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A Multi-Objective Optimization Model to Support Freshly Cut Vegetable Processing Decisions

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Abstract

This study presents a multi-objective optimization approach for decision making in fresh-cut vegetable processing, optimizing processing times and costs through the selection of alternative processes at various stages of the production. Despite the limited attention given to the fresh-cut vegetable industry, particularly in applying multi-objective optimization methods to support processing decisions, this study addresses the research need. The stages of fresh-cut vegetable processing, including peeling, cutting, washing, and packing, offer multiple alternative methods with varying costs and processing times. The problem is formulated as an integer bi-objective combinatorial optimization model aimed at optimizing total processing time and cost. Two algorithms, the discrete non-dominating sorting genetic algorithm-II (NSGA II) and the discrete non- dominated sorting particle swarm algorithm (NPSO), were applied to explore their complementary algorithmic performance. The local search behaviour of NSGA-II was enhanced through several innovative local search operators including crossover, and mutation operators, while various position and velocity update operators were used in NPSO. Both primary and secondary data were utilised in estimating the process parameters of each alternative processing methods. The results showed that NPSO exhibited more robust convergence, while NSGA-II produced a greater number of solutions in the Pareto front.

Keywords: Evolutionary meta-heuristics techniques; multi-objective optimization; NSGA-II; Particle swarm optimization; Process selection decision

Introduction

Modern lifestyle changes necessitate the availability of food that is convenient, safe, nutritious, and of high quality. The fresh-cut vegetable processing industry is one of the perfect food technological solutions to cater for the needs of hectic lifestyles. The former International Fresh-Cut Produce Association defined fresh-cut produce as trimmed, peeled, washed, and cut into 100% usable product that is subsequently bagged or pre-packaged to offer consumers high nutrition, convenience, and value while still maintaining freshness (Barrett, 2010).

Fresh-cut vegetable consumption has been on the rise due to its ease of use, versatility and health characteristics (Gil et al., 2008). Although this increasing demand is encouraging for the industries, it brings challenges related to maintaining product quality and responding fast enough yet cost-effectively. Meeting these objectives requires efficient decision support systems that are embedded with

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the complicated optimization trade-offs associated with how manufacturing-related decisions should be processed.

Manufacturing process selection decisions play an important role in several industries where a certain process can be done through multiple alternative ways. In the literature, the choice of manufacturing processes has been identified as a difficult multi-criteria decision-making problem with technical, technological, economic and environmental criteria (Lukic et al., 2017). One of the common problems addressed in the literature is the parameter selection of tools. For instance, choosing the best cutting parameters for machining processes such as feed rate, depth of cut, and cutting speed is essential to improving surface smoothness and tool life while reducing machining time and expenses (Gopalakrishnan, 1990). Guptaa et al.(2011) has studied tool and machine selection to minimize the cost, especially in terms of turning and cylindrical grinding operations. Zaman et al.(2018) paid attention to select optimal material-machine combinations for additive manufacturing to enhance machining efficiency and product quality.

A number of techniques have been used in the literature to support process selection decisions (Parkan & Ming-Lu Wu, 1998; Lukic et al., 2017) . Mainly, these techniques fall into two clusters, multi-criteria decision-making and multi-objective optimization. Zaman et al.(2018) used the Analytical Hierarchy Process and Ashby's charts to select optimal material-machine combinations for additive manufacturing. Chen (1999) developed an integer programming model to minimize overall manufacturing process costs and machine acquisition/installation costs over multiple periods solving an equipment selection problem.

In recent years, many advances have been achieved in the domain of evolutionary algorithms to solve multi-objective optimization problems arising from various fields (Deb, 2011). Discrete non-dominating sorting genetic algorithm-II (NSGA-II) and discrete non- dominated sorting particle swarm optimisation (NPSO) are widely used techniques for different applications to discover Pareto-optimal solutions in terms of best trade-offs among conflicting objectives. Nevertheless, although they have succeeded in other applications, their use in fresh-cut vegetable processing has remained largely unexplored.

The study aims to bridge this gap by applying NSGA-II, and NPSO to support fresh-cut vegetable processing decisions providing support to select processes best suited for a particular application including what combination of processing techniques might be optimal with respect to operational goals and consumer demands.

Materials and Methods

Problem Formulation

The manufacturing process planning problem considered in this study focuses on process selection decisions of the fresh-cut vegetable processing industry, aiming to minimize both processing time and cost. Consider a single unit of a vegetable that is produced through a sequence of processes. The stages of the process indicated by S where **S = {1, 2, 3, …, s}**, having M alternative type of methods at each stage where **M = {1,2,3, …,m).** At each process stage, each method has a cost of C_m and a time of T_m. To generate manufacturing process plan, one method is selected from the each stage.

The decision variables for the problem are:

$$z_s = \begin{cases} 1 \,; select\ the\ process\ stage\ s \\ 0 \,; otherwise \end{cases}$$

$$y_m = \begin{cases} 1 \,; select\ the\ method\ m \\ 0 \,; otherwise \end{cases}$$

$$Minimize : F = (f_1, f_2)$$

The general mathematical model is as follows:

$$f_1 = \sum_{s=1}^{S} z_s \left[\sum_{m}^{M} y_m . C_m \right] \quad (1)$$

$$f_2 = \sum_{s=1}^{S} z_s \left[\sum_{m}^{M} y_m . T_m \right] \quad (2)$$

Constraint:

$$\sum_{s=1}^{S} z_s \sum_{m}^{M} y_m = 1 \quad (3)$$

The overall objective is to minimise both processing cost and time. Equations (1) and (2) represent two objectives respectively: the total processing cost and the total processing time of all stages. Equation (3) represents the constraint of selecting one method from each stage.

The Proposed Solution

The multi-objective combinatorial optimization model was solved using both the NSGA-II and NPSO. The application of both algorithms is presented below.

NSGA-II Algorithm

As illustrated in Figure 1, NSGA-II requires the generation of an initial population, P_t of size N, a new population Q_t, and the combination of the populations to obtain a new population R_t. The non-dominated sorting will rank the members into different fronts. The members are promoted to the next generation if the size of the first front is less than N as shown in Figure 1. This information is used to construct the next generation, P_{t+1}. Unless stopping criteria are met, this process continues.

NPSO Algorithm

The NPSO improves on the basics of particle swarm optimisation (PSO) by utilizing particles' offspring and personal bests, returning more useful non-dominating comparisons. Pareto search, position update, velocity update, and non-dominated sorting principles lead to a non-dominated sorting PSO-based philosophy.

As presented in Figure 2, the NPSO procedure involves generating an initial population P_t of size N. The non-dominated sorting procedure is performed to identify the global best particle and stored global best particle. The particles are then iteratively updated with their locations and velocities. The archived solutions are mixed with these sets of non-dominated solutions. Finding the archive survival members involves non-dominated sorting of the archive. Archives are updated during this procedure. Every member of the merged set that is dominated is eliminated during this process. Iterating through this method leads the non-dominated search process to provide a solution front that is in close proximity to the Pareto region. The solution set kept in the archive constitutes the outcome after the termination requirement is fulfilled.

Step 1: Initialize the initial population and calculate the fitness function for all individual in initial population

Step 2: Perform non-dominated sorting on P_t to classify individuals into different fronts F_i, and calculate the crowding distance for all individuals in each front.

Step3: Combine parent and offspring populations: Perform a non-dominated sorting to combine population, and identify pareto fronts F_i: i =1,2,..., etc.

Step 4: **Repeat steps 2 and 3** until the maximum number of generations is reached.

Figure 1: NSGA-II Procedure

Step 1: Generate the swarm and velocity

Step 2: Evaluate the all particles and perform non-dominated sorting to identify global best

Step 3: Iterative Process (repeat until t_max=100): Update positions, increment iteration counter (t=t+1), evaluate particles, perform non-dominated sorting to update , update archive, and update velocities.

Step 4: Repeat steps 2 and 3 until the maximum number of iterations is reached

Figure 2: NPSO Procedure

Results and Discussion

Process selection decisions related to the fresh-cut vegetable industry were considered in this study. The production process consists of four stages namely, peeling, disinfecting, cutting and packing. The data related to the production process in given Table 1, Table 2, Table 3 and Table 4. Alternative manufacturing processes were generated using both NSGA II and NPSO implementing them on the python platform. In NSGA-II the scale of the population (N) is set as 100 and the probability of mutation is set as 0.2 and the cross-over is set as 0.7. For the NPSO algorithm the parameter setting is set as follows: size of population N is 100, the max of iteration 50, acceleration constants C1 =2, C2=2, C3=3; velocity coefficients U1=0.3, U2=0.5, U3=0.6. The performance of each algorithm was evaluated based on the total cost and total time objectives. In terms of algorithmic performance, NSGA-II and NPSO take 1.25 seconds and 3.71 seconds for convergence respectively. The Inverted Generational Distance (IGD) values for NSGA-II and NPSO are 18.1213 and 14.512, respectively. Figures 3 and 4 illustrate the Pareto fronts obtained from NSGA-II and NPSO. Each point on the Pareto front represents a non-dominated solution, indicating an optimal trade-off between processing time and cost.

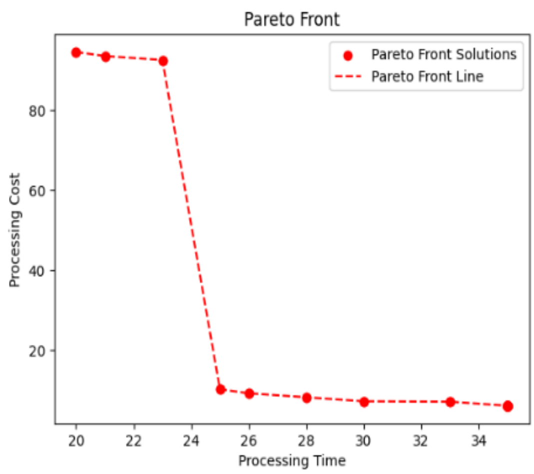

Figure 3: Final Pareto Front - NSGA-II

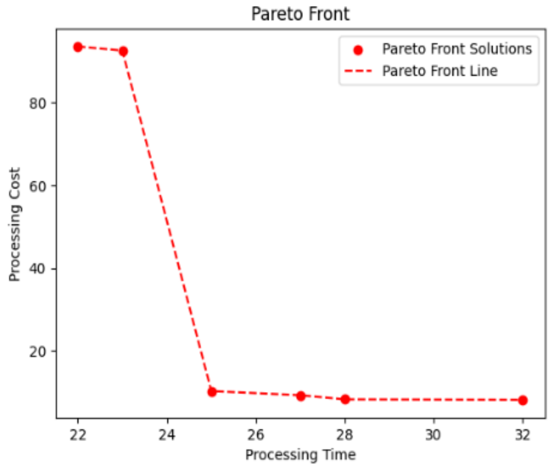

Figure 4: Final Pareto Front - NPSO

Table 1: Disinfectant Process Data

Disinfectant Agent	Time (min)	Cost (Rs.)
D1	15	0.14
D2	05	86.59
D3	15	29.84
D4	10	59.68
D5	10	1.25

Table 2: Cutting Process Data

Cutting Type	Time (min)	Cost (Rs.)
C1	5	2
C2	7	3
C3	6	1
C4	9	2

Table 3: Peeling Process Data

Peeling Type	Time (min)	Cost (Rs.)
P1	10	5
P2	12	4
P3	8	6

Table 4: Packing Process Data

Packing Type	Time (min)	Cost (Rs.)
PA1	2	1
PA2	3	2

Conclusion

The manufacturing process selection is an important decision when alternative options are available to manufacture products and when distinct objectives exist. This study considered a four-stage fresh-cut vegetable processing having alternative processing methods at each stage. Two prominent meta-heuristics algorithms, NSGA-II and NPSO with distinct local search techniques have been used in making process selection decisions. Both algorithms have complementary performance, NPSO demonstrated a more robust convergence performance than NSGA-II whereas the number of solutions are higher in NSGA-II than NPSO.

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