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A Location centric Power Factor Based Path Switching Model for Efficient Electric Vehicle Span Maximization

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Abstract: The problem of vehicle span maximization and path switching has been well studied. There exists number of approaches towards maximizing the span of electric vehicles. However, the methods suffer to achieve higher performance in maximizing the span of the vehicle. Towards this, an efficient Location centric power factor path switching model (LPPSM) is presented in this article. As the electric vehicles has the limited span which is being affected by various factors like speed, wind, traffic, number of junctions, distance and so on. It is necessary to perform path switching towards maximizing the span of the vehicle. The model fetches the location of the vehicle at all the time; it finds the routes and measures the traffic at each route. According to the factors like number of junctions, traffic, distance, speed of the vehicle, the method estimates the Span Maximization Support (SMS) for various routes. According to the value of SMS, the method selects the most optimal route to reach the destination. Also, the method focused on maximizing the span of the vehicle and performs efficient path switching. The proposed method improves the performance of span maximization and path switching.

Index Terms: Vehicle Control, path switching, span maximization, LPPSM, SMS.

1.Introduction:

Increased cost and scarcity of fuels challenges the vehicle manufactures in selling their vehicles. However, the entry of electric vehicles has supported them in selling the vehicles. However, the electric vehicles have set of limitation in terms of the cost and the span of single charge. The electric vehicle has to be recharged when the span has been reached. Also, the vehicle span mentioned by the product manufacturer will not be achieved when the vehicle moves on highly traffic routes with many junctions with higher speed. This challenges the manufacturer in providing exact solution for the customer.

Path switching is the process of finding set of routes and alternate routes for the vehicle. By finding such routes, and by measuring the support of the route, the vehicle can be diverted through number of other routes which have limited traffic. Also, it is necessary to consider the wind speed and vehicle speed which have great impact on the vehicle span.

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Towards routing the vehicle there are number of methods available, which consider only limited parameters like number of junctions and distance and traffic of the routes. This kind of approaches does not achieve higher performance in terms of routing as well as span maximization.

The span maximization is the process of increasing the distance to which the vehicle can use the battery charge. As the electric vehicles have the specific battery configuration, it can store only limited power to support the navigation. If the battery drains quickly, then the vehicle would stop at the midway and the customer would be in trouble. In most countries, there is no such infrastructure where the vehicle can be charged. This troubles the customer in charging the vehicle in midway. So, it is necessary to provide the support for the customer in maximizing the span of vehicle. At least, the vehicle should reach the specific span configuration. Towards span maximization, there are many approaches which consider only the residual energy of the vehicles but do not consider the possibility of getting charged at the midway. It is necessary to consider the number of charging stations present in the route before it has been used for navigation.

With all these consideration, an efficient Location centric Power Factor Path Switching algorithm with span maximization (LPPSM) is presented in this article. The main aim of the method is to maximize the span of the vehicle. The method is focused to consider number of factors like speed, distance, number of junctions, traffic, and number of charging units and so on. By considering all these, with the routes being discovered, the method computes the value of SMS (Span Maximization Support) for various routes. By choosing the route accordingly, the span of vehicle can be maximized and life of battery can be increased. The detailed working of the method is discussed in this section.

2.Related works:

There exist number of approaches to perform path switching and span maximization is available in literature. This section details set of methods around the problem.

A model predictive control (MPC) path-tracking controller is presented in [1], towards reducing lateral tracking deviation and maintains vehicle stability for both normal and high-speed conditions. Such path tracking controller support the stability management of vehicle even at different speed conditions and improves the span of the vehicle.

A switched velocity-dependent path-following control method is presented in [2], towards supporting autonomous ground vehicles under uncertain cornering stiffness and time-varying velocity. The variance in velocity of vehicle has been considered in path control towards maximizing the span of vehicle.

A artificial potential field (APF) with model predictive control (MPC) is presented in [3], towards vehicle motion control. The method combines cooperative maneuver switch and the continuous vehicle motion control is introduced into a multi-vehicle cooperative control system. This helps multiple vehicles to be navigated in a cooperative manner to maximize the span.

A command filtered control technique and globally uniformly ultimately bounded (GUUB) path following control structure is presented in [4]. By using different commands produced by the control, the path of vehicle has been controlled towards maximizing the vehicle span.

A game planning based smooth path planning scheme is presented in [5], to support intelligent air–ground vehicle. The method uses game theory in the selection of navigation path to maximize the span of the vehicle.

To handle path constrained switching, a novel approach is presented to enforce guaranteed feasibility in [6]. The method uses a bilevel algorithm to find optimal switch times and the optimal input with guaranteed satisfaction of path constraints over the entire time horizon. The bilevel algorithm identifies the navigation path according to different constraints at various time stamp which support the maximization of vehicle span.

An adaptive reinforcement learning based path switching model is presented in [7]. The reinforcement learning algorithm trains the model with various path constraints and performs path switching according to the weight measure computed for different paths to maximize vehicle span.

A graph based novel coupled path planning and energy management is presented in [8], towards supporting hybrid unmanned air vehicle. The model constructs the graph with number of nodes which contains different path constraints like traffic and so on. According to the path graph produced, the method identifies the optimal path for the destination and supports the span maximization.

A stochastic Markov decision process (MDP) model is presented in [9], which represent the behaviors of the vehicles. The method uses the geometry of road and produce different driving styles to support path switching.

A reinforcement learning based autonomous Wheel Loader (WL) is presented in [10], towards autonomous vehicles support, which uses approximate dynamic programming (ADP).

A fault-tolerant controller for the path-following of independently actuated (IA) electric autonomous vehicles (AVs) with steer-by-wire (SBW) systems is presented in [11].

A deep neural network (DNN) based path planning scheme is presented in [12], which uses online three-dimensional path planning network (OTDPP-Net) to learn local path to support path planning.

An extended adaptive cruise control (ACC), named economic adaptive cruise control is presented in [13], to support increasing the fuel economy in power split hybrid electric vehicles (HEV) according to vehicle route, speed, and powertrain. By splitting the according to above factors, the model can identify the most suitable path for the vehicle and support span maximization.

All the above discussed methods suffer to achieve higher performance in path planning and span maximization.

Location centric Power Factor Path Switching Based Span maximization (LPPSM):

The proposed path switching and span maximization model monitors the location of vehicle through the GPS connected. Accordingly, the method discovers the set of routes and collects the traffic, number of junctions, speed of vehicle, distance, number of charging hubs in each route. Using these features, the method computes the Span Maximization Support (SMS) for each route. Further, based on the SMS value, an optimal route has been selected to optimize the span of the vehicle. The detailed working of the model has been sketched in this part.

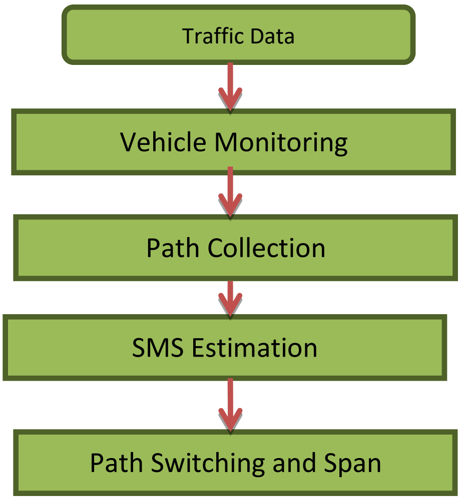

Figure 1: Architecture of Proposed LPPSM Model

The functional structure of the proposed LPPSM model is presented in Figure 1 and the functions of the model are detailed here.

Vehicle Monitoring:

The voltage monitoring function tracks the vehicle at each fraction with the use of GPS installed. At each time interval, the method performs path collection and estimates the SMS value for various routes. According to the value of SMS, the method performs path switching and span maximization.

```
Algorithm:
Given: Vehicle ID, GPS Id
Obtain: Null
Start
        Read Vid, Gid
        While true
                Collect GPS location Loc.
                Path set Ps = Perform Path collection (Gid.location, Gid.destination)
                Perform Path switching and span maximization.
                Wait for next time.
        End
Stop
```

The vehicle monitoring function monitors the vehicle mobility and collects various features to perform path switching and span maximization.

Path Collection:

The path collection algorithm uses the route map of any city where the vehicle is destined. Accordingly, the method identifies set of routes to reach the destination. For each route identified, the method collects the features like vehicle speed, distance, possible energy, wind speed, number of junctions, number of charging hubs and traffic on the roads. Collected features are converted into feature vector and used towards path switching.

The proposed path collection scheme use the vehicle id, roadmap Rmap, vehicle destination Vdest and location vloc with the speed S to perform route collection. Accordingly, the route set is identified as follows:

$$\text{Route set Rs} = \sum_{i=1}^{size(Rmap)} Rmap(i).route.destination == Vdest$$

Further, for each route r, the method identifies the no of junctions as follows:

$$\text{N of junctions Nj} = \sum Junctions \in r$$

The traffic in each route is identified as follows:

$$\text{Traffic Rt} = \sum_{i=1}^{size(Nj)} Sum(Nj(i).Traffic)$$

Similarly, the number of charging hubs in the route is identified as follows:

$$\text{No of charging hubs Nch} = \sum ChargingHubs \in r$$

Also, the wind speed Ws and Vehicle speed Vs are measured. The possible energy valule PE for the vehicle is measured as follows:

Pe = (Mobility_speed × Displacement)×μ

All these features are converted to feature vector to support the span maximization problem.

Path Switching and Span Maximization:

The path switching and span maximization algorithm uses the set of routes and by computing the SMS value for the routes according to various factors, it selects a optimal route for the vehicle and divert the vehicle in the route identified. It supports the span maximization by choose least energy depletion route according to the SMS value.

Algorithm:
Given: Route set Rs and Fv Set Fvs
Obtain: Null
Start
  Read Rs and Fvs
  For each route r

$$\text{SMS} = \frac{Fv.Rt}{Fv.Nj} \times \frac{Fv.Pe}{Fv.Vs} \times \frac{Fv.Ws}{Fv.Nch}$$

  End
  Route r = choose route with maximum SMS.
  Switch the vehicle on the route identified.
Stop

The above algorithm measures the SMS value and based on that path switching is performed.

3.Results and Discussion:

The proposed location centric power factor path switching model (LPPSM) has been implemented using Network simulator. The method has been evaluated for its performance using different scenarios. Obtained results are compared with the result of others.

Factor	Value
Tool	Network Simulator
Number of vehicles	100
Number of Paths	300
Time	10 minutes

Table 1: Experimental Setup

The experimental setup being used to evaluate the performance of the proposed model is presented in Table 1 and obtained results are compared with other approaches.

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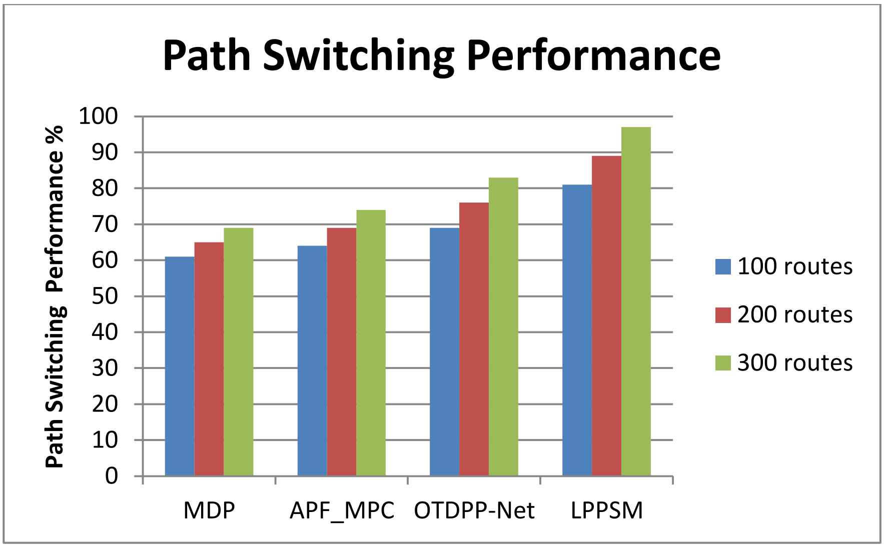

Figure 2: Path switching Performance

The performance of methods in path switching is measured and compared in Figure 2, where the LPPSM model has produced higher path switching performance than others. The analysis is performed by considering different number of routes in the network. In each case the performance of the methods are measured and presented in Figure 2. However, the proposed LPPSM model has produced noticeable growth in the path switching performance than others.

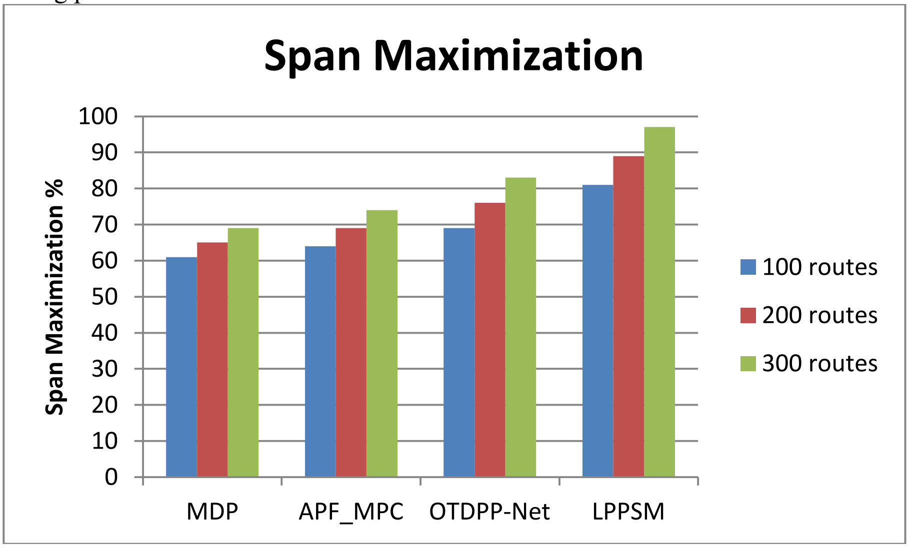

Figure 3: Span Maximization

The performance of methods in span maximization has been measured and presented in Figure 3. The proposed LPPSM model has produced higher span maximization performance than others. The performance in vehicle span is measured by considering 100, 200, and 300 routes as a test case. In each test case, the proposed LPPSM method introduces higher values compare to the other approaches.

4.Conclusion:

This paper presented a location centric path switching power factor span maximization model (LPPSM). The model monitors the location of vehicle through the GPS connected. Accordingly, the method discovers the set of routes and collects the traffic, number of junctions, speed of vehicle, distance, number of charging hubs in each route. Using these features, the method computes the Span Maximization Support (SMS) for each route. Further, based on the SMS value, an optimal route has been selected to optimize the span of the vehicle. The proposed model improves the performance of path switching and span maximization.

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