Bi-Objective Model for Multi-Warehouse Inventory for Fresh Produce with Transhipment

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Abstract

This paper presents a bi-objective multi-warehouse inventory optimization model for fresh produce, allowing transhipments between warehouses. Initially, we extended our previous proposed mixed-integer quadratic programming model by allowing transhipment between warehouses. Next, we introduce a bi-objective function, as there is a conflict between two cost components: energy cost of warehouses and product deterioration cost. In the bi-objective model, the first objective minimizes energy costs of warehouses, preparation costs of warehouses, inventory holding costs and transhipment costs. The second objective aims to minimize the quantity of deteriorated products. We performed computational experiments using Gurobi optimization using a number of randomly generated instances under three different scenarios based on the value of transhipment costs compared with holding costs (lower, similar or higher). In the first phase of the computational experiments, we consider only transhipments between warehouses (not using the bi-objective function). These results show that considering lateral transhipments decrease the overall costs in all scenarios. Next, we repeat the computational experiments, using the bi-objective function and the transhipment between warehouses. We calculated the weighted sum of both objectives using nine different combinations of weights for the two objective functions testing on the same instances. The resulted pareto fronts provide a decision-making scheme for managers to decide on the best trade-off between warehousing and inventory costs (first objective) and the quantity of deteriorated products (second objective).

Keywords
Inventory control, fresh produce inventory management, perishable products, transhipment, multi-objective integer programming.

1. Introduction
The food industry in Australia is responsible for $117 billion per year and is increasing by more than 2% per year (Hogan, 2018). It is estimated that around one-third of the food produced for human consumption is lost globally, about 1.3 billion tons per year (FAO, 2011, Juliano et al., 2019). Many challenges are associated with the food supply chain resulting in food loss, from harvesting, inventory management, production, and distribution to delivery to the final customer. Particularly in fresh produce (fruit and vegetables), a central challenge is inventory management, which involves all the decisions related to storage between harvesting and market demand. Therefore, appropriate inventory management is essential. According to (Ivanov et al., 2017), inventory cost corresponds to 50% of the total capital invested by many businesses.

Shukla and Jhakharia (2013), Lemma et al. (2014), Paam et al. (2016), and Janssen et al. (2016) are some examples of literature reviews in the area of food supply models, including production planning and inventory management considering perishable products. Shukla and Jhakharia (2013) introduce a literature review on the supply chain management of fresh produce. Lemma et al. (2014) focus on approaches to dealing with loss in the food supply chain, while Janssen et al. (2016) classify inventory models for deteriorating products. Finally, Paam et al. (2016) offer a comprehensive survey of planning and optimization models in the agricultural fresh food supply chain, considering food loss.

In this paper we deal with the multi-period, multi-product, multi-warehouse inventory control optimization problem that originates from the inventory management of fresh produce. Few studies present mathematical optimisation formulations for inventory management problems for fresh produce. Some examples are Bhunia et al. (2014), Banerjee and Agrawal (2017), Herbon et al. (2014), and Masini et al. (2007). Bhunia et al. (2014) present a mathematical model for the two-warehouse single-product inventory problem for perishable products considering backlogging. Banerjee and Agrawal (2017) propose an inventory model for perishable products when demand depends on the price and freshness of products. A non-linear mixed integer program model for inventory management of perishable products is proposed by Herbon et al. (2014), also investigating the application of dynamic pricing to products closer to their expiry dates. Finally, Masini et al. (2007) propose an integer linear programming model for determining the optimal production and inventory of fresh fruit and juice. The work of Ramakrishna et al. (2015) is one example that allows shipment between two warehouses in a two-product, two warehouses inventory control problem. The model aims to minimize total costs, including holding, ordering, shipment, and emergency order costs.

One of the most effective technologies for storing fresh produce is a controlled atmosphere storage system, where atmospheric conditions can be adjusted such that the fruits and vegetables can remain longer in storage with no deterioration (Rama and Narasimham, 2003). Regular atmosphere (RA) rooms can control only temperature and humidity, while in controlled atmosphere (CA) rooms, other atmospheric elements, such as oxygen and carbon dioxide levels, are also adjusted. As a result, fresh produce remains longer for consumption in CA rooms; however, they are more expensive.

We have proposed several optimisation mathematical models considering these types of storage for fresh produce, minimising cost and food loss while attending to the market demand. In Paam et al. (2018), we proposed a mixed-integer linear programming mathematical formulation for a single product multi-warehouse inventory problem applied to an Australian apple company. The model determines the optimal warehouse types (RA or CA), minimising cost and food loss. In Paam et al. (2019), we performed a detailed analysis on the impact of the model considering different storage configurations and provided a series of recommendations to empower the inventory performance. More recently, in (Paam et al., 2022), we extended the model to a multi-period, multi-product, multi-warehouse inventory control optimisation problem. The model is tested using real data from an Australian apple company, and the results indicate a reduction in total cost by 8% and quantity of product deterioration by 20%.

In this paper, we extend our previous mathematical model (Paam et al., 2022), making two contributions. The first contribution is the inclusion of transhipment between warehouses, where the fresh produce can be shipped from one warehouse to another. The second contribution is proposing a bi-objective optimisation formulation due to the conflict between two cost components of the objective function in the model presented in (Paam et al., 2022): energy cost of warehouses and deterioration cost. Therefore, in the bi-objective optimisation formulation, the first objective aims to to minimise total inventory and warehousing costs (including transhipment costs), and the second aims to minimise the quantity of deteriorated/loss fresh produce.

The remainder of this paper is organised as follows. Section 2 describes the mixed-integer quadratic programming model considering transhipment between warehouses and the proposed bi-objective function. Then, computational experiments, their results and analysis are depicted in Section 3. Finally, Section 4 concludes the paper.

2. The mixed-integer quadratic programming model

The problem considered in this paper is the multi-period, multi-product, multi-warehouse inventory control optimization problem for the inventory management of fresh produce. The aim is to decide the inventory flow of fresh produce from farms during harvesting, while satisfying the demand during the planning periods. It is also necessary to determine when to turn each warehouse on or off, and the warehouse's mode (RA or CA) in each period, such that the overall cost is minimized. We have proposed a mixed-integer quadratic programming model for this problem (Paam et al., 2022). Below we describe the model, including the extension proposed in this paper: a bi-objective function and considering transhipment between warehouses.

The assumptions for the mathematical formulation are the same as the ones presented in Paam et al., (2022), which are:

- The warehouses can be in RA (Regular Atmosphere) or CA (Control Atmosphere) mode.
- The warehouses always start in RA mode, to receive input, since in CA mode, the warehouse must be closed.
- Warehouses can turn on/off only at the beginning of a period.
- Warehouses can switch modes only at the beginning of a period.
- Inventory levels are calculated at the end of a period.
- A warehouse can be turned on at most once, meaning that it cannot be turned on after it is turned off, as the setup cost to turn on the warehouses is too expensive.
- Each warehouse contains only one product variety, since each product variety requires different atmosphere conditions for storage.
- Deterioration rates are constant (which is different for each product variety, and each mode).
- The inventory level decreases due to demand in RA mode, and due to deterioration rate in RA and CA modes.
- Demand is known and deterministic.
- Shortages are not allowed.

Below, the indices, parameters, and decision variables are listed, and the ones marked with (*) are the ones introduced in this paper.

Indices and sets

$t \in T$: planning periods, where T = {1, …, T'},

$h \in H \subseteq T$: harvesting periods, where H = {1, …, H'},

(*) $\boldsymbol{i}$ & $\boldsymbol{j} \in \boldsymbol{N}$: warehouse, where N= {1, …, N'},

$v \in V$: product varieties, where V= {1, …, V'},

$k \in K$: warehouse modes, where K= {1, …, K'}.

Parameters

QHV_{vh}: input product variety *v* in harvesting period *h* (bin/fortnight),

(*) $\boldsymbol{MWX_i}$: maximum capacity for warehouse *i* (bin),

DEM_{vt}: demand of product variety *v* in period *t* ((bin/ fortnight),

DER_{vk} : deterioration rate of product variety *v* in mode *k* (%/fortnight),

ICT: inventory holding cost of one unit of product ($/bin),

ECT_k: energy cost of warehouses in mode *k* ($/fortnight),

RCT : preparation cost of a warehouse ($),

(*) $\boldsymbol{TCT}$: Transhipment cost of one unit of product between two warehouses ($).

Decision Variables

$qinp_{ivh}$: input quantity of product variety *v* to warehouse number *i* in harvesting period *h*,

$qout_{ivht}$: output quantity of product variety *v* from warehouse number *i* harvested in period *h* in period *t,*

$dloss_{ivht}$: quantity of product loss of variety *v* in warehouse number *i* in period *h* in period *t,*

inv_{ivht}: inventory level of product variety *v* in warehouse number *i* harvested in period *h* at the end of period *t,*

(*) $\boldsymbol{\beta_{ijvt}}$: transhipment quantity of variety *v* from warehouse *i* to warehouse *j* in period *t,*

s_{it}: equal to 1, if warehouse number *i* turns on in period *t*, 0 otherwise,

u_{it}: equal to 1, if warehouse number *i* turns off in period *t*, 0 otherwise,

x_{ivtk}: equal to 1, if warehouse number *i* containing product variety *v* operates under mode *k* in period *t,* 0 otherwise,

y_{iv} : equal to 1, if warehouse number *i* contains product variety *v.*

Mathematical formulation

Objective function:

$$Min[\sum_i \sum_v \sum_h \sum_t ICT\ inv_{ivht} + \sum_i \sum_v \sum_t \sum_k ECT_k \times x_{ivtk} + \sum_i \sum_v \text{RCT} \times s_{it} + \sum_{\boldsymbol{N}} \sum_{\boldsymbol{v}} \sum_{\boldsymbol{t}} \boldsymbol{TCT} \times \boldsymbol{\beta_{jivt}}] \quad (1)$$

$$Min\ [\sum_i \sum_v \sum_h \sum_t dloss_{ivht}] \quad (2)$$

Subject to:

$$QHV_{vh} = \sum_i qin_{ivh} \qquad \forall h \in H, v \in V \quad (3)$$

$$\sum_h \sum_i qou_{ivht} = DEM_{vt} \qquad \forall t \in T, v \in V \quad where\ \ h \leq t \quad (4)$$

$$qin_{iv,h=t} + \sum_{h=1}^{t-1} inv_{ivh,t-1} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}} \leq MWX_i(\sum_k x_{ivtk}) \quad \forall i \in N, v \in V, t \in H, \quad inv_{ivh,t=0} = 0 \quad where\ \ h = t \quad (5)$$

$$\sum_h inv_{ivht-1} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}} \leq MWX_i(\sum_k x_{ivtk}) \quad \forall i \in N, v \in V, t \in T - H \quad where\ \ h < t \quad (6)$$

$$inv_{ivht} = +qin_{ivh} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}} - qout_{ivht} - dloss_{ivht} - \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{ijvt}} \quad \forall\ \text{i} \in \text{N}, v \in V, h \in H, t \in T \quad where\ \ h = t \quad (7)$$

$$inv_{ivht} = inv_{ivh,t-1} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}} - qout_{ivht} - dloss_{ivht} - \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{ijvt}} \quad \forall\ \text{i} \in N, v \in V, h \in H, t \in T \quad where\ \ h < t \quad (8)$$

$$qin_{ivh} + qou_{ivht} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{ijvt}} \leq M1 \times (1 - x_{ivtk=2}) \quad \forall \text{i} \in N, v \in V, h \in H, t \in T \quad where\ \ \text{k} = 2\ \text{(CA) and}\ \ h = t \quad (9)$$

$$qou_{ivht} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{ijvt}} \leq M1 \times (1 - x_{ivtk=2}) \quad \forall \text{i} \in N, v \in V, h \in H, t \in T \quad where\ \ \text{k} = 2\ \text{(CA) and}\ \ h < t \quad (10)$$

$$dloss_{ivht} = (\sum_k DER_{vk} \times x_{ivtk})\,((qin_{ivh} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}}) - qout_{ivht} - \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{ijvt}}) \quad \forall \text{i} \in N, v \in V, h \in H, t \in T \quad where\ \ h = t \quad (11)$$

$$dloss_{ivht} = (\sum_k DER_{vk} \times x_{ivtk})\,((inv_{ivh,t-1} + \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{jivt}}) - qout_{ivht} - \sum_{\mathbf{j=1}}^{\boldsymbol{N'}} \boldsymbol{\beta_{ijvt}}) \quad \forall \text{i} \in N, v \in V, h \in H, t \in T \quad where\ \ h < t \quad (12)$$

$$\sum_t s_{it} \leq 1 \qquad \forall \text{i} \in N \quad (13)$$

$$\sum_v \sum_k x_{ivtk} = \sum_{\tau=1}^{t} (s_{i\tau} - u_{i\tau}) \qquad \forall \text{i} \in N, t \in T \quad (14)$$

$$\sum_v y_{iv} \leq 1 \qquad \forall \text{i} \in N \quad (15)$$

$$\sum_t \sum_k x_{ivtk} \leq \text{K} \times T \times y_{iv} \qquad \forall \text{i} \in N, v \in V \quad (16)$$

Equation (1) is the first objective function that minimizes total inventory and warehousing costs, including the inventory holding cost, the energy cost of warehouses, the preparation cost and the transhipment cost. Equation (2) is the second objective function which minimizes the total quantity of deteriorated/loss product. Constraint (3) guarantees that all fresh produce from the harvest is stored in the warehouses. Constraint (4) ensures that the demand for each product is satisfied. Constraints (5) and (6) are the warehouse capacity constraints where $h=t$ and $h<t$, respectively. They also ensure that when a warehouse does not operate, it has no product inside. Constraints (7) and (8) are inventory balance when h = t and h < t. In the former, input only comes to the warehouses from the harvest, whereas in the latter, inventory only originates from the previous period. It should be noted that for each warehouse, we are balancing the inventory of each variety of product from each harvesting period in each planning period. Moreover, the deteriorated product is depleted from a warehouse in each period after satisfying the demand. Constraints (9) and (10) are active where $h=t$ and $h<t$. They state that if a warehouse operates in CA mode, it has no inventory flow (input or output). They also guarantee that the warehouse mode is RA whenever there is an inventory flow. Furthermore, M1 is the upper bound for $qin_{nvh} + qou_{nvht}$, which we consider to be twice the total demand, $2\ \sum_t \sum_v DEM_{vt}$.

Constraints (11) and (12), which are quadratic, quantify the amount of deteriorated product per period for $h=t$ and $h<t$, respectively. In each period, first, product is taken out of the warehouse to satisfy the demand, and then the

remaining inventory deteriorates based on a fixed deterioration rate. Constraint (13) states that a warehouse is turned on at most once during the whole time horizon. Constraint (14) ensures that if a warehouse operates in period t, it must have been turned on and not turned off from the first period up to period t, and conversely. It also states that each warehouse can have a maximum of one mode in each period. Constraint (15) guarantees that a warehouse contains a maximum of one variety. Constraint (16) ensure that once a warehouse's variety is determined, it remains unchanged from that point onward.

4. Computational results

We initially tested the MIQP model considering only transhipment between warehouses. So, the objective function is the one from Paam et al. (2022). Using the default parameters, we use the mathematical optimization solver Gurobi to find the optimal solution for the MIQP. We randomly generated 25 instances based on the data ranges of the real case study presented in Paam et al. (2022) for the demand and supply of each product. Each instance includes 8 planning periods (T'=8), 3 harvesting periods (H'=3), 8 warehouses (N'=8), 1 variety (V'=1) and 2 modes of warehouses (K'=2) under three different scenarios based on the value of the transhipment cost:

- Transhipment cost less than holding cost ($TCT < ICT$): TCT=1
- Transhipment cost similar to holding cost ($TCT \sim ICT$): TCT=5
- Transhipment cost greater than holding cost ($TCT > ICT$): TCT=10

For each scenario, we run the instances for the original MIQP model from Paam et al. (2022) and the model considering transhipment between warehouses (2)-(16) to check if transhipment between warehouses improves the inventory operation costs.

Table 1 compares the average results of not having transhipment versus having transhipment under three different transhipment costs for the 25 instances. The last row shows the improvement rate for each scenario. If the rate is negative, it means considering transhipment improves the inventory system and minimizes total costs. As shown, for all three scenarios, having transhipment between warehouses improves the inventory operations' costs. Although transhipment cost increases from the lowest to highest TCT, the overall objective function (total cost) decreases. This can be attributed to the reduction in holding and deterioration costs.

Table 1. Average results of no transhipment versus transhipment under three scenarios (TCT=1, TCT=5, TCT=10) for the 25 instances.

	No Transhipment	TCT=1	TCT=5	TCT=10
Total costs ($)	215366	214316	209460	207358
holding Cost ($)	117284	117988	114781	113295
electricity cost ($)	14934	13172	13486	13758
set up cost ($)	6256	5520	5593	5679
Transhipment cost ($)	-	100	258	346
deterioration cost ($)	76892	77535	75342	74279
Total cost Improvement Rate (%)	-	-0.49	-2.82	-3.86

After ensuring that considering transhipment between warehouses improved the overall costs, we tested the model (1)-(16), which considers bi-objective function and the transhipment between warehouses. As described before, the first objective function minimizes warehousing and inventory costs; and the second objective minimizes the quantity of deteriorated products.

For each scenario, we obtained the weighted sum (WeiSum) of the objective function values (OBVs) for nine different combinations of weights between 0 and 1 (w1=0.1 and w2=0.9; w1=0.2 and w2=0.8; …; w1=0.9 and w2=0.1). Table 2 shows the weighted sum of the OBVs for three scenarios of TCT=1, TCT=5 and TCT=10 under nine different combinations of weights for the objective functions.

Table 2. Weighted sum (WeiSum) of OBVs for the bi-objective model with transhipment for three scenarios of TCT=1, TCT=5 and TCT=10; w1: weight for the first objective, w2: weight for the second objective.

Weights	TCT=1			TCT=5			TCT=10		
	OBV1	OBV2	WeiSum	OBV1	OBV2	WeiSum	OBV1	OBV2	WeiSum
w1=0.1, w2=0.9	157291	190	87671	149467	181	83568	152504	184	84710
w1=0.2, w2=0.8	153707	188	93825	141121	173	86470	143513	176	87800
w1=0.3, w2=0.7	152757	191	102120	140009	183	95830	144243	179	95935
w1=0.4, w2=0.6	151643	196	110091	139462	182	101715	141757	182	102553
w1=0.5, w2=0.5	143112	195	112429	137697	186	107857	137932	184	107579
w1=0.6, w2=0.4	133766	194	112817	134957	194	113597	134562	193	113150
w1=0.7, w2=0.3	130908	206	117652	133104	204	118843	132734	202	118362
w1=0.8, w2=0.2	128741	222	121613	129274	223	122171	129228	228	122503
w1=0.9, w2=0.1	121832	332	123608	120826	386	124947	121347	354	124101

Figures 1-3 display the pareto fronts of objective function values for scenarios of TCT=1, TCT=5 and TCT=10, respectively. In all figures, moving from left to right, the points represent w1=0.9 and w2=0.1, w1=0.8 and w2=0.2, …, w1=0.1 and w2=0.9. These pareto fronts provide a decision-making scheme for managers by allowing them to decide on the best trade-off between warehousing and inventory costs (OBV1) and the quantity of deteriorated products (OBV2).

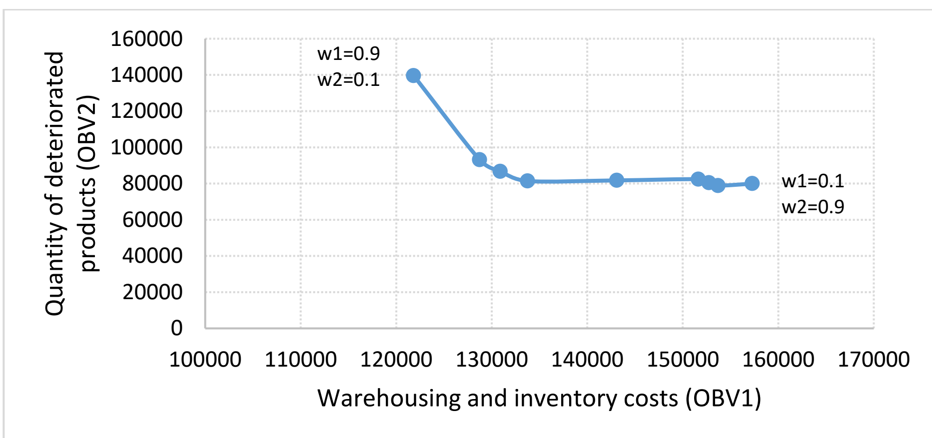

Figure 1. Pareto front of OBVs for TCT=1

Figure 2. Pareto front of OBVs for TCT=5

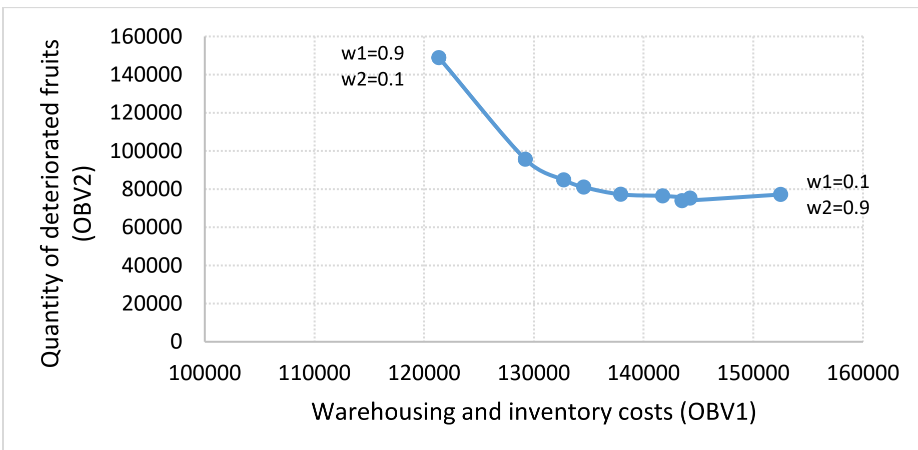

Figure 3. Pareto front of OBVs for TCT=10

6. Conclusion

This paper considered the multi-period, multi-product, multi-warehouse inventory control optimization problem for the inventory management of fresh produce. We have extended a proposed mixed-integer quadratic programming model (Pam et al., 2022), allowing transhipments between warehouses and presenting a bi-objective function.

We tested the mathematical formulations in two phases. First, we tested the performance of the model only with transhipment between warehouses (without the bi-objective function). Next, we tested the model employing the bi-objective function and transhipment between warehouses. For both computational tests, we used the mathematical optimisation software Gurobi using 25 instances randomly generated based on the case study from Pam et al. (2022).

In the first phase of the computational experiments, the transhipment costs are divided into three categories, which are less, similar, or greater than the electricity costs. The results show that, independently of the transhipment cost, the overall inventory system costs are minimised.

Finally, in the second phase, we conducted computational experiments using the model with the bi-objective function and allowing transhipment between warehouses. We have summed both objective functions with weights from w1=0.1 and w2=0.9, to w1=0.9 and w2=0.1, and we presented the Pareto front results. The Pareto front results (Figure 1, 2 and 3) shows the trade-offs between both objective functions, suggesting possible strategies to managers.

One of the limitations of this study is not considering supply uncertainties due to, for example, weather conditions. In addition, demand uncertainties and shortage allowance. Another limitation is the computational time needed to run mixed-integer programming problems using optimal methods, such as those available in software packages such as Gurobi. One possible extension is developing and implementing heuristics and metaheuristics to improve the computational efficiency when applying the model in larger instances of the problem.

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Biographies

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