k: Probability of failure of biorefinery k

cc: Congestion cost

mr_j: Maximum preservation resource once loading and unloading hub j encounters a disruption

mr_k: Maximum preservation resource once biorefinery k encounters a disruption

$\tilde{B}_j$: Preservation budget for loading and unloading hub j

$\tilde{B}_k$: Preservation budget for biorefinery k

p_j: Proportion of resource consumed for recovery loading and unloading hub j

p_k: Proportion of resource consumed for recovery biorefinery k

oc_j: Outsourcing cost for loading and unloading hub j per unit time

oc_k: Outsourcing cost for biorefinery k per unit time

$\tilde{u}_k$: Penalty coefficient for each unit of unprocessed biofuel at biorefinery k

β: Penalty coefficient of transportation cost

C. Decision variables

Continuous variables:

x_{ik}: Amount of biomass transported from supplier i to biorefinery k

x_{ijk}: Amount of biomass transported from supplier i through loading and unloading hub j to biorefinery k

z_{jk}: Number of containers utilized to transport biomass from loading and unloading hub j to biorefinery k

p_{lk}: Amount of biofuel produced at biorefinery k with capacity l

π_k: Amount of unprocessed biofuel at biorefinery k

t_j: Time of recovery for loading and unloading hub j

t_k: Time of recovery for biorefinery k

rs_j: Budget consumed for recovery loading and unloading hub j

rs_k: Budget consumed for recovery biorefinery k

ob_j: Outsourcing budget consumed for loading and unloading hub j

ob_k: Outsourcing budget consumed for biorefinery k

Binary Variables:

y_{lj}: 1 if a loading and unloading hub with capacity l is opened in location j; 0 otherwise

y_{lk}: 1 if a biorefinery with capacity l is opened in location k; 0 otherwise

D. Mathematical model

$$\begin{aligned}\mathrm{M}in\ Z_1 = & \sum\nolimits_{l\in L}\sum\nolimits_{j\in J}\widetilde{w}_{lj}y_{lj} + \sum\nolimits_{l\in L}\sum\nolimits_{k\in K}\widetilde{w}_{lk}y_{lk} + \sum_{j\in J}\sum_{k\in K}\tilde{\delta}_{jk}z_{jk} + \sum_{l\in L}\sum_{k\in K}\widetilde{cp}_{lk}p_{lk} \\ & + \sum_{k\in K}\tilde{u}_k\pi_k + \sum_{k\in K} cc\left(\frac{\sum_{i\in I}x_{ik} + \sum_{i\in I}\sum_{j\in J}x_{ijk}}{\sum_{l\in L}ca_{lk}y_{lk} - \left(\sum_{i\in I}x_{ik} + \sum_{i\in I}\sum_{j\in J}x_{ijk}\right)}\right) \\ & + \sum_{j\in J}\left(ob_j + rs_j\right) + \sum_{k\in K}\left(ob_k + rs_k\right) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\tilde{c}_{ijk}\left(1-q_j\right)\left(1-q_k\right)x_{ijk} \\ & + \sum_{i\in I}\sum_{k\in K}\tilde{c}_{ik}\left(x_{ik} + \beta\sum_{j\in J}\left(q_j + q_k - q_jq_k\right)x_{ijk}\right)\end{aligned} \tag{1}$$

$$\mathrm{M}in\ Z_2 = \sum_{j\in J}t_j + \sum_{k\in K}t_k \tag{2}$$

S.t.:

$$\sum_{k\in K}\left(x_{ik}+\sum_{j\in J}x_{ijk}\right)\leq \tilde{s}_i \qquad \forall i\in I \tag{3}$$

$$\sum_{i\in I}\sum_{k\in K}x_{ijk}\leq \sum_{l\in L}ca_{lj}y_{lj} \qquad \forall j\in J \tag{4}$$

$$\sum_{i\in I}x_{ik}+\sum_{i\in I}\sum_{j\in J}x_{ijk}\leq \sum_{l\in L}ca_{lk}y_{lk} \qquad \forall k\in K \tag{5}$$

$$\sum_{i\in I}\varphi x_{ik}+\sum_{i\in I}\sum_{j\in J}\varphi x_{ijk}=\sum_{l\epsilon L}p_{lk} \qquad \forall k\in K \tag{6}$$

$$\sum_{i\in I}x_{ijk}\leq cap_{jk}z_{jk} \qquad \forall j\in J,\forall k\in K \tag{7}$$

$$\sum_{l\epsilon L}y_{lj}\leq 1 \qquad \forall j\in J \tag{8}$$

$$\sum_{l\epsilon L}y_{lk}\leq 1 \qquad \forall k\in K \tag{9}$$

$$z_{jk}\leq \sum_{l\in L}\left[\frac{ca_{lj}}{cap_{jk}}\right]y_{lj} \qquad \forall j\in J,\forall k\in K \tag{10}$$

$$z_{jk}\leq \sum_{l\in L}\left[\frac{ca_{lk}}{cap_{jk}}\right]y_{lk} \qquad \forall j\in J,\forall k\in K \tag{11}$$

$$p_{lk}\leq pca_{lk}y_{lk} \qquad \forall l\in L,\forall k\in K \tag{12}$$

$$\sum_{l\epsilon L}p_{lk}+\pi_k=\tilde{d}_k \qquad \forall k\in K \tag{13}$$

$$rs_j=mr_jq_jy_{lj} \qquad \forall l\in L,\forall j\in J \tag{14}$$

$$rs_k=mr_kq_ky_{lk} \qquad \forall l\in L,\forall k\in K \tag{15}$$

$$t_j=\left(\frac{1}{p_j}\right)rs_jy_{lj} \qquad \forall l\in L,\forall j\in J \tag{16}$$

$$t_k = \left(\frac{1}{p_k}\right) rs_k y_{lk} \qquad \forall l \in L, \forall k \in K \tag{17}$$

$$ob_j = t_j oc_j \qquad \forall j \in J \tag{18}$$

$$ob_k = t_k oc_k \qquad \forall k \in K \tag{19}$$

$$\sum_{l \in L} (rs_j + ob_j) y_{lj} \leq \tilde{B}_j \qquad \forall j \in J \tag{20}$$

$$\sum_{l \in L} (rs_k + ob_k) y_{lk} \leq \tilde{B}_k \qquad \forall k \in K \tag{21}$$

$$x_{ik}, x_{ijk}, z_{jk}, p_{lk}, \pi_k, t_j, t_k, rs_j, rs_k, o_j, o_k \geq 0 \quad \forall k \in K, \forall j \in J, \forall l \in L, \forall i \in I \tag{22}$$

$$y_{lj}, y_{lk} \in \{0,1\} \quad \forall k \in K, \forall j \in J, \forall l \in L, \forall i \in I \tag{23}$$

The first objective function (1) minimizes the total costs of the biomass supply chain, in which the first and second terms calculate the opening costs of loading and unloading hubs and biorefineries, respectively. The third term calculates the fixed costs of employed containers. The fourth and fifth terms compute the costs of production and penalty costs at biorefineries, respectively. The sixth term computes the costs of congestion in biorefineries. The seventh and eighth terms compute the outsourcing and recovery budgets consumed at disrupted loading and unloading hubs and biorefineries, respectively. The ninth term computes the expected transportation costs for transported biomasses when loading and unloading hubs are available. The tenth term calculates the costs of transportation under disruption circumstances. The second objective function (2) minimizes the total recovery of disrupted loading and unloading hubs and biorefineries, respectively. Constraint (3) signifies its availability limits the amounts of biomass transported from suppliers. Constraint (4) ensures that its capacities restrict the total amount of biomasses transported to loading and unloading hubs. Similarly, constraint (5) ensures that its capacities restrict the total amount of biomass transported to biorefineries. Constraint (6) signifies the flow balance among facilities. Constraint (7) guarantees that the amount of biomass carried to biorefineries cannot exceed the capacities of containers. Constraints (8) and (9) guarantee that, at most, one capacity level of loading and unloading hub and biorefinery can be chosen. Constraint (10) and (11) restrict the maximum number of containers and ensures that loading and unloading hub and biorefinery have been opened by the time they could provide related service. Constraint (12) limits the capacity of production in biorefineries and guarantees that a biorefinery has been opened by the time it could produce biofuel. Constraint (13) represents a relation between demand, production, and unprocessed biomass. Constraints (14) and (15) calculate the amount of budget that is consumed for recovery of loading and unloading hubs ad biorefineries, respectively (Hatefi et al., 2019). Constraints (16) and (17) calculate the recovery time of loading and unloading hubs ad biorefineries, respectively (Hatefi et al., 2019). Constraints (18) and (19) calculate the amount of budget that is consumed for outsourcing activities of loading and unloading hubs ad biorefineries, respectively (Hatefi et al., 2019). Constraints (20) and (21) signify the limitation of the preservation budget for loading and unloading hubs ad biorefineries, respectively. Constraints (22) and (23) indicate the type of decision variables.

E. Robust counterpart model

In the proposed model, many influential factors, including opening, transportation costs, demand, supply capacity, and budget, are considered uncertain parameters to offer the robust counterpart model. Each of them is regarded as a box uncertainty set. This type of uncertainty set can provide the most conservative solution, while these uncertain parameters can be considered in the worst possible circumstances, simultaneously (Ben-Tal et al., 2009; Vahdani, 2014; Mousavi and Vahdani, 2017; Vahdani et al., 2018a). The box uncertainty set can be represented as follows:

$$u_{Box} = \left\{\xi \in \Re^n : \left|\xi_t - \overline{\xi_t}\right| \leq \rho G_t, \qquad t = 1,2,\dots,n\right\} \tag{24}$$

where ρ denotes the level of uncertainty, G_t signifies the scale of uncertainty, and $\overline{\xi_t}$ is ξ_t the normal value of the tth parameter of vector ξ (Ben-Tal et al., 2009; Saedinia et al., 2019). Concerning the above description, the changed objective functions and constraints are reformulated as follows:

$$\mathrm{M}in\ W_1 \tag{25}$$

$$\mathrm{M}in\ W_2 = \sum_{j\in J} t_j + \sum_{k\in K} t_k \tag{26}$$

S.t.:

$$\begin{aligned}
&\sum\nolimits_{l\in L}\sum\nolimits_{j\in J}\left(\overline{w}_{lj}y_{lj} + \eta_{lj}^{w}\right) + \sum\nolimits_{l\in L}\sum\nolimits_{k\in K}\left(\overline{w}_{lk}y_{lk} + \eta_{lk}^{w}\right) + \sum_{j\in J}\sum_{k\in K}\left(\bar{\delta}_{jk}z_{jk} + \eta_{jk}^{\delta}\right) \\
&\quad + \sum_{l\in L}\sum_{k\in K}\left(\overline{cp}_{lk}p_{lk} + \eta_{lk}^{cp}\right) + \sum_{k\in K}\left(\bar{u}_k\pi_k + \eta_k^{u}\right) \\
&\quad + \sum_{k\in K} cc\left(\frac{\sum_{i\in I} x_{ik} + \sum_{i\in I}\sum_{j\in J} x_{ijk}}{\sum_{l\in L} ca_{lk}y_{lk} - \left(\sum_{i\in I} x_{ik} + \sum_{i\in I}\sum_{j\in J} x_{ijk}\right)}\right) + \sum_{j\in J}\left(ob_j + rs_j\right) \\
&\quad + \sum_{k\in K}\left(ob_k + rs_k\right) + \sum_{i\in I}\sum_{j\in J}\sum_{k\in K}\left(\bar{c}_{ijk}x_{ijk} + \eta_{ijk}^{c}\right)\left(1 - q_j\right)\left(1 - q_k\right) \\
&\quad + \sum_{i\in I}\sum_{k\in K}\left(\left(\bar{c}_{ik}x_{ik} + \eta_{ik}^{c}\right) + \beta\sum_{j\in J}\left(q_j + q_k - q_jq_k\right)\left(\bar{c}_{ik}x_{ijk} + \eta_{ik}^{c}\right)\right) \leq W_1
\end{aligned} \tag{27}$$

$$\rho_w \mathcal{G}_{lj}^{w} y_{lj} \leq \eta_{lj}^{w} \qquad \forall l, j \tag{28}$$

$$\rho_w \mathcal{G}_{lj}^{w} y_{lj} \geq -\eta_{lj}^{w} \qquad \forall l, j \tag{29}$$

$$\rho_w \mathcal{G}_{lk}^{w} y_{lk} \leq \eta_{lk}^{w} \qquad \forall l, k \tag{30}$$

$$\rho_w \mathcal{G}_{lk}^{w} y_{lk} \geq -\eta_{lk}^{w} \qquad \forall l, k \tag{31}$$

$$\rho_\delta \mathcal{G}_{jk}^{\delta} z_{jk} \leq \eta_{jk}^{\delta} \qquad \forall k, j \tag{32}$$

$$\rho_w \mathcal{G}_{jk}^{w} z_{jk} \geq -\eta_{jk}^{\delta} \qquad \forall k, j \tag{33}$$

$$\rho_{cp} \mathcal{G}_{lk}^{cp} p_{lk} \leq \eta_{lk}^{cp} \qquad \forall l, k \tag{34}$$

$$\rho_{cp} \mathcal{G}_{lk}^{cp} p_{lk} \geq -\eta_{lk}^{cp} \qquad \forall l, k \tag{35}$$

$$\rho_u \mathcal{G}_k^u \pi_k \le \eta_k^u \qquad \forall k \tag{36}$$

$$\rho_u \mathcal{G}_k^u \pi_k \ge -\eta_k^u \qquad \forall k \tag{37}$$

$$\rho_c \mathcal{G}_{ijk}^c x_{ijk} \le \eta_{ijk}^c \qquad \forall i,j,k \tag{38}$$

$$\rho_c \mathcal{G}_{ijk}^c x_{ijk} \ge -\eta_{ijk}^c \qquad \forall i,j,k \tag{39}$$

$$\rho_c \mathcal{G}_{ik}^c x_{ik} \le \eta_{ik}^c \qquad \forall i,k \tag{40}$$

$$\rho_c \mathcal{G}_{ik}^c x_{ik} \ge -\eta_{ik}^c \qquad \forall i,k \tag{41}$$

$$\sum_{k \in K} \left(x_{ik} + \sum_{j \in J} x_{ijk} \right) \le (\bar{s}_i - \rho_s \mathcal{G}_i^s) \qquad \forall i \in I \tag{42}$$

$$\sum_{l \in L} p_{lk} + \pi_k \ge \left(\bar{d}_k - \rho_d \mathcal{G}_k^d \right) \qquad \forall k \in K \tag{43}$$

$$\sum_{l \in L} p_{lk} + \pi_k \le \left(\bar{d}_k + \rho_d \mathcal{G}_k^d \right) \qquad \forall k \in K \tag{44}$$

$$\sum_{l \in L} \left(rs_j + ob_j \right) y_{lj} \le \left(\bar{B}_j - \rho_B \mathcal{G}_j^B \right) \qquad \forall j \in J \tag{45}$$

$$\sum_{l \in L} (rs_k + ob_k) y_{lk} \le \left(\bar{B}_k - \rho_B \mathcal{G}_k^B \right) \qquad \forall k \in K \tag{46}$$

$$\eta_{lj}^w, \eta_{lk}^w, \eta_{jk}^\delta, \eta_{lk}^{cp}, \eta_k^u, \eta_{ijk}^c, \eta_{ik}^c \ge 0 \tag{47}$$

III. SOLUTION METHOD

To solve the proposed bi-objective model in the previous section, TH method as a multi-objective solution approach, which was proposed by Torabi and Hassini (2008), is employed as follows:

Step 1: Determining the positive and negative ideal solutions for each OF. For this purpose, the presented model is separately solved for each of OFs, and the positive ideal solutions (PISs) is obtained, $(\mathcal{W}_1^{PIS}, x_1^{PIS})$ and $(\mathcal{W}_2^{PIS}, x_2^{PIS})$. In what follows, the harmful ideal solutions (NISs) are calculated as follows:

$\mathcal{W}_1^{NIS} = \mathcal{W}_1(x_2^{PIS}), \mathcal{W}_2^{NIS} = \mathcal{W}_1(x_1^{PIS}),$

Step 2: Computing the membership function for each objective as follows:

$$\mu_h(x) = \begin{cases} 1 & if \quad \mathcal{W}_h < \mathcal{W}_h^{PIS} \\ \dfrac{\mathcal{W}_h^{NIS} - \mathcal{W}_h}{\mathcal{W}_h^{NIS} - \mathcal{W}_h^{PIS}} & if \quad \mathcal{W}_h^{PIS} \leq \mathcal{W}_h \leq \mathcal{W}_h^{NIS} \\ 0 & if \quad \mathcal{W}_h > \mathcal{W}_h^{NIS} \end{cases} \tag{48}$$

where the satisfaction degree is denoted by $\mu_h(x)$ for the h^{th} objective function.

Step 3: Converting the multi-objective model to a single objective one as follows:

$$max \;\; \lambda(x) = \psi\lambda_0 + (1-\psi)\sum_h \theta_h\, \mu_h(x) \tag{49}$$

S.t.:

$$\lambda_0 \leq \mu_h(x), \quad h = 1,2,3 \tag{50}$$

$$x \in F(x), \quad \lambda_0 and \;\; \lambda \in [0,1] \tag{51}$$

where $\lambda_0 = min\{\mu_h(x)\}$ signifies the minimum degree of satisfaction degree of objective functions, and ψ and θ_h specify the coefficient of restitution and relative importance of h^{th} objective function.

IV. NUMERICAL EXAMPLE

So, by demonstrating the validity and correctness of the presented model, some test problems are examined in this section. The specifications of the parameters are given in Table I. In this regard, both deterministic and robust counterpart models were coded in GAMS software. Furthermore, three different test problems have been considered, and their results are provided in Table II under various uncertainty levels.

Table I. Parameters related to main distribution centers

Parameters	***Values***	***Parameters***	***Values***
$\tilde{w}_{lj}, \tilde{w}_{lk}$	Uniform (50000,100000)	$cap_{jk}, ca_{lk}, pca_{lk}$	Uniform (300,800)
$\tilde{\delta}_{jk}$	Uniform (10,60)	φ	Uniform (0.2,0.4)
$\tilde{c}_{ik}, \tilde{c}_{ijk}$	Uniform (100,150)	q_j, q_k	Uniform (0.05,0.25)
$\widetilde{cp}_{lk}$	Uniform (100,200)	cc	Uniform (20,40)
$\tilde{s}_i$	Uniform (200,400)	mr_j, mr_k	Uniform (400,600)
$\tilde{d}_k$	Uniform (150,300)	$\tilde{B}_j, \tilde{B}_k$	Uniform (10000,20000)

As is shown in Table II, the obtained results from the counterpart model have worse quality in the whole examined test problems compared to the crisp model. In a robust state, the worst circumstance is reflected to mitigate the risk of programming. What is more, the influences of changing the importance degrees of objective functions are represented in Table III. As can be seen, the method can offer appropriate solutions for the investigated problem.

Table II. Sensitivity analysis of the level of uncertainty (ρ) given that ψ =0.4

Test problem	*Deterministic*		*Robust*		
	(z_1, μ_1)	(z_2, μ_2)	ρ	(z_1, μ_1)	(z_2, μ_2)
1	(1.85800E+14,0.73)	(857.33 , 0.78)	0.1	(1.91230E+14,078)	(1134.82,0.81)
			0.3	(2.14156E+14,0.68)	(1461.94,0.77)
			0.5	(2.90810E+14,0.61)	(2315.09,0.72)
2	(3.04310E+14,0.68)	(4315.54,0.87)	0.1	(3.76116E+14,0.57)	(4874.78, 0.86)
			0.3	(4.35466E+14,0.68)	(5613.43,0.67)
			0.5	(4.98204E+14,0.71)	(6109.18, 0.71)
3	(7.15579E+14, 0.77)	(7651.43,0.67)	0.1	(7.55087E+14,0.77)	(8346.43, 0.70)
			0.3	(8.65113E+14,0.57)	(8901.64, 0.66)
			0.5	(9.25467E+14,0.81)	(9377.14, 0.79)

Table III. The results of the sensitivity analysis on θ -value for problems

Test problem	(θ_1, θ_2)	*Deterministic*	
		(z_1, μ_1)	(z_2, μ_2)
1	(0.5,0.5)	(1.85800E+14,0.73)	(857.33, 0.78)
	(0.3,0.7)	(2.23114E+14,0.60)	(7912.46,0.86)
	(0.7,0.3)	(1.60116E+14,0.78)	(8841.05,0.68)
2	(0.5,0.5)	(3.04310E+14,0.68)	(4315.54,0.87)
	(0.3,0.7)	(3.31614E+14,0.55)	(3905.51,0.93)
	(0.7,0.3)	(2.81267E+14,0.77)	(4699.06,0.75)

Moreover, to reveal the effect of changing the conversion rate on the addressed problem, a sensitivity analysis is conducted, and its results are provided in Fig. 1. Indeed, this rate can be improved by enhanced processes and using novel technologies, so this effect can be considered for further investigation. Obviously, when the conversion rate grows, the biofuel production also increases, and eventually, the total costs of the system decrease.

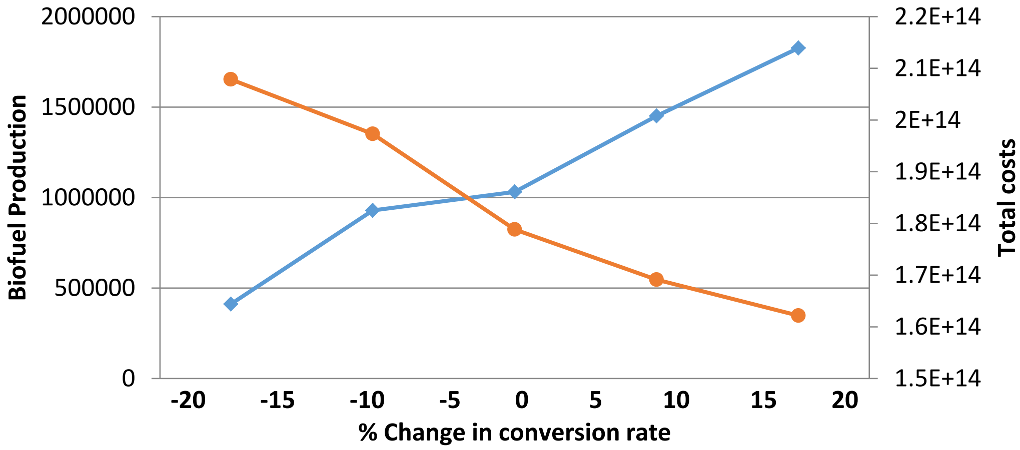

Fig 1. The effect of the conversion rate on biofuel production and total costs

V. CONCLUSION

A bi-objective optimization model was offered to plan a reliable biomass-biofuel supply chain network, in which loading and unloading hubs and biorefineries can be encountered with disruption. For this purpose, the first objective function minimized the total costs. The second one minimized the total times of recovery of disrupted facilities, in which several decisions, including facilities location-allocation, recovery time, recover budget, number of containers, and production amount of biofuel, were determined. Furthermore, due to the uncertain essence of the biomass supply chain, two efficient approaches, including robust optimization and congestion effect, considered to overcome this challenge. Finally, so many test problems were investigated to demonstrate the validity of the suggested mathematical model.

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