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A Joint Optimization Model for Dispatching Straw Balers and Transporters in Sustainable Agriculture

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Abstract

As sustainable agriculture continues to develop, straw recycling has become an effective step for conserving agricultural residues. In practice, farmers submit recycling requests to an enterprise, which then dispatches balers before arranging transporters. This sequential planning process creates delays between baling and transportation and increases total costs. A synchronized baling transportation framework is developed in this study. A joint optimization model is formulated to minimize total costs, and a Branch and Bound Algorithm strengthened with strong valid inequalities is developed to solve it. Numerical experiments using data from Heilongjiang, China, show that the proposed approach obtains high-quality solutions within reasonable computation times and lowers total cost. This study offers a practical method for the operation and management of straw recycling enterprises.

Keywords: straw recycling; agricultural machine scheduling; agricultural machinery management; sustainable agriculture

1. Introduction

Agricultural mechanization is an important means of improving production efficiency [1]. It is reducing the dependence of field operations on manual labor [2], shortening operation cycles, and improving timeliness [3]. However, a lack of synchronization between upstream operating fleets and downstream transport fleets weakens the benefits of mechanization in multi-stage operations [4–8]. This inefficiency also limits the carbon reduction potential of straw recycling. Therefore, efficient agricultural residue recovery is important for supporting low-carbon and sustainable development [9].

In agricultural production, upstream operating fleets are arranged first, and downstream transport fleets are then organized based on the results of upstream operations. This approach tends to cause waiting and empty travel, reduce machine utilization, and prolong the overall operation cycle, thereby increasing ineffective energy consumption and operating costs. It weakens the benefits of mechanization and is not conducive to sustainable agricultural production. Therefore, joint scheduling and synchronized optimization of multi-stage operations provide a methodology for resource conservation and efficient utilization in sustainable agriculture.

Existing studies have investigated agricultural machinery scheduling problems, including minimizing non-working travel distance in in-field routing [10], minimizing to-

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tal operational costs [11,12], scheduling machinery with time-window constraints [13], and minimizing total working time [5]. In addition, harvesting transportation scheduling [6,14–17] and harvesting-straw returning problems [18] are also studied. Despite these advances, the integrated optimization of baling transportation has received limited attention. Compared with conventional harvesting transportation coordination, straw baling transportation operations involve stricter precedence relationships and capacity-dependent unloading decisions. These characteristics strengthen the coupling between balers and transporters, making sequential planning inefficient.

This study aims to investigate the coordinated scheduling problem of straw balers and transporters in straw recycling operations. First, a joint optimization model is proposed to minimize total costs by determining the routes of straw balers and transporters. The model considers that different field sizes should be served by different types of agricultural machines. It also incorporates the capacity constraint of transporters. If a transporter does not have sufficient remaining capacity to serve the next field during operation, it unloads its current load before working. Second, exploiting the properties of the optimal solution, two strong valid inequalities are derived to strengthen the formulation, and an enhanced Branch and Bound Algorithm (BB) is developed. Finally, numerical experiments using a real-world dataset from Heilongjiang Province, China, are conducted to evaluate the effectiveness and efficiency of our method.

This study makes three main contributions. First, this research focuses on a real-life agricultural machine scheduling problem for straw recycling in sustainable agriculture. Particularly, the relationship between machine type and field size is considered in this model. Second, two strong valid inequalities are derived by analyzing the properties of the optimal solution, and a Branch and Bound Algorithm enhanced with these inequalities is developed to solve the problem. Comparative results with existing algorithms demonstrate that the proposed method obtains more optimal solutions within reasonable computation times. Third, the results show that improving only the efficiency of balers or transporters does not necessarily minimize total costs, which theoretically reveals the structural coupling between the two stages and practically offers clear guidance for capacity investment. These results indicate that straw recycling enterprises should pay attention to the matching of machine efficiency between the two operation processes. Therefore, the proposed integrated scheduling method facilitates less costly straw recycling for recycling enterprises and contributes to the development of sustainable agriculture.

The remainder of this study is organized as follows. Section 2 reviews the literature on straw management. Section 3 describes the research problem and develops the mathematical model. Section 4 introduces the proposed Branch and Bound Algorithm with strong valid inequalities (BBW). Section 5 reports numerical experiments and computational performance analyses. Section 6 summarizes this study and discusses future research directions.

2. Literature Review

To clarify how this study differs from prior work, this section reviews research on straw collection and baling, agricultural machinery scheduling, and algorithms for agricultural machinery scheduling.

The utilization, collection, and treatment of straw, as a by-product, received increasing attention in recent years [19–21]. Existing studies cover resources, feed, and substrate uses of straw [22–27]; the environmental and farming household impacts of straw collection [28–30]; and the industrial applications of straw [31–33]. In addition, the research on straw baling has focused on the design of balers [34,35], the baling process [36,37], and the economic benefits of straw baling [38–40]. Although existing studies have investigated straw utilization, collection, and baling, most focus on technical or economic aspects rather than operational decision making. Consequently, the scheduling of straw balers remains insufficiently addressed.

Agricultural machinery scheduling has been investigated across different machine types, agricultural processes, and operating conditions. In harvester scheduling, existing studies have optimized field service sequences, machinery allocation, and harvesting time arrangements to reduce harvesting periods, operational costs, and quality losses [41–44]. Beyond harvesting machinery, the scheduling of planters, refilling vehicles, tractors, and tillage equipment has also been studied to reduce operational delays and timeliness losses [45–47]. For harvest operations, researchers have further considered harvest and transport coordination as well as harvester and operator assignment, with attention to vehicle capacity, time-window constraints, operator capability matching, scheduling cost, and machine waiting time [48–51]. Agricultural machinery scheduling has also been extended to maintenance service planning and emergency rescheduling under machine failures, indicating the importance of machine availability and disturbance response in mechanized agricultural operations [52–54]. Moreover, some studies have incorporated operating condition factors, such as soil workability, field readiness, semi-arid production systems, and wet or non-workable soil conditions, showing that environmental and soil conditions can affect the feasibility and timing of machinery operations [47,55]. For straw management operations, Wang, Wei [18] developed an integrated scheduling framework for synchronizing harvesting and straw returning, and Wang, Zhou [56] further proposed a synchronized framework for straw recycling logistics. However, matching between field area and machine capability, as well as exact algorithmic solutions, remains insufficiently investigated in straw baler and transporter routing. Therefore, this study develops a joint optimization model and a Branch and Bound Algorithm strengthened with valid inequalities for this problem.

Algorithms used for agricultural machinery scheduling include the adaptive large neighborhood search [13,57], the particle swarm optimization [18,58], the genetic algorithm [15,59,60] and the Tabu search algorithm [44]. In addition, the Branch and Bound Algorithm [43,49,61] has also been widely applied. The Branch and Bound Algorithm tends to suffer from a weak lower bound in the initial linear relaxation and a large search space. Therefore, this study introduces two strong valid inequalities to reduce that and develops a BBW to solve the proposed problem.

Overall, prior studies have paid limited attention to straw recycling logistics as an integrated scheduling problem. A coordinated optimization framework is established for straw baling and transportation. A Branch and Bound Algorithm with strong valid inequalities is further developed to improve solution efficiency. The framework is tested using field-operation data from Heilongjiang Province, China, and the results provide operational guidance for improving the coordination and cost efficiency of straw recycling enterprises.

3. Problem Formulation

The problem considered a two-fleet dispatching and routing problem in mechanized field operations, where the straw balers and the transporter fleet are coordinated under precedence and capacity constraints. Field size is used as the basis for matching machines to tasks. Once assigned, each machine follows a planned route from the origin depot to the designated fields and finally returns to the destination depot. Transportation service at each field is initiated only after the baling task has been completed. In practical operations, the bale output from a single field generally remains within the transporters' load capacity. It is assumed that the bale output from any single field does not exceed the capacity of any transporter. In field operations, once a transporter lacks sufficient remaining capacity for the next field or becomes fully loaded, it first travels to the unloading point and then proceeds with subsequent collection tasks. In addition, basic maintenance should be performed on the agricultural machines before working.

The symbols and parameters adopted are described below.

0: starting warehouse;

r: terminal depot;

X: farmland set, with x, y, and z representing field indices;

I: baler set, with i representing a baler;

L: transporter set, with l representing a transporter;

N: transportation route-type set, $N = \{1, 2\}$. Type 1 denotes direct travel from field x to field y. Type 2 denotes travel from field x to field y after visiting one unloading point;

φ_l: maximum carrying capacity of transporter l;

e_i: working efficiency of baler i;

a_l: working efficiency of transporter l;

b_{xl}: load state of transporter l upon reaching field x;

c_{xl}: load state of transporter l after completing service at field x;

q_x: area of farmland x;

$q_x{}'$: bale quantity generated from farmland x after baling;

ω_{xy}: travel time from node x to node y for balers;

ω_{xy}^{n}: travel time from node x to node y under transporter route type $N = \{1, 2\}$;

ω_{xi}: arrival time of baler i at field x;

ω_{xl}: arrival time of transporter l at field x;

ω_{zxi}^{setup}: setup time for baler i before moving from z to x;

$\omega_{zxl}^{n,setup}$: setup time for transporter l before moving from z to x under route type $N = \{1, 2\}$;

M: a sufficiently large constant;

m_{yi}: =1 if baler i is suitable for field y according to field area and machine capability, =0 otherwise;

m'_{yl}: =1 if transporter l is suitable for field y according to field area and machine capability, =0 otherwise;

ρ_{xyi}: binary variable equal to 1 if baler i travels from x to y; and 0 otherwise;

ε_{xyl}^{n}: binary variable equal to 1 if transporter l travels from x to y via route type $N = \{1, 2\}$, and 0 otherwise;

d_{xy}: travelling cost incurred by baler i from x to y;

$d_{xy}^{n'}$: travelling cost incurred by transporter l from x to y under route type $N = \{1, 2\}$;

The baler-transporter scheduling model is expressed as follows:

$$Min \sum_{x\in X\cup\{0\}} \sum_{y\in X\cup\{r\}} \left(\sum_{i\in I} d_{xy} \cdot \rho_{xyi} + \sum_{l\in L} \sum_{n\in N} d_{xy}^{n'} \cdot \varepsilon_{xyl}^{n} \right) \quad (1)$$

Subject to

$$\sum_{y\in X} \rho_{0yi} = 1, \forall i \in I \quad (2)$$

$$\sum_{y\in X} \rho_{xri} = 1, \forall i \in I \quad (3)$$

$$\sum_{y\in X} \sum_{n\in N} \varepsilon_{0yl}^{n} = 1, \forall l \in L \quad (4)$$

$$\sum_{x\in X} \sum_{n\in N} \varepsilon_{xrl}^{n} = 1, \forall l \in L \quad (5)$$

$$\sum_{i\in I}\sum_{x\in X\cup\{0\}}\rho_{xyi}=1,\forall y\in X \tag{6}$$

$$\sum_{l\in L}\sum_{x\in X\cup\{0\}}\sum_{n\in N}\varepsilon^{n}_{xyl}=1,\forall y\in X \tag{7}$$

$$\sum_{x\in X\cup\{0\}}\rho_{xyi}=\sum_{z\in X\cup\{r\}}\rho_{yzi},\forall i\in I,y\in X \tag{8}$$

$$\sum_{x\in X\cup\{0\}}\sum_{n\in N}\varepsilon^{n}_{xyl}=\sum_{z\in X\cup\{r\}}\sum_{n\in N}\varepsilon^{n}_{yzl},\forall y\in X,l\in L \tag{9}$$

$$b_{0l}=0,\forall l\in L \tag{10}$$

$$b_{rl}=0,\forall l\in L \tag{11}$$

$$c_{yl}-b_{yl}=q'_{y}\cdot\sum_{x\in X\cup\{0\}}\sum_{n\in N}\varepsilon^{n}_{xyl},\forall y\in X,l\in L \tag{12}$$

$$b_{yl}\le c_{xl}+\varphi_{l}\cdot\left(1-\varepsilon^{1}_{xyl}\right),\forall x\in X,y\in X\cup\{r\},l\in L \tag{13}$$

$$b_{yl}\le\varphi_{l}\cdot\sum_{x\in X}\varepsilon^{1}_{xyl},\forall y\in X\cup\{r\},l\in L \tag{14}$$

$$b_{yl}\ge c_{xl}-\varphi_{l}\cdot\left(1-\varepsilon^{1}_{xyl}\right),\forall x\in X,y\in X\cup\{r\},l\in L \tag{15}$$

$$c_{yl}\le\varphi_{l},\forall y\in X,l\in L \tag{16}$$

$$\omega_{xi}+\sum_{z\in X\cup\{0\}}\rho_{zxi}\cdot\left(\omega^{setup}_{zxi}+\frac{q_x}{e_i}\right)+\rho_{xyi}\cdot\omega_{xy}-\omega_{yi}\le(1-\rho_{xyi})\cdot M,\forall x\in X\cup\{0\},y\in X\cup\{r\},i\in I \tag{17}$$

$$\omega_{xl}+\sum_{z\in X\cup\{0\}}\sum_{n\in N}\varepsilon^{n}_{zxl}\cdot\left(\omega^{n,setup}_{zxl}+\frac{q'_x}{a_l}\right)+\sum_{n\in N}\varepsilon^{n}_{xyl}\cdot\omega^{n}_{xy}-\omega_{yl}\le\left(1-\sum_{n\in N}\varepsilon^{n}_{xyl}\right)\cdot M,\forall x\in X,y\in X\cup\{r\},l\in L \tag{18}$$

$$\sum_{i\in I}\omega_{xi}+\sum_{z\in X\cup\{0\}}\sum_{i\in I}\rho_{zxi}\cdot\left(\omega^{setup}_{zxi}+\frac{q_x}{e_i}\right)\le\sum_{l\in L}\omega_{xl}+\sum_{z\in X\cup\{0\}}\sum_{n\in N}\sum_{l\in L}\varepsilon^{n}_{zxl}\cdot\omega^{n,setup}_{zxl},\forall x\in X \tag{19}$$

$$\omega_{xl}-M\cdot\sum_{z\in X\cup\{0\}}\sum_{n\in N}\varepsilon^{n}_{zxl}\le 0,\forall x\in X,l\in L \tag{20}$$

$$\omega_{xi}-M\cdot\sum_{z\in X\cup\{0\}}\rho_{zxi}\le 0,\forall x\in X,i\in I \tag{21}$$

$$\sum_{x\in X\cup\{0\}}\rho_{xyi}-m_{yi}\le 0,\forall y\in X,i\in I \tag{22}$$

$$\sum_{x\in X\cup\{0\}}\sum_{n\in N}\varepsilon^{n}_{xyl}-m'_{yl}\le 0,\forall y\in X,l\in L \tag{23}$$

$$\rho_{xyi}\in\{0,1\},\forall i\in I,x\in X\cup\{0\},y\in X\cup\{r\},x\ne y \tag{24}$$

$$\varepsilon^{n}_{xyl}\in\{0,1\},\forall l\in L,x\in X\cup\{0\},y\in X\cup\{r\},n\in N,x\ne y \tag{25}$$

$$m_{yi}\in\{0,1\},\forall y\in X,i\in I \tag{26}$$

$$m'_{yl}\in\{0,1\},\forall y\in X,l\in L \tag{27}$$

$$b_{xl}\ge 0,\forall l\in L,x\in X\cup\{0,r\} \tag{28}$$

$$c_{xl}\ge 0,\forall l\in L,x\in X\cup\{0,r\} \tag{29}$$

$$\omega_{xi}\ge 0,\forall i\in I,x\in X\cup\{0,r\} \tag{30}$$

$$\omega_{xl}\ge 0,\forall l\in L,x\in X\cup\{0,r\} \tag{31}$$

Objective (1) minimizes the total costs. Constraints (2)–(5) define the departure and return requirements for the machines, requiring each baler and transporter to start from the origin depot and finish at the destination depot. Constraints (6) and (7) assign each field to exactly one baler and one transporter, respectively. Constraints (8) and (9) maintain flow balance for straw balers and transporters for each field, respectively. Constraints (10) and (11) specify that each transporter has 0 load at the origin and destination depots. Constraint (12) describes the load update after a transporter completes service at a field. Constraints (13)–(15) ensure the load-transfer logic under the two transportation route types: for route type 1, the carried load is transferred directly to the next field, whereas for route type 2, the transporter unloads before continuing. Constraint (16) restricts the transporter load within its capacity. Constraints (17) and (18) determine the arrival times of balers and transporters along their assigned routes. Constraint (19) imposes the precedence relation between baling and transportation, requiring transportation at a field to start only after baling has been completed. Constraints (20) and (21) force the arrival time to be 0 when the corresponding machine does not visit a field. Constraints (22) and (23) ensure that fields of different sizes are cultivated by agricultural machinery with matching working capabilities. Constraints (24)–(31) introduce decision variables and non-negative variables.

4. Solution Methodology

This section introduces the proposed methodology for solving the straw baling transportation synchronization problem. To better capture the structural characteristics of the problem, two families of strong valid inequalities are developed.

Proposition 1. $\varepsilon^2_{0yl} \leq \varepsilon^1_{0yl}, \forall y \in X, l \in L.$

Proof. In this problem, transporters are provided with two routing types based on their remaining capacity. If a transporter has sufficient residual capacity to serve the next field after completing service at the current field, it will select "Route 1" (i.e., $\varepsilon^1_{xyl} = 1$). Conversely, if the remaining capacity is insufficient for the next field, the transporter selects "Route 2" (i.e., $\varepsilon^2_{xyl} = 1$). It is assumed that each transporter departs from the starting warehouse with zero load, and full capacity is sufficient to serve any single field. Therefore, unloading is unnecessary when a transporter travels from the starting warehouse to the first field. Accordingly, a constraint is imposed that enforces the "Route 1" selection for this initial trip. □

Proposition 2. $\varepsilon^2_{xrl} \geq \varepsilon^1_{xrl}, \forall x \in X, l \in L.$

Proof. Similarly, when a transporter completes service at the last field and prepares to return to the terminal depot, the constraint requiring the transporter to arrive at the depot with zero load enforces the selection of "Route 2" (i.e., $\varepsilon^2_{xyl} = 1$), detouring to unload before reaching the terminal depot. □

A Branch and Bound Algorithm is developed for the proposed baler-transporter routing problem. Figure 1 summarizes the main search logic of the proposed procedure. The solution procedure involves branching, bounding, node pruning, and integer feasibility verification. The algorithm starts from the root node (P = 0) and generates child nodes level by level (e.g., nodes 2–4 at P = 1 and nodes 5–7 at P = 2). When the relaxation at a node already satisfies integrality, its objective value is used to update the incumbent solution. If its objective value is worse than the current best solution, the node is pruned. The proposed procedure differs from a standard tree search by embedding route-type cuts during node evaluation rather than relying on the original relaxation (e.g., node 5 at

P = 2). The added route-type cuts remove relaxation solutions that violate the loading-state logic while preserving all feasible integer schedules. This strengthens node-level bound evaluation and reduces unnecessary exploration in the search tree. At each active node, the linear programming relaxation solution is checked against the route-type inequalities derived from Propositions 1 and 2. If any inequality is violated, the corresponding route-type cut is generated and appended to the current node relaxation before the relaxation is re-optimized.

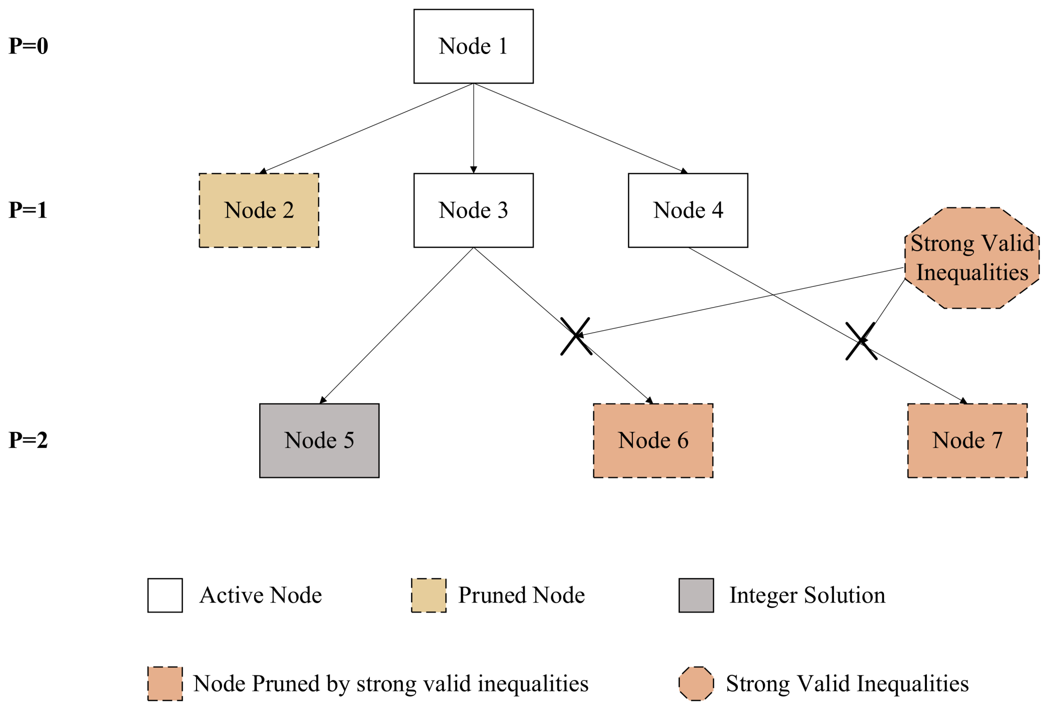

Figure 1. The Branch and Bound Algorithm with strong valid inequalities.

5. Numerical Experiment

This section first applies our method to a real-world dataset and evaluates its effectiveness via a comparison with a Branch and Bound Algorithm. Second, the practicality of our method is demonstrated by comparing the results with other heuristic algorithms. Finally, the minimum total cost is analyzed under different efficiency levels of straw balers and transporters.

5.1. Experiment Description and Design

The computational case is based on field data collected in Heilongjiang Province, China, involving 55 fields, six straw balers, and five transporters. The baler fleet consists of two types, including three units with a working efficiency of 0.006 km^2/h and three units with a working efficiency of 0.0043 km^2/h. The transporter fleet includes two capacity classes, with three 6000 kg transporters and two 4500 kg transporters. The instance sizes and machinery configurations were selected based on actual straw recycling operations in Heilongjiang Province to represent different operational scales encountered in real-world applications. The field and machinery data were obtained from operational records, and the transporter fleet consists of five units, one fewer than the baler fleet.

The proposed methodology is bench-marked against a Branch and Bound Algorithm on a real-world case to verify effectiveness. Further tests are performed on additional instances with different field scales and fleet configurations. The proposed method is evaluated against three benchmark algorithms, Tabu search (TS), simulated annealing (SA), and ant colony optimization (ACO), based on the average objective values obtained from

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15 independent runs. The effect of baler and transporter efficiency levels on the minimum total cost is examined.

All algorithms are implemented in Python 3.13 and run on a workstation with an Intel Core i7-13620H processor at 2.40 GHz and 16.0 GB RAM. The total cost values are reported in units of CNY 10 to avoid scale effects. Thus, a reported value of 1000 corresponds to an actual cost of CNY 10,000.

5.2. Comparison Analysis with the Branch and Bound Algorithm

The proposed method is bench-marked against the standard Branch and Bound Algorithm on instances of different scales, with the number of fields varying from 25 to 55. The total runtime of the algorithm is set to 7200 s. The *Gap* is computed as the difference between each performance metric obtained by the proposed method and the corresponding value yielded by the Branch and Bound Algorithm. A positive *Gap* indicates that the proposed method performs better.

Table 1 presents the computational results. Columns 1–3 describe the instance size in terms of fields, straw balers, and transporters. Columns 4–7 report the objective value (*ObV*) and MIP*Gap* of the proposed algorithm and BB, while the final column gives the *ObV* difference between the two methods.

Table 1. Performance comparison of BBW and BB algorithm.

Instance			*ObV*		MIP*Gap*		*Gap*
$\vert X\vert$	$\vert I\vert$	$\vert L\vert$	BBW	BB	BBW	BB	
25	3	2	378.85	383.96	21.14%	24.51%	5.11
30	4	3	463.66	464.72	31.11%	31.42%	1.06
35	4	3	513.43	532.44	37.58%	39.71%	19.01
40	5	4	592.23	610.25	37.67%	39.31%	18.02
45	5	4	611.20	611.31	35.65%	36.06%	0.11
50	6	5	713.07	725.38	41.26%	41.78%	12.31
55	6	5	1248.76	1273.24	44.02%	44.62%	24.48

The numerical results support the following observations.

- As the problem size increases, both algorithms experience greater difficulty in reaching convergence within the prescribed computational time limit. When the number of fields increases from 25 to 55, the MIP*Gap* rises from 21.14% to 44.62%. This indicates that increasing the problem size results in a rapid expansion of the branch and bound search space, thereby substantially increasing computational difficulty within a time limit.
- In terms of the *ObV*, our method obtains a lower cost within the fixed time limit for the majority of instances. The *Gaps* are positive for all instances, and the advantage becomes more pronounced for medium-scale and large-scale cases, reaching a maximum of 24.48. Overall, our method identifies higher-quality feasible solutions within a limited time budget, thereby helping relevant enterprises reduce operational costs and improve efficiency.
- In terms of MIP*Gap*, the incorporation of strong valid inequalities improves the quality of feasible solutions and enhances overall convergence toward optimality. The MIP*Gap* values produced by our approach are lower than those of the BB algorithm. This suggests that strong valid inequalities tighten the relaxation and eliminate ineffective branches, enabling the algorithm to identify lower-cost solutions within the same time budget. Although large-scale instances still have relatively high gaps of around 40%, our method demonstrates more stable convergence than the BB algorithm.

In summary, under a limited time budget, increasing instance size substantially raises the computational difficulty. Meanwhile, our method achieves both a lower total cost and a smaller MIP*Gap* for all instances, with advantages that are more pronounced in large-scale operating scenarios. Therefore, our approach is well suited as a high-quality solution method in practical applications.

5.3. Comparison with Other Solutions

This section benchmarks BBW against ACO, TS, and SA using instances with different numbers of fields, balers, and transporters. Each algorithm is run independently 15 times for each instance, and the average objective value is reported. For all instances, the maximum iteration number was set to 500; the number of ants in ACO was set to 100; the Tabu length in TS was set to 20; and the initial temperature and cooling rate in SA were set to 2000 and 0.95, respectively.

Table 2 reports the experimental results. Columns 1–3 describe the instances, and Columns 4–6 report the ObV obtained by ACO, TS, and SA over 15 independent runs. Columns 7–9 provide the ObV gaps relative to these baselines. The *Gap* is calculated as the relative difference between BBW and the corresponding comparison algorithm, normalized by the latter. Positive gaps imply that BBW yields better results. The mean *Gap* is provided in the last row.

Table 2. Computational results of BBW compared with ACO, TS, and SA.

Instance			*ObV*			*Gap*		
$\lvert X \rvert$	$\lvert I \rvert$	$\lvert L \rvert$	**ACO**	**TS**	**SA**	**ACO**	**TS**	**SA**
20	3	2	481.79	679.79	604.85	27.84%	48.86%	42.52%
25	3	2	538.89	762.39	734.83	29.70%	50.31%	48.44%
30	4	3	646.69	1005.39	920.76	28.30%	53.88%	49.64%
35	4	3	715.49	1199.48	1041.34	28.24%	57.20%	50.70%
40	5	4	888.34	1302.58	1224.65	33.33%	54.53%	51.64%
45	5	4	985.74	1514.85	1372.44	38.00%	59.65%	55.47%
50	6	5	1167.41	1782.71	1648.75	38.92%	60.00%	56.75%
55	6	5	1567.78	2469.69	2355.79	20.35%	49.44%	47.00%
					Avg	30.59%	54.23%	50.27%

The numerical experiments lead to the following findings.

- The *Gap* values are positive across all instances, indicating that our method stably generates solutions superior to those of ACO, TS, and SA within the 2 h time limit. The average *Gap* in the last row demonstrates BBW improvements of 30.59%, 54.23%, and 50.27% over ACO, TS, and SA, respectively. This performance advantage is attributed to the incorporation of strong valid inequalities, which tighten the feasible region and improve the efficiency of the branch and bound search process. In contrast, ACO, TS, and SA rely on heuristic search mechanisms and experience a reduction in solution quality as problem size increases. As a result, the superiority of BBW becomes more pronounced for these instances.
- From the comparative results across algorithms, ACO delivers higher-quality solutions than TS and SA. This suggests that our method obtains better solutions within a limited time budget since it has stronger search and convergence performance, although ACO exhibits strong search capability for these synchronized scheduling problems.
- With the instance size increases, our method maintains a pronounced advantage over the three heuristic algorithms. The improvement over ACO ranges from 20.35% to 38.92%, the improvement over TS ranges from 48.86% to 60.00%, and the improve-

ment over SA ranges from 42.52% to 56.75%. These results indicate that the BBW more effectively reduces the search space and obtains higher-quality feasible solutions within a limited time budget, thereby sustaining its performance advantage in complex scenarios.

- Overall, our method achieves a lower total cost in all tested instances within the limited time budget. Therefore, it is not only well suited as a high-quality solution approach for practical production scheduling but also serves as a reliable benchmark for evaluating the solution quality of heuristic algorithms.

5.4. Sensitivity Analysis

Straw baling and transportation constitute two interdependent stages in straw recycling logistics. This study formulates a joint optimization problem to capture their interactions and to derive new insights into multi-stage scheduling. To examine the influence of machine performance variation, several baler and transporter configurations with different efficiency levels are evaluated. Six representative working efficiency levels are selected based on practical operating conditions, and experiments are conducted across these six levels. The six efficiency levels were designed to represent different practical machinery performance scenarios observed in straw recycling operations, ranging from relatively low to high operating efficiencies. Ensure that each machine operates at a different efficiency within each level. Table 3 reports the detailed results. Table 3 lists the field number and the two efficiency-level settings, *ObV*, and MIP*Gap*.

Table 3. Sensitivity results under different baler and transporter efficiency levels.

Instance			*ObV*	MIP*Gap*
$\lvert X \rvert$	Efficiency Level of Straw Balers	Efficiency Level of Transporters		
55	1	3	1249.48	43.86%
	2		1126.24	37.70%
	3		1083.33	34.96%
	4		1116.31	37.27%
	5		1169.65	39.99%
	6		1224.25	42.57%
	3	1	1244.45	43.57%
		2	1156.13	38.87%
		3	1083.33	34.96%
		4	1055.31	33.41%
		5	1150.60	38.51%
		6	1098.37	36.10%

With the transporter efficiency fixed at the third level, increasing the baler efficiency leads to a non-monotonic change in the objective function value. The *ObV* first decreases from 1249.48 to 1083.33, reaches its optimum at the third level, and then increases to 1224.25. Correspondingly, the MIP*Gap* first decreases from 43.86% to 34.96% and then increases again to 42.57%. These results indicate that, when transportation capacity is constant, a moderate increase in baling capacity effectively reduces total cost. However, when the baling efficiency is further improved without a corresponding increase in transportation capacity, the operational bottleneck shifts from the baling stage to the transportation and handover stages. This leads to increased waiting at the post-baling, pre-transport stage, causing both the total cost and the MIP*Gap* to rise again.

Furthermore, the baler efficiency is fixed at the third level. When the transportation efficiency increases from the first level to the fourth level, the *ObV* decreases significantly from 1244.45 to 1055.31, corresponding to a reduction of about 14.5%. Meanwhile, the MIP*Gap* decreases from 43.57% to 33.41%, indicating that enhancing transportation capacity improves the total cost within the time limit. Notably, when the transportation efficiency further increased, the *ObV* began to rise. This implies that upgrading transportation capacity alone may increase hidden costs, such as empty trips, waiting, or congestion at unloading points, thereby preventing reductions in the total cost.

In summary, three managerial insights are drawn from the sensitivity analysis. First, improving baler efficiency does not necessarily reduce the total cost when transportation capacity remains unchanged. Second, increasing transporter efficiency may also lead to diminishing returns due to operational imbalances between the two stages. Third, the coordinated matching of baler and transporter capacities is more important than pursuing the maximum efficiency of a single machine type. Therefore, straw recycling enterprises should emphasize balanced machinery configuration when planning recycling operations.

6. Conclusions

A synchronized decision framework is established to coordinate straw baling with transportation. A MILP formulation coupled with route scheduling decisions and a Branch and Bound Algorithm with strong valid inequalities are designed to improve computational efficiency. Field-operation data from Heilongjiang Province, China, are used to evaluate the model and derive managerial implications for straw recycling services.

The computational results show that BBW obtains lower objective values and smaller MIP*Gap* values than the standard Branch and Bound Algorithm under the same runtime limit. In particular, under a fixed time budget, BBW achieves lower objective values and more stable convergence in most instances, with its advantage becoming pronounced as the instance size grows, highlighting its robustness in large-scale instances. Compared with ACO, TS, and SA, BBW outperforms them in each instance and maintains an advantage as the problem size increases. Furthermore, the working matching between different efficiency levels of straw balers and transporters is investigated. It is observed that an increase in the efficiency of one operation stage shifts the bottleneck to the other stage, resulting in an increase in total costs. These findings suggest that straw recycling enterprises should emphasize capacity matching rather than maximizing the efficiency of a single machine type when configuring machinery fleets. In practical operations, balancing the efficiencies of balers and transporters could help reduce waiting, avoid resource underutilization, and achieve lower operational costs. The proposed methodology shows reliable computational efficiency and robustness across the instances.

Future research should extend the model to multi-objective scheduling of straw balers and transporters. An improved heuristic algorithm should also be developed to ensure that the optimal solution is obtained in a shorter time. Time-window requirements and links with other operations, such as harvesting and straw storage, should be included to represent the full straw-recovery logistics chain more completely.

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