COBEM 2021 26th International Congress of Mechanical Engineering
ABCM Associação Brasileira de Engenharia e Ciências Mecânicas
November 22-26, 2021, Virtual Congress, Brazil

COB-2021-1614. METHODOLOGY FOR OPTIMIZING BATTERY SIZE WHEN CONVERTING INTERNAL COMBUSTION UTILITIES VEHICLE TO ELECTRIC TRACTION

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Abstract. *Methodology for optimizing battery size when converting internal combustion utilities vehicle to electric traction vehicles. Electric vehicles are seen by many as the cars of the future, as they are highly efficient, quiet, low maintenance costs and they do not produce local pollution. Currently, however, electric cars are still considered expensive. An alternative to buying an electric vehicle is to convert an internal combustion engine vehicle into an electric vehicle. For this, there is a need for a methodology capable of simulating the power and energy needs of the vehicle that leads to specify the optimized size of the engine and battery capacity to do a specific job. This is specially the case with utility vehicles who have a more or less fixed daily trajectory pattern in the highly dense urban areas with relatively short distances and several idle waiting times along its route. The methodologies to dimension electric vehicles converted from combustion vehicles normally work with predetermined or standard (closed) driving cycles, ignoring unexpected variations in urban traffic routes and realistic demands. The objective of the present work is the development of a methodology for dimensioning and optimization of an electric vehicle based on the survey of the needs of the vehicle and its user. The survey of the needs of the vehicle consists of recording, by means of GPS, the daily trajectory traveled by the vehicle to be converted into electric and the idling waiting time along its trajectory. Thus, with these data, it will be possible to calculate the power and energy necessary for the vehicle to travel the path determined by the user, which will allow the selection of the engine and the battery module to be installed in the vehicle according to the needs raised. An optimization algorithm, based on the maximum flow problem, can calculate the best battery configuration. Taking into account cost restrictions, size and weight allocated in the vehicle for the batteries, idling time along its paths and battery recharging time. As a result, the algorithm can indicate in which stopped the user can recharge the vehicle along its path, considering, of course, the time allocated for recharging the batteries at each stop. With this, it is expected to optimize the number of batteries to be installed in the vehicle, in order to minimize the costs of converting the combustion vehicle to an electric one.*

Keywords: *electric vehicle, electric vehicle methodology, electric vehicle dimensioning, battery methodology, battery dimensioning size, converted electric vehicle.*

1. INTRODUCTION

Electric vehicles (EV) are seen by many as cars of the future, because they are efficient, silent and don’t pollute locally. However, they are considered generally expensive and have low autonomy compared with internal combustion engine vehicles (ICEV) (FREITAS, 2012) (SETH, 2009). An alternative to buy a new EV is the conversion of an ICEV into an EV with the installation of an electric motor and a battery bank capable of giving the car sufficient autonomy at relative lower cost compared to the acquisition cost of a new EV.

In this context started the Tecnomobelet project at the Faculty of Engineering of the University of Brasilia, campus Gama. The objective of this project is to design a conversion methodology of ICEV to EV and develop technology to electrify utilities vehicles. Through the conversion of a diesel utility VAN, it is intended to gain knowledge on the conversion of commercial vehicles and analysis its technical and economic feasibility, contributing with the advancement of transport electrification in society (ELS, 2018).

The high costs of a new EV are due to the high cost of the batteries. Even when converting an ICEV to electric, the acquisition cost of the electric motor, controller, and auxiliary components is minor compared to the acquisition cost of the batteries. However, the owner of this converted EV can relativize this cost in obtaining an amount of batteries necessary for its initial functioning and increase the autonomy of through addition of new batteries or even install other forms of electricity conversion through using a series hybrid configuration with a dedicated internal combustion engine/generator or fuel cells. In addition, already having an ICEV without significant market value, its conversion to electric gives new life to a used vehicle and though also contributes to attend the requirement of reuse, recycle and reduce the pollutant emissions in a context of environmental sustainability. In this way, vehicle conversion can be an affordable alternative to democratize EV in society.

The focus of the project is on utility vehicles for passenger transport. These vehicles have an have a more or less fixed daily trajectory pattern in the highly dense urban areas with relatively short distances and several idle waiting times along its route. This driving pattern permits the implementation of some innovative strategies to reduce the conversion costs.

In this context emerges this present work, whose objective is to define a methodology to dimension the necessary power and energy of an electrified vehicle and to determine and optimize the amount of batteries that has to be installed considering the real operation trajectory of the vehicle, the acquisition cost of the batteries and the possibility to recharge the batteries in charging points along its daily trajectory.

In order to achieve this objective, a minimum flux cost algorithm, traditionally used in operation research, is used to optimize the quantity of batteries to be installed into the vehicle.

2. METHODOLOGY TO SIMULATE POWER AND ENERGY NEED

The objective of the present work is the development of a methodology for dimensioning and optimization of an electric vehicle based on the survey of the needs of the vehicle and its user. For this, there is a need for a methodology capable of simulating the power and energy needs of the vehicle that leads to specify the optimized size of the engine and battery capacity to do a specific job.

The dimensioning of the amount of energy needed for a vehicle to track a given path is the integration of the requested power at every instant through the path. The requested power is due to the forces acting during its movement known as aerodynamic resistance force, rolling resistance force and inertial resistance force (GILLESPIE, 1992).

The required total power is the product of these forces and the vehicle velocity:

$$P_t = F_t * V \tag{1}$$

Where P_t corresponds to the total mechanical power needed by the vehicle and F_t the sum of the resistance forces. Expanding equation (1) gives:

$$P_t = \frac{V}{(\eta_t \eta_m \eta_{cc})} * \left[\frac{1}{2} * \rho * A * (V + V_v)^2 + 0{,}01 * M * g * \left(1 + \frac{V}{100}\right) * cos\theta + M * g * sin\theta + 1{,}05 * M * a_x\right] \tag{2}$$

Where $\eta_t \eta_m \eta_{cc}$ corresponds to the global efficiency of the motor and the vehicle, and ρ, A, C_d , V, V_v , θ , M, g, a_x are respectively, air density in (kg/m^3), front area of the vehicle (m^2), aerodynamic drag coefficient, vehicle velocity (m/s), wind velocity (m/s), road inclination angle, vehicle weight (kg), gravitational acceleration (m/s^2) and linear acceleration.

The required energy is given by the equation:

$$E_t = \int P_t \, dt \tag{3}$$

The amount of energy that the vehicle battery bank can save equals the number of batteries multiplied by the energetic density of each battery. The density of a battery is the quantity of energy divided by units of volume or mass. In this case density of volume is used, so we can associate the volume of the battery bank to the destined space in the vehicle.

The energetic density is given by the equation:

$$DE = \frac{CN * T}{V} \tag{4}$$

Where:
CN = nominal capacity of the battery in (Ah);
T = nominal voltage of the battery (Volts);
V = volume of the battery in (liters).

The amount of energy that is saved in every battery by units of volume, represented by variable *Carreg(i)*, during the charging time, must take into account the time destined for its charging, the charging rate, and the energetic density, alongside the nominal capacity of the battery charger. Equation 5 resumes the amount of energy stored for each battery:

$$Carreg(i) = \frac{DE}{\frac{CN}{CC} * 60} * t(i) \tag{5}$$

Where *CC* is the nominal capacity of the charger, *CN* is the nominal capacity of the battery and *t(i)* is the charging time. The lower the charging time, the higher the charging rate will be and so more amount of energy the battery bank will receive per unit of time.

2.1 Driving cycles

The methodologies to dimension electric vehicles converted from combustion vehicles normally work with predetermined or standard (closed) driving cycles, ignoring unexpected variations in urban traffic routes and realistic demands.

Standard driving cycles are known to consist of a different set of parameters: speed, distance, acceleration, driving time, duration and frequency of starts and stops in order to simulate a driving pattern close to reality (BENTO, 2014). Usually used for the analysis of vehicular pollution emission and fuel consumption by vehicles with combustion engines, these cycles have been adopted as a methodology to size engine power and the number of batteries that an electric vehicle would need to run (SOUZA, 2010). The cycle path considers some performance factors, such as: speed, acceleration, distance between determined points and energy consumed per cycle section (SOUZA, 2010). The most used driving cycles are: American driving cycles, European driving cycles and Japanese driving cycles (UNECE, 2015) (TANAKA, 2013).

Standard driving cycles represent trajectories in urban, rural or mixed areas, which combine the urban and extra-urban trajectories in a single driving cycle (FREITAS, 2012). Its main advantage is the low cost of using it to analyze the performance of an assembled vehicle or just the vehicle's engine, which can be connected to a system of axles and wheels and simulated using a dynamometer installed in a closed environment.

On the other hand, standard driving cycles do not represent all the geographic vicissitudes and sudden and often unexpected variations experienced by vehicle drivers in regions not represented by the standard cycle used. In this sense, a standard cycle developed in a region of low slope has little effectiveness in determining the power requirement and energy consumption of an electric vehicle that is used in areas with high slopes and slopes and large slopes compared to the region where the cycle was recorded.

Therefore, the use of a standard driving cycle in a preliminary analysis of an electric vehicle can be welcome when all that is desired is to analyze the performance of the vehicle and its components in isolation. However, if you want to obtain the real needs of power and energy of an electric vehicle based on the needs and financial and economic capabilities of its user, it is necessary to obtain field data relating to the actual trajectory performed daily by the analyzed vehicle.

Because of this, the methodology that makes use of GPS to obtain data on real trajectories carried out by drivers and their vehicles has been used in the acquisition of data on the trajectory carried out by certain groups of drivers, their behavior when driving, the way in which the vehicle is used and the distances actually covered by the different groups of drivers in order to optimize energy use, determine the best configuration of the vehicle's battery bank based on the driver's needs, and cooperate in reducing the emission of effect gases greenhouse by the production chain and use of electric vehicles (MEINRENKEN and SHOU and DI, 2020).

Obtaining data from real trajectories taken by drivers using GPS, however, is not new. In 2010, it was already used to determine the distances actually covered daily by drivers and their vehicles, in order to determine their daily energy needs and limit the amount of batteries to the actual requirements of electric vehicle users (PEARRE et all, 2010).

Unlike the standard driving cycle traditionally used in vehicular dynamics, obtaining data from the use of GPS makes it possible to obtain more accurate and realistic data on the power and energy needs required by vehicles depending on the trajectories actually performed by their drivers, which allows a better location, for example, charging points along public roads (YUN et all, 2019) or the optimization of the number of batteries in an electric vehicle, in order to adjust the cost of the system of electric vehicle energy storage to the needs and possibilities of its owners (PEARRE et all, 2010).

2.2 Real demand

Embedded electronic systems in automotive vehicles created the possibility of integration of artificial intelligence and vehicle connection to the internet, giving rise to a gamma of possibilities to enhance driving optimization and management tools for large fleets through real time vehicle operation and traffic monitoring.

Within this context, the survey of the needs of the vehicle consists of recording, by means of GPS, the daily trajectory traveled by the vehicle to be converted into electric and the idling waiting time along its trajectory. Thus, with these data, it will be possible to calculate the power and energy necessary for the vehicle to travel the path determined by the user, which will allow the selection of the engine and the battery module to be installed in the vehicle according to the needs raised.

The daily trajectory with latitude, longitude, altitude and timestamp is captures through a GPS device and a velocity profile is obtained. Along with the vehicle characteristics an algorithm implemented in MATLAB calculates the power profile and energy demand. The output of this algorithm is an interactive map with the trajectory and velocity as shown in figure 1, and the power profile and energy needs shown in figure 2.

Next, the algorithm outputs the graphs of the terrain elevation, the distance covered by the vehicle, the slope angle of the track, the vehicle speed and acceleration at each instant, the power, both in Watts when in Horsepower, and the energy consumed during the course.

There is also the possibility of issuing graphics of the forces acting on the vehicle for further analysis. With this, the analyst obtains the power necessary for the vehicle to travel the determined path and the amount of energy to carry out the route as a whole.

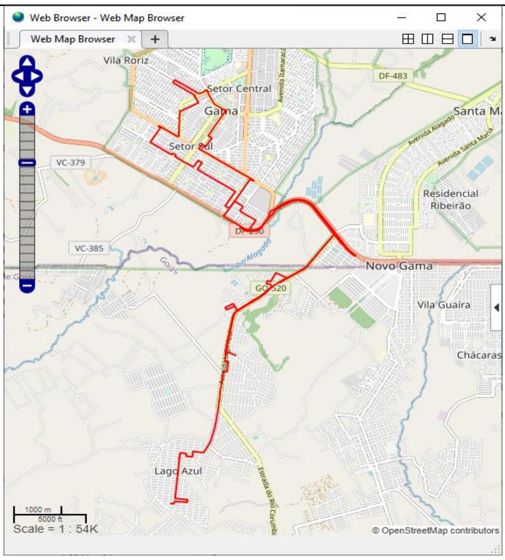

Figure 1 - Interactive trajectory map

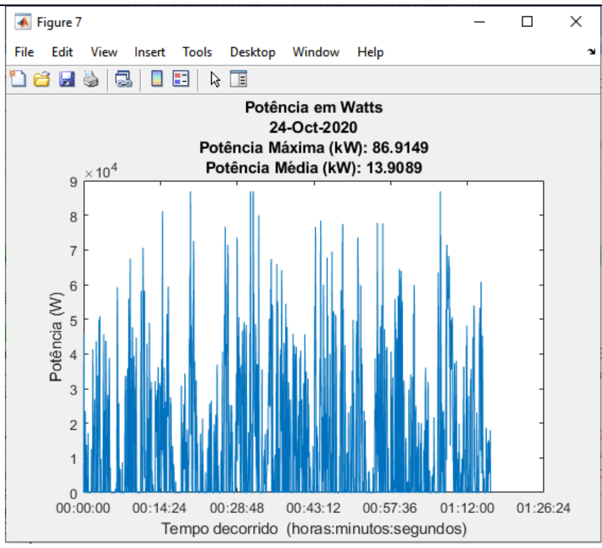

Figure 2 - Power profile along trajectory

2.3 Optimizing algorithm

An optimization algorithm based on the maximum flow problem can calculate the best battery configuration considering cost restrictions, size and weight allocated in the vehicle for the batteries, idling time along its paths and battery recharging time.

The Minimum Cost Flow Problem (MCFP) is a type of network problem that consists of circulating a flow in an s-t network, paying as little as possible for the traffic (GOLDBARG, 2005) (WINSTON, 2004). As in the case of the maximum flow problem, the MCFP considers the traffic subject to arcs with limited capacities. Like the shortest path problem, it considers the cost as part of the arc (HILLIER and LIEBERMAN, 2006), and allows the problematization with several nodes, exit points, arrival points and several arcs.

According to HILLIER and LIEBERMAN (2006), the minimum cost flow problem can be described by the following 8 propositions, which are:

1) The network is targeted and connected.
2) At least one of the nodes is a supply node.
3) At least one of the nodes is a demand node.
4) All other nodes are passing nodes.
5) The flux propagates only in one direction in the arc and the arc capacity is known. If the arc allows flow propagation in more than one direction, you need to create two arcs, one for each direction of flow propagation.
6) The network has enough arcs and nodes so that all the flow coming from the supply node can reach the demand node.
7) The cost of flow in each arc is proportional to the flow in that arc.
8) The objective is to minimize the total cost of sending the flow from the supply node to the demand node.

Thus, a MCFP algorithm could be represented by the graphic form of Figure 3:

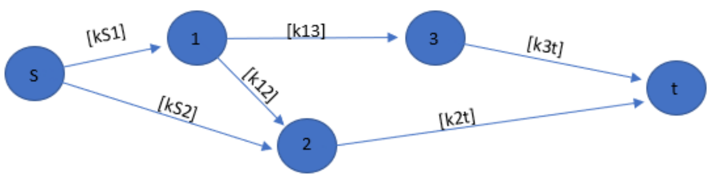

Figure 3: Minimum Cost Flow Problem

In this case, the flow that leaves the supply node S, travels through the arcs at cost [kij], passing through nodes i, until arriving at the demand node t.

The MCFP model can be simplified by the linear programming algorithm:

$$ObjectiveFunction: minZ = \sum_{i=1}^{n}\sum_{j=1}^{n} c_{ij}x_{ij} \tag{6}$$

Subject to restriction:

$$\sum_{j=1}^{n} x_{ij} - \sum_{j=1}^{n} x_{ij} = b_i, foreachnodei \tag{7}$$

The first sum of the restriction corresponds to the flow that leaves node i, while the second represents the flow that arrives at node i (HILLIER and LIEBERMAN, 2006). AND:

$$0 \le x_{ij} \le u_{ij}, foreacharci \rightarrow j$$

Where:

$$x_{ij} = flowthroughthearci \rightarrow j$$
$$c_{ij} = costperflowthroughthearci \rightarrow j$$
$$u_{ij} = arcarccapacityi \rightarrow j$$
$$b_i = flowgenerated \in thenodei$$

Normally, the condition for the MCFP model to generate a viable solution is that $b_i = 0$, so that everything that enters the node is equal to everything that leaves. This condition already integrates the stock that may be left over at the exit of the node or arriving at it.

The flow path design was the first step taken in the development of the least cost flow algorithm.

The flow is composed of the vehicle exit point (So), the arrival point (St), the intermediate stops or nodes (Si) and arcs with a single direction between the nodes. The arrival node (St) was considered to be the same exit node (So), since the objective is to optimize the amount of energy used by the vehicle throughout its trajectory, from the starting point, passing through the intermediate stops and returning to the exit point, which, in a real situation, could correspond to the vehicle owner's home or business. The network built from these elements was drawn in Figure 4.

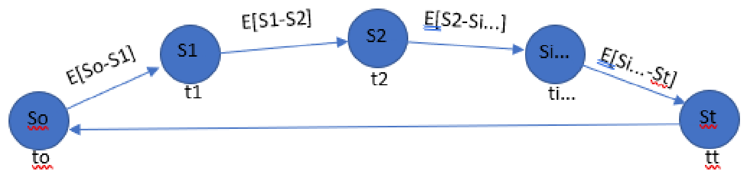

Figure 4: flow representative of the energy flow within the vehicle path

Where:
So = exit;
St = arrival;
S1 = *S2* = *Si* = intermediate stop nodes;
E[Si – Si+1] = Energy consumed between node Si and the next node Si+1;
ti = vehicle recharging time i at stop Si;
tt = 0;

In the flow of Figure 4, the vehicle leaves point So, passes through points *S1*, *S2*, and other stopping points represented by Si, where it stops for time *t0*, *t1*, *t2*, *ti*..., and reaches the final point St, which corresponds to the starting point So, and that, therefore, its stop time for reloading *tt* is equal to *to*. However, for the time to not be computed twice, we make *tt* = 0, and the reload time at the arrival location is restricted to the load time at the departure point.

The electrical energy consumed in each part of the trajectory is *E[Si – S(i+1)]*, where *Si* represents the previous node and, *Si+1*, the next node. In the first route, between *So* and *S1*, the vehicle will need enough energy to travel this route and still maintain a stock for the route of section *S1-S2*, given that it is considered that the time *t1* for recharging the batteries at node *S1* does not it will be enough to obtain all the energy necessary for the vehicle to travel the path *S1-S2*. Thus, for each stretch of the path, the vehicle will need energy to travel that stretch and an additional amount of energy in stock, to complement the energy acquired in the next node, and be able to travel the path from the next node to the subsequent node and, thus, successively. Where $St = So$, there is no energy consumed between the incoming and outgoing nodes, and $E[St\text{-}So] = 0$.

Thus, the sum of flows entering and leaving each node can be described by the restriction algorithm:

$$Carreg(i)*X + Stock(i) - Stock(i+1) - ConsE(i) >= 0 \tag{8}$$

Where:
X = number of batteries installed in the vehicle;
Carreg(i) = amount of energy charged in the batteries at stop i;
ConsE(i) = energy consumption by the vehicle when traveling the path Si-Si+1 computed at the stop i subsequent to the covered stretch;
Stock(i) = energy stock that arrives at node i;
Stock(i+1) = energy stock that leaves node i and arrives at node i+1;
Stock(So) = 0;
Stock (St) = 0;

In the Minimum Cost Flow Problem (MCFP), every flow that arrives at node i must be equal to every flow that leaves. Thus, the energy that arrives at node i through the Carry(i) and Stock(i) variables must be equal to the energy that will leave this node through the Carreg(i+1) and Stock(i+1) variables. Part of this energy will be used in the Si-S(i+1) path, so that, in the S(i+1) node, a new energy balance must be performed, resulting in the quantification of the energy that will leave S(i+1) and reach the S(i+2) node and so on.

Considering that, at the output node, the energy stored in the batteries is represented by the variable Carreg(i) (or, more specifically, Carreg(1)), and that the vehicle had not come from anywhere until then, the Stock(1) can be null. Considering also that, at the arrival node (St), the vehicle must be stopped waiting for a new restart of the cycle in a later period, the Stock(n), being in the number of stops, must be equal to zero, as it does not need keep energy stock after completing the trajectory.

With this, we close the cycle of energy flow within the vehicle's trajectory, and all the energy that the vehicle has stored at the exit point added to the energy it will obtain at the recharging stops along its trajectory must be equal or greater to the energy it will need to complete the journey from start to finish, without leaving any energy stock stored in the batteries.

Finally, the amount of energy that the battery pack can store during the recharging period is equal to Carreg(i)*X.

It is necessary to add a safety coefficient (CS) to the amount of stored energy, so that there is always a small amount of energy in the batteries, not only for the maintenance of vehicle electronic systems, as well as to reduce the percentage of error propagated by the calculations.

The installation of a set of batteries inside a vehicle must be done without prejudice to the number of passengers that the vehicle is capable of carrying and, much less, without causing discomfort to the vehicle's occupants. In this sense, it is necessary to take into account that the space for the installation of the battery pack should be restricted to the vehicle's trunk.

This creates a new constraint for the model that can be summarized in the equation:

$$X * V \leq VE \tag{9}$$

Where *X*, *V* and *VE* are, respectively, the number of batteries, the volume of each battery in liters and the vehicle space, in liters, reserved for installing the battery pack. With this, we can close the model and establish the objective function, which will aim to minimize the cost of acquiring batteries by optimizing the number of batteries to be installed in the vehicle. Thus, the objective function to be minimized is:

$$OFMin = Cost * X \tag{10}$$

And the constraints of the model are summarized by the equations:

$$Carreg(i) \leq loadingrate * t(i) \tag{11}$$
$$Carreg(i) \leq (1 - CS) * DE \tag{12}$$
$$X * V \leq VE \tag{13}$$
$$Carreg(i)*X + Stock(i) - Stock(i+1) - ConsE(i) >= 0 \tag{14}$$
$$Stock(1) = 0 \tag{15}$$
$$Stock(St) = 0 \tag{16}$$
$$X >= 0 \tag{17}$$
$$X = integer \tag{18}$$

And the input parameters of the model are:
CN = nominal battery capacity (Ah);
T = nominal battery voltage (Volts);
V = battery volume (liters);
CC = charger rated capacity (Ah);
V = volume of each battery (liters);
VE = total vehicle volume for the installation of the battery pack (liters);
CS = safety factor (%).
Cost = cost of each battery in monetary unit;
n = number of stops, considering departure and arrival;
t(i) = vector with the stop time, in minutes, for reloading at each stop i, where T(St) = 0;
ConsE(i) = vector with the amount of energy, in Wh, consumed in each path between node Si and node Si+1 computed at each stop i, where *ConsE(1)* = 0.

3. RESULTS AND CONCLUSION

As a result, the algorithm can indicate in which stops the user can recharge the vehicle along its path, considering, of course, the time allocated for recharging the batteries at each stop. With this, it is expected to optimize the number of batteries to be installed in the vehicle, in order to minimize the costs of converting the ICEV to electric.

In a preliminary simulation, data was entered for a 16-seater Long Boxer VAN commonly used in student transport. Vehicle trajectory data were obtained using a GPS device, whose gpx file was inserted into Matlab and initially treated using a 4-point moving average and Matlab's own tool to remove outliers called "filloutliers". Then, the vehicle data, the route and the stops for recharging along the trajectory, the batteries, the charger, and the space destined for the batteries inside the vehicle were entered. Table 1 brings the model input data.

Table 1. Data input

Input	**Value**
Cx aerodynamic drag coefficient	0.7
M vehicle weight (kg)	3500
Size vehicle (L x H) in mm	1988 x 245
Number of stops	4
Charging time in minutes in each stop	[600 100 80 0]
Distance in km between stops	[8.5 10.5 14]
Battery voltage (V)	3.2
Battery nominal capacity (Ah)	50
Battery size (L x W x H) in mm	152 x 50 x 190
Cost US$	100
Charger capacity	10 A
Space allocated to batteries (L x W x H) in mm	800 x 500 x 400

As a result, we obtained the amount of batteries and cost of acquisition of these components described in Table 2:

Table 2. Preliminary results obtained in the calculation of optimization of the quantity of batteries for electric vehicles

VALUES CALCULATED WITHOUT USING THE OPTIMIZATION ALGORITHM	
Number of batteries (units)	167
Total Cost (U$$)	16,700.00

RESULTS OBTAINED BY THE OPTIMIZATION ALGORITHM	
Number of batteries (units)	100
Total Cost (U$$)	10,000.00

As can be seen, without the use of the optimization algorithm and the consideration of intermediate stops to recharge the batteries along the path, it would be necessary to purchase 167 batteries for the simulated vehicle to travel the analyzed path at a cost of U$$16,700.00. On the other hand, with the optimization algorithm and considering the stops for recharging along the route, only 100 batteries will be needed, acquired at a total cost of U$$10,000.00, so that the vehicle user can travel the considered trajectory.

Below, Figure 5 shows, as a result of the simulation, the power that the vehicle would need to cover its path and the energy needed to complete each stretch of the considered path.

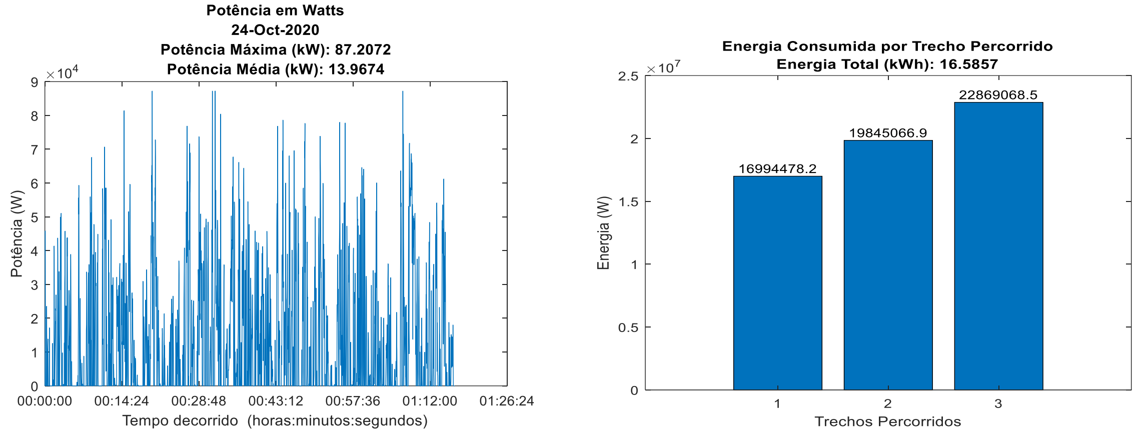

Figure 5 – Power and energy required by the vehicle to travel the mapped path scaled by the high-rhythm: a) Average power and maximum power; b) Energy required per stretch and total energy for the journey.

In conclusion, the optimization algorithm based on the Minimum Cost Flow Problem reduced by approximately 40% the number of batteries to be installed in the electric vehicle, considering possible stops for energy recharging along the trajectory. Thus, if, without optimization, the vehicle would need to charge 16,5857 kWh of embedded energy, with the optimization model, it will only need to charge 9,93 kWh in potential energy storage capacity in its battery pack, considering that, throughout its trajectory, he will be able to obtain part of the energy needed to complete the entire journey. Finally, the simulation resulted in a saving of approximately 40% in the cost of purchasing batteries for the vehicle.

4. ACKNOWLEDGEMENTS

The authors wish to thank the *Fundação de Apoio à Pesquisa do Distrito Federal* (FAPDF) for funding the Tecnomobelet project.

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