HYBRID SIMULATION-BASED OPTIMIZATION FOR THE SECOND-GENERATION BIOFUEL SUPPLY CHAIN NETWORK DESIGN

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ABSTRACT

The goal of this study is to contribute to commercialization of the second-generation cellulosic biofuels (SGCBs) by reducing its operational cost. A hybrid simulation-based optimization approach is devised to design a cost-effect SGCB supply chain. The proposed approach adopts a two-stage approach consisting of feedstock yield estimation and location-allocation of feedstock storages between farms and refineries. Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC) model has been adopted for precise estimation of potential yield of feedstock such as 'Alamo' switchgrass regarding environmental dynamics (e.g., growth competition and weather). In addition, agent-based simulation (ABS) implemented in AnyLogic[®] is utilized to estimate operational cost of a SGCB supply chain. The simulation-based optimization with adaptive replication (AR) is devised to find an appropriate SGCB network design in terms of operational cost without causing heavy computational demand. The approach is applied to a SGCB network design problem in Southern Great Plains of U.S.

1 INTRODUCTION

The second-generation cellulosic biofuels (SGCBs) such as ethanol made of 'Alamo' switchgrass have been received nationwide attention to mitigate harmful impact of the first-generation biofuels (i.e., grain-based ethanol) on food supply. In 2018, 5.60 of 14.62 billion bushels of corn were used for ethanol production in U.S. (U.S. Department of Agriculture Economic Research Service 2019), and this amount can feed 159 million people.

The goal of this study is to mitigate transportation cost of a SGCB supply chain by finding appropriate locations of feedstock storages between farms and refineries. The hybrid simulation-based optimization approach proposed by Kim et al. (2018) is extended with a new simulation-based optimization (SBO) approach with adaptive replication (AR) to mitigate its computational demand. The hybrid simulation model includes (1) Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC) model for estimation of feedstock yield regarding environmental dynamics and (2) agent-based simulation (ABS) involving detail operations of actors (farms, storages, and refineries) in a supply chain for operational cost estimation. In addition, the optimizer with AR will find best locations of storages

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for mitigation of operational cost of a SGCB supply chain. The proposed approach was applied to the supply chain network design problem in Southern Great Plains of U.S. involving Alabama, Arkansas, Louisiana, Mississippi, Oklahoma, Texas, and Tennessee - see Kim et al. (2018) for more information about feedstock vield data.

2 **METHDOLOGY**

As mentioned in Section 1, ALMANAC estimates potential yield of feedstock, and ABS utilizes it as an available yield in a SGCB supply chain model. In the study, 24 operating biorefineries in Georgia, Texas, Missouri, Mississippi, Tennessee, and Kansas states have been considered with 13 feedstock farms in Southern Great Plans of U.S. The ABS is implemented in AnyLogic[®], and the proposed SBO with AR tends to find appropriate locations of storages between farms and refineries. Equations (1)-(6) show the objective function of the devised mixed integer programing (MIP) model (Kim et al. 2018).

> $\begin{aligned} Min \ z &= PC + TC_{FS} + TC_{SR} + TC_{FR} + HC \\ PC &= \sum_{i \in I} \sum_{t \in T} C_{it}^P Q_{it}^P \\ TC_{FS} &= \sum_{k \in K} x_k \sum_{i \in I} \sum_{t \in T} C_{ist}^S Q_{ikt}^S \end{aligned}$ (1)

$$PC = \sum_{i \in I} \sum_{t \in T} C_{it}^{P} Q_{it}^{P}$$
(2)

$$TC_{FS} = \sum_{k \in K} x_k \sum_{i \in I} \sum_{t \in T} C_{ikt}^S Q_{ikt}^S$$

$$TC_{SR} = \sum_{k \in K} x_k \sum_{j \in J} \sum_{t \in T} C_{kjt}^S Q_{kjt}^S$$

$$TC_{FR} = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} C_{ijt}^S Q_{ijt}^S$$

$$HC = \sum_{k \in K} x_k \sum_{j \in J} \sum_{t \in T} C_{ijt}^H Q_{ijt}^H$$
(6)

$$I C_{SR} = \sum_{k \in K} x_k \sum_{j \in J} \sum_{t \in T} C_{kjt}^{k} Q_{kjt}^{k}$$

$$\tag{4}$$

$$\mathcal{C}_{FR} = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \mathcal{C}_{ijt} \mathcal{Q}_{ijt}^{j}$$
(5)

$$HC = \sum_{k \in K} x_k \sum_{t \in T} C_{kt}^H Q_{kt}^H \tag{6}$$

Equation (2) is total production cost of farms; equation (3) is total transportation cost from farms to storages; Equation (2) is total production cost of family, equation (3) is total transportation cost from family to storages, equation (4) is total transportation cost from storages to refineries; equation (5) is total transportation cost from farms to refineries; and equation (6) is total holding cost of storages. C_{it}^{P} is production cost of farm *i* at time *t*; C_{ikt}^{S} is transportation cost from farm *i* to storage *k*; C_{kjt}^{S} is transportation cost from storage *k* to refinery *j*; C_{ijt}^{S} is transportation cost from farm *i* to refinery *j*; and C_{kt}^{H} is holding cost of storage *k* at time *t*. Quantity variables (e.g., Q_{it}^{P} , Q_{ikt}^{S} , Q_{kjt}^{S} , Q_{ijt}^{S} , and Q_{kt}^{H}) have similar definition used for the cost variables. The optimization problem shown in equation (1) is solved via AR. Unlike a commercial optimization

engine (e.g., OptQuest[®]) with the fixed number of replications of simulation, AR changes the number of replications during its SBO. To achieve a statistically reliable solution without sacrificing modeling accuracy of the proposed hybrid simulation model, AR determines the number of replications of each candidate solution based on a confidence interval given by sampling process. Although meta modeling techniques (e.g., Kriging and artificial neural network) aggregates a high-fidelity simulation (HFS) models to reduce their computational demand, the proposed AR uses the original HFS model to maintain its advantages (e.g., modeling accuracy).

3 **CONCLUSION**

The hybrid simulation-based approach involving ALMANAC and ABS was proposed to conduct costeffective location-allocation of feedstock storages. To this end, the mixed integer programing (MIP) has been devised, and its computational demand is resolved by SBO with AR algorithm. Although the proposed SBO tends to find near optimal solution, it can provide a practical and reliable solution under realistic search space given by the HFS models (i.e., ALMANAC and ABS) regarding dynamic operations in a SGCB supply chain.

REFERENCES

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