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Influence of Battery Capacity on Performance of an Electric Vehicle Fleet

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Abstract

In this study, the influence of electric vehicle (EV) range on overall performance of an EV fleet is analysed. Various case-studies are investigated in which the EV fleet is simulated to cover a number of target points in a typical delivery problem. A trip scheduling algorithm is proposed in order to get all target points while considering the EVs range. The critical role of EV range in performance improvement of the whole fleet is analysed and an optimum EV range is obtained with regard to the whole fleet mileage. The results demonstrate that 250 km is an optimum range for an EV fleet to work in an area of 100×100 km². The number of target points, called task density, doesn't affect the optimum EV range very much and it can be determined only based on size of the service area. Finally, lithium-sulfur battery is discussed as a promising technology to extend EV range.

Keywords: electric vehicle range, fleet management, trip scheduling, battery capacity, lithium-sulfur.

1 Introduction

Electrified transportation systems would be inevitable in the near future. The existing delivery or taxi fleets are going to be replaced by clean and sustainable fleets in the near future. The existing fleet management systems need to be modified in respect to the features of an electric vehicle (EV) fleet. Fleet management software (FMS) is computer software that controls a series of specific tasks done by a fleet of vehicles. Various versions of FMS have been developed for conventional vehicles however; it is a new area for an EV fleet. In [1] the concept of using an EV fleet for ancillary services is discussed which works based on mobility and charging demand forecast. This needs enough data of the EV users and the infrastructure.

There are a number of useful references in the literature focusing on vehicle routing problems (VRP) [2]-[4] or trip-to-vehicle assignment problem developed for a fleet of conventional vehicles. The VRP, first defined by Dantzig e Ramser in 1959 [5] is a more general form of the traveling salesman problem adjusting for customers' demands and vehicles' capacities [6]. Another group of studies in the literature is focused on the applications of global positioning system (GPS) or global systems for mobile communication (GSM) in monitoring and management of a fleet of vehicles [7]-[9]. In this study, it is assumed that these technologies are available in EVs and they can find the best route to a target point using these devices.

This study is specifically focused on an EV fleet managed to do delivery tasks in a surrounded area. A framework is proposed in which each EV moves based on a pre-scheduled trip plan every day while guaranteeing enough charge to return to a depot at the end. For this purpose, a trip-scheduling algorithm has been developed. The EV fleet get charged during night at a depot. This has advantages such as charging the batteries slowly which provides benefits in terms of battery degradation minimization and more efficient vehicle-to-grid interactions. On the other hand, the disadvantage of such a framework is its high dependency on the EV range. To make it clearer, a separate section is allocated to investigation of the effect of EV range on fleet's performance. The whole fleet mileage is considered as an evaluation criterion of the fleet's performance. Four case-studies are designed and simulated by considering different task densities. In each case, the range of EV is changed from 100 km to 400 km and total mileage of the fleet is obtained.

Main contributions of this study are: (i) a trip- scheduling algorithm has been developed while considering the EV range constraint, (ii) the effect of EV battery capacity on an EV fleet's performance is analysed.

2 Electric Vehicle Fleet

2.1 Problem statement and EV fleet's structure

In this study, a delivery task problem is considered in which a number of target points should be reached by an EV fleet. The fleet consists of a number of electric trucks that go out for their daily tasks and should be able to return to a depot every day. The EVs are assumed to be charged slowly over night by considering battery degradation in the proposed scenario. An algorithm is used to set the EVs' trip plans every day regarding the number of target points and their locations. The advantages of the proposed scenario are: (i) the trip scheduling algorithm considers EV range constraints, (ii) the EV fleet is charged slowly during night at the depot which provides benefits in terms of battery degradation minimization and more efficient vehicle-to-grid interactions, (iii) although the simulations are performed off-line, the proposed trip scheduling algorithm is fast enough to perform on-line as well. The assumptions which are considered here are: (i) the target points for each day are determined a day before and this is not a real-time target planning like a taxi booking system, (ii) the trip scheduling algorithm is run on a server in the depot assuming the availability of GPS and GSM communication facilities, and (iii) all the EVs should return to a depot after finishing their daily tasks.

In such a scenario, the number of EVs, needed to be dispatched for getting all the target points, depends on the number of the points, target points' locations and range of the EVs. As an example, a random distribution of 100 target points in a squared city with dimension of 100 km is illustrated in Figure 1. In Cartesian coordinate, the origin (0,0) is located in the left bottom corner and for simplicity, the depot is located in the centre of the city (x=50, y=50) as shown in Figure 1.

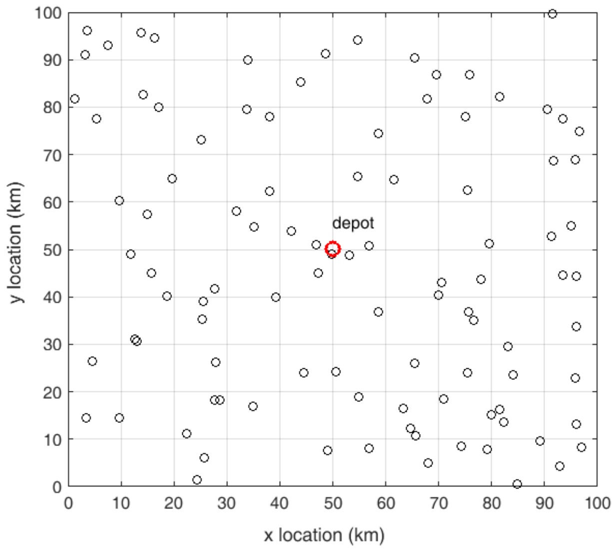

Figure 1: a random distribution of 100 points in a squared city

2.2 Fleet management algorithm

A 'trip ordering plan' (trip scheduling plan) is needed in order to get all the target points in an optimum way. Different objective functions can be considered in such an optimization problem. Investigation and comparison of different optimization techniques is out of the framework of this study since it is specifically focused on the effect of EV battery capacity (EV range) in an EV fleet management system. Determination of the sequence of target points and number of EVs in a semi-optimum way while considering EV's constraints is a challenging task which is done here by proposing a trip planning algorithm. For this purpose, a simple and efficient algorithm is proposed as follows:

(i) the proposed trip ordering algorithms allocate a sequence of target points to each EV in a specified order,

(ii) the plan for each EV is set in such a way that guarantees enough charge to cover all the target points and return to depot at the end without the need of fast charging during the journey,

(iii) the fleet is charged slowly during night and all the EVs are fully charged every day before their journeys,

(iv) the proposed algorithm works based on a concept presented in Figure 2.

A disadvantage of this algorithm is its high dependency on the initial condition i.e. the starting point. Starting from different points can lead to significantly different results in this algorithm. To overcome this limitation, all possible initial conditions can be considered since the number of points is limited. This means that the algorithm is run as many times as the number of points (using different initial conditions) and the best initial point is determined based on an objective function (f).

$$f(X_{best\ init}) = \min(f(X_i)) \quad , \quad for\ i = 1 \ldots n \qquad (1)$$

where $X_{best\ init}$ is the best point to start with, X_i is a target point, n is the number of all target points and f is an objective function that should be minimized. Here, the objective is to minimize the whole fleet mileage defined as follows:

$$f(X_i) = \sum_{j=1}^{N_{dispatch}} D_j \quad , \quad for\ i = 1 \ldots n \qquad (2)$$

where D_j is the total distance (mileage) that the jth EV has moved to catch all the corresponding target points and return to the depot and $N_{dispatch}$ is the number of EVs dispatched until all the target points are caught.

It should be noted that the proposed algorithm gives a fast solution but not the optimum one. Obtaining the optimum solution of such a trip scheduling problem needs much more time and computational effort especially when the number of the target points goes up especially in an on-line application.

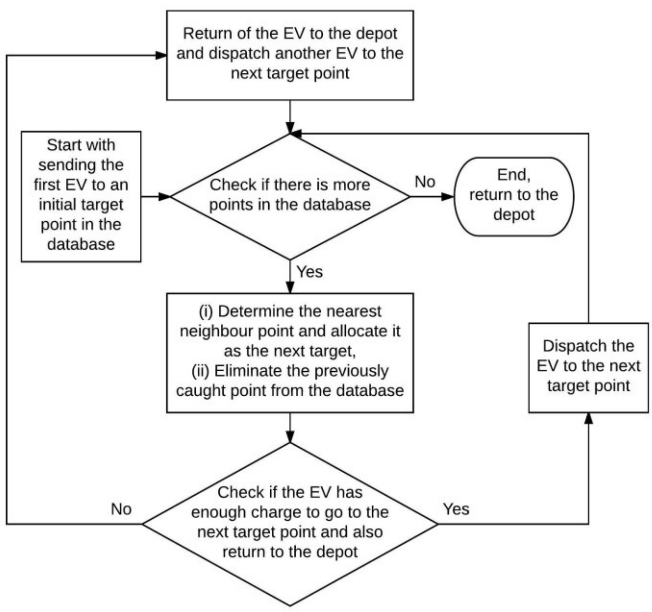

Figure 2: flowchart of the proposed fleet management algorithm

2.3 EV fleet movement simulation

Performance of the proposed fleet management algorithm is evaluated by simulating different scenarios like the one presented in Figure 1. Referring to that figure, the trip ordering algorithm should be able to cover all the target points by dispatching EVs as much as needed. In Figure 3, a solution of the trip ordering problem is presented for the distribution shown in Figure 1. As demonstrated in Figure 3, all the target points are covered by the algorithm using 8 EVs. Mileage of the EVs are different but none of them is more than 200 km which is defined here as a constraint. As mentioned before, it is important to select the first point properly. To consider the effect of the initial condition, the algorithm is run at all the possible initial points and the best point is then selected. Indeed, simplicity and speed of the proposed algorithm allows us to try all the points as a candidate to start with. In Figure 3, the best initial condition has been used and the total fleet mileage is 1338 km in this case. The results of all possible initial conditions are demonstrated in Figure 4 in which the total fleet mileage changes between

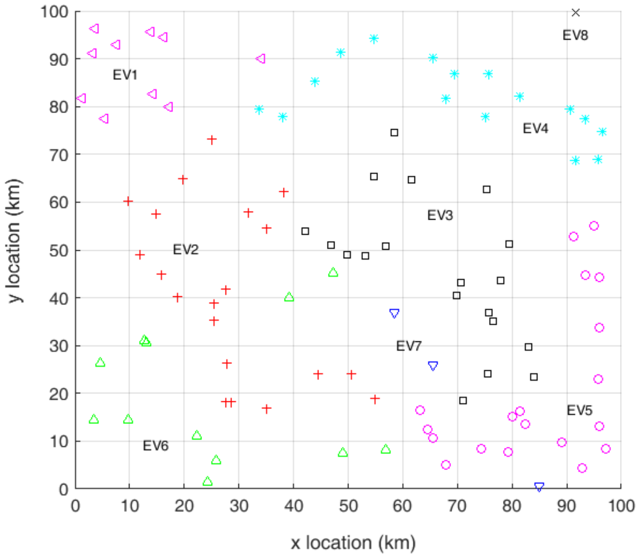

Figure 3: dispatching EVs to cover 100 target points

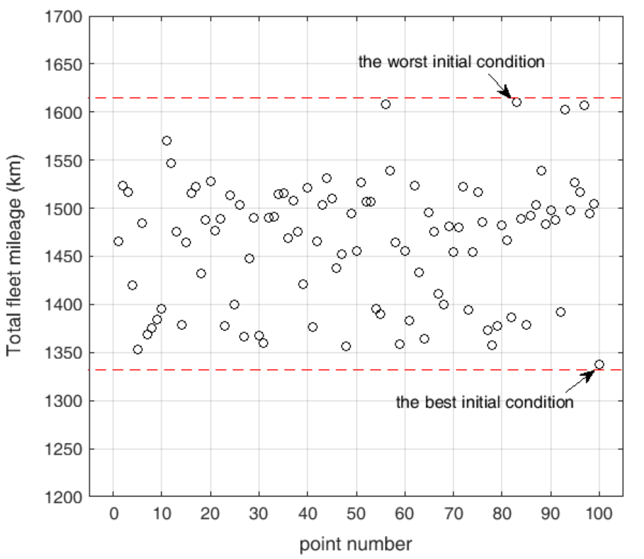

Figure 4: the effect of initial condition on total fleet mileage

3 Effect of battery capacity on EV fleet's performance

In this section, the effect of EV range on the performance of the whole fleet is investigated. It is expected that the range of the EVs plays an important role in such a scenario however, a quantitative relationship between the EV range and the total fleet mileage has not been addressed in the literature. In other words, we are trying to find an answer for questions like: how much percent does the total fleet mileage reduce by 10% increase in EV range?

For this purpose, various case-studies are considered. In each case, the effect of EV range on the overall fleet mileage is assessed using the simulation technique explained in previous section. In order to produce different scenarios, either of the city dimension or the number of target points can change. Here, a combination of the both factors is used in a new variable called 'task density' which is defined as the number of target point per km². Four case-studies are analysed in which the task density changes from 0.01 to 0.1 as follows:

Case-study 1: 100 target points randomly distributed in a 10000 km² squared city. Task density is obtained 0.01 point per km².

Case-study 2: 200 target points randomly distributed in a 10000 km² squared city. Task density is obtained 0.02 point per km².

Case-study 3: 500 target points randomly distributed in a 10000 km² squared city. Task density is obtained 0.05 point per km².

Case-study 4: 1000 target points randomly distributed in a 10000 km² squared city. Task density is obtained 0.1 point per km².

Random distributions of target points in the four case-studies are depicted in Figure 5. The goal is to cover all the target points by dispatching EVs using the proposed algorithm. The main contribution of this study, which is investigation of the influence of EV range on the overall fleet mileage, is also analysed by changing the EV range from 100 km to 400 km. In order to make the results more usable for future studies, a more general factor called "range to area ratio" (RAR) is also used as follows:

$$RAR = \frac{EV\ Range}{City\ Area} \quad (1/km) \tag{3}$$

Fleet simulation results in the four case-studies are presented in Table 1. Six EV range values are considered in each case-study: 100 km, 150 km, 200 km, 250 km, 300 km and 400 km. As expected, there is a direct relationship between the EV range and the number of needed EVs or the total mileage of the fleet. However, an interesting outcome is the highly nonlinear shape of this relationship. For example in case-study 1, a 100% increase in the EV range from 100 km to 200 km leads to 75% decrease in total fleet mileage whereas a 100% increase in the EV range from 200 km to 400 km leads to 24.5% decrease in total fleet mileage.

Doing the same analysis for case-study 4, gives a bit different numbers. A 100% increase in the EV range from 100 km to 200 km leads to 88% decrease in total fleet mileage whereas a 100% increase in the EV range from 200 km to 400 km leads to 24.1% decrease in total fleet mileage. This result demonstrates the effect of EV range at various levels of task density. The whole picture is more clearly presented in Figure 6 where the effect of EV range on the overall fleet mileage reduction is illustrated in four case-studies. The fleet mileage reduction (%) is calculated in comparison to the case of 100 km range of EV. These numbers are valid for a city in a same size (around 10000 km²). Two significant outcomes of Figure 6 are: (i) doing such an analysis gives us an optimum range of EV regarding the overall fleet performance. This optimum range depends on dimensions of the service area. In this case, 100×100 km² area, an EV range around 250 km would be a good choice. The results demonstrate that an EV range less than 200 km leads to a poor performance of the fleet whereas a range more than 300 km in this case doesn't improve fleet's performance anymore. (ii) the task density doesn't affect the results very much since we can consider same optimum EV range in all case-studies.

In order to scale the optimum EV range up or down, both the EV range and the city dimensions need to be multiplied by a same factor. For example, an EV range around 500 km would be a good choice for a 200×200 km² area.

Table 1: fleet simulation results in four case-studies

Case-study	Task density (point per km²)	EV range (km)	EV range/ area ratio (1/km)	Number of EVs	Total fleet mileage (km)
1	0.01	100	0.010	54	5332
1	0.01	150	0.015	17	1841
1	0.01	200	0.020	8	1338
1	0.01	250	0.025	7	1106
1	0.01	300	0.030	5	1143
1	0.01	400	0.040	3	1010
2	0.02	100	0.010	99	9648
2	0.02	150	0.015	21	2425
2	0.02	200	0.020	12	1677
2	0.02	250	0.025	8	1501
2	0.02	300	0.030	6	1391
2	0.02	400	0.040	5	1349
3	0.05	100	0.010	193	19118
3	0.05	150	0.015	32	4213
3	0.05	200	0.020	18	2906
3	0.05	250	0.025	12	2559
3	0.05	300	0.030	10	2470
3	0.05	400	0.040	7	2315
4	0.1	100	0.010	343	35755
4	0.1	150	0.015	49	6142
4	0.1	200	0.020	26	4331
4	0.1	250	0.025	18	3821
4	0.1	300	0.030	14	3414
4	0.1	400	0.040	10	3288

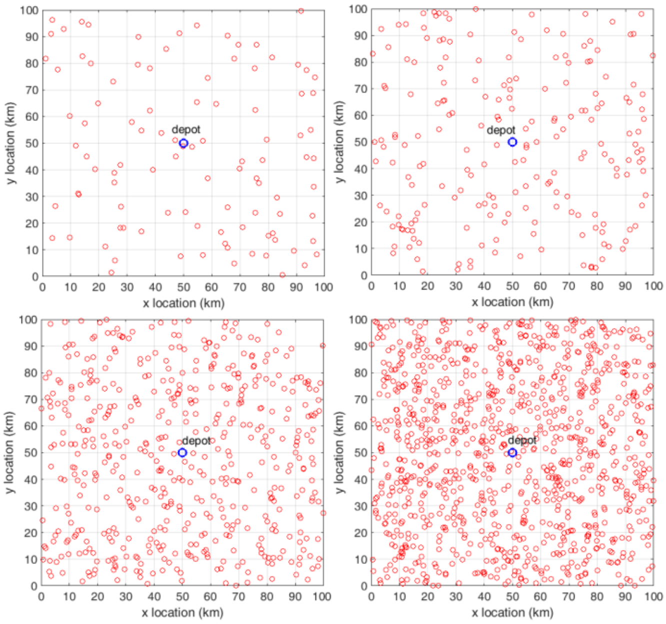

Figure 5: distribution of target points in the case-studies

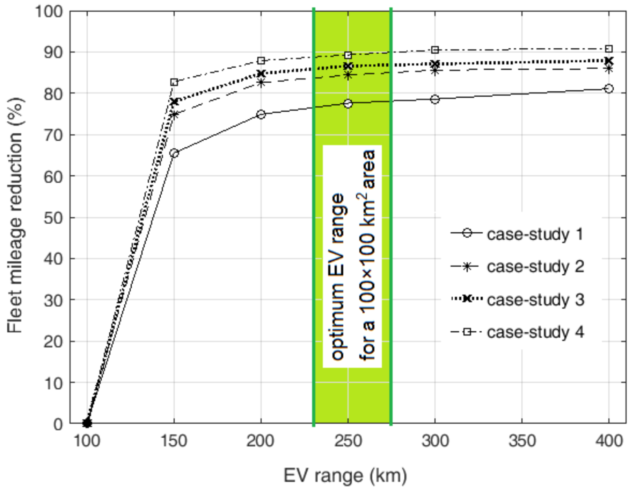

Figure 6: the effect of EV range on overall fleet mileage at various levels of task density

4 Lithium-Sulfur battery

It was demonstrated in the previous section that how the EV range can significantly affect the overall performance of an EV fleet. This would in turn require a larger battery. Taking the best of today's Lithium-ion technology with a specific energy of around 250 Wh/kg, a 212 kWh battery with a range of 200 km would require 848 kg of cells [10]. This could severely limit the payload of the EV, therefore new, lighter energy storage technologies should be considered. Among the new battery technologies developed for more capacity, lower cost and greater safety, lithium-sulfur (Li-S) is a promising technology, with a suggested specific energy up to 650 Wh/kg. This number is roughly two to three times more than the specific energy of the existing Li-ion batteries in the market at the same price [11]. This offers the potential for the

EVs to have a higher payload without compromising range due to a lighter battery. Referring to the results of this study, Li-S technology can be considered as a practical solution to improve an EV fleet's performance.
Although there are similarities between a Li-ion cell and a Li-S cell, different electrochemical reactions taking place inside each of them make their performance different. Various reactions may take place inside a Li-S cell at different charge levels, cause that Li-S cell's behaviour highly depends on state-of-charge (SOC). A number of useful sources of study on Li-S battery are reviewed in [12] and [13]. Figure 7 shows a Li-S cell and its schematic consisting of layers: 1) A Lithium metal anode; 2) A Sulfur-based cathode, which includes carbon or a polymer binder; and 3) A non-flammable electrolyte rendering the cell inherently safe [11].
Li-S technology has developed dramatically, though it has not yet been deployed in a full-scale EV to date. In addition to the high complexity of the electrochemical reactions taking place inside a Li-S cell [14],[15], this type of battery has unique challenges from the control engineering point of view as well. For example, the state-of-charge (SOC) estimation methods, used successfully for other battery types, are not easily applicable for a Li-S battery due to the large flat region in open-circuit-voltage curve of this type of battery as shown in Figure 8. Sufficient power output and lifetime are currently two limiting factors for the application of Li-S battery in automotive industry. Assuming that mature Li-S technologies in near future will also provide required power and cycling life in an EV, Li-S advantages make it very attractive in his area. More research on development of Li-S batteries is going on.

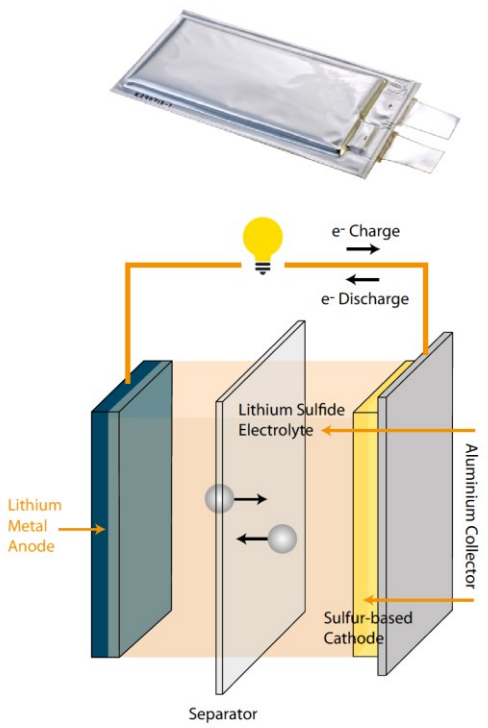

Figure 7: OXIS Lithium-Sulfur cell and schematic of its components [11]

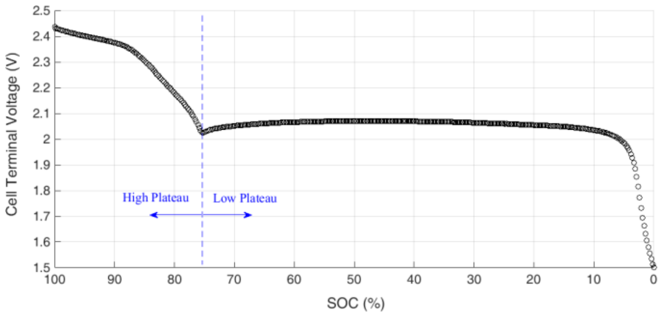

Figure 8: Li-S cell terminal voltage during slow discharge at C/30

5 Conclusions

A framework was developed for an EV fleet used for delivery tasks in a surrounded area. The proposed framework has advantages such as charging the batteries slowly during night at the depot which provides benefits in terms of battery degradation minimization and more efficient vehicle-to-grid interactions. On the other hand, the disadvantage of such a framework is its high dependency on the EV range. For this reason, the EV fleet's performance was studied with focus on the effect of EV range. Four case-studies were considered and simulated with different task densities. In each case, the effect of EV range on fleet's overall mileage was investigated by changing the EV range from 100 km to 400 km.
The simulation results demonstrate a significant reduction in fleet's overall mileage by increasing the EV range. A 100% increase in the EV range can lead to 24% to 88% reduction in fleet's overall mileage. However, this is not a linear relationship and an optimum EV range can be determined based on the fleet's service area. The results were presented for a 100×100 km² area. In this case, an optimum EV range around 250 km was obtained. It was also concluded that the task density doesn't affect the results very much whereas the service area can significantly affect the results. So the optimum EV range needs to be scaled up/down with regard to the service area as discussed in section 3.
An assumption in the simulations was a same EV range for the whole fleet. However, different factors can lead to a change in EV range such as load weight, road's grade, battery degradation, etc. which are not considered here. Considering different EV ranges in a fleet is also possible in the proposed trip scheduling algorithm by applying minor modifications.
Finally, Li-S battery technology was presented as a practical solution for increasing EV range by having around three times higher energy density in comparison to the existing Li-ion batteries in the market at the same price.

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