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Supply chain management of butyric acid-derived butanol: Stochastic approach

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HIGHLIGHTS

- Optimization for butyric acid to butanol (Ba-to-Bu) SCN is considered.
- Uncertainties in butyric acid processing and butanol demand are considered.
- A stochastic programming model for Ba-to-Bu SCN is developed.
- A case study of Ba-to-Bu SCN in South Korea in 2030 is presented.

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ABSTRACT

In this study, a stochastic model for strategic planning of the butyric acid-to-butanol supply chain network (Ba-to-Bu SCN) is developed to consider variations in the butanol (Bu) demand and butyric acid (Ba) supply derived from industrial/municipal waste. The proposed stochastic model can help determine where and how much Ba to process, Bu to produce, and Ba/Bu to transport to minimize the total cost of the Ba-to-Bu SCN design under Ba processing and Bu demand uncertainties. The features and capabilities of the stochastic model are validated and compared to those of the deterministic model by application of the future Ba-to-Bu SCN design for South Korea in 2030. The optimization results illustrate that the expected total cost of Ba-derived Bu by the stochastic model (US $4898.55 thousand per year) was at least 0.18% more economical that that of the deterministic model (US $4889.72 thousand per year). The goal of this study is to develop a decision making tool for a stochastic strategic problem to improve bio-economy caused by uncertainties. The proposed approach will help balance cost efficiency with stability in the uncertain future biorefinery infrastructure.

1. Introduction

Biorefineries produce bioenergy and bio-based products from a variety of biomass resources, including agricultural waste, industrial/municipal (I/M) waste, and energy crops [1]. The recent rapid development of biorefinery technologies is expected to be a major factor in reducing CO_2 emissions to minimize their influence on global climate change [2]. The economics of biorefinery are still the bottleneck to the transition from the current fossil fuel-based economy to a new bioenergy-based economy for jet fuel [3], ethanol-gasoline [4], liquid hydrocarbon fuel [5], nylon monomer [6], fuel additive [7], solvent [8], platform chemicals [9] sectors. To this end, many studies have been conducted on the development of a supply chain network (SCN) model to evaluate the economic feasibility of large-scale biorefineries. This model comprises an entire fully integrated value chain, including feedstock supply, transportation, and demand. Most previous studies to plan biorefinery SCNs used deterministic programming based on predetermined fixed values for future situations or second- (agricultural waste) [10] and third-generation (algae) biomass according to model type: single period [11] vs. multi-period [12] or applicability of utility [13] vs. CO_2 infrastructure [14].

I/M waste, as a source of biomass, has been used mainly for compost as a fertilizer [15], and its energy-recovery applications have received significant attention recently as a sustainable option [16]. Most previous works showed that the energy recovery from I/M waste to bioenergy, as heat or electricity, in a large-scale SCN is economically feasible [17]. I/

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M waste-derived biogas or butyric acid (Ba) is also considered a promising feedstock for the production of green methane (CH_4) [18] or butanol (Bu) [2] as biofuels. Bu is the most widely tested component used as blends with conventional diesel fuel for compression-ignition engine applications [19]. However, few studies have developed economically feasible large-scale SCN designs that include emerging technologies to produce biofuels using I/M waste.

This study addresses the problem of designing a butyric acid-to-butanol supply chain network (Ba-to-Bu SCN) model that considers the both effects of uncertain Ba processing and Bu demand capacities in the future. Our study (feedstock: butyric acid and the number of uncertainty types: exceeds two) differs from previous research, considering uncertainties, on biorefinery SCN in several aspects: (i) different feedstock type (microalgae [20] and lignocellulose [21]) and (ii) different uncertainty type (diesel demand [22] and CO_2 emission [23]). The Ba-to-Bu SCN design is modeled as a two-stage stochastic mixed-integer linear programming (MILP) optimization problem and is compared with a deterministic MILP model to assess the variation in Ba and Bu. The objective of the model is to minimize the expected total cost of the Ba-to-Bu SCN design, taking into consideration a number of strategic decisions including: (i) number, location, and capacity of biorefinery facilities and (ii) Ba/Bu flow rates and type of transportation links to be established. A real scenario-based case study of South Korea in 2030 is provided to demonstrate the applicability of the model.

2. Problem statement

The design problem of the Ba-to-Bu SCN model is to optimize from all possible configurations of four components: Anaerobic digestion (AD) facilities, biorefineries, fuel stations, and transportation modes (Fig. 1). This model seeks the location of biorefineries to establish a long-term (strategic) relationship between certain local/regional AD facilities to stabilize Ba supply and certain fuel stations in demand cities to consume Bu. The model also applies uncertainty effect which rationalizes changing environments of Ba supply and Bu demand.

The Ba-to-Bu SCN model is formulated as a two-stage stochastic mixed-integer programming problem (Fig. 2). The decision variables of the model are divided into those of two different stages. The first-stage decision variables include binary/integer variables that determine the capacities and locations of biorefineries, whereas the second-stage variables include the volume of Ba processed, Bu produced, and Ba/Bu transported. This model is based upon the following assumption and parameters: (1) AD facilities are assumed to be constructed in the existing infrastructure, which limits Ba production capacity; however, the quantity of the generated Ba products varies from region to region, depending on the I/M quantities processed from AD facilities built in each region with their mass and energy consumption collected from the previous study [24], (2) the number and location of biorefineries and transportation modes have no limit, but are determined by their capacity and cost per unit, (3) the unit processing/production/transportation cost of each component for the Ba-to-Bu SCN model is precalculated based on the process simulation and economic analysis, and (4) local/regional biofuel demand is estimated based on the population and policy data, which limits Bu demand capacity.

The General Algebraic Modeling System (GAMS), a commercial mathematical programming and optimization tool, is used to solve the Ba-to-Bu SCN model. The input parameters for the model, namely, capacity and cost datasets, are generated in Excel and transformed into GAMS Data eXchange (GDX) data. In particular, the Ba processing and Bu demand capacities have uncertain scenarios associated with a probability of occurrence $Prob_s, Prob_w$, where the sum of the probabilities for all scenarios equal to 1. The output data for the model, such as decision variables, are determined from GAMS.

3. Mathematical model formulation

The Ba-to-Bu SCN mathematical model is formulated as a two-stage stochastic MILP. It consists of an objective function (Section 3.1) and constraints (Section 3.2). The set, parameter, variable notations for the Ba-to-Bu SCN model are provided in the Appendix.

3.1. Objective function

The objective function minimizes the present value of the total expected SCN costs (TAC^{Exp}) consisting of four elements: facility cost (FC), operating cost ($OC_{s,w}$), transportation cost ($TC_{s,w}$), and penalty cost ($PC_{s,w}$), as formulated in Eq. (1). The first-stage costs are related to investment (construction) decisions, FC. The expected second-stage costs are related to operating (quantities) decisions, $OC_{s,w}$, $TC_{s,w}$, and $PC_{s,w}$ under uncertain scenarios of Ba processing ($WCAP_{i,w}$) and Bu demand ($TD^{Bu}_{m,s}$) capacities. A reasonable assumption is to be neutral (unbiased) about the expected risk. This assumption means that three equally probable ($prob_s = \frac{1}{3}, prob_w = \frac{1}{3}$) scenarios of uncertain Ba processing/Bu demand are considered: below average (s1/w1, −20%), average (s2/w2, 0%), and above average (s3/w3, +20%).

$$\text{Minimize } TAC^{Exp} = FC + \sum_s \sum_w Prob_s Prob_w \left(OC_{s,w} + TC_{s,w} + PC_{s,w} \right) \tag{1}$$

FC is the total cost of establishing biorefinery facilities, which is calculated by multiplying the required number of biorefineries by the corresponding fixed capital and operating costs.

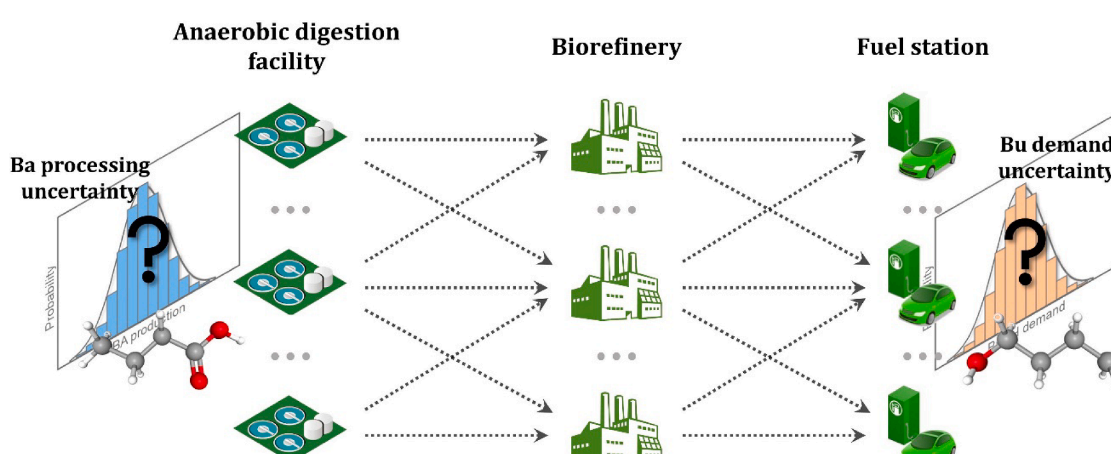

Fig. 1. Schematic diagram of Ba-to-Bu SCN under Ba production and Bu demand uncertainties.

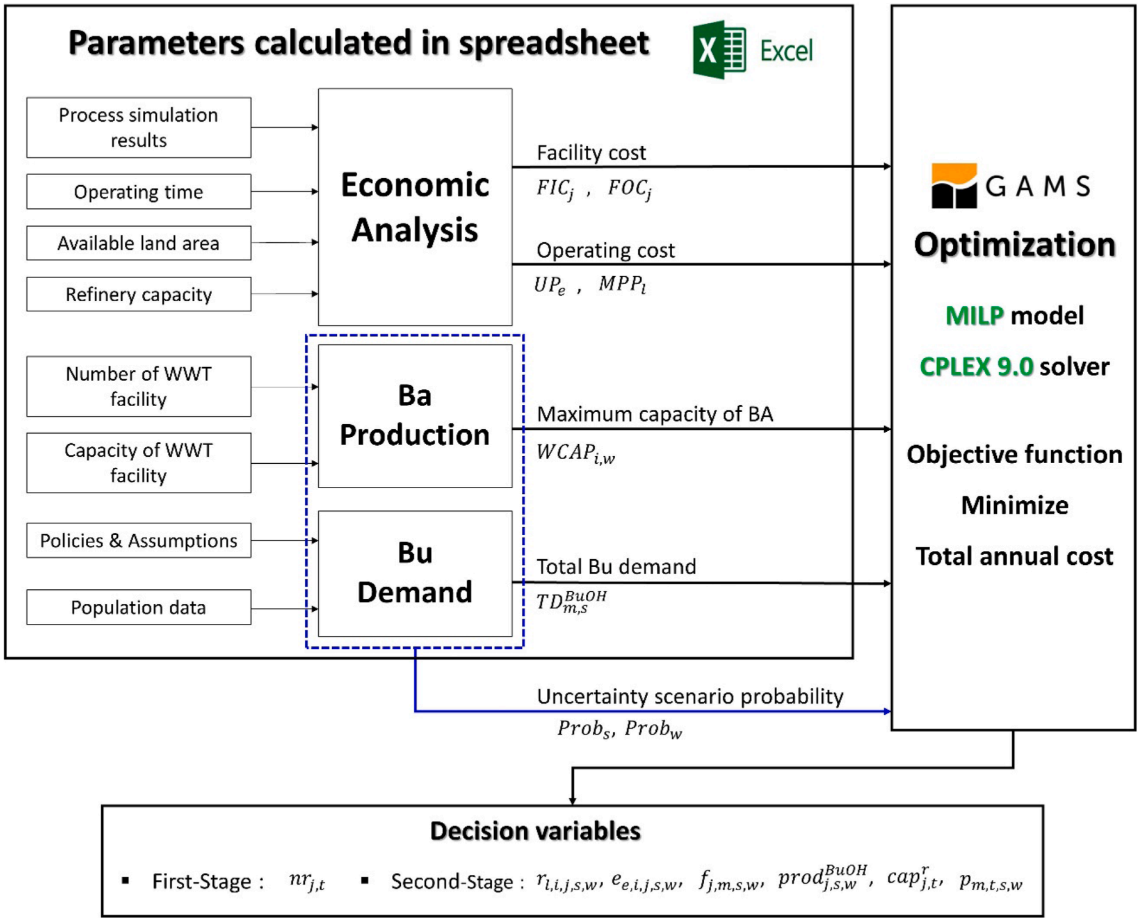

Fig. 2. Overview of the proposed Ba-to-Bu SCN stochastic model-optimization framework.

$$FC = \sum_j \left(FIC_j + FOC_j\right) nr_j \tag{2}$$

$OC_{s,w}$ is the sum of the material cost ($MC_{s,w}$) and energy cost ($EC_{s,w}$) required to operate the biorefineries.

$$OC_{s,w} = MC_{s,w} + EC_{s,w} \tag{3}$$

$MC_{s,w}$ and $EC_{s,w}$ are calculated by multiplying the material and energy requirements of the biorefinery facilities by their price factors, respectively:

$$MC_{s,w} = \sum_j \sum_l \left(MPP_l \times r_{l,i,j,s,w}\right), \tag{4}$$

$$EC_{s,w} = \sum_e \sum_i \sum_j UP_e e_{e,i,j,s,w}, \tag{5}$$

where $TC_{s,w}$ is the sum of the costs of operating transport modes, Ba ($TC^{Ba}_{s,w}$) and Bu ($TC^{Bu}_{s,w}$).

$$TC_{s,w} = TC^{Ba}_{s,w} + TC^{Bu}_{s,w} \tag{6}$$

$TC^{Ba}_{s,w}$ and $TC^{Bu}_{s,w}$, are obtained by multiplying the Ba or Bu flows by the respective cost term of each transport mode and then summing.

$$TC^{Ba}_{s,w} = \sum_j \sum_{l\in\{Ba\}} \sum_i \left(\frac{\left(DDTC + \frac{TDTC}{v}\right) \times Dist_{i,j}}{TLC_{Ba}} + LUC \right) \frac{r_{l,i,j,s,w}}{CF^{ttog}} \tag{7}$$

$$TC^{Bu}_{s,w} = \sum_j \sum_m \left(\frac{\left(DDTC + \frac{TDTC}{v}\right) \times Dist2_{j,m}}{TLC_{Bu}} + LUC \right) f_{j,m,s,w} \tag{8}$$

$PC_{s,w}$ is the cost of responding to shortages, not meeting the Bu demand from biorefinery facilities, by importing Bu from other sources:

$$PC_{s,w} = \sum_m c^{shortage}{}_m \times p_{m,s,w} \tag{9}$$

3.2. Constraints

The constraints can be divided into two groups in the proposed two-stage model. The first-stage constraints are Eqs. (10)–(11), and Eqs. (12)–(17) are associated with the second-stage variables. The Bu production capacity of the designed biorefinery (cap^r_j) is bounded by multiplying the maximum capacity of each biorefinery ($RCAP_j$) by the required number of biorefineries (nr_j).

$$\mathrm{cap}^r_j \le RCAP_j \times nr_j \quad \forall j \tag{10}$$

The number of biorefineries (nr_j) to be constructed is bounded by the available land area within the specified region:

$$RLA \times nr_j \le ALA_j \quad \forall j. \tag{11}$$

The Ba processing ($WCAP_{i,w}$) and Bu demand ($TD^{Bu}_{m,s}$) capacities are defined using subscript sets w and s to represent the uncertainty scenarios "below average," "average," and "above average." The Bu demand in city m under uncertain scenario s ($TD^{Bu}_{m,s}$) is equal to the sum of the amounts of Bu delivered from biorefinery j ($f_{j,m,s,w}$) and from other sources during the supply shortage of Bu ($p_{m,s,w}$).

$$\sum_{j} f_{j,m,s,w} + p_{m,s,w} = TD^{Bu}_{m,s} \quad \forall m; \quad s \in \{1,2,3\}, w \in \{1,2,3\} \tag{12}$$

Ba fed to the biorefineries ($r_{l,i,j,s,w}$) cannot exceed the maximum processing capacity of Ba from the AD facilities under uncertain scenario w ($WCAP_{i,w}$).

$$\sum_{j} \sum_{l \in \{Ba\}} r_{l,i,j,s,w} \le WCAP_{i,w} \quad \forall i; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{13}$$

The amounts of Bu transported from biorefinery facilities to demand cities under uncertain scenarios s and w are equal to those of Bu produced at the biorefinery ($prod^{Bu}_{j,s,w}$).

$$\sum_{m} f_{j,m,s,w} = prod^{Bu}_{j,s,w} \quad \forall j; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{14}$$

The raw material ($r_{l,i,j,s,w}$) and energy requirements ($e_{e,i,j,s,w}$) of biorefinery facility j under uncertain scenarios s and w are calculated by multiplying the amount of Bu produced at the biorefinery facilities by their unit material and energy consumption.

$$RMC_l \times prod^{Bu}_{j,s,w} = \sum_{i} r_{l,i,j,s,w} \quad \forall j, l; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{15}$$

$$EMC_e \times prod^{Bu}_{j,s,w} = \sum_{i} e_{e,i,j,s,w} \quad \forall j, e; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{16}$$

The amounts of Bu actually produced at biorefinery facility under uncertain scenarios s and w cannot exceed the designed capacity of the biorefinery (cap^r_j).

$$prod^{Bu}_{j,s,w} \le cap^r_j \quad \forall j; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{17}$$

Some decision variables of the Ba-to-Bu SCN model must be non-negative, as indicated in Eqs. (18)–(23).

$$prod^{Bu}_{j,s,w} \ge 0 \quad \forall j; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{18}$$

$$e_{e,i,j,s,w} \ge 0 \quad \forall e, i, j; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{19}$$

$$p_{m,s,w} \ge 0 \quad \forall m; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{20}$$

$$r_{l,i,j,s,w} \ge 0 \quad \forall l, i, j; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{21}$$

$$f_{j,m,s,w} \ge 0 \quad \forall j, m; s \in \{1,2,3\}, w \in \{1,2,3\} \tag{22}$$

$$nr_j = \{0,1\} \quad \forall j. \tag{23}$$

4. Results and discussion

4.1. Case study

A realistic scenario-based case study of South Korea in 2030 was examined to validate the proposed stochastic model for the Ba-to-Bu SCN. All facilities are assumed to be constructed until that time, at fully operated capability. All the regions (15 provincial-level divisions) in South Korea have enough industrial infrastructure to install biorefineries, but have different available land size for biorefineries (Table S6). A previous algae-based biodiesel SCN case study [12] was adopted as a benchmark and revised with the following considerations: different types of feedstock fields (AD facilities), biorefineries (Ba to Bu), and transportation (Ba and Bu). Based on the South Korea's renewable portfolio standard according to which biodiesel would satisfy 62.4% of bioenergy demand until 2030 [25], the butanol demand (as a 3% biodiesel blend fuel) for each region was estimated. The versatility of the proposed model is examined through four case studies that vary according to uncertainty and model type (Table 1). Specifically, nine uncertain scenarios for the stochastic model were validated with respect to the combined set from each uncertain scenario (Table 2).

To use the Ba-to-Bu SCN model, the following data and parameters, collected from previous studies, were applied: cost parameters (RMC_l, EMC_e, MPP_l, UP_e, FIC_j, and FOC_j for biorefinery in Tables S1, S2, and S3: feedstocks and utilities (including cost parameters) were collected from the previous study using ASPEN plus simulator [2]); transportation in Table S4, capacity parameters ($RCAP_j$ for biorefinery in Table S5; $WCAP_{i,w}$ for AD facilities in Fig. 3(c)); $TD^{Bu}_{m,s}$ for Bu demand cities in Fig. 3(d), and others (ALA_j in Table S6 and $Dist_{i,j}$ in Table S7).

The proposed model was computed using GAMS with the CPLEX 9.0 solver on a computer equipped with an Intel® Core™ i7-7700 processor operating at 3.60 GHz.

4.2. Computation time

The optimized solutions of the presented Ba-to-Bu SCN model were computed at short time with a low optimality gap (Table 3). The stochastic model required slightly more time to solve than the deterministic model, owing to its larger number of equations and variables. Interestingly, the computational load differed depending on uncertainty type, even though the number of variables and equations were the same in both Cases 2 and 3.

4.3. Optimal design

The optimal infrastructure configuration was obtained using a Ba-to-Bu SCN deterministic model (Fig. 3), which differed from the results of the stochastic model (Fig. 4). The total number of biorefineries (thirteen) was lesser in the stochastic results than in the deterministic ones (sixteen), but the total number of regions in which they were to be constructed was greater. This is because the deterministic model considered a fixed scenario with average data, but the stochastic model also considered above-average data. The most important factor to determine the number and location of biorefinery facilities was the land price FIC_j, which indicated that they should be constructed in seven regions, namely, 4, 8, 9, 10, 11, 12, 15, for both models. However, in the stochastic model region, 3 was also assigned as a biorefinery location to supply Bu closer to region 6, thus reducing Bu transport costs as a tradeoff with biorefinery construction costs. In addition, a larger number of transportation links for Bu supply was assigned by the stochastic model, as it decided to construct biorefinery facilities in more diverse regions.

Unlike Bu supply configurations, the stochastic model determined various Ba supply configurations depending on the uncertain scenario type (Fig. 4). Case 2, which only considers Bu demand uncertainty, supplied a total of 139.04 kt Ba/yr from AD facilities in fifteen regions to sixteen biorefineries within seven biorefinery facilities. The Ba configuration results of Case 2 were the same as those of Case 1 (deterministic model). However, Case 3, which only considered Ba processing uncertainty, and Case 4, which considers both Ba processing and Bu demand uncertainty, showed that the total amount of Ba processing decreased by 19.6% to 111.80 kt Ba/yr, resulting in a decrease in the amount of Bu produced at biorefineries and transported by trucks from 16.0 MMgal/yr

Table 1
Analysis conditions selected for the case study.

	Uncertainty		Model
	Ba processing	Bu demand	
Case 1	x	x	deterministic
Case 2	x	o	stochastic
Case 3	o	x	stochastic
Case 4	o	o	stochastic

Table 2
Set of uncertain scenarios.

		w		
	{s, w}	1	2	3
	1	sc1	sc2	sc3
s	2	sc4	sc5	sc6
	3	sc7	sc8	sc9

*Sc 5 represent the deterministic scenario.

Table 3
Summary of computational results for each case.

	Case 1	Case 2	Case 3	Case 4
No. of constraints	455	1,207	1,207	3,463
No. of integer variables	30	30	30	30
No. of continuous variables	3,155	9,337	9,337	27,883
Optimal gap (%)	0	0	0	0
CPU time (s)	0.047	0.078	0.157	0.25

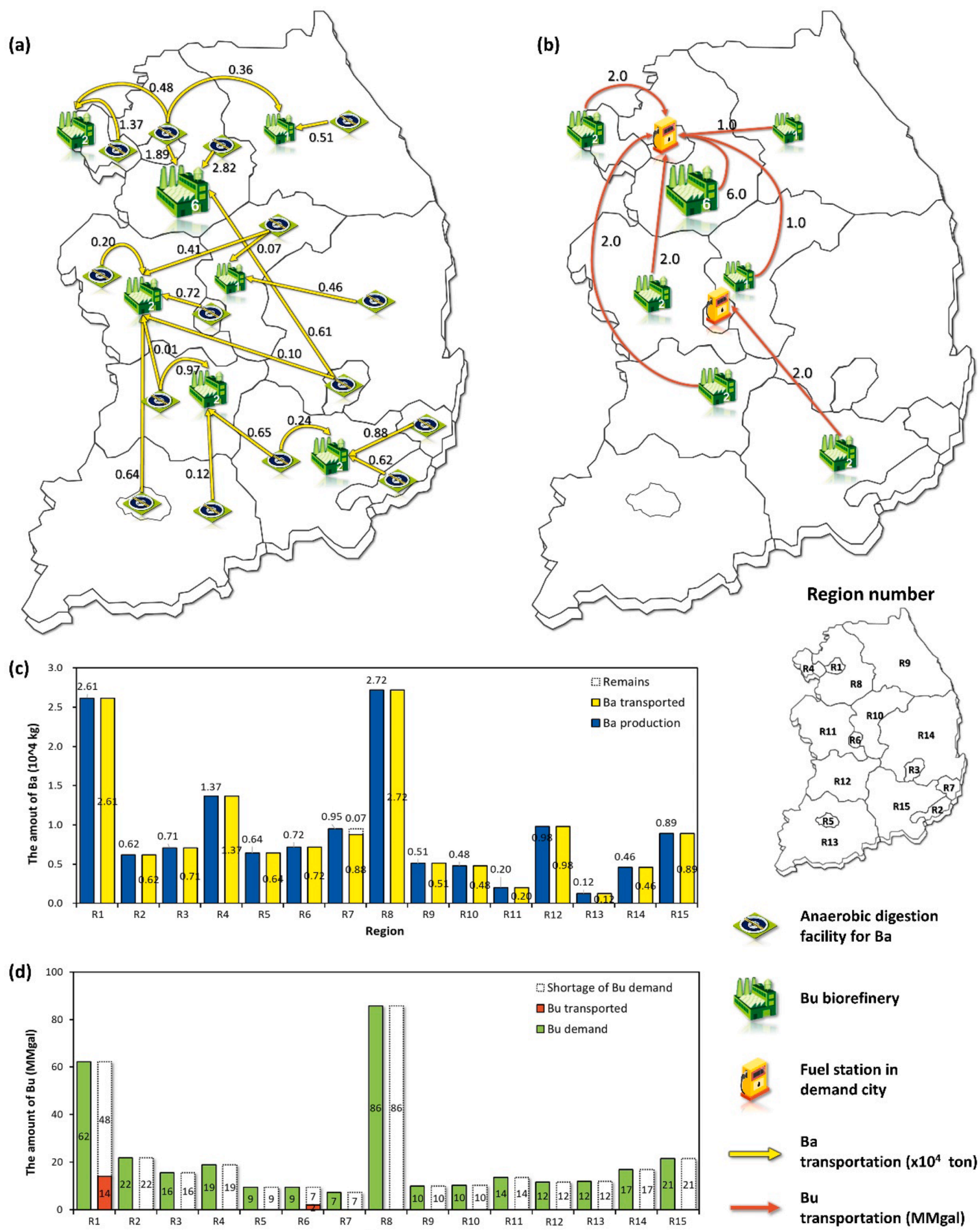

Fig. 3. Optimal result of deterministic model for Case 1. Distribution of (a) Ba from AD facility to biorefinery and (b) Bu from biorefinery to fuel station. (c) The volume of Ba produced and transported in each region. (d) The average Bu demand, transportation, and shortage volumes in each region.

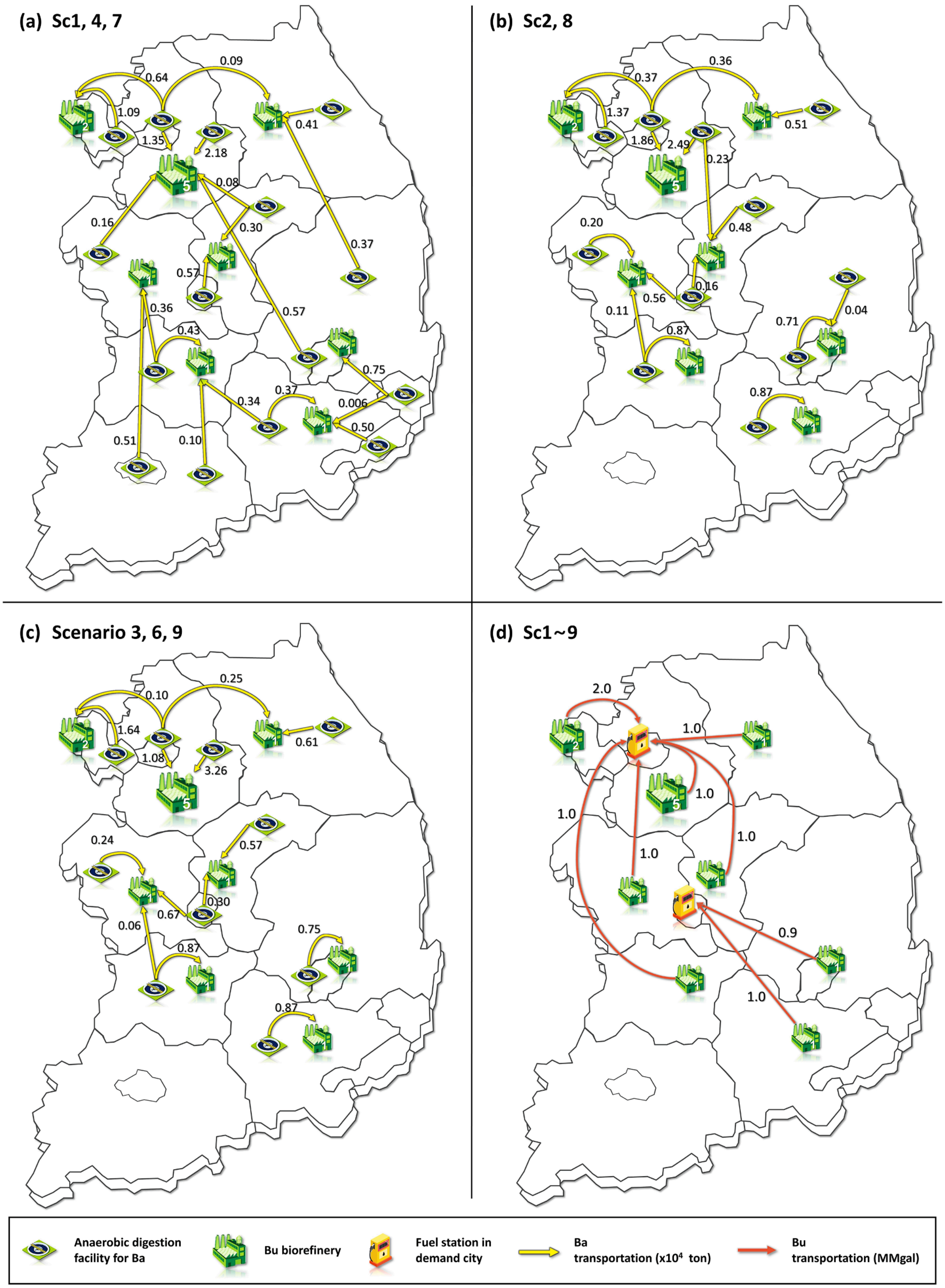

Fig. 4. Optimal result of stochastic model for Case 4. Distribution of Ba from AD facility to biorefinery in (a) Sc1, 4, 7; (b) Sc2, 8; and (c) Sc 3, 6, 9. (d) Bu from biorefinery to fuel station in all scenarios.

to 12.87 MMgal/yr.

4.4. Optimal cost

To estimate the expected total expected SCN costs (TAC^{Exp}), an average present value was calculated using Eq. (1) for all hypothetical Ba processing and Bu demand situations. The difference in TAC^{Exp} between the deterministic and the stochastic models of each case is enumerated in Table 4. The variation in Ba processing resulted in a 0.18% increase in TAC^{Exp} in Case 3, which is the same as Case 4. This increase is mainly a result of increases in the penalty cost ($PC_{s,w}$), which occur because the uncertain scenarios enforce reduced Ba processing,

Table 4
Results summary of proposed models.

	Case1	Case2			Case3			Case4		
					Scenario					
	X	Sc2	Sc5	Sc8	Sc4	Sc5	Sc6	Sc1,4,7	Sc2,5,8	Sc3,6,9
No. of biorefineries	16 (R4, 8, 9, 10, 11, 12, 15)	16 (R4, 8, 9, 10, 11, 12, 15)			13 (R3, 4, 8, 9, 10, 11, 12, 15)			13 (R3, 4, 8, 9, 10, 11, 12, 15)		
No. of AD facilities	15 (R1–R15)	15 (R1–R15)			15 (R1–R15)	11 (excepting R2, 5, 7, 13)	10 (excepting R2, 5, 7, 13, 14)	15 (R1–R15)	11 (excepting R2, 5, 7, 13)	10 (excepting R2, 5, 7, 13, 14)
No. of fuel stations	2 (R1, R6)	2 (R1, R6)			2 (R1, R6)			2 (R1, R6)		
Transport volume of Ba (kt)	139.04	139.04			111.80			111.80		
Transport volume of Bu (MMgal)	16.00	16.00			12.87			12.87		
Bu demand fulfillment (%)	4.92	6.14	4.92	4.10	3.95			3.95		
	Cost results									
Facility cost (k$/yr)	115.85	115.85			94.16			94.16		
Operating cost (k$/yr)	93.73	93.73			75.37			75.37		
Transportation cost (k$/yr)	2.34	2.34			1.63			1.63		
Penalty cost (k$/yr)	4677.80	4677.80			4727.39			4727.39		
Total annualized cost (k$/yr)	4889.72	4889.72			4898.55			4898.55		

biorefinery construction, and Bu transportation rather than outsourcing to compensate for the supply shortage of Bu.

The facility cost (*FC*), operating cost ($OC_{s,w}$), and transportation cost ($TC_{s,w}$) decreased with respect to the variation in Ba processing. In particular, $TC_{s,w}$ was more sensitive to changes in Ba processing uncertainty than other costs were. In Cases 3 and 4, the change in $TC_{s,w}$ was −30.1%, but the changes in *FC* and $OC_{s,w}$ were −18.7% and −19.6%, respectively. Despite the decrease in $TC_{s,w}$, a larger number of transportation links for Bu supply in more diverse regions was assigned by the stochastic model. This could be explained by the short delivery distances within South Korea, which result in increasing transport links for Bu between regions under Ba processing uncertainty. This is a more economically feasible option than increasing the amount of Bu produced by the biorefinery facilities themselves. To maintain stability in an uncertain environment for both Ba and Bu, increasing Bu transportation is preferable to increasing Bu production and Ba transportation.

5. Conclusions

This study presented the development of a stochastic model that determines the optimal design of a SCN for butyric acid-derived butanol when Ba processing and Bu demand are uncertain. The objective of the proposed stochastic model was to minimize the expected total SCN costs, including AD facilities to supply Ba, biorefinery facilities to produce Bu, and distribution costs of Ba and Bu. As a case study to evaluate the proposed stochastic model, three uncertain scenarios of South Korea in 2030 were applied, and the results were compared with those of the deterministic model. The solution of the proposed model strongly suggests that the SCN model is more sensitive to Ba processing uncertainty for organic waste-derived biodiesel than to Bu demand uncertainty. The stochastic models needed less Ba processing at AD facilities and Bu production at biorefinery facilities, resulting in a decrease in Ba and Bu transportation amounts. These results lead to an increase in outsourcing due to Bu supply shortages.

The consideration of uncertainty in the optimal SCN design for butyric acid-derived butanol can significantly impact the model feasibility and decision reliability. Such models can be advanced further by incorporating other uncertainties (e.g., conversion factors, economic parameters) into the model.

CRediT authorship contribution statement

Oseok Kwon: Investigation, Writing - original draft. **Jeehoon Han:** Conceptualization, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2021.117119.

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GlossarySets

e,: Types of utility
j,: Potential locations for biorefineries
l,: Types of feedstock
i,: Locations of feedstock
m,: Potential locations of demand city
s,: Bu demand scenario
w,: Ba processing scenarioParameters
$Prob_s$,: Bu demand uncertainty probability
$Prob_w$,: Ba processing uncertainty probability
FIC_j ,: Annualized fixed-investment capital cost of refinery j (MM$/yr)
FOC_j ,: Annualized fixed operating cost of refinery j (including labor, overhead, maintenance, insurance, and taxes) (MM$/yr)
MPP_l,: Material price of feedstock l ($/t)
UP_e ,: Energy price of utility e ($/kJ)
$c^{shortage}{}_m$,: Shortage cost of Bu demand scarcity at demand city m ($/gal)
$DDTC$,: Distance-dependent transportation cost ($/km/truckload)
$TDTC$,: Driving time-dependent transportation cost ($/h/truckload)
v,: Average driving speed (km/h)
$Dist_{ij}$,: Distance between nodes i and j (km)
$Dist2_{jm}$,: Distance between nodes j and m (km)
TLC_{Ba},: Ba capacity of truck (gal)
TLC_{Bu},: Bu capacity of truck (gal)
LUC,: Truck loading and unloading cost ($/gal)
CF^{ttog},: Conversion factor from tons to gallons (t/gal)
$RCAP_j$,: Maximum allowable capacity of refinery j (gal/yr)
RMC_l,: Amount of feedstock l (t/yr)
EMC_e,: Amount of utility e (kJ/yr)
RLA,: Required land size of refinery (km^2)
ALA_j,: Available land size for refinery j (km^2)
$TD^{B3}_{m,s,w}$,: Demand at city m (gal/yr)
$WCAP_{i,w}$,: Maximum production capacity of butyric acid from organic waste treatment facility in feedstock location i in scenario w (t/yr)Variables
$r_{l,i,j,s,w}$,: Amount of type-l feedstock transported from field i to refinery j in scenario s, w (t/yr)
$e_{e,i,j,s,w}$,: Amount of type-e utility supplied from field i for refinery j in scenario s, w (kJ/yr)
$p_{m,t,s,w}$,: Shortage of diesel demand from city m in scenario s, w (gal/yr)
$f_{j,m,s,w}$,: Amount of butanol transported from refinery j to demand city m in scenario s, w (gal/yr)
$prod^{Bu}_{j,s,w}$,: Bu production at refinery j (gal/yr)
cap^r_j,: Designed refinery capacity of refinery j (gal/yr)
nr_j ,: 1 if refinery j is opened; 0 otherwise
FC,: Total facility cost of Ba-to-Bu SCN model (MM$/yr)
$MC_{s,w}$,: Total material cost of Ba-to-Bu SCN model (MM$/yr)
$EC_{s,w}$,: Total energy cost of Ba-to-Bu SCN model (MM$/yr)
$PC_{s,w}$,: Total shortage cost of Ba-to-Bu SCN model (MM$/yr)
$TC^{Ba}_{s,w}$,: Ba delivery cost from organic waste treatment facility field i to biorefinery j (MM $/yr)
$TC^{Bu}_{s,w}$,: Bu delivery cost from biorefinery j to demand city m (MM$/yr)