SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Executive Summary of the Thesis

The E-bike Charger Location Problem

Laurea Magistrale in Automation and Control Engineering - Ingegneria dell'automazione

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1. Introduction

The urgency of facing climate change has had a positive impact on the electric vehicle market, which, combined with the pandemic situation of the last few years, is leading customers to move on a new way of sustainable mobility, choosing low range electric vehicles such as scooters and e-bikes. This trend importantly reflects in holiday resorts where the e-bike is becoming the most requested activities for tourists of every kind, promoting a way of enjoying the natural attractions and appreciating the landscapes of the resorts. In this scenario the range of the battery mounted on e-bikes could be a limit to this activity, especially in resorts characterized by steep climbs and long trails. This thesis proposes two main optimization models that are able to properly find a solution for the problem of locating charger facilities. A first formulation provides a solution to a scenario where a set of predefined itineraries is devoted to the specific cultural journey and hence a Location Problem is derived to cover the charge demand on the network. Then the methodology exposed by the Tourist Trip Design Problem is exploited to formulate a Location Routing Problem in case of a network where the set of trails is not devoted to specific experiences. The derived models are applied to three randomly generated instances. Finally we validate the programs on a real test case scenario, evaluating their performances and deriving some conclusions.

2. Methodologies

Analyzing how many charging stations are needed on a specific topological area and which is their best position is a quite complex aspect for administration executives. It follows that a proper analysis and evaluation of the possible infrastructure is mandatory to ensure an e-charger network able to face the needs of the costumers and ensure a certain level of reliability. In the literature the charger location problem for Electric Vehicles has been extensively studied. Many papers propose a way to solve this problem taking into account complicated factors such as people driving behaviors or the amount of charging request. A fundamental aspect of these formulations is the knowledge of the flow location along the network. When the itineraries followed by the vehicles are not known, papers such as [1] exploit a routing algorithm to identify the itineraries on the network. This kind of problems appertains to the family of the so called Location Routing Problems (LRP), which aim at finding the optimal location of some facilities and the routes of the vehicles to serve the customers demand under facilities and vehicles constraints. However, the existing works mainly develop models for long range electric vehicles such as cars and buses, which are then applied to urban areas. Hence, the literature presents a lack of knowledge for what concern the charger location problem for electric bicycle on touristic destinations, requiring a quite different formulation from the standard EV charging location problem. Speaking of touristic destinations, the Tourist Trip Design Problem (TTDP) perfectly fits this scenario: exploiting territory and cultural information, this kind of models proposes different techniques to design an optimal set of itineraries which aims at maximizing the competitiveness of the entire infrastructure. It follows that by combining a LRP with the methodology of the TTDP, it is possible to design a network of paths that exploits the attraction points of the territory to optimally locate charging facilities, minimizing the implementation costs and maximizing the resort attractiveness. To do so, we based our routing model on a paper proposed in [2], where an attractiveness function ruled the reward along the itineraries for different classes of cyclists. Hence, this thesis proposes two promising models, respectively classified as a Location Problem and a Location Routing Problem for E-bike charging facilities on a touristic network. In particular the formulations are modeled as Mixed Integer Linear Programs (MILP) applied to direct graphs $G(N, A)$, faithful representation of the grid of trails, muleteer and roads present in cyclist resorts. Moreover the complexity of the second formulation results in an exponential number of constraints that require the implementation of a Branch & Cut to be resolved.

2.1. Notations

To facilitate reading, before introducing the models formulations, this section is devoted to a brief introduction of the notation used:

- y_i Binary decision variable corresponding to charger location at node i;
- b_i^p Continuous decision variable corresponding to the remaining battery capacity at node i for path p;
- x_{ij}^{up} Routing binary decision variable associated to arc (i, j) for user u on path p;
- γ_i^{up} Routing binary decision variable associated to node i for user u on path p.

3. Location Problem

For this model we assume to have an infrastructure where a set of paths P followed by the e-bike users are constrained by conformations of the territory or by cultural objectives, resulting in a grid of isolated itineraries that shares possible common sites. Hence we can model the territory as direct graph $G(N, A)$ where nodes correspond to points of interest and arcs to trails. Then it is possible to associate an energy consumption e_{ij} to each traveled arc (i, j) and a charger implementation cost c_i to the nodes $i \in N'$. Where $N' \subset N$ collects the sites provided with a connection to the electric grid and hence possible hosts for charger facilities. On this data we modeled an optimization program that aims at minimizing the total implementation costs, installing charger facilities that satisfy the energy requirements along the network. The formulation is a MILP of the following form:

$$\min_{b\,y} \quad g(y_i) \tag{1}$$

$$\textbf{s.t.}$$

$$l_1(b_i^p,\ y_i) = 0 \qquad \forall\, p \in P, \tag{2}$$

$$l_2(b_i^p,\ y_i) < 0 \qquad \forall\, p \in P, \tag{3}$$

Stated in this way the object function (Eq. 1) minimizes the total costs finding the best values for the binary variable y_i. The constraints from Eq. (2) to Eq. (3) define the remaining battery at each node i for each path p, hence variable b_i^p. This value is bounded to be grater than zero, doing so we ensure that, placing a charger stations on the right positions, the remaining battery capacity at each node, is always greater or equal to zero. Allowing the cyclist to reach the next station without recharging.

4. Location Routing Problem

Matching the formulation stated by the Tourist Trip Design Problem with the Location Problem exposed in Section 3, a Location Routing Model is here formulated to provide a solution to the E-bike Charger Location Problem. Starting from a pool of origin-destination pairs previously defined, a routing model exploits a modified version of the attractiveness function described by Malucelli et al. [2] to properly collect the rewards over the network nodes and arcs, reflecting the preferences of different classes of users u. In particular we suggest three different category of cycle tourists, namely the classic tourist, the gastronomic and the sporty, however different kind of profiles can be considered without loss of generality. Hence the formulation here proposed, exploits the binary variables x_{ij}^{up} and γ_i^{up}, correspondingly associated to the arcs and nodes chosen by the routing routine, to activate the constraints of the charger location model, ensuring a routing solution that matches the charge demand of the electric bicycle. Indeed, bounding the routing problem to satisfy the never empty battery requirement, collocates a certain number of charger facilities along the tracks. Then the objective function states the maximization of the attractiveness reward collected by the routing problem, while it minimizes the total implementation costs of the charger facilities. It follows that the derived solution exploits the attraction points of the network to design a set of tracks with different perspective that match the users behaviors. At the same time the program allocates possible common sites to the installation of charging facilities, satisfying the energy needs and minimizing the chargers implementation investments. The LRP can be stated as a MILP of the following form:

$$\max_{b\ y\ x\ \gamma} \quad f(x_{ij}^{up},\ \gamma_i^{up}) - W g(y_i) \tag{4}$$

s.t.

$$r_1(x_{ij}^{up},\ \gamma_i^{up}) = 0 \qquad \forall p \in P, \forall u \in U \tag{5}$$

$$r_2(x_{ij}^{up},\ \gamma_i^{up}) < 0 \qquad \forall p \in P, \forall u \in U \tag{6}$$

$$l_1(x_{ij}^{up},\ b_i^{up},\ y_i) = 0 \qquad \forall p \in P, \forall u \in U \tag{7}$$

$$l_2(x_{ij}^{up},\ b_i^{up},\ y_i) < 0 \qquad \forall p \in P, \forall u \in U \tag{8}$$

The objective function (4) maximizes a value that corresponds to a trade off between the total attractiveness collected by each user on each path $f(x,\ \gamma)$ and the total costs related to the e-charger implementations $g(y)$. It is important to underline that this last term is scaled by a weight W that must be properly tune in accordance with the objectives of the resort. The eq.s (5) and (6) are linear constraints defining the routing variables x_{ij}^{up} and γ_i^{up} for each user u and path p. These variables are then used to activate the next constraints (7-8) derived by the covering equations (2- 3) defined in section 3. The routing decisions variables give hence a perfect knowledge of what are the tracks followed by the cycle tourists, defining visited arcs and nodes; allowing to properly populate the positional variables y_i, locating the charger facilities which cover the energy demand along the paths.

4.1. Branch & Cut

The strong formulation of the Location Routing Program exposed above includes an exponential number of constraints that could limit the performance of the algorithm when applied to big scenarios. Models of this kind can be directly handled by the solver available on the market only for small instances. Indeed, adding all these constraints at once is usually not practical, asking for a strong computational effort by the machine that can lead to a not convergence of the algorithm. This kind of problems can be solved by a method of combinatorial optimization called Branch & Cut, in which cut generation is combined with branching. To implement this methodology we implemented the model using a Python package called MIP [3]. This program could be useful also to produce lazy constraints: cutting planes applicable to integer solutions. In our model, this approach is used to avoid sub-tours elimination constraints, which are stated for every subset of nodes, leading to have an exponential number of constraints. To do so a Separation Routine is solved thanks to a Minimum Cut Problem able to automatically identify when and which are the missing violated sub-tour elimination constraints, allowing the program to activate the relatives lazy constraints.

4.2. Multiple Level Extension

The LRP formulation obtained above allows to find the best charger facilities positions along the network to cover the energy demand of the cycle tourists travelling on a strategically designed offer of trails. However following the Tourist Trip Design methodology, the routing problem should allow the cyclists to visit multiple times an arc or node encountered on the path. Indeed, since the cycle tourist rides for pleasure, it could happen that riding for more than one time along the same track increases the satisfaction of the cyclist even though it is not a new experience.

It follows that the LRP model exposed above limit the possibility to obtain a bigger reward from a routing problem with multiple visits as in [2]. However the mathematical formulation exposed in this model cannot be used here because, although if it is able to keep track of the number of traversal, it does not allow to know the right sequence of arcs from origin to destination. Moreover, the LRP formulation here proposed already presents many variables and constraints, hence adding other terms could lead to have a not easy solvable problem. Hence we propose suitable modified data to allow multiple visits of the same arc or node. By duplicating the nodes of the graph in two levels, we can associate a first level to the first visit of the network and the second one to the revisit. In general it is possible to use this technique to create more than two levels, allowing the cyclists to do more traversals. However after the third ride along the same track the pleasure of the tourist start, is likely to reasonably to decrease. Hence here we propose only two levels leading to have a maximum number of three traversal of the same arc and only two of the same node. The graph $G(N, A)$ is now composed by two levels, between them, a pair of arcs are stated for each connected node in the original grid, one to go up and one to go down as shown in Figure 1.

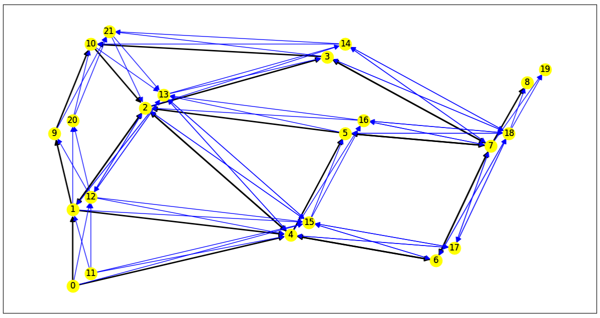

Figure 1: Multi-Level Network Example

The two levels are defined by a shift in the nodes enumeration ($n0$), equal to the cardinally of the original nodes set $N0$. The data used for the original LRP model, such as the energy consumption, the time and the installation costs associated to each candidate sites, are the same for both the levels and for the arcs moving between them. The only difference is the attractiveness function that associates different values on each level. In particular considering that the pleasure at the second and third traversal should be smaller than the one obtained at the first one, the attractiveness value associated to each arc of the upper level are half with respect to the original one; the same is done for the arcs which rise between the first and the second level, leaving to a full attractiveness value the fallen arcs. In this way the routing problem is allowed to obtain a bigger reward, designing paths on the first level and only in case of high attractiveness choose to route on the second one.

To enforce the routing of the cyclists on the first level before going to the second one, some additional constraints on variables x_{ij}^{up} are defined. Moreover to remain consistent with the e-charger implementation, a constraint on the binary decision variables y_i, is stated for both the levels:

$$y_i = y_{i+n0} \qquad \forall i \in N0 \tag{9}$$

In this way we ensure that if a node is chosen to hold a charger facility, the charger is present on both levels. Finally, in the object function, the term associated to the total implementation cost $g(y)$ is calculated only for the nodes of the first level. The final formulation is identical to the one stated for the LRP (4) with the modifications proposed above and it will take the name of Location Routing Problem with Multiple Level Extension LRP-ML.

5. Results

To test and analyze the performance of the models proposed in this thesis, a first approach was the implementation of the different formulations on a data set that simulates the characteristic of a real resort. Then the models were applied to the Asiago Test Case scenario, where a realistic network of trails and muleteers were retrieved to create the graph $G(N, A)$. Here the methods used to generate the data for both the scenarios are in brief summarized, to finally show the main results of this work.

5.1. Data Generation

The generation of the data-set used for the simulations is a crucial aspect of this section, resulting than in a less or more realistic output of the program. In particular the data-set required from the models comprehend a directed graph $G(N, A)$, main representation of the resort under analysis, a proper energy consumption and timing associated to the arcs of the graph, the subset of nodes chosen to possibly implement the charger facilities and the associated costs; finally the values of attractiveness of the entire network. To properly generate all this data more than 3000 lines of code were written in Python, exploiting different Python packages and scripts.

5.1.1 Virtual Graph Generation

Speaking about e-bikes the high differences in altitude make the mountain territories the best scenario to implement the e-bike charger location problem, indeed e-bikes are used by tourists of every kind to face the steep mountain trails, leading to a fast and frequent discharge of the battery. Hence in this work we developed a program able to design three-dimensional directed graphs with uncross arcs (Figure 2), simulating a real network of trails, beaten roads and muleteers, normally present on a mountain resort.

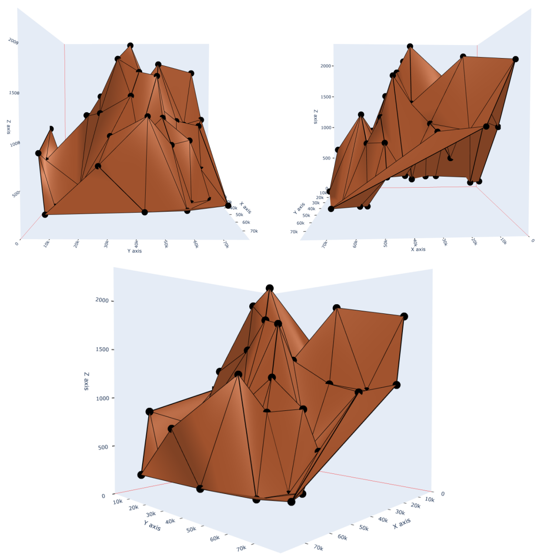

Figure 2: 3-D Network Example

The arcs slopes are properly generated ranging from a minimum value of 3% to a maximum of 12%. This choice was made considering reasonable limitations of achievable human power, friction and the center of mass of the system.

5.1.2 E-bike Model

A proper characterization of the battery consumption along the trails is mandatory to end up with a realistic solution that reflect the needs of the cyclists. However understanding the energy consumed by the e-bike is a quite challenging task that must consider heterogeneous factors such as the e-bicycle dynamic, the terrain type, the weight and physical preparation of the cyclist under analysis. In the literature many papers try to find an accurate modelization of this system, however they proposed complicated mathematical formulations far form the scope of this thesis. The optimization problems here formulated aims at finding the best chargers locations to ensure a full charged battery along the traveled itinerary, hence a simple model that describes the battery consumption in the biggest effort scenario is enough to create the required data. In particular a balance of powers for a fixed speed of travel is done over the bicycle model (Figure 3).

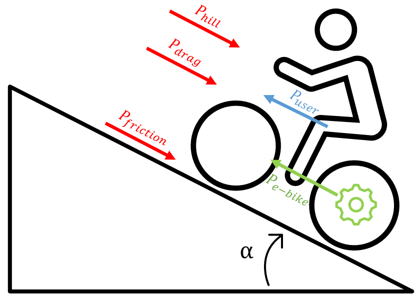

Figure 3: Power Balance E-bike

Then the consumed energy is retrieved as a product between the required power and the traveled time. In this way we end up with a proper data set describing the energy consumption along each arc of the network.

5.1.3 Attractiveness Values and Implementation Costs

For the LRP and LRP-ML the attractiveness values associated to the arcs and nodes of the network were generated taking into account different users behaviors. Finally the implementation costs were associated to the various nodes considering data of position and accessibility to the electric grids.

5.2. Computational results

The program was coded in Python and solved on a two-core machine with an Intel i7 processor and 2.50GHz of clock. The used solver was

GUROBI, one of the fastest and most powerful solver available on the market. The models were firstly tested on 3 different realistic graphs with random generated itineraries for the Location Problem and a selected set of origin destinations for the LRP and the LRP-ML. The results shows that the models are perfectly able to find the best locations for the charger facilities, privileging the nodes which are shared by multiple itineraries. Better results can be obtained by the Location Routing Model with Multiple Level Extension that is able to strategically design the offers of trails to limit the number of charging stations required on the network. Indeed it ends up with a smaller number of installed facilities that can be further decreased by playing with the weigh of the object function (4). Instead the result of the Location Problem strongly depends on the set of predefined itineraries, statistically leading to higher implementation costs. The performance of the Branch & Cut are clearly visible in the LRP-ML, when it is applied to huge instances as the one shown in figure 2. Here the number of arcs and nodes brings the model to have 20692 variables and 92166 constraints, however the program is able to find the optimal solution only after 484 seconds.

5.2.1 Asiago Test Case

The last task of this work was the implementation of the models on a real test case. To do so the Asiago Plateau represent a perfect instance to test our models, where a grid of trails, muleteer, and roads creates a paradise for cycle tourist, connecting farm holidays, typical municipalities and mountain peaks. After modelling this territory as a directed graph, a set of maps have been combined to generate the attraction scores of trails and point of interests. The proposed models gives different interpretation of the charger demand, ending up with a number of facilities that decreases to a minimum value of two stations with the LRP-ML model. As done for the realistic graph, these stations are positioned to face the needs of three class of cyclists along six different itineraries. Here for brevity only the graphic solution of LRP-ML for the sporty path from Primolano to Asiago is shown:

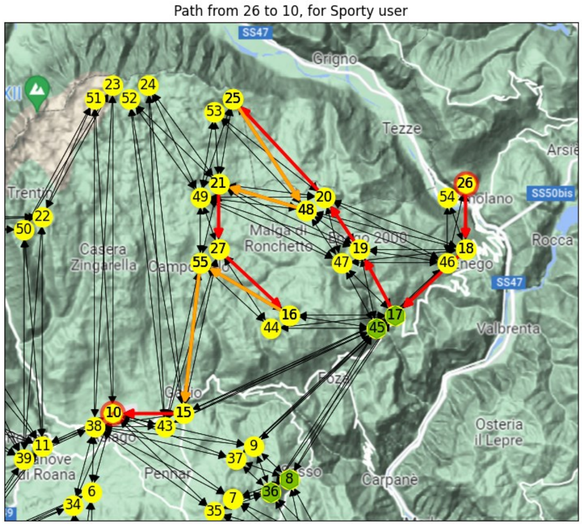

Figure 4: Asiago LRP-ML Solution

Where the green nodes are the charger implementation points, the red lines show the path on the first level of the graph and the orange ones highlight the arcs moving between the two levels.

6. Conclusions and Future Developments

The developed models are able to find an optimal solution to the Charger Location Problem for E-bikes, providing flexible formulations that reflects the needs of the resorts. Further implementation should consider possible partial charges taking into consideration the time spent on each charging point.

References

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