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The optimal location of the wireless charging infrastructure for electric vehicles with heterogeneous batteries in the highway

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Abstract: Dynamic wireless charging makes it possible to charge electric vehicles without contact while in motion from the transmitters buried under the road (segments and inverters). Our contribution to this work is to study the problem of locating wireless charging infrastructure on a long highway road between origin O and destination S with heterogeneous battery vehicles. Each type of vehicle requires its allocation of segments in the road because of the heterogeneity of batteries, which increases the number of recharge transmitters on the highway; for this purpose, we search to ensure the trip of each type of vehicle without remaining out of load, by the minimum number of segments and inverters on the road. We propose to model the problem as a mathematical problem and validate it with a CPLEX optimiser for limited instances. In the last step of this work, we will solve the problem using a multi-agent metaheuristic.

Keywords: mathematical programming; transportation problem; metaheuristic methods; electric vehicles; EVs; heterogeneous batteries; long road.

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Ahmed El Hiali Alaoui is currently a Full Professor with Euromed University, Fes. He has supervised many PhD students working on optimisation, multimodal transport, vehicle routing problems, and scheduling problems. He was a Full Professor with the faculty of sciences and Technologies (FST), Fez, Morocco, and a member of the Modelling and Scientific Computing Laboratory, Sidi Mohamed Ben Abdellah University, Morocco.

1 Introduction

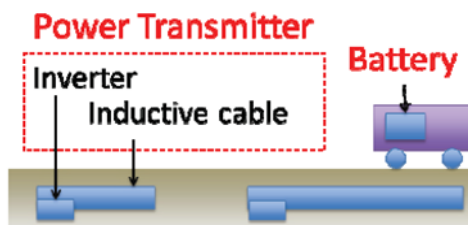
EVs do not emit CO₂ when in motion, which helps reduce the travel impact on air quality. It is one of the reasons why the state encourages the acquisition of EVs by making several purchasing aids available to individuals and businesses. The Electric vehicle (EV) essentially comprises a battery system that plays the role of the fuel tank and the electric motor (s).

Since the previous years, the characteristics of EV batteries have improved considerably. For the same weight and volume, the quantity of energy available increased, which increases their autonomy, and it is sufficient to travel on daily trips (for small to medium trips). However, it is not enough for long journeys like the highway. It is characterised by a long distance between the origin and the destination, and the high speed of vehicles on this kind of road drains their battery very quickly.

DWC is an effective solution for long journeys; since it can charge the batteries dynamically while the vehicle is in motion from a set of inductive cables and inverters placed on the road to meet the vehicle's charging requirements at all times. This technology makes it possible to transfer several tens of kilowatts over short distances (a few tens of centimetres) with good efficiency and safety for the human body if a correctly sized magnetic shielding is present. The advantage would thus be to recharge vehicles on the highway.

The DWC system (DWCS) is composed of EV and power transmitters (see Figure 1). An inverter converts the DC power into high-frequency AC or voltage. After converting the alternating magnetic fields generated by an underground electric power line to electric power, a pickup coil installed on the bottom of the vehicle receives this electric power. The received power goes through a rectifier and regulator before arriving at the battery (Qiu et al., 2014).

Figure 1 wireless charging system (see online version for colours)



The battery is the central element of the EV. The battery is designed to convert chemical energy into electrical energy when the vehicle is supplied with electricity and reverse the vehicle's charging process. It is a complex element containing many electrochemical reactions and constitutes a very large part of the value of an EV. The capacity, the charging rate, the discharging rate, and the EV's autonomy differ from one vehicle to another and depending on the type of battery used, so we talk about the heterogeneous vehicles (Table 1 shows the main types of EV batteries).

In the same context, the charging and discharge rate of an EV is affected by a combination of factors related to driving behaviour such as instantaneous speed and acceleration, type of road, traffic, temperature, and auxiliary systems such as radio,

windscreen wipers, air conditioning, and lights. The dynamic model of discharge rate can be defined in terms of the driving forces acting on a vehicle when it is in motion.

Table 1 The main types of EV batteries

Batteries	Advantages	Disadvantages
Cadmium nickel	• Lightweight • Long service life	• High toxicity of cadmium (no longer used)
Nickel metal hydride	• Lightweight • Large capacity (energy storage) • Little polluting	• Expensive • Temperature rise proportional to the load, therefore the need for a cooling system
Lithium	• High nominal voltage (3 to 3.7 volts/cell) • Stable in charge and discharge • High mass and volume energy densities (160 Wh/Kg and 400 Wh/l)	• Delicate use (need for automated power management) • Recycling not yet controlled (UN 3490 – UN 3090 regulation for the transport and packaging of these batteries)
Lithium-ion	• High specific and volume energy	• Flammability

The required power $P(t)$ is defined in Mouhrim et al. (2019) by the following relation:

$$P(t) = \gamma ma + F_a + F_r + F_g \times V(t)$$

with:

- γ The rotating parts inertia coefficient
- m The EV masse
- a The EV acceleration
- F_a The aerodynamic resistance
- F_r The rolling resistance force or gravitational load
- F_g The gradient resistance

The gradient resistance F_g is defined in [19] by $F_g = m \times g \times \sin(\alpha)$, where g is the gravity acceleration and α is the road gradient. The expression $\sin(\alpha)$ takes a negative value when the EV goes downhill (see Figure 2) (Mouhrim et al., 2019) or during braking.

Energy is dissipated before reaching the motor in the form of heat or light, or sound. As a result, the discharge rate becomes: $D(t) = P(t)/\delta$ with δ is the efficiency loss. When a vehicle passes through a portion of the route where no DWCS, its battery level decreases as follows: $\frac{dI(t)}{dt} = -D(t)$.

The charging rate of the EV $T(t)$ depends essentially on the magnetic flux $\overline{B}_1$ Figure 3 generated by the charging transmitters, which changes as a function of time. The analytical model for estimating the charging rate $T(t)$ of an EV at each time t is explained

in Caillierez (2016). When a vehicle passes through a portion of the route where a wireless transmitter is installed, its battery level increases as follows: $\frac{dI(t)}{dt} = T(t)$.

Figure 2 Gradient of the road in accordance with the rise/run

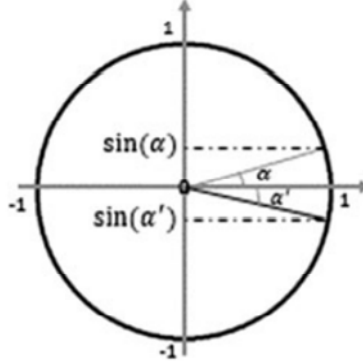
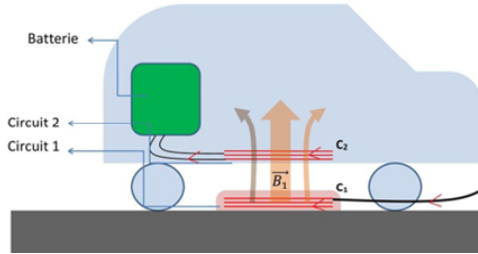


Figure 3 The magnetic flux $\vec{B}_1$ generated by the charging transmitters (see online version for colours)



Many works presented the problem of locating a minimum cost infrastructure of EV induction charge. However, researchers considered the vehicle's batteries to be homogeneous. In reality, each vehicle battery has its characteristics, as previously mentioned. Therefore, our contribution is to find an optimal location of the EV infrastructure with heterogeneous batteries in the highways.

The WCS is an ideal solution for the highway, but the high cost of this technology limits the use only when the charge is needed. However, the places of lack of charge differ from a vehicle to another because each vehicle type has its characteristics (autonomy, puissance, battery capacity), which increases the number of recharge transmitters in the highway; for this purpose, we search to minimise the infrastructure cost by reducing the number of segments and inverters in the highway. We search for modelling the problem as a mathematical model with constraints to find a minimum cost infrastructure that ensures the trip of each type of vehicle without remaining out of load at each point of the highway; this is precisely our goal to this work.

2 Literature review

EVs are becoming the mode of transport and the future of green logistics; this technology ensures travel without using different types of fuel; for this, there are many works concerning this technology.

Works focus on reducing the impact of EV charging on smart grids by bidirectional charging (Tanguy, 2013). In this context, Diop and Hennebel (2016) proposed two strategies for planning the charging of EVs to reduce the financial cost of charging; centralised and decentralised strategy. Benetti et al. (2015) present a concealed time management method for the charging process of EVs.

Some research has focused on routing problem EV (EVRP) allocation. Conrad and Figliozzi (2011) propose mathematical modelling of EVRP with specific demands of customers and limited vehicles capacity. Schneider et al. (2014) treated the same case with time windows and proposed hybridisation for this variant. Furthermore, Barco et al. (2013) study the EVRP from the point of view of public transport and present a case study on the transport of passengers from an airport to a hotel using EVs and respecting the notion Dial-a- Ride problem (DARP).

Among the exciting works, we quote that of Wang (2007), which proposes a deterministic mathematical model for the allocation of charging stations for electric scooters during their visits to tourist sites, Wang and Lin (2013) proposed another model for the location of several types of stations. Giménez-Gaydou et al. (2016) proposed a new approach to determine the optimal locations of public charging stations in urban areas and maximise the demand covered.

The problem of battery replacement consists of removing exhausted batteries and replacing them with fully charged batteries, known by their designation in English battery-swapping stations (BSS). In general, there are two types of operation for BSS, central load and local load (Tan et al., 2014). In central mode, EVs exchange their batteries in BSS, and the empty batteries are sent to the central charging station; once the empty batteries are fully charged, they are sent back to the BSS. The other model uses a local charging system that charges the depleted batteries of the local BSS (Mak et al., 2013). Although this avoids tedious battery charging, the local charging method requires careful planning of land use to reserve a sufficient number of spaces for waiting for parking a bus and installing a local charger Li (2016). In addition, BBS requires significant capital investment to purchase additional batteries, which will be exchanged for batteries near their exhaustion. The location of the BBS and the choice of charger types become an inevitable problem in the design of a battery exchange system to balance the trade-off between their charging speed and cost.

Wireless charging (WC) allows charging the vehicle's battery without contact, known by wireless power transmitters (WPT), existing in two types. The first type is the stationary WPT, which presents a recharging mode from which the VE can be charged by induction when it is stopped. The WPT is equivalent to using a charging cable, except that stationary WPT technology has the advantage of being practical and more secure for more details see Jang et al. (2016). The second type is dynamic WPT, which allows an EV to be charged by induction while it is in motion. The Korean Advanced Institute of Science and Technology KAIST has installed this technology on its campus to allow its buses to charge by induction while running called by one line electric vehicle (OLEV) (Jang et al., 2012).

Ko et al. (2014) presented a mathematical model and solved it with the particle swarm optimisation algorithm. Their mathematical model minimises the power transmitter cost in the road and the battery cost of homogeneous battery buses. They assumed that the battery cost was according to the battery capacity. Jeong et al. (2014), but in their work added the battery life cycle impact, according to the charging and discharging of the battery.

We cite Jang et al. (2012) among the best-known works. They proposed a mathematical model to determine a compromise between the battery capacity of an EV and the location of the charge transmitters inductive on a fixed route a single path. They assumed that the bus travel speed was preset, and the batteries were identical. Liu and Song (2017) modelled the dynamic version of this model as a nonlinear model, and they used the genetic algorithms to solve it. Jeong et al. (2015) developed the model of Young and added the term of battery degradation to find a compromise between the infrastructure cost and the battery life. Ko et al. (2014) compared the initial investment costs of three types of charging systems. Ko et al. (2014) compared the initial investment costs of three types of charging systems. The first type is stationary wireless charging (SWC), which can charge an EV without contact when it is parked. The second type is quasi-dynamic wireless charging (QWC), in which the EV can be charged when it is moving slowly. The last mode is DWC, which can charge an EV in motion mode. The generation of the multiple paths is done by Mouhrim et al. (2019) do the generation of the multiple paths. They considered a multipath network between the origin and the destination station. They sought a compromise between the cost of installing the power transmitters and the cost of the batteries, which are assumed identical. Hassane and Ahmed (2020) search for a compromise between the infrastructure cost and the battery capacity in a multipath network, round-trip. Sun et al. (2020) investigated the optimal deployment of static and dynamic charging infrastructure considering the interdependency between transportation and power networks.

3 Problems and modelling

3.1 Problem description and objective

Our goal in this work is to find an optimal location for the WC infrastructure on a long highway road, ensures the trip of a set of heterogeneous vehicles batteries going from an origin O to a destination S. We consider a highway of origin O and destination S, and a set of vehicles with heterogeneous batteries, and we seek to satisfy by the least cost its needs of the load during their journeys from O to the destination S by the allocation of the power transmitters on the road like a dynamic station Figure 4.

We assume that the highway is divided into two zones, the 1st zone road without stations, and the 2nd that we will put the dynamic stations Figure. 5.

The 2ed zone is subdivided into segments with the same length, and we will consider each segment as a potential transmitter. If the charging is needed, the segment will be equipped with an inductive emitting cable plus an inverter or will fit only with an emitting cable, and if the loading is not needed, the segment will be inactive (Mouhrim et al., 2019) (see Figure 6).

Figure 4 Highway with dynamic stations (see online version for colours)

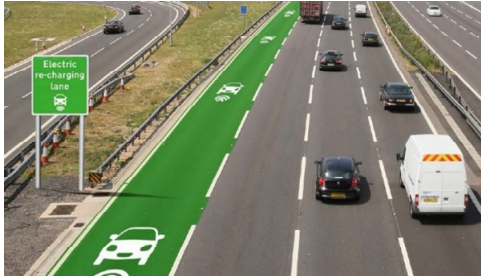


Figure 5 The decomposition of the road according to our assumption (see online version for colours)

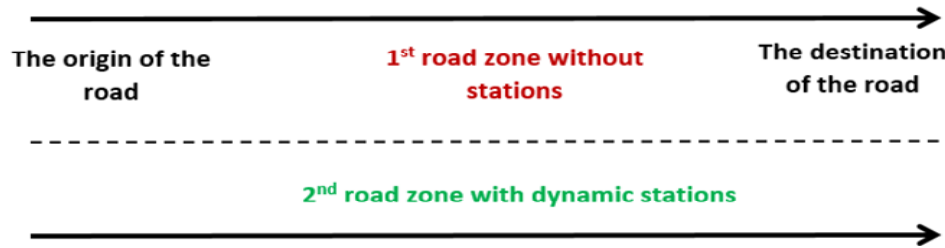


Figure 6 Types of segments (see online version for colours)

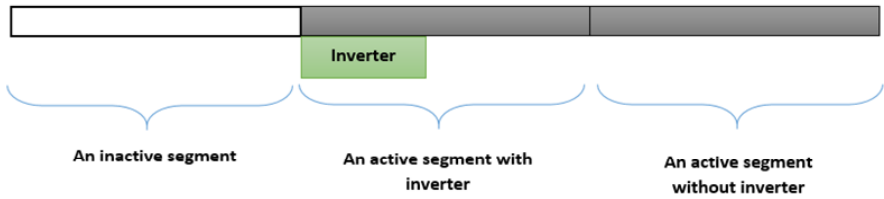
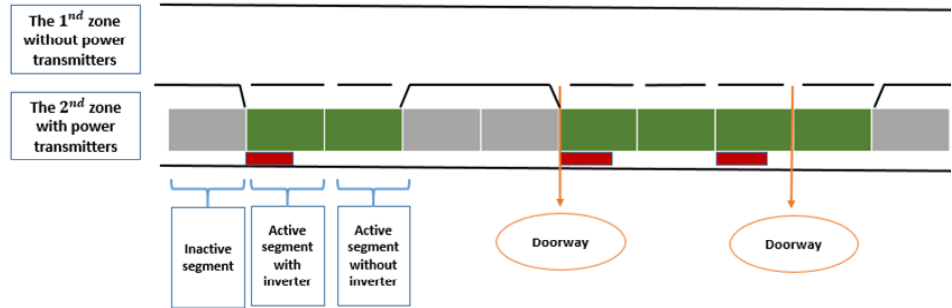


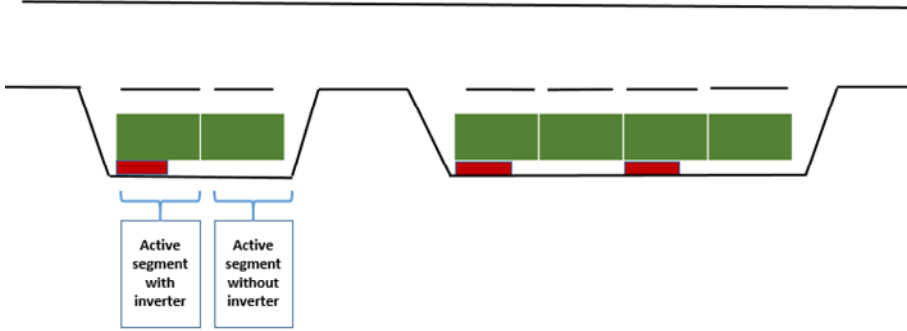
Figure 7 Highway with active and inactive segment (see online version for colours)



We note that a single inverter can power a limited series of successive active segments, so if the inverter capacity is exceeded, in this case, we need another inverter to power up the other active segments. Figure 7 shows the highway with active and inactive segments,

which we assumed that the inverter capacity is 2. If a vehicle needs the load, it will enter zone 2 through the doorways at the beginning and end of each active segment, and it cannot leave zone 2 until the next door, so if a vehicle decides to use an active segment, it will use it completely.

Figure 8 Highway with power transmitters (see online version for colours)



Each type of battery requires its allocation of the segments because of the heterogeneity of batteries for that, we search to determine the minimum of active segments and inverters in the 2ed zone to meet the energy needs of each vehicle type.

When we find the active segments in the second zone, the inactive segments will be deleted automatically, and in this case, we get the highway with power transmitters Figure 8.

3.2 Mathematical model

We seek to model the problem as a mathematical problem with constraints. We present as follows a set of notations, data, constraints, and objective function. In this work, we assume that the WC system can supply each type of vehicle.

3.2.1 Notations and data

The vehicles are considered to have a heterogeneous battery, let ϕ be the set of batteries and α the index of a type of vehicles with $\alpha \in \{0, \dots, |\phi|\}$.

The infrastructure cost is composed of the cost of the recharge segments and the price of the inverters. Let C_{sgt} and C_{inv} respectively the unit cost of an active segment without an inverter and the unit cost per inverter.

As we mentioned earlier, we discretised the second zone of the highway into segments of the same length; the first segment will be denoted by O , the last segment by f , and the other segments by g with $g \in \{O, \dots, f\}$. The entry point of a segment g is at the beginning of the segment and the exit point is at the end of the segment. We consider one vehicle of each type making the trip from O to S , and we note that t_O the arrival time of the fleet of vehicles at the entry point of the segment O (the starting point of the highway). As mentioned earlier, each vehicle type has its characteristics, so they do not have the same speed and acceleration on the highway, for that, each vehicle type α has its arrival time at the entry point of each g^{th} segment, which we note by t_g^α . We assume that

we know the arrival time t_g^α and it is independent of the zone where the vehicles are located.

Figure 9 An example of the arrival time of vehicles at the entry of the segments (see online version for colours)

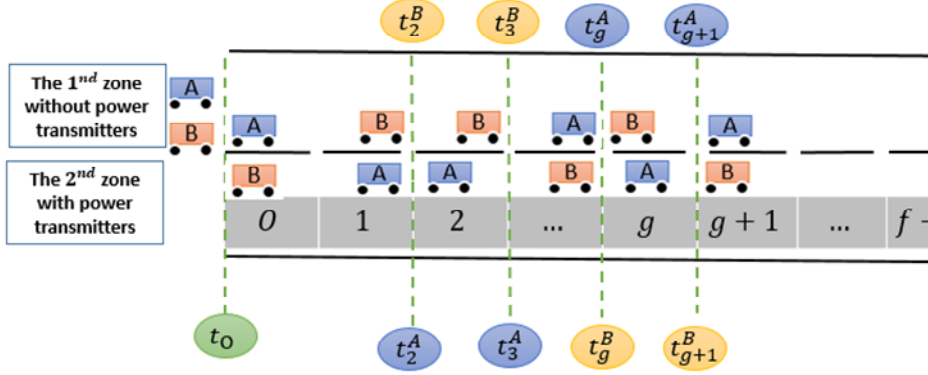


Figure 9 gives the discretisation of the road with the number of each segment, which starts from O to f , with two types of vehicles. Both types are placed at the entry of the segment O at instant t_0 (the starting point of the highway), then they will decide to enter the segment to load or not, this decision will deal with the decision variables and in the constraints of our model. The arrival time of vehicles A and B at the entry of segment g is t_g^A and t_g^B respectively.

The degree to which energy fluctuates over time depends on energy consumption and supply quantities. We define $D^{\alpha o}(t)$ as a rate of battery power consumption. This quantity depends on the energy consumption rate of the vehicle determined by the speed path, the slope of the road and the use of peripherals such as the car air conditioner. We define $T^{\alpha o}(t)$ as a battery power supply at time t . This amount is actually the charge rate of the battery and depends on the allocation of the power transmitter and the magnetic flux generated by the charging transmitters, which changes as a function of time.

We consider the following notations:

- I_{bat}^α : The battery capacity of vehicle α
- I_{low}^α and I_{up}^α : Are the lower and upper limits of the battery level, respectively. These values have the following relationship. $I_{low}^{\alpha o} = I_{bat}^\alpha \times \delta$ and $I_{up}^{\alpha o} = I_{bat}^\alpha \times \beta$ with $\delta, \beta \in [0, 1]$.
- N_{inv}^α : The maximum number of the active segment in each series that can use one inverter.

3.2.2 Decision variables

The second zone of the highway is subdivided into several congruent segments, and we search the minimum number of active segments and inverters into the road, that we define two decision variables X_g and Z_g such as

$$X_g = \begin{cases} 1 & \text{if the } g^{th} \text{ segment is active} \\ 0 & \text{otherwise} \end{cases}$$

If $X_g = 1$, in this case, the segment g will be active and the vehicles can enter to the second zone by the doorway at the beginning of the segment g to use it. If $X_g = 0$, In this case, the segment g is inactive, and any vehicle can not use the segment g and there are no doorways to enter this segment.

$$Z_g = \begin{cases} 1 & \text{if the } g^{th} \text{ segment has an inverter} \\ 0 & \text{otherwise} \end{cases}$$

If $Z_g = 1$, the active segment g needs an inverter, else the segment g will be without inverter.

Each type of vehicle has its character because of the heterogeneity of the batteries, so the use of the segments is different from a kind of vehicle to another so an active segment maybe used by some vehicle and not for others; we then define the decision variable y_g^α such as:

$$y_g^\alpha = \begin{cases} 1 & \text{if the vehicle decides to charge the energy via the segment } g \\ 0 & \text{otherwise} \end{cases}$$

If $y_g^\alpha = 1$ the vehicle α will charge the energy via the segment g , in this case, the vehicle α enters the zone 2 by the doorway at the beginning of the segment g . If $y_g^\alpha = 0$, the vehicle α does not use to the segment g in the second zone to charge, and this case the vehicle continues the trip on zone 1 of the road. In the Figure 7, $y_g^A = 1$, $y_{g+1}^A = 0$, $y_g^B = 0$ and $y_{g+1}^B = 1$.

Let $I^\alpha(t)$ be the amount of energy in the battery α at time t , this quantity is described as:

$$\frac{dI^\alpha(t)}{dt} = \begin{cases} T^\alpha(t) & \text{if the vehicle is in charging mode on the zone 2} \\ -D^\alpha(t) & \text{if the vehicle is in the zone 1} \end{cases}$$

3.2.3 Constraints

The problem is modelled under a set of constraints described below:

$$I^\alpha(t_0) = I_{up}^\alpha = \quad \forall \alpha = 0, \dots, |\varphi| \quad (1)$$

We assume that vehicles start at the beginning of the highway with the maximum load, for that, the amount of energy in each battery α at time t_0 is equal I_{up}^α .

$$I^\alpha(t_g^\alpha) + \int_{t_g^\alpha}^{t_{g+1}^\alpha} (-D^\alpha(t)(1 - y_g^\alpha) + T^\alpha(t)ny_g^\alpha) dt \geq I_{low}^\alpha \quad (2)$$

$$\forall \alpha = 0, \dots, |\varphi|; \forall g = 0, \dots, f - 1$$

The first term of (2) presents the level of the load of the vehicle α at the instant of arriving at the segment g . The second term presents the energy consumption of the

vehicle α between the beginning of the segment g and the beginning of the segment $g + 1$, this energy level is consumed if the vehicle has not used the segment g ($y_g^\alpha = 0$). In the case where the vehicle uses the segment g ($y_g^\alpha = 1$), the second term will cancel because the battery is in recharging mode in the segment g and the third term presents the amount of energy recharged by the vehicle during the use of the segment g . Therefore, the equation (2) represents the remaining charge at the beginning of each segment $g + 1$, which it must always be greater than the battery's lower limit. In other words, the vehicles need to use the segments in such a way that the energy level is greater than the lower limit.

$$I^\alpha(t_{g+1}^\alpha) = \min \left\{ I_{up}^\alpha; I^\alpha(t_g^\alpha) + \int_{t_g^\alpha}^{t_{g+1}^\alpha} (-D^\alpha(t)(1 - y_g^\alpha) + T^\alpha(t)ny_g^\alpha) dt \right\} \quad (3)$$

$$\forall g = 0, \dots, f-1, \quad \forall \alpha = 0, \dots, |\phi|$$

Equation (3) updates the remaining charge at the beginning of each segment $g + 1$. The battery energy level of each vehicle α should be less than the upper limit of the battery I_{up}^α . If the energy amount is more than the upper limit, then the energy level would be I_{up}^α .

$$y_g^\alpha \leq X_g \quad \forall \alpha = 0, n, |\phi|, \forall g = 0, \dots, f \quad (4)$$

Equation (4) ensures that if at least one type of vehicles decides to charge the energy via the segment g , the segment g must be active.

$$X_g \leq \sum_{\alpha \in \phi} y_g^\alpha, \quad \forall g = 0, \dots, f \quad (5)$$

Equation (5) guarantees that if any one of vehicle type decides to charge the energy via the segment g , the segment g should be inactive.

$$Z_g \leq X_g \quad \forall g = 0, \dots, f \quad (6)$$

Equation (6) confirm that if a segment g is inactive, it do not equipped by an inverter.

$$Z_o = X_o \quad (7)$$

$$Z_g = (1 - X_{g-1}) X_g \quad \forall g = 1, \dots, N_{in} \quad (8)$$

$$Z_g = 1 - \left[\sum_{k=1}^{N_{in}-1} Z_{g-k} \times \prod_{a=1}^k X_{g-a} \right] X_g \quad \forall g = N_{in} + 1, \dots, f \quad (9)$$

The equation (7) guarantees that if the first segment is active, it will be equipped with an inverter, the equations (8) and (9) place an inverter in the start of each series of active segments.

By the equation (8) if the segment g is active ($X_g = 1$) and its predecessor segment $g-1$ is active ($X_{g-1} = 1$), in this case, the segment g does not have an inverter because it belongs to an active series of length less than or equal to N_{in} , otherwise, if a segment g is active ($X_g = 1$) and its predecessor $g-1$ is inactive ($X_{g-1} = 0$), in this case, the segment g will have an inverter.

The equation (9) ensures that a segment g may contain an inverter only if:

- The segment g is the beginning of an active series, i.e., g is active ($X_g = 1$) and its predecessor segment $g-1$ is inactive ($X_{g-1} = 0$) then

$$\prod_{a=1}^k X_{g-a} = 0, \forall k = 1, \dots, N_{in} - 1.$$

- The segment g is preceded by an active series of length exceeds N_{in} segments, i.e., the segment g is active and its $N_{in}-1$ previous segments are active

$$\left(\prod_{a=1}^k X_{g-a} = 1; \forall k = 1, \dots, N_{in} - 1 \right) \text{ but no segment of its previous has an inverter} \\ \left(\sum_{k=1}^{N_{in}-1} Z_{g-k} = 0 \right).$$

3.2.4 Objective function

We seek to minimise the cost of the infrastructure by reducing the number of active segments and inverters on the road. The first term of (10) calculates the cost of the active segment in the road, which equal the number of active segments times the unit cost of segment, the second term of calculates the inverters cost, which equal the number of inverters in the road times the unit cost of the inverter.

$$\text{Min} \left[C_{sgt} \times \sum_{g=0}^f X_g + C_{inv} \times \sum_{g=0}^f Z_g \right] \quad (10)$$

4 Problem solving

Our objective in this work is to build at the lowest cost a WC infrastructure that ensures the trip of the heterogeneous fleet of vehicles without remaining out of charge going from an origin to a destination of the highway. Firstly, the problem is transformed into an equivalent linear programming problem and solved with a CPLEX optimiser for a limited instance; secondly, we seek to solve it using a multi-agent meta-heuristic called Coalition-based meta-heuristic (CBM).

4.1 Problem validation

The CPLEX optimiser (Anand et al., 2017) was named for the simple x method as implemented in the C programming language, although today it also supports other types of mathematical optimisation and offers interfaces other than C. The IBM ILOG CPLEX Optimiser solves integer programming problems, very large linear programming problems using either primal or dual variants of the simplex method or the barrier interior point method, convex and non-convex quadratic programming problems, and convex quadratically constrained problems. To validate our mathematical model by CPLEX we modified some constraints

Equation (3) is replaced by the following constraints.

$$I^\alpha(t_g^\alpha) + \int_{t_g^\alpha}^{t_{g+1}^\alpha} (-D^\alpha(t)(1 - y_g^\alpha) + T^\alpha(t)ny_g^\alpha) dt \geq I_{up}^\alpha \Rightarrow I^\alpha(t_{g+1}^\alpha) = I_{up}^\alpha \quad (11)$$

$$I^\alpha(t_g^\alpha) + \int_{t_g^\alpha}^{t_{g+1}^\alpha} (-D^\alpha(t)(1 - y_g^\alpha) + T^\alpha(t)ny_g^\alpha) dt < I_{up}^\alpha \Rightarrow I^\alpha(t_{g+1}^\alpha) = I^a(t_g^\alpha) + \int_{t_g^\alpha}^{t_{g+1}^\alpha} (-D^\alpha(t)(1 - y_g^\alpha) + T^\alpha(t)ny_g^\alpha) dt \quad (12)$$

To complete the linearisation process, we propose to replace equation (8) by the equivalent following constraints:

$$X_g = 0 \Rightarrow Z_g = 0 \quad (13)$$

$$X_g = 1 \Rightarrow Z_g = 1 - X_{g-1} \quad (14)$$

Finally, the following constraints should be added to replace equation (9):

$$X_g = 0 \Rightarrow Z_g = 0 \quad (15)$$

$$X_g = 0 \text{ and } X_{g-1} \Rightarrow Z_g = 1 \quad (16)$$

$$X_g = 1 \text{ and } \sum_{k=1}^{N_{in}-1} X_{g-k} = N_{in} - 1 \Rightarrow Z_g = 1 \quad (17)$$

$$X_g = 1 \text{ and } \sum_{k=1}^{N_{in}-1} X_{g-k} \leq N_{in} - 2 \text{ and } X_{g-1} = 1 \Rightarrow Z_g = 0 \quad (18)$$

The other constraints remain the same.

4.1.1 Transport network data

To solve the problem by CPLEX optimiser, we consider a road between the origin O and destination S is 7,500 metres, and we consider 4 type of vehicles need to go from O to S without remaining out of charge by the minimum infrastructure cost. Tables 2 and 3 contain the energy supply rate, the energy consumption rate of each vehicle type, and the other data. We take a segment of length 100 metres as a reference unit and then deduct the necessary data relative to each segmentation used during the resolution.

Table 2 Vehicles data

	Battery capacity I_{bat}^α	The energy supply rate (kw)	The energy consumption rate (kwh/100km)
Vehicle 1	8.8	4.2	25.2
Vehicle 2	32.2	3	19.6
Vehicle 3	18.4	5	19.5
Vehicle 4	25	5.5	34.7

Table 3 Others data

<i>Notation</i>	<i>Description</i>	<i>Value</i>
N_{inv}	The maximum number of the segment in each series can use one inverter	10
C_{inv}	The unit cost per inverter	8,000
C_{sgt}	The unit cost of an active segment without an inverter	120
δ	The lower limit coefficients	0.2
β	The upper limit coefficients	0.8

4.1.2 Results

We will discretise the route into segments of the same length to determine the active segments and the location of the inverters. The choice of the length of the segments is very important since it influences the cost of the infrastructure. In the literature and the works already cited, the length chosen is between 1.9 and 50 metres, but these works are done in the cities; for this, our discretisation will be a little long compared to these lengths.

We solved the problem using a different length of the segment, we discretised the road in the segment of 150, 200, 250, and 300 metres, and we searched to minimise the infrastructure cost. Table 4 contains the results for each discretisation.

Table 4 Results for each length of segments

<i>Segment length</i>	<i>Actives segments number</i>	<i>Inverters number</i>	<i>Infrastructure cost</i>
150	36	6	24,480
200	21	5	20,040
250	18	5	20,400
300	17	5	21,120

The results found by CPLEX Table 4 all meet the constraints determined by our mathematical model. The length of the segments chosen influences the infrastructure cost. When a vehicle type uses an active segment, it uses the whole segment even if its battery saturates just in the middle of the segment, for example. Therefore, while the length of the segments is more suitable with the needs of the vehicle's load, the more the cost of the infrastructure will be better; this explains our results and shows its quality, as we have found several solutions depending on the length of the segment. We found that the length 200 gives the best infrastructure cost for our instance.

Table 5 shows the use of active segments by vehicles for the discretisation into segments of 200 metres. We notice that most of the active segments are used by three vehicles. It is logical because we seek to minimise the infrastructure cost; then, if a segment is going to be active, the best case is to be usable by all or the maximum type of vehicles. Which again shows the quality of the results and the validity of our mathematical model.

CPLEX solves our problem and gives the results for every discretisation used on the road; however, it solves our problem for limited instances. To solve the problem for a higher number of instances, we will use a multi-agent meta-heuristic.

Table 5 The use of active segments for discretisation into segments of 200 m

<i>Segment number</i>	<i>used number of vehicles</i>	<i>Segment number</i>	<i>used number of vehicles</i>	<i>Segment number</i>	<i>used number of vehicles</i>
2	2	11	3	24	3
3	3	12	2	25	3
4	1	15	3	26	2
5	3	16	2	31	3
6	3	17	4	34	4
9	2	20	3	35	2
10	3	23	3	36	3

4.2 *The approach to solving the problem*

In this paragraph we seek to apply a multi-agent metaheuristic (Coalition-based metaheuristic) to approach solving our problem, we will describe the principles of the method and then apply it to our problem.

4.2.1 *Coalition-based meta-heuristic*

The term ‘coalition’, taken from Parunak et al. (2003), refers to an organisation where agents have the same capacities and cooperate through direct interactions. The CBM is the name of a multi-agent metaheuristic. It uses the decentralised control and the individual and collective learning mechanisms. Each agent manages a solution and researches with several operators of intensification and diversification. Intensification operators refer to improvement processes such as local research, and diversification operators correspond to generational, mutation, or crossing operators. In CBM, the coalition is made up of a fixed number of identical agents. An agent manages a current solution and iteratively applies operators to this solution. The CBM loop is summarised in algorithm 1 (Meignan et al., 2010). In this algorithm, all agents are activated at each iteration. The only hypothesis about agent-to-agent synchronisation is that they must act at a similar rate to ensure collective behaviour. No explicit synchronisation between agents is required. One agent may perform a local search while another could apply a mutation operator at the same time.

Algorithm 1 CBM algorithm

```

1  Initialise the coalition.
2  while stopping criterion is not reached do
3      for each agent A in the coalition do
4          Activate agent A.
5      end for
6  end while

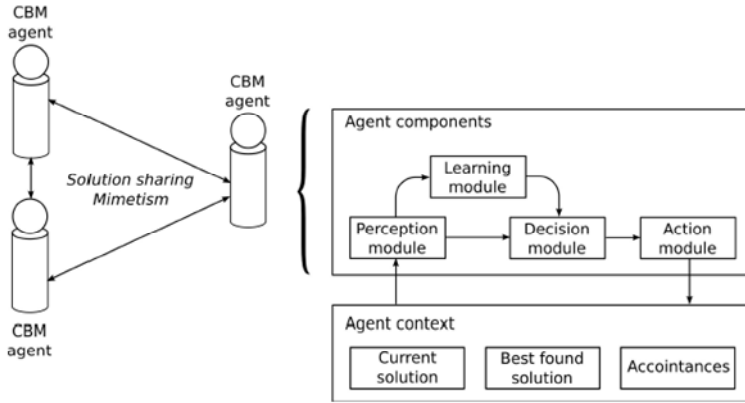
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The main features of a coalition official are a decision process, learning mechanisms, and means of cooperation. These elements are shown in Figure 10. The choice of an operator is made by a decision process that takes into account the optimisation context. The term

‘context’ describes the environmental and agent-related characteristics that may support an agent’s decision. The behaviour of an agent is adapted when optimised by learning mechanisms. In addition, agents can cooperate in two ways (Ropke and Pisinger, 2006).

On the one hand, an agent shares its most available solution. Other agents can use this solution with cross-operators. This cooperation aims to guide research through a promising new region of the research space. On the other hand, an agent can share its internal decision-making rules to allow behavioural mimetics. This second cooperation mechanism fosters decision-making behaviour that has often found new and better solutions.

Figure 10 CBM agent architecture (see online version for colours)



As shown in Algorithm 2, a basic agent iteration consists of four steps: perception, learning, deliberation, and action. Perception allows characterising the optimisation context by calculating the agent’s current state and possibly finding an agent to imitate. Second, learning adapts the agent’s behaviour through reinforcement and mimetic learning. Delivering is the choice of an operator to apply. Finally, the action corresponds to the actual application of the operator.

Algorithm 2 CBM agent iteration

-
- 1 Compute the current state s .
 - 2 Decide of an operator o to apply considering s .
 - 3 Learn by reinforcement and mimetic.
 - 4 Apply the operator o .
-

The decision process allows selecting an operator according to the optimisation context. The different actions refer to all operators, and a set of states characterises the optimisation context. We use the mechanism described in Holland et al. (2000) to select operators, which has some similarities with the (Sutton and Barto, 1998) and is based on a set of condition/action rules. Let’s S be the set of states and O the set of operators. For a state s_i , a weight $w_{i,j}$ is associated with each operator o_j . The weight $w_{i,j}$ corresponds to the potential of execution of the operator o_j in the state s_i . The actual choice of an operator is made by a roulette wheel selection principle. Thus, the probability $P(o_j|s_i)$ to apply the operator o_j in the state s_i is computed using the following formula:

$$P(o_j|s_i) = \frac{w_{i,j}}{\sum_{k=1}^M w_{i,k}}$$

The initialisation of the weight matrix is done with parameter G , which corresponds to the initial weight. To restrict an agent's behaviour, weights that match undesirable actions are set to zero. Then, during optimisation, a learning process will adjust the weights according to the agent's experiences. The determination of all states is an important step in the design of the algorithm. A state must characterise the optimisation context well to make an appropriate decision. Here, the number of states is limited to several exclusive conditions that characterise the current step.

Given that an agent has many operators, we have chosen to define the state of an agent by reference to the last operator applied to its current solution. The state 'finished' is reached when an agent applies the operator. Thus, an agent's status represents information about its current solution and the progress of the optimisation process. This definition of states and actions allows an agent to adjust the order of operators applied.

Agents use two learning mechanisms to adjust their behaviours: reinforcement and mimetic learning. Reinforcement learning (Sutton and Barto, 1998) is done during optimisation research to promote the sequences of operators that positively impact solution improvement. Since all intensification operators can improve the solution at the beginning of the search, all sequences where they appear can be strengthened. At the same time, as the optimisation process progresses, only a particular order of operator applications may impact the quality of the solution. In this case, only these sequences will be reinforced. The mimetic mechanism is to share the decision weight matrix between agents (Wang and Lin, 2013). It can be seen as a recombination operation operating at the meta-level of the decision-making process. A given initiating agent of the interaction modifies its weight matrix by considering the best performing agent found by a comprehensive review of the coalition of agents.

4.2.2 *Specialising CBM for solving the problem*

To illustrate the specialisation of CBM in the context of our problem, we consider that a solution of an instance of L segments and K vehicle type is described, on the one hand, by the status of segments and the location of inverters that we can code them by a matrix $A = (a_{2j})_{j=0,\dots,L}$ with:

$$a_{1j} = \begin{cases} 1 & \text{if segment } j \text{ is active} \\ 0 & \text{otherwise} \end{cases} \quad a_{2j} = \begin{cases} 1 & \text{if segment } j \text{ has an inverter} \\ 0 & \text{otherwise} \end{cases}$$

On the other hand, the set of segments used by each vehicle type noted by a matrix $M = (m_{ij})_{i=0,n,L}^{j=0,n,K}$ with:

$$m_{ij} = \begin{cases} 1 & \text{if thesegment } i \text{ is used by the vehicle } j \\ 0 & \text{otherwise} \end{cases}$$

Specialisation of the CBM for a particular optimisation problem requires the definition of diversification and intensification operators. The operators used in our approach are derived from operational research and evolutionary algorithms. Generation, crossover,

and mutation operators perform the task of diversification. Several standard local search heuristics are used as intensification operators.

Figure 11 Crossover operator

<i>The set of segments used by vehicles of the 1st solution</i>			
	Vehicle 1	Vehicle 2	Vehicle 3
Segment 1	1	0	1
Segment 2	0	1	0
Segment 3	1	1	1
Segment 4	1	0	1

<i>The set of segments used by vehicles of the 2nd solution</i>			
	Vehicle 1	Vehicle 2	Vehicle 3
Segment 1	1	1	1
Segment 2	1	0	1
Segment 3	0	1	1
Segment 4	1	0	0

<i>The set of segments used by vehicles of the new solution</i>			
	Vehicle 1	Vehicle 2	Vehicle 3
Segment 1	1	1	1
Segment 2	0	0	0
Segment 3	1	1	1
Segment 4	1	0	1

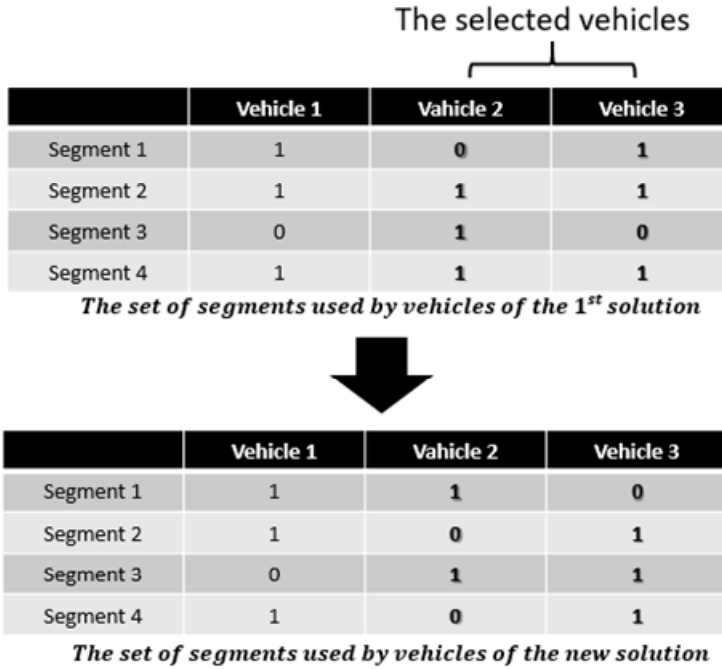
For diversification operators, we propose generation, crossover, and mutation operators, described below.

- *Generation operator*: Initial solutions are obtained by the generation operator. These operators are also used as diversification operators during optimisation. Two steps are taken to create a solution. Initially, a random number of segments are activated randomly, and vehicles use all activated segments. The second step is to find the places of lack of load for each type of vehicle and activate the necessary segments until the load constraints are met. At the start of each series of active segments, an inverter is installed while respecting the constraints.
- *Crossover operator*: We propose a uniform crossing. To obtain a new solution, we initially choose, in an equiprobable way, the set of segments used by vehicles between two solutions $M = (m_{ij})_{i=0,n,L}^{j=0,n,K}$ et $N = (n_{ij})_{i=0,n,L}^{j=0,n,K}$ for example) Figure 11. The segment state matrix $(A = (a_{ij})_{j=0,n,K})$ will be constructed so that a segment will be inactive if it is not used by any vehicle type and will be active if not. At the start

of each series of active segments, an inverter is installed while respecting the constraints.

- *Mutation operator*: It is based on the remove-and-reinsert procedure on the segment usage matrix $M = (m_{ij})_{i=0,\dots,L}^{j=0,\dots,K}$. The procedure consists of selecting a random number of vehicle types and removing the set of segments used by the selected types. Then each vehicle type randomly reuses the segments while respecting load constraints for each vehicle type Figure 12. The segment status and the inverter location matrix $A = (a_{2j})_{j=0,\dots,L}$ will change their coefficients so that a segment will be inactive if it is not used by any vehicle type and will be active if not.

Figure 12 Mutation operator



The intensifying operators used in CBM allow obtaining a local minimum from an initial solution. When a neighbourhood structure has been defined, the local search procedure consists of improving the fitness by a set of moves on the current solution and is replaced by the neighbouring solution as soon as the fitness is improved, and the procedure ends when the solution is a local minimum. Four different local search operators are used for the intensification:

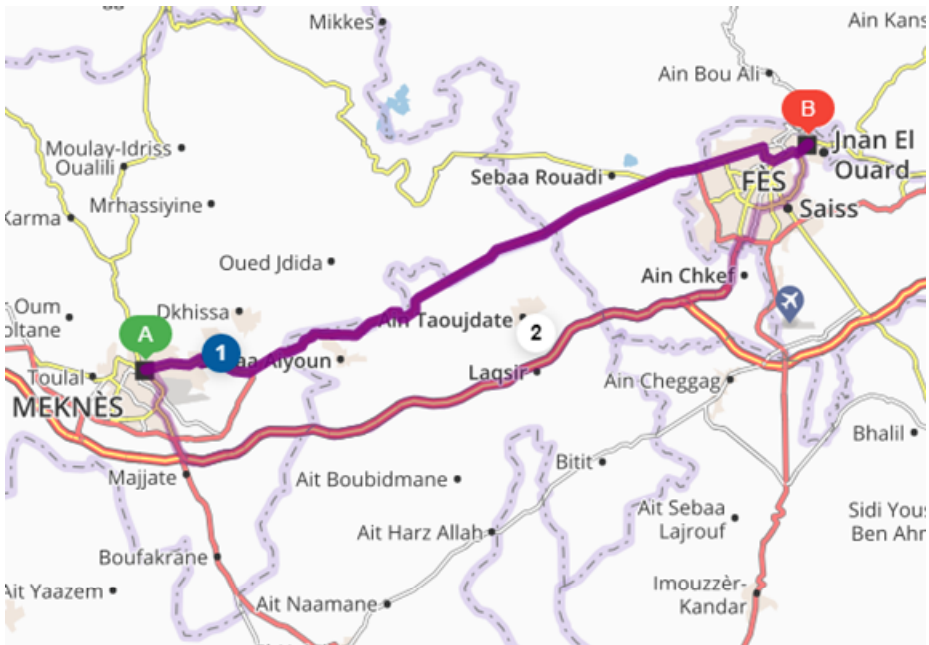
- I_1 : This heuristic randomly selects a type of vehicle and deletes one segment of the set of segments used by the selected type. It is necessary to check that the solutions respect the constraints of the load at the start of each segment. A solution that does not respect these constraints is not considered in the neighbourhood.

- I_2 : This heuristic randomly selects a type of vehicle and adds one segment of the set of segments not usable by the selected type in a random fashion; checking the load constraints is unnecessary in this case.
- I_3 : This heuristic randomly selects two types of vehicles and chooses a random segment, making it unusable for the two selected types; in this case, it is necessary to check that the solution respects the load constraints at the start of each segment. A solution that does not respect these constraints is not considered in the neighbourhood
- I_4 : This heuristic randomly selects two types of vehicles and chooses a random segment, and makes it usable for the two selected types; checking the load constraints is unnecessary in this case.

4.2.3 Case study

We use the Morocco highway (Meknes-Fez) (see Figure 13) for a case study of our work, and we choose five vehicles types to begin the journey from Meknes to Fez. We search the minimum number of active segments and inverters that ensure the trip of the different vehicles without remaining out of charge.

Figure 13 The morocco highway (Meknes-Fez) (see online version for colours)



4.2.4 Transport network data

Our objective in this paragraph is to build an induction-charging infrastructure for EVs of minimum cost, capable of ensuring the trip of the different types of vehicles from

Meknes to Fez. We use a different type of segmentation during the resolution to improve as much as possible the solution. Then we will generate the necessary data relative to each length of the segment. Tables 6 and 7 contain the energy supply rate, the energy consumption rate of each vehicle type, and the other data. We take a segment of length 150 metres as a reference unit and then deduct the necessary data relative to each segmentation used during the resolution.

Table 6 Vehicles data

	<i>Battery capacity</i> I_{bat}^{α} (kw)	<i>The energy supply rate on an</i> <i>active segment of length 150</i> <i>metres (kw)</i>	<i>The energy</i> <i>consumption rate</i> <i>(kwh/100km)</i>
Vehicle 1	7.6	1.1	29.5
Vehicle 2	42.2	0.9	17.8
Vehicle 3	11.6	1.3	30.6
Vehicle 4	18.4	0.4	19.5
Vehicle 5	16	1.2	25.8

Table 7 Other data

<i>Notation</i>	<i>Description</i>	<i>Value</i>
N_{inv}	The maximum number of the segment of length 150 metres in each series can use one inverter	6
C_{inv}	The unit cost per inverter	3,000
C_{sgt}	The unit cost of an active segment of length 150 metres without inverter	180
δ	The lower limit coefficients	0.2
β	The upper limit coefficients	0.8

4.3 *Experimental result and comment*

We solved the problem using a different length of the segment, we discretised the road in the segment of 150, 200, 250, and 300 metres, and we searched to minimise the infrastructure cost. Table 8 contains the number of active segments, the number of inverters, and the infrastructure cost for each segmentation.

Table 8 Results for each length of segments

<i>The segment length</i>	<i>The active segments number</i>	<i>The inverters number</i>	<i>The infrastructure cost</i>
150	249	58	218,000
200	210	54	212,400
250	163	53	207,900
300	142	56	219,120

When we used the 150-metre length segments in the route discretisation, we found 249 active segments, and this number is the largest compared to the active segments found by the other types of discretisation. This result is confused with reality because if the length of the segment used is small, then the number of segments required in the route increases.

The infrastructure costs found by the CBM depend on the type of discretisation used in the road, and this is the same case found by the CPLEX optimisation. For the same reason, we can explain this phenomenon that when a vehicle uses an active segment, it will use the whole segment even if its battery saturates just in the middle of the segment, for example. Therefore, while the length of the segments is more suitable with the needs of the load of the vehicles, the more the infrastructure cost will be better.

The infrastructure cost is higher when we use the 150 and 300-metres length segments compared to the second discretisation, so the 200-metres length segments are more adaptable to the needs of the vehicle's load than the 150 and 300 metres length segments.

When we used 250-metres length segments, we found 163 active segments, 53 inverters, and infrastructure of cost 207,900; this solution is the best compared with 200-metres length segments, and it is the best among all the lengths segments used. Therefore, for the instances used, the discretisation of the road into segments of 250 metres is the best.

Figure 14 The use of the active segments according to the number of vehicles (see online version for colours)

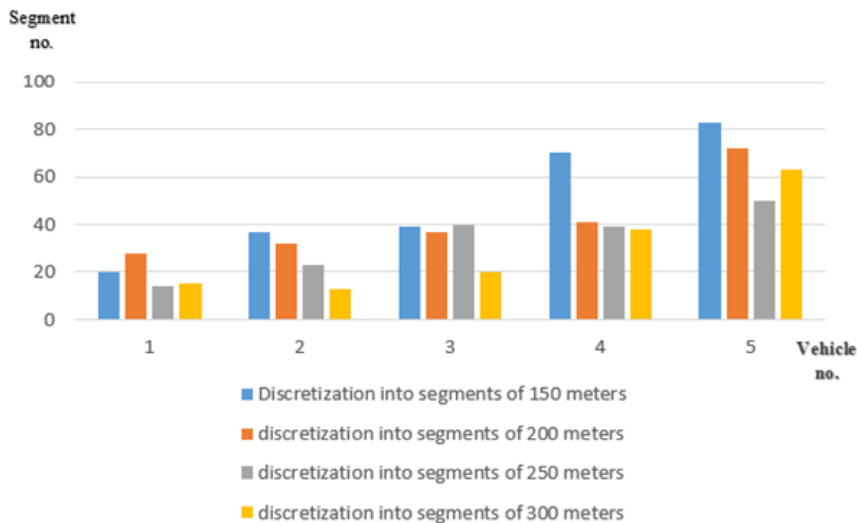


Figure 14 gives the use of the active segments according to the number of vehicles. For the discretisation into segments of 250 metres, among the active segments, less than 20 segments are used by a single type of vehicle, and less than 25 segments are used by two types of vehicles. The number of segments used by 3 and 4 vehicles times is 40 and 39 segments, respectively. More than 50 segments are used by 5 vehicles. We remark that most active segments are used by 4 or 5 vehicles in all discretisation because we seek to minimise the infrastructure cost. Therefore, when a segment is active, the best case is to be usable by all or the maximum type of vehicles, which shows the reality of the results found by the CBM.

In Table 9, for each discretisation value, we allocate active segments and inverters allowed by the CBM and CPLEX for the instances in Tables 2 and 3. It can be highlighted that the result obtained by the CBM coincide with those obtained by CPLEX

for the discretisation into segments of 150m. The results are very similar when the length of the segment was 200 m or 250 m, but the results are somewhat similar for the last discretisation. The obtained allocation shows that the performance of CBM becomes higher as the length of the segment used in the discretisation of the road decreases. The reason for this phenomenon is that the principle of CBM to improve solutions, make permutations between active and inactive segments, to delete or add segments in the vehicle use matrix, and the smallness of the segment length increases the segments number in the road, which increases the solution search space.

Table 9 Comparison between the CBM and CPLEX allocation

	<i>The segment length</i>	<i>The active segments number</i>	<i>The inverters number</i>	<i>The infrastructure cost</i>
CPLEX optimiser	150	36	6	24,480
	200	21	5	20,040
	250	18	5	20,400
	300	17	5	21,120
CBM	150	36	6	24,480
	200	25	5	21,000
	250	22	6	24,600
	300	19	7	27,840

5 Conclusion s

This work presented a mathematical model of the optimal location of the EV infrastructure with heterogeneous batteries in the highway. Our model aims to find the best location of the WPT, which gives the minimal infrastructure cost and ensures the trip of the heterogeneous fleet of vehicles without remaining out of charge for each vehicle type. We adapted the multi-agent Metaheuristic CBM to solve the problem, and we considered the Morocco highway (Meknes-Fez) for a case study to demonstrate the application of our model. Furthermore, we used a different length of segments during the resolution to find the best infrastructure cost because as long as the length of the load segments is proportional to the load requirements of the vehicle, the infrastructure cost will be better. For our instances, we found that the segment of length 250m gives the minimum infrastructure cost. In this work, we assume that charging segments can be allocated at each point on the road. Sometimes feeding the whole road by the induction charging system is prohibited due to the road geometry or the lack of electricity to power the inverters. For future research, it would be more challenging to consider the prohibited allocation of charging transmitters on predefined areas of the road.

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