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A multi-objective approach to sugarcane harvest planning in Thailand: Balancing output maximization, grower equity, and supply chain efficiency

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ABSTRACT

This paper addresses a multi-objective sugarcane harvesting problem in Thailand, where several conflicting objectives and local restrictions are regarded as major obstacles to a sustainable sugar production environment. A multi-objective modeling approach that balances three different objectives of different key supply chain actors, namely (*i*) maximizing output in terms of total sugar production volume, (*ii*) maximizing grower equity in terms of a fair harvesting time-slot distribution, and (*iii*) maximizing supply chain efficiency in terms of a lower variability in resource requirements across the harvesting season, is introduced and solved by a state-of-the-art multi-objective evolutionary genetic algorithm. To better help the algorithm generate efficient solutions forming the Pareto front, two local searches are also embedded and intermittently performed during algorithm execution. Based on the information of an operating mill in Kanchanaburi Province, Thailand, we have found that our approach produces solutions that are close to optimal in terms of production output. Nonetheless, by sacrificing a small amount of production output, these solutions provide significant improvements in terms of grower equity and supply chain resource efficiency, which are crucial for the survivability of involved actors.

1. Introduction

Sugar is an important food product globally. According to Statista, a commercial data provider, in 2019, global sugar production reached a level of more than 178 million tons, which grew about 4.7% compared to 2017. In terms of production quantities, India was the largest contributor with a share of 18.7% of global sugar production, followed by Brazil (16.5%), the European Union (9.8%), Thailand (8.7%), and China (6.0%). Despite the increase in sugar production, global sugar consumption is gradually decreasing, which, in turn, adds pressure to sugar prices. This is especially challenging for countries that sell a significant share of their sugar product to the global market, such as Thailand (Rojrak, Manutchai, Komsan, & Wacharapong, 2017).

In Thailand, sugarcane – the main raw material of sugar – is cultivated throughout most of the country, except in the South where the weather is not suitable for sugarcane growing. According to Rojrak et al. (2017), about 427,395 households, or equivalently 927,447 people, are directly involved in Thai sugarcane farming. Unlike other sugarcane producing countries such as Brazil or Australia, Thai sugarcane growers are typically with small-scale farm areas, whose individual sugarcane production is less than 300 tons per crop year (Thuankaewsing, Khamjan, Piewthongngam, & Pathumnakul, 2015).

These many small-scale growers often end up with sugarcane production quantities that are inconveniently small for large-scale milling operations in the next stage of the sugar supply chain. To simplify their procurement process and ensure maximum production output without stoppages, sugar mills typically ask small sugarcane growers to voluntarily collaborate with one another to achieve certain minimum production quotas as a group (Thuankaewsing et al., 2015). For instance, given a transportation quota of 1000 tons, a grower whose sugarcane production quantity is less than 1000 tons must be grouped with others. The number of sugarcane growers in a group may vary from 2 to 8 growers, with up to 50 sugarcane fields per group. This type of collaboration not only simplifies supply chain planning and coordination for the sugar mills, as a large number of growers are now reduced into a smaller number of grower groups, but also allows these small-scale growers to jointly buy or rent expensive harvesting and transportation machinery over the entire season.

This collaborative setting, however, leads to complications, especially in the financial compensation of individual growers, resulting

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from the fact that growers are still paid based on the sugar yields related to the sugarcane fields they contribute to the group. Commonly, these yields are determined by both sugarcane production quantities and their corresponding sugar content, referred to as the *Commercial Cane Sugar* (CCS) value – a tonnage of sugarcane with the CCS of β is equivalent to $10 \cdot \beta$ kilograms of sugar production quantity. This CCS value is also found to be highly dependent on the right harvest timing and the time between harvesting and milling, as the amount of sugar content in sugarcane naturally increases during growth but starts to decrease after its maturity peak; and, once harvested, the CCS value – and so the amount of sugar produced – gradually drops.

While the CCS value lies at the core of most sugarcane harvesting operations, it is normally impossible to harvest every field at its corresponding optimal time period, due to limited harvesting and milling resources (Florentino et al., 2018). As such, growers within the same group must negotiate a harvesting schedule that builds up transportation amounts satisfying production quotas and, at the same time, provides good expected yields for their fields. The resulting schedules may, unfortunately, require some or all of the growers to harvest their sugarcane fields long before or after the optimal harvesting periods in order to settle possible conflicts.

In addition to these local issues, coordinating sugarcane supply across an entire area to a single sugar mill adds even more complexity to the problem. For the sugar mill, this means that there can be long queues of delivery trucks in some time periods – as each group of sugarcane growers independently and uncoordinatedly decides its own harvesting periods – which, in turn, lead to additional waiting times that further deteriorate sugar yields. Higgins (2002) also pointed out that this additional supply variability might adversely affect utilization of related expensive infrastructure – and so the total supply chain cost – benefiting none of the supply chain actors. In contrast, by simply reducing supply variability to the mills, the whole system could be largely improved.

All in all, there is a need to study the collaboration and coordination in the Thai sugar supply chain, especially in relation to different objectives of different supply chain actors. For this purpose, this paper introduces the *Multi-Objective Sugarcane Harvesting Problem* (MOSHP): a multi-objective modelling approach that balances (*i*) sugar mill output, (*ii*) sugarcane grower equity, and (*iii*) sugarcane supply variability across the season. To better explore the multi-dimensional solution space and trade-offs between objectives, this paper also develops a heuristic solution methodology based on state-of-the-art evolutionary algorithms. With this multi-objective approach, we are then able to (*i*) explore the value of cooperation among growers and their contracted mills, (*ii*) understand the impacts of critical parameters on the resulting harvesting plans, and (*iii*) improve the efficiency and effectiveness of subsequent operational plans, including resource and harvest front scheduling, over the milling season.

The remainder of this paper is organized as follows. In Section 2, we first provide a more detailed description of different operations in the Thai sugar supply chain, where related literature is thoroughly discussed in Section 3. The formal description of the MOSHP – along with its mathematical formulation – is provided in Section 4. Our solution approach is introduced in Section 5, followed by intensive computational results in Section 6. Finally, Section 7 concludes our work and discusses future research directions.

2. Thai sugar supply chain

While local restrictions and practices may make the detailed structure of the Thai sugar supply chain different from those of other world sugar producers, like Brazil or Australia, they all share the same broad objective – that is, to maximize sugar production within the harvesting/milling season – as well as the four main in-bound logistical operations: (*i*) planting, (*ii*) harvesting, (*iii*) transporting, and (*iv*) milling. These four processes are markedly crucial as they account for most of the production cost, or about 60% in the Thai context (Kanjana, 2016). Additionally, the performances of these four processes greatly affect the efficacy of the whole supply chain as sugar production predominantly depends on the CCS value, which subsequently depends on how efficient these four processes are organized.

2.1. Planting process

Planting is the first in-bound logistical process of the sugar supply chain, where sugarcane growers need to first prepare the fields, select suitable sugarcane species, plant, and monitor sugarcane until the harvesting season has been reached. As the CCS value gradually increases during growth and starts to decrease once sugarcane reaches its maturity peak and there is no exact method that precisely estimates such a value, growers therefore need to periodically evaluate and check for the CCS value of their planted sugarcane – especially, when the planned harvesting periods are closing by. The traditional approach for estimating peak periods is based on the elapsed time since a predefined date, *i.e.* the date in which sugarcane is planted (Florentino et al., 2018; Jiao, Higgins, & Prestwidge, 2005; Pagani et al., 2017), although such a prediction may be imprecise due to several uncontrollable factors, including unexpected weather conditions, sugarcane types, and plant diseases (Florentino et al., 2018; Grunow, Gunther, & Westinner, 2007).

2.2. Harvesting process

The most suitable time for harvesting sugarcane is when its CCS value expectedly reaches its peak – about 8–12 months after planting. Nonetheless, this time period may vary depending on weather, sugarcane species, and types, *i.e.* primary or secondary (ratoon) sugarcane. Practically, ratoon crops should be harvested first because their CCS value decays much faster than the newly planted ones. Furthermore, burnt sugarcane must be immediately harvested and transported to the mills as the CCS value of burnt sugarcane drops much faster than fresh sugarcane harvested by either manpower or harvest machinery (Larrahondo, Briceno, Rojas, & Palma, 2006; Larrahondo, Viveros, & Victoria, 2009).

While sugar mills prefer fresh sugarcane for its purity over burnt sugarcane, the latter is much easier to harvest – if landscape conditions do not allow for maneuvering large machinery or if the minimum distance between sugarcane patches does not meet harvester track requirements (about 1.5–1.6 meters). Unfortunately, the milling season in Thailand is relatively short – about 5 months from late November to early May. Part of it also overlaps with the harvesting seasons of other agricultural crops, such as rice, and a long holiday season known as *Songkran Festival* in April. As such, a majority of small sugarcane growers in Thailand tend to burn sugarcane fields before harvesting in order to speed up the harvesting process. Although burning sugarcane fields may help save scarce labor force, it adversely affects both sugar productivity and the environment of neighborhood areas. Accordingly, sugarcane field burning is now prohibited in Thailand – but it is sometimes still done by growers. Fig. 1 illustrates the timing of sugarcane harvesting in Thailand, where the best time periods start from January to February of each calendar year.

Resource allocation is another problem that may arise during harvesting seasons in Thailand as these many small sugarcane growers are not capable of possessing expensive harvesting machinery, such as harvesters, forwarders, and transporting trucks. A group of growers then needs to correspondingly rent such machinery from the mills, third-party service providers, or large-scale growers, and share it within the group during the seasons. Besides, a sequential, field-by-field harvesting operation is strictly performed to avoid mixing of harvests from different fields (Pitakaso & Sethanan, 2019). With these limited resources but more dynamic operations, the optimal harvesting plan is therefore less likely to be devised and executed, but rather suboptimal ones satisfying all constraints posed by involved players (Guan, Nakamura, Shikanai, & Okazaki, 2009).

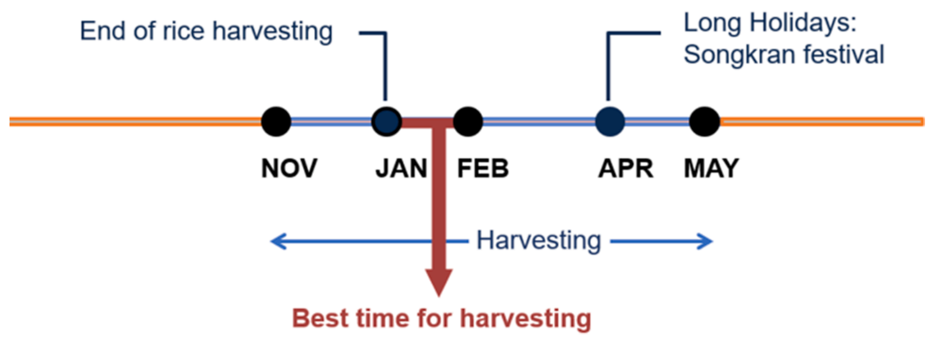


Fig. 1. The best harvesting periods for sugarcane in Thailand.

2.3. Transporting process

After harvesting, sugarcane will be loaded onto trucks and transported to the mills immediately in order to preserve the CCS value of harvested sugarcane at its maximal level. There are four types of vehicles used in this process, (*i*) 10-wheeler trucks with a 20-ton capacity, (*ii*) 10-wheeler trucks with a 40-ton capacity, (*iii*) 6-wheeler trucks with a 10-ton capacity, and (*iv*) grower-owned trucks with less than 10 tons of capacity.

To accommodate growers with considerably small transporting vehicles, some mills may set up local sugarcane loading stations within their operating areas so that transport of harvests by growers is consolidated and directly shipped to the mills (Khamjan, Khamjan, & Pathumnakul, 2013; Saranwong & Likasiri, 2017). While loading station networks may help improve supply chain efficiency – and so total transportation cost – this strategy, however, requires high upfront investments and adds complexity to operation schedules that can potentially affect the quality of sugar produced, *i.e.* double handling and waiting times for batch moves.

2.4. Milling process

When loaded trucks arrive at the mills, the trucks have to wait in queues for the evaluation of sugarcane quantity (by weight) and quality (by the CCS value). The management of these queues follows one of three systems (Kanjana, 2016): (*i*) a first-come first-served (FCFS) system, (*ii*) a queue-locked (QL) system, or (*iii*) a mixed system – an integration between the FCFS and QL systems. While the FCFS system is generally applied to all types of growers, the QL system is specifically designed for contract growers that have detailed agreements with the mills regarding the amount of sugarcane to be delivered and the time periods at which it must be delivered (*i.e.* their places in the queue are locked in). These different queuing systems are normally exercised at different time periods of the harvesting season due to unstable sugarcane supplies caused by traditional sugarcane cultivation practices in Thailand. More specifically, the QL system is adopted in the middle of the season, where sugarcane supply exceeds the mill capacity, while the FCFS system is adopted early and late in the season, when sugarcane supply is less than the mill capacity.

Regarding the current practice, Thai sugarcane growers tend to cultivate sugarcane early in the rainy season to ensure that the crops will get enough water and be ready within the next harvesting season (Pongpat, Gheewala, & Silalertruksa, 2017). Since all growers cultivate their sugarcane with similar timelines, all the crops will then be ripe at approximately the same time, causing oversupply in some periods and undersupply in others. When the sugarcane supply exceeds the mill capacity, it would take additional time for harvested sugarcane to be milled. But, since the CCS value of harvested sugarcane decreases over time, both mills and growers would be at risk of losing benefits from such occurrences.

The situation is made even worse if mills have no control over harvesting decisions made by growers, as they still need a constant feed of sugarcane over the entire season. In order to avoid periodic supply shortages that could interrupt processing activities, most mills generally form contractual agreements with growers to settle on the amounts of sugarcane to be delivered in certain time periods and then prioritize the deliveries from these contract growers in the QL system. With this practice, mills can ensure that sugar production is more stable, while contract growers would not have to worry about lost CCS value resulting from long delivery queues at the mills. Despite these supply chain benefits, not many growers join the QL system due to the risk of misalignment between planned (contracted) and optimal harvesting periods, *i.e.* the delivery time windows specified in the contracts may not be the same as the optimal harvesting periods due to the uncontrollable factors mentioned above.

3. Related literature

Most of the existing research has focused on several interrelated sugar supply chain aspects – often on the tactical and operational planning levels (Carvajal, Sarache, & Costa, 2019) – even in the early work by Singh and Pathak (1994) that explored harvesting and transportation activities in the Thai sugar supply chain by a simulation technique. These integrated approaches stem from the fact that sugarcane quality dynamics and the central role of CCS value are both impacted by different supply chain actors, as well as impacting on the performances of these supply chain actors at the same time (Higgins, 1999).

In terms of solving these complex supply chain problems, different approaches have been applied, and the focus within the research has differed over time. For instance, Grunow et al. (2007) developed a hierarchical decision framework for the sugarcane supply problem in Venezuela, where the whole problem was decomposed into three decision stages, namely (*i*) cultivation planning, (*ii*) harvest scheduling, and (*iii*) resource dispatching, while Paiva and Morabito (2009) integrated the production of sugar, ethanol, and molasses into one single framework and modeled the resulting sugarcane supply chain problem with mathematical programming.

Lamsal, Jones, and Thomas (2016) and Junqueira and Morabito (2019), on the contrary, focused more on the operational issues of sugar supply chains in two different geographic locations. In particular, Lamsal et al. (2016) explored the logistics of harvested sugarcane in the United States so that the fleet size of trucks required for transportation was minimized, while Junqueira and Morabito (2019) investigated a so-called *Harvest Front Scheduling Problem* (HFSP) that combined harvesting and resource scheduling into one decision-making framework. In Junqueira and Morabito (2019), a harvest front was defined as a group of machinery and crews required to harvest and transport sugarcane to the mills, which could be alternatively viewed as a production line (it should be noted that *harvest front* is sometimes used to describe a set of sugarcane fields, as for instance in Stray, van Vuuren, & Bezuidenhout (2012)). The objective of the HFSP was simply to assign and relocate all the fronts in such a way that total operational cost – including both realizable and opportunity costs – was minimized.

Such operational issues were also explored in the Thai context by Sethanan and Neungmatcha (2016) and Pitakaso and Sethanan (2019), where the use of harvesters expectedly increased due to labor force shortages and sugarcane farm burning malpractices. While it is apparent that the use of harvesting machinery, such as harvesters and forwarders, is far more efficient when compared to labor force (Pongpat et al., 2017), a majority of small Thai sugarcane growers are, unfortunately, incapable of owning one due to its relatively high initial investment. They correspondingly rent it from large-scale growers, third party service providers, or the mills whom they have contracts with, and share it over during the harvesting season. To better utilize these mechanical harvesters, efficient harvester route planning is thus required; and, the total harvested distance is generally set as the primary objective in such plans.

Nonetheless, Sethanan and Neungmatcha (2016) observed that the least cost routing might not necessarily lead to plans providing maximum yields due to competition among conflicting objectives. As such, in their work, a multi-objective harvester route planning problem was explored and solved by a variant of particle swarm optimization. As an extension to Sethanan and Neungmatcha (2016), Pitakaso and Sethanan (2019) further integrated both the assignment and schedule of mechanical sugarcane harvesters into one single framework. They found that the quality of harvester route planning largely depended on the availability of harvest equipment and it might be better to solve both simultaneously. Besides, the performance of this subsequent operational planning also depended on the quality of its input – namely, the harvesting plan – which was vulnerable to any slight disruptions in each of the aforesaid four processes. This remark was in-line with Grunow et al. (2007) that the optimal but inflexible plans were rarely executable; rather, suboptimal but flexible ones with recourse actions throughout the planning horizon were more practical.

While grower equity is a very important issue in the Thai and Australian sugar supply chains, it seems less relevant in Brazil, Venezuela, or other South American countries, where most sugarcane fields are large-scale mill-owned or individual-owned farms. Notwithstanding such a fact, equity issues between growers have been addressed in the literature. For instance, Thuankaewsing et al. (2015) proposed a tabu search heuristic for the harvest scheduling problem that implicitly took grower equity, as measured by yield proportion – a ratio of total harvested sugarcane yield to the best estimated sugarcane yield (in tons) – into consideration, as a part of constraint sets. In their setting, the minimum yield proportion for all growers was equally set at the beginning of the search, *i.e.* all growers achieved at least the same minimum fraction of sugarcane output. This number was then maximized through an iteratively search procedure while maintaining problem feasibility; and, once the algorithm terminated, the solutions that maximized total sugar production with the highest yield proportion were then returned. Their concept of grower equity was a bit different from Higgins (1999) and Jiao et al. (2005), due to different harvesting practices, where the proportion of harvested sugarcane in each round was applied so that each grower would have approximately the same amount of sugarcane harvested in each period; and, no one would be left too far behind or ahead of others across the entire season.

While almost all of the aforesaid literature addressed issues in the sugar supply chain with one single objective, da Silva, Marins, and Dias (2015) and Florentino et al. (2018) explored more interesting decision-making problems related to sugarcane harvest scheduling in Brazil with multiple conflicting objectives. More specifically, in da Silva et al. (2015), the authors attempted to determine harvesting plans that minimized total deviational costs of different players, taking into account uncertainties in harvest conditions, cutting decisions, and agricultural logistics. Meanwhile, Florentino et al. (2018) focused more on harvesting plans that maximized the quality of harvested sugarcane while minimizing movement of machinery across the planning horizon. Different variations of goal programming were applied by the authors, namely a new revised multi-choice goal programming approach addressing parameter uncertainties without use of binary decision variables by da Silva et al. (2015) and an extended goal programming approach (scalarization technique) that reduced a multi-objective model to a more pragmatic model with a single objective by Florentino et al. (2018).

As has been demonstrated in the previous literature, in order to devise flexible and executable harvesting plans for the Thai sugar supply chain, we do need to include not only the contextually specific constraints – such as grower equity and field-by-field harvesting practice – but also the competing objectives from both mills and growers into consideration. In the following section, we will define the resulting problem as the *Multi-Objective Sugarcane Harvesting Problem* (MOSHP). Technically speaking, the MOSHP is a reflection of the Thai sugar supply chain's in-bound logistical activities focusing on three different objectives: (*i*) the maximization of sugar production over the entire season, (*ii*) the minimization of grower inequity resulting from unbalanced CCS value losses, and (*iii*) the minimization of variability in deployed resources across harvesting periods. Since these three objectives are not easily combined into one measurement, we therefore focus on generating a diverse set of efficient non-dominated solutions – known as Pareto-optimal solutions – and let key supply chain actors decide on the execution of plans that best suit their current situation. Similar multi-objective modeling approaches have also been studied in wine grape harvest operations by Varas, Basso, Maturana, Osorio, and Pezoa (2020) and in the paper industry by Vafaeenezhad, Moghaddam, and Cheikhrouhou (2019), but with different algorithmic frameworks for generating the Pareto-optimal solutions.

It is worth remarking that our proposed methodology differs greatly from those of da Silva et al. (2015) and Florentino et al. (2018), as their solution quality largely depends on the aspiration levels set by decision makers and their corresponding weights (Khorramshahgol & Hooshiari, 1991), while ours is immune to such parameter settings. To be precise, all objectives in our approach are concurrently optimized based on their absolute terms rather than relative terms defined by deviational variables in the adopted goal programming approaches. On top of that, solutions produced by goal programming could be dominated violating the fundamental concept of decision theory (Hannan, 1985) – although detection and restoration techniques can be included to safeguard the final results when violations occur (Tamiz, Mirrazavi, & Jones, 1999).

4. Problem description

4.1. Multi-Objective Sugarcane Harvesting Problem (MOSHP)

Consider a sugar mill with a set of contract growers (I), each of whom owns a different number of sugarcane fields, denoted by $J(i)$. Each sugarcane field $j \in J(i)$ differs in terms of area (a_{ij}), sugarcane yield (w_{ij}), and the CCS value pertaining to such a field – which, in turn, depends on the expected time period when a field is harvested. More formally, given a set of harvesting periods (T), f_{ijt} denotes the expected CCS value of field $j \in J(i)$ that belongs to grower $i \in I$ in time period $t \in T$; and, b_{ij} is the expected best harvesting period for such a field.

It is worth noting that, as stipulated by the Thai Sugar Association, a sugarcane field whose expected CCS value is less than a certain minimum CCS^L may not be harvested. In addition, grower $i \in I$ may be in a group with other small growers so that transportation quota set by the mill is satisfied; and, in such a case, sugarcane fields j_1 and $j_2 \in J(i)$ may belong to different growers within the same group $i \in I$.

The capacity of a mill, as denoted by Q_t^U, is relatively constant over the season (but might differ slightly due to maintenance activities). To avoid lengthy startup procedures, the mill must continuously operate with a capacity of at least Q_t^L in each time period, where $Q_t^L \leqslant Q_t^U$.

As we assume that field-by-field harvesting practice is adopted, the main decision needed to be made is which sugarcane field $j \in J(i)$ will be harvested in each period $t \in T$ such that the following three objectives are optimized.

- Mill's objective: Maximize total amount of sugar production, as measured by the total CSS value over the entire season.
- Grower's objective: Equalize grower benefits by minimizing the standard deviation of misalignment between planned and optimal harvesting periods among all parties.
- Both players' objective: Smoothen the resource requirements for harvesting in each period by minimizing the standard deviation of harvested sugarcane field areas over the entire season (supply variability).

In addition to several logical constraints derived from the definition of variables, the following sets of constraints have to be considered for the underlying Multi-Objective Sugarcane Harvesting Problem (MOSHP).

- Capacity-related constraints at both the grower's and the mill's ends.
- Rules and regulations imposed by either the Government or the Thai Sugar Association.

4.2. Mathematical formulation

The following notation will be used in the MOSHP investigated in this paper.

4.2.1. Sets and parameters

- $i \in I$ is a set of growers, or groups of growers.
- $j \in J(i)$ is a set of sugarcane fields that belongs to grower $i \in I$.
- $t \in T$ is a set of harvesting periods (weeks).
- a_{ij} denotes the area of sugarcane field $j \in J(i)$ (rais, 1 rai $= 0.395$ acres).
- w_{ij} denotes the estimated yield of sugarcane field $j \in J(i)$ (tons/rai).
- b_{ij} denotes the expected best harvesting period for sugarcane field $j \in J(i)$.
- f_{ijt} denotes the estimated CCS value of sugarcane field $j \in J(i)$ in period $t \in T$.
- D denotes the loss of quality in sugarcane inventory, as measured by weekly percentage drop of the CCS value, *i.e.* the CCS value of harvested sugarcane constantly decreases by D% per week.
- CCS^L denotes the minimum level of CCS value required by the Thai Sugar Association.
- Q_t^U denotes the upper limit of mill capacity in time period $t \in T$ (tons).
- Q_t^L denotes the lower limit of mill capacity in time period $t \in T$ (tons).
- M is a large number.

4.2.2. Decision variables

- x_{ijt} is a binary decision variable indicating whether sugarcane field $j \in J(i)$ is harvested in time period $t \in T$:

$$x_{ijt} = \begin{cases} 1, & \text{sugarcane field } j \in J(i) \text{ is harvested in time period } t \in T, \\ 0, & \text{otherwise.} \end{cases}$$

4.2.3. Auxiliary variables

- y_i is the sum of absolute differences between the time periods at which sugarcane fields in $J(i)$ are harvested when compared to their expected best time periods (b_{ij}).
- $\bar{y}$ is the average sum of harvesting differences from the best time periods for all growers.
- g_t is the sum of sugarcane field areas harvested in time period $t \in T$.
- $\bar{g}$ is the average harvested areas of sugarcane fields over the entire season.
- $Mill_t$ is the amount of sugarcane milled in period $t \in T$.
- o_t is the amount of sugarcane inventory at the end of period $t \in T$.
- $\overline{CCS}_t$ is the average CCS value of harvested sugarcane fields in period $t \in T$.

Using this notation, the MOSHP can be mathematically formulated as follows.

4.2.4. Objective function and constraints

$$\text{Minimize}: \quad z_1: \sum_{i\in I}\sum_{j\in J(i)}\sum_{t\in T} -\left(a_{ij}w_{ij}f_{ijt}x_{ijt} - D\overline{CCS}_t\, o_t\right), \tag{1}$$

$$z_2: \sqrt{\frac{\sum_{i\in I}(y_i-\bar{y})^2}{|I|}}, \tag{2}$$

$$z_3: \sqrt{\frac{\sum_{t\in T}(g_t-\bar{g})^2}{|T|}} \tag{3}$$

s.t.

$$\sum_{i\in I}\sum_{j\in J(i)} a_{ij}w_{ij}x_{ijt} + o_{t-1} = Mill_t + o_t, \qquad \forall t \in T \tag{4}$$

$$Mill_t \leqslant Q_t^U, \qquad \forall t \in T \tag{5}$$

$$Mill_t \geqslant Q_t^L, \qquad \forall t \in T \tag{6}$$

$$Mill_t \geqslant o_{t-1}, \qquad \forall t \in T \tag{7}$$

$$\sum_{t\in T} x_{ijt} \leqslant 1, \qquad \forall j \in J\left(i\right), i \in I \tag{8}$$

$$y_i = \sum_{j\in J(i)}\left| b_{ij} - \sum_{t\in T} t\cdot x_{ijt}\right|, \qquad \forall i \in I \tag{9}$$

$$\bar{y} = \frac{\sum_{i\in I} y_i}{|I|} \tag{10}$$

$$g_t = \sum_{i\in I}\sum_{j\in J(i)} a_{ij}x_{ijt}, \qquad \forall t \in T \tag{11}$$

$$\bar{g} = \frac{\sum_{t\in T} g_t}{|T|} \tag{12}$$

$$\overline{CCS}_t = \frac{\sum_{i\in I}\sum_{j\in J(i)} a_{ij}w_{ij}f_{ijt}x_{ijt}}{\sum_{i\in I}\sum_{j\in J(i)} a_{ij}w_{ij}x_{ijt}}, \qquad \forall t \in T \tag{13}$$

$$CCS^L \leqslant f_{ijt}x_{ijt} + \left(1 - x_{ijt}\right)M, \qquad \forall j \in J\left(i\right), i \in I, t \in T \tag{14}$$

$$x_{ijt} \in \left\{0, 1\right\}, \qquad \forall j \in J\left(i\right), i \in I, t \in T \tag{15}$$

$$o_t \geqslant 0, \qquad \forall t \in T \tag{16}$$

As sugar content – and so its total production – can be calculated by the CCS value, the mill's objective, *i.e.* maximizing the total amount of sugar produced over the entire season, could be written as Eq. (1), with a slight modification, where the whole expression is converted into minimization for consistency with the other objectives – namely, z_2: equalizing grower benefits and z_3: resource smoothing. Observe that, when sugarcane is over harvested, inventory of sugarcane, as denoted by o_t, gradually loses its quality. In particular, the loss of CCS value is approximated by the average CCS value of harvested sugarcane in that period ($\overline{CCS}_t$), defined by Eq. (13), and the deterioration rate (D). Eq. (4) preserves the amounts of harvested sugarcane across periods until the end of the season. Inequalities (5) and (6) ensure that fresh sugarcane is steadily supplied to the mill over the entire season without violating mill capacity in any single period, while Constraint (7) helps prevent sugarcane inventory from building up. Constraint (8) makes sure that each sugarcane field $j \in J(i)$ could be harvested in one of the harvesting periods $t \in T$. The misalignment between the planned and the optimal peak period for sugarcane field $j \in J(i)$, along with its average sum, is defined by Eqs. (9) and (10). Likewise, the total area of harvested sugarcane fields in time period $t \in T$ and its average are defined by Eqs. (11) and (12), respectively. Lastly, Constraint (14) allows only sugarcane fields, whose CCS values are at least CCS^L to be harvested – if $x_{ijt} = 1, f_{ijt}$ must be at least CCS^L; otherwise, this constraint conveys no additional information.

5. Solution approach

5.1. Multi-objective evolutionary algorithms

The MOSHP investigated in this paper is a multi-objective optimization problem, in which trade-offs between competing objectives have to be made. In terms of computation, solving multi-objective optimization problems is relatively challenging, especially when there are more objectives to be optimized, as the number of efficient solutions defining a Pareto front exponentially grows – but yet unknown. Also, once the dimension of problems exceeds three, visualization – and so evaluation of such solutions – has become more complicated.

While multi-objective optimization problems may be solved by scalarization techniques that combine multiple objectives into one, such methods are of limited used as they could provide only one Pareto-optimal solution at a time – and, some might be inapplicable for non-convex objective spaces (Li, Deb, Zhang, Suganthan, & Chen, 2019). As such, multi-objective optimization problems are practically solved by *Multi-Objective Evolutionary Algorithms* (MOEAs), or nature-inspired search heuristics, whose concepts are based on the evolution of solution populations under different algorithmic frameworks (Coello, Lamont, & Van Veldhuizen, 2007).

Emmerich and Deutz (2018) classified MOEAs into three main groups based on selection paradigms, including (*i*) Pareto Dominance-Based MOEAs (NSGA-II and SPEA2), (*ii*) Indicator-Based MOEAs (IBEA and Hypervolumn-Based MOEAs), and (*iii*) Decomposition-Based MOEAs (MOEA/D and NSGA-III). Zhou et al. (2011), on the other hand, divided MOEAs into several more classes based on their algorithmic frameworks, selection and reproduction procedures, and other computational issues. Among these MOEAs, the well-known *Elitist Non-Dominated Sorted Genetic Algorithm II* (NSGA-II) is one of the solution methodologies that has been widely applied in the literature (see Bandyopadhyay & Bhattacharya, 2013; Ren, Wen, Hu, & Li, 2020; Wang, Fu, Huang, Huang, & Wang, 2017, for example).

NSGA-II is a Pareto Dominance-Based MOEA that allows only elite populations to reproduce by elite-preserving operators and maintains the diversity of non-dominated solutions by crowding distances (Deb, Pratap, Agarwal, & Meyarivan, 2002). While the NSGA-II has performed quite well for low dimensional problems, it tends to lose the designed selection pressure during the evolutionary process in higher dimensional problems as the proportion of non-dominated solutions grows much faster with a slight increment in the number of objectives (He & Yen, 2016). In addition, these many non-dominated solutions may occupy limited elite slots, which, in turn, slows down the search process (Deb & Jain, 2014).

To overcome such shortcomings, Deb and Jain (2014) have recently introduced a modified version of the NSGA-II, called the *Reference-Point Based Many-Objective NSGA-II*, or the *NSGA-III*, for short. The concept of NSGA-III is quite similar to that of NSGA-II except for the selection procedure, where the NSGA-III uses relative distances between the solutions and reference points instead of crowding distances to help preserve the diversity of Pareto-optimal solutions. In terms of algorithmic design, these reference points might be regarded as search directions during the evolutionary process (Li et al., 2019).

Deb and Jain (2014) showed that the NSGA-III outperformed the NSGA-II and other recent Decomposition-Based MOEAs in terms of both solution quality and diversification as measured by the *Inverse Generational Distance* (IGD). Their results were in-line with Li et al. (2019), where the NSGA-III was applied on several sets of multi-objective optimization benchmark instances. Based on its recent successes, the NSGA-III is therefore adopted as a part of the devised algorithm in this work (see Algorithm 1 in the Appendix for an overview of the NSGA-III).

It is worth remarking that, similar to the NSGA-II, the NSGA-III might be regarded as a generic selection operator that could be applied along with varieties of reproduction/recombination operators that well suit the problems.

5.2. Multi-objective evolutionary genetic algorithm

The MOSHP in this paper is solved by means of the *Multi-Objective Evolutionary Genetic Algorithm* (MOEGA) embedded with the NSGA-III – as a selection procedure – whose implementation outline is provided in Algorithm 2 in the Appendix. This algorithm includes five computational modules for the generation of MOSHP's non-dominated solutions as follows.

- Initial Population Generation Module (*IntGen*): This module is called to create the initial solution population (P_1).
- Repair Module (*Repair*): This module is repeatedly called whenever a solution is constructed so that feasibility is maintained at all time.
- Uniform Crossover Module (*U-Cross*): This module contains one of the deployed reproduction operators iteratively called for offspring generation.
- Uniform Mutation Module (*U-Mutation*): This module contains another reproduction operator iteratively called for offspring generation.
- Local Search Module (*LocalSearch*): This module helps guide the algorithm towards Pareto-optimal fronts, where two local search operators – namely relocation and swap – are applied every a fixed number of generations.

5.2.1. IntGen

IntGen creates a pool of initial solution populations, each of which is referred to as a chromosome, or a collection of genes, in the GA setting. While the definition of chromosomes may be different elsewhere, in this paper, a chromosome is defined as a sequence of harvesting periods for all sugarcane fields. More formally, given a number of sugarcane fields N_f and a set of time periods T, *IntGen* first creates a chromosome of length N_f and then assigns a planned harvesting period $t \in T$ to each of the genes until all genes are attached with some values $t \in T$. For example, a chromosome $[2, 3, 1, 5, 6, 4]$ indicates the sequence of harvesting periods for six sugarcane fields, where Field 1 is harvested in time period 2, Field 2 is harvested in time period 3, and so on (see Table 1 for detailed planning).

To help guide the proposed MOEGA towards the Pareto front, while maintaining solution diversity, two sets of initial solutions are constructed: (*i*) randomly initiated solutions (P_1^R) and (*ii*) objective-wise

Table 1
The detailed harvesting plan of a chromosome $[2,3,1,5,6,4]$.

Field	Time Period					
	1	2	3	4	5	6
1		√				
2			√			
3	√					
4					√	
5						√
6				√		

initiated solutions (P_1^L), where $P_1 = P_1^R \cup P_1^L$.

The process for generating P_1^R is quite straightforward as planned harvesting periods are randomly generated and assigned to all genes. However, to avoid generating inefficient solutions, for each sugarcane field $j \in J(i)$, a random integer number r_j is selected from a normal distribution with a mean of b_{ij} – the expected best time period for sugarcane field $j \in J(i)$ – and a standard deviation between 1 and 3 periods. More specifically, $r_j \in \mathscr{Z}^+$ and $r_j \tilde{} N(b_{ij}, Unif[1,3]), \forall j \in J(i), \forall i \in I$.

For solution set P_1^L, one of the best four solutions in each domain will be randomly selected and applied with two local search operators, namely *relocation* and *swap*. The concepts of these two local search operators are equivalent to Swap(1,0) and Swap(1,1) suggested by Fleszar and Hindi (2002), where a field is relocated from one period to another by the relocation operator and two fields are interchanged by the swap operator. Once these two local searches terminate, three best solutions with respect to each objective will be added to the initial solution pool.

5.2.2. *Repair*

The initial (or offspring) solutions may be infeasible as they are constructed without any MOSHP constraints. Hence, a repairing mechanism is needed to maintain solution feasibility at all time; and, we achieve this by the *Repair* module. The *Repair* module first checks whether a solution is feasible – and if not, such a solution will be repeatedly repaired by the Undersupply, Oversupply, and *MinCCS* submodules. In particular, *Undersupply* preserves the mill's minimum capacity by relocating the best possible fields to periods that need additional supply. *Oversupply* and *MinCCS*, on the other hand, randomly remove fields violating the mill's maximum capacity and the minimum CCS constraint, and then reinsert them into best possible periods with respect to the CCS values. Algorithms 3–6 in the Appendix give a precise description of the detailed steps for *Repair*, *Undersupply*, *Oversupply*, and *MinCCS*, respectively.

5.2.3. *U-Cross*

U-Cross is a reproduction operator used to combine the information from two parent chromosomes and generate a new offspring based on a random number p – the crossover probability that ranges between 0 and 1 – and a crossover threshold α.

- If $p < \alpha$, two random chromosomes from the solution pool will be selected as parent solutions for the creation of an offspring solution whose genes inherit the values from each of its parents with equal probability.
- If $p \geqslant \alpha$, *U-Mutation* will be called.

It is worth noting that the offspring solution might be infeasible – and if so, the *Repair* module will be subsequently called.

5.2.4. *U-Mutation*

U-Mutation is another reproduction operator used to maintain diversity of the population. It also helps algorithm avoid getting stuck in local extrema from too similar parent solutions in the solution pool. *U-Mutation* is called only when $p \geqslant \alpha$; and, once it is called, each of the selected chromosome's genes is prone to mutate (change) from its initial value to one within a predefined range with equal probability. Similar to *U-Cross*, the resulting solution might be infeasible; and, in such a case, the *Repair* module will be subsequently called.

5.2.5. *LocalSearch*

In order to help the algorithm generate good offsprings, *LocalSearch* will be called every a fixed number of generations. The implementation of this *LocalSearch* submodule is similar to that of P_1^L, where four best objective-wise solutions in the non-dominated solution pool will be randomly selected and applied with two local search operators – namely relocation and swap. Once *LocalSearch* terminates, three best objective-wise solutions will join other offspring solutions in P_t.

6. Results and discussion

6.1. *Experimental design*

The proposed MOEGA has been tested on four different instance sizes, each with different numbers of growers and sugarcane fields, total sugarcane field areas, harvesting periods, and mill capacities as summarized in Table 2.

For each problem size, 10 different experimental instances are generated – except for the practical ones, with only five experimental instances each, but with four different variants. The first three variations are the namesake early, middle, and late maturation scenarios, describing when within the harvesting season the sugarcane matures (Florentino et al., 2018; Jiao et al., 2005), while the last variation is created to reflect a balanced sugarcane supply throughout the entire season. For computational consistency, the percentages of matured sugarcane in each scenario over the entire season are set as in Table 3.

All parameter values of the practical instances are generated based on the operational data of a mill in Kanchanaburi Province, Thailand, whose daily capacity is about 8,200 tons (Q^u). The numbers of growers (I) and sugarcane fields ($J(i)$), together with total sugarcane field areas (a_{ij}), are generated based on a report by the *Office of Cane and Sugar Board* (OCSB), publicly available at http://www.ocsb.go.th. In addition, the CCS values of all sugarcane fields (f_{ijt}), along with their best harvesting periods (b_{ij}), are estimated from the least squares polynomial of degree 3 (Jiao et al., 2005). But, only three sugarcane species will be considered in this research as they represent most of sugarcane planted in this area – LK92-11, LK95-84, and KK3.

In order to ensure that the harvested sugarcane is of good quality and the mill is steadily supplied with sugarcane for the whole season, the minimum level of CCS value required (CCS^L) and the lower capacity limit of a mill are set at 10 and 80% of its maximum capacity, respectively. Lastly, the discount factor for loss of sugarcane quality (D) is set at 8.37% per week as reported by the OCSB, while the parameter values of all other instance sizes are randomly created (or selected) from the practical instances.

Table 2
A summary of the MOSHP information for each instance size.

Instance Sizes	Number of Growers	Number of Sugarcane Fields	Total Sugarcane Field Area (rais)	Harvesting Period (weeks)	Mill Capacity (tons/week)
Small Instance	19	25	820	8	1,275
Moderate Instance	196	278	8,925	12	9,330
Large Instance	668	970	31,168	20	19,455
Practical Instance	1,962	2,845	91,726	20	57,300

Table 3
Percentages of matured sugarcane in each of the four scenarios over the entire season.

Scenarios	Early of the season	Middle of the season	Late of the season
Early Mature	60	20	20
Middle Mature	20	60	20
Late Mature	20	20	60
Balance	33	34	33

In addition to the aforesaid MOSHP parameters, the MOEGA parameters, as reported in Table 4, are set based on the results of preliminary experimental runs so that the resulting sugar yields are close to the ideal yields derived from the single-objective sugarcane harvest scheduling problem, with no consideration on either grower equity or supply chain efficiency, *i.e.* the output maximization model. For comparability and consistency, all experiments are conducted on a laptop with an Intel Core i7 CPU (1.99 GHz) and a memory of 8 GB.

6.2. Solution quality

We assess the quality of solutions generated by the proposed MOEGA with those of the *Preemptive Goal Programming* (PGP), where we first solve single-objective models and use the results of these so-called upper level models as additional constraints in the lower level ones (Taha, 2017). In doing so, the MOSHP is decomposed into three different single-objective mathematical programming models, each of which aims to optimize one of its original objectives: (*i*) the output maximization model ($M1$), (*ii*) the grower equity model ($M2$), and (*iii*) the supply chain efficiency model ($M3$). All non-linear expressions are also linearized based on the deviations from their ideal best values resembling those of Florentino et al. (2018) – namely b_{ij} and $\overline{g}$ for grower equity and supply chain efficiency models, respectively. This may, however, affect the interpretation of solutions as grower equity and supply chain efficiency in these models are measured by total absolute deviations, *i.e.* $\sum_{i\in I} y_i$ and $\sum_{t\in T}|g_t - \overline{g}|$, while those of the MOEGA are measured by standard deviations.

Depending on the sequences of objective priorities, these three models will be successively solved by CPLEX, each with a time limit of two hours as to avoid excessive computation times (the longest computational time for each instance is therefore six hours). For small instances, four different benchmark solutions are generated based on mill-oriented and grower-oriented priority sequences, while fewer benchmark solutions are generated for larger instances due to the dominance of higher priority models that leaves no room for improvement in the lower priority ones. Besides, the computational times of CPLEX drastically rise as instance sizes become larger. This is especially evident for the practical instances, where run-out-of-memory errors consistently occur when M_2 is executed. Hence, only one priority sequence is explored for all practical variants. The results from the PGP approach are then compared with those of the MOEGA in terms of average solution deviations and coefficients of variation as reported in Table 5. It is worth noting that deviations of solutions, or solution gaps, in Table 5 are reported based on the PGP solutions, *i.e.* $(x_{MOEGA} - x_{PGP})/(x_{PGP})\cdot 100$, while the coefficients of variation are computed by $SD_{x_{MOEGA}}/\overline{x}_{MOEGA}$.

Table 4
The MOEGA algorithmic settings.

Parameters	Values
Generation	200
Number of generations before calling local searches	10
Number of reference points	91 (12 divisions)
Size of solution population	100
Number of randomly initiated solutions	97
Number of objective-wise initiated solutions	3
Mutation Threshold (α)	0.7

It is evident from Table 5 that the MOEGA performs relatively well when compared to the PGP approach as it could provide solutions that are close to optimal in terms of sugar production (mill-oriented solutions) – but with much better grower equity and supply chain efficiency as measured by the standard deviations of harvesting period misalignment and harvested areas across the season. The coefficients of variation among the MOEGA solutions are also low indicating that there is not much variability within the MOEGA solution pool. In contrast, the quality of PGP solutions largely depends on priority sequences, whose solutions rarely change due to the dominance of higher priority models over the lower priority ones. Instead of favoring one objective over the others, the MOEGA tries to concurrently optimize all different aspects of different actors within the sugar supply chain so that well-balanced solutions could be established; and, this could be regarded as one major advantage of the MOEGA over the PGP approach.

Regarding the amount of sugar produced, it is evident that mill-oriented solutions are superior to the MOEGA solutions, with a maximal average gap of 2%. Nonetheless, grower inequity and variability in harvested areas derived from these solutions are observably high. This implies that, under a good collaboration framework where all parties centrally decide on the harvesting periods based on one another's decisions, growers can receive higher profits, while mill operations are smoothed out. Although the production of sugar slightly decreases, savings from subsequent resource allocation phases may offset such loss leading to a more sustainable production environment.

A similar conclusion could be drawn from the two grower-oriented models with priority sequences $M2-M1-M3$ and $M2-M3-M1$. Although significant improvements in grower equity are evident, the MOEGA solutions are still better off in terms of standard deviations on both metrics, with slight differences on the total CCS values. We also observe that grower-oriented models tend to underperform in terms of sugar production when the problems become larger, which seems surprising as more sugarcane fields are expected to be harvested in their best periods. The reason behind this unexpected outcome is the negligence of field information – including the CCS values, sugarcane yields, and field ownership – in $M2$ and $M3$. As no information regarding the sugarcane fields is incorporated into these models, all the fields will be treated equally important; and, the harvesting plans with the least total absolute deviations may not be the ones providing highest sugar yields nor the highest grower equity. These settings are even worse for poorly coordinated systems – such as the one investigated in this paper – as grower-oriented solutions would only create higher chances of over harvests that further deteriorate compensation for both players due to the CCS decay.

These observations clearly stress the importance of collaboration and coordination to sustainability in the Thai sugar supply chain; and, we expect that our devised framework will serve as a stepping stone for such a development.

6.3. Exploration of the solution space

In terms of flexibility, as the MOEGA provides multiple non-dominated solutions as output, planners will have more freedom to pre-screen and select individual solutions that best suit their specific conditions for further evaluation and execution.

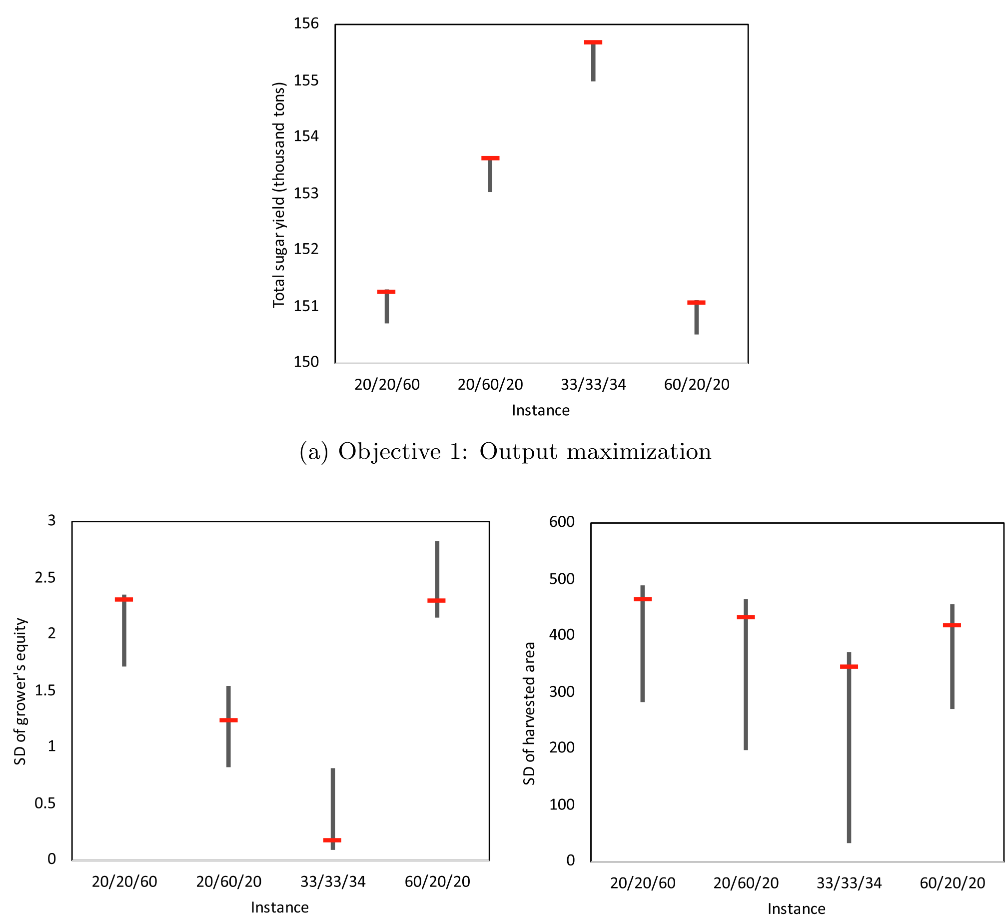
For instance, Fig. 2 shows a sample set of solutions to the four practical instances having the CCS values of at least 99.5% of the maximum CCS values obtained from the PGP solutions.

Based on Fig. 2, traditional plans that prioritize the CCS value typically lead to situations with higher grower inequity and resource usage imbalance implied by the second and the third objectives. By executing alternative plans with slight decreases in sugar production, grower equity could be lifted significantly, while the mill could benefit from better utilization of the machinery fleet that has been rented to contract growers – this is especially evident for middle and late maturation

Table 5
The overall results from the proposed MOEGA when compared to the PGP solutions in terms of solution deviations and coefficients of variation.

Instance	PGP Order	Average percentages[a] of solution deviations[b] and coefficients of variation[c]								
		CCS			Grower Equity			Harvested Area		
		Best	Average	CV	Best	Average	CV	Best	Average	CV
Small	M1-M2-M3	−0.071	−0.548	0.004	−70.7963	−38.1743	0.340	−84.8728	−19.1498	0.510
	M1-M3-M2	−0.071	−0.548	0.004	−70.7963	−38.1743	0.340	−84.8728	−19.1498	0.510
	M2-M1-M3	0.197	−0.281	0.004	−55.2912	−4.3610	0.340	−86.3524	−28.1174	0.510
	M2-M3-M1	0.249	−0.229	0.004	−53.9995	−1.5920	0.340	−84.7687	−22.1981	0.510
Moderate	M1-M2-M3	−0.297	−1.178	0.007	−53.961	−26.217	0.367	−86.883	−47.258	0.351
	M2-M1-M3	0.581	−0.308	0.007	−38.953	−2.116	0.367	−89.852	−59.251	0.351
Large	M1-M2-M3	−0.305	−1.745	0.011	−46.116	−20.703	0.170	−70.119	−33.028	0.235
	M2-M1-M3	2.478	0.997	0.011	−34.2703	−3.342	0.170	−77.425	−49.305	0.235
Practical (Early)	M1-M2-M3	−0.169	−1.913	0.012	−43.184	−22.502	0.143	−69.190	−29.764	0.230
Practical (Middle)	M1-M2-M3	−0.131	−1.399	0.009	−47.412	−20.764	0.158	−73.001	−33.029	0.285
Practical (Late)	M1-M2-M3	−0.156	−1.652	0.010	−53.852	−23.810	0.177	−62.809	−25.430	0.217
Practical (Balance)	M1-M2-M3	−0.079	−0.551	0.004	−43.235	−24.950	0.296	−76.622	−36.883	0.282

[a] The quality of solutions for small, moderate, and large instances is averaged over 10 MOEGA replications, while that of practical instances is averaged over five MOEGA replications due to comparatively long computation times.
[b] Percentage of solution deviation is computed by $(x_{MOEGA} - x_{PGP})/(x_{PGP})\cdot 100$.
[c] CV is the coefficient of variation as computed by $SD_{x_{MOEGA}}/\overline{x}_{MOEGA}$.



(a) Objective 1: Output maximization

(b) Objective 2: Grower Equity

(c) Objective 3: Supply chain efficiency

Fig. 2. Solution ranges (black vertical bar) for the three objectives based on the selected practical instances with at least 99.5% of the maximum CCS values obtained from the PGP solutions. Also included are red horizontal bars showing the solutions of the PGP approach.

scenarios. Since harvesting machinery is typically expensive with high variable operating costs, less usage variation will lead to a more favorable situation for the mill as smaller fleet sizes are expected to be operated at higher utilization rates.

Besides these explicit benefits at both growers' and mills' ends, the proposed MOEGA could potentially help reduce the implicit costs of sugarcane field burning and opportunity losses from CCS decay due to a more balanced resource usage over the entire season. Further prescreening could have been done on the second and the third objectives depending on planner knowledge, current state of operations, and other related issues at time of decision making.

6.4. The impact of cultivation patterns

We have also conducted a comparative study on the Pareto fronts of the practical instances, where we shift cultivation patterns of data sets to match the four scenario settings, as demonstrated in Fig. 3.

It could be seen that, among all four variants, the one with a balanced yield provides not only the best sugar production but also the least standard deviations in terms of both grower equity and harvested area, while the worst two variants are the early and late maturation scenarios with lease sugar output and higher standard deviations on both domains.

Based on these results and the current practice in Thailand, where harvesting occurs mostly from early to middle of the season, the Thai sugar industry could be largely improved simply by balancing the sugarcane yields over the entire season. In doing so, the OCSB and mills must promote a new cultivation practice that leans towards such a scenario. For instance, growers should be informed by the OCSB regarding proper sugarcane species that best suit their growing areas, as well as the amount and time periods in which sugarcane should be cultivated, so that oversupply of sugarcane output in any specific time period can be avoided.

On the other side of the supply chain, the mills must support growers by promptly responding to any slight changes that might take place on future periods. This could be achieved by an introduction of supportive information systems, such as the *Geographic Information System* (GIS), together with viable multi-objective decision support frameworks that take into account the conflicting objectives of different stakeholders, like the one introduced in this study. Without these technological supports, new equilibrium is less likely; and, the additional surplus would be futile.

6.5. MOEGA implementation issues

It is evident from the previous analyses that the MOEGA has several advantages over traditional harvest planning techniques. Firstly, the MOEGA generates a set of well-balanced solutions that concurrently benefits both growers and mills, with only slight decrease in sugar output, while traditional harvest planning techniques tend to generate smaller sets of optimal solutions that largely depend on parameter settings and predefined sets of constraints. The MOEGA also helps decision makers explore not only the multi-dimensional solution space but also the trade-offs among three different conflicting objectives, which can potentially lead to new supply chain management practices that further enhance the Thai sugar supply chain as a whole.

Nonetheless, the solutions provided by the MOEGA – and from other solution approaches in the literature – are only preliminary harvesting plans as they heavily rely on yield predictions, with no consideration on any other potential disturbances that might impede sugarcane harvesting activities in future periods, such as weather conditions or the availability of limited harvesting resources. Since yield predictions are inherently uncertain, especially for periods far into the future, a selected harvesting plan is therefore rarely executable throughout an entire season. Rather, suboptimal plans with recourse actions may be more practical and thus are implemented for shorter periods within the season. For example, during a rainy period, harvesting with heavy machinery might have to be delayed or replaced with green teams – groups of laborers with comparatively low cutting capacities of 1.5–2 tons/man-day (Pongpat et al., 2017). In either case, amendments on the adopted harvesting plan are inevitable; and, they are required not only for this specific period but also for those in the future until the end of planning horizon. Similar propagated changes on the selected harvesting plans may also originate from field adjustment as to avoid excessive moves of harvest fronts in each harvesting period (Florentino et al., 2018).

To properly address uncertainties and possible forecast updates, the MOEGA could be performed in a rolling horizon fashion, where harvesting decisions corresponding to the current period are assessed along with other detailed operational decisions, *i.e.* daily harvest front scheduling, taking into consideration the most up-to-date information. With availability of multiple non-dominated harvesting plans and improvements in supply chain data, more fine-tuned harvesting plans with minimal adverse effects on both growers and mills could be potentially devised and successfully executed. We expect that, under this integrated framework, a more sustainable sugar supply chain could be established;

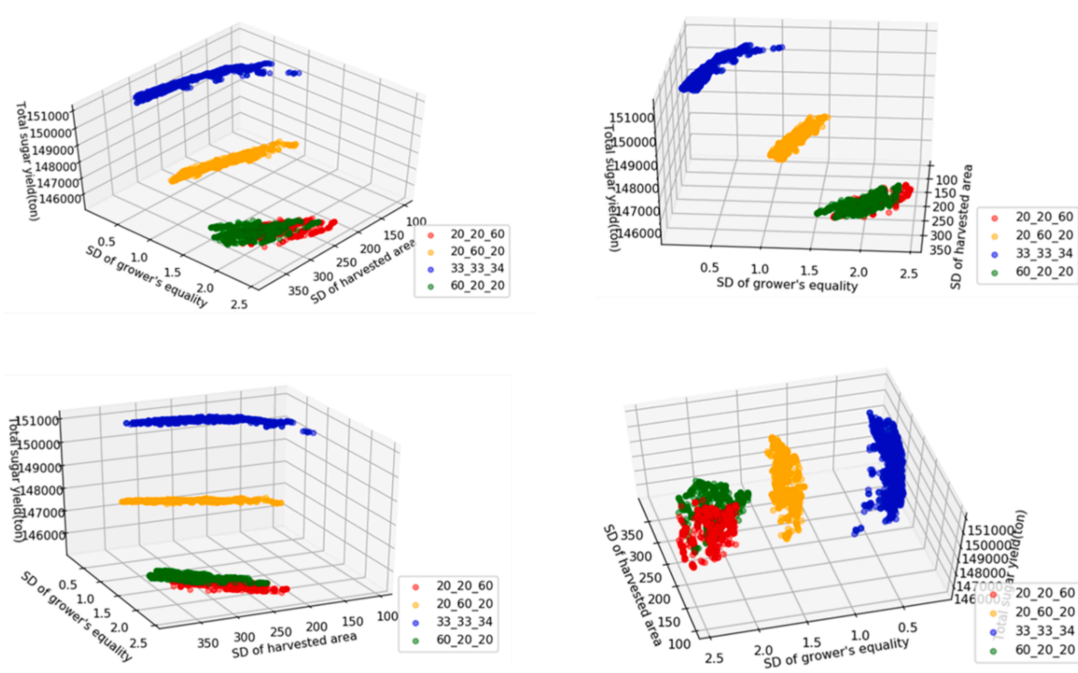


Fig. 3. The Pareto Fronts of the selected four practical case's variants.

and, it is something worth exploring in future studies.

7. Conclusions

Sugarcane harvest planning in Thailand is relatively unique due to discussions around grower equity and other local planning considerations that potentially lead to conflicts among actors within the supply chain. In order to balance conflicting objectives while satisfying all posed constraints, this paper develops the *Multi-Objective Sugarcane Harvesting Problem* (MOSHP) that concurrently optimizes both grower's and mill's objectives, namely (*i*) the amount of sugar produced over the entire season, (*ii*) grower equity within and across parties, and (*iii*) efficiency in deployed resources across harvesting periods. We also develop a solution methodology based on genetic algorithms, but with a more intricate selection procedure, known as the NSGA-III in the literature. To better help the algorithm move towards the Pareto front, two local search operators are also embedded in the algorithm and intermittently called every a fixed number of generations. Once the algorithm terminates, a pool of diverse harvesting plans is returned from which planners can pre-screen and select specific plans that best suit their particular situation for further evaluation and execution.

We have applied the model and proposed solution methodology on the MOSHP instances of various sizes, where the largest instances comprise of 1,962 growers and 2,845 sugarcane fields with a total area of 91,726 rais. All information regarding these instances are generated based on the current operational information of a mill in Kanchanaburi Province, Thailand. We find that, when compared to mill-oriented solutions, our approach is able to produce a set of diverse solutions with comparable quality, as the maximal average gap (in terms of sugar output) is only 2%. Nonetheless, our solutions show that, with slight decrease in sugar production, grower equity and supply chain efficiency could be largely improved. By improving these two other objectives, growers can receive higher profits, while mills can enjoy lower operational costs that potentially offset the decrease in sugar production. We also find that the greatest improvement can be achieved by moving the whole supply chain towards a balanced yield scenario, which, however, requires a relatively high level of collaboration throughout the Thai sugar supply chain.

It should be remarked that the harvesting plans provided by the MOEGA are only preliminary plans with no detailed information regarding the schedules of harvest fronts. Nonetheless, the MOEGA is still useful as it could be combined with other detailed planning, *i.e.* daily harvest front scheduling, for the development of fine-tuned operational plans, which is worth exploring in future studies.

CRediT authorship contribution statement

Pisit Jarumaneeroj: Conceptualization, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Nutchanon Laosareewatthanakul:** Methodology, Software. **Renzo Akkerman:** Formal analysis, Investigation, Writing - review & editing.

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Appendix A

In this appendix, pseudocode is included for the different parts of the solution methodology described in Section 5.

Algorithm 1. Generation t of the NSGA-III.

Input: H structured reference points (Z^r) (or predefined reference points), parent population P_t with size N.
Create: Create offspring population Q_t from P_t.
Sort: Sort the pool of solutions $R_t = P_t \cup Q_t$ into different Pareto-optimal fronts ($F_1, F_2, \ldots, F_L$) based on non-dominated sorting procedure.
Fill: Sequentially select and fill population P_{t+1} from the first front's solutions (F_1) until those of front l (F_l), where $S_t = \sum_{i=1}^{l} \left|F_i\right| \geqslant \left|N\right|$.
if $|S_t| = |N|$ **then**
  Return: Terminate and return population P_{t+1}.
else
  Normalize: Normalize the objective points so that they are with the same unit range.
  Create: Create H structured reference points (Z^r) on a normalized hyperplane.
  Attach: Attach each solution in S_t with a reference point based on the closest perpendicular distances between such a solution and the reference points.
  Compute: Compute niche counts for each reference point based on niche-preservation operation. Technically speaking, the niche count of reference point j, denoted by σ_j, is defined as the number of solutions in $S_t \backslash F_l$ associated with the j^{th} reference point.
  Select: Select the solutions from F_l based on the niche count until $|P_{t+1}| = |N|$.
end if
Return: Population P_{t+1}

Algorithm 2. The structure of MOEGA.

Input: Information regarding the MOSHP, together with other pre-specified parameters for the NSGA-III.
Initialization: Initialize all parameters.
Create and Repair: Create initial solution population and repair those infeasible solutions violating MOSHP constraints by *IntGen* and *Repair*.
while current generation $t < gen$ **do**
  Initialization: Initialize offspring solution (Q_t).

(*continued on next page*)

(*continued*)

while the number of offspring solution ($|Q_t|$) $< N$ **do**
  Generate: Generate an offspring based on the value of random variable p, whose value is bounded between 0 and 1.
  if $p < \alpha$ **then**
    Crossover: Call the uniform crossover operator (*U-Cross*) for generating an offspring solution.
  else
    Mutation: Call the uniform mutation operator (*U-Mutation*) for generating an offspring solution.
  end if
  Repair: Repair the offspring solution if it is found to be infeasible by *Repair*.
end while
Local Search: Apply local search operators to help guide the algorithm every a fixed number of generations.
NSGA-III Selection Procedure (Algorithm 1)
Update: Update generation by $t = t + 1$.
end while
Return All non-dominated solutions to the MOSHP.

Algorithm 3. *Repair* Module.

Input: A solution to the MOSHP at generation t.
Check: Check whether such a solution is feasible.
if the given solution is feasible **then**
  Evaluate: Evaluate all three objectives of such a solution.
  Terminate: Terminate and return the solution back to the solution pool P_t.
else
  while the given solution is infeasible **do**
    Undersupply: Repair the chromosomes violating the mill's minimum capacity by *Undersupply*.
    Oversupply: Randomly remove the fields violating the mill's maximum capacity to F_O by *Oversupply*.
    MinCCS: Randomly remove the fields violating the minimum CCS constraint to F_{CCS} by *MinCCS*.
    Relocate: Relocate unassigned fields, *i.e.* $F_O \cup F_{CCS}$, to the best-possible periods, in terms of CCS values.
  end while
  Evaluate: Evaluate all three objectives of the repaired solution.
end if
Return A feasible solution.

Algorithm 4. *Undersupply* Submodule.

Input: A solution to the MOSHP at generation t.
Minimum Capacity Check: Check whether the mill's minimum capacity constraint is violated on any period p.
while there exists a period p' at which the mill's minimum capacity constraint is violated **do**
  Create: Create a list of fields that should be harvested in period p' based on the CCS values, *i.e.* F_b.
  Repair: Relocate a field from F_b to its best-possible period p' until the mill's minimum capacity constraint is met.
  Update: Update the chromosome, total capacity, remaining capacity, and oversupply in each period p.
end while
Return An updated chromosome.

Algorithm 5. *Oversupply* Submodule.

Input: A solution to the MOSHP at generation t.
Maximum Capacity Check: Check whether the mill's maximum capacity constraint is violated on any period p.
if there exists a period p' at which the mill's maximum capacity constraint is violated **do**
  Remove: Randomly remove a field f in p' to a temporary list F_O.
end if
Update: Update the chromosome, total capacity, remaining capacity, and oversupply in each period p.
Return An updated chromosome with F_O.

Algorithm 6. *MinCCS* Submodule

Input: A (partially completed) solution to the MOSHP.
Min CCS Check: Check whether the minimum CCS constraint is violated on any period p.
while there exists a period p' at which the minimum CCS constraint is violated **do**
  Remove: Remove all fields f in p' that have CCS values lower than 10 and store such fields in a list F_{CCS}.
end while
Update: Update the chromosome, total capacity, remaining capacity, and oversupply in each period p.
Return An updated chromosome with F_{CCS}.

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