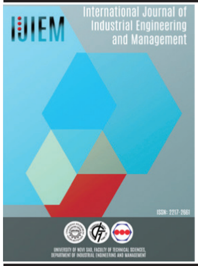
ISSN 2683-345X
journal homepage: http://ijiemjournal.uns.ac.rs/



International Journal of Industrial Engineering and Management

2025 / ARTICLE-IN-PRESS / 372

Original research article

Application of the extended two-stage network DEA model for the biomass-biofuel logistics network design

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ABSTRACT

Network Data Envelopment Analysis (N-DEA) models have been applied to measure efficiency scores for Decision-Making Units (DMUs), where DMUs under evaluation represent network processes. The Biomass-Biofuel Logistics Network (BBLN) design problems with the risk of biofuel facility shutdown have been approached by applying the regular two-stage network DEA (R-TSN DEA) model. This paper proposes and demonstrates how to apply the extended TSN (E-TSN) DEA model for designing efficient BBLN systems more accurately and consistently than the R-TSN DEA approach. We simultaneously apply a Weighted Goal Programming (WGP) model for the BBLN design problem by considering five performance metrics. Various BBLN configurations are generated by solving the WGP model with multiple weight values assigned to five performance metrics. Decision makers are usually interested in the top efficient DMUs before deciding to select the most appropriate option. The proposed E-TSN DEA approach more consistently identifies top-notch BBLN schemes than the R-TSN DEA. A case study utilizing available data in South Carolina, USA, shows that the proposed E-TSN DEA suggests more accurate, consistent, and robust schemes for the BBLN network than the previously approached DEA models. The proposed method can play a significant role in attracting future investors when planning a strategic BBLN design.

ARTICLE INFO

Article history:

Received June 14, 2024
Revised October 19, 2024
Accepted October 30, 2024
Published online February 14, 2025

Keywords:
Network Data Envelopment Analysis (NDEA);
Biomass-Biofuel Logistics Network;
Weighted Goal Programming;
Extended Two-Stage Network DEA;
Regular Two-Stage Network DEA

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1. Introduction

Biofuel or bioenergy was considered a possible energy basis, gathering much attention again due to the unstable gas price, especially after the pandemic. Zhang et al. [1] consider the impact of the Ukraine-Russia war on crude oil prices by saying that the war augmented oil price unpredictability and deeply changed the movement of crude oil prices. In addition, the Middle East war also could cause oil price shock. The pandemic and these recent wars would force us to realize the importance of biofuel production again. However, less attention has been given to comprehending the Biomass-Biofuel Supply Chain (BBSC) and reducing its costs [2].

As Pimentel [3] points out, biofuel production has been connected to high levels of carbon emissions. Pimentel [3] maintains that bioethanol production causes environmental degradation and that significant water and air pollution issues are linked to bioethanol produced by chemical plants, causing harmful effects

Published by the University of Novi Sad, Faculty of Technical Sciences, Novi Sad, Serbia.

https://doi.org/10.24867/IJIEM-372

on air quality. Several reports show that some areas producing biofuels in bulk have suffered from air pollution, including China and the United States[1].

Gold and Seuring [4] mention the problems of biomass supply chain design and operations and challenges for securing competitively-priced biomass feedstock supply for biorefineries. They classify those problems and tasks into detailed operations: reaping and gathering, storage, shipment, and pre-treatment methods [4]. Another research insisted that, in recent years, bioenergy supply chain design, operation, and management subjects have gained considerable attention along with the growing attention to bioenergy sources [5]. Poudel et al. [6] consider a planning model for a reliable biofuel supply chain network design considering linkage disruption risks.

Similarly, Maheshwari et al. [7] develop an optimization model for the supply chain design that combines the risk of link failures to minimize the total cost incurred during disruption and the non-disruption scenarios weighted by their respective occurrence risks. Albashabsheh and Stamm [8] have recently developed an optimization model to minimize ethanol production costs from lignocellulosic biomass. They illustrate a case study considering a variety of biomass forms and types and the potential for mobile pelleting [8]. Ji and Nananukul [9] suggest an optimization model to meet the electricity demand by formulating the optimization model to minimize the lowest operating cost for simultaneously finding appropriate locations for biomass power plants, optimal collection and production of biomass stocks, and allocation of suppliers. Balaman [10] also emphasizes that developing combined frameworks for designing efficient and resilient BBSC should be one of the central priorities to enhance this topic's research. Hong and Mwakalonge [2] consider a single-stage biofuel supply chain network and combine three single-stage Data Envelopment Analysis (DEA) methods to design efficient biofuel logistics network schemes. Hong [11] uses the two-stage DEA method to consider a two-stage biofuel supply chain network.

Cook and Zhu [12] insist that researchers have been developing DEA applications for the area wherein Decision-Making Units (DMUs) denote network processes. Thus, in the DEA area literature, a network DEA is one of the significant flows that control several sub-stage efficiencies in a complex structure. DMUs with intermediate measures between the stages are considered in most cases. Previous research found that the single-stage DEA (SS-DEA) model treats a DMU as a 'black box,' neglecting intervening processes [13]. The SS-DEA's underlying assumption is that a DMU's performance depends on the inputs used and outputs generated. Thus, the 'black box' approach cannot offer managers specific process guidance to improve DMU's efficiency or provide insights into the interrelationships among the components' inefficiencies.

This paper considers two kinds of Two-Stage Network (TSN) DEA models (see Kao [14]). The first one is called a regular TSN (R-TSN) DEA, where the intermediate measures, outputs from the first stage, are the only inputs to the second stage. The second model is called the extended TSN (E-TSN) DEA, where the second stage has intermediate measures and its own inputs. Figure 1 depicts the difference between the R-TSN and E-TSN DEA structures.

Hong [11] applies the R-TSN DEA for the BBLN design problem, whereas this paper proposes the E-TSN DEA method in a pre-disruption scenario. We present a case study using real data from South Carolina to show that the proposed E-TSN DEA method makes a more accurate, consistent, and robust evaluation of various BBLN configurations than the R-TSN DEA model. The proposed method would provide the top-notch BBLN configurations for decision-makers to consider implementing them.

2. Weighted goal programming model

This paper applies the models of Eksioglu et al. [15], Poudel et al. [6], and Hong [11] and considers the BBLN consisting of four supply chain points: a supply point – farm or harvest site, a storage point – storing facility, and a production point - biorefinery, and a demand point – blending station. The structure of BBLN is depicted in Figure 1 (see Eksioglu et al. [15]). The inbound flows to a production point signify the collection of biomass stocks, storing them, and shipping them. Trucks take the biomass collected at each farm site (FS) to a local storage facility (SF). The SF stocks smaller loads of biomass collected from the FS. An SF is a potential facility to store and pre-process/treat biomass to a more valuable density, ship it more cost-effectively, and make a better-quality biomass feedstock with higher efficiency of converting biomass stocks to biofuel. Large-capacity trucks take consolidated biomass stocks from SF to a BioReFin-

[1] https://www.epa.gov/risk/biofuels-and-environment#:~:text=Biofuel%20production%20and%20use%20has,on%20an%20energy%20%2Dequivalent%20basis

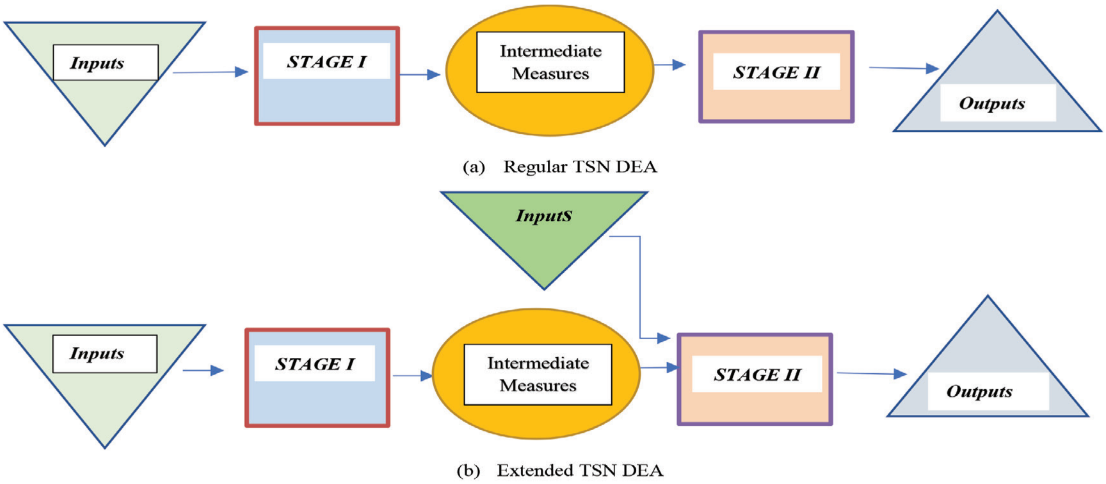

Figure 1. Regular vs. extended two-stage network DEA structure

ery (BRF) for processing into biofuel. Direct transportation of biomass from an FS to a BRF is possible, but it requires more space for the biomass stocks. Direct transportation of biomass requires higher transportation costs due to the low biomass density and more preparation and operations to be processed into biofuel. In addition, the conversion rates of biomass feedstock shipped from an FS to BRFs are usually lower than those shipped from an SF to BRFs. Also, as van Dyken et al. [16] emphasize the importance of SF, proper operation at SFs would significantly affect the quality of produced biofuel, mainly depending on the moisture content in the biomass.

The outbound flows in Figure 2 illustrate that biofuels produced at BRFs are transported to BS, where they will be blended with gasoline. Then, the gasoline blended with biofuels is distributed to each gas station. In these kinds of supply chain networks, finding the locations of SFs and BRFs would be the most essential decision because a BRF usually requires several million dollars in annualized construction and operation costs.

The following nomenclature is used to model goal programming (see Hong [11]):

Sets:

F: set of all potential biomass storage facilities (SFs), that is, all FSs, indexed by f.

G: set of capacities of SF, indexed by g.

I: set of biofuel production facilities, BRFs, indexed by i.

J: set of located SFs, indexed by j.

K: set of blending stations, BSs, indexed by k.

L: set of capacities of BRF, indexed by l.

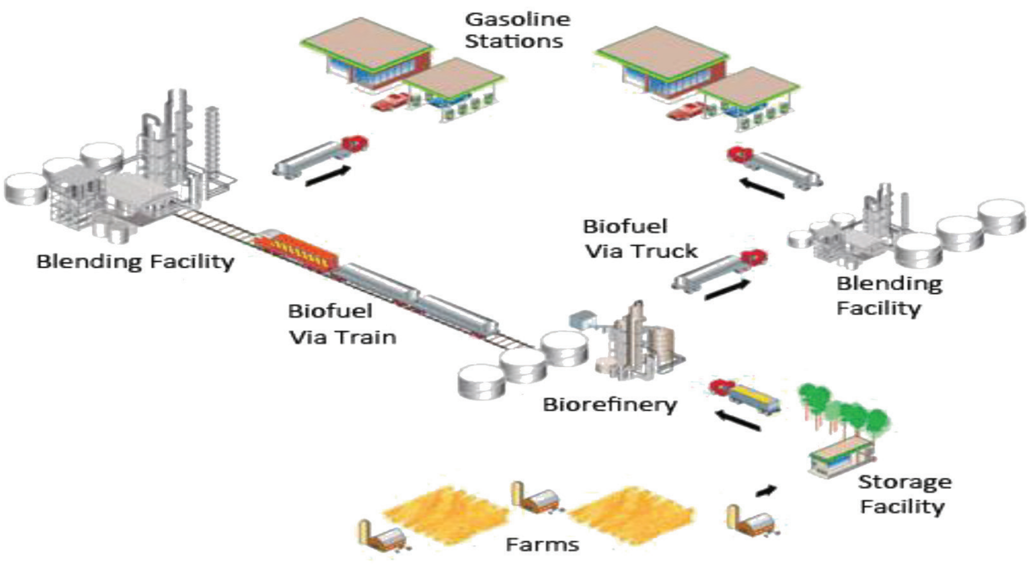

Figure 2. Schematic of the biofuel supply chain network (adapted from [16])

Parameters:

C_l^b: capacity of l^{th} size of BRF.
C_g^c: capacity of g^{th} size of SF.
D_k: demand of biofuels for BS_k.
N_b: maximum number of BRFs to be located.
N_c: maximum number of SFs to be located.
S_f: yield of biomass feedstock from FS_f.
β_f: conversion rates of regularly shipped biomass feedstock to biofuel.
γ_f: conversion rates of biomass feedstock to biofuel, which are directly shipped from FSs.
δ_i: maximum number of FSs that ship biomass directly to BRF_i.
ψ_{il}^b: amortized annual locating and operating cost for a BRF_i with the l^{th} size.
ψ_{jg}^c: amortized annual locating and operating cost for an SF_j with the g^{th} size.
d_{fj}^1, d_{fi}^2, d_{ji}^3, and d_{ik}^4: unit shipping cost from FS_f to SF_j, from FS_f to BRF_i, from SF_j to BRF_i, and from BRF_i to BS_k, respectively.

Decision Variables:

x_{il}^b: binary variable. If a BRF of size l is located at site i, it is one; otherwise, it is zero.
x_{jg}^c: binary variable. If an SF of size g is located at site j, it is one; otherwise, it is zero.
y_{fj}^1: binary variable. If biomass collected from FS_f is shipped to SF_j, it is one; otherwise, it is zero.
y_{fi}^2: binary variable. If FS_f ships biomass directly to BRF_i, it is one; otherwise, it is zero.
y_{ji}^3: binary variable. If SF_j is allocated to BRF_i, it is one; otherwise, it is zero.
y_{ik}^4: fraction of biofuels produced by BRF_i, which are shipped to BS_k.

Assumptions:

(i) All FSs are potential sites for locating SFs. In contrast, a BRF can only be located at the designated BRF location because BRF candidate locations should satisfy some realistic requirements, such as air pollution and water contamination problems.
(ii) The risk of disruptions affects the operation of the two facilities in the inbound flows, SF and BRF. The risk of disruptions implies that, as Cui et al. [17] define, disrupted facilities may shut down due to major disasters.

The Total Logistics Cost (TLC) in the WGP model consists of the annualized locating and operation cost for SFs and BRFs and the shipping costs from FSs to SFs, FSs to BRFs, SFs to BRFs, and BRFs to BSs. Let N_c and N_b denote the maximum number of SFs and BRFs to be located. The first goal of the WGP model is to minimize the TLC

$$TLC=\left[\sum_{i\in I}\sum_{l\in L}\psi_{il}^b x_{il}^b+\sum_{j\in J}\sum_{g\in G}\psi_{jg}^c x_{jg}^c\right] +\left[\sum_{j\in J}\sum_{f\in F}S_f c_{fj}^1 d_{fj}^1 y_{fj}^1+\sum_{i\in I}\sum_{f\in F}S_f c_{fi}^2 d_{fi}^2 y_{fi}^2\right] \left[\sum_{i\in I}\sum_{j\in J}\left(\sum_{f\in F}S_f\right)c_{ji}^3 d_{ji}^3 z_{fji}\right]+\left[\sum_{i\in I}\sum_{k\in K}D_k\, c_{ik}^4 d_{ik}^4 y_{ik}^4\right], \tag{1}$$

where

$$Max\{0, y_{fj}^1+y_{ji}^3-1\}\le z_{fji}=y_{fj}^1 y_{ji}^3 \le y_{fj}^1. \tag{2}$$

The second goal is related to minimizing the worst-case level of service/transportation of the *BSCLN* system, which is equivalent to minimizing the maximum demand-weighted coverage distance (*MDWCD*), which is expressed as

$$MDWCD = Max\{S_f d_{fj}^1 y_{fj}^1, S_f d_{fi}^2 y_{fi}^2, S_f d_{ji}^3 y_{fj}^1\} \quad \forall f, i, and\ j. \tag{3}$$

The third goal is to maximize the expected amount of biomass feedstocks (*EABF*) shipped to BRFs. Now, let p_j^c and p_i^b denote the risk probability that the biomass and biofuel facilities, SF_j and BRF_i, are disrupted, respectively. The EABF is given by

$$EABF=\sum_{i\in I}\sum_{j\in J}\left[\sum_{f\in F}S_f\, z_{fji}(1-p_j^c)(1-p_i^b)\right] + \left[\sum_{i\in I}\sum_{f\in F}S_f\, y_{fi}^2(1-p_i^b)\right]. \tag{4}$$

The fourth goal is to maximize the expected amount of biofuel production (*EABP*), which is given by

$$EABP=\sum_{i\in I}\sum_{j\in J}\left[\sum_{f\in F}S_f\, z_{fji}(1-p_j^c)(1-p_i^b)\right]\beta_f + \left[\sum_{i\in I}\sum_{f\in F}S_f\, y_{fi}^2(1-p_i^b)\right]\gamma_f. \tag{5}$$

Let τ_σ^i and R_σ^i denote the pollution-free score and the population living inside an σ-mile radius of the BRF_i, respectively. To denote the effect of pollution on the population residing around the biorefineries, we define the total pollution-free score (*TPFS*) for the located BRFs as

$$TPFS = \sum_{i\in I}\sum_{l\in L} x_{il}^{b} \sum_{\sigma=1}^{M} \tau_{\sigma}^{i}(R_{\sigma}^{i} - R_{\sigma-1}^{i}), \tag{6}$$

where $\tau_{\sigma}^{i} \le \tau_{\sigma+1}^{i}$. The fifth goal is to maximize *TPFS* given in (6)

Let {*TLC**, *MDWCD**, *EABF**, *EABP**, *TPFS**} denote the target values of five performance measures and the nonnegative deviation variables, λ_1^+, λ_1^-, λ_2^+, λ_2^-, $\lambda_3^-, \lambda_3^+, \lambda_4^-, \lambda_4^+$, λ_5^-, and λ_5^+, denote the amounts by which each value of the five performance measures deviates from the corresponding target value. Then, the following equations show the relationships between the deviation variables and the target values:

$$TLC\ in\ (1) + \lambda_1^- - \lambda_1^+ = TLC^*, \tag{7}$$

$$MDWCD\ in\ (3) + \lambda_2^- - \lambda_2^+ = MDWCD^*, \tag{8}$$

$$EABF\ in\ (4) + \lambda_3^- - \lambda_3^+ = EABF^*, \tag{9}$$

$$EABP\ in\ (5) + \lambda_4^- - \lambda_4^+ = EABP^*, \tag{10}$$

$$TPFS\ in\ (6) + \lambda_5^- - \lambda_5^+ = TPFS^*. \tag{11}$$

Letting $\boldsymbol{\alpha} = \{\alpha_1^+, \alpha_2^+, \alpha_3^-, \alpha_4^-, \alpha_5^-\}$ be the weights assigned to the five goals, we formulate the *BBLN* design problem as a weighted goal programming (WGP) model as follows:

$$Minimize\ G(\boldsymbol{\alpha}) = \alpha_1^+ \frac{(\lambda_1^+ + \lambda_1^-)}{TLC^*} + \alpha_2^+ \frac{(\lambda_2^+ + \lambda_2^-)}{MDWCD^*} + \alpha_3^- \frac{(\lambda_3^+ + \lambda_3^-)}{EABF^*} + \alpha_4^- \frac{(\lambda_4^+ + \lambda_4^-)}{EABP^*} + \alpha_5^- \frac{(\lambda_5^+ + \lambda_5^-)}{TPFS^*}, \tag{12}$$

subject to

Constraints (7)-(11)

$$X_i^b = \sum_{l\in L} x_{il}^b, \forall i \in I \tag{13}$$

$$X_j^c = \sum_{g\in G} x_{jg}^c, \qquad \forall j \in J \tag{14}$$

$$\sum_{i\in I} X_i^b \le N_b, \tag{15}$$

$$\sum_{j\in J} X_j^c \le N_c, \tag{16}$$

$$\sum_{j\in M} y_{fj}^1 + \sum_{i\in I} y_{fi}^2 = 1, \forall f \in F \tag{17}$$

$$X_j^c u_j \le \sum_{f\in F} y_{fj}^1 \le X_j^c U_j, \forall j \in J \tag{18}$$

$$\sum_{f\in F} S_f y_{fj}^1 \le \sum_{g\in G} C_g^c x_{jg}^c, \qquad \forall j \in J \tag{19}$$

$$\sum_{j\in J}\sum_{f\in F} \beta_f S_f z_{fji} + \sum_{f\in F} \gamma_f S_f y_{fi}^2 \le \sum_{l\in L} C_l^b x_{il}^b, \quad i \in I \tag{20}$$

$$\sum_{i\in I} y_{ji}^3 = X_j^c, \qquad \forall j \in M \tag{21}$$

$$\sum_{f\in F} y_{fi}^2 \le \sum_{l\in L} \delta_i x_{il}^b, \ \forall i\in I, \tag{22}$$

$$\sum_{i\in I}\left(\sum_{j\in J}\sum_{f\in F} \beta_f S_f y_{ji}^3 + \sum_{f\in F} \gamma_f S_f y_{fi}^2\right) \ge \sum_{k\in K} D_k\,(y_{ik}^4), \tag{23}$$

$$\sum_{i\in I} y_{ik}^4 = 1, \forall k \in K. \tag{24}$$

where α_q^+ and α_q^- are relative importance weights for the overachievement and underachievement deviation variables, respectively, such that, $\sum_{q=1}^{2} \alpha_q^+ + \sum_{q=3}^{5} \alpha_q^- = 1$ and $0 \le \alpha_q^+$ or $\alpha_q^- \le 1$. It is necessary to find the five performance metrics' target values first to solve the above WGP model. There is no standard procedure for assigning values to the weight factors since no procedure can guarantee the most desirable solution to a WGP problem. An iterative procedure using a particular set of weights is suggested by Ragsdale [18], who concludes that finding the most desirable solution for decision-makers would require the process to repeat with all possible sets of weights. The imminent question is how the most desirable solution is selected so decision-makers are satisfied with the solution. This paper proposes that the TSN DEA models evaluate the efficiency of all different BBLN options generated by solving the WGP model with various importance weights. Selecting the most efficient or productive BBLN configuration would eliminate the decision-maker's subjective or biased assessments.

3. Regular and extended two-stage network models

Liang et al. [19] apply a Constant Returns-to-Scale (CRS) two-stage centralized model to maximize Efficiency Scores (ESs) for the two-stage process where the stages cooperatively determine a set of optimal multipliers on the intermediate features. The BBLN system in this study aims to determine the three factors to maximize ESs: the amount of biomass feedstocks collected jointly, the locations of two biofuel facilities, SFs and BRFs, and the production amount of biofuel. The R-TSN DEA model for the BBLN system is shown in Figure 3, considering *TLC* and *MDWCD* as two inputs to Stage 1, *EABF* as an intermediate measure, and *EABP* and *TPFS* as two outputs. In the CRS R-TSN DEA model, the ESs of the two individual stages are obtained using the DEA multipliers, $\{v_1, v_2, w_1, u_1, u_2\} \geq 0$, by the following expressions:

$$\theta_\omega^1 = \frac{w_1 EABF_\omega}{v_1 TLC_\omega + v_2 MDWCD_\omega}, \tag{25}$$

$$\theta_\omega^2 = \frac{u_1 EABP_\omega + u_2 TPFS_\omega}{\widetilde{w}_1 EABF_\omega}, \tag{26}$$

where θ_ω^1 and θ_ω^2 are ESs of stages 1 and 2, respectively. In the leader-follower model (see Liang et al. [20]), θ_ω^1 for stage 1 is obtained from the following model:

$$\theta_\omega^1 = Max\,\{w_1 EABF_\omega\} \tag{27}$$

subject to

$$w_1 EABF_\kappa - (v_1 TLC_\kappa + v_2 MDWCD_\kappa) \leq 0, \quad \kappa = 1, 2, \dots \omega, \omega + 1, \dots, \Omega, \tag{28}$$

$$v_1 TLC_\omega + v_2 MDWCD_\omega = 1, \tag{29}$$

The efficiency model to determine θ_ω^2 is obtained, utilizing the optimal value of θ_ω^{1*}, from the following model:

$$\theta_\omega^2 = \frac{Max\{u_1 EABP_\omega + u_2 TPFS_\omega\}}{\theta_\omega^{1*}}, \tag{30}$$

subject to

$$(u_1 EABP_\kappa + u_2 TPFS_\kappa) - w_1 EABF_\kappa \leq 0, \quad \kappa = 1, 2, \dots \omega, \omega + 1, \dots, \Omega, \tag{31}$$

$$w_1 EABF_\kappa - (v_1 TLC_\kappa + v_2 MDWCD_\kappa) \leq 0, \quad \kappa = 1, 2, \dots \omega, \omega + 1, \dots, \Omega, \tag{32}$$

$$v_1 TLC_\omega + v_2 MDWCD_\omega = 1, \tag{33}$$

$$w_1 EABF_\omega = \theta_\omega^{1*}, \tag{34}$$

$$u_1, u_2, w_1, v_1, v_2 \geq 0.$$

Then, Liang et al. [20] and Kao and Hwang [21] suggesed the two equations for the Overall Efficiency Score (OAES) for the two-stage model as follows:

$$\theta_{\omega M}^* = \theta_\omega^{1*} * \theta_\omega^{2*} \tag{35}$$

and

$$\theta_{\omega A}^* = [(\theta_\omega^{1*} + \theta_\omega^{2*})/2], \tag{36}$$

where Eq. (35) is called multiplicational OAES, while Eq. (36) is called average OAES.

Note that the R-TSN DEA approach does not correctly reflect the network flows since *TLC*, *MDWCD*, and *EABF* in (1), (3), and (4) include the inputs to Stage 2. Thus, we separate these metrics into the inputs for each stage. *TLC*, *MDWCD*, and *EABF* are decomposed into *TLC1* and *TLC2*, *MDWCD1* and *MDWCD2*, and *EABF1* and *EABF2* as follows:

$$TLC1 = \left[\sum_{j\in J}\sum_{g\in G} \psi_{jg}^c x_{jg}^c + \sum_{j\in J}\sum_{f\in F} S_f c_{fj}^1 d_{fj}^1 y_{fj}^1\right], \tag{37}$$

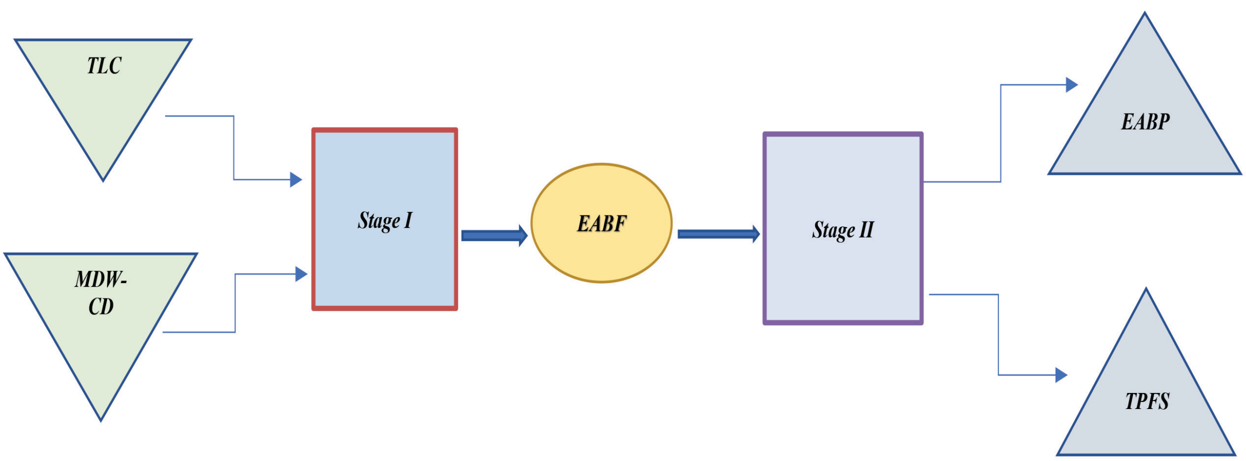

Figure 3. The regular two-stage network structure for the BBLN system

$$TLC2 = \left[\sum_{i\in I}\sum_{l\in L} \psi_{il}^{b} x_{il}^{b}\right] + \left[\sum_{i\in I}\sum_{f\in F} S_f c_{fi}^{2} d_{fi}^{2} y_{fi}^{2} + \sum_{i\in I}\sum_{j\in J}\left(\sum_{f\in F} S_f\right) c_{ji}^{3} d_{ji}^{3}\, z_{fji}\right] + \left[\sum_{i\in I}\sum_{k\in K} D_k\, c_{ik}^{4} d_{ik}^{4} y_{ik}^{4}\right], \quad (38)$$

$$MDWCD1 = Max\{\, S_f d_{fj}^{1} y_{fj}^{1}\}, \forall i \text{ and } j, \quad (39)$$

$$MDWCD2 = Max\{S_f d_{fi}^{2} y_{fi}^{2},\ S_f d_{ji}^{3} y_{fj}^{1}\}, \forall j \text{ and } g, \quad (40)$$

$$EABF1 = \sum_{i\in I}\sum_{j\in J}\left[\sum_{f\in F} S_f\, z_{fji}(1-p_j^{c})(1-p_i^{b})\right], \quad (41)$$

$$EABF2 = \left[\sum_{i\in I}\sum_{f\in F} S_f\, y_{fi}^{2}(1-p_i^{b})\right]. \quad (42)$$

Then, {*TLC1*, *MDWCD1*} and {*TLC2*, *MDWCD2*, *EABF2*} become inputs to Stage 1 and Stage 2, respectively, and {*EABF1*} is the intermediate measure, as depicted by Figure 4. Since each stage in Figure 4 cooperates to accomplish the best performance of the BBLN network, a centralized model is applied for the E-TSN DEA.

$$\phi_\omega^1 = \frac{w_1 EABF1_\omega}{v_1 TLC1_\omega + v_2 MDWCD1_\omega}, \quad (43)$$

$$\phi_\omega^2 = \frac{u_1 EABP_\omega + u_2 TPFS_\omega}{w_1 EABF1_\omega + [Q_1 TLC2_\omega + Q_2 MDWCD2_\omega + Q_3 EABF2_\omega\ ]}, \quad (44)$$

where ϕ_ω^1 and ϕ_ω^2 are efficiency scores of stages 1 and 2, respectively, for DMU$_\omega$, and the multipliers for each input, intermediate one, and output are $\{v_1, v_2, w_1, Q_1, Q_2, Q_3\ u_1, u_2\} \geq 0$. Now, using the conventional DEA model, the overall centralized CE, θ_ω^{cen}, can be given by:

$$\phi_\omega^{cen} = Max\ \{\phi_\omega^1 \ in\ (43)) * \ \phi_\omega^2\ in\ (44)\}, \quad (45)$$

subject to

$$\frac{w_1 EABF1_\kappa}{v_1 TLC1_\kappa + v_2 MDWCD1_\kappa} \leq 1, \forall\kappa \quad (46)$$

$$\frac{u_1 EABP_\kappa + u_2 TPFS_\kappa}{w_1 EABF1_\kappa + [Q_1 TLC2_\kappa + Q_2 MDWCD2_\kappa + Q_3 EABF2_\omega\ ]} \leq 1, \forall\kappa \quad (47)$$

Due to the term of $[Q_1 TLC2_\kappa + Q_2 MDWCD2_\kappa + \ Q_3 EABF2_\omega\ ]$ in (47), the above model cannot be converted into an LP model. Let ϕ_ω^{1max} be the maximum ES of stage 1, then we formulate the following LP model for the model in (45)-(47) as follows:

$$\phi_\omega^{1max} = max\{w_1 EABF_\omega\}, \quad (48)$$

subject to

$$w_1 EABF1_\kappa - (v_1 TLC1_\kappa + \ v_2 MDWCD1_\kappa) \leq 0, \forall\kappa \quad (49)$$

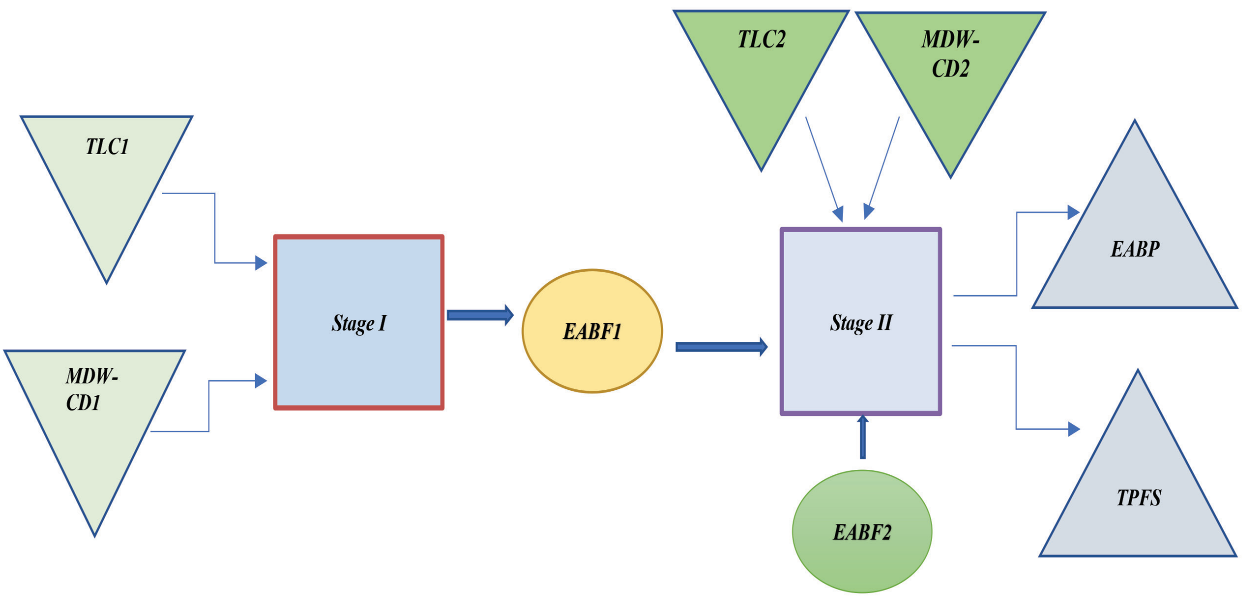

Figure 4. The extended two-stage network DEA structure for the BBLN system

$$(u_1 EABP_\kappa + u_2 TPFS_\kappa) - w_1 EABF1_\kappa$$
$$-[Q_1 TLC2_\kappa + Q_2 MDWCD2_\kappa + Q_3 EABF2_\omega] \leq 0, \forall\kappa \quad (50)$$

$$v_1 TLC1_\omega + v_2 MDWCD1_\omega = 1. \quad (51)$$

From (48)-(51), the optimal value of (45) is an estimator ϕ_ω^1, whose maximum value is ϕ_ω^{1max}, for the first stage. Now, the OAES for the two-stage model, $\phi_\omega^{cen,1*}$, is a function of ϕ_ω^1 and can be formulated as

$$\phi_\omega^{cen,1*} = max\{\phi_\omega^1 * [u_1 EABP_\omega + u_2 TPFS_\omega]\}, \quad (52)$$

subject to

$$w_1 EABF_\kappa - (v_1 TLC1_\kappa + v_2 MDWCD1_\kappa) \leq 0, \forall\kappa \quad (53)$$

$$(u_1 EABP_\kappa + u_2 TPFS_\kappa) - w_1 EABF1_\kappa$$
$$-[Q_1 TLC2_\kappa + Q_2 MDWCD2_\kappa + Q_3 EABF2_\omega] \leq 0, \forall\kappa \quad (54)$$

$$Q_1 TLC2_\omega + Q_2 MDWCD2_\omega + Q_3 EABF2_\omega + w_1 EABF_\omega = 1, \quad (55)$$

$$w_1 EABF1_\kappa - \phi_\omega^1 (v_1 TLC1_\kappa + v_2 MDWCD1_\kappa) = 0, \quad (56)$$

$$\phi_\omega^1 \leq \phi_\omega^{1max}. \quad (57)$$

Setting $\phi_\omega^1 = \phi_\omega^{1max} - \tau\Delta\varepsilon$, where $\Delta\varepsilon$ is a step size and $\tau = 0, 1, 2, \ldots, \tau^{max} + 1$, $\tau^{max} \leq \left[\frac{\theta_\omega^{1max}}{\Delta\varepsilon}\right]$. The optimal global efficiency is estimated as $\phi_\omega^{cen,1*} = \max_\tau \phi_\omega^{cen,1}(\tau)$. See Li et al. [22] for the computational procedure. Now, we state the formal procedure as follows:

Procedure

Step 1: **[Finding efficient DMUs for R-TSN DEA Model]**

- (i) Let G denote the maximum number of efficient DMUs to compare.
- (ii) Assess all DMUs by solving the LP given in (25)-(34).
- (iii) Rank all DMUs based on $\theta_{\omega M}^*$ in (35) or $\theta_{\omega A}^*$ in (36),
- (iv) Stratify DMUs whose rankings are at least #G into a set Θ.

Step 2: **[Applying E-TSN DEA Model After Decomposing]**

- (v) For DMUs in Θ, decompose the R-TSN to the E-TSN model.
- (vi) Setting $\phi_\omega^1 = \phi_\omega^{1max} - \tau\Delta\varepsilon$, $\tau = 0, 1, 2, \ldots, \tau^{max} + 1$, $\tau^{max} \leq \left[\frac{\theta_\omega^{1max}}{\Delta\varepsilon}\right]$, set $\phi_\omega^{cen,1*} = \max_\tau \phi_\omega^{cen,1}(\tau)$.
- (vii) Rank the DMUs in Θ^1 based on $\phi_\omega^{cen,1*}$ in (v) and compare the ranks generated by Step 1.

4. Case study and observations

We apply the proposed E-TSN-DEA model for the case study that Hong [11] studies, following the scenario depicted in Figure 5 (see [23]). Figure 5 indicates sixteen (16) counties whose biomass resources are classified as 'good' or better. We select these sixteen counties as the farm sites (FSs). One city from each county is selected using a centroid approach, and these cities are considered to have storage facility (SF) location potential. We choose five (5) potential/candidate locations for BRFs and ten (10) locations for BSs throughout SC, respectively. The possible locations for BRFs are selected based on easy access to I-26, I-20, and I-95, major interstate highways, proximity to major FSs, etc. We use Google Maps to measure the actual distances among cities representing FSs, SFs, BRFs, and BSs. Table 1(a) presents the hypothetical demands for all BSs. Table 1(b) summarizes the input parameters. Table 1(c) summarizes the minimum, maximum, and average volumes of biomass yield at each FS, as shown in Table 5. For the case study, we use the average amount of biomass yield. Using major disaster declaration records in South Carolina, we calculate the risk probability of being disrupted based on the Federal Emergency Management Agency (FEMA) database. Table 1(c) also lists the risk probabilities for the candidate sites for SFs and BRFs.

As Step I says, we solve the model to find the target values of five performance measures, TLC_{min}, $MDWCD_{min}$, $EABF_{max}$, $EABP_{max}$, *and* $TPFS_{max}$. The WGP model is solved for multiple values of weight set, $\boldsymbol{\alpha}$, where each α_q^+ or α_q^- changes subject to the constraint $\sum_{q=1}^{2} \alpha_q^+ + \sum_{q=3}^{5} \alpha_q^- = 1, 0 \leq \alpha_q^+, \alpha_q^- \leq 1$. Setting an increment value equal to 0.1 yields a total of 1,001 configurations, and we find that some configurations have the same values of five performance measures with different values of the weight set, $\boldsymbol{\alpha}$. Thus, this study reduces 1,001 BBLN configurations into 306 alternatives.

The R-TSN and E-TSN DEA are applied to compute the OAESs of these 306 consolidated configurations. We select the top 14 configurations ranked by the OAESs generated by either TSN DEA method. There are 23 configurations ranked in the top 14

Table 1(a). Hypothetical demand for blending station (BS)

Blending Station	Demand (in K gallons)
Spartanburg	200
Summerville	150
Santee	150
Lancaster	200
Aiken	200
Bishopville	200
Greenville	200
Clinton	300
Dillon	200
Manning	250

Table 1(b). Input data used for the case study

Symbol	Value
ψ_{jg}^{c}	\$120K, \$150K, and \$200K for g=1, 2, 3.
ψ_{il}^{b}	\$0.7M, \$0.8M, and \$1M for l=1, 2, 3.
C_{g}^{c}	400K, 800K, 1M tons for g=1,2,3.
C_{l}^{b}	500K, 800K, 1M gallons for l=1, 2, 3.
β_f	70%
γ_f	40%
δ_i	16
N_b	2
N_c	4
d_{fj}^{1}	\$0.005/mile/K metric tons
d_{fi}^{2}	\$0.01/mile/K metric tons
d_{ji}^{3}	\$0.007/mile/K metric tons
d_{ik}^{4}	\$0.01/mile/K gallons

Table 1(c). Biomass yield and risk probability

No	Harvest Site	Minimum Yield (K Metric Tons)	Average (K metric Tons)	Maximum Yield (K Metric Tons)	Risk Probability
1	York	150	225	300	0.32
2	Darlington	150	225	300	0.40
3	Greenwood	150	225	300	0.24
4	Lexington	100	175	250	0.44
5	Allendale	100	150	200	0.36
6	Richland	250	400	550	0.44
7	Dorchester	150	225	300	0.36
8	Orangeburg	150	225	300	0.44
9	Hampton	150	225	300	0.28
10	Newberry	250	400	550	0.36
11	Berkeley	150	200	250	0.44
12	Georgetown	250	400	550	0.48
13	Chester	150	225	300	0.28
14	Horry	100	175	250	0.64
15	Florence	150	225	300	0.48
16	Colleton	100	200	300	0.36

by either method, and Table 2 reports the results. We note from Table 2 that, for some configurations, there are significant differences in the OAESs and the corresponding rankings between these two DEA methods. For example, Configuration #247, ranked #1 by the E-TSN DEA, is ranked #233 and #230 by R-TSN, while Configuration #303, ranked #8 by R-TSN, is ranked #28 by the E-TSN DEA. Only Configuration #302 is ranked #1 by both methods.

Now, we apply both TSN DEA methods to these 23 configurations and report the OAESs, the corresponding ranks, R, the expected ranks, E[R], and the absolute rank difference (ARD) between R and E[R] in Table 3. The E[R] is grounded on the original rank in Table 2, which shows the results with all 306 configurations. For example, Configuration #272, ranked #23, based on multiplicational OAES, and #27, based on average OAES, by the R-TSN method when all 306 configurations are evaluated, is expected to be ranked #16 and #18 among the selected 23 configurations. The ARD can measure the robustness of generated rankings. It can be observed

Table 2. Efficiency results for the top-14 BBLN schemes by either method with 306 configurations under evaluation

No	Configuration # (ω)	Input 1		Intermed. Measure	Input 2			Output		Regular TSN DEA				Extended TSN DEA	
		TLC1	MDWCD1	EABF1	TLC2	MDWCD2	EABF2	EABP	TPFS	$\theta^*_{\omega M}$	R	$\theta^*_{\omega A}$	R	$\phi^{cen,1*}_{\omega}$	R
1	246	$1,270	499628	1740	$3,931	50504	256	1320.512	519.2	0.7648	47	0.8786	45	0.7743	14
2	247	$1,530	38596	1935	$4,034	555908	0	1354.304	519.2	0.7196	233	08598	230	1.0000	1
3	252	$1,342	38596	1825	$4,189	536812	171	1346.096	519.2	0.7228	231	0.8573	231	0.9551	5
4	264	$350	54096	730	$5,631	159081	1795	1229.168	519.2	0.6601	241	0.8153	241	0.9971	4
5	270	$420	21492	695	$43,956	101657	1378	1037.728	483.9	0.8281	26	0.9139	25	0.8132	12
6	272	$315	18904	594	$3,962	101657	1405	977.744	483.9	0.8354	23	0.9104	27	0.9010	7
7	279	$373	54096	659	$4,774	101657	1720	1149.44	519.2	0.7780	39	0.8886	35	0.8461	9
8	281	$808	32212	879	$3,344	297894	894	973.152	498	0.8646	5	0.9310	3	0.6145	49
9	282	$804	32212	972	$3,380	282094	834	1014	498	0.8654	3	0.9310	5	0.6807	32
10	283	$704	32212	706	$3,486	227838	1202	974.832	498	0.8570	10	0.9259	12	0.5254	92
11	290	$808	32212	879	$3,344	297894	894	973.152	498	0.8646	5	0.9310	4	0.6145	49
12	291	$709	25506	994	$3,379	206308	789	1011.064	483.9	0.8655	2	0.9307	6	0.8332	10
13	292	$754	32212	777	$3,417	254526	1090	980.208	498	0.8619	9	0.9284	9	0.5611	78
14	295	$530	27004	766	$3,626	163233	1189	1012.024	483.9	0.8515	13	0.9241	13	0.7124	25
15	298	$597	19244	869	$3,425	235480	811	933.008	483.9	0.8647	4	0.9323	2	0.9212	6
16	299	$536	19244	748	$3,496	178740	1045	941.432	483.9	0.8641	7	0.9296	7	0.8308	11
17	300	$410	18904	594	$3,656	159747	1301	936.424	483.9	0.8560	12	0.9260	11	0.7562	19
18	301	$315	18904	594	$3,962	101657	1405	977.744	483.9	0.8313	25	09129	26	0.9010	7
19	302	$586	19244	942	$3,463	206308	789	975.224	483.9	0.8670	1	0.9327	1	1.0000	1
20	303	$659	25506	799	$3,412	178740	1045	977.272	483.9	0.8626	8	0.9288	8	0.6947	28
21	304	$353	18904	738	$3,763	163233	1189	991.864	483.9	0.8560	11	0.9262	10	1.0000	1
22	305	$344	18904	551	$3,756	140834	1397	944.248	483.9	0.8504	14	0.9240	14	0.7643	18
23	306	$330	19490	546	$3,828	125954.3	1405	944.312	483.9	0.8410	19	0.9187	19	0.7931	13

Note. R: Rank

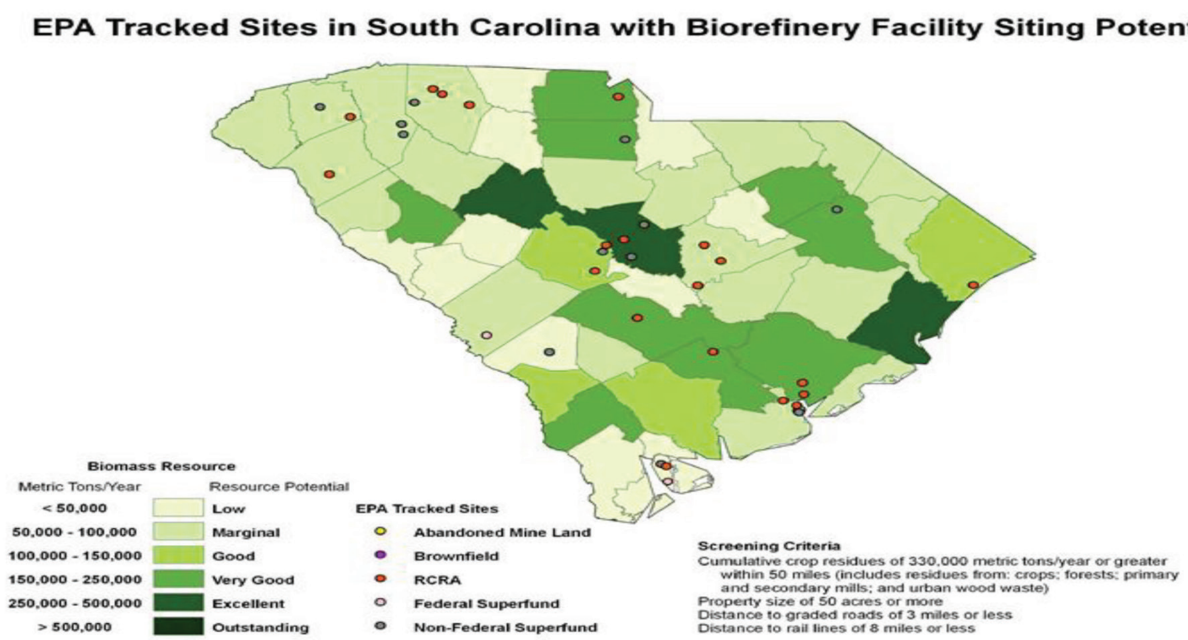

Figure 5. EPA traced sites in South Carolina with biorefinery facility siting potential

Table 3. Comparison of efficiency results when the top 20 configurations are rated

No	Configuration # (ω)	Regular TSN DEA								Regular TSN DEA			
		$\theta^*_{\omega M}$	R	E[R]	ARD	$\theta^*_{\omega A}$	R	E[R]	ARD	$\phi^{cen,1*}_{\omega}$	R	E[R]	ARD
1	246	0.7777	20	20	0	0.8853	20	20	0	0.7743	14	14	0
2	247	0.7318	22	22	0	0.8659	21	21	0	1.0000	1	1	0
3	252	0.7350	21	21	0	0.8636	22	22	0	0.9551	5	5	0
4	264	0.6658	23	23	0	0.8191	23	23	0	0.9971	4	4	0
5	270	0.8293	18	18	0	0.9147	17	16	1	0.8132	12	12	0
6	272	0.8375	16	16	0	0.9177	16	18	2	0.9010	7	7	0
7	279	0.7810	19	19	0	0.8905	19	19	0	0.8462	9	9	0
8	281	0.8789	5	5	0	0.9383	4	3	1	0.6145	20	20	0
9	282	0.8799	3	3	0	0.9385	3	5	2	0.6807	19	19	0
10	283	0.8712	10	10	0	0.9337	12	12	0	0.5254	23	23	0
11	290	0.8789	5	5	0	0.9383	4	4	0	0.6145	20	20	0
12	291	0.8800	2	2	0	0.9383	6	6	0	0.8332	10	10	0
13	292	0.8762	9	9	0	0.9361	9	9	0	0.5611	22	22	0
14	295	0.8658	13	13	0	0.9323	14	13	1	0.7124	17	17	0
15	298	0.8791	4	4	0	0.9396	2	2	0	0.9212	6	6	0
16	299	0.8786	7	7	0	0.9373	7	7	0	0.8308	11	11	0
17	300	0.8703	12	12	0	0.9341	11	11	0	0.7562	16	16	0
18	301	0.8332	17	17	0	0.9140	18	17	1	0.9010	7	7	0
19	302	0.8815	1	1	0	0.9397	1	1	0	1.0000	1	1	0
20	303	0.8771	8	8	0	0.9367	8	8	0	0.6947	18	18	0
21	304	0.8703	11	11	0	0.9343	10	10	0	1.0000	1	1	0
22	305	0.8646	14	14	0	0.9323	13	14	1	0.7643	15	15	0
23	306	0.8535	15	15	0	0.9260	15	15	0	0.7931	13	13	0

Note. R: Rank

that the multiplicational OAES, $\theta^*_{\omega M}$, generated by R-TSN and the centralized OAES, $\phi^{cen,1*}_{\omega}$ by E-TSN generate perfectly robust ranks, while the average OAES, $\theta^*_{\omega A}$, by R-TSN, exhibits seven cases of nonzero ARDs. E-TSN DEA still generates the same three top-ranked configurations.

For further investigation, we select the top five DMUs by either method and present the results in Table 4. Table 4 demonstrates the robustness of rankings, with all zero ARDs generated by the proposed R-TSN DEA. We summarize each method's total, mean, and maximum ARDs in Table 5. The E-TSN DEA does not depend as much on the DMUs under evaluation as the R-TSN DEA, implying that the proposed method, analyzing the BBLN model closer to the actual flow of input and output measures, generates more robust ranks than the R-TSN method.

Figure 6 depicts the optimal locations of two biofuel facilities, their allocations, and assignments of BRFs to BSs for the three configurations, Configuration #302, #304, and #247, which are ranked as #1 by each method. A yellow arrow line indicates a shipment from an SF to a BRF, a solid green arrow indicates a direct shipment from an FS to a BRF, and a black solid arrow line a shipment of biomass from an FS to an SF. In contrast, a black dotted arrow line indicates a biofuel shipment from a BRF to a BS.

For example, Configuration #302 selects {Chester, Allendale, Orangeburg} as the optimal locations of SFs and {Lake City, Prosperity} as the optimal locations of BRFs. The allocation scheme in Configuration #302 indicates: The farm sites (FSs), {York, Chester}, ship biomass to SF {Chester}, FSs {Allendale, Hampton} ship to SF {Allendale}, FSs { Dorchester, Colleton} ship to SF {Orangeburg}. All other FSs directly ship biomass stocks to BRF {Lake City} or {Prosperity}. SFs {Allendale, Orangeburg, Chester} ship the treated biomass feedstock to BRF {Prosperity}. The BRF {Lake City} ships produced biofuels to BSs {Summerville, Dillon, Manning}, and the BRF {Prosperity} ships to BSs {Bishopville, Clinton, Santee, Spartanburg, Lancaster, Aiken, Greenville}.

Table 4. Comparison of efficiency results when the top-5 configurations are rated

No	Configuration # (ω)	Regular TSN DEA								Regular TSN DEA			
		$\theta^*_{\omega M}$	R	E[R]	ARD	$\theta^*_{\omega A}$	R	E[R]	ARD	$\phi^{cen,1*}_{\omega}$	R	E[R]	ARD
1	247	0.7426	10	9	1	0.8713	9	8	1	1.0000	1	1	0
2	252	0.7459	9	8	1	0.8692	10	9	2	0.9551	5	5	0
3	264	0.7477	8	10	2	0.8738	8	10	2	0.9971	4	4	0
4	281	0.8919	5	5	0	0.9450	5	3	2	0.6145	9	9	0
5	282	0.8929	3	3	0	0.9452	3	5	2	0.6807	8	8	0
6	290	0.8919	5	5	0	0.9450	5	4	1	0.6145	9	9	0
7	291	0.8931	2	2	0	0.9451	4	6	2	0.8332	7	7	0
8	298	0.8922	4	4	0	0.9461	2	2	0	0.9212	6	6	0
9	302	0.8946	1	1	0	0.9464	1	1	0	1.0000	1	1	0
10	304	0.8832	7	7	0	0.9416	7	7	0	1.0000	1	1	0

Note. ARD: Absolute Rank Difference =|R -E[R]|

Table 5. Summary of rank differences for the top-five DMUs

ARD	Regular TSN DEA		Extended TSN DEA
	$\theta^*_{\omega M}$	$\theta^*_{\omega A}$	$\phi^{cen,1*}_{\omega}$
Total ARD	4	12	0
Mean ARD	0.4	1.2	0.0
Maximum ARD	2	2	0

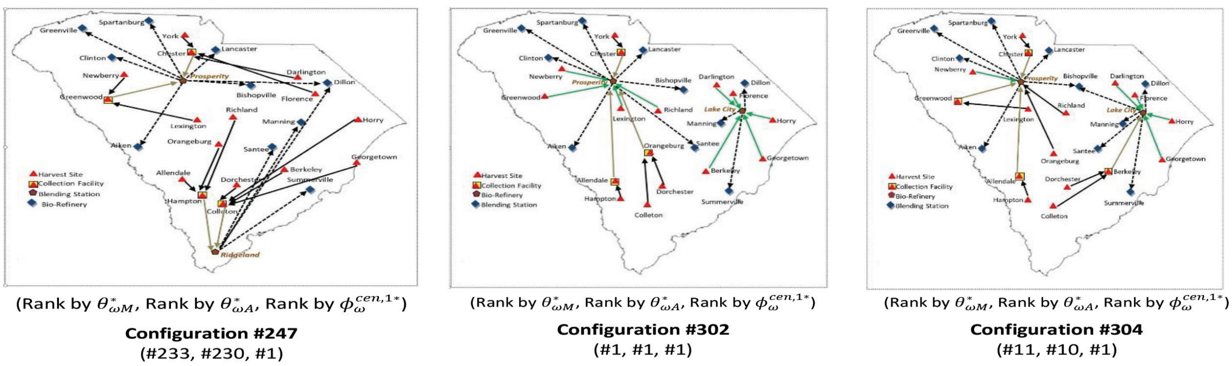

Figure 6. The three most efficient BBLN schemes by R-TSN and E-TSN DEA methods

The location and allocation of Configuration #304 are similar to those of Configuration #302 with the same locations of BRFs {Lake City, Prosperity}. Rather than SF {Orangeburg}, Configuration #304 selects {Berkeley} as an SF. Consequently, FSs {Colleton, Dorchester} ship biomass stocks to SF {Berkeley}. Then, SF {Berkeley} ships the treated biomass feedstock to BRF {Lake City}. Note that, with Configuration #304, BRF {Prosperity} covers 26% of the demand for BS {Bishopville}, while BRF {Lake City} covers 74% of the demand of {Bishopville}.

Note that the two top-ranked BBLN schemes select {Lake City, Prosperity} as the optimal locations for two BRFs. In contrast, Configuration #247 finds a different BRF site {Ridgeland} located in the deep south in South Carolina rather than {Lake City}. The last configuration in Figure 6 shows that the inputs, *TLC1*, *TLC2*, *MDWCD1*, and *MDWCD2*, are much higher than the other top configurations, Configuration #302 and 304. However, it can produce much higher outputs, such as *EABP* and *TPFS* (See Table 2).

We notice that the proposed E-TSN DEA method would reveal some efficient options in the BBLN configurations, such as Configurations #304 and #247. If only R-TSN DEA is applied, those efficient configurations identified by the proposed method could be excluded from the candidates for the decision-makers to consider. As shown in the case study, the E-TSN DEA would help decision-makers consider the differences among these top three network configurations before making a final decision.

5. Computational experience

We implement the E-TSN DEA model in an Excel spreadsheet with VBA (Visual Basic for Applications) on Intel® Xeon ® Gold 5122 HP Z4 Workstation PC (2 processors) with 32GB of RAM installed using a 64-bit version of Windows 10. We solve the model using the Excel Analytical Solver Platform using the 'Gurobi' Solver Engine[2], setting $\Delta\varepsilon = 0.001$ and $\tau_{max} = 9$. A DEA software, *DEAFrontier*, using an Excel spreadsheet, is run for the R-TSN DEA model on the same computer to compare the running times. The results for each # of BBLN configuratons considered in the case study are listed in Table 6. Solving the E-TSN DEA takes more time in terms of running times since it requires τ (= τ_{max}+1) iterations to find the optimal global efficiency, $\phi_{\omega}^{cen,1*}$ in (52). To increase the precision of computations, $\Delta\varepsilon$ should reduce. Then, the reduced $\Delta\varepsilon$ would increase the running times.

Table 6. Summary of running time (unit: seconds)

	Number of BBLN Configurations		
	10	23	306
Regular TSN DEA	3.3s	8.2s	145.2s
Extended TSN DEA	4.6s	14.2s	229.8s

6. Conclusions

Rather than a single objective of cost minimization considered by the conventional supply chain network models, this paper focuses on five (5) performance metrics at the same time for designing more efficient and balanced BBLNs under the risk of disruptions. Those five performance metrics are the total logistics cost (*TLC*), the maximum demand-weighted coverage distance (*MDWCD*), the expected amount of biomass feedstocks (*EABF*), the expected amount of biofuel production (*EABP*), and the total pollution-free score (TPFS). We propose transforming the BBLN network evaluation and design problem into an extended two-stage network DEA (E-TSN DEA) rather than a regular TSN (R-TSN) DEA. In fact, the proposed model represents the actual BBLN systems in terms of performance measures better than the R-TSN DEA model that many researchers have applied to evaluate the supply chain systems.

The proposed procedure aims to identify efficient BBLN configurations based on the robust rankings of various supply chain network schemes. The case study demonstrates that the proposed E-TSN DEA approach produces more consistent and robust rankings, whereas R-TSN rankings are not as consistent or robust as the proposed method. The efficiency rankings generated by E-TSN DEA are not affected by the network schemes under evaluation, while the rankings by conventional R-TSN are significantly affected.

Another contribution of this study is that the proposed E-TSN DEA could reveal possibly hidden BBLN configurations as efficient schemes, so the R-TSN method would not rank as high as the proposed E-TSN method. As discussed before, Table 2 shows several cases, let alone the top-ranked Configuration #247 by R-TSN. For example, the #4 ranked Configuration #264, ranked #241 out of 306 configurations by R-TSN, produces the highest intermediate measure, *EABF*, and two very high outputs, *EABP* and *TPFS*. If the R-TSN method is applied only, Configuration #264 would be excluded for the decision-makers to consider as the final BBLN scheme to be implemented.

The case study suggests that the proposed approach should be used as an essential tool, along with the traditional R-TSN DEA, for decision-makers to find the top-efficient BBLN configurations. Future research would be necessary and exciting if the proposed E-TSN DEA is applied extensively in real-world applications to design various supply chain network systems.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

[1] Q. Zhang, Q., Y. Hu, J. Jiao, and S. Wang, "The impact of Russia-Ukraine war on crude oil prices: an EMC framework," Humanities and Social Sciences Communications, vol. 11, no. 8, pp. 1-12, 2024, doi: 10.1057/s41599-023-02526-9.

[2] www.solver.com

[2] J. D. Hong and J. Mwakalonge, "Biofuel logistics network scheme design with combined data envelopment analysis approach," Energy, vol. 209, p. 118342, 2020, doi: 10.1016/j.energy.2020.118342.

[3] D. Pimentel, "Ethanol fuels: Energy balance, economics and environmental impacts are negative," Natural Resources Research, vol. 12, no. 2, pp. 127-134, 2003, doi: 10.1023/A:1024214812527.

[4] S. Gold and S. Seuring, "Supply chain and logistics issues of bio-energy production," Journal of Cleaner Production, vol. 19, pp. 32-42, 2011, doi: 10.1016/j.jclepro.2010.08.009.

[5] Y.-F. Huang, M.-W. Weng, and C.-J. Fu, "A two-stage sustainable production-inventory model with carbon credit demand", Int J Ind Eng Manag, vol. 15, no. 2, pp. 96–108, 2024, doi: 10.24867/IJIEM-2024-2-350.

[6] S. R. Poudel, M. Marufuzzaman, and L. Bian, "Designing a reliable biofuel supply chain network considering link failure probabilities," Computers and Industrial Engineering, vol. 91, pp. 85-99, 2016, doi: 10.1016/j.cie.2015.11.002.

[7] P. Maheshwari, S. Singla, and Y. Shastri, "Resiliency optimization of biomass to biofuel supply chain incorporating regional biomass pre-processing depots," Biomass Bioenergy, vol. 97, pp. 116-131, 2017, doi: 10.1016/j.biombioe.2016.12.015.

[8] N.T. Albashabsheh, and J. L. H. Stamm, "Optimization of Lignocellulosic biomass-to-biofuel supply chains with mobile pelleting," Transportation Research Part E: Logistics and Transportation Review, vol. 122, pp. 545-562, 2019, doi: 10.1016/j.tre.2018.12.015.

[9] J. Ji, and N. Nananukul, "Supply chain for sustainable renewable energy from biomass," International Journal of Logistics Systems and Management, vol. 33, no. 4, pp. 568-590, 2019.

[10] S. Y. Balaman, Decision-making for biomass-based production chains: The basic concepts and methodologies, Cambridge, MA, USA. Academic Press, 2019.

[11] J. D. Hong, "Two-stage efficiency-based approach to biofuel supply chain logistics network design under the risk of disruptions," International Journal of Industrial and Systems Engineering, vol. 36, no. 3, pp. 339-360, 2020.

[12] W. D. Cook, and J. Zhu, "DEA for two-stage networks: Efficiency decompositions and modeling techniques," in Data envelop analysis: A handbook on the modeling of internal structures and networks, W. D. Cook, and J. Zhu, Eds, NY, USA: Springer, 2014, pp. 1-29.

[13] J.-D. Hong, J. Mwakalonge, and K.-Y. Jeong, "Design of disaster relief logistics network system by combining three data envelopment analysis-based methods", Int J Ind Eng Manag, vol. 13, no. 3, pp. 172–185, 2022, doi: 10.24867/IJIEM-2022-3-310.

[14] C. Kao, Network Data Envelopment Analysis: Foundation and Extensions, NY, USA; Springer, 2017.

[15] S. D. Eksioglu, A. Acharya, L. E. Leightley, and S. Arora, "Analyzing the design and management of biomass-to-biorefinery supply chain," Computers and Industrial Engineering, vol. 57, no. 4, pp. 1342-1352, 2009, doi: 10.1016/j.cie.2009.07.003.

[16] S. van Dyken, B. H. Bakken, and H. I. Skjelbred, "Linear mixed-integer models for biomass supply chains with transport, storage and processing," Energy, vol. 35, no. 3, pp. 1338–1350, 2010, doi: 10.1016/j.energy.2009.11.017.

[17] T. Cui, Y. Ouyang, and A. M. Shen, "Reliable facility location under the risk of disruptions," Operations Research, vol. 58, no. 4, pp. 998-1011, 2010, doi: 10.1287/opre.1090.0801.

[18] C. T. Ragsdale, Spreadsheet Modeling & Decision Analysis: A Practical Introduction to Business Analytics, 9th Edition, MA, USA; Cengage Learning, 2021.

[19] L. Liang, F. Yang, W. D. Cook, and J. Zhu, "DEA models for supply chain efficiency evaluation," Annals of Operations Research, vol. 145, no. 1, pp. 35-49, 2006, doi: 10.1007/s10479-006-0026-7.

[20] L. Liang, W. D. Cook, and J. Zhu, "DEA models for two-stage processes: Game approach and efficiency decomposition," Naval Research Logistics, vol. 55, pp. 643-653, 2008, doi: 10.1002/nav.20308.

[21] C. Kao, and S. N. Hwang, "Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan," European Journal of Operational Research, vol. 185, no. 1, pp. 418-429, 2008, doi: 10.1016/j.ejor.2006.11.041.

[22] Y. Li, Y. Chen, L. Liang, and J. Xie, "DEA models for extended two-stage network structures," Omega, vol. 40, no. 5, pp. 611-618, 2012, doi: 10.1016/j.omega.2011.11.007.

[23] EPA. "Tracked Sites in South Carolina with Biorefinery Facility Siting Potential." National Service Center for Environmental Publications (NSCEP). [Online]. Available: www.epa.gov/renewableenergyland/maps/pdfs/biorefinery_sc.pdf. [Accessed: 14-DEC-2023].