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# Pick-up & Deliver in Maintenance Management of Renewable Energy Power Plants

Carchiolo Vincenza*, Di Dio Francesco‡, Alessandro Longheu†, Michele Malgeri†, Giuseppe Mangioni†, Antonio Romeo†, Natalia Trapani†

*Dipartimento di Matematica ed Informatica - Universitá di Catania - Catania - Italy
†Dipartimento di Ingegneria Elettrica Elettronica Informatica - Universitá di Catania - Catania - Italy
‡ Development and Support Center - BaxEnergy - Catania, Italy

***Abstract*—Logistic optimization is a strategic element in many industrial processes, given that an optimized logistics makes the processes more efficient. A relevant case, in which the optimization of logistics can be decisive, is the maintenance in a Wind Farm where it can lead directly to a saving of energy cost. Wind farm maintenance presents, in fact, significant logistical challenges. They are usually distributed throughout the territory and also located at considerable distances from each other, they are generally found in places far from uninhabited centers and sometimes difficult to reach and finally spare parts are rarely available on the site of the plant itself. In this paper, we will study the problem concerning the optimization of maintenance logistics of wind plants based on the use of specific vehicle routing optimization algorithms. In particular a pickup-and-delivery algorithm with time-window is adopted to satisfy the maintenance requests of these plants, reducing their management costs. The solution was applied to a case study in a renewable energy power plant. Results time reduction and simplification and optimization obtained in the real case are discussed to evaluate the effectiveness and efficiency of the adopted approach.**

## I. Introduction

THE maintenance of wind power plants is a complex problem with several critical issues, whose optimization plays a significant role in determining the final costs of the energy produced [1].

The essence of improving wind turbine reliability is to reduce downtime and increase availability by optimizing its design and prescribing a well-organized maintenance schedule. These strategies require a full understanding of the system and a detailed analysis of its failure mechanisms and causes.

Several strategies have been devised for this purpose, like the Supervisory Control and Data Acquisition System (SCADA) that provides rich information about the plant itself, giving both error signals as well as components' performance information[2][3][4][5][6]. SCADA can connect individual turbines, the substation, and the meteorological stations to a central computer which allows the operator to supervise the behavior of the single wind turbine as well as the whole wind farm. Several research works exist using these systems as a primary source and using power-curve and temperature analysis[7]; they achieved good results in reporting failures and problems. Some of these research outcomes have been recognized by industry and turned into applications [8][9]. The performance of a wind turbine can be monitored systematically through a proper analysis of the collected SCADA information that covers all its sub-assemblies. However, other researches focused on a different input that involves the use of natural language and the analysis of maintenance reports compiled by operators. This approach tries to extract meaningful information from the semi-structured text and raw notes provided by maintenance operators using Natural Language Processing (NLP) techniques. To the best of our knowledge none of the existing research related to NLP aims at detecting failures related to a wind turbine, rather they just identify technology trends [10][11] In [12] the authors present a strategy using both monitoring and historical data to optimize maintenance, trying to predict the failures in order both to plan the interventions of maintenance team as well as the need of spare parts.

Whenever several wind farms must be managed, especially if they are geographically distributed on a large scale, it is necessary to pay attention to elements related to the logistic service (correct spare parts, component footprint, timing, routing efficiency, to name a few). Effectiveness and efficiency are the keys to the success of many companies, leading to reduction of losses and high service levels. A wind turbine consists of 15-20,000 components and many affect each other even if they are not directly connected. Furthermore, hard market competition and high obsolescence of components lead to a context where demand is volatile and unpredictable, therefore traditional operating strategies as creating inventories or increasing the dedicated response time consumers are not enough to gain a competitive advantage.

This paper reports some of the results of the WEAMS project [13]. WEAMS project concern with the development of an innovative asset management platform for the wind industry. One of the aims of the this project was the engineering of the platform to manage predictive maintenance strategies in wind farms. The project analyzed some logistic matters, considering different strategies to reduce costs and downtime due to routine and emergency maintenance. Specifically, this paper presents an algorithm to optimize maintenance scheduling that takes into account the location of spare parts and distributed intervention areas also located in different places, sometimes even at great distances from each other.

Section II introduces maintenance issues, focusing on logistics matters also referring to existing literature. The case study is presented in Section III where it is detailed the pickup-and-delivery algorithm used to manage wind turbine spare parts delivery. Section IV presents a couple of experiments in different scenarios. Finally, Section V briefly discusses advantages and disadvantages of the proposed approach, as well as open questions.

## II. Maintenance & Logistic in a Wind Farm

A successfully predictive maintenance program, mainly in the context of wind farms, should take into account both visit scheduling and spare parts storage and delivery[14][15]. While the former issue can be tackled in traditional ways, the latter is quite complex due to the large geographical distribution of plants, often hard to reach. Moreover, spare parts are usually very large and heavy objects, difficult to move from storage to plant. Single components or sub-systems represent very different levels of the overall maintenance cost for a wind turbine. Other components exhibit very low-cost but they result in expensive in the life cycle perspective of the turbine because they can cause turbines to fail and thereby reduce the production (e.g. bearings, sensors). Moreover, the planned maintenance visits can be limited by external events such as snow or wave motion in the case of offshore wind farms.

### A. Maintenance of wind farms

Reactive maintenance of complex and high-value installation such as wind farms is only possible if there are both a distributed spare parts storage and an intelligent scheduling algorithm that permits to reduce costs and shutdown time.

Among other typical problems of maintenance of power plants, wind farms managers must also tackle the travel times of the workers needed to reach the site and the transport of spare parts in a location often far and difficult to reach. Moreover, the maintenance providers of a wind farm are often highly specialized and they focus only on specific parts of the product, thus generating high operational expenditures (OPEX). Therefore, to stock a lot of large and heavy spare parts in several places could result in high capital costs (CAPEX). An adequate predictive maintenance strategy must take into account not only multiple stakeholders and locations in the production processes themselves but also the movements of parts - for instance in offshore plants - and reduction of the indirect cost of parts stored in a warehouse.

The classical optimization of maintenance spans over six main categories: Facility location and demand allocation, Vehicle Routing Problems, Warehouse and stock management, Goods delivery strategy, Logistic network complexity analysis, and Network performance measurement. Facility location and demand allocation study where to place the facilities (distribution centers, regional depots, collection points, etc.) and what is the optimal number of each type of facility for the location of the customers. Note how the geographical distribution typical of Wind park changes the perspective of the problem. This matter is strictly connected with Vehicle Routing Problems (VRP) which is one of the most complex combinatorial optimization problems. It consists in finding a route sets so that the vehicles can optimally serve customers' requests (according to a specific function to be optimized) while respecting constraints. The interest in solving VRP problems is motivated by their practical relevance and their inherent difficulty. Of course, the difficulties grow up in the presence of great distance and hard to reach places.

Warehouse and stock management: the goal is to determinate the correct level of stocks to be kept in the warehouses, to guarantee business continuity, in choosing the warehouse allocation policy (centralized or distributed), in determining which component will be stored in each warehouse, which should be eliminated and in general, the procurement strategies. As mentioned above, the type of spare parts and their dimension and cost make this problem more and more difficult to solve. The same problem impacts Goods delivery strategy optimization which studies the modality of movement of spare parts among the various facilities of the logistics network, including the calculation of transport costs and any outsourcing decision.

Finally, Logistic networks complexity analysis deals with the techniques and methods for studying the complexity of networks, their growth dynamics and weaknesses, to understand their level of competitiveness and performance and the Network performance measurement that aims at identifying and measuring the metrics to evaluate the system performance.

However, the context of Energy Power Plant based on Wind turbines poses new and interesting challenges to each of the previous categories. Then the design and/or optimization of a logistics network involves different aspects and many decisions which can also be sometimes conflicting. Indeed, it is rarely possible to find a solution that optimizes all aspects. More realistically, a trade-off between different key factors must be defined to balance the costs (CAPEX and OPEX) and the overall networks performance.

As said above, one of the most investigated problems concerns vehicle routing (VRP)[16]. To overcome the problem complexity various heuristics have been developed to produce good solutions with tractable computational complexity.[17][18][19]. The problem indeed presents significant computational challenges by admitting, in its more general formulation, further constraints such as the respect of time windows on both customers and deposits or by imposing a maximum vehicle transport load capacity and a maximum speed.

In the case presented in this paper, the optimization of the logistic network of green energy production, like wind and solar plants, aiming at reducing the overall cost (i.e. number of vehicles, maintenance team dimension, etc.) and complying with the time constraints. The problem to be addressed is twofold; modeling the network using complex network theory, and optimizing costs while respecting constraints through the use of VRP optimization techniques.

### B. Related work

The effort typical of maintenance tasks in wind farms is due to several factors, as both space-related constraints, e.g. the difficulty of reaching off-shore (but also many on-shore) locations as well as time-related constraints, e.g. when trying to accomplish maintenance on the "right" day (as indicated by optimization algorithms) but a wind storm just hit that area. The work [14] provides a conceptual classification framework for the available literature about maintenance strategy optimization and inspection planning of wind energy systems.

An additional related matter is the logistics of spare parts, whose management significantly affects maintenance tasks; having the right part at the right time in the right location is critical to guarantee business continuity and maintenance performance.

To the best of our knowledge, no works are addressing this specific issue, e.g. in [20], authors focus mainly on weather conditions to determine the best time window and execution order for optimal intervention. Similarly, [17] proposes a hybrid heuristic optimization of maintenance routing and scheduling in particular for offshore wind farms, where optimal vessel allocation scheme is crucial (though spare parts are not considered). In [18], offshore wind farms are also addressed, in this case finding the best routes for the crew transfer vessels. Conversely, the work [21] focus on on-shore wind farms and considers forecast wind-speed values, multiple task execution modes, and daily restrictions on the routes of the technicians to determine optimal maintenance operations scheduling.

All these works tackle the question with different approaches, for instance [18] is based on the Large Neighbourhood Search meta-heuristic, whereas [21] adopts linear programming formulations and branch-and-check approach. In [20] the optimization is achieved simply through brute force whereas [17] adopts a hybrid optimization using first mixed particle swarm optimization to determine an optimal vessel allocation scheme and then discrete wolf pack search (DWPS) to optimize the maintenance route according to all constraints. A common feature most works share is the exploitation of real historical datasets to achieve realistic optimizations.

## III. Pickup and Delivery Vehicle Routing Problems with Time Windows

As discussed above, in this work we address the maintenance plan optimization problem by mapping it on a specific VRP problem. To be more detailed, we employ a pickup and delivery VRP with time windows algorithm to take into account all the constraints imposed by our specific problem. It is known that determining the optimal solution to VRP is NP–hard, hence to approach such a problem many heuristics have been developed. Here we employ the algorithm proposed in [22], which consists of two phases. Indeed, it is recognized that in a typical VRP minimizing the objective function directly might not be the most efficient way to decrease the number of routes and vehicles. This because the objective function leads many times to solutions with low travel costs and this could make it difficult to reach solutions with few routes but with a higher travel cost.

To avoid this problem, the above-mentioned algorithm uses a two-stage algorithm consisting in

1) The minimization of the number of routes through the use of a Simulated Annealing algorithm.
2) The minimization of the total travel cost by using a Large Neighborhood Search algorithm.

In the following, we present the Pickup and Delivery Vehicle routing problem with time windows (PDPTW) by first introducing some definitions (taken from [22]).

*Customers:* The problem is defined in terms of the $N$ customers, represented by the numbers $1, ..., N$, and a deposit, represented by the number $0$. In general, with the term site, we identify the $N$ customers and the deposit as well, i.e. sites ranges from $0$ to $N$.

- $Customers^p$ denotes the set of withdrawal points (pickup customers).
- $Customers^d$ indicates the delivery points (delivery customers).

*Travel Cost:* The cost of the path between the generic sites $i$ and $j$ is indicated with $c_{ij}$. It is supposed that such a cost must satisfy the triangular inequality: $c_{ij} + c_{jk} >= c_{ik}$. The normalized travel cost $c^{'}_{ij}$ is also defined as the cost $c_{ij}$ between sites $i$ and $j$ divided by the max cost among all couple of sites.

*Service time:* A service time is also associated with every customer $i$, together with a demand $q_i \geq 0$. If $i$ is a pickup customer, the delivery counterpart is denoted by $@i$. Given that, the demand of $@i$ is $q_{@i} = -q_i$.

*Vehicles:* In this problem, we suppose to have $m$ identical vehicles of capacity $Q$ each.

*Routes:* In general, a route starts from the depot, visits a certain number of customers at most once, and finally returns to the depot, i.e. a route is a sequence $\{0, v_1, ...v_n, \}$, where $v_i$ is the generic vertex of the path. Note that in a route all $v_i$ are different, i.e. each vertex is touched only once (excluding the depot). Given a route $r = \{v_1, ...v_n, \}$, we denote with $cust(r)$ the set of of its customers, i.e. $cust(r) = \{v_1, ...v_n, \}$, With $route(c)$ we denote the route the customer $c$ belongs to. For a given route $r$, its length is indicated by $|r|$, while the number of visited customers is denoted by $|cust(r)|$. The travel cost of a route is indicated by $t(r)$ and represents the cost of visiting all of its customers; it is defined as:

$$\begin{cases} t(r) = c_{0v_1} + c_{v_1v_2} + ... + c_{v_{(n-1)}v_n} + c_{v_n0} & \text{if route !=}\emptyset \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

*Routing plan:* it is a set of routes $\{r_1, ..., r_m\}$ with $(m \geq N)$ visiting all customers exactly once:

$$\begin{cases} \bigcup_{i=1}^{m} cust(r_i) = Customers \\ cust(r_i) \cap cust(r_j) = \emptyset \qquad (1 \leq i < j \leq m) \end{cases} \tag{2}$$

A routing plan assigns a single successor and predecessor to every customer. Given a routing plan $\sigma$ and a customer $i$, $succ(i,\sigma)$ and $pred(i,\sigma)$ are respectively the predecessor and the successor of $i$ in the routing plan $\sigma$ (shortly indicate as $i^+$ and $i^-$ in the following).

*Time Windows:* Each site is associated with a temporal window $\{e_i, l_i\}$, where $e_i$ represents the earliest arrival time and $l_i$ the latest arrival time. This means that a vehicle can arrive on a site $i$ before $e_i$, but it must wait $e_i$ to start the service. Vehicles must arrive at any site $i$ before the end of the time window $l_i$. In the specific case of the depot, its temporal window $[e_0, l_0]$ individuate the time $e_0$ in which all vehicles leave the depot and the time $l_0$ when all vehicles return to the depot. The departure time $\delta_i$ of a given customer $i$ is defined as:

$$\begin{cases} \delta_0 = 0 \\ \delta_i = max(\delta_{i^-} + c_{i^- i}, e_i) + s_i \quad (i \in Customers) \end{cases} \tag{3}$$

The Earliest Service Time $a_i$ of a given customer $i$ is defined as:

$$a_i = max(\delta_{i^-} + c_{i^- i}, e_i) \quad (i \in Customers) \tag{4}$$

The Earliest Arrival Time $a(r)$ of a route $r$ is defined as:

$$a(r) = \begin{cases} \delta_{v_n} + c_{v_n 0} \quad if \ (route! = \emptyset) \\ e_0 \quad otherwise \end{cases} \tag{5}$$

For a customer $i$ the time window constraint is satisfied if $a_i \leq l_i$ and, in particular the time window constraint for the deposit is satisfied if $a(r) \leq l_0 \ \forall r \in \sigma$.

*Capacities:* Let us define the demand of a route $r$ at customer $c$ as:

$$q(c) = \sum_{i \in cust(r) \ \& \ \delta_i \leq \delta_c} q_i \tag{6}$$

With the constraint that for a customer $c$, $q(c) \leq Q$.

*PDPTW:* A solution to the PDPTW is a routing plan $\sigma$ that satisfies all these constraints:

$$\begin{cases} q(i) \leq Q \\ a(r_j) \leq l_0 \\ a_i \leq l_i \\ route(i) = route(@i) \\ \delta_i \leq \delta_{@i} \end{cases} \tag{7}$$

where $i \in Customers$ and $1 \leq j \leq m$.

A solution to the PDPTW consists in finding a routing plan $\sigma$ satisfying the above-mentioned constraints that also minimizes the number of vehicles and, in case of ties, the total travel cost. In formal terms $\sigma$ minimizes the following objective function:

$$f(\sigma) = \langle |\sigma|, \sum_{r \in \sigma} t(r) \rangle \tag{8}$$

The algorithm used to find a solution to the PDPTW is that proposed in [22], consisting in two stages. The first one performs the minimization of the number of routes via a simulated annealing algorithm. As a classical simulated annealing algorithm, it starts from a solution and then produces a new random solution that is accepted with a probability that depends on the value produced by a domain-specific evaluation function. In particular, a new solution is produced by using a random pair relocation method (see [22] for details), while the evaluation function it uses is a lexicographic ordering function defined as in the following:

$$e(\sigma) = \langle |\sigma|, -\sum_{r \in \sigma} |r|^2, \sum_{r \in \sigma} t(r) \rangle \tag{9}$$

where the first term is the number of routes, the second term tends to favor solutions with many customers and the last term takes into account the travel cost of the routing plan.

The second stage of the algorithm proposed in [22] consists in minimizing the total travel cost by using a large neighborhood search (LNS) method. It consists of exploring the neighborhood of a given solution to find a better one, i.e. one that produces a minor value of the objective function 8. We refer the reader to [22] for additional details on the above mentioned algorithms.

## IV. Experiments

As pointed out in the above sections, the optimization of VRP in the context of maintenance of Wind turbines is very complex whilst it has a high-impact on the costs and efficiency of the whole system. Indeed, the wind farms are unevenly distributed over the territory of a country as far as the spare parts deposits. Furthermore they are located in different and often distant sites.

In this section we present two examples, the former aiming at testing the effectiveness of the algorithm with a toy example and the latter to mimic a simplified real scenario. Both examples concerns a *"single spare parts store"* scenario.

### A. Basic setup

The topology chosen for the first example is based on 10 nodes and 1 depot with a symmetric topology. The cost between each pair of nodes is assumed equal to 1. In particular, this setup encompasses five plain routes connecting five places, called $A, B, C, D, E$, each route contains only one delivery and one dispatch point. Therefore, the problem is described by 10, where $\mathcal{P}$, $\mathcal{D}$, $\mathcal{C}$ are the set of Pickups, Deliveries and Customers respectively, and by the set of routes described in eq. 11.

$$\begin{aligned} &\mathcal{P} = \{A, B, C, D, E\} \\ &\mathcal{D} = \{@A, @B, @C, @D, @E\} \\ &\mathcal{C} = \mathcal{P} \cup \mathcal{D} = \{A, B, C, D, E, @A, @B, @C, @D, @E\} \end{aligned} \tag{10}$$

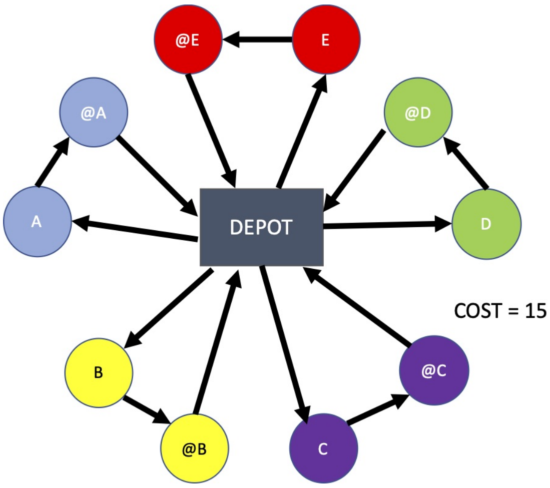


Fig. 1. Example 1: topology

$$
\begin{aligned}
r_1 &= \{depot, A, @A, depot\}\\
r_2 &= \{depot, B, @B, depot\}\\
r_3 &= \{depot, C, @C, depot\}\\
r_4 &= \{depot, D, @D, depot\}\\
r_5 &= \{depot, E, @E, depot\}
\end{aligned} \quad (11)
$$

Figure 1 illustrates all the routes that start from *depot*. Each connection ha the same cost and it is equal to 1, the earliest arrival time to the *depot* is 40 hours and the time needed to get each customer is 2 hours. The global cost is then equal to 15.

The algorithm tries to optimize the solution according to the following two steps:

SA the route is reduce with the Simulated Annealing
LNS the route is optimized with the *Travel Cost Minimize* Function

Note that the LNS step may not converge; when this happens, it is advisable to change some values of setup and restart from scratch. The setting values are summarized in Table I.

TABLE I
FIRST EXAMPLE SETTING

| Step | Item | Value |
|---|---|---|
| SA | Temperature value | 28 |
| | Temperature Limit value | 15 |
| | $\alpha$ | 0.5 |
| | Max Iterations | 1 |
| | $\beta$ | 1 |
| LNS | Max Searches | 5 |
| | Max Iterations | 1 |
| | *beta* | 2 |

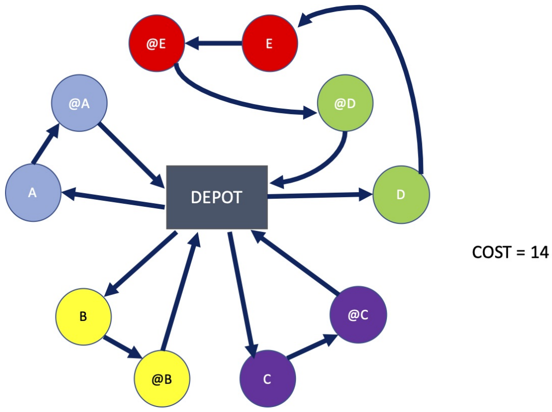


Fig. 2. Example 1: Routes after Simulation Annealing

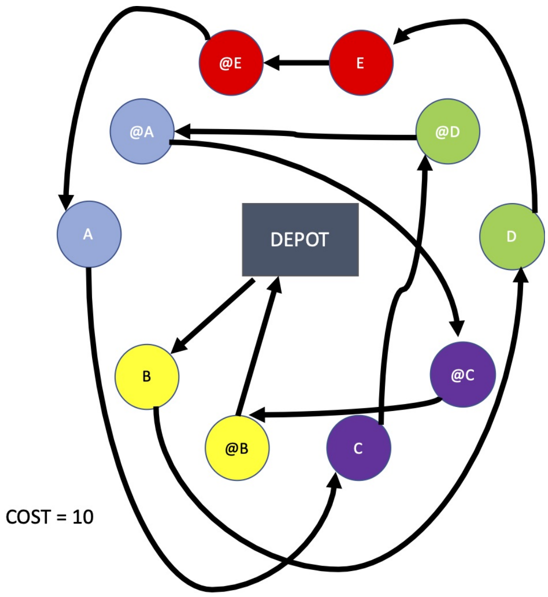


Fig. 3. Example 1: Routing after LNS

SA step looks for new routes with a better cost, in the example four routes exist with a global cost of 14.

$$
\begin{aligned}
r_0 &= \{depot, A, @A, depot\}\\
r_1 &= \{depot, B, @B, , depot\}\\
r_2 &= \{depot, C, @C, depot\}\\
r_3 &= \{depot, D, E, @E, @D, depot\}
\end{aligned} \quad (12)
$$

Figure 2 illustrates all the routes after simulation annealing. Finally, the LNS optimization produces a single route 13, shown in 3, which has a cost equal 10 that is much better the initial value.

$$
r_0 = \{depot, B, D, E, @E, A, C, @D, @A, @C, @B, depot\} \quad (13)
$$

### B. Experiments on real routes

The supply of spare parts usually deals with two different scenarios: the former concerns with a single plant where each node represents a single wind turbine and the latter scenario concerns with the portfolio of a producer where a single node represents a whole farm. However, the problem to optimize is quite the same since we look for the cheaper path connecting *depot* with several *nodes*.

In this paper we present a case study belonging to second scenario and we suppose that a single warehouse (the *depot* node) provides all the farm with the spare parts.

We search for solutions that satisfy all the constraints defined for the algorithm. Therefore, we define for each site $i$ a time window $[e_i, l_i]$ representing the lower and upper limits to perform an effective maintenance. That is, the spares must not arrive before $e_i$ and not after $l_i$, if they arrives before $e_i$ they must wait at least until $e_i$ before starting maintenance.

The experiments deals with the functional maintenance of 10 farms located in Italy covering the management of very expensive and large spare parts. Table II defines all involved nodes (pickup or delivery node), the distance among nodes was build using Google map services and Table III summarizes the setup parameters.

TABLE II
PICKUP AND DELIVERY POINTS

| Pickup | Name | Delivery | Name |
|---|---|---|---|
| Enna | A | Brindisi | @A |
| Florence | B | Genova | @B |
| Catania | C | Bari | @ C |
| Taranto | D | Naples | @ D |
| Milan | E | Pompei | @ E |
| Bologna | F | Bozen | @ F |
| Rome | G | Cagliari | @ G |
| Sassari | H | Pirri | @ H |
| Agrigento | I | Mele | @ I |
| Viterbo | L | Palese | @ L |

TABLE III
EXAMPLE SETTING

| Step | Item | Value |
|---|---|---|
| SA | Temperature value | 28 |
| | TemperatureLimit value | 3 |
| | $\alpha$ | 0.3 |
| | MaxIterations | 2 |
| | $\beta$ | 1 |
| LNS | MaxSearches | 2 |
| | MaxIterations | 2 |
| | $\beta$ | 2 |

In order to complete the setup we selected four routes 14

$$\begin{aligned} r_0 &= \{depot, A, @A, B, @B, depot\} \\ r_1 &= \{depot, C, @C, D, @D, depot\} \\ r_2 &= \{depot, E, @E, F, @F, G, @G, depot\} \\ r_3 &= \{depot, H, @H, I, @I, L, @L, depot\} \end{aligned} \tag{14}$$

We assume that each km have a cost of 1, then the global cost of this four route is calculate using the distance matrix is equal to 7791.

After SA step the new four routes are shown in 15

$$\begin{aligned} r_0 &= \{depot, A, @A, B, @B, depot\} \\ r_1 &= \{depot, C, @C, D, @D, depot\} \\ r_2 &= \{depot, E, @E, F, @F, depot\} \\ r_3 &= \{depot, H, G, , @G, @H, I, @I, L, @Ldepot\} \end{aligned} \tag{15}$$

Unluckily, In this case the LNS optimization is failed, therefore changed the setup according to Table IV.

TABLE IV
NEW SETTING

| Step | Item | Value |
|---|---|---|
| SA | Temperature value | 30 |
| | TemperatureLimit value | 9 |
| | $\alpha$ | 0.5 |
| | MaxIterations | 2 |
| | $\beta$ | 3 |
| LNS | MaxSearches | 5 |
| | MaxIterations | 2 |
| | $\beta$ | 1 |

Finally, after both steps, we find the following three routes (see 16) that save more than 15% of the cost.

$$\begin{aligned} r_1 &= \{depot, A, C, D, @D, @C, @A, B, @B, depot\} \\ r_2 &= \{depot, E, @E, F, @F, G, @G, depot\} \\ r_3 &= \{depot, H, @H, I, @I, L, @L, @D, @L, depot\} \end{aligned} \tag{16}$$

## V. CONCLUSIONS AND FUTURE WORK

In this paper we described a case study concerning Logistic optimization, in particular the maintenance in a Wind Farm, where many challenges exist, from wind turbines location (sparse and sometimes difficult to reach, especially off-shore ones), to spare parts management (from stock to wind farm), to vehicle routing optimization algorithms.

We introduced a pickup-and-delivery algorithm with time window in a renewable energy power plant scenario, and results show that both effectiveness and efficiency are achieved.

Further works concern the extension of the proposed approach to the case of multiple stocks and the adoption of machine-learning based algorithm to manage and refill these stocks, with the same purpose of optmizing procurement time and costs. Moreover, other case studies can be examined to validate the proposed approach, also considering features as multi-site and multi-team in addition to multi-stock.

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