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Optimal mechanical harvester route planning for sugarcane field operations using particle swarm optimization

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Abstract

Since current agricultural production systems such as the sugarcane supply system in the sugar industry are developing towards larger and more complicated systems, there is consequently increasing use of agricultural machinery. Even though mechanization can help to increase the sugarcane yield, if the mechanical operation efficiency is low, then higher harvest costs and machinery shortages will occur. Global route planning for mechanical harvesters is one of the most important problems in the field of sugarcane harvesting and transporting operations. Improved efficiency and realistic implementation can be achieved by applying advanced planning methods for the execution of field operations, especially considering the field accessibility aspect. To address this issue, participative research was undertaken with a sugar milling company to produce and implement a mixed integer programming model that represents the mechanical harvester route plan. Particle swarm optimization was applied to find a solution to the model, leading to potential cost savings versus schedules produced manually by the mill officer. The model was also applied to explore regional planning options for a more integrated harvesting and transport system.

Keywords : Sugarcane, Harvester, Route planning, Particle swarm optimization

1. Introduction

Increased global sugarcane production is expected in response to increasing world sugar consumption [1]. Many countries who are sugarcane producers and sugar exporters are expected to expand their production on a large scale. Moreover, the problem of labor shortage has led to introduction of mechanical sugarcane harvesting to overcome the

shortage of labor and to control rising labor costs. Therefore, there is strong interest in machinery use, particularly in harvesting operations. It is required to increase the efficiency and profitability of the sugarcane supply chain. In many parts of the world where sugarcane production is steadily increasing, the harvesting mode has switched from manual harvesting to mechanical harvesting [2].

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Mechanical harvesting of sugarcane is performed by cutting the sugarcane at the base of the stalk, stripping the leaves, chop the sugarcane into short sticks (billets) and depositing it into a transporter following alongside. It is likely to be the most important factor in reducing future sugarcane production costs [3], since it can complete the harvest faster with more yield (more sugarcane harvested per unit of time) than manual cutting and loading. However, mechanical harvesting is quite capital and machine intensive, requiring mechanical harvesters, extra tractors and trucks for transportation. Moreover, once cut, sugarcane begins to lose its sugar content, and damage to the cane during mechanical harvesting accelerates this process. Managerial tasks are required to increase the mechanical operation efficiency. Improved sequence of the harvesting route provides one such opportunity, as it would reduce the length of a route and save travelling time leading to the least-cost routes and increased sugarcane harvested per unit of time. Here, a theoretical approach is presented to determine the optimal path for route planning as an example of the well-known combinatorial optimization problem “Shortest Path Problem” (SPP). The SPP method adopted for mechanical harvester route planning of sugarcane field operations is presented as directed graphs. Mechanical harvesting has less flexibility to access between fields. Field preparation becomes stricter, as mechanical harvesters require the same direction of sugarcane planting groves to plan the movement properly (see figure 1) so that the mechanical harvester can move between Field 1 to Field 2, due to their planting groves being in the same direction.

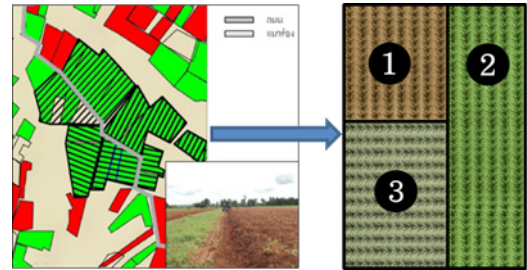


Figure 1 Direction of sugarcane planting groves

Particular movement of a harvester between different directions of sugarcane planting groves will be too time-consuming and cause cane damage. The harvester turning to another direction should be performed at the termination of the plantation boundary. For a directed graph, the definition of path requires that consecutive vertices (fields) be connected by an appropriate directed edge. It can therefore be useful to identify suitable path routing in field operations and the field accessibility will make realistic implementation achievable. Furthermore, sugarcane is continuously sourced in diverse quantities and qualities from hundreds of geographically dispersed haciendas and supplied to the milling process. The harvesting of sugarcane at a proper time, i.e. peak maturity, is necessary to realize increasing average commercial cane sugar (CCS) yields. Therefore, the optimal mechanical harvester route planning of sugarcane field operations which considers both travelling distance and sugarcane quantity is the most efficient.

This paper presents an approach for determining the harvesting route for a sugarcane harvester in field operation with consideration of the field accessibility aspect. The method relies on the SPP and uses the well-known Particle Swarm Optimization (PSO) to determine the optimal route,

taking into account constraints for the sugarcane supply in the considered period, restricted in terms of the contracted amount of sugarcane and the queue sequence that is agreed with the mill. The next section provides a review of the relevant literature. The mathematical model is described in Section 3 and the methodology is presented in Section 4. Section 5 outlines simulation results and comparison with the case study. Finally, a summary is given in Section 6.

2. Literature review

The sugarcane supply operations can comprise a large percent of the overall production costs as discussed in Iannoni and Morabito [4]. Recently, the supply of sugar mills has attracted some attention in the academic literature. Several studies have pointed out the development of advanced methods to manage the supply system for transporting the harvested crops from the rural fields to the processing plant which assures continuous feeding and low operation costs. For example, Di'az and Pe'rez [5] sketch a simulation model for the road transport of sugarcane in Cuba. Higgins [6] presents an optimization model formulation for scheduling the individual vehicles in a road-bound transportation system. In addition to the large-scale solution, two alternative solution methods based on meta-heuristics are proposed.

The works are almost exclusively addressed to road or railway transportation where the solution space is not covered for the in-field transporting operations, especially when applying the mechanical harvesting mode. Some intensification of machinery use, particularly in harvesting operations, has been increased in response to increasing production. The global route planning of a mechanical harvester is one of the most important problems in the field of sugarcane harvesting and transporting operations.

Regarding the route planning for agricultural field operations, advanced methods based on combinatorial optimization have recently been introduced [7]. For example, Sørensen et al. [8] proposed a heuristic approach for optimizing vehicle routes in agricultural field operations by defining the field nodes as a graph and formulating the routing problem as the Chinese Postman Problem and the Rural Postman Problem. Bochtis et al. [9] proposed a multi-travelling salesman problem for planning a fleet of combine harvesters operating in a field.

The shortest path problem (SPP) is one of the transportation models concerned with finding the optimal path in a given network. Numerous applied variations of the SPP in real-world systems have been addressed, including public transport, movement of industrial goods, and also in the path planning of agricultural field operations as presented by Bochtis and Sørensen [10]. However, in agriculture, the path routing problem has only very recently been applied to the planning of field operations. Most previous research has focused on minimizing the total traveling distance, but the quality of product (such as sugar content or CCS in sugarcane) is not included. Moreover, the consideration of field accessibility to achieve realistic implementation has been not proposed in any papers before. There are many well-known algorithms for solving SPP including the Bellman–Ford algorithm, Dijkstra's algorithm and Gabow's algorithm. However, these traditional algorithms have some shortcomings. They converge very slowly when applied to a complex problem with many constraints. Therefore, recently, powerful evolutionary programming techniques such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) or Differential Evolution (DE) have become important for more efficient solutions.

The PSO method is becoming very popular because of its simplicity of implementation as well as its ability to swiftly converge to a good solution. The basic philosophy behind PSO is based on the social behavior of a bird flock and was first proposed by Kennedy and Eberhart [11]. PSO has been applied in many applications. Network graphs and SPPs are problems that been successfully solved using PSO [12]. However, there is no reported work on the use of PSO to determine the optimal mechanical harvester route planning for sugarcane field operations. Because of the attractive features of PSO, it is the proposed method for solving the path planning in our paper.

3. Mathematical model

As mentioned in previous sections, the mechanical harvester route planning of sugarcane field operations is similar to the SPP. The basic form of the SPP is related to a graph $G \in \{V, E\}$, where $V = \{0, 1, \dots, n, 0'\}$ is the node set and E is the arc set. Nodes 0 and 0' correspond to the depot (mill factory), while the remaining node set $N = V \setminus \{0, 0'\}$ corresponds to the customers (sugarcane fields). In our solution, each arc $(i, j) \in E$ is presented in the directed graph as shown in figure 2. Mixed-integer programming (MIP) is presented to find the optimal solution. The details of indices, parameters, decision variables, objective functions and constraints are as follows:

3.1 Indices

i, j node index ($i, j = 0, 1, 2, \dots, n, 0'$)

3.2 Parameters

n number of sugarcane fields

a_i quantity of sugarcane in field i

e_i sugar yield or CCS of sugarcane in field i

d_{ij} distance between nodes i and j

s quantity of sugarcane supply that must be satisfied

β cane selling price [Baht/ton/CCS]

α cost of cane transport [Baht/km]

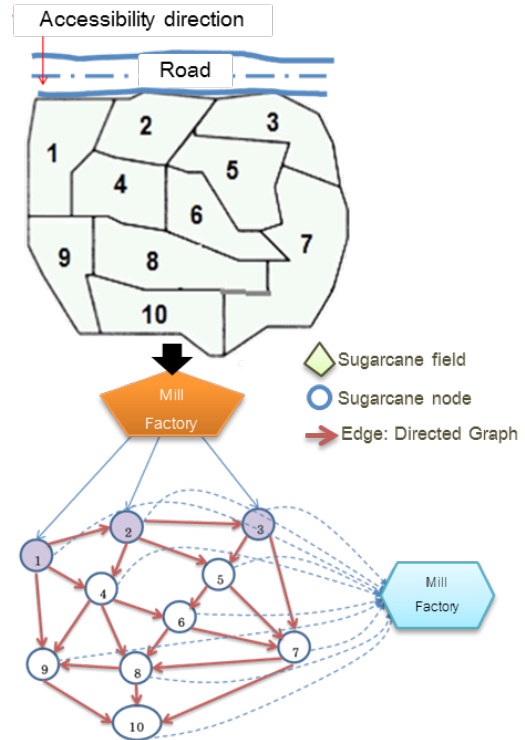


Figure 2 Directed graph of harvester

3.3 Decision Variables

q_i ratio of sugarcane quantity that is harvested from field i

$x_{ij} = 1$ if you can travel directly from node i to node j ($i, j \in E$), Otherwise 0

$$\text{Maximize } a \sum_{i \in N} a_i \times e_i \times q_i - b \sum_{i, j \in E} d_{ij} \times x_{ij} \quad (1)$$

Subject to

$$\sum_{j \in N} x_{0, j} = 1 \quad (2)$$

$$\sum_{i \in N} x_{i, 0'} = 1 \quad (3)$$

$$\sum_{j \in N} x_{ij} = \sum_{j \in N} x_{ji}; i \in V \quad (4)$$

$$\sum_{j \in N} x_{ji} \geq q_i; i \in N \quad (5)$$

$$\sum_{i \in N} a_i \times q_i = s \quad (6)$$

The objective function (1) is the maximization of the total profit, composed of the revenue given by the sugar production (depends on selling price and sugar content in cane) and the total cost for cane transportation. Constraints (2) and (3) are used to ensure that there is a route which leaves depot 0 for harvesting in some fields and then returns back to the depot 0'. The role of constraints (4) is to ensure that when a harvesting route arrives at a field i , it also leaves that field. Constraints (5) reflect that if some sugarcane field i is left or entered that sugarcane field i is harvested. Constraints (6) ensure that the sugarcane supply must be satisfied. The model has $2n + 5$ constraints and $n + |A_{ij}|$ variables. The MPL/CPLEX software V. 42 for Windows (MPL Modeling System, 2012) was used to find the optimal solution.

4. Particle swarm optimization

Although an optimal solution was obtained for the problem, the computational time was excessive. Attempts to solve larger problems were unsuccessful as they required too much CPU time. Particle Swarm Optimization (PSO) is hence employed to obtain a near-optimal solution for realistic-sized problems because of its easy implementation and inexpensive computation, its simplicity in coding and consistency in performance [13]. However, in the standard PSO algorithm, the global best position is used as the only source of communication among particles, leading to the swarm clustering very quickly and it may be easily trapped in a local optimal solution. Therefore, our

proposed method for the main PSO algorithm is developed based on GLNPSO with multiple social structures [14].

4.1 GLNPSO algorithm

For a specific problem solution, a swarm of L particles serves as the searching agent. A particle's position (Θ_i) , which consists of H dimensions, represents a solution of the problem. The ability of a particle movement to search for a solution is based on its velocity vector (Ω_i) . The personal best of each particle (Ψ_i) is defined as the position that gives the best objective function among the positions that have been visited by the particle. The global best (Ψ_g) is the position that gives the best objective function of the swarm. The local best (Ψ_i^L) is the best position among several adjacent particles. The near neighbor best (Ψ_i^N) is a social learning behavior which is determined based on fitness-distance-ratio (FDR). The outline of the proposed algorithm is presented in the following:

Begin

1. Initialize L particles as a swarm
2. Generate the initial particles with random position using priority-based encoding
3. Decode each particle into a harvester route
4. Evaluate the fitness function following Eq.(1)

While (not terminating condition) do

5. Update pbest, if $Z(\Theta_i) < Z(\Psi_i)$

$$\text{then } \Psi_i \leftarrow \Theta_i$$

6. Update gbest, if $Z(\Psi_i) < Z(\Psi_g)$

$$\text{then } \Psi_g \leftarrow \Psi_i$$

7. Update lbest,

$\Psi_i^L \leftarrow$ the pbest from K neighbors of i^{th} particle which has the least fitness value

8. Update nbest, set $\mathbf{y}_{lh}^N \leftarrow \mathbf{y}_{oh}$ that maximizes FDR for $o = 1, 2, \dots, L$ where

$$FDR = \frac{Z(\Theta_l) - Z(\Psi_o)}{|\theta_{lh} - \psi_{oh}|}, l \neq o \quad (7)$$

\mathbf{q}_{lh} position of the l^{th} particle in the h^{th} dimension
 \mathbf{y}_{lh} pbest position of the l^{th} particle in the h^{th} dimension

9. Update the velocity and the position of each particle:

$$w(\tau) = w(T) + \frac{\tau - T}{1 - T} [w(1) - w(T)] \quad (8)$$

$$\begin{aligned} \omega_{lh}(\tau+1) &= w(\tau)\omega_{lh}(\tau) + c_p u(\psi_{lh} - \theta_{lh}(\tau)) \\ &+ c_g u(\psi_{gh} - \theta_{lh}(\tau)) + c_l u(\psi_{lh}^L - \theta_{lh}(\tau)) \\ &+ c_n u(\psi_{lh}^N - \theta_{lh}(\tau)) \end{aligned} \quad (9)$$

$$\theta_{lh}(\tau+1) = \theta_{lh}(\tau) + \omega_{lh}(\tau+1) \quad (10)$$

where

\mathbf{t} iteration index; $\mathbf{t} = 1, \dots, T$

u uniform random number $[0, 1]$

c_p, c_g, c_l, c_n acceleration constant

End

4.2 Solution representation or encoding

One of the key issues in PSO is finding a suitable mapping between problem solution and particle position. The solution representation used here is priority-based encoding. The PSO particles, n numbers of dimensions with a randomly generated real number between 0 and 1, are presented as the priority of n sugarcane fields for constructing a path among candidates. Moreover, the last dimension ($n+1$ th) of each particle is involves the number of sugarcane fields that are split harvesting (Sp). The particle representation of our problem is shown in figure 3.

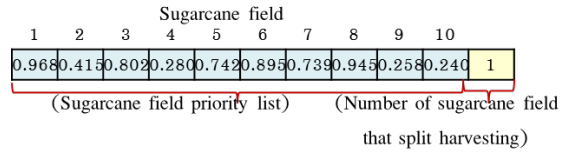


Figure 3 Example of encoding with 10 fields

4.3 Decoding

The decoding is done in two phases. Firstly, the harvester route is constructed by priority-based values.

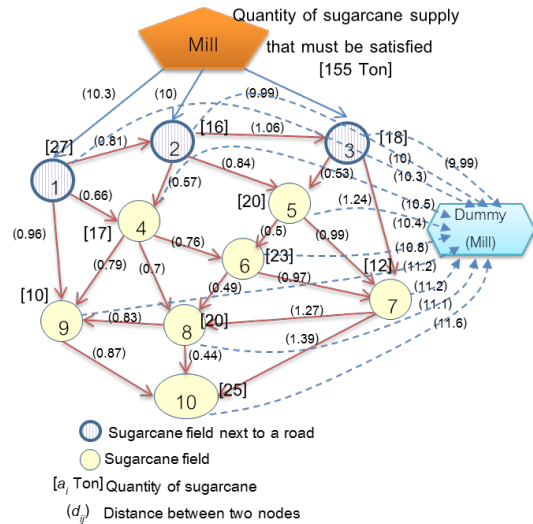


Figure 4 Data and directed graph of the decoded path

Illustration of the priority-based decoding is shown in figure 4. At the beginning, the field nodes that are next to the road will be considered to assign in the path. From the example, Node 1, 2 and 3 are eligible, and their priorities are 0.968, 0.415 and 0.802, respectively. Node 1 has the highest priority so it is inserted into the path. The possible nodes which are adjacent to node 1 are Nodes 2, 4 and 9. Since node 2 has the largest priority value, it is inserted into the path. The set of nodes available for the next position is formed and the one with the highest priority selected. Repeat these steps until the sugarcane supply requirements are equal or more than the

requirement, or the destination node (mill) is inserted. The decode path is shown in figure 5.

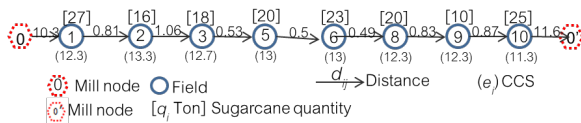


Figure 5 Priority-based decoding and its decoded path

The total quantity of sugarcane in the first phase is 159 ton. In the second phase, the Sp sugarcane fields are split harvested based on the integer value in the last dimension of the particle. From the example $Sp = 1$, the sugarcane fields are randomly selected to split harvest. Field 5 is selected, therefore, it will be split harvested until all the demand is satisfied. The complete path is shown in figure 6.

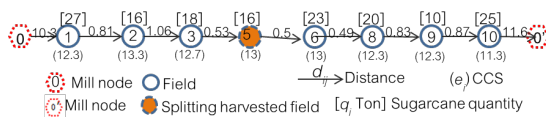


Figure 6 Example of the complete path

5. Experimental results

In order to test the model, the performance of GLNPSO in the sugarcane mechanical harvesting problem was validated by comparing the solutions given the optimal solution obtained by the MPL/CPLEX software, and the current practice of the sugar mill in the case study. The current practice is based on the experience of the planner and sugarcane growers.

The performance of the proposed method was tested by using five different sizes of test problem as given in Table 1.

Table 1 Design of test problems

Problem	n	Sp	t	L
1	10	2	200	500
2	15	2	150	1000
3	20	2	150	1000
4	30	2	150	1500
5	50	2	100	1500

Computational results are presented in terms of solution quality and computational speed of the optimal solutions obtained from the mathematical model, and the best values of the GLNPSO over the 10 runs for each problem as shown in Table 2. The GLNPSO were developed in an effort to find a near optimal solution for problems with average or large sizes within a reasonable time. Based on the %Gab of each solution result shown in Table 3, the solution improvement compared with the current practice for the MPL/CPLEX ranges between 0.214-2.861% and 0.215-1.925% for the GLNPSO. The results indicate that the proposed GLNPSO yields better solutions than the current practice and can get the optimal solution for the small-sized problem. Moreover, for larger problem size, the GLNPSO can save computational time and the qualities of solutions are different from the optimal solutions obtained from the mathematical model ranges between 0.736-1.412%.

Table 2 Computational results [Baht/trip]

Problem	Current practice	MPL/CPLEX		GLNPSO	
		Optimal solution	Time (sec.)	Best	Time (sec.)
1	12570.3	12600.0	1.03	12600.0	2.45
2	12570.8	12610.2	2.45	12610.2	4.66
3	19730.4	20320.6	241	20030.9	7.29
4	18910.5	19420.7	435	19280.4	138.0
5	25190.7	25930.9	1936	25680.2	180.1

Table 3 %Gab of each solution result

Problem	Current vs CPLEX	Current vs GLNPSO	GLNPSO vs CPLEX
1	0.214	0.215	0.000
2	0.270	0.270	0.000
3	2.913	1.546	1.412
4	2.636	1.951	0.736
5	2.861	1.925	0.991

6. Conclusion

In this paper, we consider the problem of the sugarcane supply system through the mechanical harvesting part in order to improve transportation efficiency of the sugar supply system. The mixed integer programming model was used to plan the mechanical harvester route. GLNPSO was applied to find a solution to the model, leading to potential cost savings versus schedules produced manually by the mill officer. As the experimental results show, the proposed GLNPSO is a better solution than current practice. Hence, the GLNPSO can be used to help solve sugarcane supply system problems by improving mechanical harvesting and transportation efficiency. This helps the growers increase profit, reduce transportation costs and helps the mill maintain a steady supply of sugarcane for its smooth operation, resulting in sustainable production.

In addition, although GLNPSO has shown an outstanding ability to solve the problem at hand, there are possibilities to use other metaheuristics or hybrid methods to solve the problem.

7. Acknowledgements

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