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Research article

Optimal assignment of infrastructure construction workers

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Abstract: Worker assignment is a classic topic in infrastructure construction. In this study, we developed an integer optimization model to help decision-makers make optimal worker assignment plans while maximizing the daily productivity of all workers. Our proposed model considers the professional skills and physical fitness of workers. Using a real-world dataset, we adopted a machine learning method to estimate the maximum working tolerance time for different workers to carry out different jobs. The real-world dataset also demonstrates the effectiveness of our optimization model. Our work can help project managers achieve efficient management and save labor costs.

Keywords: infrastructure management; worker assignment; integer programming; machine learning

1. Introduction

Transportation infrastructure connects cities, facilitates human's social activities and plays an important role in urbanization and economy [1–3]. And, transportation infrastructure needs to be renovated and maintained frequently because of factors such as traffic safety, urbanization and new travel demands [4]. In the process of transportation infrastructure construction, a large number of workers are required to engage in high-intensity labor work [5] and the costs are high [6]. New technologies, such as automation technology and communication technology, are widely applied in transportation infrastructure construction (see [7–13]). And, many studies have put forward new methodologies for solving problems in transportation infrastructure [14–16]. Unlike machines, workers are full of uncertainty in the process of work, and their productivity is affected by many factors. For example, construction workers will feel tired after working continuously for a period of time, and workers' different physical fitness levels mean that they feel different degrees of fatigue [17]. As construction workers play an irreplaceable role in projects, attention should be paid to allocating workers to suitable jobs to achieve efficient project completion while taking into account their professional skills and individual characteristics. In this study, we explore the optimal assignment of transportation infrastructure construction workers in consideration of their skills and maximum working tolerance time as determined by fatigue level and other physical indicators.

The worker assignment problem is a classic research topic in the field of transportation. Yan et al. [18] adopted a scheduling model to allocate port state control officers in maritime transport; they took into account the officers' needs for rest and lunch. Zhang et al. [19] paid attention to the railway infrastructure maintenance planning problem and developed models and algorithms to solve this problem efficiently. Wen et al. [20] proposed algorithms to predict the railway volume, which could be the reference of the worker assignment. Chargui et al. [21] solved the worker assignment problem in container terminals by using heuristic methods which balance the workers' workload the moving distance. Yi and Wang [22] explored the optimal laborer assignment program by considering worker safety; their findings can help to save money, time and manpower on projects. Yi and Wang [23] also developed a mixed-integer linear model to solve the construction worker schedule problem in hot weather. Skibniewski and Armijos [24] developed models that are both applicable to worker assignment and equipment evaluation. Park et al. [25] put forward a simulation model to minimize the transportation time in high-rise residential building projects; their model identifies the optimal zoning divisions, which further improves workers' efficiency. Lim et al. [26] pointed out that increased data volumes have led to better-informed decision-making in transportation. Big data is indispensable in the research on intelligent transportation [27–29]. Cheng et al. [30] used the real-world license plate recognition data to validate their proposed model. Qu et al. [31] developed data-driven models to generate a fundamental diagram for freeway traffic. Lee et al. [32] adopted digital imaging methods to inspect coating rust defects in bridges. Avetisyan et al. [33] used data analysis to evaluate metrics related to sustainability in construction processes. The above literature review states that the worker assignment problem is important in the field of transportation, and that data can bring new insights. However, few studies have focused on the worker assignment problem in transportation infrastructure while considering the workers' maximum work durations by adopting a real-world dataset.

Our study had two objectives. First, we developed an integer programming scheme [34,35] to help decision-makers to maximize daily project efficiency while taking into account the workers' maximum working tolerance times and professional skills. The solutions of our proposed model can help project managers to make optimal assignments of workers. Second, using real-world data, our work provides insights into predicting workers' maximum work durations, and our proposed model is proven to be effective. The theoretical and practical contributions of our study are summarized below.

1) Theoretical contribution. The existing literature does not take into account the individual characteristics of workers when formulating worker assignment plans. As workers' health and safety are essential factors influencing plan-making and job conducting, this paper contributes to the area of transportation infrastructure health and safety by demonstrating models considering workers' health and safety. Moreover, this study adopted real-world data from infrastructure construction workers in Hong Kong to delineate the physical features of different workers and estimate their maximum work durations by using an advanced machine learning method. And, the real-world dataset also proves the applicability of our optimization model.

2) Practical contribution. Our proposed integer programming model can help project managers to

make an optimal assignment plan to maximize the workers' efficiency in practice, which will further contribute to saving labor costs.

The reminder of this paper is organized as follows. Section 2 develops our mathematical model. Section 3 presents the numerical experiments to show the applicability of our proposed model. And, the conclusions are drawn in Section 4. The main symbols used in this study are listed in Table 1.

Table 1. Feature and label explanations.

Sets	
M	Set of types of jobs, $i \in M$
J	Set of workers, $j \in J$
M_j	Set of jobs that Worker j has the expertise to carry out, $M_j \subset M$
Parameters	
T	Rest time to recover (minutes)
t_{ij}	A construction worker j has to take a rest after performing Job i for t_{ij} minutes
m_{ij}	Binary parameter that equals 1 if Worker j can carry out Job i, and 0 otherwise
Q_i	Job i should be conducted for at least Q_i minutes for a working day
W_{ij}	The daily working minutes of Worker j when he conducts Job i
Decision Variables	
x_{ij}	Binary decision variable that equals 1 if Worker j performs Job i, and 0 otherwise

2. Integer optimization model

A construction site often has multiple jobs going on at the same time, so we use $M = \{1, \dots, \vee M \vee\}$ to denote the types of jobs, $i \in M$, such as bar bending, concreting, digging and welding. There are a total of $J \vee$ workers in the construction site, so $J = \{1, \dots, \vee J \vee\}$ is used to denote different workers. A worker can have the expertise to carry out different jobs. However, in order to facilitate management and assessment, a worker will only conduct one type of job per day in practice even if he is versatile. We use M_j to denote jobs that Worker j can do. For example, suppose that there are three types of jobs at a construction site, i.e., cutting steel bars ($i = 1$), laying walls ($i = 2$) and painting walls ($i = 3$), that is, $M = \{1,2,3\}$. Worker 1 has the expertise to carry out the jobs of cutting steel bars and painting walls, and Worker 2 is competent in cutting steel bars, laying walls and painting walls. Then, $M_1 = \{1,3\}$ and $M_2 = \{1,2,3\}$. We must have

$$\cup_{j \in J} M_j = M. \tag{1}$$

That is, there is at least one worker that has the expertise to conduct every job in M. To simplify notation, we replace the set M_j with the binary parameter m_{ij} that equals 1 if Worker j can perform Job i. Mathematically,

$$m_{ij} = \begin{cases} 1, i \in M_j \\ 0, i \notin M_j \end{cases}, i \in M, j \in J. \tag{2}$$

In the above example, $m_{11} = 1$, $m_{21} = 0$ and $m_{31} = 1$.

During a working day, construction workers need to have a rest to recover. The rating of perceived exertion (RPE) is an indicator widely used to measure the physical fitness level of workers as they are working [36,23]. The RPE is an integer that ranges from 1 to 10. A larger value of RPE implies that workers are more tired [37]. When the RPE value is 8, it indicates that workers are very tired and they cannot fully control their actions. Therefore, a construction worker needs to take a rest when his RPE value reaches 7. Suppose that the worker can recover after T minutes of rest. The value of RPE and the rate of its increase are affected by many factors, such as the type of job, the environment and the physical quality of workers [38]. Suppose that a construction worker j's RPE value reaches 7 after he performs Job i for t_{ij} minutes, i.e., a construction worker j should have T minutes of rest after conducting Job i for t_{ij} minutes. Obviously, if a construction worker j is not competent in Job i, the value of t_{ij} will be 0. That is,

$$\begin{cases} t_{ij} > 0, m_{ij} = 1 \\ t_{ij} = 0, m_{ij} = 0 \end{cases}, i \in M, j \in J. \tag{3}$$

As the legal working time is 8 hours per day, the daily working minutes of Worker j can be calculated by using the following formula if he conducts Job i:

$$W_{ij} = \frac{t_{ij}}{t_{ij}+T} \times 8 \times 60. \tag{4}$$

According to the progress, Job i must be conducted at least Q_i minutes in a working day. In order to improve the project schedule, decision-makers need to decide what job each worker will undertake each day to maximize the total workload, i.e., to maximize the total working minutes of all workers. We define a binary decision variable x_{ij} to represent whether Worker j performs Job i for the working day. Then, the worker assignment plan considering the degree of fatigue can be obtained via the following optimization model.

[M1]

$$max \sum_{i \in M} \sum_{j \in J} W_{ij}\, x_{ij} \tag{5}$$

subject to

$$\sum_{i \in M} x_{ij} = 1, \forall j \in J \tag{6}$$

$$x_{ij} \leq m_{ij}, \forall i \in M, j \in J \tag{7}$$

$$\sum_{j \in J} W_{ij} x_{ij} \geq Q_i, \forall i \in M \tag{8}$$

$$x_{ij} \in \{0,1\}, \forall i \in M, j \in J. \tag{9}$$

Objective function (5) maximizes the total working time of all workers in a working day, i.e., Objective function (5) maximizes the workload for a working day. Constraint (6) ensures that a construction worker can only do one job each day. Constraint (7) ensures that a construction worker will only be assigned to jobs for which he is competent. Constraint (8) guarantees that the daily progress of each job meets the requirements. Constraint (9) places the domain of decision variables. [M1] is an integer programming model that can be solved by state-of-the-art optimization solvers [39–41].

3. Case study

3.1. Estimating the maximum work duration

As mentioned in Section 2, a construction worker has to stop to take a rest after t_{ij} minutes of work, and t_{ij}, a key parameter in [M1], is determined by many factors. For example, high temperatures will affect the physical condition of workers, and different workers may react differently to heat stress depending on their physical fitness level [42]. Older workers with vascular disease, which is usually associated with a drinking habit, may be more sensitive to heat stress. We collected a real dataset from an infrastructure construction project in Hong Kong. In this project, workers mainly engaged in two types of jobs: bar bending and bar fixing. We collected data from 550 workers, and the dataset contained variables related to the working environment (e.g., temperature), each worker's physical fitness level (e.g., age and RPE), job type (bar bending and bar fixing) and work duration. That is, this dataset contained information on the values of RPE because it contained data on different workers in different environments who have worked for long times. The detailed information about the dataset is shown in Table 2, and the distribution of variables is shown in Figure 1.

Table 2. Interpretation of the dataset.

Category	Variable name	Explanation
Working environment	Temperature	Temperature (℃) of the construction site when workers work
	Relative humidity	Relative humidity (%) of the construction site when workers work
Worker physical fitness level	Age	Worker's age
	BMI	Body mass index
	Alcohol drinking habit	Variable that equals 1 if a worker drinks alcohol occasionally, 2 if a worker drinks alcohol usually and 0 otherwise
	Smoking habit	Variable that equals 1 if a worker smokes occasionally, 2 if a worker smokes usually and 0 otherwise
	RPE	The rating of perceived exertion
Job type	Job nature	Variable that equals 0 if a worker engages in bar bending and 1 if a worker engages in bar fixing
Work duration	Work duration	How long the worker has worked (minutes)

We use a vector e to denote the working environment variables, vector a to denote each worker's physical fitness variables, variable b to denote job type and variable t to denote work duration. Then, we can train a machine learning model $t = F(e, a, b)$ to estimate the maximum work duration after which the worker's RPE will reach 7 and he has to stop to have a rest. We adopted extreme gradient boosting (XGBoost), which is a tree-based model, to obtain the maximum work duration. XGBoost has advantages in making predictions. The first advantage is that high accuracy can be obtained because a regular term has been added to prevent overfitting; and, XGBoost supports many types of classifiers. The second advantage is the high training speed. XGBoost does column sampling and subsampling, and it ranks feature importance and only selects highly correlated features for prediction. XGBoost has proven to be very effective and robust in many studies [18]. The hyperparameters were determined by GridSearchCV. We randomly removed 10 samples from the dataset for later numerical experiments. That is, we use the trained XGBoost network to predict the 10 workers' maximum work durations by their feature variables. (Because we want to estimate the maximum work time before a worker's RPE reaches 7, the RPE values of these 10 samples will was set to 7.) The detailed information and the results are shown in Table 3.

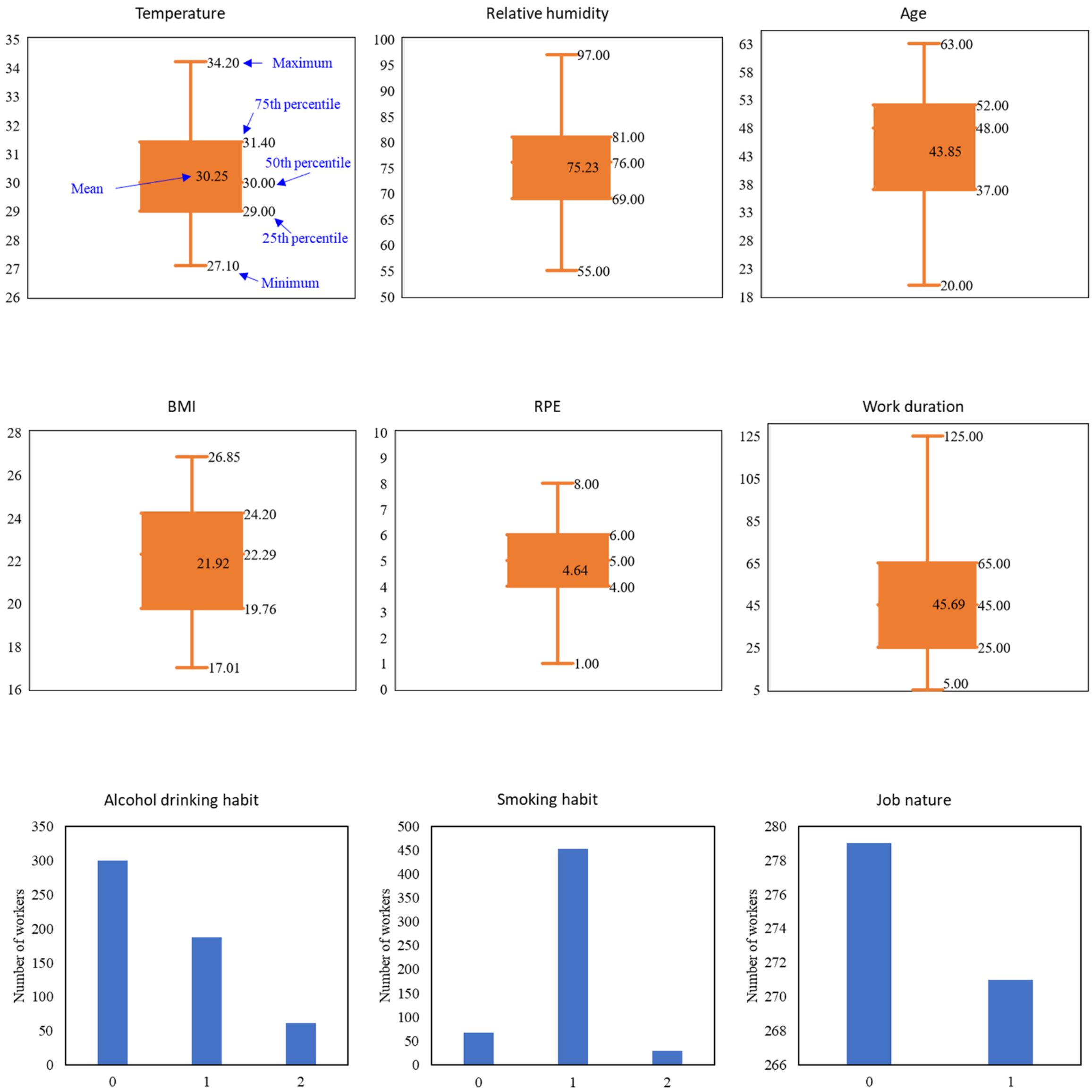

Figure 1. Distribution of variables.

The feature importance of the trained XGBoost model is shown in Figure 2. We can see that the RPE plays the most important role in predicting the worker's work time. And, job nature ranks second in importance, which is in line with real-life practice, as different types of jobs have different work intensities. Smoking and alcohol habits have similar degrees of importance. The temperature and relative humidity are not particularly important.

Table 3. Input feature variables and results of XGBoost model.

No.	a		e					b	$\hat{t}$
	Temperature	Relative humidity	Age	BMI	Alcohol drinking habit	Smoking habit	RPE	Job nature	Work duration
1	30.9	76	24	18.63	1	1	7	0	85.80
	30.9	76	24	18.63	1	1	7	1	54.94
2	29.4	79	29	26.15	2	1	7	0	95.26
	29.4	79	29	26.15	2	1	7	1	99.67
3	30.6	74	20	17.01	0	1	7	0	91.94
	30.6	74	20	17.01	0	1	7	1	80.37
4	28.2	79	54	19.76	0	0	7	0	47.94
	28.2	79	54	19.76	0	0	7	0	53.09
5	31.5	66	55	18.94	2	1	7	0	91.20
	31.5	66	55	18.94	2	1	7	1	60.23
6	28.8	75	42	20.48	0	1	7	0	44.73
	28.8	75	42	20.48	0	1	7	1	50.00
7	30.2	76	24	18.63	1	1	7	0	65.05
	30.2	76	24	18.63	1	1	7	1	60.59
8	30.4	76	20	17.01	0	1	7	0	88.10
	30.4	76	20	17.01	0	1	7	1	71.81
9	30.4	76	20	17.01	0	1	7	1	88.10
	30.4	76	20	17.01	0	1	7	1	71.81
10	30.9	68	42	20.48	0	1	7	0	101.11
	30.9	68	42	20.48	0	1	7	1	68.81

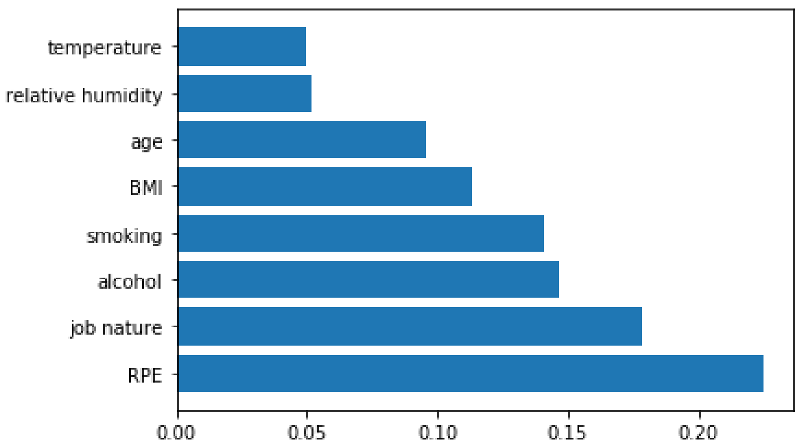

Figure 2. Feature importance.

3.2. Worker assignment

Next, we used these 10 samples to conduct a case study, i.e., $|M| = 2$, where Job 1 is bar bending and Job 2 is bar fixing, and $|J| = 10$. We set $T = 15$ minutes, $Q_1 = 2000$ minutes and $Q_2 = 1800$ minutes. Suppose all workers have the expertise to carry out the two types of jobs; the maximum work duration, i.e., t_{ij}, is shown in Column 10 of Table 3. For example, t_{11} = 85.50 and t_{23} = 80.37. The model was solved by using CPLEX Python API 20.1.0. The optimal objective value was 4009 minutes, and we report the results in Table 4. Therefore, five construction workers were assigned to carry out bar bending, and five workers were assigned to conduct bar fixing. The computing time for this case was less than 1 second. It is worth mentioning that the technology of state-of-the-art integer linear optimization solvers is mature, and that the computing efficiency is mainly affected by the number of decision variables and constraints. As our integer programming model is simple and there are not too many workers at a construction site at a time, i.e., not too many decision variables, the solution efficiency of our model is sufficient for practical needs.

Table 4. Results of case study.

No.	Job 1 (bar bending)	Job 2 (bar fixing)
Worker 1	1	0
Worker 2	0	1
Worker 3	0	1
Worker 4	0	1
Worker 5	1	0
Worker 6	0	1
Worker 7	0	1
Worker 8	1	0
Worker 9	1	0
Worker 10	1	0

Table 5. Optimal solutions of sensitivity analysis.

No.	$m_{22} = 0$		$Q_2 = 1000$ minutes		$t_{11} = 60$ minutes	
	Job 1	Job 2	Job 1	Job 2	Job 1	Job 2
Worker 1	1	0	1	0	0	1
Worker 2	1	0	1	0	1	0
Worker 3	0	1	1	0	0	1
Worker 4	0	1	0	1	0	1
Worker 5	1	0	1	0	1	0
Worker 6	0	1	0	1	0	1
Worker 7	0	1	0	1	0	1
Worker 8	1	0	1	0	1	0
Worker 9	0	1	1	0	1	0
Worker 10	1	0	1	0	1	0

Then, we conducted sensitivity analysis to analyze the influence of each parameter. Suppose that Worker 2 is not up to bar fixing, i.e., $m_{22} = 0$. The optimal objective value is 3993 minutes; the solutions are shown in Columns 2 and 3 of Table 5. We can see that Worker 2 transitions to Job 1 and Worker 9 transitions to Job 2 because of the minimum requirements of Q_2. Suppose that $Q_2 = 1000$ minutes. The optimal objective is 4014 minutes (see Columns 4 and 5 of Table 5 for optimal solutions). Worker 2 and Worker 3 both transition to Job 1 because the minimum working minutes for Job 2 are met and the two workers perform Job 1 more efficiently. Suppose that $t_{11} = 60$ minutes. The optimal objective value is 3975 minutes; Worker 1 and Worker 2 will swap the types of jobs as shown in Columns 6 and 7 of Table 5. This is because Worker 1 is now more efficient at Job 2 and both jobs have minimum time requirements.

4. Model extension

In Section 3, our goal was to maximize daily productivity and help project managers to develop worker assignment plans for a working day. However, before the start of a project, decision-makers may want to have a holistic view of the manpower needed throughout the entire project. Different from daily plans, the long-term plan usually pays attention to cost. We use the subscript t to represent different days and $t \in T$. The binary variable x_{ijt} indicates whether Worker j performs Job i in a day t. We use P_i to denote the minimum time requirements for Job i for the entire project. Then, [M1] can be extended to an optimization model for cost minimization from a long-term perspective.
[M2]

$$min \sum_{t\in T} \sum_{i\in M} \sum_{j\in J} x_{ijt} \tag{10}$$

subject to

$$\sum_{i\in M} x_{ijt} \leq 1, \forall j \in J, t \in T \tag{11}$$

$$x_{ijt} \leq m_{ij}, \forall i \in M, j \in J, t \in T \tag{12}$$

$$\sum_{t\in T} \sum_{j\in J} W_{ij} x_{ijt} \geq P_i, \forall i \in M \tag{13}$$

$$x_{ijt} \in \{0,1\}, \forall i \in M, j \in J, t \in T. \tag{14}$$

Objective function (10) minimizes the total manpower for a project, i.e., Objective function (10) minimizes the labor costs. Constraints (11) and (12) have the same meaning as Constraints (6) and (7), respectively. Constraint (13) guarantees that the total working time meets the requirements. Constraint (14) places the domain of the decision variables. [M2] is also an integer programming model that can be solved by using state-of-the-art optimization solvers.

5. Conclusions

In this study, we first developed an integer optimization model to help decision-makers to develop construction worker assignment plans with the goal of maximizing the daily productivity of all workers while taking into account the workers' individual physical characteristics and maximum working tolerance times. Then, we used a real-world dataset from infrastructure construction workers to conduct a case study. We adopted XGBoost to estimate the maximum work durations for different feature variables classified as the working environment, worker's physical fitness level and job type. We also explored the influence of each of the parameters set in our proposed model. Our findings will guide managers to develop optimal worker assignments, maximize productivity and reduce labor costs.

Moreover, our findings are also applicable to other infrastructure construction projects apart from transportation-related infrastructure construction projects. In future studies, we will consider linking our dataset with social and engineering variables to seek optimal solutions that improve overall engineering efficiency and even social efficiency. This work is not without limitations. First, we did not consider uncertain external interference factors, such as rainy days. Second, we did not make too many comparisons in the selection of machine learning methods.

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Conflict of interest

The authors declare that there is no conflict of interest.

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