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# Multi Variant Range Maximization Model for Improved Performance of Electric Systems Using Genetic Algorithm

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The driving range provided by any electric vehicle is the most concern now days. The problem of range maximization in electric system has been approached with various methods in literature. However, they suffer to achieve higher range due to the factor that they consider only limited parameters. To handle this issue, an efficient Multi variant range maximization model with genetic algorithm (MRMM-GA) is presented in this article. The model use the road map of the area where the vehicle is moving and finds the routes available. With the routes and traffic data available, the method generates number of combinatory routes possible. With the routes produced, the method applies genetic algorithm to measure the fitness value for the possible routes. At each population, the method measure the Multi variant range support (MVRS) for the routes and population. Based on the value of MVRS, the method performs route selection towards maximizing the range of the vehicle. The proposed method improves the performance of electric system and range maximization.

**Keywords:** Range Maximization, MRMM-GA, Genetic Algorithm, MVRS.

## 1. Introduction

The modern society has great impact from the electric vehicles as the cost of fuel being used by the commercial and personal vehicles are getting increased. The fuel market is the most dominant one which decides the economy of the country and the most countries import the fuels from abroad and they spend huge amount in buying the crude oil which increases the economy of the foreign country and the home country loose their economy due to this conditions[9]. This has been considered by the finance ministry of the country and decides to reduce the fuel consumption by neglecting the introduction of LPG vehicles. As an alternate for them, they have decided to use the electric vehicles in the place of LPG vehicles. But it has lot of risks and many factors must be analyzed before using the EV on the road.

The EV manufacturers publish the vehicle with the span of specific K kilometers. The user can drive the vehicle for the above mentioned distance but in reality, the span mentioned would not be perfect and the user has the risk of standing at the middle without any drive support. This must be considered as important factor and the road support must be provided in terms of route selection. There are number of drive span maximization algorithms available which consider the traffic conditions alone on the road to perform route selection. But in reality, various factors like traffic, distance, number of routes and junctions available must be considered. By choosing the constraints towards route selection, the performance of the vehicle in terms of span can be improved.

The performance of EV is depending on the span it provides without any trouble and how the vehicle supports on various traffic and road conditions. For example, even the vehicle provides specific span, if the road conditions is poor then it absorbs maximum energy and leads to the reduction of span. So, it is necessary to consider various factors apart from traffic, routes and so on. Apart from data mining techniques, the machine learning techniques can be used around the problem which is capable of handling missing data. In terms of route discovery, the Genetic algorithm can be used in finding the routes available and measure the support of vehicle towards range maximization.

By considering the various factors of vehicle and the road map, an efficient Multi variant range maximization model with genetic algorithm (MRMM-GA) is presented in this article. The model uses the road map of the area where the vehicle is moving and finds the routes available. With the routes and traffic data available, the method generates number of combinatory routes possible. With the routes produced, the method applies genetic algorithm to measure the fitness value for the possible routes. At each population, the method measure the Multi variant range support (MVRS) for the routes and population. Based on the value of MVRS, the method performs route selection towards maximizing the range of the vehicle. The proposed model would increase the span of the vehicle and improves the quality drive. The complete working of the model has been sketched in this section.

## 2. Related works:

There exist number of approaches around the problem of drive span maximization and this section briefs some of the methods around the problem.

In [1], a sophisticated energy management system is introduced. This system is designed to facilitate the adaptable functioning of grid-connected electric vehicles (EVs) fueled by solar energy. It takes into account many factors such as the availability of solar power, the load on the grid, and the data related to EV charging. The model tracks the accessibility of photovoltaic systems on the road and the grid networks that are accessible for managing vehicle energy.

In [22], a disturbance observer (DOB)-based model predictive voltage control (MPVC) is introduced as a means of providing assistance to electric vehicles. The model predicts the voltage levels that can be achieved at different time intervals in order to carry out regulation and voltage management.

In [23], a control law generation model based on particle swarm optimization (PSO) is introduced[3]. This model aims to maximize the voltage output from a photovoltaic generator

(GPV) and uses PSO to regulate the power supply to the vehicle[13]. The Particle Swarm Optimization (PSO) algorithm has been employed to determine the optimal charging site and route for the car to navigate[27].

The paper presents a multi battery block module (MBM) topology, as described in reference [4]. This topology is designed to support electric vehicles by integrating a multi-battery block module and a photovoltaic (PV) panel into an asymmetrical half-bridge (AHB) converter. The purpose of this converter is to provide a multilevel bus voltage for the SRM drive. This technology monitors the storage capacity of batteries to optimize the duration of vehicle power supply. In [17], a tracking absorption approach is introduced. This strategy involves modifying the charging process of electric vehicles using an electric vehicle aggregator (EVA) and use the soft actor-critic (SAC) algorithm to schedule the operation.

An electric-drive-reconstructed onboard charger (EDROC) is described in [25]. It utilizes a six-phase machine drive and power traction inverter to enhance the charging process. The on-board charger optimizes the range, although its effectiveness is limited by the vehicle's battery capacity.

In [15], a synchronous MPPT over DPP architecture is introduced. This topology aims to enhance targeted decoupling and simplify the process by reducing its difficulty and complexity. The MPPT (Maximum Power Point Tracking) system enhances the optimization of power output[16]. In [8], a model is introduced that utilizes a long short-term memory (LSTM) recurrent neural network (RNN) to efficiently manage the charging and discharging of several electric vehicles (EVs)[6]. The LSTM model enhances the efficiency of vehicles and the utilization of RNN promotes the expansion of vehicles in terms of maximizing their span.

In [21], a model is described that outlines a three-stage process for allocating and distributing voltage in order to facilitate the charging of electric two wheelers at a charging station[19]. The three-stage approach facilitates vehicle navigation to optimize range by strategically locating charging stations.

In [24], a framework for analyzing the stability of power grid voltage is described. This framework utilizes Monte Carlo simulation to examine power generation and load demand. The method takes into account the demand from different users and the power generation capacity of power plants to ensure the stability of power supply in power networks[10].

The driving data of the Toyota Prius vehicle has been showcased and examined in reference [18]. A scheduling technique that is highly efficient is introduced in reference [12], specifically designed for managing the allocation of mobile energy storage devices. In [20], a hierarchical coordination architecture is introduced for the management of residential load employing solar (PV) units, battery-energy-storage-systems (BESs), and electric vehicles (EVs).

Multi variant range Maximization Model with Genetic Algorithm (MRMM-GA):

The proposed Multi variant range maximization model with genetic algorithm (MRMM-GA) model use the road map of the area where the vehicle is moving and finds the routes available[11]. With the routes and traffic data available, the method generates number of combinatory routes possible. With the routes produced, the method applies genetic algorithm to measure the fitness value for the possible routes[7]. At each population, the method measure the Multi variant range support (MVRS) for the routes and population[2]. Based on the value of MVRS, the method performs route selection towards maximizing the range of the vehicle[5].

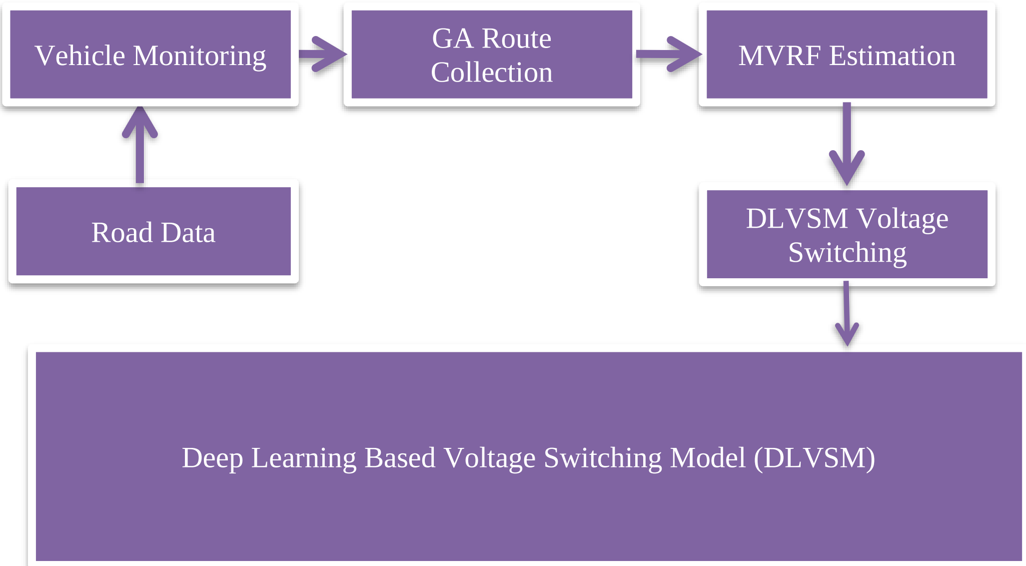


Figure 1: Block Diagram of Proposed MRMM-GA model

The working diagram of proposed MRMM-GA has been presented in Figure 1 and the functions of the model have been sketched in this section.

Vehicle Monitoring:

The proposed method monitors the vehicle for its state at all the fraction of its travel time. The method monitors the vehicle for its residual energy, speed, traffic on road. Such data being fetched has been converted into feature vector. Such feature vector generated has been used towards estimating MVRS (Multi Variant Road Support) for the route considered. The value of MVRS has been used towards route selection and drive span maximization.

Algorithm:

Given: Road Taxonomy RT, Vehicle V

Obtain: Feature Vector Fv.

Start

Read RT and V.

While true

Vehicle Speed Vs = Speed $\in$ V

Vehicle Energy VE = Energy $\in$ V

Vehicle Destination Vd = Destination $\in V$

Route Set Rs = GA Route Collection (RT, Vd, Vs, VE)

Route R = Perform MRMM-GA Drive Span Maximization.

Divert EV on route selected.

End

Stop

The vehicle monitoring function fetches the vehicle data and performs GA route collection. Further, the method performs MRMM-GA drive span maximization.

GA Route Collection:

The genetic algorithm has been used in several scientific problems and the same can be used in span maximization of electric vehicles. To perform this, the proposed approach uses the genetic algorithm towards collecting the routes available. With the features of the vehicle, the method identifies the set of routes according to the taxonomy. With the initial routes, the method applies genetic algorithm towards detecting uncovered routes. The method produces number of mutations till there is repeat of routes. Such routes identified are used to perform span maximization.

Algorithm:

Given: Road Taxonomy RT, Feature vector Fv

Obtain: Route set Rs.

Start

Read RT and Fv.

Route set Rs = $\sum \mathrm{RT(i).Destination} == \mathrm{Fv.vd}\ \&\&\ \mathrm{RT(i)} \in \mathrm{Fv.location}$ $\quad$ $\mathrm{size(RT)}$ $\quad$ $\mathrm{i = 1}$

For each route R

For each diversion d

Generate Mutation M.

Add mutation to route set RS = $\sum(\mathrm{Routes} \in \mathrm{Rs}) \cup \mathrm{M}$

End

End

Stop

The genetic algorithm based path collection function discovers the set of routes and add the routes to the route set to support span maximization.

Multi Variant Range Support Estimation (MVRS):

The multi variant range support is the measure which represents the efficacy of the routes towards span maximization. It has been measured based on the vehicle residual energy, speed, traffic in the route, number of diversions in the route and so on. According to the above mentioned features, the method estimates the value of MVRS. Estimated MVRS value has been used to perform drive span maximization.

Algorithm:

Given: Route R, Feature Vector Fv

Obtain: MVRS

Start

Read R and Fv.

Compute no of diversion Nd = $\sum \text{diversions} \in R$

Compute Traffic Tr = $\text{Traffic} \in R$

Compute MVRS = $\frac{\text{Tr}}{\text{Nd}} \times \frac{\text{Fv.Speed}}{\text{Fv.Energy}}$

Stop

The MVRS estimation algorithm computes the value of MVRS according to the traffic conditions and features of the vehicle to support span maximization problem.

MRMM-GA Drive Span Maximization:

The proposed MRMM-GA drive span maximization algorithm discovers the hidden routes by applying the genetic algorithm. For each route identified, the method computes the value of MVRS and based on that a single route has been selected to perform navigation.

Algorithm:

Given: Route Set Rs

Obtain: Null

Start

Read route set Rs.

For each route R

Compute MVRS = MVRS Estimation.

End

Route R = $\underset{i=1}{\overset{\text{size(Rs)}}{\text{Max}}}(\text{Rs(i).MVRS})$

Perform navigation with the selected route R.

Stop

The proposed algorithm performs route selection according to the MVRS measure computed to support vehicle navigation and span maximization.

### 3. Results and Discussion:

The proposed Multi variant range maximization model with genetic algorithm (MRMM-GA) has been implemented with Simulink. The performance of the model has been evaluated under various parameters and presented in this section.

Table 1: Experimental Details

| Parameter | Value |
|---|---|
| Tool Used | Simulink |
| No of Roads | 100 |
| Time | 10 minutes |

The experimental details used towards performance analysis are presented in table 1.

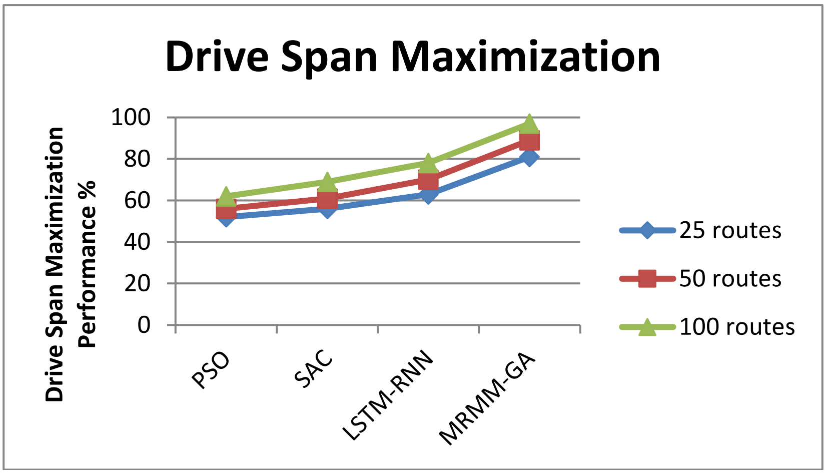


Figure 2: Drive Span Maximization Performance

The performance of method in drive span maximization is measured and presented in Figure 3. The MRMM-GA model introduces higher performance than others. The performance of span maximization is measured according to the number of routes available. In each case, the proposed MRMM-GA model has produced higher span performance than others.

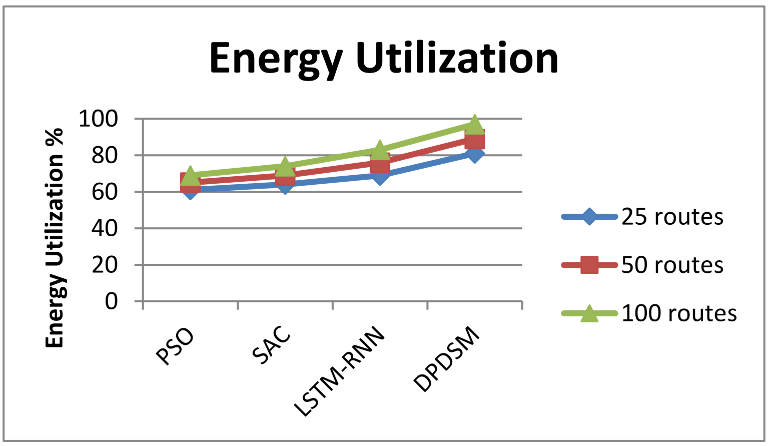


Figure 3: Energy Utilization Performance

The performance of methods in energy utilization is measured and presented Figure 3. The proposed MRMM-GA method produces higher energy utilization performance than others. The performance of energy utilization is measured for various methods at different number of routes in the network. In all the cases, the proposed method DPDSM has produced higher performance than other methods.

## 4. Summary:

This paper presented a Multi variant range maximization model with genetic algorithm (MRMM-GA) model use the road map of the area where the vehicle is moving and finds the routes available. With the routes and traffic data available, the method generates number of combinatory routes possible. With the routes produced, the method applies genetic algorithm to measure the fitness value for the possible routes. At each population, the method measure the Multi variant range support (MVRS) for the routes and population. Based on the value of MVRS, the method performs route selection towards maximizing the range of the vehicle. The proposed method improves the performance of drive span maximization and energy utilization.

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