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Stochastic Programming Model for Household Waste Transportation based on Benders Decomposition Algorithm

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Abstract

To adapt to the current new situation of waste classification and deposition in Shanghai, the article built a stochastic programming model for the collection and transportation network of household waste, with the lowest total cost as the goal. It was a multi-stage transportation model aiming at determining the best operation time of all stations and the optimal flowing scheme of waste. The article considered the uncertainty of the quantity of household waste produced by residents, and used Benders decomposition algorithm to solve the model. Its acceleration effect was verified by simulation examples. Meanwhile the critical number of discrete scenes in the model was also determined which made the optimal value of objective function tend to be stable. The model proposed in this paper can provide decision-making basis for the dispatching and route selection of waste collection and transportation vehicles in Shanghai.

Keywords

Household Waste; Transportation; Stochastic Programming; Benders Decomposition.

1. Introduction

Since the implementation of the Shanghai Municipal Household Waste Management Regulations in July 2019, the quality of waste classification in Shanghai, China has steadily improved, with a significant increase in the proportion of wet waste compared to the past. At the same time, the types of boxes for dry and wet waste are also different, which has forced the front-end collection, middle-end transfer, and end-of-life disposal to adjust as quickly as possible to adapt to Shanghai's current waste classification environment. So far, in the actual operation process, there have been incidents of leaking and blockages of wet waste transportation vehicles due to limited quantity and performance, and a serious shortage of wet waste treatment facilities, leading to their incineration. Therefore, the re-planning of Shanghai's household waste collection and transportation network has become one of the most urgent tasks.

The planning of household waste collection and transportation network is an important part of comprehensive management of household waste in the existing literature [1]. With the exponential growth of the world's population and industries, waste generation has become a major environmental and public health concern [2]. Uncontrolled waste disposal can lead to contamination of soil, water, and air, which can cause significant harm to human health and the ecosystem [3]. Under such circumstances, waste management has gained significant attention in recent years. Its primary objective is to ensure proper disposal of waste while minimizing its impact on human health and the environment [4]. Therefore, proper waste management practices are crucial to the sustainable development of society, and existing research often uses a multi-level transportation model to study waste management systems and processes [5].

In Shanghai, due to the introduction of waste classification regulations and the concept of Zero-waste city, the process of household waste treatment has also changed. It is currently generally

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divided into the following steps: classification at the source of waste generation, with dry and wet waste being transported and transferred by different vehicles, and disposed of in different places, and finally all residues are landfill. This process involves many strategic and decision-making behaviors, such as the location of processing sites and landfill areas, expansion strategies for waste treatment facilities, allocation of waste flow, division of service areas, and scheduling of routes and collection vehicles [5]. These are essentially a series of combinatorial optimization problems that require the basis of operations research and computer technology to be solved.

Waste management is a very complex system with a high degree of uncertainties from waste generation sources to final disposal facilities, failing to address such uncertain features in the system can consequently influence the associated optimization methods and decision-making process [6]. Therefore, this article aims to establish a stochastic programming model for the multi-level transportation of household waste, taking into account the uncertainty in the amount of waste generated by residents and the current environment for waste classification and disposal in Shanghai. The focus is on selecting the operating time for each site and planning the waste flow for each site at different time points. Due to the large scale of the problem, the Benders decomposition algorithm is used to solve the model.

2. Literature Review

An article discussing uncertain factors in the process of integrated management of municipal solid waste would generally use methods such as interval analysis, chance constraints, and fuzzy programming to model and optimize urban solid waste management systems under uncertain conditions, in order to reduce the overall system cost or environmental impact. Ghoushchi et al. proposed a Multi-Criteria Decision-Making method based on spherical fuzzy sets which is applicable to selecting the optimal landfill for medical waste under uncertainty [7]. Yang et al. propose a statistical method driven by a probabilistic model, which integrates the digital twinning, Gaussian mixture, and the hidden Markov model to dynamically predict the generation of disassembly waste under uncertainty [8]. Sun and Gu proposed an multi-agent stochastic game model to capture the uncertainty existing in the external environment and evaluate the evolutionary behavior of the government agencies, waste recyclers, and waste producers [9]. Dzhuguryan and Deja present a new model using the material flow analysis methodology to allow to determine the number of transport fleet units needed for the implementation of various supply chain scenarios of municipal production waste under uncertainty [10]. In particular, Celik et al. proposed a four-phased integrated methodology that involves Intuitionistic Fuzzy Weighted Averaging (IFWA), IF Analytical Hierarchy Process, IF Technique for Order Preference by Similarity to Ideal Solution and One-Dimensional Sensitivity Analysis to handle intense uncertainty in the evaluation process of medical waste management [11].

In recent years, research on solid waste management systems under uncertainty has expanded beyond traditional uncertain factors such as waste generation rates. For example, Muneeb et al. considered the uncertainty of waste transportation time and its associated cost increase in their decentralized two-layer decision planning model, solved using the Knitro 10.2.0 solver on the NEOS server [12]. Diaz-Barriga-Fernandez et al. presents a multi-objective optimization approach for the strategic planning of a municipal solid waste (MSW) management system under uncertainty [13]. The main variables that are considered under uncertainty were the MSW availability and the prices of the products made from the recovered MSW. However, these articles did not consider the uncertainty in the traffic mechanism from different collection points to transfer stations or in the amount of waste generated. Golrizgashti et al. developed a mathematical model for hospital waste management that not only aimed to minimize costs but

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also to minimize individual safety risks [14]. They also mentioned the uncertainty in the minimum waste disposal level, waste processing capacity of the facility, and the facility's recycling capacity. However, they did not explicitly include these uncertainties in the mathematical model and only adjusted these three indicators to verify their impact on costs and safety risks. Although the study did not focus on reducing hospital waste generation, future research directions could aim to reduce hospital pollution through effective hospital management.

As the number of uncertain factors increases, it becomes a challenge for researchers to incorporate these elements into the model within a feasible range. Wang and Jin considered the uncertainty of transportation costs and approximated it as an imprecise linear function of waste flow [15]. For the uncertainty of operating costs of future landfill sites and WTE facilities, the method of stochastic programming was adopted to discuss different scenarios; and the uncertainty of the capacity of WTE facilities was also represented by several rough intervals. Jin and Fu et al. applied a non-precise trapezoidal T2 fuzzy method to traditional fuzzy linear programming to solve the fuzziness problem in urban solid waste management [16]. This method can include more uncertain information and reduce the cost range of the objective function. Broitman et al. conducted an economic analysis of possible investments in treatment technologies of agricultural vegetative waste, while accounting for fluctuating output prices [17]. They described price changes by a coefficient of variation of the output prices. However, in practical situations, solid waste systems should have idle costs, and treatment facilities will not have zero costs, for example, landfill equipment should not be idle and not process any waste during a certain period of time.

In addition, in solving the models, some scholars have also conducted research on innovative algorithms. Xu and Liu et al. proposed a genetic algorithm-assisted fuzzy chance-constrained programming model, which combines genetic algorithm with fuzzy chance-constrained programming to solve the uncertainty of safety factors and processing capacity of waste incineration and landfill in urban solid waste management [18]. However, due to the computational limitations of genetic algorithms, the proposed optimization model cannot handle large-scale and complex practical management problems, as the computational burden is too heavy. Saif et al. Formulated a two-stage stochastic MILP model to examine the effects of the supply-demand, and power price uncertainties [19]. An L-shaped decomposition algorithm is shown to be effective in obtaining solutions for the stochastic model. This kind of decomposition algorithm gives a great inspiration to the solution of the model in this article.

Although scholars have conducted relatively comprehensive modeling and research on various aspects of waste management considering uncertainties, the key problem is that these models can not conform to the current situation of Shanghai's collection, transportation, and disposal of household waste. For example, there are differences in the transportation and processing of dry and wet waste, and they need to be separated and modeled separately to be more practical. Moreover, these models generally contain many variables and constraints, and solving them may be very difficult and time-consuming, which requires an acceleration algorithm to improve computational efficiency.

3. Methodology

This article uses the Benders decomposition algorithm to solve the constructed model. The basic idea is as follows:

Assume that the original problem is:

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$$\begin{aligned}&z=\max cx+hy\\&s.t.\\&Ax+Gy\le b\\&x\in Z_+^n, y\in R_+^n\end{aligned} \tag{1}$$

Where x represents the more complex variables in the problem, and y represents the remaining simpler variables [20].
Assign a fixed value x' to x, then the original problem becomes:

$$\begin{aligned}&z'=\max hy\\&s.t.\\&Gy\le b-Ax'\\&y\in R_+^n\end{aligned} \tag{2}$$

The dual problem is:

$$\begin{aligned}&\min \mu(b-Ax')\\&s.t.\\&\mu G\ge h\\&\mu\in R_+^m\end{aligned} \tag{3}$$

Solve the problem (3) above to obtain the optimal solution μ' and the minimum value of the z' objective function. If there is no optimal solution, then solve the following problem (4), and obtain the optimal solution μ''.

$$\begin{aligned}&\min e=0\\&s.t.\\&\mu(b-Ax')=1\\&\mu G\ge 0\\&\mu\in R_+^m\end{aligned} \tag{4}$$

Substitute the obtained results into the following problem (5) to obtain the optimal solution x' and the maximum value η' of the objective function. This completes one iteration.

$$\begin{aligned}&\max \eta\\&s.t.\\&\eta\le cx+\mu'(b-Ax)\\&0\le \mu''(b-Ax)\\&x\in Z_+^n, \eta\in R\end{aligned} \tag{5}$$

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If z'-$\eta' > \varepsilon$, continue the iteration by substituting the solution x' into the original problem (3); otherwise, terminate the computation.

4. Model Establishment

Currently, the process of collecting and disposing of domestic waste in Shanghai is different from before. After the waste is sorted at the source, dry waste is transported to a collection station, a compression station, or a transfer station, and then transferred to an incineration plant for incineration treatment. Then, the residue is transported to landfills for disposal. Wet waste is directly transported to a specialized wet waste disposal site. After treatment, the remaining residue is transported to the incineration plant for incineration and then transported to a landfill site for landfill disposal. The products such as fertilizers generated from wet waste disposal and the incineration power generation will enter the market and generate revenue, as shown in Figure 1. Recyclables can be treated well by market operation, and the amount of hazardous waste is small. Therefore, this article does not consider them.

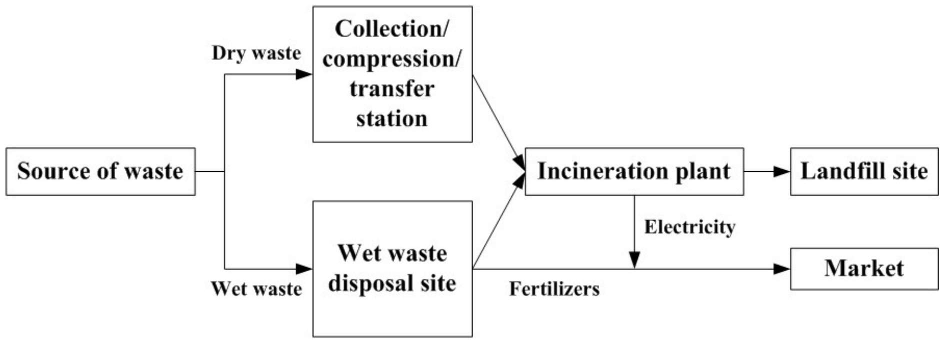

Figure 1. Flowchart of domestic waste collection and disposal process

Based on the above flowchart, this article establishes a stochastic programming model, aiming to pre-allocate the waste flow between any two nodes at different times and plan whether each site should operate at different times. The specific model is established as follows.

Parameters:
T: set of time, including Monday to Sunday.
S: set of scenarios.
V: set of all locations.
V0: set of communities.
V1: set of wet waste disposal sites.
V2: set of dry waste compression and transfer stations.
V3: set of incineration plants.
V4: set of landfill sites.
A1: set of wet waste transportation paths.
A2: set of dry waste transportation paths.
gs(r,i,t): actual amount of wet waste generated by community i at time t under scenario r.
gg(r,i,t): actual amount of dry waste generated by community i at time t under scenario r.
Pr(r): probability of scenario r occurring, $r \in S$.
f(j): fixed cost of daily operation for each location.
d(i,j): distance between two locations.

u(j): maximum processing capacity for waste at location j, $j \in V$.
l(j): minimum processing capacity for waste at location j, $j \in V$.
rat(j): ratio of output to input waste at location j, $j \in V_1 \cup V_2 \cup V_3$.
Cs(j): cost of processing one unit of wet waste at location j, $j \in V_1 \cup V_3 \cup V_4$.
Cg(j): cost of processing one unit of dry waste at location j, $j \in V_2 \cup V_3 \cup V_4$.
Ps(j): revenue generated from processing one unit of wet waste at location j, $j \in V_1 \cup V_3$.
Pg: revenue generated from processing one unit of dry waste.
ku(j): storage capacity limit for waste at location j, $j \in V_1 \cup V_2$.
tr(i): transportation cost per unit of waste per unit distance, $i \in V$.
Exs: penalty cost per unit of wet waste for the difference between actual and planned transportation.
Exg: penalty cost per unit of dry waste for the difference between actual and planned transportation.

Variables:
m(j,t): binary variable indicating whether location j operates at time t.
ks(j,t): inventory level of wet waste at disposal site j at time t, $j \in V_1, t \in T$.
kg(j,t): inventory level of dry waste at compression and transfer station j at time t, $j \in V_2, t \in T$.
Xs(i,j,t): planned amount of wet waste transported from location i to location j at time t.
Xg(i,j,t): planned amount of dry waste transported from location i to location j at time t.
Zs(r,i,t): difference between actual and planned transportation amount of wet waste generated by community i at time t under scenario r.
Zg(r,i,t): difference between actual and planned transportation amount of dry waste generated by community i at time t under scenario r.

Objective function:

$$\begin{aligned}\min\Big(&\sum_{t}\sum_{j\in V_1\sim V_4} f(j)m(j,t) + \sum_{t}\sum_{j\in V_1} kc(j)ks(j,t) + \sum_{t}\sum_{j\in V_2} kc(j)kg(j,t) + \\ &\sum_{t}\sum_{i,j\in A_1} tr(i)d(i,j)Xs(i,j,t) + \sum_{t}\sum_{i,j\in A_2} tr(i)d(i,j)Xg(i,j,t) + \\ &\sum_{t}\sum_{i,j\in A_1} Cs(j)Xs(i,j,t) + \sum_{t}\sum_{i,j\in A_2} Cg(j)Xg(i,j,t) - \sum_{t}\sum_{i,j\in A_1} Ps(j)Xs(i,j,t) - \\ &\sum_{t}\sum_{i\in V_2, j\in V_3} PgXg(i,j,t) + \sum_{r}\sum_{i\in V_0}\sum_{t} Exs\Pr(r)|Zs(r,i,t)| + \sum_{r}\sum_{i\in V_0}\sum_{t} Exy\Pr(r)|Zy(r,i,t)|\Big)\end{aligned} \tag{6}$$

Constraints:

$$\sum_{j\in V_1} Xs(i,j,t) + Zs(r,i,t) = gs(r,i,t), \forall i \in V_0, t \in T \tag{7}$$

$$\sum_{j\in V_2} Xg(i,j,t) + Zg(r,i,t) = gg(r,i,t), \forall i \in V_0, t \in T \tag{8}$$

$$\sum_{i\in V_0} Xs(i,j,t)rat(j) + ks(j,t) = \sum_{i\in V_3} Xs(j,i,t) + ks(j,t+1)), \forall j \in V_1, t \in T \tag{9}$$

$$\sum_{i \in V_0} Xg(i,j,t)rat(j) + kg(j,t) = \sum_{i \in V_3} Xg(j,i,t) + kg(j,t+1), \forall j \in V_2, t \in T \tag{10}$$

$$\sum_{i \in V_1} Xs(i,j,t)rat(j) = \sum_{i \in V_4} Xs(j,i,t), \forall j \in V_3, t \in T \tag{11}$$

$$\sum_{i \in V_2} Xg(i,j,t)rat(j) = \sum_{i \in V_4} Xg(j,i,t), \forall j \in V_3, t \in T \tag{12}$$

$$ks(j,t) \le m(j,t)ku(j), \forall j \in V_1, t \in T \tag{13}$$

$$kg(j,t) \le m(j,t)ku(j), \forall j \in V_2, t \in T \tag{14}$$

$$\sum_{i \in V_0} Xs(i,j,t) \le m(j,t)u(j), \forall j \in V_1, t \in T \tag{15}$$

$$\sum_{i \in V_0} Xg(i,j,t) \le m(j,t)u(j), \forall j \in V_2, t \in T \tag{16}$$

$$\sum_{i \in V_1} Xs(i,j,t) + \sum_{i \in V_2} Xg(i,j,t) \le m(j,t)u(j), \forall j \in V_3, t \in T \tag{17}$$

$$\sum_{i \in V_3} (Xs(i,j,t) + Xg(i,j,t)) \le m(j,t)u(j), \forall j \in V_4, t \in T \tag{18}$$

$$\sum_{i \in V_0} Xs(i,j,t) \ge m(j,t)l(j), \forall j \in V_1, t \in T \tag{19}$$

$$\sum_{i \in V_0} Xg(i,j,t) \ge m(j,t)l(j), \forall j \in V_2, t \in T \tag{20}$$

$$\sum_{i \in V_1} Xs(i,j,t) + \sum_{i \in V_2} Xg(i,j,t) \ge m(j,t)l(j), \forall j \in V_3, t \in T \tag{21}$$

$$\sum_{i \in V_3} (Xs(i,j,t) + Xg(i,j,t)) \ge m(j,t)l(j), \forall j \in V_4, t \in T \tag{22}$$

$$Xs(i,j,t) \ge 0, \forall i \in V, j \in V, t \in T \tag{23}$$

$$Xg(i,j,t) \ge 0, \forall i \in V, j \in V, t \in T \tag{24}$$

$$ks(j,t) \ge 0, \forall j \in V_1, t \in T \tag{25}$$

$$kg(j,t) \ge 0, \forall j \in V_2, t \in T \tag{26}$$

The first term in the objective function represents the fixed costs of operating each site, the second and third terms represent inventory costs, the fourth and fifth terms represent transportation costs, the sixth and seventh terms represent processing costs, the eighth and

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ninth terms represent revenue from processing wet and dry waste, and the tenth and eleventh terms represent additional penalty costs for the difference between actual waste production and planned transportation amounts.

Constraints (7)-(12) represent the conservation of input and output quantities of waste, (13)-(18) represent the limits on the inventory and processing of waste at each site, and (19)-(22) represent the minimum processing requirements for each site [21].

Based on the methodology of Benders decomposition algorithm in Part 3, we can divide the model into two parts: a subproblem that contains only variables ks(j,t), kg(j,t), Xs(i,j,t), Xg(i,j,t) with the form of Equation (2), and a main problem that contains the subproblem and the rest of the model with the form of Equation (5). Due to space limitations, the specific Benders conversion and solving process for this model is not shown in the text, but can be seen from the code in the supplementary material.

5. Simulation Results

The article sets the actual amount of household waste produced by each community as an uncertain quantity. Tong and Ma studied the probability distribution of waste production at Shanghai city waste collection points, using a case study of a certain district in Shanghai, and ultimately confirmed that it approximates a normal distribution [22]. Based on the data mentioned in this study and Shanghai Environmental Science Research Institute's research on the characteristics and classification of urban household waste in Shanghai, the average daily household waste production per household (Unit: kg/day) is estimated to be approximately normally distributed with a mean of 1.01 and a variance of 0.1174. The peak periods for waste production are Saturdays, Sundays, Mondays, and Tuesdays, with a range of (0.95, 1.2), and dry waste accounts for about 51.03%-54.16%, while wet waste accounts for about 34.15%-41.2%. The amount of waste produced on Wednesdays, Thursdays, and Fridays is relatively small, with a range of (0.77, 1.04), and dry waste accounts for about 44.41%-48.99%, while wet waste accounts for about 42.82%-46.08%. Therefore, to ensure that the randomly generated waste production is realistic, the daily household waste production for each household on Saturdays, Sundays, Mondays, and Tuesdays can be randomly generated using a normal distribution N(1.01, 0.1174) within the range of (0.95, 1.2), and a value within the range of (51.03%, 54.16%) can be selected as the proportion of dry waste. Multiplying these two values, and then multiply by the number of households in the community gives the amount of dry waste produced on that day, and the same process is followed for wet waste. If more specific data can be collected in the future, the results can be made more accurate and reliable.

For simplicity, the article sets the region of the problem to be solved within a small area containing 31 communities, with 3 compression transfer stations, 2 wet waste disposal sites, 2 incineration plants, and 1 landfill site. Only residential household waste is considered, excluding waste generated by shopping malls, restaurants, and institutions. The number of households is set according to the actual situation of communities in Shanghai. Only one week of waste collection and disposal is calculated, and up to 200 scenarios of dry and wet waste production are randomly generated with the method mentioned above for each community at each time. If necessary, the number of scenarios can be increased in future studies. In addition, the values of all parameters in the article are obtained by asking relevant managers in field surveys, which can be seen from the code in the supplementary material.

The article uses GuroBi 8.1.1 version to solve the model, and the computer is equipped with a 2.50 GHz Intel i7 processor, 8 GB system memory, and a 64-bit operating system.

This section first examines the change in total cost as the number of sample scenarios increases, and then verifies the acceleration effect and accuracy of the Benders decomposition algorithm. Due to the large number of model variables, ordinary solution takes a long time. When the gap

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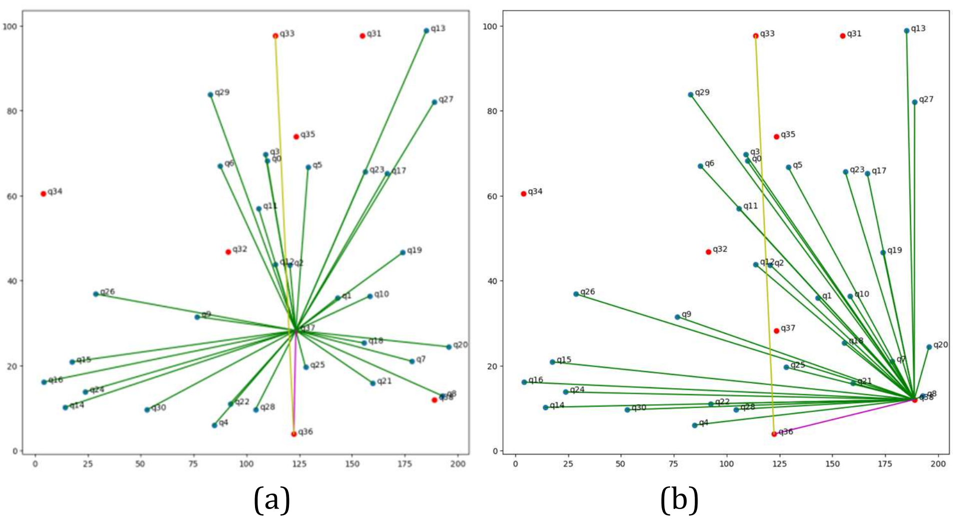
is reduced to 0.2, the objective function value no longer shows significant changes. Therefore, the article sets the gap at 0.2 and records the required time. The results and time required for ordinary solution and Benders decomposition algorithm are shown in Table 1 below. Compared with the ordinary solution, the Benders decomposition algorithm saves 87.4% time on average, and its average error is only 0.068%.

Table 1. Calculation results and time values

Number of Scenarios	Ordinary Solution			Benders Decomposition Algorithm			Error
	Optimal Solution (CNY)	Gap	Time (s)	Optimal Solution (CNY)	Gap	Time (s)	
20	164330.772	19.0%	2	164267.337	0.270%	2	0.04%
30	165212.336	20.0%	5	165148.218	0.268%	3	0.04%
40	164886.009	19.1%	25	165010.371	0.268%	4	0.08%
50	165134.534	19.8%	79	165200.519	0.268%	5	0.04%
60	165489.275	20.0%	167	165660.515	0.267%	7	0.10%
70	165713.712	20.0%	212	165804.039	0.267%	9	0.05%
80	165739.270	19.9%	205	165858.372	0.267%	10	0.07%
90	165948.699	19.0%	293	166072.520	0.266%	11	0.07%
100	166107.247	20.0%	315	166177.164	0.266%	12	0.04%
110	166054.276	19.8%	361	166148.748	0.266%	14	0.06%
120	166093.370	20.0%	513	166240.266	0.266%	15	0.09%
130	166190.286	20.0%	513	166327.021	0.266%	18	0.08%
140	166292.918	19.9%	796	166451.937	0.266%	19	0.10%
150	166379.366	20.0%	522	166526.758	0.266%	22	0.09%
160	166308.381	19.9%	628	166420.492	0.266%	26	0.07%
170	166324.309	19.8%	671	166450.612	0.266%	28	0.08%
180	166337.388	20.0%	753	166461.550	0.266%	30	0.07%
190	166404.769	19.9%	808	166507.187	0.266%	33	0.06%
200	166420.875	24.6%	1005	166525.531	0.266%	37	0.06%

Due to the large penalty costs set, the total cost obtained here is higher than the actual situation. In theory, the more scenarios, the stronger the applicability of the results. So we show the transport path of dry waste and wet waste during a week in the situation that the number of scenarios is 200 as an example, as shown in Figure 2.



(a) (b)

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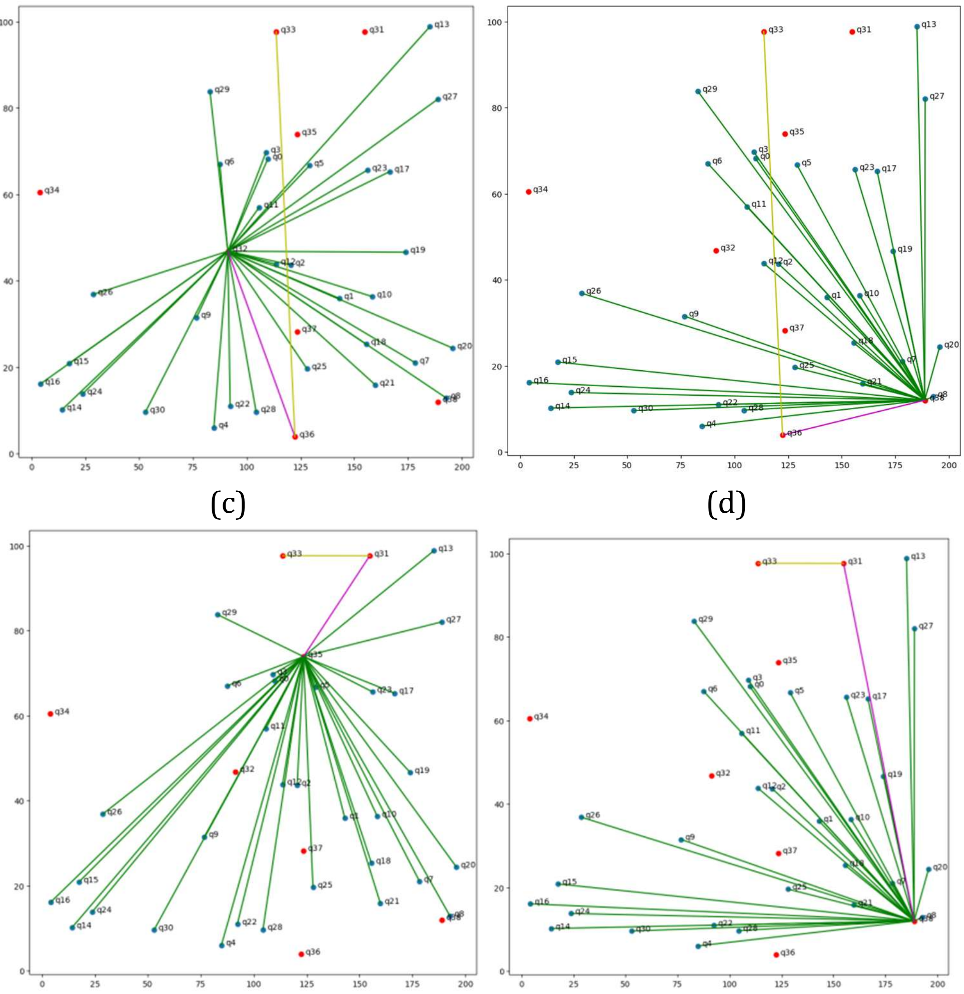

(c) (d)

(e) (f)

Figure 2. Transportation path of dry and wet waste (Figure 2(a) and 2(b) respectively represents the dry and wet waste transport routes on Monday, Tuesday and Wednesday; Figure 2(c) and 2(d) respectively represents the dry and wet waste transport routes on Thursday; Figure 2(e) and 2(f) respectively represents the dry and wet waste transport routes on Friday, Saturday and Sunday)

In the Figure 2, q32, q35 and q37 are dry waste compression transfer stations, q34 and q38 are wet waste disposal sites, q31 and q36 are operating incineration plants, q33 is the final landfill site. The remaining blue points are all communities. The colored line segments are their transportation paths, and the red points not on the line segments are non-operating stations. According to Figure 2, we can see that in order to minimize the total cost within a week, there are three different waste transportation modes at different times.

6. Discussion

To more intuitively reflect the changes in the optimal solution and solution time with the increase of scenarios, the change curves of the optimal solution and solution time under two methods are respectively plotted as shown in Figure 3 and 4.

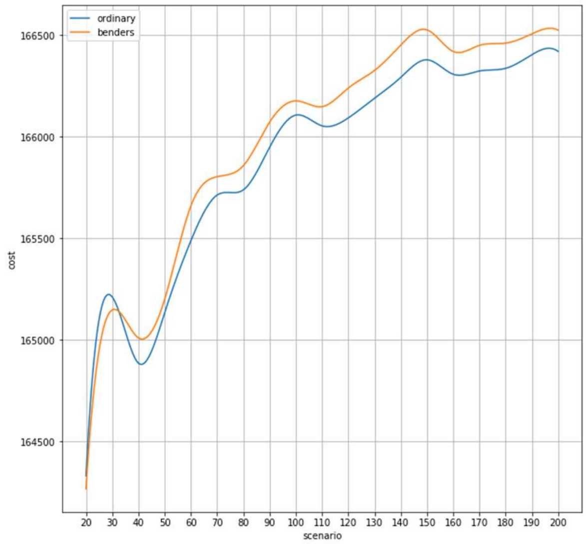

Figure 3. Change curve of calculation result (total cost)

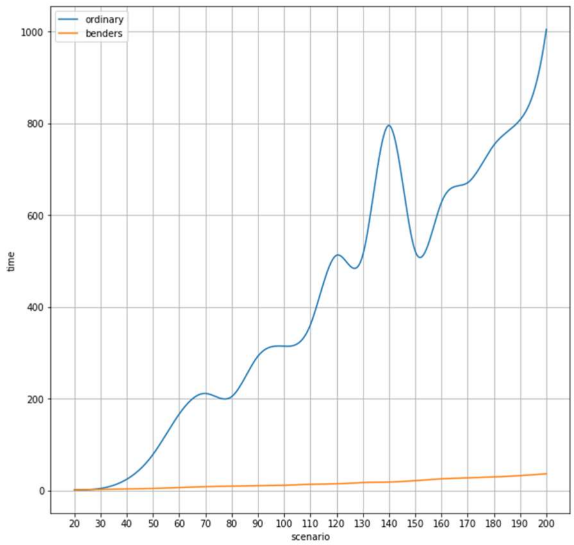

Figure 4. Solving time variation curve

Figure 3 shows the curve of the total cost changing with the number of scenarios, while Figure 4 shows the curve of the solution time changing with the number of scenarios. It can be seen that when the number of scenarios is greater than 160, the total cost is relatively stable and the change is no longer significant. The results of the two solutions are very close, which shows that the Benders decomposition algorithm is reliable. Moreover, after using the Benders decomposition algorithm, the solution speed is greatly increased.

In reality, when the scope of the region is large, the time required by the ordinary solution will increase significantly due to the substantial increase in the complexity of the problem. At this point, the acceleration effect of the Benders Decomposition Algorithm is more obvious. Besides, from the simulation in the fifth part, we can find that different ranges of daily waste production in the same region will affect its transport path. Therefore, in order to minimize transportation costs, Shanghai's sanitation department should adopt differentiated transportation routes in different districts on different days.

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7. Conclusion

In order to alleviate the pain points after the implementation of Shanghai's waste classification regulations, reduce waste at source, promote the construction of recycling and transportation networks, maximize utilization of waste, and establish a zero-waste city with harmless disposal, this article established a stochastic programming model for a multi-level transportation of household waste that is suitable for the current Shanghai waste classification and considers the uncertainty of household waste generation. The model plans the waste flow of each station and whether each site operates or not at each time. Simulation proves that using the Benders decomposition algorithm can significantly speed up the calculation and stabilize the results when the number of scenarios is greater than 160. The results can provide a basis for decision-making for the waste management in Shanghai.

This article only deals with the planning of waste flow and has not yet touched on the specific selection of vehicle transportation routes. Future research can further plan vehicle routes and personnel scheduling and other more specific issues based on the foundation of this article.

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