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Model Predictive Control Design for Electric Vehicle Based on Improved Physics-Inspired Optimization Algorithms

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Abstract: This paper introduces the mathematical model of the leader-follower electric vehicle (EV). Consequently, the system was analyzed to obtain stability and performance. Model Predictive Control (MPC) is also proposed to fix the EV system issues. Moreover, two optimization algorithms are applied to optimize the performance of the MPC: electrically charged particle optimization (ECPO) and improved chaotic electromagnetic field optimization (ICEFO). The MPC scheme is based on the Adaptive Cruise Control System (ACCS), applied to two vehicles: the leader and follower. In this context, the simulation results of both optimization methods with the MPC scheme are presented in the result section. Finally, a comparison is made to show the proposed controller's effectiveness with the improved optimization algorithms. Also, the ACC electric vehicle tracking system was achieved at 98% with the reference input.

نمذجة وتصميم مسيطر بالطرق المثلى لمنظومة السيطرة على السرعة المكيفة

مصطفى سعيد عبد الكريم، نزار هادي عباس
قسم الهندسة الكهربائية / كلية الهندسة / جامعة بغداد / بغداد – العراق.

الخلاصة
في هذا البحث، تم تقديم النموذج الرياضي للمركبة الكهربائية (المتابع والقائد). وبالتالي تم تحليل النظام من أجل الحصول على الاستقرار والأداء. بالإضافة إلى ذلك، تم اقتراح نموذج التحكم التنبئي (MPC) لإصلاح المشكلات في نظام EV. علاوة على ذلك، يتم تطبيق خوارزميتين لتحسين أداء MPC وهما تحسين الجسيمات المشحونة الكهربائية (ECPO) وتحسين المجال الكهرومغناطيسي الفوضوي المحسن (ICEFO). يعتمد مخطط MPC على نظام التحكم التكيفي في التطواف (ACCS) الذي يتم تطبيقه على مركبتين (القائد والتابع). في هذا السياق، يتم عرض نتائج المحاكاة لكل من طرق التحسين باستخدام مخطط MPC في قسم النتائج. أخيراً، تم إجراء مقارنة لإظهار فعالية وحدة التحكم المقترحة مع خوارزميات التحسين المحسّنة. أيضًا، تم تحقيق تتبع نظام السيارة الكهربائية ACC بنسبة 98٪ مع الإدخال المرجعي.

الكلمات الدالة: نظام التحكم التكيفي في السرعة؛ تحسين الجسيمات المشحونة بالكهرباء؛ تحسين المجال الكهرومغناطيسي الفوضوي؛ القائد والتابع؛ نموذج التحكم التنبؤي.

1.INTRODUCTION

Electric vehicles (EVs) are vehicles powered by an electric motor and a rechargeable battery instead of an internal combustion engine. EVs have gained popularity in recent years due to their lower environmental impact and decreased dependence on fossil fuels. Adaptive cruise control (ACC) is an advanced driver assistance system that uses sensors and cameras to maintain a safe distance between the vehicle and the car in front of it. ACC can automatically adjust the vehicle's speed to maintain a safe following distance and even bring the car to a complete stop if necessary [1-3]. Model-predictive control (MPC) is a control strategy that uses mathematical models to predict a system’s behavior and optimize its performance. MPC can be applied to electric vehicles and adaptive cruise control systems to improve energy efficiency and driving performance. MPC can predict the behavior of an electric vehicle's battery and optimize its charging and discharging patterns to maximize battery life and range. Using predictive models, MPC can estimate the state of charge (SOC) of the battery and adjust the vehicle's driving behavior to maintain the desired SOC level, which reduces the risk of battery depletion and extends the vehicle's range, which is a key concern for many electric vehicle drivers [4–7]. In the case of ACC systems, MPC can be used to optimize the vehicle’s driving behavior and reduce fuel consumption. Using predictive models to estimate the distance to the next vehicle, the optimal speed, and acceleration profiles; MPC can adjust the vehicle's driving behavior to maintain a safe following distance while minimizing energy consumption, which reduces fuel costs and improves the overall efficiency of the vehicle. Furthermore, integrating MPC with electric vehicles and ACC systems can result in more intelligent and efficient driving behavior. MPC considers factors; such as traffic conditions, road gradients, and weather conditions; and optimizes the vehicle's driving behavior accordingly, resulting in smoother and more comfortable driving, as well as reduced energy consumption and emissions. In summary, integrating model predictive control with electric vehicles and adaptive cruise control systems results in more intelligent and efficient driving behavior, improved energy efficiency, and extended battery life and range. As technology advances, advancements in MPC-based control strategies for electric vehicles and ACC systems can be expected, improving the driving experience and contributing to a more sustainable transportation system [8-10]. In this regard, many recent works showed the efforts and contributions of other researchers. A dual-mode ACC strategy that combines MPC and NN was proposed based on a neural network (NN) using data about driver behavior to create an intelligent ACC system [11]. A new method of managing energy usage has been proposed, which involved creating a model of the driver's behavior using real-time data and a Markov chain, which was then used in a stochastic MPC algorithm [12]. A new type of adaptive cruise control (ACC) algorithm, which combines model predictive control (MPC) and active disturbance rejection control (ADRC), was presented. The upper controller of the ACC system utilizes the MPC algorithm [13]. A feature called Energy-Optimal Adaptive Cruise Control (EACC) was designed for electric vehicles. This function was based on Model Predictive Control (MPC) and aimed to improve the energy efficiency of the vehicle by utilizing real-time information on traffic and road conditions to plan the optimal speed trajectory of the car [14-17]. Moreover, a model predictive control (MPC) algorithm was used to develop an adaptive cruise control (ACC) system that was tailored to eco-driving and optimized for four objectives: comfort, tracking capability, safety, and eco-friendliness [18]. A fractional order model reference adaptive control (FOMRAC) system was proposed for the cruise control of a DC motor-driven electric vehicle.

The powertrain model of the vehicle was disclosed, and the control design was elaborated. The contribution of the work was utilizing fractional-order reference adaptive controllers for the two-layer control loop [19]. A new adaptive cruise control (ACC) algorithm, combined model predictive control (MPC) and active disturbance rejection control (ADRC) methods was presented to improve control accuracy and address the fluctuation in vehicle acceleration [20-23]. In this paper, MPC with ACC property is implemented to compensate for a leader-follower EV system. An MPC controller is also applied to control the velocity and distance between the leader and follower vehicles. Moreover, two optimization algorithms (ICEFO and ECPO) are used to tune the parameters of the MPC controller. Eventually, the results of ICEFO and ECPO are compared and presented with a detailed discussion to validate this controlling scheme.

The rest of the paper is organized as follows: The mathematical model of EV is introduced in Section 2. The MPC method is explained in Section 3 to present and discuss its principle operation with the ACC concept. The optimization methods are presented in Section 4. The simulation results and discussion of the results with a comparison table are explained in Section 5. Eventually, the conclusion is presented in Section 6.

2. EXPERIMENTAL PROGRAM

2.1. Apparatus

2.1.1.The Mathematical Model of Electric Vehicle

As the electric machine or motor is the sole source of propulsion for an electric vehicle (EV), controlling EV motion can be simplified to controlling the motion of the electric machine. For optimal performance, the driving motor must have a high power output at high speeds to ensure rapid acceleration and an applicable torque output at low speeds with high overload capacity. Various mathematical models of EV motors were developed to describe the characteristics of the EV system that must be controlled. The selection of a motor for a specific EV depends on various factors, including the intended use of the EV, permissible speed and torque variations, and ease of control. Assuming that the motor is an armature-controlled DC motor, the open-loop transfer function for a DC motor with no load attached can be expressed using Eq. (1) [24]:

$$G_{speed}(s) = \frac{\omega(s)}{V_{in}(s)} = \frac{K_t}{[(L_a J_m)s^2 + (R_a J_m + b_m L_a)s + (R_a b_m + K_t K_b)]} \quad (1)$$

Eq. (2) presents a simplified open loop transfer (GF (s)) function for the EV model based on all of the computed force/torque equations, armature input voltage (V_{in}), and tachometer output voltage (V_{tah}), as well as all of the combined load characteristics [21].

$$G_F(s) = \frac{2k_{tah} * K_t}{[(sL_a + R_a)(2J_e + 2B_e s + c_r) + s(L_a + R_a)r^2 M_c + (2K_t K_b)]} \quad (2)$$

where L_a is the armature inductance, R_a refers to the armature resistance, M_C is the mass of the car (kg), C_r is the rolling coefficient of EV, r^2 is the radius of the wheel, k_{tah} the tachometer gain, J_e is the total equivalent inertia of the rotor, K_t is the torque constant, K_b refers to the electromotive force constant, and B_e is total equivalent damping friction.

2.1.2.Model Predictive Control

Model-predictive control (MPC) is a popular control strategy widely applied in process control, electric vehicles, aerospace, robotics, and many other fields. MPC has been applied to control electric vehicles (EVs) due to its ability to handle constraints and optimize the control inputs over a finite time horizon. Fig. 1 shows the default block diagram of the MPC with the system used in this study.

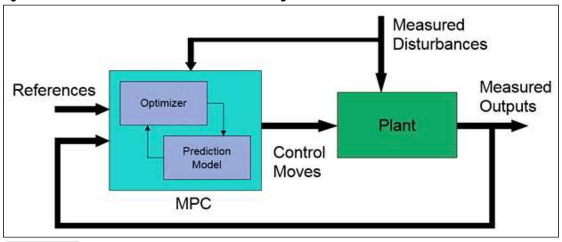


Fig. 1 Overall Black Diagram of MPC with the System.

In this paper, the MPC algorithm predicts the future behavior of the EV using a dynamic model and optimizes the control inputs to achieve the desired performance while considering the constraints of the EV's components, such as battery voltage and current limits. MPC has been successfully applied to adaptive cruise control (ACC) systems in automotive applications. An ACC system maintains a desired distance from the lead vehicle by adjusting the throttle and brake inputs of the following vehicle. Using MPC in ACC systems improves the system performance and reduces the risk of collisions. The dynamic model used in the MPC algorithm can be represented in Eq. (3) [25]:

$$x(k+1) = f\big(x(k), u(k)\big) \quad (3)$$

where $x(k)$ is the state of the EV at time $k, u(k)$ is the control input at time k, and $f()$ is the dynamic model that describes how the state evolves over time. The state of the EV includes variables such as the vehicle speed, battery state of charge, and motor torque.

2.1.3.Optimization Algorithms

In this section, two types of optimization methods are applied to optimize the MPC. Additionally, these optimization methods are new to the control literature and were contributed by Bouchekara [26, 27].

A-Electric Charged Particles Optimization Algorithm

Electric Charged Particle Optimization (ECPO) is a physics-inspired optimization algorithm based on the behavior of charged particles in an electric field. The ECPO algorithm starts by randomly initializing a population of charged particles, where each particle represents a candidate solution to the optimization problem. The fitness of each particle is evaluated using the objective function of the problem. The particles are then sorted based on their fitness, and the best particle is selected as the global best solution. In ECPO, each particle is assigned a charge that represents its fitness value, and an electric field is generated based on the charges of the particles. The electric field exerts a force on each particle, which moves them towards the best global solution. The movement of the particles is modeled using Newton's laws of motion. The ECPO algorithm has certain steps for each iteration: initialization, pool archiving, selection, interaction, checking bounds, diversification, updating population, criteria of termination, and handling constraints. ECPO solves various optimization problems, such as function optimization, parameter estimation, feature selection, and pattern recognition. Its effectiveness stems from its ability to efficiently explore the search space and overcome local optima, resulting in improved convergence and the possibility of finding better solutions than traditional optimization techniques. Overall, ECPO provides a versatile and powerful optimization approach that applies electromagnetism principles to complex optimization problems in various domains [26]. The following is the main equation to compute the next ECP [26]:

$$\boldsymbol{ECP_{New} = ECP + \beta \times (ECP_{Best} - ECP_1) + \beta \times (ECP_1 - ECP_2)} \quad (4)$$

B-Improved Chaotic Electromagnetic Field Optimization

The Improved Chaotic Electromagnetic Field Optimization (ICEFO) algorithm is a computational optimization technique inspired by the principles of chaotic systems and electromagnetic fields. Additionally, this algorithm was proposed to solve optimal power flow after its first version, Chaotic Electromagnetic Field Optimization (CEFO). The ICEFO algorithm is based on simulating the behavior of charged particles in an electromagnetic field. The ICEFO algorithm introduced a new approach to generating the electromagnetic field using chaotic maps, which improved the convergence rate and global search capability of the EMO algorithm. After that, the chaotic maps used in the ICEFO algorithm were deterministic and nonlinear, which exhibit complex and unpredictable behavior that can help the algorithm escape local optima. Moreover, the ICEFO algorithm had several advantages over other optimization techniques, including its ability to handle non-convex, nonlinear, and multi-modal problems. Furthermore, the algorithm is highly scalable and can be easily parallelized to solve large-scale optimization problems. The original EFO uses the neutral field's EMP to generate a new candidate solution with positive feedback from the positive field and negative feedback from the negative field. In the ICEFO, the following new search equation is proposed:

$$\boldsymbol{EMP_j^{New} = \begin{cases} EMP_j^{P_j}, \; if\; rand < Ps\_rate \\ EMP_j^{RW_j} + (\varphi * rand)\left(EMP_j^{P_j} - EMP_j^{K_j}\right) \\ \quad -rand\left(EMP_j^{N_j} - EMP_j^{K_j}\right) \\ , \quad otherwise, j = 1, \dots, N_{var}. \end{cases}} \quad (5)$$

where P_j , N_j, and K_j are the indexes of the selected EMPs from positive, negative, and neutral parts, respectively. φ is the golden ratio constant to guide the candidate solutions towards the positive part. RW_j depicts the selected EMP using the roulette wheel method instead of P_j, N_j, and K_j. In other words, the ICEFO constructs the candidate EMP. As shown in Eq. (7), candidate solutions around the neutral field and around positive and negative fields, with better EMPs having a higher probability of selection, can be generated. The EFO exploitation ability will be improved if RW_j guides the search. An adaptive mechanism is then used to improve the exploitation performance of ICEFO even further. Integrating adaptive control mechanisms into meta-heuristic algorithms is a widely used technique. In ICEFO, two main control parameters, Ps_{rate} and R rate, are adaptively controlled throughout a run. As mentioned in the previous section, Ps_{rate} determines the probability of copying the EMP index from the positive field, whereas R rate determines the probability of the randomization procedure. Ps_{rate} and R rate in the ICEFO are updated at the end of each iteration, as follows:

$$\boldsymbol{Ps_{rate} = Ps_{RMin} + \frac{Iter \times (Ps_{RMax} - Ps_{RMin})}{MaxIter}} \quad (6)$$

$$\boldsymbol{R_{rate} = R_{RMin} - \frac{Iter \times (R_{RMax} - R_{RMin})}{MaxIter}} \quad (7)$$

where $Iter$ and $MaxIter$ denote the current and maximum iteration values, respectively. Ps_{rate} increases from PsRMin to PsRMax during the search process, as shown in Eq. (6). R rate is also reduced adaptively from R_{RMax} to Ps_{RMin} . Ps_{RMin} , Ps_{RMax}, R_{RMax}, and R_{RMin} are the new ICEFO control parameters that will be set before the search process. In a nutshell, the two new control equations of Ps_{rate} and R rate will improve the exploration-exploitation balance by giving a higher probability to the random search mechanism in the early phase, while candidate EMPs are more likely to be derived from the positive field as Ps_{rate} increases. In other words, during the early stages of the search, ICEFO will efficiently explore the search space and favor exploitation around better solutions during the later stages [27]. In this work, the ICEFO algorithm is implemented to optimize the Model Predictive Control (MPC) parameter. In addition, the results of the ICEFO algorithm with MPC are compared to the ECPO algorithm. Next, the simulation results of the MPC with these optimization methods are presented to show the effectiveness of both of them.

2.2.Experimental Sets (Simulation Parameters Settings)

First of all, the EV system parameters, optimization methods, coefficient settings, and optimal parameters of MPC are included in the following tables: Table 1 shows the system parameters before MPC implementation.

Table 1 The Valued Parameters of the EV System [29].

No.	Parameters	Values	Parameters	Values
1	V_{in}	36 $volt$	K_b	0.023 $V.s/rad$
2	J_m	0.02 $kg.m^2$	R_a	1 Ohm
3	b_m	0.03	L_a	0.23 $Henery$
4	K_t	0.023 $N.m/A$	K_{tacho}	0.4696
5	r	0.5	n	3.1

Additionally, Table 2 lists the ECPO and ICEFO optimization settings with the optimized parameters of the MPC.

Table 2 ECPO and ICEFO Algorithm Parameters with MPC Controller.

No.	MPC with ECPO Parameters		MPC and ICEFO Parameters	
	Parameters	Values	Parameters	Values
1	H_T	3.1258 $sec.$	H_T	0.1575 $sec.$
2	*Dimension of the problem*	1	*Dimension of the problem*	1
3	*Population size*	75	*Population size*	50
4	*Number of iterations*	50	*Number of iterations*	50
5	*Lower boundaries*	0.055835	*Lower boundaries*	0.005116
6	*Upper boundaries*	10.047232	*Upper boundaries*	2.000472
7	*number of runs*	1	*number of runs*	1
8	-	-	*Positive_field*	0.01
9	-	-	*Negative_field*	0.045
10	-	-	*Neutral_field*	0.02
11	-	-	*Random electromagnet*	0.03

Where H_T is the optimal time gap of the MPC controller.

3. RESULTS AND DISCUSSION

This section presents the results and discussion of the electric vehicle system. Consequently, the implementation of the proposed MPC with the ICEFO and ECPO methods is shown. Additionally, the Integral Square Error (ISE) Performance Index (PI) is represented as the cost function in those optimization methods, as follows [28]:

$$\boldsymbol{Performance\ Index} = \int_0^t e^2(t)\,dt \qquad \textbf{(8)}$$

Where $e(t)$ is the difference value between the model reference output and the system output.

3.1.Results of First Set Case 1: Electric Vehicle Without MPC

In this subsection, the EV model is presented without being controlled to show the system's actual performance. Fig. 2 shows the performance of leader-follower velocity and distance of the vehicles with their relatives without a controlling scheme. It can be seen that the system has bad performance in following the vehicle to follow the leader vehicle. The difference in distances between the leader and follower was 55 m. Also, the leader approached zero in 9 sec, while the follower reached zero in 7 sec.

3.2.Second Set of Results Case 2: Electric Vehicle with MPC and ECPO Algorithm

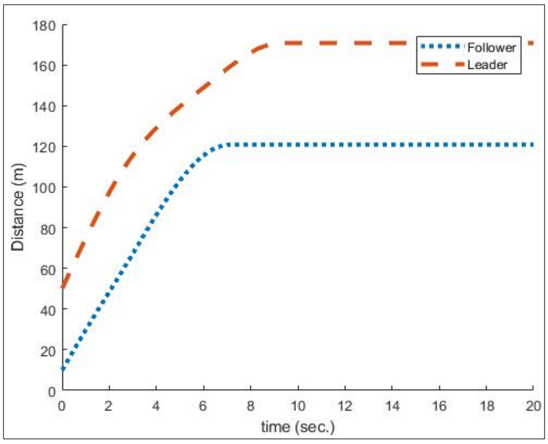
In this subsection, Fig. 3 shows the controlled EV system with MPC after it was optimized by the ECPO algorithm. Additionally, the leader-follower velocity and distance of the vehicle with their relatives were improved. It can be seen that the following vehicle was closer to the leader's vehicle. The difference in distance between the leader and follower became almost 30 m. Consequently, the leader approached zero in 6.5 sec, while the follower reached zero in 4.8 sec. Eventually, the relative distance was matched up with the safe distance at the fifth second.

3.3.Results of the Third Set Case 3: Electric Vehicle and MPC with ICEFO Algorithm

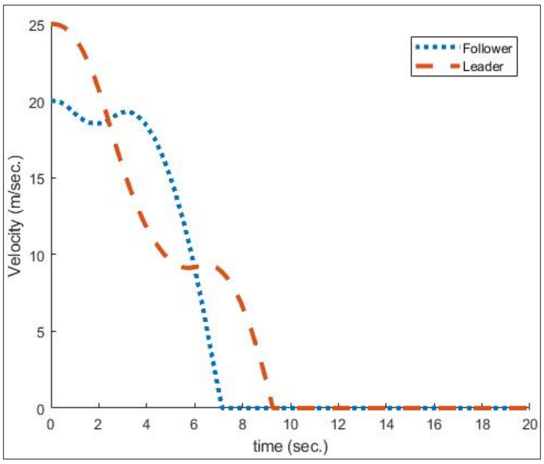
In this subsection, Fig. 4 presents the controlled EV system with MPC after it was optimized by the ICEFO algorithm. Moreover, the leader-follower velocity and distance of the vehicle with their relatives were improved more than ECPO. It can be shown that the difference in the distances between the leader and follower became almost the same as in the ECPO case. Further, the leader approached zero in 4.8 sec, while the follower reached zero in 5 sec. Eventually, the relative distance was matched up with the safe distance at the fifth second. Table 2 lists a comparison between the ECPO and ICEFO algorithms results.

3.4.Performance Comparison of Improved Physics-Inspired Optimization Algorithms

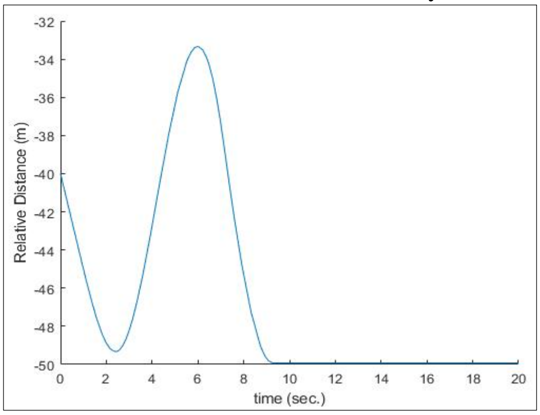
In this section, the simulation results show that the MPC-controlled system improved with the ECPO and ICEFO. However, the results showed that the MPC with ICEFO has a much better impact on the system than the MPC without ICEFO. Table 3 compares the ECPO and the ICEFO algorithms' results.



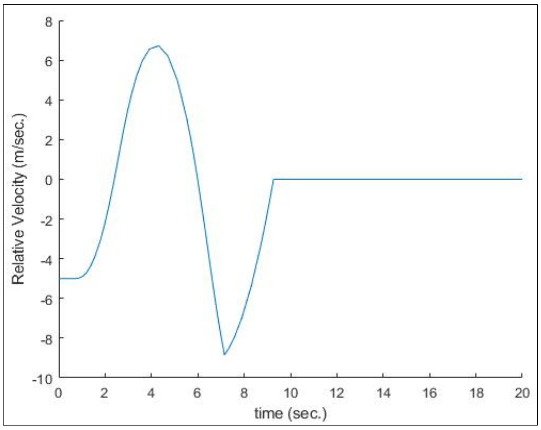
(a) Leader-Follower Distance



(b) Leader-Follower Velocity

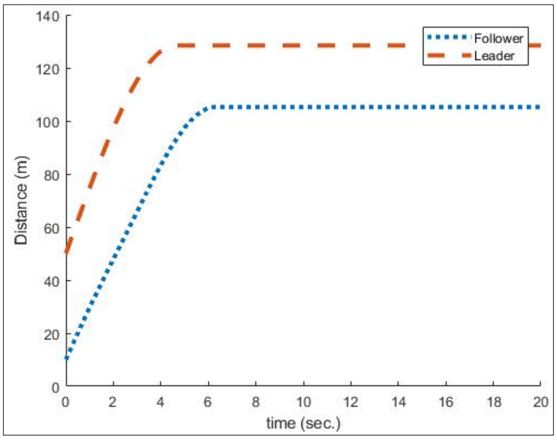


(c) Relative Distance

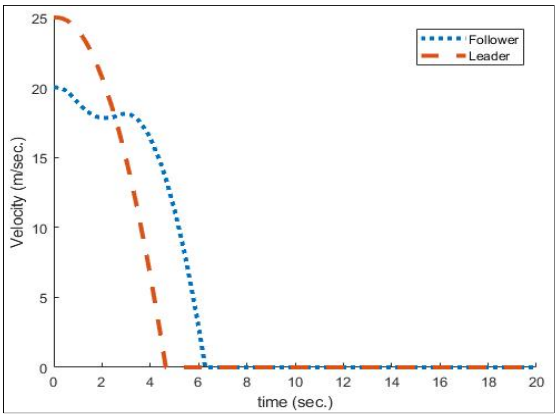


(d) Relative Velocity

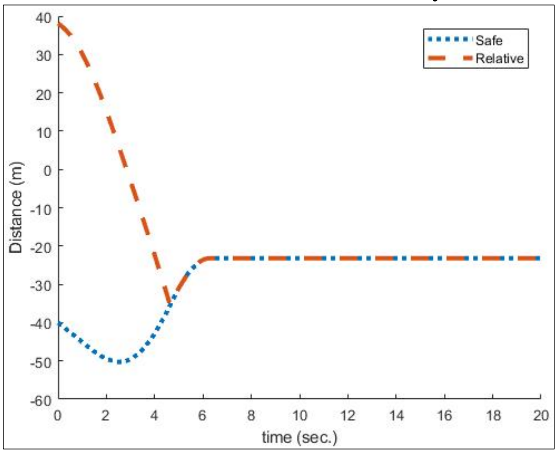
Fig. 2 (CASE.1) The Uncontrolled EV System.



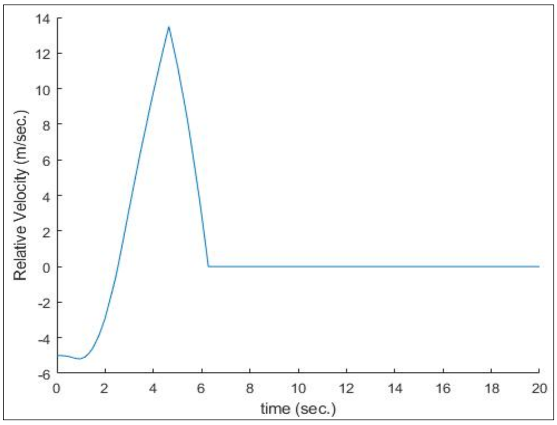
(a) Leader-Follower Distance.



(b) Leader-Follower Velocity.

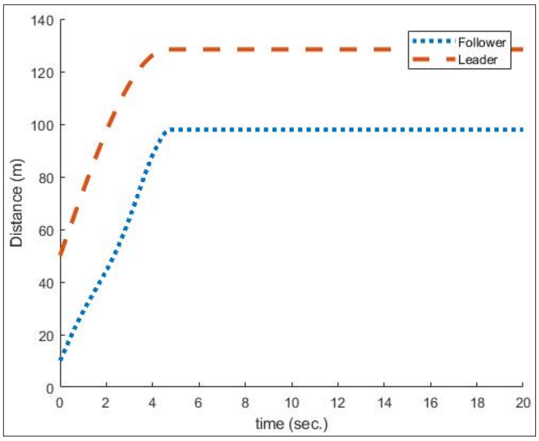


(c) Relative-Safe Distance.

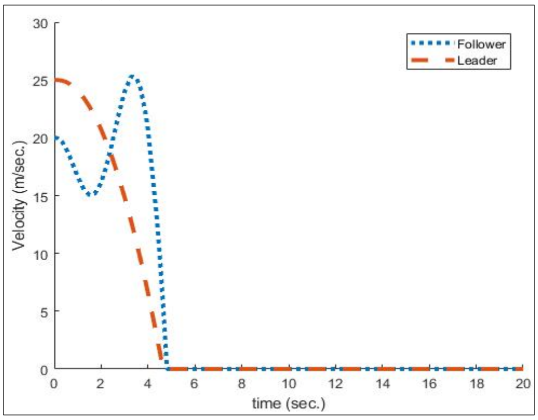


(d) Relative Velocity.

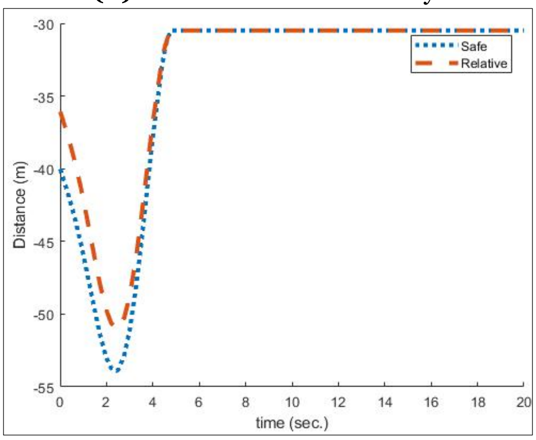
Fig. 3 (CASE.2) The MPC and EV Controlled System.



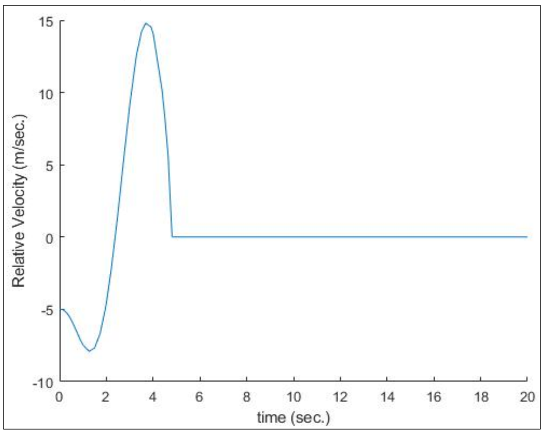
(a) Leader-Follower Distance.



(b) Leader-Follower Velocity.



(c) Relative-Safe Distance.



(d) Relative Velocity.

Fig. 4 (CASE.3) The MPC and EV Controlled System.

Table 3 A Comparison Between ECPO and ICEFO.

No.	Leader-Follower	ECPO Algorithm	ICEFO Algorithm
1.	Velocity	Converged to zero at 6.5 sec.	Converged to zero at 5 sec
2.	Distance	Around 130m and 100m at 6 sec.	Around 130m and 100m at 5 sec.
3.	Relative Distance	Matched up at 5 sec.	Matched up at 4 sec.
4.	Relative Velocity	Sewing between -5m/sec. and 14m/sec.	Sewing between -8m/sec. and 15m/sec.

4.CONCLUSIONS

Electric vehicles are becoming increasingly popular due to their environmental benefits and the decreasing cost of batteries. In this work, an MPC method is proposed to control the leader-follower EV system to compensate for its stability and performance. Additionally, the uncontrolled system showed some lack of performance and bad tracking of the following vehicle towards the leading car. After that, the MPC was applied to the leader-follower system with the ECPO optimization method to obtain the optimal MPC. Also, the MPC was applied to another optimization method, i.e., ICEFO, to gain better results. Moreover, the simulation results showed that the MPC-controlled system improved with the ECPO and ICEFO. However, the results showed that the MPC with ICEFO had a much better impact on the system than the MPC without ICEFO. Eventually, the results of the ICEFO algorithm were better and more preferable than ECPO, with an optimal time gap of 3.1258 sec in ECPO to 0.1575 sec in ICEFO. Also, the velocities were more matched up and converged to zero at 6.5 sec in ECPO for the leader, which reduced to 5 sec in ICEFO, while the follower convergence remained the same at 4.8 sec. Consequently, the relative velocities and distance improved much more with both optimization algorithms, especially with ICEFO.

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NOMENCLATURE

B_e	Total equivalent damping friction
C_r	Rolling coefficient of EV
J_e	Total equivalent inertia of the rotor
K_b	Electromotive force constant
K_t	Torque constant,N
L_a	The armature inductance
M_C	Mass of the car, (kg)
R_a	Armature resistance
k_{tah}	Tachometer gain
r^2	Radius of the wheel
$Psrate$	The probability of copying the EMP index from the positive field.
$Rrate$	The probability of the randomization procedure
Greek symbols	
β	Random number
φ	The golden ratio constant

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