Directional Optimization Model for Efficient Vehicle Control in Photovoltaic Systems

Dr. I Wayan Suryasa[1], SS., Raúl Clemente Ulloa de Souza[2], Luis Jheovanny Reyna Tenorio[3], José Luis Sampietro Saquicela[4], Alejandro Javier Martínez Peralta[5], Byron Fernando Chere Quiñónez[6]

[1]Assistant Professor, Institut Teknologi dan Bisnis STIKOM Bali, Denpasar, Indonesia, email: suryasa@stikom-bali.ac.id
[2]Universidad Técnica Luis Vargas Torres de Esmeraldas-Ecuador, raul.ulloa@utelvt.edu.ec
[3]Universidad Técnica Luis Vargas Torres de Esmeraldas-Ecuador, luis.reyna.tenorio@utelvt.edu.ec
[4]Universidad Técnica Luis Vargas Torres de Esmeraldas-Ecuador, jose.sampietro@utelvt.edu.ec
[5]Universidad Técnica Luis Vargas Torres de Esmeraldas-Ecuador, alejandro.martinez@utelvt.edu.ec
[6]Universidad Técnica Luis Vargas Torres de Esmeraldas-Ecuador, byron.chere@utelvt.edu.ec

The problem of electric vehicle control with photovoltaic system and maximizing the span of the vehicle has been well studied. The methods estimate the span of vehicle based on the residual energy but does not consider the span maximization by diverting the vehicle according to various factors. This affects the performance of the vehicle and reduces the span expected. To handle this issue, an Directional Optimization Model (DOM) is presented to control the electric vehicle runs with the photovoltaic systems. The model is focused to increase the span of the vehicle than the expected one which is possible by choosing the direction for the vehicle in an optimized way. To perform this, the method uses the route map of the region and collects the traffic data. With the traffic data, the method identifies various routes in the direction of the vehicle and for each of them; it estimates the Directional Span Maximization Support (DSMS). With the value of DSMS, the method identifies the suitable route to reach the destination. The value of DSMS is measured according to number of factors like distance, energy depletion, speed, traffic, number of signals and diversions and so on. By performing directional optimization, the vehicle span has been greatly increased. The proposed method improves the performance of energy utilization and span maximization.

Keywords: Vehicle control, Directional Optimization, PV systems, DOM, DSMS.

Introduction

The increased use of fuel usage by the citizens of any country highly affects the economy of the country as well. The fuel-distributing organization of the country suffers to maintain and supply such huge volumes of fuel for the citizens. Also, the most gain of the organizations goes to other country as they import the raw fuel from the other countries. This increases the dependency of the country on the others. This produces political issues and affects external policy as well. This increases the requirement of changing the energy type and motivates the country to search for another type of energy.

This is the reason why countries are moving towards using electric vehicles. Electrical energy is produced from limited sources and also it increases the cost of electricity. However, the electric vehicles are more economic than other kind of vehicles. But in reality, when the vehicle moves through high traffic conditions, its energy consumption gets increases and affects the vehicle span. To handle this, the manufacturer can adapt high energetic and range batteries for the vehicle but is increase the cost of vehicle.

The people look for a more economical vehicle for their use. This increases the requirement of designing more range vehicles for the consumers. To maximize the vehicle range there are number of methodologies are prescribed in the literature. Some of the methods uses reduction of load in the vehicle as the key and some of them uses the energy as the single factor. However, the methods suffer to achieve higher performance in span maximization.

To solve this issue, a Directional Optimization Model (DOM) is presented to control the electric vehicle runs with the photovoltaic systems [6][15]. The model is focused on increasing the span of the vehicle than the expected one which is possible by choosing the direction for the vehicle in an optimized way [2][8][13]. To perform this, the method uses the route map of the region and collects the traffic data. With the traffic data, the method identifies various routes in the direction of the vehicle and for each of them; it estimates the Directional Span Maximization Support (DSMS). With the value of DSMS, the method identifies the suitable route to reach the destination. The value of DSMS is measured according to a number of factors like distance, energy depletion, speed, traffic, number of signals and diversions, and so on. By performing directional optimization, the vehicle span has been greatly increased [4-5].

Existing system:

- There are a number of approaches have been presented in literature and some of the methods are described in detail.
- 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.
- A switched velocity-dependent path-following control method is presented in [14], for supporting autonomous ground vehicles under uncertain cornering stiffness and time-varying velocity.
- An artificial potential field (APF) with model predictive control (MPC) is presented in [3][11][17][25], towards vehicle motion control. The method combines a cooperative maneuver switch and the continuous vehicle motion control is

introduced into a multi-vehicle cooperative control system [18].

- A command filtered control technique and globally uniformly ultimately bounded (GUUB) path following control structure is presented in [21].
- A game planning-based smooth path planning scheme is presented in [26], to support intelligent air-ground vehicles.
- To handle path-constrained switching, a novel approach is presented to enforce guaranteed feasibility [24]. 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.
- An adaptive reinforcement learning-based path-switching model is presented in [7].
- A graph-based novel coupled path planning and energy management is presented in [23], towards supporting hybrid unmanned air vehicles.
- 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 [27], 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 [19].
- A deep neural network (DNN) based path planning scheme is presented in [12], which uses an online three-dimensional path planning network (OTDPP-Net) to learn the local path to support path planning.
- An extended adaptive cruise control (ACC), named economic adaptive cruise control is presented in [16], to support increasing the fuel economy in power-split hybrid electric vehicles (HEV) according to vehicle route, speed, and powertrain.
- All the above-discussed methods suffer to achieve higher performance in path planning and span maximization.

Directional Optimization Model (DOM):

The proposed directional optimization model (DOM) focuses on increasing the span of the vehicle to the expected one which is possible by choosing the direction for the vehicle in an optimized way [20][22]. To perform this, the method uses the route map of the region and collects the traffic data. With the traffic data, the method identifies various routes in the direction of the vehicle and for each of them; it estimates the Directional Span Maximization Support (DSMS). With the value of DSMS, the method identifies the suitable route to reach the destination. The value of DSMS is measured according to a number of factors like distance, energy depletion, speed, traffic, number of signals and diversions and so on. By performing directional optimization, the vehicle span has been greatly increased[10].

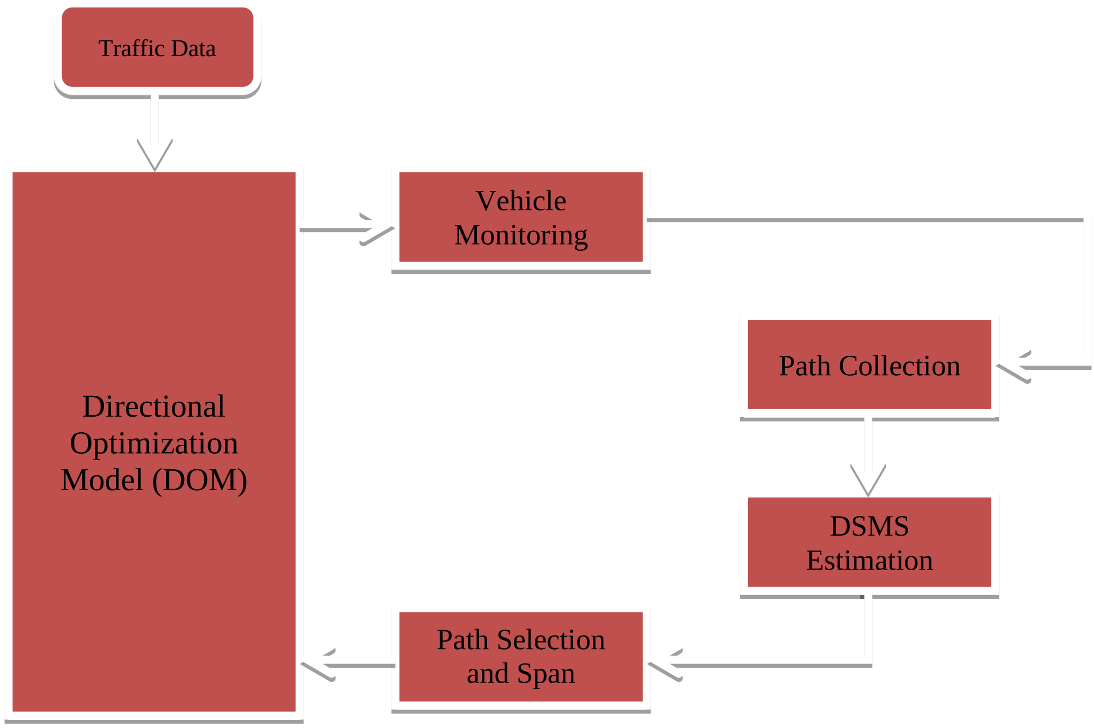

Figure 1: Architecture of Proposed DOM Model

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

Vehicle Monitoring:

The proposed model monitor the vehicle in all the time stamp. The method tracks the vehicle according to the location parameters and at each time, the method collects the routes available towards the destination. Collected routes are given to DOS Path selection and span maximization which in turn estimates the DSMS value for various routes available to choose an optimal one for the navigation.

Algorithm:

Given: Vehicle VID, GPS Id Gid

Obtain: Null

Start

Read Vid, Gid

While true

Collect GPS location Loc.

Path set Ps = Perform Path collection (location, destination)

Perform DOM Path selection 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 presence of routes to reach the destination for the vehicle according to the location has been identified by the path collection algorithm. The method finds set of routes from the current location of the vehicle. For any route found, the features like traffic, speed, junctions and charging points and junctions are identified. Such features collected are converted into feature vector to support path selection.

Algorithm:

Given: Vehicle ID Vid, Road Map Rmap, Vehicle Destination Vdest

Obtain: Feature Vector set Fvs

Start

Read vid, Rmap, Vdest

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

For each route r

Compute no of junctions Nj = $\sum Junctions \in r$

Compute traffic Rt = $\underset{i=1}{\overset{size(Nj)}{Sum}}(Nj(i).Traffic)$

Compute No of charging points Ncp = $\sum ChargingPoints \in r$

Compute vehicle speed Vs = Mobility_speed

Generate feature vector Fv = {Nj, RT, Ncp, Vs}

Add to feature vector set Fvs = FVs ∪ Fv

End

Stop

The path collection algorithm finds the route set for the vehicle to reach the destination. For all the routes identified, the method collects set of features and converts them into feature vector to support path selection and span maximization.

Path Selection and Span Maximization:

The path selection and span maximization algorithm uses the set of routes and by computing the DSMS value for the routes according to various factors, it selects a optimal route for the vehicle and divert the vehicle in the route identified. The directional span maximization support is the measure which represents the efficacy of any route in achieving higher vehicle span. It has been measured according to various factors like vehicle speed, , number of junctions, number of charging points and traffic on the roads. Estimated DSMS value has been used to perform path switching and span maximization. It supports the span maximization by choosing a route with higher DSMS value.

Algorithm:

Given: Route set Rs and Fv Set Fvs

Obtain: Null

Start

Read Rs and Fvs

For each route r

$$\text{DSMS} = \frac{\text{Fv.Rt}}{\text{Fv.Nj}} \times \frac{\text{Fv.Vs}}{\text{Fv.Ncp}}$$

End

Route r = choose a route with maximum DSMS.

Switch the vehicle on the route identified.

Stop

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

Results and Discussion:

The proposed directional optimization model DOM has been implemented using a Network simulator. The method has been evaluated for its performance using different scenarios. Obtained results are compared with the results of others.

Table 1: Experimental Setup

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

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.

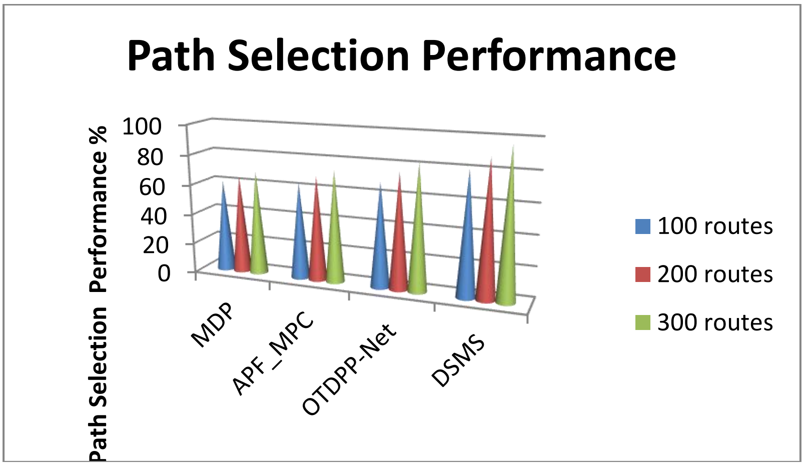

Figure 2: Path Selection Performance

The performance of methods in path selection is measured and compared in Figure 2, where the DSMS model has produced higher path selection performance than others. The performance of path selection is measured according to different routes available. In each case, the DSMS algorithm achieves higher performance than others.

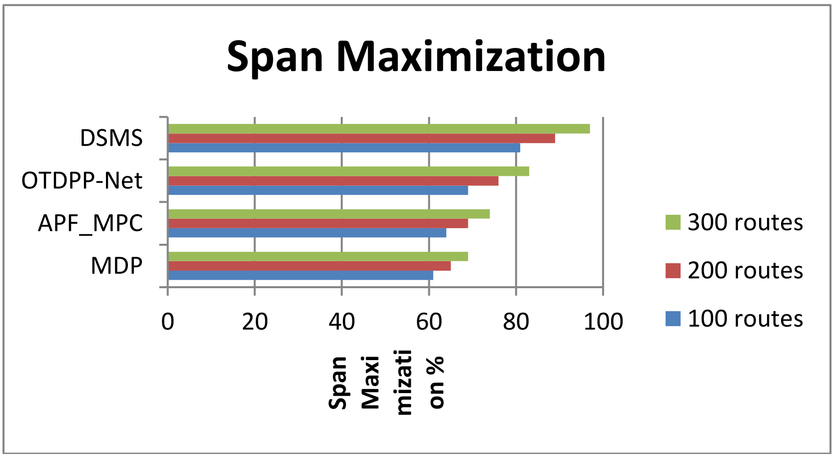

Figure 3: Span Maximization

The performance of methods in span maximization has been measured and presented in Figure 3. The proposed DSMS model has produced higher span maximization performance than others. The span maximization performance is measured according to a different number of routes available. In each case, the DSMS algorithm has produced higher performance than others.

Conclusion:

This paper presented a Directional Optimization model (DOM) for span maximization and path selection for electric vehicles. To perform this, the method uses the route map of the region and collects the traffic data. With the traffic data, the method identifies various routes in the direction of the vehicle and for each of them; it estimates the Directional Span Maximization Support (DSMS). With the value of DSMS, the method identifies the suitable route to reach the destination. The value of DSMS is measured according to a number of factors like distance, energy depletion, speed, traffic, number of signals and diversions and so on. By performing directional optimization, the vehicle span has been greatly increased.

References

1. C. Sun, X. Zhang, Q. Zhou and Y. Tian, "A Model Predictive Controller With Switched Tracking Error for Autonomous Vehicle Path Tracking," in IEEE Access, vol. 7, pp. 53103-53114, 2019, doi: 10.1109/ACCESS.2019.2912094.
2. Srinivasareddy, S., Narayana, Y.V., & Krishna, D. (2021). Sector beam synthesis in linear antenna arrays using social group optimization algorithm. National Journal of Antennas and Propagation (NJAP), 3(2), 6-9.
3. Z. Huang, D. Chu, C. Wu and Y. He, "Path Planning and Cooperative Control for Automated Vehicle Platoon Using Hybrid Automata," in IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 3, pp. 959-974, March 2019, doi: 10.1109/TITS.2018.2841967.
4. Veerasamy, K., & Fredrik, E. T. (2023). Intelligent Farming based on Uncertainty Expert System with Butterfly Optimization Algorithm for Crop Recommendation. Journal of Internet Services and Information Security, 13(3), 158-169.
5. Saadawi, E.M., Abohamama, A.S., & Alrahmawy, M.F. (2024). IoT-based Optimal Energy Management in Smart Homes using Harmony Search Optimization Technique. International Journal of Communication and Computer Technologies (IJCCTS), 12(1), 1-20.
6. Babenko, V., Danilov, A., Vasenin, D., & Krysanov, V. (2021). Parametric Optimization of the Structure of Controlled High-voltage Capacitor Batteries. Arhiv za tehničke nauke, 1(24), 9–16.
7. C. Zhang and J. Fu, "An Efficient Dynamic Optimization Algorithm for Path-Constrained Switched Systems," in IEEE Transactions on Neural Networks and Learning Systems, vol. 34, no. 8, pp. 4451-4459, Aug. 2023, doi: 10.1109/TNNLS.2021.3113345.
8. Punriboon, C., So-In, C., Aimtongkham, P., & Rujirakul, K. (2019). A Bio-Inspired Capacitated Vehicle-Routing Problem Scheme Using Artificial Bee Colony with Crossover Optimizations. Journal of Internet Services and Information Security, 9(3), 21-40.
9. C. You, J. Lu, D. Filev and P. Tsiotras, "Autonomous Planning and Control for Intelligent Vehicles in Traffic," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 6, pp. 2339-2349, June 2020, doi: 10.1109/TITS.2019.2918071.
10. Elfarra, B.K., Salha, M.A., Rasheed, R.S., Aldahdooh, J., & Abusamra, A.A. (2023). Enhancing the Lifetime of WSN Using a Modified Ant Colony Optimization Algorithm. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 14(3), 143-155.
11. Prasad Babu, P., & Vasumathi, A. (2023). Role of Artificial Intelligence in Project Efficiency Mediating with Perceived Organizational Support in the Indian IT Sector. Indian Journal of Information Sources and Services, 13(2), 39–45.
12. K. Wu, H. Wang, M. A. Esfahani and S. Yuan, "Achieving Real-Time Path Planning in Unknown Environments Through Deep Neural Networks," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 3, pp. 2093-2102, March 2022, doi: 10.1109/TITS.2020.3031962.
13. Sinha, P. (2013). Particle swarm optimization for solving economic load dispatch problem. International Journal of Communication and Computer Technologies (IJCCTS), 1(2), 100-105.
14. P. Li, J. Lam and R. Lu, "Robust Switched Velocity-Dependent Path-Following Control for

Autonomous Ground Vehicles," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 5, pp. 4815-4826, May 2023, doi: 10.1109/TITS.2023.3236113.
15. You, G., Kim, G., Cho, S. J., & Han, H. (2021). A Comparative Study on Optimization, Obfuscation, and Deobfuscation tools in Android. Journal of Internet Services and Information Security, 11(1), 2-15.
16. H. Liu, C. Miao and G. G. Zhu, "Economic Adaptive Cruise Control for a Power Split Hybrid Electric Vehicle," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 10, pp. 4161-4170, Oct. 2020, doi: 10.1109/TITS.2019.2938923.
17. Camgozlu, Y., & Kutlu, Y. (2023). Leaf Image Classification Based on Pre-trained Convolutional Neural Network Models. Natural and Engineering Sciences, 8(3), 214-232.
18. Madhan, K., & Shanmugapriya, N. (2024). Efficient Object Detection and Classification Approach Using an Enhanced Moving Object Detection Algorithm in Motion Videos. Indian Journal of Information Sources and Services, 14(1), 9–16.
19. X. Wu, C. Wei, H. Tian, W. Wang and C. Jiang, "Fault-Tolerant Control for Path-Following of Independently Actuated Autonomous Vehicles Using Tube-Based Model Predictive Control," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 11, pp. 20282-20297, Nov. 2022, doi: 10.1109/TITS.2022.3191755.
20. Boualem, A., De Runz, C., & Ayaida, M. (2022). Partial paving strategy: application to optimize the area coverage problem in mobile wireless sensor networks. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 13(2), 1-22.
21. H. Wang, Y. Tian and H. Xu, "Neural Adaptive Command Filtered Control for Cooperative Path Following of Multiple Underactuated Autonomous Underwater Vehicles Along One Path," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 52, no. 5, pp. 2966-2978, May 2022, doi: 10.1109/TSMC.2021.3062077.
22. Isabel, M.V., Carlos, L., Lourdes, I.C.A., Doris, I.G.P., Yoni Magali Maita Cruz, Jessica Paola Palacios-Garay and Aracelli del Carmen Gonzales-Sánchez. (2023). Improved Butterfly Optimization Algorithm for Energy Efficient Antenna Selection Over Wireless Cellular Networks. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 14(2), 121-136.
23. S. G. Manyam, D. W. Casbeer, S. Darbha, I. E. Weintraub and K. Kalyanam, "Path Planning and Energy Management of Hybrid Air Vehicles for Urban Air Mobility," in IEEE Robotics and Automation Letters, vol. 7, no. 4, pp. 10176-10183, Oct. 2022, doi: 10.1109/LRA.2022.3191810.
24. J. Fu and C. Zhang, "Optimal Control of Path-Constrained Switched Systems With Guaranteed Feasibility," in IEEE Transactions on Automatic Control, vol. 67, no. 3, pp. 1342-1355, March 2022, doi: 10.1109/TAC.2021.3071035.
25. Arora, G. (2024). Desing of VLSI Architecture for a flexible testbed of Artificial Neural Network for training and testing on FPGA. Journal of VLSI Circuits and Systems, 6(1), 30-35.
26. J. Zhao et al., "A Game-Learning-Based Smooth Path Planning Strategy for Intelligent Air–Ground Vehicle Considering Mode Switching," in IEEE Transactions on Transportation Electrification, vol. 8, no. 3, pp. 3349-3366, Sept. 2022, doi: 10.1109/TTE.2022.3142150.
27. T. Sardarmehni and X. Song, "Path Planning and Energy Optimization in Optimal Control of Autonomous Wheel Loaders Using Reinforcement Learning," in IEEE Transactions on Vehicular Technology, vol. 72, no. 8, pp. 9821-9834, Aug. 2023, doi: 10.1109/TVT.2023.3257742.