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A Temporal-Spatial Cleaning Optimization Method for Photovoltaic Power Plants *

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Abstract

Cleaning is critical for photovoltaic (PV) systems, as it can remove dust deposition and keep the systems operating efficiently. Existing studies on PV cleaning focus predominately on determining optimal cleaning frequencies or intervals. In practice, however, route planning is also an indispensable decision to be made when cleaning large-scale PV plants. In this work, we study a temporal-spatial cleaning optimization problem for large-scale PV plants. A two-stage cleaning optimization policy that consists of a periodic planning stage and a dynamic adjustment stage is proposed. In the former stage, tentative cleaning intervals are determined; in the latter stage, the temporal scheduling and spatial routing problems are jointly optimized in a dynamic fashion, so as to minimize the total economic loss. We model the problem as an extended version of the classical traveling salesman problem (TSP), that is, a production-driven traveling salesman problem with time-dependent cost (PD-TSP-TC). Genetic algorithm is employed to solve the corresponding nonlinear 0-1 integer programming problem. A case study on a real PV plant is conducted to demonstrate the performance of the proposed method, which shows that the temporal-spatial cleaning optimization method results in a better performance than the one that ignores route planning and that models route planning as classical TSP.

Keywords— Photovoltaic power plants, cleaning, scheduling, routing, traveling salesman problem, genetic algorithm (GA).

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Nomenclature

	Parameters of the power generation[a]
p	ideal generated power
h	total daytime hours
e	electricity selling price
d	dust accumulation degree
	Symbols in the periodic planning stage
t	time index in the scheduling time range, $t \in [0, T]$
$\boldsymbol{c}$	periodic cleaning schedule
w_0	cleaning cost per time
y	total economic loss of the scheduling time range
η	economic loss per unit time
α	cleaning interval in the periodic planning stage
	Symbols in the temporal-spatial optimization model
w_t	cost of vehicle, tools, and resources for each day
w_w	daily manpower cost for each cleaner
m	index of adjustment cycles, $m \in \{1, 2, ..., M\}$
N_f	predictable time length
$\mathcal{W}$	adjustment window
τ	time index
i, j	sub-array index
u, x	decision variables in the model (boolean variables)
P_w	workload can be finished by one cleaner within one day
P_r	workload of one sub-array
$N_t^{\max}$	maximum number of cleaners in one team
$N_d^{\max}$	maximum number of cleaners can be dispatched in the scheduling
N_τ	number of cleaners dispatched in date τ
L^d	daily economic loss caused by dust deposition for all sub-arrays
C^d	daily cleaning team cost for all sub-arrays
T^d	daily travel cost for all sub-arrays

Note[a]: The symbols of the parameters with a '' mean they are forecasted value. Capital letters mean they are seasonal average values.

1 Introduction

Nowadays, photovoltaic (PV) power generation has become one of the mainstream ways to utilize solar energy [1]; PV modules are key equipment in a PV system that are able to transfer solar energy to electricity. Although various technologies have been dedicated to improve PV efficiency, dust deposition on the surface of PV modules could significantly reduce the efficiency of power output by obstructing solar radiations [2,3]. Pulipaka et al. [4] propose that soiling on a panel can decrease the amount of horizontal irradiance received by the panel ranging from 22% to 52%. Said et al. [5] study the reduction in PV module energy output due to dust deposition, and such reduction can account for up to 60%. The research of Khodakaram-Tafti et al. [6] shows that a dust storm can reduce the daily average energy generated of PV modules by 58.2%. In addition, dust deposition could induce hot spots, reducing the efficiency and reliability of PV systems and even damaging the modules [7,8]. As a result, *cleaning*—as a key element of operations and maintenance (O&M) [9,10]—is critical for PV systems, since it can remove dust deposition and thus keep the systems operating in an efficient manner [11,12]. However, cleaning incurs expenditure [13]. In general, if the cleaning interval is too long, the power loss caused by dust deposition will be large; while if a PV system is cleaned too frequently, then the cleaning cost incurred might exceed the reduction in power loss. Therefore, it is important to specify an optimal cleaning policy by properly balancing the reduction in power loss and the cleaning cost incurred.

In general, cleaning optimization for PV systems/plants involves two inter-related problems: *temporal scheduling* and *spatial routing*. The former focuses on the determination of optimal cleaning intervals or dates over a specific planning horizon, whereas the latter deals with the specification of optimal route that cleaning operations should follow. In the literature, existing studies on PV cleaning focus predominately on the temporal scheduling problem. Jones et al. [14] optimize the cleaning cost and schedule based on observed soiling conditions for photovoltaic plants in Central Saudi Arabia. Jiang et al. [15] conclude that in a desert area, modules should be cleaned when the power output reduction and the particle concentration are equal to 5% and 100μ g/m3, respectively. Zapata et al. [16] design a cleaning program for a PV plant installed in northern Chile based on an analysis of energy losses. Luque et al. [17] study the effect of soiling and cleaning schedule optimization for bifacial PV modules. This stream of research usually adopts a periodic cleaning policy and only considers historical data of dust accumulation process, PV generation, and meteorological parameters when optimizing the cleaning interval for a specific PV system or plant; daily variations in meteorological parameters as well as PV generation are not taken into consideration. Al-Kouz et al. [18] investigate the effects of dust deposition on a PV system built at Jordan and, as a result, a recommendation for cleaning frequency of every two weeks is proposed. Ashley et al. [19] theoretically analyze the rationality of periodic cleaning for concentrating solar power (CSP) systems. Furthermore, Ullah et al. [20] argue that the optimal cleaning intervals for PV systems should not be constant.

In reality, PV power generation relies on solar radiations and other meteorologic parameters, which are time-varying in nature; meanwhile, the dust accumulation process is also changing over time. In this sense, a constant cleaning interval would be suboptimal. In the literature, there are only a few studies exploring beyond the periodic cleaning policy. Micheli et al. [21] determine an optimal cleaning interval based on the identification and prediction of daily soiling profiles. Rodrigo et al. [22] study a cleaning scheduling problem for PV systems located in Mexico based on levelized cost of energy. In their work, the cleaning intervals are adjusted according to environmental conditions. Truong-Ba et al. [23] develop a condition-based cleaning policy for CSP systems with stochastic soiling, rain events, and imperfect cleanings. The optimal cleaning policy turns out to be a time-varying reflectivity threshold, below which cleaning is triggered. Wang et al. [24] present a dynamic scheduling method that is able to make cleaning decision dynamically based on forecasted power generation and dust deposition. Recently, Wang et al. [25] further develop a hybrid cleaning scheduling framework (including a periodic planning stage and a dynamic adjustment stage) that is able to fully utilize both historical and forecasting data.

In recent years, the scale of PV plants has become increasingly large [26]. The largest PV plant in the world takes up a considerable 57 square kilometres [27]. Cleaning such a large-scale PV plant is complicated. The total travel cost of cleaning—influenced by route planning—is non-negligible. Given the locations of PV modules in a plant and the distances between them, it is not easy to find out an optimal route that visits each module exactly once with the aim of minimizing the total loss of power generation. To the best of our knowledge, currently there are only two studies (i.e., [28, 29]) addressing the spatial routing problem of cleaning, despite its significance from both practical and academic perspectives. However, Truong-Ba et al. [28] and Picotti et al. [29] focus only on the heliostat fields in CSP plants. In this study, we aim to contribute to this field by investigating a temporal-spatial cleaning optimization problem for large-scale PV plants.

In essence, the spatial routing problem of PV cleaning can be modeled as an extended *traveling salesman problem* (TSP) [30], in which the salesman is the cleaning team and the customers are the PV modules in the plant. As one of the most classical combinatorial optimization problems, TSP has been intensively studied and extended since its inception [31–33]. Among its extensions, the one that comes closest to the spatial routing problem is the traveling salesman problem with time-dependent service times (TSP-TS). Taş et al. [34] and Valentina et al. [35] consider not only the time/cost of salesman traveling in the arcs, but also the time/cost of services for the nodes in this extension problem.

In the route planning problem of PV cleaning, a unique feature is that the cleaning team's visit to a specific module affects not only the team's travel time/cost, but also the module's power output. More specifically, different cleaning routes imply not only different travel times/costs for cleaning team, but also different power losses caused by dust deposition. With the aim of minimizing the total economic loss (consisting of the loss of power production and the cleaning cost), we model the PV cleaning problem as a new version of the classical TSP, i.e., a production-driven traveling salesman problem with time-dependent cost (PD-TSP-TC). In the PD-TSP-TC, the power production of all modules (with the impact of cleaning) and the total cost (regarding to traveling and cleaning) are jointly considered to design an optimal cleaning plan. The plan involves not only spatial routing but also temporal scheduling, because both the power production and the total cost are time-dependent.

In this paper, we extend the temporal cleaning scheduling problem in Wang et al. [25] to the temporal-spatial cleaning optimization problem. The main contributions of this paper are as follows:

- To our knowledge, this research represents the first to study the temporal-spatial cleaning optimization problem for large-scale PV plants, in which temporal cleaning-dates scheduling and spatial cleaning-route planning are jointly addressed.

- Moreover, the PD-TSP-TC, constructed from the temporal-spatial cleaning optimization problem, is a novel extension of the classical TSP. The perspective—from which the cleaning problem is solved—is shifted from the salesman to the whole system including the salesman and the nodes (which are the cleaning team and the PV modules, respectively, in the cleaning problem).

- Finally, the two-stage framework in [25] is modified to solve the temporal-spatial cleaning optimization problem. In the medium-term periodic planning stage, a segmentation step is presented to divide the whole PV plant into multiple segments and the cleaning interval for each segment is optimized separately. In the short-term dynamic adjustment stage, temporal cleaning-dates scheduling and spatial cleaning-route planning are jointly optimized. Accordingly, a nonlinear 0-1 integer programming problem is formulated and solved by the genetic algorithm (GA).

2 Problem Description

In this work, we formulate the temporal-spatial PV cleaning optimization problem into the PD-TSP-TC, in which the decision variables are the temporal cleaning schedules, the cleaning route, and the dispatch of cleaners.

2.1 Assumptions

To facilitate modeling and analysis, the following assumptions are adopted throughout this paper:

- Only one cleaning team is considered. The team has only one cleaning vehicle, though it can equip up with different numbers of cleaners. All cleaners are identical in a statistical sense and the manpower cost per day is the same for each cleaner.
- Only one depot is considered for the cleaning team, which means that the team should start off from the depot and then return to it every day. In addition, the capacity of cleaning resources that the team can take is sufficient for one day, and thus the team does not need to return to the depot amid cleaning.
- The planning unit of PV cleaning is the PV sub-array. A piece of sub-array consists of some PV modules that locate close to each other. The cleaning planning within a sub-array is ignored.

2.2 Overview of the Method

Overall, the cleaning optimization method consists of three steps. The first step is to divide all PV sub-arrays in the whole plant into several array-segments, where the modules in a specific segment exhibit a similar dust accumulation situation. When segmenting sub-arrays, the geographical location and the type of modules are key factors that should be considered. On the one hand, the geographical location of a sub-array influences its dust deposition process, due to, e.g., the wind direction and the mountains or pollution-generating factories nearby. On the other hand, the power productions of different module types are not the same even in the same environmental condition.

The second step is medium-term periodic planning, aiming to determine a tentative cleaning interval for each segment so as to minimize the power loss caused by dust and the cleaning team cost. The third step is short-term dynamic adjustment, which coordinates cleaning-dates adjustment and route planning by doing a joint temporal-spatial optimization to minimize the power loss, cleaning team cost, and travel cost. The second and third steps are detailed in Sections 3 and 4, respectively.

3 Production-Driven Temporal Scheduling

The temporal scheduling model presented in this section is adapted from Wang et al. [25], which includes a periodic planning stage and a dynamic adjustment stage. In our work, the former stage focuses only on temporal scheduling, which is introduced below, and the latter stage is modified to coordinate cleaning-dates adjustment and cleaning-route planning, which is introduced in Section 5.

The objective of the periodic planning stage is to determine an optimal (tentative) cleaning interval based on the average values of power generation, dust accumulation process, and electricity selling price, etc. We assume that the dust deposition will be removed completely after cleaning, i.e., the cleaning is perfect. For a specific array-segment in the PV plant, the economic loss (consisting of power loss due to dust deposition and the cleaning cost) over an extended time period $[0, T]$ can be expressed as

$$y(T, \boldsymbol{c}) = \int_0^T p(t)d(t, \boldsymbol{c})e(t)dt + Iw_0, \tag{1}$$

where $p(t)$ is the ideal power output, which is the power output of clean PV modules without dust deposition and $p(t)$ depends on the meteorological conditions; $d(t, \boldsymbol{c}) \in [0, 1]$ is the dust deposition degree, which is valued by the power loss rate due to dust deposition; $e(t)$ is the selling price of electricity; I is the number of cleanings during this period; and w_0 is the unit cleaning cost. Here, $\boldsymbol{c} = [c_1, c_2, \cdots, c_I]$ denotes the cleaning schedule, where $0 = c_0 < c_1 < c_2 < \cdots < c_I < T$ are cleaning execution instants.

The expression of dust deposition degree $d(t, \boldsymbol{c})$ consists of a deterministic term $f(t)$ and a random term $\Delta f(t)$, where $f(t)$ is a monotonically increasing function representing the dust deposition progress without cleaning and $\Delta f(t)$ represents the stochastic fluctuation modeled by a Wiener process [36, 37]:

$$\begin{aligned} &d(t, \boldsymbol{c}) = f(t - c_i) + \Delta f(t - c_i), \\ &t \in [c_i, c_{i+1}), i = 0, 1, \cdots, I, \\ &\Delta f(t) \sim Normal(0, \sigma_f^2 t), \end{aligned} \tag{2}$$

where σ_f is the diffusion coefficient of the Wiener process.

In practice, the meteorological conditions in a specific PV plant are relatively stable in one season. Because power generation depends on the meteorological conditions, it should also be relatively stable in one season. Moreover, according to the current electricity market, the selling price of electricity is usually set at the beginning of one year and is kept constant throughout the year. Therefore, for one season, $p(t)$ and $e(t)$ can be approximated by their seasonal average values P and E, respectively. Then, Eq. (1) can be rewritten as:

$$y(T, \boldsymbol{c}) = \int_0^T PEd(t, \boldsymbol{c})dt + Iw_0. \tag{3}$$

According to Wang et al. [25], when the number of cleanings is fixed, a periodic cleaning policy is optimal. In the periodic planning stage, our aim is to specify an optimal cleaning interval for each array-segment. For this purpose, we turn to minimize the expected economic loss per unit time:

$$\eta(\alpha) = \frac{E[y(T, \boldsymbol{c})]}{T} = \frac{PE\int_0^\alpha f(t)dt + w_0}{\alpha}, \tag{4}$$

where α is the cleaning interval.

In order to obtain the optimal cleaning interval α^*, we take the first derivative of $\eta(\alpha)$ with respect to α:

$$\eta'(\alpha) = \frac{PE[f(\alpha)\alpha - \int_0^\alpha f(t)dt] - w_0}{\alpha^2}. \tag{5}$$

Setting $\eta'(\alpha) = 0$ yields

$$f(\alpha)\alpha - \int_0^\alpha f(t)dt = \frac{w_0}{PE}. \tag{6}$$

Proposition 1. *There exists a unique and finite solution α^* to* (6)*, and the resultant economic loss per unit time is given by*

$$\eta(\alpha^*) = f(\alpha^*). \tag{7}$$

Proof. Define $\zeta(\alpha) = f(\alpha)\alpha - \int_0^\alpha f(t)dt$. Then, we have $\zeta'(\alpha) = f'(\alpha)\alpha \geq 0$. Notice that $\zeta(0) = 0$ and $\zeta(\alpha) \to \infty$ as $\alpha \to \infty$. This implies that $\zeta(\alpha)$ is increasing in α from 0 to ∞. Therefore, the solution to (6) is unique and finite. Given the optimal solution α^* to (6), rearranging its terms yields (7). □

Note that the optimization model can be transformed into a discrete form as the temporal scheduling aims to determine the cleaning dates. The period from $t = 0$ to T is divided into N days, from date $n = 0$ to date N. In this manner, the optimal cleaning interval α^* should be rounded to the nearest date.

4 Spatial Routing Problem

The spatial routing problem without considering power production is addressed in this section, which is modeled as the classical TSP. The objective is to determine an optimal cleaning route so as to minimize the cleaning travel cost. This model will be extended to the PD-TSP-TC in Section 5.

4.1 Cleaning Duration

Cleaning one array-segment per time may last for a few days. Manpower dispatched in each day can be different. A cleaning team with more cleaners can complete more workloads in one day. However, considering the vehicle's capacity, the number of cleaners in one team has an upper limit. Let $N_t^{\max}$ and $N_d^{\max}$ be the maximum number of cleaners in one team and the maximum number of cleaners can be dispatched, respectively. The cost related to the cleaning team includes two parts: cost of vehicle, tools, and resources (e.g., water) and cost of manpower. We assume that the cost of vehicle, tools, and resources is constant for each day, denoted by w_t, and the daily manpower cost for each cleaner is also constant, denoted by

w_w. Suppose that cleaning a specific array-segment takes t_c days, then the cost for cleaning team is given by

$$w_0 = w_t t_c + \sum_{\tau \in \mathcal{T}_c} N_\tau w_w, \tag{8}$$

where N_τ is the number of cleaners dispatched in date $\tau \in \mathcal{T}_c$, and $\mathcal{T}_c = \{1, 2, \cdots, t_c\}$ is the set of cleaning dates.

Let $\mathcal{N} = \{0, 1, \cdots, n\}$ denote the set of nodes in the graph of PV sub-arrays to be cleaned, where node 0 is the depot. Each node in $\mathcal{N} \backslash \{0\}$ corresponds to a sub-array. Here, the workload of cleaning is evaluated by the rated power of PV modules. Let P_{r_i} denote the rated power of modules in sub-array i, and further let P_w represent the workload that can be finished by one cleaner within one day. All PV modules in the array-segment should be cleaned in one cleaning, thus the following constraint on cleaning workload should be met:

$$\sum_{\tau \in \mathcal{T}_c} N_\tau P_w \geq \sum_{i \in \mathcal{N}} P_{r_i}. \tag{9}$$

Based on Eqs. (8) and (9), we have

$$w_0 \geq w_t t_c + \frac{\sum_{i \in \mathcal{N}} P_{r_i}}{P_w} w_w. \tag{10}$$

This means that the cleaning should be finished as soon as possible so as to minimize the cleaning cost of team and manpower. The minimum number of cleaning days, $t_c^{\min}$, can be calculated by

$$t_c^{\min} = \left\lceil \frac{\sum_{i \in \mathcal{N}} P_{r_i}}{P_w \min\{N_t^{\max}, N_d^{\max}\}} \right\rceil. \tag{11}$$

It is worth noting that if we consider the influence of cleaning optimization on power loss when choosing the best cleaning date for each sub-array, then the cleaning days might be longer than $t_c^{\min}$.

4.2 Route Planning

As stated earlier, the route planning problem is similar to the classical TSP, where the cleaning team is the salesman and the sub-arrays are the nodes to be visited. The main difference is that the cleaning might last for several days and there is only one depot. As a result, the cleaning team should start off from the depot and return to it every day. In this sense, fewer cleaning days is preferred, in terms of minimizing the travel cost. According to Eq. (11), the cleaning route should be planned within $\mathcal{T}_c^{\min} = \{1, 2, \cdots, t_c^{min}\}$. The decision variables of the route planning problem are defined as follows: $u_{\tau i} \in \mathcal{U}$ takes the value 1 if node i is visited on day τ, and 0 otherwise; $x_{ij} \in \mathcal{X}$ takes the value 1 if node j is visited, immediately after node i, and 0 otherwise. In essence, $\mathcal{U}$ and $\mathcal{X}$ determine the cleaning workload assignment in each day (i.e., the cleaner dispatch plan) and the cleaning route.

For one PV plant, the travel cost between two sub-arrays is determined by two main factors, distance and height difference. $f_t(s_{i,j}, a_{i,j})$ is defined as the cost function associated with the route from sub-array i to j, where $s_{i,j}$ is the distance from i to j, and $a_{i,j}$ is the height difference from i to j. It is noted that $s_{i,j}$ is the distance along the road that the vehicle passes through, rather than the straight-line distance. f_t is asymmetrical, as $a_{i,j}$ is asymmetrical though $s_{i,j}$ is symmetrical. Specifically, distance is undirected, which means

$s_{i,j} = s_{j,i}$. However, height difference is directed and $a_{i,j} = -a_{j,i}$. In the optimization model, the travel cost function is not specified to give a general analysis. When the cleaning policy is applied for PV plants, the function can be specified according to the conditions of the plants.

The objective is to minimize the total travel cost considering the distances and height differences:

$$\min_{\mathcal{U},\mathcal{X}} \sum_{\tau \in \mathcal{T}_c^{\min}} \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N}} u_{\tau i} x_{i,j} f_t(s_{i,j}, a_{i,j}), \tag{12}$$

The constraints can be formulated as follows.

$$s.t. \quad x_{ij} \in \{0,1\},\ i,j \in \mathcal{N} \tag{13}$$

$$\sum_{j \in \mathcal{N}\backslash\{i\}} x_{ij} \begin{cases} = 1,\ i \in \mathcal{N}\backslash\{0\} \\ \geq 1,\ i = 0 \end{cases} \tag{14}$$

$$\sum_{i \in \mathcal{N}\backslash\{j\}} x_{ij} \begin{cases} = 1,\ j \in \mathcal{N}\backslash\{0\} \\ \geq 1,\ j = 0 \end{cases} \tag{15}$$

$$\sum_{i \in \mathcal{M}} \sum_{j \in \mathcal{M}} x_{ij} \leq |\mathcal{M}| - 1,\ \forall \mathcal{M} \subset \mathcal{N}\backslash\{0\}, 2 \leq |\mathcal{M}| \leq n \tag{16}$$

$$u_{\tau i} \in \{0,1\},\ i \in \mathcal{N}, \tau \in \mathcal{T}_c^{\min} \tag{17}$$

$$\sum_{\tau \in \mathcal{T}_c^{\min}} u_{\tau i} = \begin{cases} 1,\ i \in \mathcal{N}\backslash\{0\} \\ |\mathcal{T}_c^{\min}|,\ i = 0 \end{cases} \tag{18}$$

$$\sum_{i \in \mathcal{N}\backslash\{0\}} u_{\tau i} x_{i0} = 1,\ \tau \in \mathcal{T}_c^{\min} \tag{19}$$

$$\sum_{i \in \mathcal{N}\backslash\{0\}} u_{\tau i} P_{r_i} \leq P_w \min\{N_t^{\max}, N_d^{\max}\},\ \tau \in \mathcal{T}_c^{\min} \tag{20}$$

In the route planning problem model, constraints (13), (14),(15) and (16) are similar to the constraints in the classical TSP model. Constraint (13) defines the domains of decision variable x_{ij}. Constraints (14) and (15) require to have an outgoing arc and an ingoing arc for each node except the depot 0. This means that each sub-array will be cleaned only once. Node 0 (the depot) has more than one outgoing arcs and ingoing arcs. Constraint (16) is used to eliminate sub-loop. However, the main differences between this problem and the classical TSP are reflected in the objective function and constraints from (17) to (20). Constraint (17) defines the domains of decision variable $u_{\tau i}$. Constraint (18) ensures that each sub-array is assigned to only one day for cleaning. It also ensures that the depot is the start point of the path on each day. Constraint (19) indicates that the depot is the end point of the route on each day and there have to be one sub-array as the previous node of the depot. Constraint (20) ensures that the cleaning workload in each day is below the upper limit of the cleaning team's capacity. The introduction of $u_{\tau i}$ solves modeling the cleaning workload assignment in each day. However, it brings nonlinearity to the objective function (12) and constraint (19). In addition, the uniqueness of the depot (node 0) makes (13), (14) and (17) to be piecewise function. In summary, the route planning problem is more complex than the classical TSP to solve. TSP has been testified as NP-hard. Therefore, the route planning problem is NP-hard as well. Metaheuristic algorithm is thus needed to obtain a quasi-optimal solution. The algorithm will be introduced after the modeling of temporal-spatial cleaning optimization problem in the next section.

5 The PD-TSP-TC

5.1 Coordination of Temporal-Spatial Cleaning Optimization

The "optimal" cleaning interval obtained in Section 3 is for medium-term scheduling, as it is determined based on the average values of some key parameters. In real applications, the cleaning dates in each cycle should be dynamically adjusted (advanced or postponed), by considering daily variations in power generation and meteorological parameters. Meanwhile, the "optimal" cleaning route obtained in Section 4 guarantees a minimal travel cost, while the power loss and the cleaning team cost might not be minimum. Hence, we need to coordinate the temporal adjustment and spatial routing problems in an integrated manner. To this end, following Sections 2.2 and 3, respectively, we first partition the whole plant into several array-segments and then optimize the cleaning interval for each segment; afterwards, cleaning-dates adjustment and spatial routing are optimized coordinately in the dynamic stage. In addition to planning for each individual array-segment, there might be another situation: the adjustment windows of several array-segments are conflicting. In this case, the cleaning-dates adjustment and route planning for all sub-arrays in these array-segments should be performed simultaneously.

We specify an *adjustment window* for each cycle to determine the cleaning dates and route of the sub-arrays, based on the fixed cleaning interval. The adjustment relies upon real and forecasting data of power production and dust accumulation. Thus, the length of adjustment window, N_f, should be set based on the forecasting capability. According to the existing studies [38, 39], the PV power forecasting for about 7-10 days is reliable for cleaning scheduling, and the duration is long enough to complete one cleaning. The adjustment window is thus set to be centered on the planning date with the length of N_f, i.e.,

$$\mathcal{W}_m = \left[\underline{W_m}, \overline{W_m}\right] = \left[m\alpha^* - \frac{N_f}{2}, m\alpha^* + \frac{N_f}{2}\right],$$

where m is the index of windows.

For a specific adjustment window, the first date to make cleaning plan is $\underline{W_m}$, and the plan includes the cleaning schedule and route for each date in the window. When the cleaning plan for the decision-making date is executed, certain sub-arrays are cleaned. Then, after that day, we can obtain more historical data and the forecasting for the remaining dates will thus be more accurate. The planning of the remaining dates in this window for the rest sub-arrays to be cleaned will be repeated until all sub-arrays have been cleaned.

Let $k \in \mathcal{W}_m$ be the date that we are making the adjustment decision. It should be noted that when we say making decision on date k, it means that the decision is made in the evening of date $k-1$, thus the schedule includes date k. The period between the two cleaning dates is divided into two intervals: We have real (historical) data in the first interval $[r_{m-1,i}, k-1]$, whereas we have to rely on forecasting data over the period from k to the next cleaning date. For sub-array i, when we make decision on date $k \in \mathcal{W}_m$ in the mth adjustment window, the estimated economic loss caused by dust deposition from the last cleaning date $r_{m-1,i}$ to the planned cleaning date in this window is given by

$$L_{i,k} = \sum_{\tau=r_{m-1,i}}^{k-1} p_{i,\tau} h_\tau e_\tau d_{i,\tau} + \sum_{\tau=k}^{\overline{W_m}} u_{\tau i} \left(\sum_{\rho=k}^{\tau} p'_{i,\rho}(k) h'_\rho(k) e'_\rho(k) d'_{i,\rho}(k) \right), \tag{21}$$

where $p_{i,\tau}$ and $d_{i,\tau}$ are the ideal power output and dust deposition degree of sub-array i on date τ, respectively; h_τ and e_τ are the total daytime hours and the electricity price on date

τ, respectively. The four quantities with the prime symbol (') represent the forecasting data over the period from k to the next cleaning date, and their accuracies are dependent on k.

$u_{\tau i}$ in Eq. (21) is the decision variable to integrate temporal scheduling and route planning. As the description in Section 4.2, $u_{\tau i} \in \mathcal{U}$ is boolean variable, which takes the value 1 if node i is visited on day τ, and 0 otherwise. Thus, $u_{\tau i}$ determines the exact date to clean sub-array i, which in turn influences the sub-array's location along the cleaning route. In the economic loss model, it can be regard as a "filter". One sub-array i only belongs to the cleaning plan in one day, and the $u_{\tau i}$ in that day is 1. Only the estimated economic loss corresponding to this cleaning decision is added. In other days, $u_{\tau i} = 0$. We use $u_{\tau i}$ in the same idea in the following equations, (22), (23), (24), (25). In this sense, the functions of the three parts of total economic loss, power loss, cleaning team cost, and travel cost, can be modeled by the same decision variables in order to optimize the cleaning schedule.

To facilitate joint temporal-spatial optimization, the objective function should incorporate the power loss, the cleaning team cost, and the travel cost. We solve this optimization problem by minimizing the average daily economic loss. If the average daily loss between the two cleaning dates for every adjustment window is minimized, then the average daily loss of the whole horizon is also minimized, implying that the total economic loss is minimized. For sub-array i, when we make decision on date k in the mth adjustment window, the estimated cleaning interval is $\sum_{\tau \in \mathcal{W}_m} u_{\tau i}(\tau - r_{m-1,i} + 1)$. Hence, the sum of daily losses of all sub-arrays is given by

$$L^d = \sum_{i \in \mathcal{N} \setminus \{0\}} \frac{L_{i,k}}{\sum_{\tau \in \mathcal{W}_m} u_{\tau i}(\tau - r_{m-1,i} + 1)}. \tag{22}$$

Suppose that the cleaning team is paid by day. We can decompose the total cleaning cost into the cost for each sub-array according to the cleaning workload. The total workload in date τ is $\sum_{i \in \mathcal{N} \setminus \{0\}} u_{\tau i} P_{r_i}$, and the manpower dispatched in this date is $N_\tau = \sum_{i \in \mathcal{N} \setminus \{0\}} u_{\tau i} P_{r_i} / (P_w \min\{N_t^{\max}, N_d^{\max}\})$. The total cleaning cost in this date is $N_\tau w_w + w_t$. Thus, the cleaning cost of sub-array i in date τ can be expressed as

$$C_{i,\tau} = \frac{u_{\tau i} P_{r_i}}{\sum_{i \in \mathcal{N} \setminus \{0\}} u_{\tau i} P_{r_i}} (N_\tau w_w + w_t). \tag{23}$$

The sum of the daily cleaning costs for all sub-arrays is given by

$$C^d = \sum_{i \in \mathcal{N} \setminus \{0\}} \frac{\sum_{\tau \in \mathcal{T}_c} C_{i,\tau}}{\sum_{\tau \in \mathcal{W}_m} u_{\tau i}(\tau - r_{m-1,i} + 1)}. \tag{24}$$

Similarly, the sum of the daily travel cost for all sub-arrays is given by

$$T^d = \sum_{i \in \mathcal{N}} \sum_{j \in \mathcal{N} \setminus \{0\}} \sum_{\tau \in \mathcal{W}_m} \frac{u_{\tau j} x_{i,j} f_t(s_{i,j}, a_{i,j})}{\tau - r_{m-1,j} + 1} + \sum_{i \in \mathcal{N}} \sum_{\tau \in \mathcal{W}_m} \frac{u_{\tau i} x_{i,0} f_t(s_{i,0}, a_{i,0})}{\tau - r_{m-1,i} + 1}. \tag{25}$$

Note that the second term represents the case in which the route's end point is the depot (node 0).

We use the same decision variables in the route planning problem in Section 4.2 to model the PD-TSP-TC. Thus, the PD-TSP-TC has different objective function, but the same decision variables and constraints. In summary, the temporal-spatial cleaning optimization problem can be formulated as

$$\begin{aligned} &\min_{\mathcal{U}, \mathcal{X}} \; L^d + C^d + T^d \\ &s.t. \; (13) - (20). \end{aligned} \tag{26}$$

In the PD-TSP-TC model, the optimization objective, total economic loss, consists of three parts, power loss caused by dust L^d, cleaning team cost C^d, and cleaning travel cost T^d. Due to the continuity of PV production in the time dimension, in order to optimize the cleaning schedule in a long span of time, the total loss of the system needs to be converted into daily loss. Therefore, the model is highly nonlinear as product of decision variables x and u and denominator with decision variables existing. This model is established based on the production-driven temporal scheduling model in Section 3 and route planning model in Section 4.2. It is more complex than the two optimization problems. Solving the optimal result directly is difficult as it is NP-hard and metaheuristic algorithm is thus needed to obtain a quasi-optimal solution. The design of solving algorithm is introduced in Section 5.2.

It is noted that, in reality, the cleaning plans of more than one array-segments might be conflicting. They cannot always be satisfied simultaneously due to the constraint on cleaning capacity. In this situation, a global optimization that jointly considers all the modules in these array-segments is required.

Figure 1 illustrates the joint optimization framework. In the static stage, there are 3 steps: array-segments division, periodic optimization for each array-segment, and identification of conflicting adjustment windows. Based on the medium-term plan in the static stage, the short-term cleaning schedule is adjusted dynamically. The adjustment starts from $k = \underline{W_m}$, the beginning of the mth adjustment window. If the adjustment windows are conflicting, then the set of sub-arrays to be cleaned should include all sub-arrays in these segments. In this manner, the cleaning plan for this window can be optimized by Eq. (26). On the next date, the set of sub-arrays to be cleaned and the cleaning plan for the remaining dates are updated. When all sub-arrays have been cleaned, i.e., the set becomes empty, the adjustment for this window is completed; otherwise, the optimization is repeated by using the updated historical data and forecasting information. The program will continuously proceed until the whole cleaning problem is finished. For an in-service PV plant, it might be a time duration of several years.

5.2 Genetic Algorithm

At present, the main metaheuristic algorithms used to solve the TSP include ant colony algorithm [40], particle swarm optimization [41], simulated annealing algorithm [42], genetic algorithm [43] and so on. For brevity, the theories of these algorithms are not introduced in detail. In this paper, we choose GA as the metaheuristic algorithm to solve the problem based on the characteristics of the model and GA.

There are two main characteristics of PD-TSP-TC different from the classical TSP. First, the optimization route is composed of multiple closed loops with a common starting point, rather than one loop. In other words, the depot is one repeated node in the whole path. Second, route planning problem in space dimension needs to be jointly considered with the cleaning dates scheduling in time dimension. In view of the two characteristics, GA after targeted design is suitable for solving these problems. First, the form of chromosome coding can express the cleaning routes intuitively, and daily assignments of cleaning workloads can be expressed by hybrid encoding [44]. Second, GA has good performance in solving temporal-spatial coupling problem and eliminating internal loops, and the fitness function can be easily adapted to the optimization objective function in optimization problem [35].

In conclusion, we solve PD-TSP-TC by a designed GA which searches the quasi-solution by population evolution. The individuals in the population correspond to the solutions of

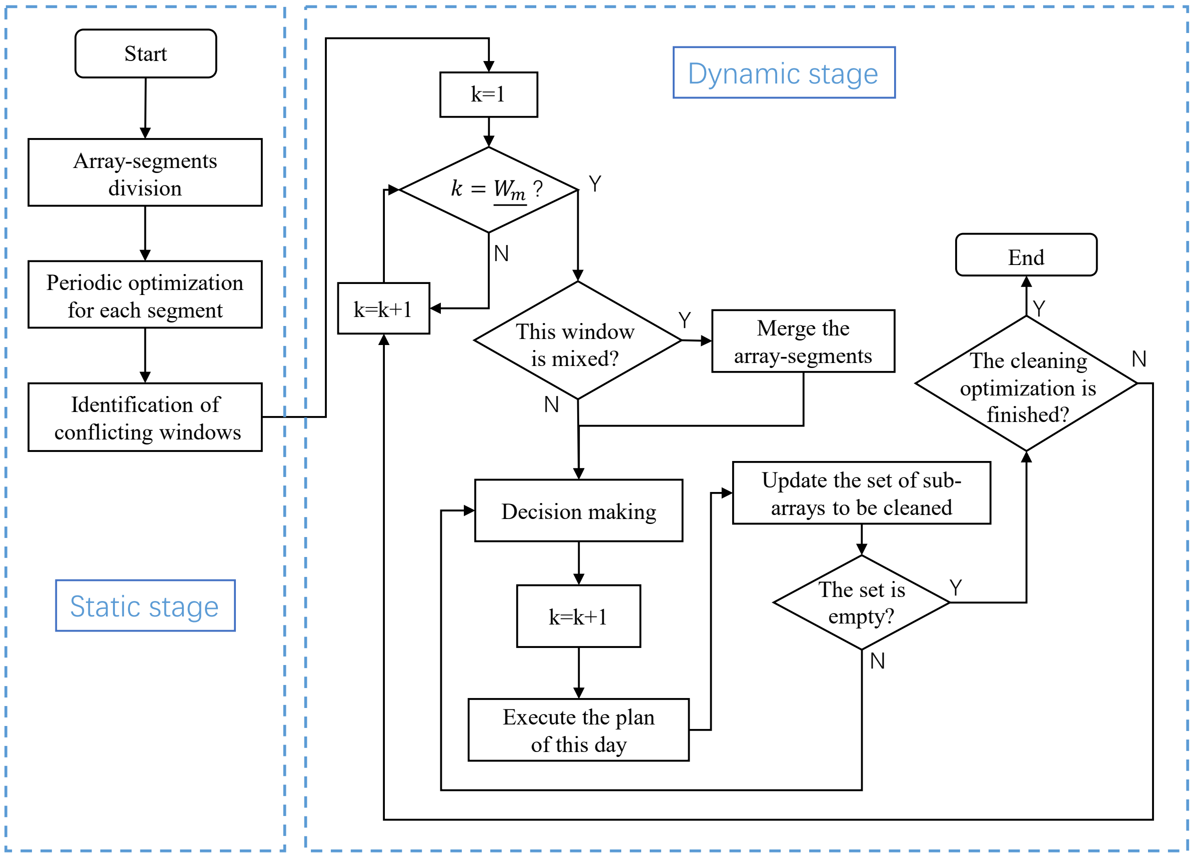


Figure 1: Diagram of the temporal-spatial cleaning optimization method.

the problem to be solved. In our proposed GA, each individual corresponds to a cleaning plan for the sub-arrays to be cleaned (in one array-segment or several array-segments). The population size is set to 100 and the algorithm design is detailed below.

1) Solution encoding: The encoding of chromosomes is hybrid, with a piece of permutation encoding, which is the permutation of all sub-arrays to be cleaned, and a piece of real-integers encoding, which is the encoding of the workload assignment to each day. For instance, for an array-segment with 5 sub-arrays, assuming that the length of adjustment window is 3 days, (1, 2, 3, 5, 4, 3, 2, 0) is the encoding of an individual cleaning plan. It means that sub-arrays #1, #2, and #3 will be cleaned in the first day, with the route (1, 2, 3); sub-arrays #5 and #4 will be cleaned in the second day, with the route (5, 4); there will be no workload distributed to the third day. In the genetic operation, crossover and mutation of the two pieces chromosomes can be independently controlled, so as to avoid unnecessary trials and error, and improve the convergence speed by setting constraints respectively.

2) Initialization: In GA, the initial population is usually selected at random with the goal of covering the entire search space. We use a random set of 100 solutions to be the initial generation.

3) Fitness: The fitness function determines the search direction. In our proposed GA, the fitness of each solution is measured by the objective function, i.e., Eq. (26). One fitness value can be calculated from one solution encoding, i.e., one value of total economic loss can be computed from one cleaning plan in our problem. Then, the minimal economic loss can be obtained by searching the minimal fitness. According to the workload constraint, we specify a penalty fitness for two kinds of encodings: the total workload in one cleaning plan is not equal to the total workload of all sub-arrays, and the workload assignment in one day is beyond the cleaning capacity.

4) Selection: After the fitness values of the initial random solutions have been calculated, the GA selects a subset of individuals as the parents of the next generation. In this work, we adopt the *Elitist Tournament Selection* (ETSM) that integrates Tournament selection and Elite selection.

In the tournament selection, every individual has the opportunity to compete with others (even the worst individual may be matched to himself as a competitor). Thus, the tournament method is not easy to fall into the local optimum. It also has a low complexity and is easy to be parallelized. However, this method does not pay enough attention to the elites with better fitness. On the other hand, elite selection is a method that keeps all the elites and eliminates the mediocrities. However, the elite method is easy to fall into the local optimum. Combining the advantages of both tournament selection and elite selection, the ETSM ensures that the best individual of every generation has an opportunity to join the tournament.

5) Crossover: After the parents have been selected, GA will generate offsprings that inherit the characteristics from their parents by two methods: crossover and mutation.

Crossover, also known as pairing or recombination, refers to the exchange and recombination of the genetic codes of two parent individuals to generate a new individual. The purpose is to guarantee the stability of the population, so that the population moves towards the direction of the optimal solution. For the piece of chromosomes with real-integers encoding, the crossover method is two-points crossover: It first chooses two parent individuals and generates a random start point and a random end point; then the code fragments between the start and end points of the parents are switched.

For the piece of chromosomes with permutation encoding, the crossover method is partially matched crossover, which is extended from the two-points crossover. Because this piece corresponds to the cleaning route, there should be no duplicated genes in one chromosome. In general, the switch of two fragments might lead to invalid chromosomes and duplication of individual genes. In order to repair chromosomes, the matching relationship of each chromosome can be established within the crossover region, and then the conflict can be eliminated by applying the matching relationship to duplicate genes outside the crossover region. For both pieces of encodings, the probability of crossover between the chromosomes of two individuals are set to 0.7, which is an experience value in GA [45].

6) Mutation: Mutation is an aid to the creation of new individuals, as a complementary algorithm to crossover. The genes in the chromosomes of individuals after crossover have an opportunity to mutate. Like genetic mutations in organisms, the probability of mutation in GA is much lower than crossover. For the piece of chromosomes with permutation encoding, the method is invertion mutation, in which a random fragment of random length in every chromosome may be inverted with a specific probability. For the piece of chromosomes with real-integers encoding, the method is mutation of breeder GA [46], whose details are omitted for space consideration.

7) Stopping Criteria: The offsprings can be generated after selection, crossover, and mutation. Each time an evolution is finished, we obtain a new generation. Then, the fitness values of all individuals are calculated. The evolution is then repeated until the stopping criteria is met, i.e., the number of generation comes up to 2000 for optimization of one array-segment and 3000 for more than one array-segments.

6 Case Study

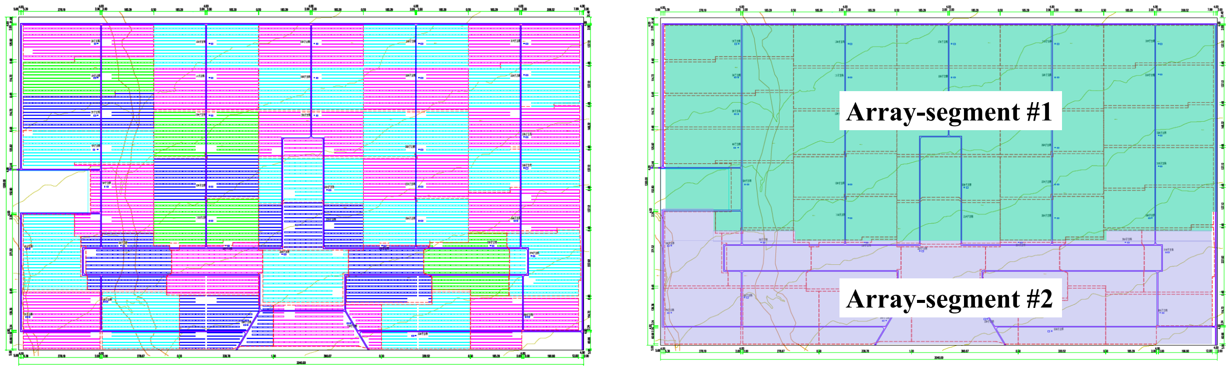
In this case study, we demonstrate the performance of the proposed method by comparing it with three cleaning policies. In total, we consider the following four policies:

1. No artificial cleaning.
2. Temporal scheduling only, without spatial routing.
3. Cleaning interval optimization and spatial routing, corresponding to the classical TSP.
4. The proposed temporal-spatial cleaning optimization method, corresponding to the PD-TSP-TC.

6.1 Description of the PV Power Plant

The case study is based on a 100MWp grid-connected PV plant located in Xinjiang, China. The plant consists of 38 sub-arrays (365926 modules) and covers an area of about 2.5 square kilometers (2040m×1200m). All the PV modules are polycrystalline silicon modules with 275Wp rated power, and the size of each module is 1650mm×992mm×40mm. The PV modules are installed facing south with a slope of 35°, without a tracking system. The height difference between the highest and lowest points in the plant is 17.5m. The layout of this plant is illustrated in Figure 2(a), in which each colored block represents a sub-array and the white block in the middle of the left is the depot. The small rectangles in the colored blocks are the PV modules. The blue lines represent the roads for cleaning vehicles. In addition, the colors of the blocks are used to distinguish sub-arrays and do not contain other information.

The information of location, height and rated power of all the 38 sub-arrays are shown in Table 1.



(a) (b)

Figure 2: (a) General layout of the 100MWp PV plant; (b) Array-segments division.

Table 1: Location, height and rated power of the sub-arrays.

Sub-array	1	2	3	4	5	6	7	8	9	10	11	12	13
Abscissa/m	0	0	0	0	92.5	-139	-139	115	139	277	277	277	277
Ordinate/m	491.5	372	258	138.5	0	-135	-371	-180	-371	490.5	353.5	211	68.5
Height/m	-4	-4	-2	-2	0	0	4	2	4	-4	-2	0	0
Rated power/kW	2649.9	2662	2662	2649.9	2662	2662	2649.9	2655.95	2662	2637.8	2637.8	2662	2637.8
Sub-array	14	15	16	17	18	19	20	21	22	23	24	25	26
Abscissa/m	277	362	447	654	654	654	654	654	654	811	1031	1031	1031
Ordinate/m	-68.5	-195.5	-371	490.5	353.5	211	68.5	-68.5	-195.5	-371	490.5	353.5	211
Height/m	2	4	4	-2	0	0	2	4	4	6	0	0	2
Rated power/kW	2649.9	2631.75	2662	2637.8	2637.8	2631.75	2655.95	2625.7	2662	2619.65	2637.8	2637.8	2662
Sub-array	27	28	29	30	31	32	33	34	35	36	37	38	
Abscissa/m	1031	1031	974	1166	1408	1408	1408	1408	1408	1294	1614	1511	
Ordinate/m	68.5	-68.5	-195.5	-371	490.5	353.5	211	68.5	-68.5	-195.5	-195.5	-371	
Height/m	8	4	6	8	0	2	2	4	6	6	8	10	
Rated power/kW	2637.8	2643.85	2631.75	2668.05	2662	2662	2631.75	2662	2649.9	2662	2643.85	2668.05	

[1] Define the depot as the origin of location, (0,0). The coordinate value of one sub-array is simplified as the position of the central point.
[2] Height of one sub-array is defined as the average height difference between it and the depot.

6.2 Array-Segments Division and Temporal Scheduling

The whole PV plant can be divided into two array-segments according to the dust deposition characteristics (see Figure 2(b)). Array-segment #1 has 25 sub-arrays while array-segment #2 has 13 sub-arrays. We adopt a widely used dust deposition function to model the efficiency reduction due to dust deposition [47–49]:

$$f(t) = \kappa(1 - e^{-\lambda t}) + \Delta f(t). \tag{27}$$

One can see that $f(t)$ is an asymptotic curve, where κ is the asymptotic value, λ is the accumulation rate, and $\Delta f(t)$ is the random fluctuation. These parameters can be fitted from historical data.

The PV modules in array-segment #2 experience more serious dust accumulation situation than those in array-segment #1. The parameters of dust deposition function for array-segments #1 and #2 are $\kappa = 0.2$, $\lambda = 0.002$, and $\kappa = 0.3$, $\lambda = 0.004$, respectively. Both

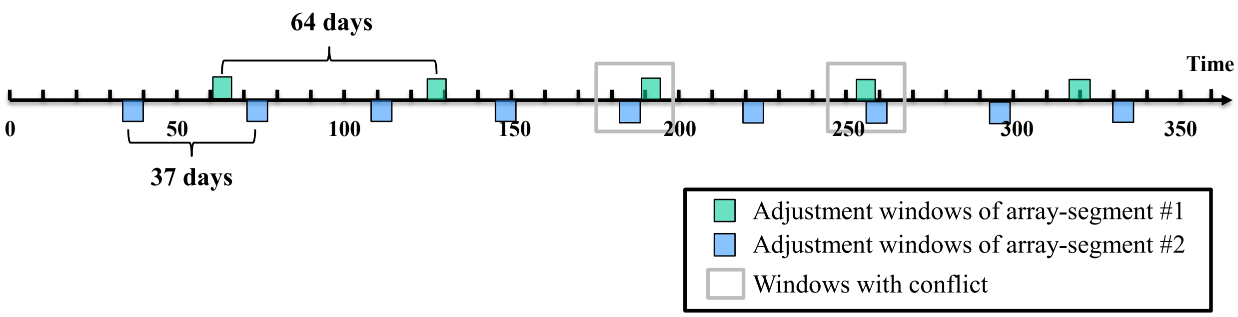


Figure 3: Adjustment windows of the two array-segments.

the asymptotic value and the accumulation rate of array-segment #2 are larger than those of array-segment #1. Total rated power of PV modules in array-segment #1 and #2 are 66MWp and 34MWp, respectively. According to the current electricity market, the electricity price is set to $E = 1$ currency unit/kWh, and the general cleaning cost per 1 kW rated power is set to 3 currency units.

Based on the settings above, we can calculate the optimal cleaning intervals for medium-term scheduling of the two array-segments (according to Section 3), which are 64 days for array-segment #1 and 37 days for array-segment #2, respectively. The planning horizon for PV cleaning in this case study is 1 year, i.e., 365 days. Referring to the existing power forecasting studies [38, 39], the predictable time length is set to $N_f = 8$ days, i.e., the length of each adjustment window is 8 days. Based on the optimal cleaning intervals, the adjustment windows for the two array-segments are illustrated in Figure 3. In the entire planning horizon, there will be 5 adjustment windows for array-segment #1 and 9 windows for array-segment #2. For most windows, we only need to consider one array-segment for cleaning scheduling. However, the third window of array-segment #1 and the fifth window of array-segment #2, as well as the fourth window of array-segment #1 and the seventh window of array-segment #2, are conflicting with each other. The cleaning plans for all PV sub-arrays in two conflicting segments should be optimized jointly.

6.3 Route Planning

The parameters related to cleaning capacity and cost are set as follows. The maximum number of cleaners in one team is $N_t^{\max} = 25$, and the maximum number of cleaners that can be dispatched is $N_d^{\max} = 40$. The workload that can be completed by one cleaner within one day is $P_w = 600$kW. The cost of vehicle, tools, and resources for each day is w_t=10000 currency units, and the daily manpower cost for one cleaner is w_w=300 currency units. Cost function of the route from node i to j is set as $f_t(s_{i,j}, a_{i,j}) = 6s_{i,j} + 1000a_{i,j}$ based on the engineering practice of this PV plant. Based on Eq. (11), the minimum cleaning duration of array-segments #1, #2, and #1 & #2 can be calculated as $t_c^{\min} = 5$, 3, and 8, respectively. When optimizing cleaning route without considering power generation, the time duration of route planning should be $\mathcal{T}_c^{\min} = \{1, 2, \cdots, t_c^{\min}\}$. According to Section 4.2, the quasi-optimal cleaning routes for array-segment #1, #2, and #1 & #2 can be obtained by GA.

Table 2: Cleaning dates of all sub-arrays in the first and second cleanings.

Sub-array	1	2	3	4	5	6	7	8	9	10	11	12	13
First cleaning date	63	65	63	63	62	63	63	65	64	64	65	65	65
Second cleaning date	128	127	127	128	126	128	127	127	126	127	125	125	125
Sub-array	14	15	16	17	18	19	20	21	22	23	24	25	
First cleaning date	64	64	62	62	62	62	65	61	61	61	61	61	
Second cleaning date	125	125	128	129	128	129	126	129	129	129	126	126	

6.4 Joint Temporal-Spatial Optimization

In our proposed method, spatial routing should be coordinated with temporal scheduling. Thus, the cleaning duration might be beyond $\mathcal{T}_c^{\min}$, and the cleaning plan should be updated everyday. In the whole time horizon, there are 3 cleanings for array-segment #1, 7 cleanings for array-segment #2, and 2 cleanings for the two array-segments together, as shown in Figure 3. To illustrate the scheduling process, we take the second cleaning of array-segment #1 as an example.

According to the optimization process, the first cleaning adjustment window extends from day 61 to day 68, i.e., $\mathcal{W}_1 = [61, 68]$, and the first cleaning dates of all sub-arrays are summarized in Table 2. The second adjustment window is $\mathcal{W}_2 = [125, 132]$. The adjustment begins when the current date is $k = 125$. According to Eq. (26), GA searches the optimal solution based on the historical data from the last cleaning dates to date k and the forecasting information within the adjustment window. The optimal workload (the number of sub-arrays to be cleaned) assignment for each day is (5, 4, 3, 0, 4, 4, 0, 5), and the optimal routing plan is shown in Figure 4(a). According to the plan, 5 sub-arrays (15, 13, 12, 11, 14) are cleaned on day 125. The schedule will be updated on $k = 126$ for the rest sub-arrays, with new historical data and more accurate forecasting information.

On day $k = 126$, the optimal cleaning workload assignment is (5, 0, 3, 3, 4, 5, 0), and the routing plan is shown in Figure 4(b). Note that the black lines represent the sub-arrays that have been cleaned. After the cleaning task on day 126 has been executed, the cleaning plan will be updated day by day until all sub-arrays have been cleaned. The whole process is shown in Figure 4(c), 4(d) and 4(e). In summary, the second cleaning lasts for 5 days, and the cleaning dates of all sub-arrays in this window are recorded in Table 2.

Other dynamic adjustments of cleaning scheduling for array-segments #1, #2, and #1 & #2 follow the same procedure, which are thus omitted for space consideration.

6.5 Performance Comparison

Now, we compare the performance of the proposed method with its three counterparts. Power losses and cleaning costs of the four methods are shown in Table 3 and Figure 5. For method #1, i.e., no artificial cleaning to be executed, the costs of cleaning team and travel are 0, but the power loss is up to 1246.40×10^4. If the PV plant is cleaned according to the temporal schedule specified by method #2, the power loss becomes 204.72, decreased by 83.5%, with total cleaning cost being 250.37. Thus, the total economic loss of method #2 is 455.09, decreased by 63.5% compared with method #1. Method #3 incorporates the cleaning-route planning and thus the travel cost is reduced to 78.09, while the power loss increases slightly as the travel cost has the highest priority in route planing. The total economic loss of method

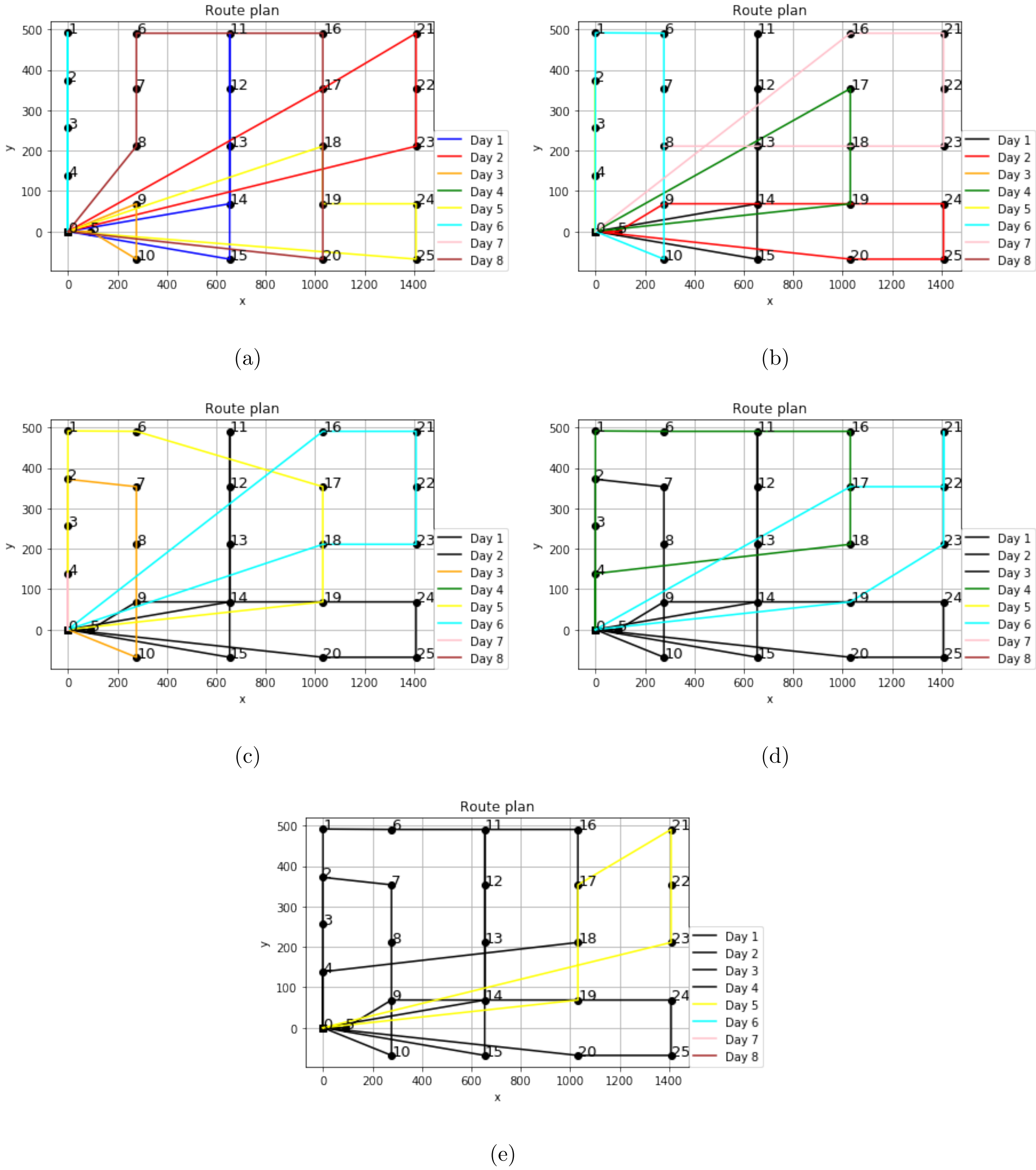


Figure 4: Route plan for array-segment #1, the second adjustment window: (a) $k = 125$; (b) $k = 126$; (c) $k = 127$; (d) $k = 128$; (e) $k = 129$.

Table 3: Comparison of the Four Methods (Units: 10^4 currency units).

Method	Power loss	Team cost	Travel cost	Total economic loss
#1	1246.40	0	0	1246.40
#2	204.72	91	159.37	455.09
#3	206.66	91	78.09	375.75
#4	188.43	91	86.88	366.31

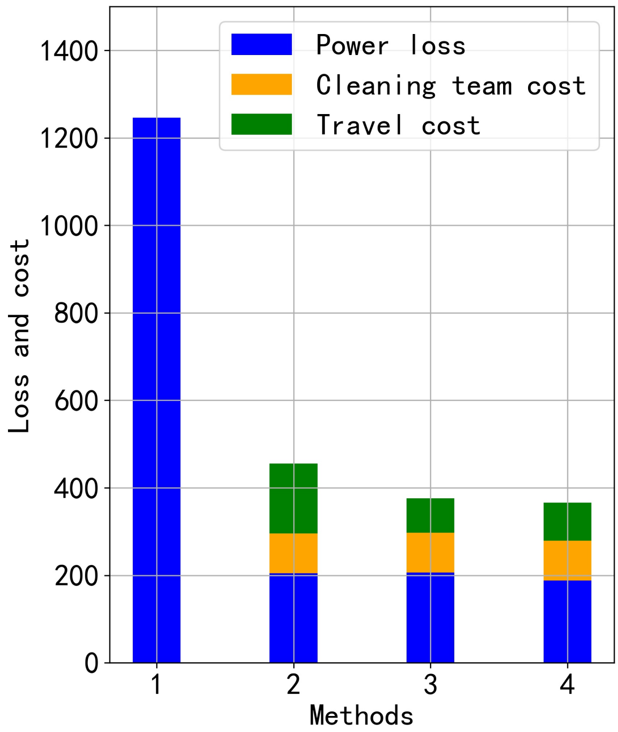


Figure 5: Power losses and cleaning costs of the four methods.

#3 is 375.75, reduced by 17.4% compared with method #2.

For method #4, i.e., the proposed temporal-spatial cleaning optimization method, the cleaning route is planned by taking into account power generation. As a result, the travel cost is slightly higher than method #3, increased from 78.09 to 86.88. However, the power loss is reduced by 8.8%, from 206.66 to 188.43. The cleaning team cost of method #4 is the same as that of method #3 in this case, yet it might be higher because the cleaning duration might be longer than the optimal duration in some cases. Overall, the total economic loss is reduced from 375.75 to 366.31, by 2.5%. The joint coordination method minimizes the total economic loss by seeking the optimal trade-off between temporally and spatially optimal solutions. Compared with no cleaning, method #4 can reduce the economic loss by 70.6%.

7 Conclusion

Cleaning is a vital element of O&M for a PV power plant to keep it operating in an efficient manner. The cleaning process is usually oversimplified in the literature. The existing studies focus predominately on the temporal scheduling problem and adopt a periodic cleaning policy. In this paper, considering a more realistic PV cleaning process, we extend the temporal cleaning scheduling problem to the temporal-spatial cleaning optimization problem. Regarding the cleaning team as the salesman and the PV modules as the nodes, the cleaning problem is formulated as a PD-TSP-TC problem, which is a novel extension of the classical TSP. The cleaning plan is optimized by jointly considering time-dependent production of PV modules and time-dependent cost of the cleaning team from traveling and cleaning. The objective is to minimize the total economic loss including the power loss caused by dust deposition, the cleaning team cost, and the travel cost.

To solve the cleaning problem, a modified two-stage optimization method is proposed. In the medium-term periodic planning stage, the whole PV plant is divided into several array-segments based on its spatial distribution and the dust deposition process; then, the cleaning interval for each array-segment is optimized as a medium-term plan. In the dynamic adjustment stage, based on historical data and forecasting information, the temporal scheduling and spatial routing problems are jointly optimized in a dynamic fashion. A nonlinear 0-1 integer programming problem is modeled and solved by the GA. Based on a 100MWp PV plant located in China, a case study is conducted to demonstrate the performance of the proposed method. Three counterpart cleaning methods are considered and compared. The result shows that the temporal-spatial optimization method based on the PD-TSP-TC has a better performance than that without artificial cleaning, that ignores route planning, and that models route planning as the classical TSP.

In the future research, it is interesting to investigate cleaning optimization methods by considering the dynamics of electricity market. In this case, the electricity pricing mechanism and loads variation are factors that would affect the cleaning decision. Furthermore, the PV systems with energy storage are another challenge for cleaning planning.

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