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A multi-objective modeling approach to harvesting resource scheduling: Decision support for a more sustainable Thai sugar industry

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ABSTRACT

This paper develops a multi-objective modeling approach for the scheduling of harvesting resources in the Thai sugar industry, in which different objectives stemming from different industry stakeholders are concurrently optimized with the overall goal to create a more sustainable sugar supply chain. In addition to traditional economic objectives, the environmental impact of sugarcane farm burning is included into the model to better reflect the current harvesting practice, where sugarcane growers often resort to burning their fields due to the lack of available harvesting resources during the season. An evolutionary algorithm based on a variant of Particle Swarm Optimization (PSO) is also devised to help solve the resulting Multi-Objective Harvesting Resource Scheduling Problem (MOHRSP), which normally becomes intractable for real-life problem instances. We find that the proposed PSO framework is notably efficient as it provides diverse sets of non-dominated solutions with markedly low coefficients of variation in a reasonable amount of time. We also find that, by sacrificing a slight amount of sugar production volume, the whole sugar supply chain could be largely improved, especially for the sugarcane growers, whose profitability turns out to be sensitive in the trade-offs with other objectives.

1. Introduction

In Thailand, sugarcane is one of the major agricultural crops that annually generates more than 6 billion US dollars, according to a report by the Office of Cane and Sugar Board (OCSB). Based on this figure, Thailand has been ranked fourth in the list of the world's largest sugar producers in 2019; and, it is even ranked second in terms of the world's largest sugar exporters, due to a comparatively low domestic demand (International Sugar Organization).

Compared to other sugar-producing countries, the structure of the Thai sugar supply chain is relatively unique, as it involves many smallholder sugarcane growers (around 400,000 households), a limited number of highly regulated sugar mills, and complex harvesting regulations with many governing bodies. For instance, the sugarcane harvesting (milling) period in Thailand is fixed and controlled by the OCSB, where growers (mills) may start harvesting (milling) as early as late November, but no later than early May of the subsequent calendar year. The exact time period may, however, vary from region to region depending on the end of the rainy season. Furthermore, field-by-field harvesting practice is commonly exercised by most sugarcane growers in order to prevent harvest mixing; but, due to their limited small farm areas, these sugarcane growers may need to collaborate with other growers so that the mill's transportation requirements are satisfied. To ensure that all members within a grower group will be equally paid based on their sugarcane yields, while satisfying transportation quotas set by the mills, some growers may need to sacrifice their own benefits by harvesting their fields long before or after the optimal harvesting periods, which, in turn, leads to disputes among involved growers (Thuankaewsing et al., 2015).

The performance of the Thai sugar supply chain is further affected by the current cultivation practice, where cultivation patterns across parties are approximately the same in terms of timeline. This results in significant supply fluctuations – and so production problems from the sugar mill's perspective. On the one hand, when sugarcane supply is low, milling activities might be interrupted since a constant minimum feed of sugarcane must be maintained to avoid stoppages (Kadwa &

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Bezuidenhout, 2015). On the other hand, when sugarcane supply is excessive, long queues of transporting trucks might be formed, requiring additional time for it to be milled. However, since sugarcane quality, as measured by the Commercial Cane Sugar (CCS) value, gradually drops after harvesting, the longer the sugarcane waits in queues, the less sugar is extracted (Larrahondo et al., 2006).

Another problem that often arises during sugarcane harvesting seasons in Thailand is the environmental problem caused by the harvesting (mal)practice, known as sugarcane farm burning. Sugarcane farm burning is a common pre-harvesting process in Thailand – and some other countries, including the United States – where sugarcane fields are set on fire in order to remove leaves and tops of sugarcane before harvesting (Pongpat et al., 2017). While sugarcane farm burning helps save scarce labor forces and speed up the harvesting process, it unfortunately creates environmental issues, such as the emissions of greenhouse gases (GHG) and the spread of fine particulate matter (PM2.5 for short), not only in the immediate vicinity of the field but also in the whole region (Yuttitham et al., 2011). Although, the Thai government prohibits sugarcane farm burning, the amount of sugarcane burnt in 2019 as reported by the OCSB was still far too high – about 61.11% of the total sugarcane supply, or 80 out of 130 million tons.

To reduce the amount of burnt sugarcane, along with its adverse environmental effects, more efficient harvesting machinery has recently been promoted by a number of government agencies, as well as commercial sugar mills (Amaruchkul, 2021). Unfortunately, most sugarcane growers in Thailand are incapable of owning such machinery due to its relatively high upfront investment costs. Rather, the machinery is often rented by groups of growers and shared during the harvesting season (Pitakaso & Sethanan, 2019). Since the available harvesting machinery is practically limited and insufficient for all grower demands, especially in the peak harvesting periods, sugarcane farm burning is inevitably adopted. Efficient harvesting resource scheduling is therefore crucial not only for the improvement of related parties' performance but also for the reduction of sugarcane farm burning occurrences, which will, in turn, promote sustainability within the Thai sugar supply chain.

Notwithstanding such a fact, the efficiency of harvesting resource scheduling is not straightforward, as there are still conflicts among supply chain actors. For instance, grower's benefits are generally worse off when the mill's benefits are emphasized (Jarumaneeroj et al., 2021). In order to create a more sustainable sugar production environment, collaborative practices that take into account conflicting objectives of different supply chain actors are therefore needed. To this end, Thuankaewsing et al. (2015) proposed a collaborative framework that let a mill centrally decide harvesting periods of all contract growers, *i.e.* harvesting plans, so that the amount of sugar produced was maximized, while growers were equally paid based on yield proportion. The authors found that, with this collaborative scheme, harvesting operations could be significantly improved at both mill's and grower's ends. Their result was in-line with previous works by Kaewtrakulpong (2008) and Kumar et al. (2021), where centralized planning was one of the key success factors for improving supply chain efficiency.

Grunow et al. (2007), however, pointed out that these optimal long-term harvesting plans were rarely executable throughout the season as there were a number of uncontrollable factors that might affect harvesting activities in future periods, *e.g.* the variability of available harvesting resources or weather conditions. To better address these issues, Jarumaneeroj et al. (2021) suggested that a more detailed operational decision framework should be constructed and executed alongside long-term harvest planning so that proper recourse actions could be promptly devised and executed. Furthermore, this framework should focus not only on the economic objectives of growers and mills but also on other key environmental objectives due to the ever-increasing urgency of environmental concerns (He et al., 2020; Kumar et al., 2020).

Considering these findings, this paper aims to contribute to these developments by introducing the Multi-Objective Harvesting Resource Scheduling Problem (MOHRSP): an operational modeling approach that concurrently considers four different objectives of different sugar supply chain stakeholders – namely (*i*) the total amount of sugar produced at the mill, (*ii*) the average profit of growers from selling sugarcane and its byproducts, (*iii*) the industrial opportunity loss, and (*iv*) the environmental impact resulting from the current harvesting practice. Furthermore, a heuristic solution methodology based on Particle Swarm Optimization (PSO) is devised to help solve intractably large MOHRSP instances. With this proposed framework, planners would be able to create well-balanced harvesting schedules that meet the needs of different supply chain actors. It also allows planners to explore the feasibility of such schedules based on the current harvesting conditions, which is of paramount importance to the development of proper recourse actions throughout the planning horizon.

The remainder of this paper is organized as follows. In Section 2, related literature concerning decision problems in the sugar supply chains and the multi-objective modeling approaches is thoroughly discussed, followed by the formal description of the MOHRSP in Section 3. Section 4 then introduces the proposed PSO-based solution methodology, while Section 5 subsequently presents all computational results. Finally, Section 6 concludes our work and discusses further research directions.

2. Related literature

2.1. Managing operations in sugar supply chains

While the supply chains of world sugar producers may vary depending on local restrictions and practices, their operational settings are, however, similar, especially the costly inbound logistical processes from which sugarcane is cultivated, harvested, and transported to sugar mills (Morales Chavez et al., 2020). Related to these activities, previous research has focused mostly on three important issues: (*i*) yield forecasting, (*ii*) harvest planning, and (*iii*) transportation scheduling.

Yield forecasting is among the most fundamental issues in sugar supply chains as it significantly affects the economic performance of both growers and mills. This is due to the fact that sugarcane prices predominantly depend on the sugar content of sugarcane, as measured by the Commercial Cane Sugar (CCS) value. Reliable CCS value forecasting thus provides a good basis for timing decisions related to harvesting and milling. While more accurate CCS forecasting techniques are desirable for both players, most are naturally imprecise due to several uncontrollable factors, including weather and cultivation conditions (Som-ard et al., 2018). Traditionally, CCS values – and so the optimal harvesting periods of sugarcane fields – are estimated based on the elapsed time after a predefined date, coupled with some simulation and statistical models as demonstrated by Jiao et al. (2005) and Pagani et al. (2017). Apart from these approaches, more advanced prediction methods that rely on image processing techniques have also been explored (see Zhao et al. (2016) and Som-ard et al. (2018), for example).

Harvest planning is another operational issue in sugar supply chains that has been widely studied in the literature. Thuankaewsing et al. (2015), for instance, addressed the harvest scheduling problem in Thailand, whose objective was to maximize the total amount of sugar produced while equalizing grower equity (as measured by yield proportion) based on a tabu search heuristic. Florentino et al. (2018) and Jarumaneeroj et al. (2021), on the other hand, proposed genetic algorithm-based approaches for their respective harvest scheduling problems with multiple conflicting objectives in two different supply chain settings. Particularly, Florentino et al. (2018) established harvesting plans that maximized the quality of sugarcane supply and, at the same time, minimized the movement of mechanical harvesters across harvesting periods in the Brazilian sugar supply chain, while Jarumaneeroj et al. (2021) further included supply variability to better reflect the fluctuation of sugarcane supply for the Thai context.

Apart from tactical harvest planning, more detailed transportation scheduling of harvesting resources, such as mechanical harvesters, was also explored by Sethanan and Neungmatcha (2016), Cerdeira-Pena et al. (2017), and Pitakaso and Sethanan (2019) – each with different objectives and different solution methodologies. In this regard, Sethanan and Neungmatcha (2016) explored and solved the so-called Harvester Route Planning Problem (HRPP) in the Thai sugar supply chain by a variant of PSO so that sugarcane yields and total traveling distance of harvesters were concurrently optimized. Pitakaso and Sethanan (2019) later extended this work by combining the Harvester Assignment Problem (HAP) with the HRPP. The resulting problem was then solved by means of an Adaptive Large Neighborhood Search (ALSN) heuristic so that the harvested sugarcane farm areas were maximized. Cerdeira-Pena et al. (2017), on the contrary, regarded the HRPP as a variant of the Traveling Salesman Problem (TSP), and subsequently developed a Simulated Annealing (SA) algorithm to solve such a problem.

In addition to the three main problems discussed above, some research has specifically focused on the impacts of sugarcane quality dynamics on the logistics of harvested sugarcane. Satidnuwat (2005), for example, evaluated three different queuing systems in the Thai sugar supply chain so that the arrival streams of transporting trucks at mills became more stable. They found that different queuing systems should be adopted according to sugarcane output and a higher proportion of fixed queues typically resulted in lesser waiting times. Likewise, Lamsal et al. (2016) determined the optimal fleet size of sugarcane transportation in the United States that minimized the cumulative deviation between unloading targets and actual deliveries to the facility.

More elaborate sugar supply chain problems that integrated two or more supply chain activities were also investigated in the literature. For instance, Grunow et al. (2007) explored the production of sugar in Venezuela by disintegrating the whole decision framework into three different planning processes, starting from long-term cultivation planning to weekly harvest scheduling and crew dispatching at operational levels. In addition to the production of sugar, Paiva and Morabito (2009) included the production of other sugarcane byproducts, such as ethanol and molasses, into consideration, with the overall goal to maximize the entire agro-industrial contribution. The Harvest Front Scheduling Problem (HFSP) that combined harvest planning and resource scheduling was also studied by Junqueira and Morabito (2019), based on the operations of the Brazilian sugar supply chain.

It should be remarked that the work presented here has a similar scope as that of Junqueira and Morabito (2019) in terms of operational setting, as both focus on the detailed operations of harvesting resource scheduling in sugar supply chains. Nonetheless, our problem setting – and so our proposed solution methodology – entails not only economic benefits of growers and mills but also social benefits from the deployment of various harvest fronts that differ greatly in terms of availability, harvesting efficiency, and environmental impacts. Furthermore, two different sets of harvesting resources, namely harvest fronts and transporting trucks, are separately tracked at a more granular level so that the quality dynamics of harvested sugarcane are properly captured.

2.2. Multi-objective modeling approaches

Multi-objective optimization is one of the multi-criteria decision-making approaches that concerns the determination of solutions to problems with two or more conflicting objectives. Solving multi-objective optimization problems is ordinarily challenging, especially when a large number of objectives are concurrently optimized, as each of these objectives generally differs in terms of measurement. Although, it is possible to combine different objectives into one single expression by means of scalarization or goal programming techniques (see *e.g.* Florentino et al., 2018; Tiammee and Likasiri, 2020), the practicality of such techniques is limited as they could provide only one Pareto optimal solution at a time. Also, their solution quality largely depends on the weight at which decision-makers assign to each objective (Khorram-shahgol & Hooshiari, 1991).

To better avoid subjectivity of parameter weighing, multi-objective optimization problems are often solved by means of Multi-Objective Evolutionary Algorithms (MOEAs), or nature-inspired search heuristics, whose concepts are based on the evolution of solution populations (Coello et al., 2007). Prominent examples of MOEAs that have been widely studied in the literature include the Reference-Point Based Many-Objective NSGA-II – or NSGA-III, for short – and Particle Swarm Optimization (PSO).

NSGA-III is a Pareto dominance-based algorithm that allows only elite populations (solutions) to reproduce, while maintaining the diversity of non-dominated solutions by relative distances between such solutions and predefined reference points (Emmerich & Deutz, 2018). According to Deb and Jain (2014) and Li et al. (2019), the performance of NSGA-III was superior to that of other MOEAs, as it better explored multi-dimensional solution spaces – and so trade-offs between objectives – especially in higher dimensional problems. PSO, on the other hand, is a nature-inspired search heuristic that mimics the food-finding behavior of animal flocks (Kennedy & Eberhart, 1995). The fundamental concept of PSO is rather simple and intuitive, as it iteratively adjusts the positions of solutions – or particles in the PSO context – based on both individual and social learning mechanisms until a predefined stopping criterion has been met (see Freitas et al. (2020) for a review of PSO).

While both NSGA-III and PSO have been successfully applied to various single- and multi-objective optimization applications (see *e.g.* Chutima and Chimklai (2012); Sheikh et al. (2018); Dehghani et al. (2019); Mahmud et al. (2019); Worasan et al. (2020); Jarumaneeroj et al., (2021); and Hop et al., (2021)), the implementation of PSO is relatively simpler, with less computational requirements (Sethanan & Neungmatcha, 2016). Accordingly, PSO is adopted as a solution methodology in this research; and, the detailed implementation of our proposed PSO framework is described in Section 4.

3. Problem Definition

3.1. Multi-Objective harvesting resource scheduling problem (MOHRSP)

Consider a number of sugarcane fields to be harvested and all available harvesting resources, namely transporting trucks (T) and harvest fronts (R), in a particular harvesting period (p). Let $J = \{1, 2, \ldots, |J|\}$ denote a set of such fields, each of which may be owned by the same or different growers in I – and, when grower $i \in I$ owns multiple sugarcane fields, the expression $J(i)$ describes the set of sugarcane fields in J that belongs to grower i. Besides ownership, sugarcane fields j_1 and $j_2 \in J$ may also differ in terms of location (f), estimated sugarcane yield (μ, in ton), and estimated sugarcane quality (π, in CCS).

All of these sugarcane fields are inter-connected with one another, and with the contracted mill ($\varnothing$) whose crushing capacity is m tons/hour, by an arc set A. The distance (d, in km), along with the traveling time (τ, in hour) required by harvesting resources to traverse between a pair of locations, is a priori knowledge that has been embedded within the arc set A. For simplicity, we assume that there is only one type of transporting trucks (T), all of which are equivalent in terms of efficiency – *i.e.* loading capacity (l, in ton), fuel consumption rate (g^u, in liter/km), and CO_2 emission rate (g^e, in $kgCO_2$/liter) – and, the fuel price is assumed to be constant at g^c Baht/liter.

In addition to the set of transporting trucks (T), let $R = \{R_1 \cup R_2 \cup R_3\}$ be the set of harvest fronts to be deployed according to the current Thai harvesting practice. To be precise, we denote R_1, R_2, and R_3 as the sets of mechanical harvester-based, labor-based, and sugarcane burning-based harvest fronts, respectively. Similar to transporting trucks, harvest fronts of the same class (r *in* R_i) are equivalent in terms of operational efficiency and characteristics, including (*i*) harvesting speed (h_r^s, in ton/hour), (*ii*) harvesting cost (h_r^c, in Baht/ton), (*iii*) fuel consumption rate (h_r^g, in liter/ton), (*iv*) CO_2 emission rate (h_r^e, in $kgCO_2$/ton), (*v*) sugar loss ratio due to sugarcane trash (h_r^d), (*vi*) sugarcane loss ratio (h_r^l), (*vii*) cane leaf/bract or byproduct ratio (h_r^u), (*viii*) soil recovery cost (h_r^i, in Baht/

plot), (*ix*) penalty (incentive) for burnt sugarcane (green sugarcane) as stipulated by the OCSB (h_r^f, in Baht/ton), (*x*) daily cropping capacity (δ_r, in plot), and (*xi*) loss of sugarcane quality (φ_r, in %CCS/hour).

As harvesting resources are typically rented and shared by grower groups within the same area, the main decision that needs to be made is how to allocate and route these limited harvesting resources such that the following objectives are concurrently optimized.

- Maximizing sugar production at the mill.
- Maximizing average grower profit from selling sugarcane and its byproducts.
- Minimizing opportunity loss from harvesting.
- Minimizing CO_2 emissions from the overall inbound logistical processes.

In terms of modeling, this Multi-Objective Harvesting Resource Scheduling Problem (MOHRSP) might be regarded as a variant of the Multiple Traveling Salesman Problem (mTSP), with additional constraints related to harvesting, transporting, and milling activities, in which harvesting resources and sugarcane fields correspond to salespersons and customers in the context of mTSP, respectively.

For ease of modeling, we also assume that each sugarcane field leads to harvests that fit within the truck loading capacity. Larger fields are thus split into smaller sub-fields or plots, each with a yield close to the truck loading capacity. For example, given a truck loading capacity of 25 tons, a sugarcane field whose estimated sugarcane output is 47 tons will be split into two sub-fields, one with an output of 25 tons and the other with 22 tons, respectively. Once split, these sugarcane plots will be further grouped into clusters (G), whose number is equally set to the number of machine-based harvest fronts to better reflect the current harvesting practice, in which harvesting machinery is rented and shared within a group of growers during the season. Based on this setting, each plot will be visited by a pair of harvesting resources only once; and, if a mechanical harvester is deployed, its respective routing must be within the same cluster.

Finally, we assume that sugarcane cultivating cost (v, in Baht/ton), the minimum CCS value of sugarcane fields to be harvested (q, in CCS), the average prices of sugarcane (s, in Baht/ton-CCS), raw sugar (ϑ, in Baht/ton), and sugarcane leaf/bract (ε, in Baht/ton), as well as the incentive (fine) for higher (lower) sugarcane quality (b, in Baht/CCS), are the same across sugarcane plots. Please refer to Table A.1 in Appendix A for the summary of all MOHRSP parameter values and their data sources.

3.2. Mathematical formulation

3.2.1. Sets and parameters

- I is a set of sugarcane growers.
- $J(i)$ is a set of sugarcane plots that belong to growers $i \in I$.
- R is a set of harvest fronts $\{R_1 \cup R_2 \cup R_3\}$, where R_1, R_2, and R_3 denote the sets of mechanical harvester-based, labor-based, and sugarcane burning-based harvest fronts, respectively.
- T is a set of transporting trucks.
- G is a set of harvesting clusters for mechanical harvester-based harvest fronts.
- $\varnothing$ denotes the sugar mill.
- A is a set of arcs connecting sugarcane plots in J and the sugar mill $\varnothing$.
- d_a denotes the traveling distance of arc $a \in A$ (in km).
- τ_a denotes the traveling time required by harvesting resources to traverse arc $a \in A$ (in hour).
- f_j denotes the location of sugarcane plot $j \in J(i)$ in a two-dimensional plane.
- π_j denotes the estimated CCS value of sugarcane plot $j \in J(i)$.
- μ_j denotes the estimated yield of sugarcane plot $j \in J(i)$ (in ton).
- g^u denotes the fuel consumption rate of transporting trucks (in liter/km).
- g^e denotes the emission rate of CO_2 from diesel fuel (in kgCO_2/liter).
- g^c denotes the diesel fuel price (in Baht/liter).
- h_r^s denotes the harvesting speed of harvest front $r \in R$ (in ton/hour).
- h_r^c denotes the variable cost of harvest front $r \in R$ (in Baht/ton).
- h_r^g denotes the fuel consumption rate of harvest front $r \in R$ (in liter/ton).
- h_r^e denotes the emission rate of CO_2 from harvest front $r \in R$ (in kgCO_2/ton).
- h_r^d denotes the estimated ratio of sugarcane trash from harvest front $r \in R$.
- h_r^l denotes the estimated ratio of yield loss from harvest front $r \in R$.
- h_r^f denotes incentive or penalty from deploying harvest front $r \in R$ (in Baht/ton).
- h_r^i denotes estimated soil recovery cost caused by harvest front $r \in R$ (in Baht/plot).
- h_r^u denotes the estimated ratio of sugarcane leaf and bract that can be retrieved from harvest front $r \in R$.
- δ_r denotes the maximum harvesting capacity of harvest front $r \in R$ (in plot).
- φ_r denotes the estimated deterioration rate of sugarcane quality after harvesting by harvest front $r \in R$ (in %CCS/hour).
- m denotes the sugarcane crushing rate of sugar mill (in ton/hour).
- l denotes the loading capacity of transporting trucks (in ton).
- v Denotes average sugarcane cultivation cost (in Baht/ton).
- s denotes the average selling price of sugarcane (in Baht/ton-CCS).
- ε denotes the average selling price of sugarcane leaf and bract (in Baht/ton).
- ϑ denotes the average selling price of raw sugar (in Baht/ton).
- q denotes the minimum CCS value for sugarcane plots to be harvested (in CCS).
- b denotes incentive or penalty from supplying sugarcane with CCS value greater or lower than q to the mill (in Baht/CCS).
- p denotes the final timestamp of the current harvesting period (in hour).

3.2.2. Decision variables

- x_{ra} is a binary decision variable indicating whether harvest front $r \in R$ is assigned to sugarcane plot $j \in J(i)$ based on the traversal of arc $a \in A$, where $j \in J(i)$ is the head of a.
- y_{ta} is a binary decision variable indicating whether transporting truck $t \in T$ is assigned to sugarcane plot $j \in J(i)$ based on the traversal of arc $a \in A$, where $j \in J(i)$ is the head of a.
- θ_{rj} is a non-negative decision variable indicating the arrival time of harvest front $r \in R$ at sugarcane plot $j \in J(i)$, or equivalently the time period at which harvesting activity can commence.
- σ_{tj} is a non-negative decision variable indicating the arrival time of transporting truck $t \in T$ at sugarcane plot $j \in J(i)$.
- ρ_{tj} is a non-negative decision variable indicating the arrival time of transporting truck $t \in T$ at the mill for the delivery of harvests from sugarcane plot $j \in J(i)$, or equivalently the time period at which unloading activity can commence.
- α_a is a binary decision variable indicating unloading sequences of sugarcane plot $j \in J(i)$ based on the traversal of arc $a \in A$, where $j \in J(i)$ is the head of a.
- k_{jr}^x, k_{jt}^y, and k_j^α are counter decision variables that help eliminate subtours of all harvesting resources.

In addition to the above decision variables, the following is a list of auxiliary decision variables required for the MOHRSP.

- ω_{tjr} is a non-negative decision variable indicating the total time spent by transporting truck $t \in T$ assigned to a pair of sugarcane plot $j \in J(i)$ and harvest front $r \in R$, right after cropping until unloading.
- β_{tjr} is a non-negative decision variable indicating the waiting time of transporting truck $t \in T$ assigned to a pair of sugarcane plot $j \in J(i)$ and harvest front $r \in R$.

3.2.3. Objective functions

Equations (i) - (iv) are the objective functions of the MOHRSP. The first two expressions aim to maximize economic benefits of the mill and the growers, while the last two aim to minimize opportunity loss and environmental impact from the deployment of all harvesting resources during the planning horizon.

Maximize:

$$z_1 : \sum_{j\in J}\pi_j\mu_j - \sum_{t\in T}\sum_{j\in J}\sum_{r\in R}\omega_{tjr}\varphi_r\pi_j\mu_j - \sum_{r\in R}\sum_{a\in A}x_{ra}h^d_r\pi_j\mu_j \tag{i}$$

$$z_2 : \underset{i\in I}{\text{avg}}\left(\begin{array}{c}\sum_{r\in R}\sum_{a\in A}x_{ra}\mu_j\left(b\left(\pi_j - q\right) + s - v - h^f_r + \varepsilon h^u_r\right) - \sum_{t\in T}\sum_{j\in J}\sum_{r\in R}\omega_{tjr}\pi_j\mu_j\varphi_r b \\ -\sum_{r\in R}\sum_{a\in A}x_{ra}\left(h^c_r\mu_j + d_a g^u g^c\right) - \sum_{j\in J}\left(d_{(\varnothing,j)} + d_{(j,\varnothing)}\right)g^u g^c\end{array}\right) \tag{ii}$$

Minimize:

$$z_3 : \vartheta\left(\begin{array}{c}\sum_{t\in T}\sum_{j\in J}\sum_{r\in R}\pi_j\mu_j\left[\omega_{tjr}\left(\varphi_r - \varphi_{r_{(green)}}\right)\right] \\ +\sum_{r\in R}\sum_{a\in A}x_{ra}\pi_j\mu_j\left[\left(h^d_r - h^d_{r_{(burnt)}}\right) + \left(h^l_r - h^l_{r_{(burnt)}}\right)\right]\end{array}\right) + \sum_{r\in R}\sum_{a\in A}x_{ra}\mu_j\left[\varepsilon\left(h^u_{r_{(green)}} - h^u_r\right)\right] + \sum_{r\in R}\sum_{a\in A}x_{ra}h^i_r \tag{iii}$$

$$z_4 : \sum_{r\in R}\sum_{a\in A}x_{ra}\left(d_a g^u g^e + \mu_j h^g_r g^e + \mu_j h^e_r\right) + \sum_{j\in J}\left(d_{(\varnothing,j)} + d_{(j,\varnothing)}\right)g^u g^e \tag{iv}$$

From the mill's perspective, the total amount of sugar produced could be maximized by reducing the loss of CCS from harvesting and waiting, along with the sugarcane trash that has been mixed with the sugarcane supply, as computed by Expression (i). Regarding the grower's perspective, Expression (ii) maximizes average grower profit from the selling of sugarcane and its byproducts, less all the costs incurred from related activities. Opportunity loss from CCS decay and byproducts when compared to the best harvesting practices, together with soil recovery cost, is expressed by Equation (iii). The overall CO_2 emissions from the resulting schedule is computed by Equation (iv), which includes the emissions of CO_2 from both sugarcane farm burning and the routing of all harvesting resources.

3.2.4. Constraints

Similar to the mTSP, Constraints (1) – (4) state that, over a harvesting period p, a pair of harvest front and transporting truck could be assigned to at most one tour, while the flow of these harvesting resources is preserved by Constraints (5) and (6). Since we divide all sugarcane fields into plots whose sugarcane yields are close to the truck loading capacity, each plot will be then visited by a pair of harvesting resources only once according to Constraints (7) and (8). Furthermore, Constraints (9) – (12) ensure that there will be no route reversal or subtour in the schedules of these harvesting resources, while Constraint (13) limits the total number of plots to be visited by each harvest front during the planning period p.

$$\sum_{i\in J}x_{r,(i,\varnothing)} \le 1 \quad ;\forall r\in R \tag{1}$$

$$\sum_{j\in J}x_{r,(\varnothing,j)} \le 1 \quad ;\forall r\in R \tag{2}$$

$$\sum_{i\in J}y_{t,(i,\varnothing)} \le 1 \quad ;\forall t\in T \tag{3}$$

$$\sum_{j\in J}y_{t,(\varnothing,j)} \le 1 \quad ;\forall t\in T \tag{4}$$

$$\sum_{i\in J}x_{r,(i,j)} = \sum_{n\in J}x_{r,(j,n)} \quad ;\forall r\in R, \forall j\in J \tag{5}$$

$$\sum_{i\in J}y_{t,(i,j)} = \sum_{n\in J}y_{t,(j,n)} \quad ;\forall t\in T, \forall j\in J \tag{6}$$

$$\sum_{r\in R}\sum_{i\in J:i\neq j}x_{r,(i,j)} = 1 \quad ;\forall j\in J \tag{7}$$

$$\sum_{t\in T}\sum_{i\in J:i\neq j}y_{t,(i,j)} = 1 \quad ;\forall j\in J \tag{8}$$

$$k^x_{jr} \ge k^x_{ir} + x_{r,(i,j)} - M\left(1 - x_{r,(i,j)}\right) \quad ;\forall r\in R, \forall i,j\in J : i\neq j \tag{9}$$

$$k^x_{jr} \ge x_{r,(\varnothing,j)} - M\left(1 - x_{r,(\varnothing,j)}\right) \quad ;\forall r\in R, \forall j\in J \tag{10}$$

$$k^y_{jt} \ge k^y_{it} + y_{t,(i,j)} - M\left(1 - y_{t,(i,j)}\right) \quad ;\forall t\in T, \forall i,j\in J : i\neq j \tag{11}$$

$$k^y_{jt} \ge y_{t,(\varnothing,j)} - M\left(1 - y_{t,(\varnothing,j)}\right) \quad ;\forall t\in T, \forall j\in J \tag{12}$$

$$\sum_{a\in A}x_{ra} \le \delta_r \quad ;\forall r\in R \tag{13}$$

In addition to harvesting resource scheduling, we also need to capture unloading sequences of transporting trucks at the mill, *i.e.* $\alpha_{(i,j)}$, which are modeled through Constraints (14) – (19).

$$\sum_{i\in J}\alpha_{(i,\varnothing)} = 1 \tag{14}$$

$$\sum_{j\in J}\alpha_{(\varnothing,j)} = 1 \tag{15}$$

$$\sum_{i\in J}\alpha_{(i,j)} = \sum_{n\in J}\alpha_{(j,n)} \quad ;\forall j\in J \tag{16}$$

$$\sum_{i\in J:i\neq j}\alpha_{(i,j)} = 1 \quad ;\forall j\in J \tag{17}$$

$$k^\alpha_j \ge k^\alpha_i + \alpha_{(i,j)} - M\left(1 - \alpha_{(i,j)}\right) \quad ;\forall i,j\in J : i\neq j \tag{18}$$

$$k^\alpha_j \ge \alpha_{(\varnothing,j)} - M\left(1 - \alpha_{(\varnothing,j)}\right) \quad ;\forall j\in J \tag{19}$$

Since a pair of harvest front and transporting truck must be present at a sugarcane field before harvesting starts, the arrival time for both at a sugarcane plot $j \in J(i)$, as denoted by θ_{rj} and σ_{tj}, must therefore be the

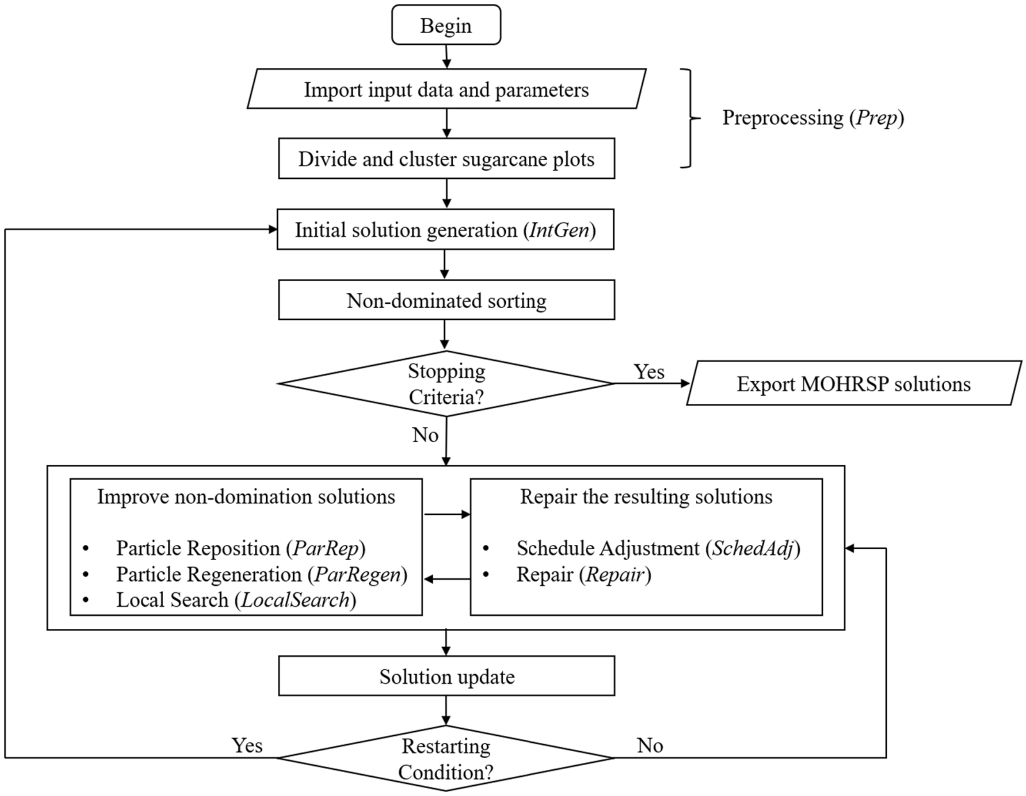

Fig. 1. Overview of the proposed PSO framework.

same as stated by Constraint (20). The dynamics of these arrival times must also follow Constraints (21) – (24), which could be regarded as a variant of time window constraints in the classical Vehicle Routing Problems with Time Windows (VRPTW). More specifically, the arrival time of harvest front $r \in R$ at sugarcane plot $j \in J$ must be at least the arrival time at its previously visited sugarcane plot i plus (*i*) the harvesting time and (*ii*) the traversal time from sugarcane plot i to j; and, the sum of these time quantities must not exceed the latest time that a harvest front is allowed to visit such a plot (Inequalities (21) and (23)). Likewise, the arrival time of transporting truck $t \in T$ at sugarcane plot$j \in J$ must be at least the arrival time at its previously visited sugarcane plot i plus (*i*) the harvesting time that depends on the assigned harvest front, (*ii*) the traversal time from sugarcane plot i to the mill, (*iii*) the unloading time, and (*iv*) the time required for traversing back to sugarcane plot j; and, the sum of these time quantities must not exceed the latest time that a transporting truck is allowed to visit such a plot (Inequalities (22) and (24)).

$$\sum_{r\in R}\theta_{rj} = \sum_{t\in T}\sigma_{tj} \quad ;\forall j \in J \tag{20}$$

$$\theta_{rj} \geq \theta_{ri} + \frac{\mu_i}{h_r^s} + \tau_{(i,j)} - M\left(1 - x_{r,(i,j)}\right) \quad ;\forall r \in R, \forall i,j \in J : i \neq j \tag{21}$$

$$\sigma_{tj} \geq \begin{pmatrix} \sigma_{ti} + \sum_{r\in R}\sum_{n\in J}\left(x_{r,(n,i)}\frac{\mu_i}{h_r^s}\right) \\ +\tau_{(i,\varnothing)} + \frac{\mu_i}{m} + \tau_{(\varnothing,j)} - M\left(1 - y_{t,(i,j)}\right) \end{pmatrix} \quad ;\forall t \in T, \forall i,j \in J : i \neq j \tag{22}$$

$$\theta_{rj} \leq p - \frac{\mu_j}{h_r^s} - \tau_{(j,\varnothing)} \quad ;\forall r \in R, \forall j \in J \tag{23}$$

$$\sigma_{tj} \leq p - \sum_{r\in R}\sum_{i\in J}\left(x_{r,(i,j)}\frac{\mu_j}{h_r^s}\right) - \tau_{(j,\varnothing)} \quad ;\forall t \in T, \forall j \in J \tag{24}$$

As there is typically one unloading station at a mill, we need Constraints (25) – (27) to help control unloading sequences. Technically speaking, the arrival time of transporting truck $t \in T$ must follow Constraints (25) and (26), while the difference between arrival times of any two consecutive trucks at the mill must be at least the time required for unloading activity of the first arriving truck, as stated by Constraint (27). It is worth remarking that Constraint (27) holds true only when transporting truck t is unloaded right after transporting truck t', *i.e.* $\alpha_{(i,j)} = y_{t'(k,i)} = y_{t(k,j)} = 1$, or else it would provide no additional information for unloading time of transporting truck t. Based on these arrival time dynamics, we can then define the total time spent by transporting truck $t \in T$ assigned to a pair of sugarcane plot $j \in J$ and harvest front $r \in R$, right after cropping until unloading, as well as its waiting time, by Equations (28) and (29). Lastly, Constraints (30) – (40) define the boundary of all predefined decision variables.

$$\rho_{tj} \geq \begin{pmatrix} \sigma_{tj} + \sum_{r\in R}\sum_{i\in J}x_{r,(i,j)}\frac{\mu_j}{h_r^s} \\ +\tau_{(j,\varnothing)} - M\left(1 - \sum_{i\in J}y_{t,(i,j)}\right) \end{pmatrix} \quad ;\forall t \in T, \forall j \in J \tag{25}$$

$$\rho_{tj} \leq p \quad ;\forall t \in T, \forall j \in J \tag{26}$$

$$\rho_{tj} - \rho_{t'i} \geq \begin{pmatrix} \frac{\mu_i}{m} \\ -M\begin{pmatrix} 3 - \alpha_{(i,j)} \\ -y_{t'(k,i)} - y_{t(k,j)} \end{pmatrix} \end{pmatrix} \quad ;\forall t,t' \in T : t \neq t', \forall i,j,k \in J \tag{27}$$

$$\sum_{r\in R}\omega_{tjr} = \left(\rho_{tj} - \sigma_{tj}\right) \quad ;\forall t \in T, \forall j \in J \tag{28}$$

$$\sum_{t\in T}\beta_{tjr} = \left(\begin{array}{c}\sum_{t\in T}\omega_{tjr} \\ -\sum_{r\in R}\sum_{a\in A}x_{ra}\mu_j\left(h_r^s + \tau_{(j,\varnothing)}\right)\end{array}\right) \quad ;\forall j\in J, \forall r\in R \tag{29}$$

$$x_{ra}\in\{0,1\} \quad ;\forall r\in R, \forall a\in A \tag{30}$$

$$y_{ta}\in\{0,1\} \quad ;\forall t\in T, \forall a\in A \tag{31}$$

$$\alpha_a\in\{0,1\} \quad ;\forall a\in A \tag{32}$$

$$\theta_{rj}\geq 0 \quad ;\forall r\in R, \forall j\in J \tag{33}$$

$$\sigma_{tj}\geq 0 \quad ;\forall t\in T, \forall j\in J \tag{34}$$

$$\rho_{tj}\geq 0 \quad ;\forall t\in T, \forall j\in J \tag{35}$$

$$\omega_{tjr}\geq 0 \quad ;\forall t\in T, \forall j\in J, \forall r\in R \tag{36}$$

$$\beta_{tjr}\geq 0 \quad ;\forall t\in T, \forall j\in J, \forall r\in R \tag{37}$$

$$k_{jr}^x\geq 0 \text{ and } k_{jr}^x \text{ is Integer} \quad ;\forall j\in J, \forall r\in R \tag{38}$$

$$k_{jt}^y\geq 0 \text{ and } k_{jt}^y \text{ is Integer} \quad ;\forall j\in J, \forall t\in T \tag{39}$$

$$k_j^\alpha\geq 0 \text{ and } k_j^\alpha \text{ is Integer} \quad ;\forall j\in J \tag{40}$$

4. Proposed methodology

The MOHRSP in this paper is solved by means of PSO, where the solutions, or particles, in a swarm are iteratively improved based on learning mechanisms until one of the stopping criteria has been met. The structure of our proposed PSO is provided in Fig. 1 and Algorithm B.1 in Appendix B, while sub-computational modules required for such a framework are listed below (please refer to Algorithms B.2 – B.8 for more details).

- Preprocessing (*Prep*): this module is initially called for the initialization of all PSO inputs.
- Initial Solution Generation (*IntGen*): this module is called for the generation of initial PSO solutions.
- Particle Reposition (*ParRep*): this module is one of the PSO improvement instruments that relies on the particle's learning mechanisms, in which particle positions are iteratively adjusted based on the global best solution (*gbest*) and their velocity.
- Particle Regeneration (*ParRegen*): this module contains another PSO improvement mechanism, intermittently called every fixed number of iterations to avoid being stuck at local solutions.
- Local Search (*LocalSearch*): this module contains the last PSO improvement mechanism that helps guide the algorithm towards the optimal solutions and, at the same time, avoid being stuck at local solutions.
- Schedule Adjustment (*SchedAdj*): this module is one of the repairing mechanisms called whenever a sugarcane plot is infeasibly paired with the selected harvesting resources due to insufficient harvesting and unloading times.
- Repair (*Repair*): this module is another repairing mechanism that helps maintain solution feasibility when schedule conflicts occur.

It is worth noting that, when PSO is applied to the Single-Objective Harvesting Resource Scheduling Problems (SOHRSP), *gbest* is defined as the solution that provides the best objective value pertaining to that domain. However, when PSO is applied to the MOHRSP, *gbest* is reported as a set of non-dominated solutions that form a Pareto-front rather than a more limited set of optimal solutions from the individual SOHRSP. In addition, the proposed PSO framework restarts every fixed number of iterations so that the MOHRSP solution space is better explored.

4.1. Preprocessing (Prep)

When *Prep* is called, all MOHRSP inputs concerning sugarcane growers, sugarcane fields, and harvesting resources, along with other MOHRSP and PSO parameters, will be imported into the PSO framework. Once completed, sugarcane fields whose yields are greater than the truck loading capacity will be divided into sub-fields, or plots, and later grouped into clusters based on the K-mean clustering algorithm. To better reflect the current harvesting practice, the number of clusters in each instance will be equally set to the number of machine-based harvest fronts.

Based on this setting, *Prep* will greatly help reduce the PSO search space while generating efficient schedules for machine-based harvest fronts as they are assumed to be routed within their respective clusters.

4.2. Initial solution generation (IntGen)

Similar to other population-based algorithms, we need to define the PSO solution structure so that solution attributes related to harvesting schedules are adequately recorded and maintained. To do so, we will represent each MOHRSP solution – or a PSO particle – as a vector of length 4 N, where N denotes the number of sugarcane plots to be harvested and the multiplication of four indicates the four main information dimensions of completed harvesting schedules. More specifically, for each sugarcane plot $j\in J$, a PSO particle will record the information of harvest front and transporting truck assignments, together with their respective start times and completion times according to particular harvesting and unloading sequences. For ease of encoding and decoding, each of these four information dimensions will be stored in each array as a real number between 0 and 1.

The initial PSO solutions will be generated under this particle structure based on a simple prioritization scheme that gives more weight to green harvesting practices. To be precise, labor-based harvest fronts will be first assigned, followed by machine-based then sugarcane burning-based harvest fronts, respectively. Every time a harvest front is assigned to a sugarcane plot, *IntGen* will create a possible harvesting time slot with respect to the current schedule. If the front is feasibly paired with the selected sugarcane plot, the schedule will be updated; else, *SchedAdj* will be called, or a new harvest front will be selected, as the remaining working time of the current front is insufficient for any of the remaining sugarcane plots.

Once a front is feasibly paired with a sugarcane plot, *IntGen* will then select a transporting truck and pair it with the current schedule. This whole process is continually repeated until all the plots are assigned, or there is no available harvesting resources for the remaining plots (*i.e.* the current harvesting plan cannot be successfully executed).

IntGen will terminate once a predefined number of feasible solutions, denoted by *NumPar*, has been successfully generated. Once terminated, each of these solutions will be further assessed and randomly assigned an initial velocity (vel_0), which will be subsequently updated along with the individual and global best solutions, as denoted by *pbest* and *gbest*, during the search.

It is worth noting that, while updating the harvesting schedule, none of the MOHRSP constraints can be violated. For instance, when a machine-based harvest front is assigned, it must be assigned to only one cluster.

4.3. Particle Reposition (ParRep)

ParRep is one of the PSO improvement mechanisms that is repeatedly called during the PSO execution in order to improve the fitness of current solutions. But, in order to avoid excessive repairing, harvesting resources of all particles will be fixed according to *gbest*, while the remaining attributes will be updated based on their velocity. The

Table 1
Summary of the MOHRSP information for each instance size.

Instance size	Number of					
	Sugarcane Plot	Sugarcane Grower	Machine Based Harvest Front	Labor-Based Harvest Front	Sugarcane Burning Based Harvest Front	Transporting Truck
Small	20	4	1	2	3	9
Moderate	50	8	1	8	11	30
Large	150	24	3	24	33	90
Practical	300	50	6	48	66	180

Table 2
Summary of the proposed PSO parameter settings.

Parameters	Values
Number of particles	15
Particle's information dimension	4 N
Value of each information dimension	[0,1]
PSO iterations	1000
Number of iterations before calling *ParRegen*	5
Number of iterations before restarting	50
Maximum number of local search iterations	50
Maximum search velocity	10% of the particle position, or ± 0.1
Inertia coefficient (w)	0.729
Acceleration coefficients (c_p, c_g)	1.49455
Inertia Damping Ratio	0.95

detailed implementation of *ParRep* is quite similar to that of *IntGen,* except for the assignment of harvesting resources to plots, which is a priori knowledge from *gbest*. During *ParRep* execution, *SchedAdj* might be called if the resulting harvesting schedule is found infeasible; else, the resulting solution will be updated with a new particle's velocity according to the update formulae proposed by Eberhart and Shi (2000) (see Appendix C).

4.4. Particle Regeneration (ParRegen)

As we observe that PSO solutions converge relatively quickly in the preliminary experimental runs, another improvement mechanism, namely *ParRegen*, is therefore embedded in the PSO framework to avoid getting stuck at local optima. In terms of algorithmic setting, *ParRegen* will be called every fixed number of iterations (*RegenIters*). When *ParRegen* is called, the solutions will be ranked and regenerated according to their fitness values. More specifically, particles that provide the lowest 20% of fitness values will be eliminated and replaced with newly generated particles by *IntGen*, while the velocity of those belonging to the next 30% will be adjusted based on the Bożena's method (Borowska, 2017) (see Appendix D).

4.5. Local search (LocalSearch)

LocalSearch is the last regularly called improvement mechanism. It is called every time a solution is found feasible in order to guide the algorithm towards Pareto-optimal solutions, and, at the same time, help it avoid being stuck at local optima. When *LocalSearch* is called, a combination of the following local search operators will be called according to a random number *LS_Random*.

Table 3
Computational results of PSO when compared to the time-restricted CPLEX[a], in terms of solution quality and computational time[b], for four SOHRSP settings.

Problem Size	Values	Sugar Production (Ton-CCS)	Grower Profit (Baht/Field)	Opportunity Loss (Baht)	Environmental Impact (KgCo2)
Small	Solution Deviation[c] (%)	0%	2.42%	0.28%	0.13%
	Coefficient of Variation	8.63×10^{-6}	1.61×10^{-3}	4.04×10^{-5}	5.48×10^{-3}
	CPU Time (sec)	7.56	16.09	7.81	17.33
Moderate	Coefficient of Variation	7.14×10^{-5}	5.49×10^{-3}	5.48×10^{-5}	7.58×10^{-5}
	CPU Time (sec)	41.18	25.05	21.38	27.48
Large	Coefficient of Variation	3.01×10^{-4}	8.63×10^{-3}	6.95×10^{-4}	2.12×10^{-3}
	CPU Time (sec)	306.9	63.79	151.96	303.35
Practical	Coefficient of Variation	6.93×10^{-4}	1.13×10^{-2}	4.98×10^{-3}	2.81×10^{-2}
	CPU Time (sec)	1,418.62	263.56	219.09	1,014.08

[a] The computational time of CPLEX is limited to three hours.
[b] The reported solution deviations, coefficients of variation, and CPU times are averaged over 10 experimental instances, each with 10 PSO replications.
[c] The time-restricted CPLEX could only solve small instances while it terminates with a "run-out-of-memory" error for larger instances.

Table 4
Computational results of the proposed PSO in terms of average percentage differences between the best and the worst PSO solutions with respect to each domain and problem size.

Problem Size	% Difference between the best and the worst solutions in each domain[a]				
	Sugar Production (Ton-CCS)	Grower Profit (Baht/Field)	Opportunity Loss (Baht)	Environmental Impact (KgCo2)	Average Computational Time[b] (Seconds)
Small	4.98%	43.30%	14.75%	83.04%	7.56 – 17.14
Moderate	3.76%	51.09%	13.76%	47.94%	47.07 – 62.86
Large	3.42%	45.75%	12.84%	50.51%	274.59 – 786.08
Practical	3.33%	42.57%	11.65%	49.57%	946.94 – 3,208.46

[a] The percentage differences between the best and the worst PSO solutions with respect to each domain are averaged over 10 experimental instances, each with 10 PSO replications.
[b] The ranges of average computational time reported are based on average computational times over 10 experimental instances, each with 10 PSO replications.

Table 5
Fitness values of best PSO solutions across domains, where **(Best)** denotes the best objective value found and the remaining are the average solution deviations when compared to the best objective value in such a domain.

Problem Size	Values	Sugar Production (Ton-CCS)	Grower Profit (Baht/Field)	Opportunity Loss (Baht)	Environmental Impact (KgCo2)
Small	Sugar Production (Ton-CCS)	**(Best)**	−30.28%	−9.34%	−541.84%
	Grower Profit (Baht/Field)	−4.31%	**(Best)**	−1.32%	−24.72%
	Opportunity Loss (Baht)	−4.44%	−9.45%	**(Best)**	−1.86%
	Environmental Impact (KgCo2)	−4.47%	−5.92%	−0.27%	**(Best)**
Moderate	Sugar Production (Ton-CCS)	**(Best)**	-33.07%	−11.26%	−114.16%
	Grower Profit (Baht/Field)	−3.04%	**(Best)**	−2.00%	−9.76%
	Opportunity Loss (Baht)	−3.27%	−27.13%	**(Best)**	−0.71%
	Environmental Impact (KgCo2)	−3.32%	−25.49%	−0.47%	**(Best)**
Large	Sugar Production (Ton-CCS)	**(Best)**	−39.17%	−13.52%	−102.29%
	Grower Profit (Baht/Field)	−3.21%	**(Best)**	−1.46%	−6.63%
	Opportunity Loss (Baht)	−3.37%	-22.98%	**(Best)**	−0.88%
	Environmental Impact (KgCo2)	−3.41%	−21.98%	−0.33%	**(Best)**
Practical	Sugar Production (Ton-CCS)	**(Best)**	−37.49%	−12.54%	−98.45%
	Grower Profit (Baht/Field)	−3.11%	**(Best)**	−1.34%	−7.45%
	Opportunity Loss (Baht)	−3.28%	−20.17%	**(Best)**	−0.97%
	Environmental Impact (KgCo2)	−3.33%	−21.06%	−0.15%	**(Best)**

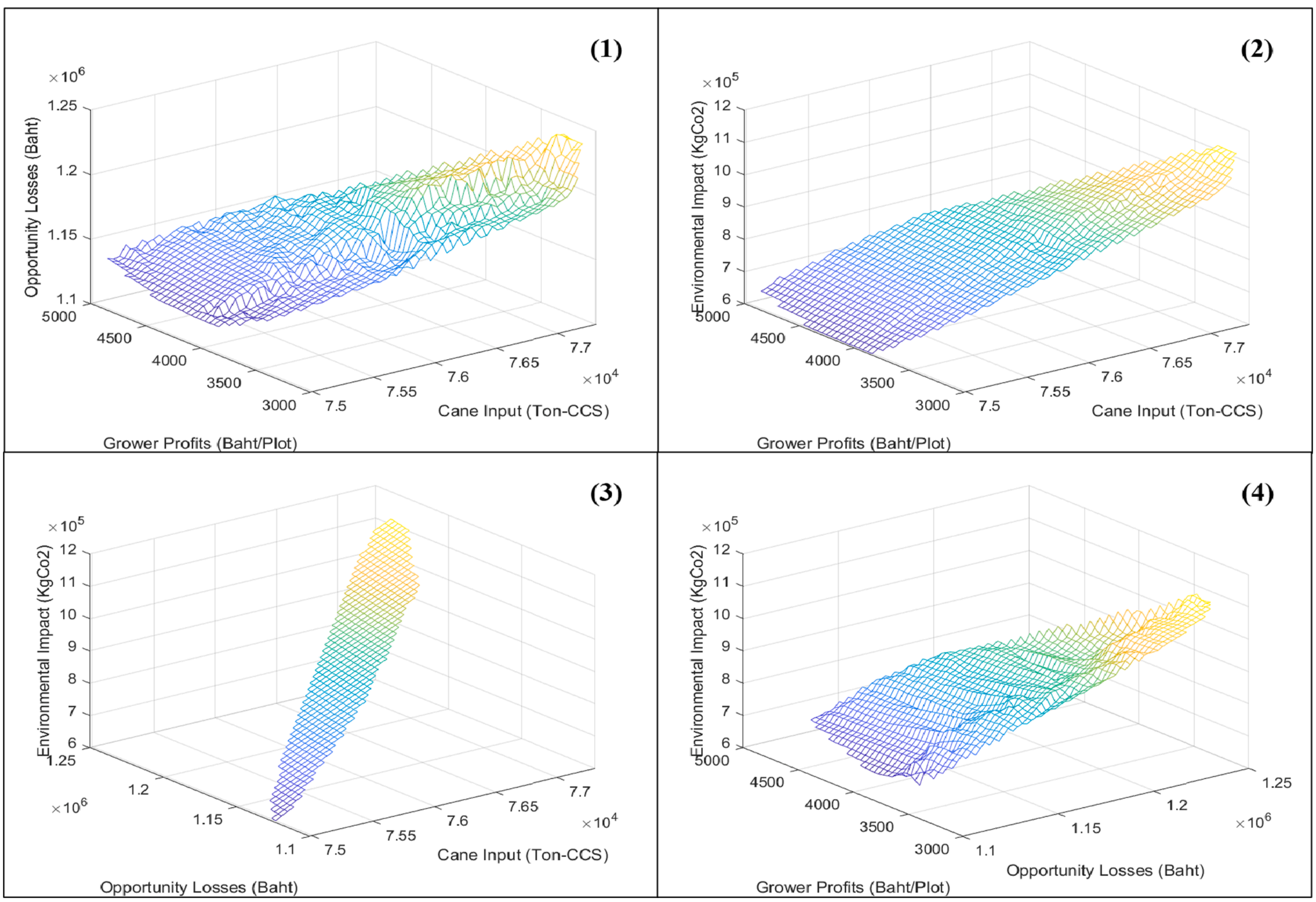

Fig. 2. Pareto-optimal plane of a practical size instance that illustrates conflicts among the four objectives.

- *FrontRelocation*: a randomly selected sugarcane plot will be relocated from one harvest front to another until an improvement is found or the maximum number of local search iterations is reached.
- *PlotSwap*: two sugarcane plots assigned to different harvest fronts will be swapped until an improvement is found or the maximum number of local search iterations is reached.
- *PlotRelocation*: two sugarcane plots assigned to a harvest front will be internally swapped until an improvement is found or the maximum number of local search iterations is reached.

It is worth remarking that, during the execution of *LocalSearch*, none of the MOHRSP constraints can be violated. And, if the resulting solution to *LocalSearch* is infeasible due to schedule conflicts, the *Repair* module will be subsequently called.

4.6. Schedule adjustment (SchedAdj)

SchedAdj is one of the repairing mechanisms called whenever the remaining operational times of harvesting resources are insufficient for harvesting and unloading activities (*i.e.* the completion times of such

Table 6
Average objective values of the remaining PSO solutions to one practical instance, when compared to the best objective values (in bold) across all domains.

Objective	Sugar Production (Ton-CCS)	Grower Profit (Baht/Field)	Opportunity Loss (Baht)	Environmental Impact ($KgCo_2$)
Sugar Production (Ton-CCS)	**77,291.79**	3,123.46	1,239,933.71	1,112,963.90
Grower Profit (Baht/Field)	75,100.56	**4,994.35**	1,137,928.28	644,120.88
Opportunity Loss (Baht)	75,075.71	3,978.55	**1,120,854.66**	626,135.01
Environmental Impact ($KgCo_2$)	74,926.72	4,124.83	1,121,664.38	**597,121.85**
Average Objective Values of the Pre-screened Solutions	75,947.63	4,424.23	1,156,982.44	870,233.54
%Difference[a]	− 1.74%	+ 41.65%	+ 6.69%	+ 21.81%
Evaluation (Baht)	−216,851.32	+390,231.00	+82,951.27	+48,546.07

[a] The reported values are based on the differences between the average objective values of the pre-screened solutions and those of the SOHRSP that maximize the total amount of sugar produced (*i.e.* the first row).

resources exceed the predefined planning horizon). When *SchedAdj* is called, the sequences of all previously assigned plots to such resources will be adjusted, one at a time, according to the resources' buffer times until the plot is feasibly assigned; else, *SchedAdj* terminates and returns the adjusted harvesting schedule for further harvesting resource scheduling.

4.7. Repair (Repair)

Repair is another repairing mechanism called whenever the generated harvesting schedule is infeasible due to schedule conflicts (*i.e.* there is a time period at which a harvesting resource is assigned to multiple harvesting/unloading tasks). The detailed implementation of *Repair* is quite similar to that of *SchedAdj*, where we adjust the timing of conflicting tasks, one at a time, until the conflicts are settled. However, if *Repair* fails, such a change will not be applied to the current harvesting schedule, and the change will be added to a Tabu list to prevent it from being selected in subsequent iterations.

5. Results & discussion

5.1. Instance generations

The proposed PSO framework has been tested on four different instance sizes that greatly differ in terms of numbers of growers, sugarcane plots, and harvesting resources. All parameters related to these instances are generated based on the sugarcane growing area in the North-Eastern region of Thailand, where the majority of growers generally own between 2 and 50 rai (1 rai = 0.395 acres) of sugarcane fields (Kaewtrakulpong, 2008).

The sugarcane field's attributes, as well as the availability of each harvest front, are generated according to surveys from the OCSB and the Department of Agriculture (publicly available at www.ocsb.go.th and www.doa.go.th), while the number of transporting trucks is set at 150% of all harvest fronts combined as there are typically a large number of trucks available in the industry.

For each instance size, 10 different experimental instances with similar problem characteristics are created, resulting in a total of 40 test instances. Table 1 below, together with Table A.1 in Appendix A, summarizes all of the information required for each of the MOHRSP instances and data sources.

In addition to the MOHRSP parameters, the PSO parameters, as shown in Table 2, are set based on either previous literature or results from preliminary experimental runs that provide the best solutions to the SOHRSP that maximizes the first MOHRSP objective, *i.e.* total amount of sugar produced. Lastly, all experiments are conducted on a computer with an Intel® Core™ i7-9750H processor and a memory of 16 GB, for computational consistency.

5.2. PSO results for single-objective problems

To assess the performance of our proposed solution methodology, we first apply the PSO framework to the four SOHRSPs. We then compare the PSO results with those of the time-restricted CPLEX, in terms of both solution quality and computational time, as reported in Table 3.

In terms of solution quality, the proposed PSO framework is comparably efficient, as it could find solutions that are relatively close to the optimal solutions for small instances. However, since no optimal solutions are reported for larger instances due to problem complexity, we can only assess the PSO solution quality based on the coefficients of variation. According to Table 3, the coefficients of variation among the PSO solutions are exceptionally low indicating that there is not much variability within the PSO solution pools.

Although, the computational time of PSO varies greatly across problem sizes and the underlying objectives, it well terminates within an acceptable time period for all four SOHRSP instances, considering that the problem of this magnitude is repeatedly solved on a daily basis.

5.3. PSO results for the MOHRSP

To better explore the multi-dimensional solution space of the MOHRSP, the proposed PSO has been applied to the underlying problem in a two-phase fashion, where the Pareto-optimal solutions to each of the four SOHRSPs are first determined as initial solutions for the MOHRSP in the second phase. It should be remarked that, while this solution approach is somewhat computationally expensive, especially when there are more objectives to be optimized, the coverage of resulting solutions is superior, as all extreme solutions in each domain are well explored and used as initial solutions for the MOHRSP in the latter phase.

When the proposed PSO terminates, all of the remaining non-dominated solutions will be reported and summarized in terms of solution ranges and fitness values across all domains, as shown in Tables 4 and 5, respectively.

According to Table 4, the average percentage differences in sugar production at the mill do not differ much across problem settings, as the gaps between the best and the worst PSO solutions are less than 5%. Nonetheless, from Table 5, we find that the solutions with higher sugar production tend to significantly underperform in the other three objectives, mainly because of the increased use of sugarcane farm burning. The rationale behind this is due to the fact that sugarcane farm burning provides relatively low yield losses, when compared to other greener harvesting practices. Thence, solutions that prioritize sugar production are more likely to adopt such fronts prior to the remaining. However, since sugarcane farm burning reduces the amount of sugarcane byproducts that can be sold to bioelectricity plants for energy generation, while requiring additional soil recovery costs, the solutions that maximize sugar production are therefore the worst from other stakeholder's perspectives.

Although, sugarcane farm burning may seem to be the best in terms of sugar production in this computational setting, the mills, in practice, ordinarily prefer fresh sugarcane over the burnt one due its purity and risk of losing quality from the CCS decay. If these indirect factors are considered, mills might be better off foregoing the additional amount of sugar produced by farm burning, as they will benefit from better sugar quality, while government agencies and communities will also benefit from the greener production activities.

Also seen from Table 5, sugarcane growers are the most vulnerable actors in the Thai sugar supply chain, as their average profits are heavily affected in the trade-offs with other objectives. This is due to the differences in harvest fronts deployed across problem settings. To be precise, sugarcane farm burning is only emphasized in the mill-oriented solutions, while the remaining solutions tend to favor green harvesting practices; and, labor-based harvesting is the most ideal practice in terms of both economic and social benefits, due to its cheaper operating cost and lower CO_2 emissions. Unfortunately, the number of labor-based harvest fronts is, in practice, limited and thus insufficient to satisfy all sugarcane plots in any harvesting period during the season. Subsequently, machine-based harvest fronts are deployed, followed by sugarcane burning-based harvest fronts – each of which generates more economic losses and higher sugar (CCS) deterioration rates. While solutions that optimize the last three objectives (*i.e.* grower profit, opportunity loss, and environmental impact) are similar in terms of harvesting resource preference, the routing of these resources, however, differs, where the least CO_2 emission routing typically leads to a situation with lower average grower profits and higher yield losses, due to the negligence of sugarcane field's attributes, such as field ownership and the CCS value of such fields.

The conflicts among these objectives could also be visualized by Fig. 2 that illustrates the Pareto-front of one practical size instance in a three-dimensional plane. Based on Fig. 2, it is evident that the mill's objective (denoted by cane input) indeed conflicts with other objectives, while average grower profit shows positive correlations with opportunity loss and environmental impact, as they all prioritize green harvesting practices over sugarcane farm burning.

Considering these findings, we can infer that, without proper operational scheduling that concurrently considers different objectives of different supply chain actors, some or all members of the supply chain will be worse off, and no sustainability would be created within the whole industry. In addition to these direct benefits, the proposed PSO framework also supports planners in exploring the feasibility of various harvesting schedules taking into account current harvesting conditions so that proper recourse actions could be devised and executed in a timely fashion.

5.4. Implementation of the PSO in practice

Although, the proposed PSO could provide a diverse pool of well-balanced solutions to the MOHRSP, the number of non-dominated solutions is far too great for planners to decide which harvesting plans should be selected and executed according to current harvesting conditions. We therefore adopt a simple pre-screening procedure similar to that of Jarumaneeroj et al. (2021) to help planners select solutions that best suit current conditions for further evaluation. Technically speaking, this procedure applies a criterion for each of the objectives set by the mill and growers to remove the solutions that are less likely to be accepted by these key supply chain actors.

Based on this pre-screening procedure, we can significantly reduce the excessive number of PSO solutions from over 15,000 to about 40 solutions. Table 6, for instance, shows the average objective values of the remaining solutions to one practical instance, when compared to the best objective values across all domains.

From Table 6, it could be seen that, with a slight decrease in sugar production volume, average grower profit, opportunity loss, and environmental impact, could be largely improved; and, if we convert these improvements into monetary units, based on raw sugar and carbon credit selling prices, the total surplus is clearly more than the loss in sugar production.

Considering all the supply chain improvements that our proposed PSO offers, and the forthcoming regulations that will further stress the environmental concerns of sugar production-related activities (Yusup et al., 2015), we expect that our proposed PSO framework will be of paramount importance to not only the improvement of key supply chain actor's performances but also the development of a more sustainable sugar-production environment in the long term.

6. Conclusions

The upstream logistics of the Thai sugar industry is rather complex as it involves many small sugarcane growers that operate and compete for limited harvesting resources in an uncoordinated, decentralized fashion. This eventually leads to inefficient schedules that negatively affect not only the economic performance of both growers and mills but also the environmental performance due to the current harvesting malpractice, known as sugarcane farm burning. To enhance the efficacy of the Thai sugar supply chain as a whole, while reducing the environmental impact from the current harvesting practice, the Multi-Objective Harvesting Resource Scheduling Problem (MOHRSP) is herein introduced and solved by means of Particle Swarm Optimization (PSO).

We have assessed the performance of the proposed PSO framework based on the SOHRSP and the MOHRSP of various sizes, where the largest instances comprise of around 50 sugarcane growers and 300 sugarcane plots, with over 200 harvesting resources combined. Regarding the SOHRSP, we find that the performance of our PSO approach is comparable to that of the commercially available solver with time restrictions, as it could provide solutions that are relatively close to the benchmark solutions, with exceptionally low coefficients of variation. Although, PSO computational times may vary, it terminates well within an acceptable period of time, while CPLEX generally terminates with a "run-out-of-memory" error in all of the larger instances. The proposed PSO approach also performs well in solving the MOHRSP, as it could provide sets of well-balanced solutions with an average percentage difference of less than 5% in terms of sugar production.

Based on our computational results, we find that mill-oriented solutions (which maximize sugar production volume) tend to underperform in other three objectives – namely, grower profit, opportunity loss, and environmental impact – due to a preference for sugarcane farm burning over greener harvesting practices. However, with a slight sacrifice of sugar production volume, the other objectives gain substantial benefits, and the whole sugar supply chain could be significantly improved – even without indirect benefits from better sugar quality and incentives for greener production activities.

Considering these findings and the existence of negative externalities (*e.g.* the decline of world sugar prices and the expected increase in environmental regulations for greener production activities), there is clearly a need for efficient decision support tools that take into account conflicting objectives of different supply chain actors. Without these tools, additional surplus would be futile, and the Thai sugar industry would be more vulnerable, especially the sugarcane growers whose average profits are sensitive in the trade-offs with other objectives.

It should be remarked that, while our focus lies on the sustainability of the Thai sugar supply chain, we expect that our proposed PSO framework would be able to serve as a stepping stone for the development of sustainability in the supply chains of other agricultural crops, or products, that share similar traits with sugarcane. It is also possible to extend our work by including other relevant objectives into the computational settings, or even compare the performance of various supply chain settings, which are all worth exploring in subsequent studies.

CRediT authorship contribution statement

Pisit Jarumaneeroj: Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Puwadol Oak Dusadeerungsikul:** Investigation, Writing – review & editing. **Tharin Chotivanich:** Methodology, Software, Validation, Writing – original draft. **Renzo Akkerman:** Investigation, Writing – review & editing.

Declaration of Competing Interest

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

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Appendix A. The MOHRSP parameter settings

See Table A1.

Table A1
Values of all MOHRSP parameters and their respective data sources.

No.	Parameter	Definition	Value	Unit	Source
1	g^u	Fuel consumption rate	0.25	Liter/km	Naparswad (2013)
2	g^e	CO_2 emission rate from diesel fuel	2.7446	$kgCO_2$/liter	Thailand Greenhouse Gas Management Organization
3	g^c	Diesel fuel price	28	Baht/liter	PTT Public Co., Ltd
4	h_r^s	Harvesting speed of harvest front	R1 = 25 R2 = 6.25 R3 = 13.5	ton/hour	Opanukul et al. (2012)
5	h_r^c	Operating cost of harvest front	R1 = 280 R2 = 250 R3 = 220	Baht/ton	Opanukul et al. (2012)
6	h_r^g	Fuel consumption rate of harvest front	R1 = 1.5 R2 = 0 R3 = 0	liter/ton	Opanukul et al. (2012)
7	h_r^e	CO_2 emission rate of harvest front	R1 = 0 R2 = 0 R3 = 219.5	$kgCO_2$/ton	Pongthornpruek and Pampasit (2017)
8	h_r^d	Sugarcane trash ratio of harvest front	R1 = 13.98 R2 = 11.04 R3 = 8.73	%	Opanukul et al. (2012)
9	h_r^l	Yield loss ratio of harvest front	R1 = 3.5117 R2 = 3.0565 R3 = 2.8269	%	Opanukul et al. (2012)
10	h_r^f	Incentive/fine from deploying harvest front	R1 = 30 R2 = 30 R3 = −30	Baht/ton	The Bank of Thailand
11	h_r^i	Soil recovery cost from deploying harvest front	R1 = 0 R2 = 0 R3 = 1000	Baht/plot	Mitr Phol Modern Farm
12	h_r^u	Ratio of cane leaf and bract retrieved from harvest front	R1 = 17 R2 = 17 R3 = 0	%	Opanukul et al. (2012)
13	δ_r	Maximum capacity of harvest front	R1 = 14 R2 = 2 R3 = 3	plot	Opanukul et al. (2012)
14	φ_r	Deterioration rate of CCS by harvest front	R1 = 0.10834 R2 = 0.04114 R3 = 0.06488	% CCS/ hour	Singh et al. (2008)
15	m	Sugar mill's crushing capacity	500	ton/hour	Buriram Sugar Public Co., Ltd
16	l	Truck loading capacity	25	ton	Department of Highways
17	v	Sugarcane cultivating cost	665	Baht/ton	Chamneansuk (2019)
18	s	Sugarcane selling price (CCS = 10)	900	Baht/ton	Office of the Cane and Sugar Board
19	ε	Sugarcane leaf and bract selling price	1,000	Baht/ton	Mitr Phol Modern Farm
20	ϑ	Raw sugar selling price	16,132.85	Baht/ton	Office of the Cane and Sugar Board
21	q	Minimum quality of sugarcane supply	10	CCS	Office of the Cane and Sugar Board
22	b	Incentive/fine from supplying sugarcane with CCS greater/lower than q	42	Baht/CCS	Office of the Cane and Sugar Board

Appendix B. Pseudocode of the proposed PSO framework

In this Appendix, pseudocode for the proposed PSO framework, along with its sub-computational modules, described in Section 4, is provided.

Algorithm B.1 The proposed PSO framework

1: **Input**: Information related to the MOHRSP, along with the pre-specified PSO parameters.
2: **Initialization**: Initialize all parameter values.
3: **Preprocessing**: Call *Prep* for field clustering.
4: **For** each of the SOHRSP comprising the MOHRSP **do**
5: **Create**: Create the initial particle swarm by *IntGen* until a predefined number of particles (*NumPar)* have been successfully generated.
6: **While** one of the stopping criteria has not been met **do**
7: **Improve**: Improve the solutions by *ParRep*, *ParRegen*, and *LocalSearch*.
8: **Restart:** Restarting every fixed number of iterations (multi-starting strategy).
9: **end While**
10: **Non-dominated sorting**: Sort and collect non-dominated solutions found so far.
11: **end For**
12: **While** one of the stopping criteria has not been met **do**
13: **Improve**: improve the non-dominated solutions found so far by *ParRep*, *ParRegen*, and *LocalSearch*.
14: **Restart:** Restarting every fixed number of iterations (multi-starting strategy).
15: **end While**
16: **Return:** Pareto-optimal solutions to the MOHRSP.

Algorithm B.2 Preprocessing Module (*Prep*)

1: **Input**: Information regarding sugarcane fields and harvesting resources.
2: **For** each sugarcane field **do**
3: **Create**: Create sub-fields or plots according to the truck loading capacity.
4: **Index**: Re-index the sugarcane plots.
5: **end For**
6: **Cluster:** Cluster the sugarcane plots by K-mean clustering approach, where the number of clusters is equally set to the number of machine-based harvest fronts.
7: **Return:** A set of sugarcane plots, along with their respective clusters.

Algorithm B.3 Initial Solution Generation Module (*IntGen*)

1: **Input**: Updated information related to the MOHRSP, along with the pre-specified PSO parameters.
2: **Initialize:** Initialize the particle structure as a vector of length 4N, *i.e.* each sugarcane plot is attached with four information dimensions.
3: **While** the number of generated particles is less than *NumPar* **do**
4: **While** the set of available harvest fronts or remaining sugarcane plots is not empty **do**
5: **Select**: Randomly select the harvest front according to a simple prioritization scheme.
6: **Pair:** Randomly select the sugarcane plot and pair it with the selected harvest front.
7: **If** the plot is feasibly paired with the harvest front **then**
8: **Update:** Update the schedule and further determine the transporting truck, as well as its respective unloading time according to the current schedule.
9: **Repeat:** Return to Line 6 for another pairing.
10: **Else** call *SchedAdj* for schedule adjustment; and, if *SchedAdj* fails, update the schedule and return to Line 4.
11: **end If**
12: **end While**
13: **If** the set of remaining sugarcane plots is empty **then**
14: **Evaluate:** Evaluate the fitness of such solution and assign the initial velocity (vel_0).
15: **Encode:** Encode the solution with respect to the predefined particle structure.
15: **Else** discard the incomplete solution.
16: **end If**
17: **end While**
18: **Return:** An initial particle swarm, along with *pbest* and *gbest*.

Algorithm B.4 Particle Reposition Module (*ParRep*)

1: **Input**: A swarm of particles, along with *pbest* and *gbest*.
2: **Initialize:** Initialize the harvesting resources (harvest fronts and trucks) of all particles according to *gbest* and place them into unscheduled lists.
3: **For** each particle **do**
4. **While** the set of unscheduled harvest fronts is not empty **do**
5. **Reposition:** Randomly select the unscheduled harvest front and determine the starting times, completion times, and unloading times of all plots based on the particle velocity.
6: **If** the schedule of a front is infeasible due to insufficient operational time **then**
7: **Adjust:** Call *SchedAdj* for schedule adjustment and remove all resources from the unscheduled lists; but, if *SchedAdj* fails, reset the schedule of such a front and return to Line 4.
8: **end If**

(*continued on next page*)

(*continued*)

Algorithm B.4 Particle Reposition Module (*ParRep*)
9: **End While**
10: **Evaluate:** Evaluate the fitness of the returning solution.
11: **Update:** Update particle velocity based on Eberhart and Shi (2000), as well as the *pbest.*
10: **end For**
11: **Update:** Update *gbest.*
12. **Return**: An updated swarm of particles, along with new *pbest* and *gbest.*

Algorithm B.5 Particle Regeneration Module (*ParRegen*)
1: **Input**: A swarm of particles, along with *pbest* and *gbest.*
2: **Sorting**: Sort the particles according to their fitness values.
3: **If** the particle belongs to the last 20% of the swarm **then**
4: **Regeneration**: Remove the particle and regenerate a new particle by *IntGen*.
5: **Else If** the particle belongs to the next 30% of the swarm **then**
6: **Regeneration**: Remove the particle and regenerate a new particle based on Bożena's method (Borowska, 2017) (see Appendix D).
7: **Evaluate:** Evaluate the fitness value of regenerated solutions and assign their initial velocity (vel_0).
8: **end If**
9: **Update:** Update *pbest* and *gbest.*
10: **Return:** An updated swarm of particles, along with new *pbest* and *gbest.*

Algorithm B.6 Local Search Module (*LocalSearch*)
1: **Input**: A swarm of particles, along with *pbest* and *gbest.*
2: **While** one of the stopping criteria has not been met **do**
3: **Create**: Create a random variable *LS_Random* within the range between 0 and 1.
4: **Apply:** Apply one of the following local search routines based on the value of *LS_Random.*
5: **Routine 1:** *FrontRelocation* → *PlotRelocation*.
6: **Routine 2:** *PlotSwap* → *PlotRelocation*.
7: **Routine 3:** *FrontRelocation* → *PlotSwap* → *PlotRelocation*.
8: **If** the resulting solution is feasible and its fitness value is better than the current one **then**
9: **Update:** Update the particle position, *pbest,* and *gbest.*
10: **Else If** the solution is infeasible **then**
11: **Repair:** Call *Repair* and/or *SchedAdj* for particle repairing; but, if both fail, add such a move into a tabu list (this tabu list will be reset when a new feasible solution is found).
12: **end If**
13: **end While**
14: **Return**: An updated swarm of particles, along with new *pbest* and *gbest.*

Algorithm B.7 Schedule Adjustment Module (*SchedAdj*)
1: **Input**: An incomplete harvesting schedule, where harvesting resources could not be assigned to a plot due to insufficient operational time.
2: **Calculate**: Calculate the buffer times of the previously assigned harvesting/transporting tasks.
3. **While** there is room for adjustment **do**
4: **Adjust:** Adjust the current schedule based on the buffer times of harvesting resources, one at a time.
5: **If** the harvesting resources are feasibly paired with the plot **then**
6: **Update:** Update the schedule and terminate.
7: **Else** Update the buffer times.
8: **end If**
9: **end While**
10: **Return:** An updated harvesting schedule.

Algorithm B.8 Repair Module (*Repair*)
1: **Input**: An incomplete harvesting schedule with schedule conflicts.
2: **Identify**: Identify the overlapping tasks.
3: **Calculate:** Calculate the buffer times of the overlapping tasks, and their neighborhood.
4: **While** there is room for adjustment **do**
4: **Adjust:** Adjust the current schedule based on the buffer times of overlapping tasks, and their neighborhood, one at a time.
5: **If** the conflicts are settled **then**
6: **Update:** Update the schedule and terminate.
7: **Else** Update the buffer times.
8: **end If**
9: **end While**
10: **Return:** An updated harvesting schedule.

Appendix C. The update formulae of particle's velocity

Let $\vec{x}_i(t)$ and $\vec{v}_i(t)$ be the position and velocity of particle i in iteration t, the update formulae proposed by Eberhart and Shi (2000) could be defined by Equations (C1) and (C2) as follows.

$$\chi = \frac{2}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}}, \tag{C1}$$

$$\vec{v}_i(t+1) = \chi\left(\underbrace{\vec{v}_i(t)}_{Inertia} + \underbrace{c_p r_1\left(\vec{x}_{pbest_i} - \vec{x}_i(t)\right)}_{Cognitive\ Learning} + \underbrace{c_g r_2\left(\vec{x}_{gbest_i} - \vec{x}_i(t)\right)}_{Social\ Learning}\right), \tag{C2}$$

where φ $= c_p + c_g > 4$,
c_p, c_g = acceleration coefficient of *pbest* and *gbest*,
r_1, r_2 = vectors of uniform random variable within the range $[0, 1]$, whose sizes are equal to the particle dimensions.

Appendix D. The Bożena's method

Let $\vec{v}_i(t)$ be the velocity of particle i in iteration t, the Bożena's method will update the velocity of particle i based on its velocity in the previous iteration, as shown in Equations (D1) and (D2); however, it will only select the one that provides better objective value.

$$\vec{v}_{i,1}(t+1) = \frac{\vec{v}_i(t)}{\vec{v}_i(t) - \vec{v}_i(t-1)}, \tag{D1}$$

$$\vec{v}_{i,2}(t+1) = \frac{\vec{v}_i(t-1) - \vec{v}_i(t)}{\vec{v}_i(t-1)}, \tag{D2}$$

where $\vec{v}_{i,1}(t+1)$ = the first updated velocity of particle i in iteration $t+1$,
$\vec{v}_{i,1}(t+1)$ = the second updated velocity of particle i in iteration $t+1$,
$\vec{v}_i(t-1)$ = the velocity of particle i in iteration $t-1$.

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