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Matheuristic approach and a mixed-integer linear programming model for biomass supply chain optimization with demand selection

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A B S T R A C T

It is crucial to identify alternative energy sources owing to the ever-increasing demand for energy and the other environmental problems associated with using fossil fuels. Biomass as a source of bioenergy is considered a promising alternative to fossil fuels. This study aims to optimize the biomass supply chain by developing an integrated model incorporating typical tactical supply chain decisions based on market or demand selection decisions. To this end, a novel mixed-integer linear programming (MILP) model is proposed to maximize the profit of the corresponding biomass supply chain and to commercialize electricity production by selecting electricity demand and making supply chain decisions regarding power plant operations, biomass feedstock purchase and storage, and biomass transport trucks. Owing to the intricacy of the MILP model, a fix-and-optimize-based solution strategy is developed and validated by applying it to several instances of a real-world case study. The results demonstrate that the proposed strategy can significantly reduce computational time while preserving high solution quality. Additionally, it helps improve planning and decision-making as it reveals the effect of essential biomass logistics characteristics on routing outcomes.

1. Introduction

Renewable energy can alleviate environmental challenges associated with conventional fossil fuel, such as source security, greenhouse gas emissions, and volatile energy prices (Ahmadvand and Sowlati, 2022; Sharma et al., 2013). Many studies have been conducted on what potential biomass offers for the international energy business. However, sustainable bioenergy criteria and indicators should be used to maximize this potential. Although a universally accepted standard for bioenergy does not exist, several organizations use indicator sets that overlap. According to Holm-Nielsen (2016), the United Nations Framework Convention on Climate Change establishes what constitutes renewable and nonrenewable biomass sources. According to current projections, bioenergy will presumably account for 30–35% of global energy needs by the end of this century, which will significantly impact the future mix of energy sources. As a sustainable renewable energy source, it is vital to consider biomass production capacity and identify potential biomass fuel suppliers globally. Biomass resources available for energy production can be divided into three broad categories: woody biomass, agricultural biomass, and biowastes (Ladanai & Vinterbäck, 2009). Biomass produced by agriculture results from the production of energy crops and agricultural waste. A tree's biomass comprises wood and the waste products left over after harvesting (logging residues, processing, wood wastes).

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Biomass feedstock can be transformed into a range of bioenergy (heat and electricity) and biofuel forms (solid, liquid, and g aseous) using various conversion processes (Ahmadvand & Sowlati, 2022; Nunes et al., 2020). Combustion and gasification are two of the most prevalent conversion processes (Ahmadvand & Sowlati, 2022; Quirion-Blais et al., 2019). In combustion, biomass is totally combusted to produce heat, while it is partially combusted in gasification to produce syngas, which may be utilized as a fuel for a variety of applications (Ahmadvand & Sowlati, 2022; Quirion-Blais et al., 2019). Utilizing biomass feedstock, particularly forest residues and harvest wastes that would otherwise be burned or discarded, for energy generation might be economically, ecologically, and socially beneficial (Cambero & Sowlati, 2014; Natural Resources Canada, 2013; Nunes et al., 2020). Nevertheless, besides technological obstacles, the forest-based biomass supply chain presents several obstacles that may impede the use of this low-value fuel for energy generation (Ahmadvand and Sowlati, 2022; Nunes et al., 2020). Due to its low density, poor calorific value, and geographically distributed availability, forest-based biomass has a huge collection and transportation cost (Ahmadvand & Sowlati, 2022; Cambero & Sowlati, 2014; Nunes et al., 2020). Additionally, given the cyclical nature of forest-based biomass supplies, it is important to stockpile biomass during times of plenty to compensate for leaner times (Akhtari et al., 2014; Nunes et al., 2020). Seasonal availability of biomass feedstock may drive up the price of these inputs (Nunes et al., 2020; Pedroli et al., 2013). Therefore, if the end-user wants to remain operational all year round, storing huge quantities of biomass for an extended period is necessary. Using several feedstocks with varying harvest dates helps mitigate issues caused by biomass' seasonal availability (Demirbas et al., 2009; Nunes et al., 2020). Two biomass sources, rather than one, can reduce costs by 15–20% (Nunes et al., 2020; Yoshioka et al., 2005). Furthermore, the quality of biomass differs depending on several factors: where it is sourced from, what species it is, what time of year it is collected, the weather, and how it is stored (Gumte et al., 2021; Nunes et al., 2020; Shabani and Sowlati, 2016; Sharma et al., 2013). Therefore, the decisions and activities performed by stakeholders in the biomass supply chain to prepare feedstock depend on the kind and quality of biomass and conversion technology (Ahmadvand and Sowlati, 2022; Nunes et al., 2020).

The supply chains for fossil fuels and biomass are similar. When planning the conversion and distribution of biomass, one must consider the locations of feedstock supply sites owing to the low energy density of biomass. Therefore, it is imperative to have an integrated planning model for the supply chain. It is necessary to have an all-encompassing plan for converting biomass to bioenergy that centers on the supply chain to ensure that biomass becomes an important part of the overall energy mix. According to the US Department of Energy, supply chains for the conversion of biomass to bioenergy have to incorporate the following components: (1) feedstock supply, (2) energy conversion, (3) energy distribution, and (4) energy usage (Seay & You, 2016). Collecting, transporting, storing, and preparing resources accounts for approximately 50–65% of the production cost of bioenergy (Ahmadvand and Sowlati, 2022; Nunes et al., 2020). Optimization of biomass supply operations can potentially improve the cost-efficiency of biomass supply chain, eventually making bioenergy more competitive than alternative fossil energy (Allen et al., 1998; Soares et al., 2019). The coupling of biomass transportation with vehicle routing, fleet assignment, and resource allocation are some of the primary challenges of biomass supply chain modeling and optimization. The use of these transportation planning tools might help determine the most cost-effective method of biomass transporting and handling, thereby enhancing the competitiveness of bioenergy products in the market (Bai et al., 2011; Han & Murphy, 2012; Miao et al., 2012; Yue &You, 2016). In practice, a producer or service provider can selectively determine a subset of downstream markets or demand zones from a set of potential markets. Such decisions on the supply chain stage would occur due to limited supply capacity or could be based solely on economic factors (Abdel-Aal et al., 2017; Abdel-Aal and Selim, 2017; Geunes et al., 2005; Taaffe et al., 2008). Integrating such decisions of demand selection flexibility into biomass supply chain-planning models enables a producer or service provider to optimally align available resources with downstream requirements, thereby creating profit enhancement opportunities (Abdel-Aal & Selim, 2019; Chahar & Taaffe, 2009; Geunes et al., 2005). Conversely, biomass supply chain models defined as mixed-integer linear programming (MILP) or mixed-integer nonlinear programming (MINLP) problems are fundamentally NP-hard problems, posing significant computing hurdles. Due to advancements in optimization algorithms and the growth of computers, we can tackle several enormous, practically significant problems (Yeh et al., 2014; Yue et al., 2014; Yue & You, 2016). However, the solution must be accelerated, and the quality of the solution must be improved for industrial-scale applications. For instance, a national biomass supply chain model encompassing several facilities, biomass feedstocks, bioenergy products, and production methods may have millions of variables and constraints. A task of this magnitude can drain computer memory in a short period without yielding feasible solutions. Additionally, computational difficulties stem from the nonlinearity and nonconvexity of the biomass supply chain model. These model characteristics exclude employing effective optimization techniques that are only applicable to linear, convex, or pseudo-convex problems. In instances when nonlinear and nonconvex functions play a significant role in the model, customized problem-solving solutions are necessary (Yue & You, 2016). This computational difficulty results from multiscale integration and enhancement of model fidelity. As more details are added to the biomass supply chain model, the number of decision variables and constraints, model characteristics, and difficulties significantly increase.

This study tackles two critical challenges. Firstly, from the perspective of the biomass supply chain, it is very challenging to examine more practical aspects of the biomass supply chain, including supplier and customer selections, as well as more detailed tactical decisions regarding contact periods with electricity customers, truck type selection to transport biomass feedstock, and the number of trips. Second, because the real-world biomass supply chain is typically represented by a large-scale mathematical model, commercial optimization solvers often fail to determine the optimal solutions to such models in reasonable computational time.

According to the literature review, the novelty of this study can be summarized as follows:

1- This is the first study to develop a novel MILP model for the biomass supply chain, considering customer selection and minimum contact period.
2- We propose a matheuristic approach to enable the decomposition of the main proposed model based on the fix-and-optimize technique. Our decomposition strategy exploits the problem structure and generates small-scale subproblems, enabling us to address large-scale problems.
3- A real-world case study of the biomass supply chain is presented to demonstrate the effectiveness of the proposed matheuristic technique and its potential in terms of computing time and the quality of the solution.

The remainder of this paper is structured as follows. Section 2 presents the literature review. Section 3 defines the problem investigated in this study, and Section 4 provides an MILP for this problem. Section 5 presents the proposed solution approach based on the fix-and-optimize matheuristic strategy. Section 6 demonstrates the application of the proposed MILP model to a real-world case study. Section 7 presents the experimental results. Section 8 presents the conclusions drawn from this study.

2. Literature review

The findings presented in the next section reflect some of the most recent findings regarding biomass utilization in bioenergy production. Irfan et al. (2020) offered a current overview and future forecast for the use of biomass energy in Pakistan. Biomass resources, including bagasse, cotton stalks, animal manure, etc., are studied and varied for easy access in huge quantities. The authors demonstrate that the share of renewable energy consumption might rise from 1.1% to 5% by 2030. Singh et al. (2020) studied electricity generation from biogas in Punjab, India, and demonstrated promising future growth. Research indicates that 3172 MW of energy may be produced by the facility using biomass. Large-scale biogas plant economic viability is also assessed in this study. The availability of rubberwood for use in Thai power plants is studied by Wongsapai et al. (2020). Based on the findings, it was determined that three provinces located on the Southern border and others within a 200 km radius had an estimated supply capacity of 40.2 MW and 187.62 MW of rubberwood for power generation, respectively. Furthermore, a projection of the materials required to launch new plants in the area is also supplied. Alberizzi et al. (2020) developed a hybrid renewable energy system in the form of a mixed integer linear programming decrease reliance on fossil fuels. The suggested method ensured a workable operational strategy for energy supply to mitigate the potentially negative environmental effect of renewable energy generation. A case study conducted in South Tyrol (Italy) examined the effectiveness of the strategy. The biomass materials obtained from the trunks of olive trees, in the form of pellets, are used by Soltero et al. (2020) as a substitute for forest biomass in the Mediterranean region. According to the findings, harvesting in Andalusia and the rest of Spain can potentially meet 70% of the market's current overall demand. The research is expanded to include other Mediterranean nations to calculate the annual potential pellet yield.

The next section discusses the most relevant prior research on modeling and optimizing biomass supply chain models. Then, the principal market and demand selection research in the supply chain literature are examined.

2.1. Biomass supply chain modeling and optimization

Logistics and information flow link together the many participants in a supply chain, which is why the term "supply chain management" describes the process of overseeing and making decisions for such networks (Liu et al., 2017). These decisions, ranging from facility investment and growth to the daily production schedule, are classified as strategic, tactical, and operational (Atashbar et al., 2016; Melis et al., 2018). Nagel (2000) presents a mixed integer linear optimization model that enables regional-scale biomass management for energy supply through dynamic economic efficiency assessment. Sedjo (1997) analyzed the financial feasibility of using forest biomass for energy generation. Bruglieri and Liberti (2008) proposed a mixed integer linear programming for designing a process that generates energy from various biomass sources, including agricultural and biological waste products. The model accounts for the varying properties of biomass (such as seasonality) and tackles the problem of recycling waste from biofuels back into biomass production areas while protecting the environment and promoting sustainable growth. Ekşioğlu et al. (2009) presented a mathematical programming approach for planning the bio-supply refinery's chain and logistics. The model calculated the optimal configuration of bio-refineries—including the number, size, and location of facilities—to convert biomass into biofuel. Vera et al. (2010) created a model to determine the optimal placement and output of a power plant that runs on byproducts from olive oil production. Leduc et al. (2010) introduced a mixed integer linear programming model to ascertain the optimal locations and sizes of methanol heat recovery facilities. Zhu et al. (2011) developed a model of the biomass conversion industry based on mixed integer linear programming. The proposed model simultaneously determined the best possible combination of candidates for bio-refinery plants, the best possible sites for new warehouses, and the best possible storage and transit capacity for biomass. Shabani and Sowlati (2013) introduced a tactical decision model for maximizing the use of forest and wood residues in power production. Monthly decisions on the supply, storage, and consumption of several forms of forest-based biomass (sawdust, shavings, roadside logging waste, and bark) were considered using a nonlinear programming model with a one-year planning horizon. The target function of the model was to maximize the produced profit, which comprised the income from selling power, the costs of biomass acquisition and storage, and the expenses of electricity generation and ash disposal. The model was used in a major forest-based biomass power facility in Canada to examine decision-making situations.

To find the optimal site for biofuel production plants while keeping expenses to a minimum, Zhang et al. (2016) utilized a generic mixed-integer linear programming model that considers the carbon footprint caused by transporting raw materials and the associated expenses to evaluate the efficacy of decisions made by supply chain managers. Liu et al. (2017) examined the feasibility of using forest biomass at a second-generation bioethanol coproduction facility to produce electricity. The most influential factors were identified by considering the cost of electricity, heating value, and raw materials. In this study, the authors offered a bi-objective model to maximize profits while reducing carbon emissions, and the findings show that electricity costs have a significant bearing on supply chain profitability. In Gonela (2018), a mathematical supply chain model for coal and biomass-based electricity generation was proposed by considering the overall cost and any potential environmental impact. The results showed that using coal and biomass to generate power is viable for long-term sustainability. Sarker et al. (2019) investigated a multi-stage biomethane gas supply chain to identify the best site to locate facilities and material flows to reduce operational expenses. Durmaz and Bilgen (2020) developed a mixed integer linear programming model to optimize a biomass supply chain for maximum profit and minimum transportation cost. Furthermore, they conducted a sensitivity analysis with real-world data from Izmir, Turkey, to investigate the impact of varying configuration factors in the supply chain. To ensure a steady supply of feedstocks for power plants, Fattahi et al. (2021) created a model for sustainable biomass supply chain planning. A two-stage model was created to aid strategic and tactical decision-making. Therefore, the authors employed a simulation model to produce many viable alternatives. Cao et al. (2021) developed a mixed integer programming approach to solve the location-routing issue in a biomass supply chain. Because finding a solution to this problem would be computationally prohibitive, the authors focused on building a heuristic approach based on a tabu search. Additionally, a sensitivity analysis was presented to explore the effect of vehicle capacity and maximum throughput of collecting facilities on the model goal, network layout, and number of used vehicles. Duc et al. (2021) designed a multi-objective biomass supply chain model to make strategic and tactical decisions considering demand uncertainty to minimize the overall cost and carbon emissions from the transportation activities in the system. Nandimandalam et al. (2022) proposed a multi-objective mathematical model of a two-echelon biomass supply chain by considering a variety of strategic decisions that must be made along the network of the supply chain, including the location of power plants, allocation of suppliers to power plants, and the alternatives for harvesting, storing, and transporting biomass. This formulation minimizes both the overall system cost and greenhouse gas emissions. For further information on the modeling and optimization of the biomass supply chain, interested readers are directed to (Ba et al., 2016; Martinez-Valencia et al., 2021; Mottaghi et al., 2022; Shabani et al., 2013; Sun and Fan, 2020).

2.2. Market and demand selection in the supply chain

The selection of markets and customer demands is a critical aspect of supply chain profit optimization as it helps businesses make informed decisions about which products to produce and distribute. By identifying the most profitable market or customer demand, businesses can allocate their resources efficiently and effectively (Abdel-Aal et al., 2017; Abdel-Aal & Selim, 2017; Geunes et al., 2005), thereby avoiding wastage of resources and ensuring products are produced and distributed in quantities that meet customer demand, leading to increased sales and profits. Effective demand selection can also help businesses stay ahead of their competitors by offering the products that their customers want when they want them (Geunes et al., 2005). Geunes et al. (2005) proposed a category of optimization models that tackle different degrees of demand selection flexibility within integrated production and demand planning. That study consolidates various recent works with a common focus on demand selection. Furthermore, these optimization models build upon the classical economic order quantity (EOQ) and newsvendor problems to permit demand selection flexibility. Furthermore, the study examines conventional dynamic and deterministic production planning models considering demand selection. Shu et al. (2013) examined an integrated demand selection and multi-echelon inventory control problem that expands on the traditional model by introducing demand selection decisions to maximize net profit by determining which sets of demand to fulfill and inventory control policy to implement. The problem is formulated as a nonlinear discrete optimization model, and the paper proposes an approach for efficient solving. Numerical experiments provide managerial insights. Abdel-Aal et al. (2017) studied the selective newsvendor problem (SNVP), where the decision maker selects the optimal set of markets to serve and the optimal order quantity to procure. It focuses on the case of a single product SNVP with uncertain demand data of unknown probability distributions for some potential markets. Three cases are presented: flexible, full, and partial market entry cases. Then, binary nonlinear programs are formulated, and solution algorithms are proposed. The study provides useful managerial insights into the problem. Abdel-Aal and Selim (2017) examine the Multi-Product Selective Newsvendor Problem (MPSNVP) under the CVaR risk criterion. The problem is formulated as binary nonlinear programs and transformed into conic quadratic mixed integer programs. Proposed solution algorithms outperform commercial solvers, and the paper provides managerial insights on the impact of risk aversion, the number of products, and market pool size. Mohammadivojdan and Geunes (2018) discuss various supply chain planning problems that arise when multiple demand sources are available. The first problem pertains to selecting a subset of available demand sources to maximize profit or minimize cost. The study highlights several open problems within each category.

More recently, Abdel-Aal and Selim (2019) presented robust models for SNVP, characterizing demand uncertainty using an uncertainty set. The study proposes efficient solution algorithms for SNVP with uncertain demand with box, ellipsoidal, and polyhedral uncertainty sets or combinations of these uncertainty sets. The study also provides useful insights through computational experiments and discussion of results. Li and Hai (2019) present an integrated supply chain network design problem incorporating inventory and pricing decisions, formulated as a nonlinear integer programming model with capacity limitations for each warehouse. A Lagrangian relaxation-based approach is used to solve the problem, an efficient algorithm is developed for the subproblem, and computational experiments are conducted to provide managerial insights. Ghadimi et al. (2023) address the problem of safety stock placement in a supply chain with market selection decisions. The study presents a model and proposes two algorithms to solve the problem, with computational experiments showing promising results. The study suggests that incorporating load-dependent lead times is most valuable when capacity is limited compared to available demand, and integrating market selection and safety stock decisions is most beneficial when capacity is limited, and marginal revenue is low.

3. Problem description

This study designed and optimized the biomass supply chain by proposing a biomass supply chain that can maximize profits and determine optimal markets to serve. The considered biomass supply chain includes three key segments: the upstream segment, which represents biomass supply zones or suppliers; the midstream segment, which represents biomass power plants and associated storage facilities; and the downstream segment, which represents electricity market or demand zones. Fig. 1 shows the proposed biomass supply chain and the associated activities with each stage of the supply chain. Multiple biomass feedstocks are transported from the suppliers to the electricity power plants by trucks. The biomass feedstocks are then stored in the warehouses and utilized to produce electricity in the power plants to satisfy the electricity demand of the selected demand zones. Biomass suppliers have limited capacities for multiple types of biomass feedstocks. The decision maker should select the suppliers, types of biomass feedstock, and quantities to acquire in each period. Limited-capacity trucks are available for transporting biomass feedstocks from the chosen suppliers. The types of trucks to be used to transport biomass feedstocks from the specified suppliers to the operating power plants and the number of trips in each period should be determined. A set of power plants is available for biomass-based electricity generation, each having a limited capacity for generating electricity and a warehouse with a limited storage capacity to store biomass feedstocks of different volumes. The decision maker has to select which electricity demand zones to serve to maximize profit, which power plants to be operational in each period, and the amount of electricity generated by each operational power plant. If a demand zone is chosen, it must be serviced for a minimum number of periods necessary to complete the contract. The following are the tactical monthly decisional items in the upstream and midstream biomass supply chain addressed in this study:

- The suppliers selected;
- The type and quantity of biomass feedstock purchased from a specific supplier (ton);
- The power plants operated;
- The type and quantity of biomass feedstock stored (ton);
- The type and quantity of biomass feedstock consumed (ton);
- The amount of electricity generated (MWh);
- The truck type utilized between each supplier and power plant;
- The frequency of trips of each truck between each supplier and power plant;

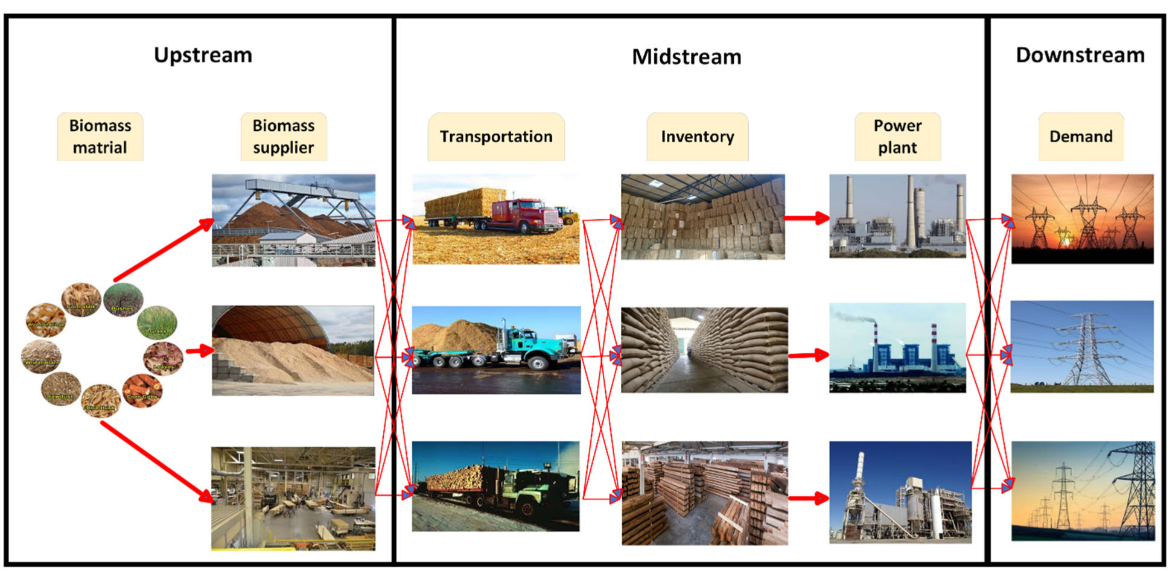

Fig. 1. Proposed biomass supply chain for electricity generation

Assumptions:

The following assumptions are considered while forming the biomass supply chain model:

1- All model parameters are considered to be deterministic.
2- The power plants can process several types of biomass feedstock to generate electricity. Consequently, processing a single type of biomass feedstock is a special case of this assumption.
3- Travel time between supplier i and biomass power plant j can be estimated by dividing the distance between the supplier and the power plant by the average truck velocity; for instance, the average truck velocity can be considered as 60 km/h.
4- The selected demand zone must be serviced for a minimum number of periods necessary to complete the contract.

4. Mathematical model

This section presents the novel mathematical model proposed for biomass supply chain planning for electricity generation.

4.1. Model notation

This section shows the notation used in setting the biomass supply chain model.

Sets and Indices:

$|S|$: cardinality of set S, i.e., the number of elements in set S

I: set of biomass suppliers

i: index for supplier ($i = 1, 2, \dots, |I|$)

B: set of the types of biomass supply

b: index for the type of biomass supply ($b = 1, 2, \dots, |B|$)

C: set of electricity power customers

c: index for customer ($c = 1, 2, \dots, |C|$)

J: set of biomass power plants

j: index for biomass power plant ($j = 1, 2, \dots, |J|$)

T: set of planning periods, planning horizon

t: index for period ($t = 1, 2, \dots, |T|$)

K: set of truck types

k: index for truck type ($k = 1, 2, \dots, |K|$)

Parameters:

TT_{ij}: traveling time in hours between supplier i and the biomass power plant j

D_{ct}: demand of customer c for electricity in Megawatt-hours in period t

ESP_{ct}: electricity price per Megawatt-hours sold to customer c in period t

S_{ibt}: available biomass supply in tons of type b from supplier i during period t

$TCap_k$: capacity in tons of truck type k

$PCap_j$: Megawatt-hours capacity of biomass power plant j

$WCap_j$: volume capacity of the warehouse at biomass power plant j

FC_{jt}: cost of operating biomass power plant j in period t

TOC_{tk}: operating cost of truck type k in period t

TCT_{tk}: transportation cost per hour using truck type k in period t

CSC_{jct}: cost of satisfying the electricity demand of customer c from biomass power plant j in period t

VOC_{jbt}: variable operating cost per ton in period t of biomass type b at biomass power plant j

H_{jbt}: holding cost per ton in period t of biomass type b inventory at biomass power plant j

$\overline{I_{jb}}$: initial inventory in tons of biomass type b at power plant j

L_{tk}: labor cost in period t using truck type k

LTP_t: length of period t in days

$\overline{WH}$: working hours per day

BP_{ibt}: per ton purchasing cost of biomass type b from supplier i during period t

W_{ijbt}: energy value in Megawatt-hours per ton of biomass type b from supplier i at power plant j in period t

EFF_{jb}: efficiency (%) of the system when using biomass type b at biomass power plant j

MC_{ibt}: proportion (%) of water per ton of the biomass of type b from supplier i in period t

HV_{ibt}: heating value of the combustion of a ton of the biomass of type b from supplier i in period t (MWh/dry ton)

V_b: volume per ton of biomass type b

$\bar{T}$: minimum contract duration, i.e., minimum number of periods necessary to execute a contract with a customer of electricity demand

CON_{ct}: down payment of signing a contract with customer c in period t

Decision variables:

Continuous variables:

x_{ijbtk}: amount in tons of biomass type b transported by from supplier i to plant j in period t using truck k

AB_{jbt}: amount in tons of biomass type b used at power plant j during period t

I_{jbt}: inventory level in tons of biomass type b at biomass power plant j in the end of period t

Integer variables:

f_{ijtk}: frequency of trips by truck k shipping biomass from supplier i to plant j during period t

Binary variables:

y_{jt}: a binary variable that takes the value 1 if biomass power plant j is operational during period t; otherwise, it takes the value 0

w_{ct}: a binary variable that takes the value 1 if customer c is selected to be served in period t; otherwise, it takes the value 0

$\bar{w}_{ct}$: a binary variable that takes the value 1 if a contract is signed with customer c in period t to be served for at least $\bar{T}$ periods; otherwise, it takes the value 0

tr_{tk}: a binary variable that takes the value 1 if truck k is used in period t; otherwise, it takes the value 0

z_{ijtk}: A binary variable that takes the value 1 if truck k is utilized to transport biomass from supplier i to plant j during period t; otherwise, it takes the value 0.

4.2. The mathematical model

This section discusses the proposed novel mathematical model for the biomass supply chain and each model equation.

<u>Objective function</u>:

Net profit maximization

$$\begin{aligned}\max z = &\sum_{c\in C}\sum_{t\in T} CON_{ct}\bar{w}_{ct} + \sum_{c\in C}\sum_{t\in T} ESP_{ct}D_{ct}w_{ct} - \sum_{j\in J}\sum_{t\in T} FC_{jt}y_{jt} - \sum_{t\in T}\sum_{k\in K} TOC_{tk}tr_{tk}\\ &- \sum_{j\in J}\sum_{c\in C}\sum_{t\in T} CSC_{jct}D_{ct}w_{ct} - \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{k\in K} TT_{ij}TCT_{tk}f_{ijtk} - \sum_{i\in I}\sum_{j\in J}\sum_{b\in B}\sum_{t\in T}\sum_{k\in K} BP_{ibt}x_{ijbtk}\\ &- \sum_{j\in J}\sum_{b\in B}\sum_{t\in T} VOC_{jbt}AB_{jbt} - \sum_{i\in I}\sum_{j\in J}\sum_{t\in T}\sum_{k\in K} L_{tk}z_{ijtk} - \sum_{j\in J}\sum_{b\in B}\sum_{t\in T} H_{jbt}I_{jbt}\end{aligned} \quad (1)$$

Eq. (1) gives the net profit function that needs to be maximized. It comprises ten terms. The first two terms are revenue from income generated by signing contracts with customers and revenue generated by meeting the demand of customers, whereas the remaining eight terms represent the costs associated with the problem. These cost terms are, in order, biomass power plants operating costs, trucks operating costs, cost of satisfying the electricity demand of the selected customers, costs of transporting biomass, biomass purchasing costs, biomass operating costs in the power plants, labor costs associated with truck use, and biomass inventory holding costs.

<u>Constraints</u>:

- Initial inventory:

$$I_{jb0} = \overline{I_{jb}}y_{j0} \;\forall j \in J, \forall b \in B \quad (2)$$

Eq. (2) represents the initial inventory of biomass type b if biomass power plant j is open.

- The amount of electricity in Megawatt-hours produced per ton of biomass:

$$W_{ijbt} = HV_{ibt}(1 - MC_{ibt})EFF_{jb}, \forall i \in I, j \in J, b \in B, t \in T \quad (3)$$

Eq. (3) is employed to calculate the amount of electricity, W_{ijbt}, in Megawatt-hours per ton of biomass type b from supplier i at biomass power plant j produced in period t. W_{ijbt} is calculated by multiplying the heating value (HV_{ibt}) by the dehydration ratio $(1 - MC_{ibt})$ (Liu et al., 2017; Shabani and Sowlati, 2013).

- Electricity demand satisfaction:

$$\sum_{i \in I} \sum_{j \in J} \sum_{b \in B} W_{ijbt} AB_{jbt} \geq \sum_{c \in C} D_{ct} w_{ct} \ \ \forall t \in T \quad (4)$$

Eq. (4) expresses the constraint of satisfying the electricity demand of all selected customers in period t. There should be enough electricity in Megawatt-hours produced by the opened power plants in period t.

- Enforcing the minimum contract duration:

$$\sum_{\tau = t}^{t + \bar{T} - 1} w_{c\tau} \geq \bar{T} \bar{w}_{ct} \ \forall c \in C, t \in T \quad (5)$$

$$\sum_{\tau = t}^{t + \bar{T} - 1} \bar{w}_{c\tau} \leq 1 \ \forall c \in C, t \in T \quad (6)$$

$$w_{ct} \leq \bar{w}_{ct} + w_{c(t-1)} \ \forall c \in C, t \in T \quad (7)$$

Eq. (5), Eq. (6), and Eq. (7) are essential logical constraints for preserving the minimum number of periods required to sign a contract with a customer of electricity demand. Eq. (5) guarantees serving customer c for at least $\bar{T}$ periods, if that customer is selected. Eq. (6) ensures signing at most a single contact with customer c during the $\bar{T}$ periods. Eq. (7) enforces serving customer c in period t if there is a signed contract with that customer during any period within the interval $[t - \bar{T}, t]$.

- Supply capacity restriction:

$$\sum_{j \in J} \sum_{k \in K} x_{ijbtk} \leq \sum_{j \in J} \sum_{k \in K} S_{ibt} z_{ijtk} \ \ \forall i \in I, b \in B, t \in T \quad (8)$$

Eq. (8) represents the upper limit of the procurement amount of biomass type b from supplier i in period t. That procurement upper limit cannot violate the available capacity of the supplier.

- Biomass power plant capacity restriction:

$$\sum_{i \in I} \sum_{b \in B} W_{ijbt} AB_{jbt} \leq PCap_j \ y_{jt} \ \forall j \in J, t \in T \quad (9)$$

Eq. (9) sets the upper limit of the produced electricity in power plant j during period t. This upper limit of the produced electricity cannot violate the capacity of the power plant.

- Warehouse capacity restriction at the biomass power plant:

$$\sum_{b \in B} V_b I_{jbt} \leq WCap_j \ y_{jt} \ \forall j \in J, t \in T \quad (10)$$

Eq. (10) represents the limited capacity of the warehouse at power plant j. Therefore, the stored amount of all biomass types must not violate the storage capacity during any period t.

- Inventory balance:

$$I_{jbt} = I_{jb(t-1)} + \sum_{i \in I} \sum_{k \in K} x_{ijbtk} - AB_{jbt} \ \forall j \in J, b \in B, t \in T \quad (11)$$

Eq. (11) ensures that the inventory level of each type of biomass b at each power plant j is balanced during any period t.

- Work time limitation:

$$TT_{ij} f_{ijtk} \leq LTP_t \overline{WH} z_{ijtk} \ \forall i \in I, \forall \in J, t \in T, k \in K \quad (12)$$

Eq. (12) shows the constraint on working time based on a round-trip travel time between supplier i and power plant j. Each vehicle is permitted a certain number of daily working hours during the number of days in the period, thereby limiting the frequency of trips made by vehicle type k transporting biomass from supplier i to power plant j during period t.

- Truck assignment:

$$\sum_{i \in I} \sum_{j \in J} z_{ijtk} \leq tr_{tk} \ \forall t \in T, k \in K \quad (13)$$

Eq. (13) guarantees that each vehicle may only be allocated to one route between from supplier i and power plant j in each period t.

- Truck capacity restriction:

$$x_{ijbtk} \leq TCap_k f_{ijtk} \; \forall i \in I, j \in J, b \in B, t \in T, k \in K \tag{14}$$

Eq. (14) shows the limitations of the procurement amount of biomass type b from supplier i to power plant j in period t using truck type k. That procurement amount is limited by truck capacity and the number of trips.

- Domain of decision variables:

$$y_{jt}, tr_{tk}, z_{ijtk}, \overline{w}_{ct}, w_{ct} \in \{0, 1\} \; \forall i \in I, j \in J, c \in C, t \in T, k \in K \tag{15}$$

$$AB_{ijb}, I_{ijb}, x_{ijbtk} \geq 0 \; \forall i \in I, \forall j \in J, b \in B, t \in T, k \in K \tag{16}$$

$$f_{ijtk} \in \mathbb{Z}_0^+ \; \forall i \in I, \forall j \in J, t \in T, k \in K \tag{17}$$

Eqs. (15), (16), and (17) identify the types of decision variables, where Eq. (15) shows the binary variables, Eq. (16) presents the continuous variables, and Eq. (17) describes the integer variables.

4.3. Model complexity

Table 1 summarizes the assessment of the proposed model's complexity and superiority and indicates the number of binary variables, integer variables, continuous variables, and constraints employed in its development. Additionally, the table presents insights into the size and attributes of the MILP mathematical model, which is crucial in assessing the model's computational efficiency and ability to tackle large-scale problems. Ascertaining the practicality and usefulness of a model in solving real-world problems requires a thorough evaluation of its complexity and superiority, making the information provided in Table 1 crucial for comprehending the quality of the proposed model and identifying opportunities for improvement.

Table 1
Size characteristics of the proposed model.

Number of binary variables	$(\lvert J\rvert \times \lvert T\rvert) + (\lvert T\rvert \times \lvert K\rvert) + (\lvert I\rvert \times \lvert J\rvert \times \lvert T\rvert \times \lvert K\rvert) + 2(\lvert C\rvert \times \lvert T\rvert)$ $= \lvert T\rvert \times (\lvert J\rvert(1 + \lvert I\rvert \times \lvert K\rvert) + \lvert K\rvert + 2\lvert C\rvert)$
Number of continuous variables	$2(\lvert I\rvert \times \lvert J\rvert \times \lvert B\rvert) + (\lvert I\rvert \times \lvert J\rvert \times \lvert B\rvert \times \lvert T\rvert \times \lvert K\rvert)$ $= \lvert I\rvert \times \lvert J\rvert \times \lvert B\rvert \times \left(2 + (\lvert T\rvert \times \lvert K\rvert)\right)$
Number of integer variables	$\lvert I\rvert \times \lvert J\rvert \times \lvert T\rvert \times \lvert K\rvert$
Number of constraints	$(\lvert J\rvert \times \lvert B\rvert) + \lvert T\rvert + (\lvert I\rvert \times \lvert J\rvert \times \lvert B\rvert \times \lvert T\rvert) + 3(\lvert C\rvert \times \lvert T\rvert) + (\lvert I\rvert \times \lvert B\rvert \times \lvert T\rvert) + 2(\lvert J\rvert \times \lvert T\rvert) + (\lvert J\rvert \times \lvert B\rvert \times \lvert T\rvert) + (\lvert I\rvert \times \lvert J\rvert \times \lvert T\rvert \times \lvert K\rvert) + (\lvert T\rvert \times \lvert K\rvert) + (\lvert I\rvert \times \lvert J\rvert \times \lvert B\rvert \times \lvert T\rvert \times \lvert K\rvert)$ $= (\lvert J\rvert \times \lvert B\rvert) + \lvert T\rvert \Big(1 + 3\lvert C\rvert + 2\lvert J\rvert + \lvert K\rvert + (\lvert I\rvert \times \lvert B\rvert) + \lvert J\rvert\big((\lvert I\rvert \times \lvert B\rvert) \times (1 + \lvert K\rvert) + \lvert B\rvert + (\lvert I\rvert \times \lvert K\rvert)\big)\Big)$

Even for a small practical problem with 50 suppliers, $|I| = 50$, 10 power plants, $|J| = 10$, 5 types of biomass, $|B| = 5$, 20 customers, $|C| = 20$, 4 types of trucks, $|K| = 4$, and 12 time periods, $|T| = 12$, the model size can be significant, as shown below:

Problem size	Number of binary variables	24648
$\lvert I\rvert = 50, \lvert J\rvert = 10, \lvert B\rvert = 5, \lvert C\rvert = 20, \lvert K\rvert = 4,$	Number of continuous variables	125000
and $\lvert T\rvert = 12$	Number of integer variables	24000
	Number of constraints	178670

As the problem size increases, the model becomes larger in size and more complex, thereby requiring a solution approach to tackle challenges associated with large-scale problems. Therefore, in the next section, we propose a matheuristic based on Fix-and-Optimize to efficiently address large-scale MILP issues.

5. Solution approach

General-purpose MIP solvers can be used to solve tiny instances of the proposed biomass supply chain. As a result, the solution of medium- and/or large-scale instances calls for applying specific solution methodologies. There are several decision variables dependent on the y_{jt} and tr_{tk} sets. If y_{jt} is known, then tr_{tk} variables' values are known; it is relatively simple to deduce the values of other variables. For example, fixing binary variables to integer values means the fix-and-optimize matheuristic might solve the problem. The fix-and-optimize matheuristic may be successful in this scenario considering the conversion of binary variables to integer values results in only two potential outcomes. Fixed variables directly impact algorithm performance and quality of the final solution, i.e., the fulfillment of the soft constraints, when applying a fix-and-optimize matheuristic to solve the problem. Therefore, the decomposition operation must be modified in terms of the kind and size of the operation. Six distinct potential decomposition approaches can be examined in this study:

- Time Decomposition (TD): a predetermined number of periods can be optimized.
- Plant Decomposition (PD): a predetermined number of power plants can be optimized.
- Supplier Decomposition (SD): a predetermined number of suppliers can be optimized.
- Customer Decomposition (CD): a predetermined number of customers can be optimized.
- Biomass type Decomposition (BD): a predetermined number of biomass types can be optimized.
- Truck (vehicle) Decomposition (VD): a predetermined number of trucks can be optimized.

For this study, when a period, power plant, supplier, customer, biomass type, or truck is free to be optimized, it indicates that none of the variables associated with this period, power plant, supplier, customer, or biomass type are fixed. We establish a parameter ρ, which represents the cardinality of the free-to-optimize subset of variables for each kind of decomposition β. For example, considering the time decomposition TD, we can release $1, 2, 3, \ldots, \rho$ time periods, given that $\rho \leq |T|$. Neighborhoods are defined by the combination of a decomposition type $\beta \in \{TD, PD, SD, CD, BD, VD\}$ and the size ρ. It is possible to express a whole neighborhood using the tuple (β, ρ). For example, a neighborhood (PD, 4) of a solution x comprises all solutions that may be obtained by solving subproblems such that $|J| - 4$ power plants are set exactly as in the solution x while 4 power plants are within the free-to-optimize subset of variables. We employ a variable neighborhood descent (VND) technique, which involves iterating over a series of neighborhoods $\mathcal{N}$ while a *first improvement* selection technique is used to find superior solutions to explore the numerous potential neighborhoods (Duarte et al., 2018; Hansen et al., 2019, 2017). Additionally, a general-purpose MIP solver is typically used to explore the neighborhoods, $(\beta, \rho) \in \mathcal{N}$, from the smallest to the largest.

5.1. Initial feasible solution

We need to initiate the fix-and-optimize process with a plausible initial solution, considering fixing decision variables are predicated on prior solutions, as discussed above. We assume that all power plants and trucks operate during all periods. Then, we assign the value one to the binary decision variables y_{jt} and tr_{tk}. The optimal solution to this reduced subproblem is determined using a MIP solver. We then enhance the obtained solution by fixing the variables f_{ijtk} and z_{ijtk} to the values obtained from the MIP subproblem and resolve the problem again, considering y_{jt} and tr_{tk} as binary decision variables, thereby enabling the algorithm to swiftly obtain an initial viable solution to the model of the biomass supply chain presented in Section 4.

5.2. The proposed fix-and-optimize algorithm

Fig. 2 shows the pseudo-code for the proposed fix-and-optimize method. The set of neighborhoods $\mathcal{N}$, terminating criteria, the permitted overall time limit ($\mathcal{OTL}$), and the allowed time limit for each subproblem ($\mathcal{STL}$) are inputs to the function $\mathcal{FAO}()$. As mentioned in Section 5.1, the procedure begins by generating an initial feasible solution x^* (line 1). If the problem is infeasible, the algorithm terminates with no feasible solution returned. Similar to the VND algorithm, the outer loop (lines 5–23) iterates across a succession of neighborhood structures $\mathcal{N}$. Each neighborhood has a finite number of subproblems $\mathcal{s}$, determined by function NumberofSubproblems() (line 6). The pseudo-code depicted in Figure 3 describes the function NumberofSubproblems(). It is worth noting that the decomposition's type, β and size ρ determine how many subproblems are created and to be solved. The algorithm iteratively assesses each subproblem within the subproblem time limit, $\mathcal{STL}$, of the neighborhood (β, ρ) until noImprovement=count according to the inner loop (lines 9-27), at which point the algorithm has exhausted all possible avenues for improving the quality of the existing solution. The pseudo-code in Figure 4 shows that the function decompose() (line 10) is used to determine the set of optimization variables $\mathcal{R}$ for the current subproblem. subsets($\mathcal{S}$; ρ; $\mathcal{s}$) is a function that, given a set $\mathcal{S}$ and a number ρ, iteratively returns the $\mathcal{s}$th subset of all subsets of $\mathcal{S}$ with precisely ρ members. The function solve() is then used to solve the subproblem; it requires three parameters: the subproblem's time restriction, $\mathcal{STL}$, the initial feasible solution, x^*, and the set of variables $\mathcal{R}$ to optimize. This function initializes the solver and sets all binary variables that do not pertain to $\mathcal{R}$ to their values in x^*. If the algorithm can determine a better solution than x^*, the better solution is retained. Alternatively, the previous current solution x^* is retained when no better solution is obtained within the allotted time. All previously fixed variables are freed when the solve() function has returned a result. If a new and better solution is obtained, it replaces the current solution, x^* (line 13), and the noImprovement variable is reset. Else, noImprovement will be incremented by 1 (line 21). The better solution, x^* (line 13), assigns the value one and is then used by fixing the values of decision variables f_{ijtk} and z_{ijtk} as obtained in x^*; this reduced MIP subproblem (line 15) is then solved to enhance the obtained solution y_{jt} and tr_{tk} as binary decision variables. Once the overall time limit, $\mathcal{OTL}$, is achieved, the algorithm terminates and returns the best solution (lines 23–25). The subsequent subproblem is referenced by the variable $\mathcal{s}$ in line 26. After investigating all neighborhoods in the outer loop, the algorithm terminates at line 28 with the best obtained solution x^*.

```
Algorithm FAO(N, OTL, STL)
x* ← CreateInitialSolution();
if x* = ∅ then
    return Infeasible Problem;
end if
for all (β, ρ) ∈ N do
    count ← NumberofSubproblems(β, ρ);
    s ← 1;
    noImprovement ← 0;
    repeat
        R ← decompose(β; ρ; s);
        x ← solve(x*; R; STL);
        if x is better than x* then
            x* ← x;
            noImprovement ← 0;
            x** ← subMIP(x*);
            x ← solve(x**; STL);
            if x is better than x* then
                x* ← x;
            end if
        else
            noImprovement++;
        end if
        if OTL is achieved then
            return x*;
        end if
        s ← (s mod count)+1;
    until noImprovement=count;
end for
return x*.
```

Fig. 2. The pseudo-code for the proposed fix-and-optimize matheuristic.

```
Algorithm NumberofSubproblems(β, ρ)
switch (β)
    case TD
        count ← (|T| choose ρ);
    case PD
        count ← (|J| choose ρ);
    case VD
        count ← (|V| choose ρ);
end switch
return count.
```

Fig. 3. The function that determines the number of subproblems within a neighborhood.

```
Algorithm decompose(β, ρ, s)
switch (β)
    case TD
        R ← { y_jt: j ∈ J, t ∈ subsets(T, ρ, s)
              tr_tk: t ∈ subsets(T, ρ, s), k ∈ K };
    case PD
        R ← { y_jt: j ∈ subsets(J, ρ, s), t ∈ T };
    case VD
        R ← { tr_tk: t ∈ T, k ∈ subsets(K, ρ, s) };
end switch
return R.
```

Fig. 4. The function of decomposition.

6. Case study

The mathematical model in Section 4.2 and the proposed solution methodology are evaluated using real and simulated parameters. Table 2 lists the parameters together with their respective values and references.

Table 2
Case study input parameters (all parameters are assumed to be uniformly distributed).

Input parameter	Value	Reference
TT_{ij}	2–10 h	Duc et al. (2021) and Liu et al. (2017)
D_{ct}	50,000–60,000 MWh/month	Duc et al. (2021) and Liu et al. (2017)
ESP_{ct}	49–91 $/MWh	Liu et al. (2017)
S_{ibt}	14,000–21,000 ton	Shabani and Sowlati (2013)
$TCap_k$	1.2–30 ton	Duc et al. (2021)
$PCap_j$	125,000–200,000 MWh/month	Liu et al. (2017)
$WCap_j$	400,000–1,500,000 m^3	Liu et al. (2017)
FC_{jt}	200,000–300,000 $	This study
TOC_{tk}	1,600–12,900 $/month	Duc et al. (2021)
TCT_{tk}	13.2–54 $/h	Duc et al. (2021)
CSC_{jct}	2.8–3 $/MWh	Liu et al. (2017)
VOC_{jbt}	100–200 $/ton	This study
H_{jbt}	3.14–8.6 $/ton	Duc et al. (2021) and Guo et al. (2022)
$\overline{I_{jb}}$	3,000–7,000 ton	Duc et al. (2021)
L_{tk}	2,300–2,500 $	Duc et al. (2021)
LTP_t	30 d	This study
$\overline{WH}$	8 h	This study
BP_{ibt}	8–30 $/ton	Liu et al. (2017)
EFF_{jb}	25–35%	Duc et al. (2021), Liu et al. (2017) and Shabani and Sowlati (2013)
MC_{ibt}	10.2–46.7%	Shabani and Sowlati (2013)
HV_{ibt}	3.68–5.34 MWh/dray ton	Shabani and Sowlati (2013)
V_b	2–7 m^3/ton	This study
$\bar{T}$	4 months	This study
CON_{ct}	10,000–15,000 $/contract	This study

Notably, no real data is available for the simulated parameters; therefore, we assume that they are distributed uniformly. A set of parameter values are created at random within a suitable range. The values generated for these parameters and the references for those values are reported in Table 2. The fundamental parameters are derived from the values obtained in the case studies that are referred to in References (Duc et al., 2021; Guo et al., 2022; Liu et al., 2017; Shabani & Sowlati, 2013), while the remaining parameters are derived from the open data available from other research or public agencies. For this experiment, we assumed that electricity production biomass power plants are located near the biomass suppliers, anywhere between 5–500 km away.

7. Results and discussion

This section outlines the computational experiments conducted to evaluate the quality of the solutions obtained from the proposed methods. The experiments were conducted on a laptop with an Intel(R) Core(TM) i7-1165G7 @ 2.80 GHz processor (with a base clock speed of 1.69 GHz) and 16 GB of RAM, operating on Windows 10 Pro. The MILP solver used was CPLEX 12.6, and the codes were written in GAMS 24.7.4. The solver's default settings were utilized, except for the maximum allowed running time, which was set to 7,200 s for small-scale and medium-scale problems and 18,000 s for large-scale problems, as indicated in Table 3.

7.1. Data generation

To evaluate the efficacy of the proposed algorithms, Table 3 presents three distinct problem sizes (small, medium, and large) along with their respective problem settings and instances, which were carefully selected to represent a wide range of problem sizes and complexities. We conducted three instances of each size. For example, S.1, S.2, and S.3 are the three instances of small-sized problems. Each of these three instances is replicated five times using different seeds of the random number generator in each replication. For example, for the first medium instance, we have M.1.1, M.1.2, M.1.3, M.1.4, and M.1.5. Using a unique seed for each replication guarantees that the sequence of random numbers produced will vary every time, thereby avoiding potential biases that could arise from employing the same sequence of random numbers in several replications. The complexity of the problems increases as the number of problems increases. Subsequently, the performance of the proposed matheuristic is rigorously evaluated and compared to that of the state-of-the-art commercial solver CPLEX through five randomly generated problems of each instance. The proposed instances encompass a range of sizes, from small to large. It considers the biomass suppliers ($|I|$), biomass power plants ($|J|$), types of biomass supply ($|B|$), electricity power customers ($|C|$), the periods ($|T|$), and the truck types ($|K|$). Parameter values for the instances are presented in Table 2.

Table 3
Characteristics of the biomass supply chain instances.

Classification	Instance	Problem size ($|I| \times |J| \times |B| \times |C| \times |T| \times |K|$)	Allowed running time
Small	S.1	$10 \times 5 \times 5 \times 5 \times 12 \times 4$	7,200 s
	S.2	$10 \times 5 \times 5 \times 10 \times 12 \times 4$	
	S.3	$10 \times 5 \times 5 \times 15 \times 12 \times 4$	
Medium	M.4	$30 \times 10 \times 5 \times 15 \times 12 \times 4$	
	M.5	$30 \times 10 \times 5 \times 20 \times 12 \times 4$	
	M.6	$30 \times 10 \times 5 \times 30 \times 12 \times 4$	
Large	L.7	$50 \times 10 \times 5 \times 20 \times 12 \times 4$	18,000 s
	L.8	$50 \times 10 \times 5 \times 30 \times 12 \times 4$	
	L.9	$50 \times 10 \times 5 \times 40 \times 12 \times 4$	

7.2. Parameter settings for the solution approach

As discussed in Section 5, we employed the tuple (β, ρ) to define the set of neighborhoods $\mathcal{N}$. We considered the decomposition type $\beta \in \{TD, PD, VD\}$ for our numerical experiments, as presented in Figure 3. The size of the free-to-optimize subset of variables was dynamically set as $\rho = max\left\{4, \left\lceil\frac{|\beta|}{5}\right\rceil\right\}$, where $|\beta|$ represents the cardinality of the selected set of decomposition type β. The objective of employing dynamic selection was to ensure that the subproblems included a manageable number of integer variables that could be handled effectively by a standard MILP solver. Simultaneously, it aimed to prevent the selection of very small intervals (less than 4) that could result in suboptimal partial solutions of low quality. It is worth noting that the use of ρ enables the overlapping of subproblems, which provides an opportunity to revise previous fixings and achieve further optimization as additional variables become available. The permitted overall time limit ($\mathcal{OTL}$) is 7,200 s for small-scale and medium-scale problems and 18,000 s for large-scale problems. The allowed time limit for each subproblem ($\mathcal{STL}$) is dynamically set as $max\left\{600, \left\lceil\frac{\mathcal{OTL}}{|\beta|-\rho}\right\rceil\right\}$, in seconds to guarantee that the execution time reflects and corresponds to the size of the subproblem. Therefore, the size of the subproblem increases, the allowed running time allowed increases, and vice versa.

7.3. Computational results

This section presents the conducted computational experiments and compares the results of the proposed matheuristic approach and those generated by the CPLEX solver in terms of both computational running times and solution quality with respect to the objective function. A summary of the computational results is provided in Tables 4–6. In the following section, we define the optimality gap for a given instance as the gap obtained by the GAMS code from the best bound. This is an essential metric for evaluating the performance of the matheuristic approach and determining its effectiveness in solving the MILP problem instances. Table 4 presents a comprehensive summary of the results obtained by the CPLEX solver for the set of 45 instances tested. The presented outcomes of the solver include the profit obtained for each instance and the optimality gap achieved by the solver when compared to the best bound found. To provide a more robust analysis of the solver's performance, the table also reports the minimum, average, and maximum profit and optimality gap achieved for each instance based on running five replications of each instance to reduce the influence of any chance occurrences or anomalies that may occur during a single run. By conducting multiple replications, the results obtained are more representative of the true performance of the solver. The results provided in Table 4 showed that the CPLEX solver obtained the optimal solution for all replications of the small-sized instances with no optimality gap. However, for the medium and large-sized instances, the solver could not find the optimal solution within the allowed computational running time. This is not unexpected, as larger instances often require more computational resources and time to solve. Furthermore, the optimality gap achieved by the solver increased as the instance size increased. The minimum and maximum achieved gaps were 2% and 13%, respectively. The average optimality gaps for the medium-sized and large-sized instances ranged from 3.6%–5.6% and 4.4%–6.4%, respectively, thereby indicating that the solver struggles to find optimal solutions for larger instances, which is common in optimization problems. Overall, the results presented in Table 4 provide valuable insights into the performance of the CPLEX solver and highlight the challenges faced when solving large optimization problems. By conducting multiple replications and analyzing the minimum, average, and maximum results obtained, we can better understand the solver's performance and limitations.

Table 4
Outcomes produced by the CPLEX solver considering the obtained gaps.

	Profit				Gap			
Label	Obtained	Min	Avg	Max	Achieved	Min	Avg	Max
S.1.1	$118,868,024.25				0.0%			
S.1.2	$145,417,751.29				0.0%			
S.1.3	$253,375,825.30	$111,068,674.42	$151,708,974.93	$253,375,825.30	0.0%	0.0%	0.0%	0.0%
S.1.4	$111,068,674.42				0.0%			
S.1.5	$129,814,599.41				0.0%			
S.2.1	$117,326,077.27				0.0%			
S.2.2	$146,970,526.98				0.0%			
S.2.3	$130,635,128.39	$117,326,077.27	$177,691,231.23	$267,847,524.56	0.0%	0.0%	0.0%	0.0%
S.2.4	$267,847,524.56				0.0%			
S.2.5	$225,676,898.97				0.0%			
S.3.1	$107,171,149.52				0.0%			
S.3.2	$135,341,280.24				0.0%			
S.3.3	$170,773,429.49	$107,171,149.52	$162,834,893.54	$206,859,840.74	0.0%	0.0%	0.0%	0.0%
S.3.4	$206,859,840.74				0.0%			
S.3.5	$194,028,767.71				0.0%			
M.1.1	$595,067,781.11				3.0%			
M.1.2	$352,176,631.05				5.0%			
M.1.3	$602,292,828.16	$352,176,631.05	$584,256,385.81	$734,585,674.14	3.0%	2.0%	3.6%	5.0%
M.1.4	$637,159,014.59				2.0%			
M.1.5	$734,585,674.14				5.0%			
M.2.1	$617,532,423.33				6.0%			
M.2.2	$424,660,847.44				3.0%			
M.2.3	$681,982,962.81	$424,660,847.44	$546,046,498.82	$681,982,962.81	6.0%	3.0%	5.6%	9.0%
M.2.4	$476,492,447.79				4.0%			
M.2.5	$529,563,812.73				9.0%			
M.3.1	$595,731,919.59				5.0%			
M.3.2	$329,120,811.21				5.0%			
M.3.3	$523,999,091.88	$329,120,811.21	$487,257,767.79	$597,449,333.34	4.0%	2.0%	3.6%	5.0%
M.3.4	$597,449,333.34				2.0%			
M.3.5	$389,987,682.92				2.0%			
L.1.1	$878,656,981.50				2.0%			
L.1.2	$582,549,350.37				9.0%			
L.1.3	$492,306,144.33	$492,306,144.33	$741,109,611.94	$898,771,493.68	4.0%	2.0%	4.4%	9.0%
L.1.4	$898,771,493.68				2.0%			
L.1.5	$853,264,089.84				5.0%			
L.2.1	$817,599,325.14				7.0%			
L.2.2	$577,634,065.33				3.0%			
L.2.3	$913,612,197.42	$577,634,065.33	$770,721,346.45	$913,612,197.42	3.0%	3.0%	5.8%	13.0%
L.2.4	$894,225,606.56				3.0%			
L.2.5	$650,535,537.78				13.0%			
L.3.1	$853,988,858.28				5.0%			
L.3.2	$628,618,932.48				4.0%			
L.3.3	$700,491,017.52	$283,334,121.56	$619,984,955.73	$853,988,858.28	10.0%	2.0%	6.4%	11.0%
L.3.4	$283,334,121.56				2.0%			
L.3.5	$633,491,848.81				11.0%			

Tables 5 and 6 and Figures 5 and 6 present a comparative analysis of the proposed fix-and-optimize (F&O) matheuristic and the CPLEX solver's performance. This comparison is based on the profit achieved and the computational time taken. Three different instance sizes were used to evaluate the performance of both methods: small-size, medium-size, and large-size problems. Table 5 and Figure 5 compare the profit generated by F&O and CPLEX for each instance size. The first column of Table 5 lists the instances that were tested, while the second and third columns show the profits generated by F&O and CPLEX, respectively. The fourth column indicates the relative percentage change in profit ($\Delta_{Profit}\%$) when comparing the outcome of the F&O to that of the CPLEX for each instance, calculated as ($\Delta_{Profit}\% = 100 \times \frac{F\&O_{Profit} - CPLEX_{Profit}}{CPLEX_{Profit}}$). The fifth column shows the average relative percentage change in profit ($\bar{\Delta}_{Profit}\%$) across the five replications of each instance. Finally, the last row of the table provides the overall average relative percentage change in profit ($\bar{\bar{\Delta}}_{Profit}\%$) across the three instances of each problem size, considering a total of 15 replications. We can see that in all small-size instances, CPLEX generates slightly higher profit than F&O, with a relative percentage change in profit, $\Delta_{Profit}\%$, ranging from 0.09% to 0.81%. The average relative percentage change in profit, $\bar{\Delta}_{Profit}\%$, across the five replications of each instance, ranges from 0.28% to 0.51%, and the overall average relative percentage change in profit, $\bar{\bar{\Delta}}_{Profit}\%$, of 0.39%. As for most medium-size instances (9 out of 15), F&O generates a higher profit than CPLEX solver, with a relative percentage change in profit, $\Delta_{Profit}\%$, ranging from 0.08% to 3.08%. In the remaining six instances, CPLEX generates slightly higher profit than F&O, with $\Delta_{Profit}\%$ ranging from 0.04% to 1.95%. The comparison of the obtained profit for the medium-size instances indicates F&O's superiority over CPLEX, with an average relative percentage change in profit, $\bar{\Delta}_{Profit}\%$, ranging from -0.51% to 1.83% and an overall average relative percentage change in profit, $\bar{\bar{\Delta}}_{Profit}\%$, of 0.77%. Moreover, for most large-size instances (11 out of 15), F&O generates higher profit than CPLEX solver, with a relative percentage change in profit, $\Delta_{Profit}\%$, ranging from 0.03% to 7.35%. For the remaining four instances, CPLEX generates slightly higher profit than F&O, with $\Delta_{Profit}\%$ ranging from 0.01% to 0.35%. The comparison of the obtained profit for the large-size instances reveals F&O's superiority over CPLEX, with an average relative percentage change in profit, $\bar{\Delta}_{Profit}\%$, ranging from 0.97% to 2.80%, and an overall average relative percentage change in profit, $\bar{\bar{\Delta}}_{Profit}\%$, of 1.77%. Table 6 and Fig. 6 compare the computational times required by F&O and CPLEX for each instance size. The first column of the table lists the instances that were tested, while the second and third columns show the computational times taken by F&O and CPLEX, respectively. The fourth column shows the relative percentage change in computational time ($\Delta_{Time}\%$) when comparing the computational times of the F&O to that of the CPLEX for each instance, which is calculated as ($\Delta_{Time}\% = 100 \times \frac{CPLEX_{Time} - F\&O_{Time}}{CPLEX_{Time}}$). The fifth column shows the average relative percentage change in computational time ($\bar{\Delta}_{Time}\%$) across the five replications of each instance. Finally, the last row of the table presents the overall average relative percentage change in computational time ($\bar{\bar{\Delta}}_{Time}\%$) across the three instances of each problem size, considering a total of 15 replications.

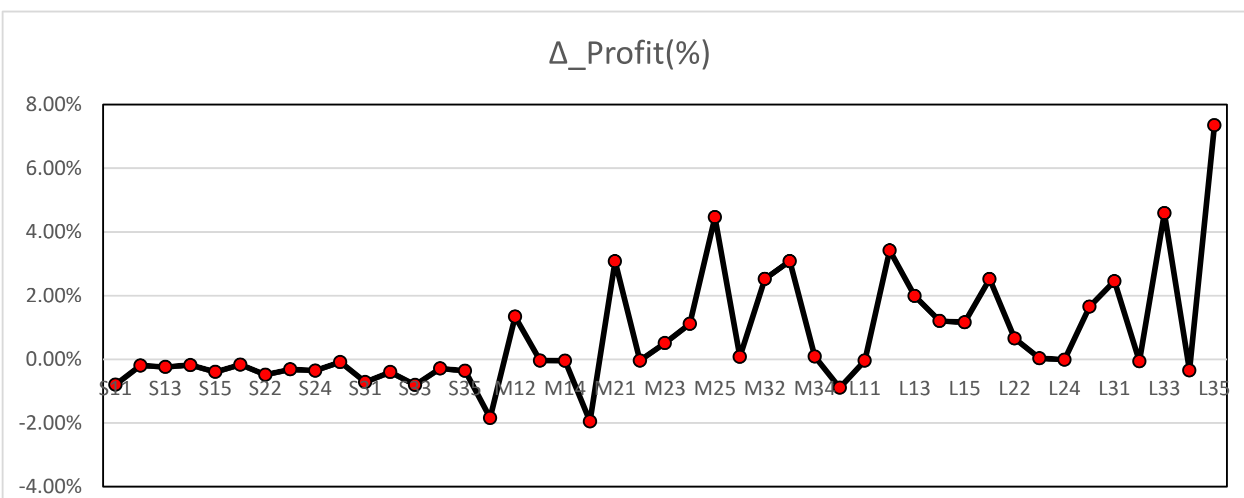

Fig. 5. The $\Delta_{Profit}\%$ to compare the obtained profit by the F&O to that of the CPLEX for each instance.

For most of the small-size instances (11 out of 15), F&O requires less computational time than CPLEX to reach the obtained profit, with a relative percentage change in profit, $\Delta_{Time}\%$, ranging from 21.92% to 89.24%. The average relative percentage change in profit, $\bar{\Delta}_{Time}\%$, across the five replications of each instance ranges from 3.85% to 55.10%, and the overall average relative percentage change in profit, $\bar{\bar{\Delta}}_{Time}\%$, is 32.95%. For the medium-size instances and the large-size instances, both F&O and the CPLEX solver consumed the entire permitted overall time limit ($\mathcal{OTL}$), which is 7200 s and 18000 s for medium-scale and large-scale problems, respectively, to reach the achieved profit. In summary, Tables 5 and 6 and Fig. 5 and Fig. 6 demonstrate that the F&O matheuristic approach and CPLEX solver perform differently in terms of generating profit depending on the size of the instances.

Table 5
A comparison of the outcomes produced by the F&O matheuristic and the CPLEX solver.

Small-scale instances					Medium-scale instances					Large-scale instances				
Label	Profit				Label	Profit				Label	Profit			
	F&O	CPLEX	$\%\Delta_{Profit}$	$\%\bar{\Delta}_{Profit}$		F&O	CPLEX	$\%\Delta_{Profit}$	$\%\bar{\Delta}_{Profit}$		F&O	CPLEX	$\%\Delta_{Profit}$	$\%\bar{\Delta}_{Profit}$
S.1.1	117922720.6	118868024.3	-0.80%		M.1.1	584106130.1	595067781.1	-1.84%		L.1.1	878305151.9	878656981.5	-0.04%	
S.1.2	145134153.8	145417751.3	-0.20%		M.1.2	356895224.8	352176631.1	**1.34%**		L.1.2	602470534.7	582549350.4	**3.42%**	
S.1.3	252771384.6	253375825.3	-0.24%	-0.36%	M.1.3	602064818	602292828.2	-0.04%	-0.51%	L.1.3	502095257.7	492306144.3	**1.99%**	**1.55%**
S.1.4	110869562.8	111068674.4	-0.18%		M.1.4	636883516.9	637159014.6	-0.04%		L.1.4	909592659.3	898771493.7	**1.20%**	
S.1.5	129300690.8	129814599.4	-0.40%		M.1.5	720250856.3	734585674.1	-1.95%		L.1.5	863197109.1	853264089.8	**1.16%**	
S.2.1	117129559.2	117326077.3	-0.17%		M.2.1	636550429.1	617532423.3	**3.08%**		L.2.1	838208557.4	817599325.1	**2.52%**	
S.2.2	146261943.3	146970527	-0.48%		M.2.2	424497227.8	424660847.4	-0.04%		L.2.2	581430660.7	577634065.3	**0.66%**	
S.2.3	130224748.7	130635128.4	-0.31%	-0.28%	M.2.3	685461354.9	681982962.8	**0.51%**	**1.83%**	L.2.3	913902678.3	913612197.4	**0.03%**	**0.97%**
S.2.4	266892518.2	267847524.6	-0.36%		M.2.4	481803258	476492447.8	**1.11%**		L.2.4	894106101.8	894225606.6	-0.01%	
S.2.5	225479809.9	225676899	-0.09%		M.2.5	553198572.1	529563812.7	**4.46%**		L.2.5	661290533.8	650535537.8	**1.65%**	
S.3.1	106404457.4	107171149.5	-0.72%		M.3.1	596201532.1	595731919.6	**0.08%**		L.3.1	874965034.2	853988858.3	**2.46%**	
S.3.2	134799103.8	135341280.2	-0.40%		M.3.2	337428646.2	329120811.2	**2.52%**		L.3.2	628221415	628618932.5	-0.06%	
S.3.3	169398390.2	170773429.5	-0.81%	-0.51%	M.3.3	540156939.2	523999091.9	**3.08%**	**0.98%**	L.3.3	732662787.3	700491017.5	**4.59%**	**2.80%**
S.3.4	206266473.9	206859840.7	-0.29%		M.3.4	597978568.5	597449333.3	**0.09%**		L.3.4	282344248.7	283334121.6	-0.35%	
S.3.5	193325114.5	194028767.7	-0.36%		M.3.5	386503382.1	389987682.9	-0.89%		L.3.5	680075351.9	633491848.8	**7.35%**	
		$\%\bar{\bar{\Delta}}_{Profit}$	-0.39%				$\%\bar{\bar{\Delta}}_{Profit}$	**0.77%**				$\%\bar{\bar{\Delta}}_{Profit}$	**1.77%**	

Table 6

Comparison of the computational time for the F&O matheuristic and the CPLEX solver

Small-scale instances					Medium-scale instances					Large-scale instances				
Label	Computational Time				Label	Computational Time				Label	Computational Time			
	F&O	CPLEX	$\%\Delta_{Time}$	$\%\bar{\Delta}_{Time}$		F&O	CPLEX	$\%\Delta_{Time}$	$\%\bar{\Delta}_{Time}$		F&O	CPLEX	$\%\Delta_{Time}$	$\%\bar{\Delta}_{Time}$
S.1.1	170.19	103.93	-63.75%		M.1.1	7200.00	7200.00	0.00%		L.1.1	18000.00	18000.00	0.00%	
S.1.2	218.20	623.84	**65.02%**		M.1.2	7200.00	7200.00	0.00%		L.1.2	18000.00	18000.00	0.00%	
S.1.3	185.75	1078.03	**82.77%**	**3.85%**	M.1.3	7200.00	7200.00	0.00%	0.00%	L.1.3	18000.00	18000.00	0.00%	0.00%
S.1.4	332.09	133.03	-149.64%		M.1.4	7200.00	7200.00	0.00%		L.1.4	18000.00	18000.00	0.00%	
S.1.5	483.81	3190.85	**84.84%**		M.1.5	7200.00	7200.00	0.00%		L.1.5	18000.00	18000.00	0.00%	
S.2.1	278.03	219.21	-26.83%		M.2.1	7200.00	7200.00	0.00%		L.2.1	18000.00	18000.00	0.00%	
S.2.2	774.90	7200.00	**89.24%**		M.2.2	7200.00	7200.00	0.00%		L.2.2	18000.00	18000.00	0.00%	
S.2.3	846.09	1083.68	**21.92%**	**39.90%**	M.2.3	7200.00	7200.00	0.00%	0.00%	L.2.3	18000.00	18000.00	0.00%	0.00%
S.2.4	213.70	301.40	**29.10%**		M.2.4	7200.00	7200.00	0.00%		L.2.4	18000.00	18000.00	0.00%	
S.2.5	275.47	1976.12	**86.06%**		M.2.5	7200.00	7200.00	0.00%		L.2.5	18000.00	18000.00	0.00%	
S.3.1	1044.72	7200.00	**85.49%**		M.3.1	7200.00	7200.00	0.00%		L.3.1	18000.00	18000.00	0.00%	
S.3.2	878.53	6843.00	**87.16%**		M.3.2	7200.00	7200.00	0.00%		L.3.2	18000.00	18000.00	0.00%	
S.3.3	846.30	7200.00	**88.25%**	**55.10%**	M.3.3	7200.00	7200.00	0.00%	0.00%	L.3.3	18000.00	18000.00	0.00%	0.00%
S.3.4	469.28	2753.25	**82.96%**		M.3.4	7200.00	7200.00	0.00%		L.3.4	18000.00	18000.00	0.00%	
S.3.5	893.00	530.37	-68.37%		M.3.5	7200.00	7200.00	0.00%		L.3.5	18000.00	18000.00	0.00%	
		$\%\bar{\bar{\Delta}}_{Time}$	**32.95%**				$\%\bar{\bar{\Delta}}_{Time}$	0.00%				$\%\bar{\bar{\Delta}}_{Time}$	0.00%	

Across all small-size instances, the CPLEX solver generates marginally higher profit than F&O, with a range of relative percentage changes in profit. However, F&O outperforms the CPLEX solver in terms of computational time for most small-size instances. Conversely, for most medium-size and large-size instances, within the same computational time limit, F&O outperforms the CPLEX solver with a higher relative percentage change in profit. The average relative percentage change in profit, $\bar{\Delta}_{Profit}\%$, and the overall average relative percentage change in profit, $\bar{\bar{\Delta}}_{Profit}\%$, further confirm that F&O is superior to the CPLEX solver in terms of generating profit for most of the problem instances analyzed. These findings and insights gained from this study can assist decision-makers in selecting the most effective approach based on the size of the instance, ultimately leading to better outcomes, and hence, are important when dealing with instances of varying sizes.

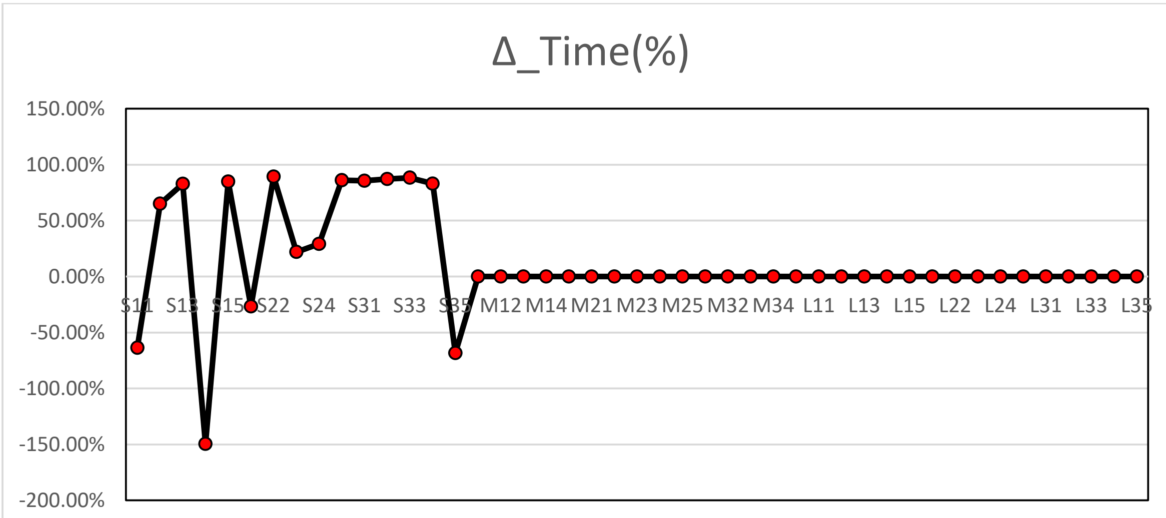

Fig. 6. The $\Delta_{Time}\%$ to compare the computational times of the F&O to that of the CPLEX for each instance.

8. Conclusions

The increasing demand for energy and environmental problems have necessitated the identification of alternative energy sources, such as biomass. However, optimizing a biomass supply chain is complex because of various factors such as the selection of electricity demand, biomass feedstock purchase and storage, power plant operations, and transportation of biomass from suppliers to power plants. Therefore, developing a robust and integrated model that incorporates typical tactical supply chain decisions with market or demand selection decisions for maximizing profit is crucial. This study proposed a novel MILP model for commercializing electricity production by selecting electricity demand and making supply chain decisions regarding power plant operations, biomass feedstock purchase and storage, and biomass transport trucks. The proposed MILP model was designed to optimize the biomass supply chain and maximize profits. Additionally, a fix-and-optimize-based solution strategy was developed to reduce computational time while preserving high solution quality. The performance of the fix-and-optimize-based solution strategy was evaluated through real-world case study experiments. The results showed that the proposed strategy significantly reduced the computational time while preserving high solution quality. The study compared the performance of the fix-and-optimize-based solution strategy with that of the CPLEX solver for different instance sizes. Furthermore, the CPLEX solver generated marginally higher profits for small-size instances than the fix-and-optimize-based solution strategy. While F&O surpassed the CPLEX solver for most small-size instances in terms of computational time, the fix-and-optimize-based solution strategy outperformed the CPLEX solver for most medium-size and large-size instances in generating profit and computational time. The relative percentage change in profit ranged from 0.08%–7.35% for medium and large-size instances, with an overall average relative percentage change in profit of 0.77% and 1.77%, respectively. These results confirm that the fix-and-optimize-based solution strategy is superior to the CPLEX solver in generating profit for most of the problem instances analyzed. The findings and insights gained from this study are crucial for decision-makers when handling instances of varying sizes and can help decision-makers choose the most effective approach based on the instance's size, leading to better outcomes. In conclusion, the study provides valuable insights into optimizing the biomass supply chain and can help maximize profit and minimize costs and environmental impact. Two prospective research areas for future investigation can be identified to expand the current analysis. One conceivable research direction is incorporating stochastic and variable model parameters, such as costs, prices, demand, feedstock availability, and travel time. Another avenue for future investigation could focus on assessing the model's performance within multi-objective scenarios where the objectives inherently conflict. These conflicting objectives might encompass profit maximization, system reliability maximization, greenhouse gas emissions minimization, and social impact maximization.

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