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Dedicated to that boy who wanted to be the best despite the difficulties and fears.

Acknowledgements

I started this job in 2021, but I did not think this journey could be too difficult. I finished this project after 2 years, and in these years I was able to learn several things. I learned to teach, love, make mistakes, and live. This experience taught me how difficult it can be to study and research, but how wonderful and unique it feels to achieve what you want. In this adventure, I was able to meet people who helped me in difficult moments. I want to thank my professor John Cortés for his help and advice, with him I learned all the control theories I know now, and today I want to study more theory and math. I want to thank my professor Jorge Neira because he taught me many things about induction machines and the components that are necessary to control this machine. I want to thank Professor Sergio Rivera for teaching me several things about the optimization theory that allowed me to achieve the objectives of my research. I want to thank the university for my scholarship for one year and finally thank Professor Fredy Olarte for giving me the opportunity to teach and to see how much I still have to learn. Therefore, I want to thank all my professors for the opportunities and all the knowledge that I was able to learn. Finally, I would like to thank my parents Santiago and Olga for supporting me when I wanted to give up and I was crying in the laboratory because nothing worked. My family and friends thank you. I especially want to thank Juan, Tefa, Laura V, Wilmar, Catalina, Luisa, Omar, Paula and Johan. Thank you for encouraging me when I was about to give up. My students, all the people who gave me the opportunity to teach something for their academic and professional life, thank you for helping me believe in myself. When I was fourteen years old I wanted to be a researcher, thanks to me, thanks to that boy who believed in his dreams no matter how crazy they were.
I will never forget sleeping in a university laboratory and feeling so cold.

This is not the end, this is the beginning, and the true challenge starts now.

Resumen

Desempeño y eficiencia energética en vehículos eléctricos utilizando un motor de inducción a través de estrategías de Rechazo Activo de Perturbaciones y Control óptimo

Actualmente, la eficiencia energética cobra gran importancia en la sociedad y sus propuestas de transición energética, incluyendo los temas de tecnología vehicular. En cuanto a los vehículos eléctricos, un desafío crítico reside en abordar las cuestiones de autonomía. Para abordar esta preocupación, se vuelve imperativo optimizar varios componentes y estrategias asociadas para estos vehículos. Un componente crítico es el motor eléctrico, y los motores de inducción son ampliamente usados por su rentabilidad y sus técnicas bien establecidas. A pesar de sus ventajas, el motor de inducción también experimenta pérdidas intrínsecas, lo que exige una mejora del rendimiento que se puede lograr con estrategias de control. Esta investigación adopta un enfoque modificado de control basado en rechazo activo de perturbaciones para abordar las incertidumbres y la dinámica compleja, junto con conceptos de control óptimos para los requisitos de eficiencia del motor de inducción. La modificación implica incluir una ponderación en el rechazo de perturbaciones, desarrollar una función de costo ponderada y ajustar todos los parámetros del controlador considerando técnicas metaheurísticas. Se realiza un análisis comparativo de los enfoques de optimización considerando el rechazo de perturbaciones y su versión ponderada. El ADRC modificado redujo efectivamente el valor de la función de costos en comparación con el enfoque ADRC clásico. Los hallazgos del estudio se validan mediante la experimentación con un motor de inducción y un generador de DC que simula las condiciones de un vehículo eléctrico. Esto sugiere que la estrategia de control propuesta, basada en el rechazo parcial de perturbaciones dentro del esquema ADRC, puede ofrecer un rendimiento superior basado en una función de costos, aunque aumenta la complejidad para el ajuste de los parámetros.

Palabras clave: Motor de inducción, Control por rechazo activo de perturbaciones, Optimización,Técnicas Metaheuristicas, Vehículos Eléctricos, Observador de estado extendido .

Abstract

Performance and energy efficiency in electric vehicles using an induction motor through Active Disturbance Rejection and Optimal Control strategies

Currently, energy efficiency holds significant importance in society and its energetic transition proposals, including vehicular technology topics. Regarding electric vehicles, a critical challenge lies in addressing autonomy issues. To tackle this concern, it becomes imperative to optimize various components and associated strategies for these vehicles. A critical component is the electric motor, and induction motors are popular for their cost-effectiveness and well-established techniques. Despite its advantages, the induction motor also experiences intrinsic losses, demanding performance enhancement that can be accomplished with control strategies. This research adopts a modified active disturbance rejection control approach to address the uncertainties and complex dynamics, along with optimal control concepts for the efficiency requirements of the induction motor. The modification involves including a disturbance rejection weight, developing a weighted cost function, and tuning all the controller parameters with metaheuristic techniques. A comparative analysis of the optimization approaches, considering the disturbance rejection, and its weighted version is conducted. The modified ADRC effectively reduced the cost function value when compared to the classic ADRC approach. The study's findings are validated through experimentation with an induction motor and a DC generator simulating electric vehicle conditions. This suggests that the proposed control strategy, rooted in partial disturbance rejection within the ADRC scheme, can deliver superior performance based on a cost function, although increasing the complexity for the parameter tuning.

keywords: Induction motor, Active Disturbance Rejection Control, Optimization , Metaheuristic techniques, Electric vehicles, Extended state observer .

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Symbols

Symbol	**Term**
ω	Mechanical motor speed
θ	Motor Position
n_p	Pole-pair
M	Mutual inductance
ψ	Magnetic flux
u, i	Voltage, current
R, L	Resistance, inductance
τ_L	Load Torque
ξ	Unified disturbance
e	Tracking error
J	Performance criterion or Cost Function
C_{id}	Direct current controller
C_{iq}	Quadrature current controller
C_ω	Angular speed controller
C_D	DC generator controller

Subscripts

Subscripts	**Term**
d,q	Direct and quadrature axis oriented to the rotor flux.
α, β	Two-phase scheme.
R, S	Rotor , Stator.

Superscripts

Superscripts	Term
$\hat{\cdot}$	Estimation
$\dot{\cdot}$	Derivative
$\cdot^*$	Reference

Abbreviations

Abbreviations	Term
ADRC	Active Disturbance Rejection Control
ADR	Active Disturbance Rejection
ESO	Extended State Observer
PSO	Particle Swarm Optimization
SA	Simulated Annealing
GA	Genetic Algorithm
TS	Tabu Search
FOC	Field Oriented Scheme

1. Introduction

A new control strategy is crucial for optimizing energy usage in electric vehicles. In the current context, there are control strategies that overlook the performance criteria necessary to enhance the functionality of electric cars. The strategy proposed in this research aims to enhance a performance criterion under electric vehicle conditions and energy utilization. In this proposal, the complexity and results of the control strategy will be compared to other well-established control strategies through both offline simulations and real-time implementations in an experimental setup.

Currently, societal development acknowledges a correlation between economic progress and environmental preservation. Thus, there is a need to envision a swiftly advancing economy within the framework of environmental conservation, making it a trending topic [43]. Globalization advocates for a rapid surge in energy consumption, and the use of fossil fuels contributes to polluting emissions. Consequently, it is imperative to consider the concept of energy efficiency. As a result, research on these subjects is on the rise in various countries [64]. Given this context, multiple frameworks are being developed to enhance energy efficiency with the aim of deriving benefits for both the economy and society [11].

One topic that it is possible to consider is vehicles, Internal Combustion Engine (ICE) vehicles generate an emission of gasses, creating research in several characteristics of vehicles [26]. Additionally, according to [13, 33], electric vehicles are proposed with the objective of facing global warming and the energy crisis, but for the functioning, it is necessary to consider the parts of vehicles: The power electronic converter, the motor, the energy storage device, and the controller. For considering maximum energy efficiency, the parts have to work harmoniously. Here, the control strategies cannot only improve energy efficiency, therefore can improve safety and driving comfort, allowing to consider electric vehicles to face vehicles based on fossil fuels. Regarding the motor of electric vehicles, it is possible to consider several machines such as Induction Motors, Switched Reluctance machines, and others. According to [33], an induction motor is one of the machines that is widely used in electric vehicles due to these motors are cheaper than other machines, are tough for harsh applications, and have good initial torque, but despite the induction motor can reach high efficiency, the performance of this machine cannot be higher than others and the precise speed control is complicated. Furthermore, the range in electric vehicles is one of the most important characteristics. For this reason, it could be important to consider the concept of energy efficiency and the performance in induction motors [6, 10, 20, 26].

In the context of energy efficiency in induction motors, this machine exhibits two types of intrinsic losses: fixed and variable losses [2, 36, 45]. The nature of these losses is contingent upon motor design. Fixed losses remain constant regardless of motor load and are associated with the magnetic core, friction, and windage. On the other hand, variable losses are contingent on motor load and are related to rotor and stator resistances, as well as stray losses. Consequently, the intrinsic losses of the induction motor can be modified through various design techniques.

Due to the difficulties that are possible to find in electric vehicles using an induction motor, it is possible to design control strategies to improve the use of energy and reach a better performance. Between the used techniques, it is possible to find Field-Oriented control, direct torque control, and Model Predictive Control. Field-oriented control is one of the strategies more used. This technique takes into account a coordinate system that allows the rotor flux and the torque can be controlled independently. This control strategy is based on a cascade control loop considering the control of the internal currents and the external speed of the motor [33].

Regarding the control, sometimes the design is based on a trial and error process. For this reason, it is possible to consider an optimal control where the control signal may satisfy physical constraints and minimize or maximize a cost function or performance criterion. Then, it is considered the optimal control problem to find the optimal control signal for minimizing the cost of a performance criterion considering an optimal trajectory [30]. Additionally, the complexity of the optimization problem varies depending on the structure of the system because this one can have nonlinear dynamics or constraints. Then, when the problem is too complicated due to the system structure or the performance criterion complexity, it is possible to consider methods or algorithms to solve the problem satisfactorily [55]. From natural processes, arises the search based on conducting the survival of the best individuals taking into account a criterion. Algorithms like genetic algorithms, simulated annealing, or other strategies have a similar objective of finding in a probabilistic mode the global solution (minimum or maximum), taking into account the complexity and the panoramic multinode. However, each of them follows different processes [49].

Additionally, sometimes a nonlinear system can have unmodeled and/or unknown dynamics, that can be represented in an unified disturbance under the Active Disturbance Rejection Scheme and the differential flatness. Through Active Disturbance Rejection approach, it is possible to consider a system such as a perturbed integrator chain, because this chain maintains the essentials of the real system [1, 51].

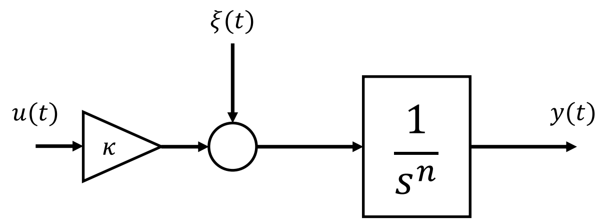


Figure 1-1.: Integrator chain - ADRC scheme

Taking into account the above, the unified disturbance that contains the nonlinear dynamics can be estimated through an Extended State Observer (ESO), considering that the disturbance can be estimated then could be rejected. For this reason, the Active Disturbance Rejection approach allows to work with systems that have a high level of uncertainty or are perturbed [53]. Thus, a system can be described by

$$y^{(n)}(t) = \kappa u(t) + \xi(t), \tag{1-1}$$

where n represents the integrator chain, $u(t)$ is the control signal, $y(t)$ is the output, and $\xi(t)$ is the unified disturbance. The value of κ varies depending on the structure of the output and its derivatives. However, in general, is considered as a constant average value.
Regarding the relationship between optimization and ADR, currently, it is possible to find several works about the optimal active disturbance rejection. One of them is based on using the genetic algorithm to optimize the performance of the ESO, taking into account a motor DC application [60]. Other work is based on optimizing through ant colony optimization algorithm with the purpose of optimizing the parameters of an ESO using an induction motor [62], the performance criterion of this problem considers the cost function taking into account the tracking error, settling time, and the rise time. This paper shows the comparison between the cost of several algorithms. Finally, regarding [18], it is possible to find the other work where the purpose is to tune the parameters of a nonlinear ESO using the particle Swarm optimization algorithm for a system based on an induction motor, the cost function is the same that is found in the work in [62]. In both works are considered metaheuristic methods, due to these methods consider complex problems. For these problems of metaheuristics are analyzed the cost of any iteration and the iteration where there is a settlement of the cost.

The works described above take into account the disturbance rejection. In general the objective is to tune the parameters of the controller or observer. These approaches have advantages with respect to the disturbance rejection, considering the nonlinear dynamics, external and internal disturbances, and uncertainties. However, when the optimization problem is considered, there are different functions for optimizing subject to constraints. Depending on the optimization problem the disturbance rejection can be considered as a problem due to the disturbance rejection could increase the cost of the performance criterion selected.

In other words, the standard Active Disturbance Rejection Control considers a linearization approximately of the system through an ESO, forcing the disturbance rejection. In the case of considering the optimization problem using the standard Active Disturbance Rejection, it is only possible to tune the parameters of the controller and/or observer. However, this research proposes a modified Active Disturbance Rejection where the disturbance rejection is not considered, there is a disturbance weighting. This proposal allows us to consider new grades of freedom taking into account new parameters for tuning and the possibility of modifying the necessary resources to reject the unified disturbance to improve the cost of the performance criterion.

To show that disturbance weighting can improve the cost of a performance criterion of an optimization problem, it is proposed a motivational example with the objective of comparing the traditional Active Disturbance Rejection Control and the modified version through a deterministic method. Then, the optimization problem is proposed for an induction motor considering the dynamics of an electric vehicle. The purpose is to compare the results of the disturbance rejection and disturbance weighting cases. Through a metaheuristic algorithm, the optimization problem is solved. Finally, the values of the tuning are compared using an experimental setup, where it is possible to conclude that the disturbance weighting shows a better performance under statistical variables taking into account the optimization problem.

Hence, the use of disturbance weighting could offer a solution when dealing with an optimization problem under the Active Disturbance Rejection scheme. This approach has the potential to enhance the cost of the performance criterion compared to disturbance rejection across various constraint functions. Nevertheless, employing disturbance weighting may introduce challenges, particularly when considering the variability in results from multiple experiments conducted under similar system conditions, as opposed to the traditional standard disturbance rejection in an offline design. This is due to the fact that the system's operational conditions may change, given that the modified version considers a nonlinear problem.

1.1. Objectives

1.1.1. General objective

This research seeks to develop a control strategy for an induction motor based on Active Disturbance Rejection and Optimal techniques with an emphasis on energy efficiency and performance considerations for electric vehicles.

1.1.2. Specific objectives

1. To formulate a performance criterion for the induction motor operation that considers energy efficiency and performance for a typical electric vehicle.

2. To implement the control strategy on a small-scale experimental setup using an induction motor and a DC generator to emulate the typical electric vehicle torque and speed conditions.

3. To evaluate the performance of the proposed control strategy in terms of energy efficiency and robustness in the experimental setup.

1.1.3. Structure of the document

The document has the following structure

- **Chapter 2**: This chapter discusses the frame of reference. In the first instance, the chapter talks about the foundations of Active Disturbance Rejection Control. On other hand, it is considered the optimization problem. In this section is possible to find the convexity approach and different metaheuristic methods which are compared according to a group of benchmark functions. Additionally, it is possible to find the hybrid algorithm that will be used in this proposal. Furthermore, an optimization problem is considered as an example, where the traditional Active Disturbance Rejection control tuned by the hybrid algorithm is compared to the optimal solution of the problem. This chapter considers a modified Active Disturbance Rejection Control.

- **Chapter 3**: This chapter discusses the dynamics of electric vehicles and the induction motor. In addition, this chapter considers the optimization problem of the induction motor under the conditions of the vehicle, and the search for the best solution in the conditions of the decision variables and constraints is given by the hybrid algorithm , several optimization problems are considered.

- **Chapter 4**: This chapter discusses the results of comparing the use of traditional ADRC and modified ADRC based on the motivational example. Both control strategies are implemented in an experimental setup that considers an induction motor and a

DC motor that functions as the load of the induction machine. These results consider a reference that is used in the electric vehicle testing scheme.

- **Chapter 5**: In this chapter, you will discover the conclusions, recommendations, and insights for future work.

1.1.4. Relationship between objectives and chapters

The relationship between the objectives and the chapters of the document is given by the figure **1-2**

	Relationship with objectives	**How is the objective achieved?**
Chapter 1: Introduction **Chapter 2:** Frame of reference		
Chapter 3: Induction motor under vehicle dynamics	- To create a criterion that considers the performance and the energy use, considering the dynamics of an electric vehicle using an induction motor	It is considered a cost function that contemplates the energy use through a power component taking into account the tracking error and the settling time. The tracking error and the settling time consider the performance of the strategy, while the power factor considers the energy use.
Chapter 4: Experimerntal Setup – Results	- To implement the control strategy on a small-scale experimental setup.	Under the cost function of Chapter 3, are implemented the parameters tuned by an optimization algorithm of the control strategy in an experimental setup.
	- To evaluate the performance of the proposed control strategy in terms of energy efficiency and robustness.	The control strategy is evaluated, considering 10 tests under the similar conditions. The robustness is evaluated under the evaluation of the variation of the cost, using similar conditions of the experiments, and the performance is evaluated, considering the cost and other parameters associated.

General Objective

Figure 1-2.: Relationship between chapters and the research objectives

The fulfillment of the objectives occurs as a result of the development of a control law that is explained in chapters 2 and 3 that involves optimization and active disturbance rejection. The cost function appears in Chapter 3 by minimizing the absolute value of the multiplication of voltage by current taking into account the tracking error. Additionally, the cost penalty is taken through the execution time of the experiment. Finally, parameter tuning is implemented in a small-scale setup of an electric vehicle in

Chapter 4, where additional analyses are carried out with respect to an electric vehicle test reference.

2. Frame of reference

This chapter focuses on establishing a frame of reference. In the first instance, the concepts of the active disturbance rejection control are mentioned due to the dynamics of the vehicle and the motor. Then, it is possible to find the optimization problem and its considerations. The optimal control problem and the convex problem are considered, then the metaheuristic approach is considered due to the complexity of the problem taking into account the structure of the system and the cost function or performance criterion. This section talks about several metaheuristic processes and it is proposed a hybrid algorithm that is compared to another traditional algorithms. The comparison is proposed using a group of benchmark functions. With the comparison of the algorithms, it is possible to conclude that the hybrid algorithm is the best selection. Finally, it is possible to consider a motivational example, where it is demonstrated that the traditional active disturbance rejection control does not represent the optimal solution considering the cost function, this demonstration uses the deterministic process of Linear Quadratic Regulator and a space state transformation.

2.1. Active Disturbance Rejection Control

In this subsection, the standard Active Disturbance Rejection is delineated. Commencing with the foundational concept of differential flatness, the exposition progresses to introduce the ADR approach. An introductory example is presented, followed by an exploration of the general case for continuous-time systems.

2.1.1. Differential Flatness

According to [50, 53], a nonlinear system can be described by

$$\dot{x}(t) = f(x, u), \quad y(t) = h(x), \tag{2-1}$$

where $y(t)$ is the output, $u(t)$ is the control signal, $x(t)$ represents the states, and f and h are functions. The objective of the differential flatness is to change the original states in terms of the flat output and its derivatives

$$\psi : x \longmapsto (y, \dot{y}, \ddot{y}, \ldots, y^{(n-1)}). \tag{2-2}$$

In other words, the differential flatness allows to parameterize diferentially the system where all variables can be described by the flat output and its derivatives. In this case, the control law depends on the flat output and its derivatives too.

Active Disturbance Rejection control

By considering differential flatness, it is possible to handle a system with nonlinearity and uncertainties using the Active Disturbance Rejection approach.

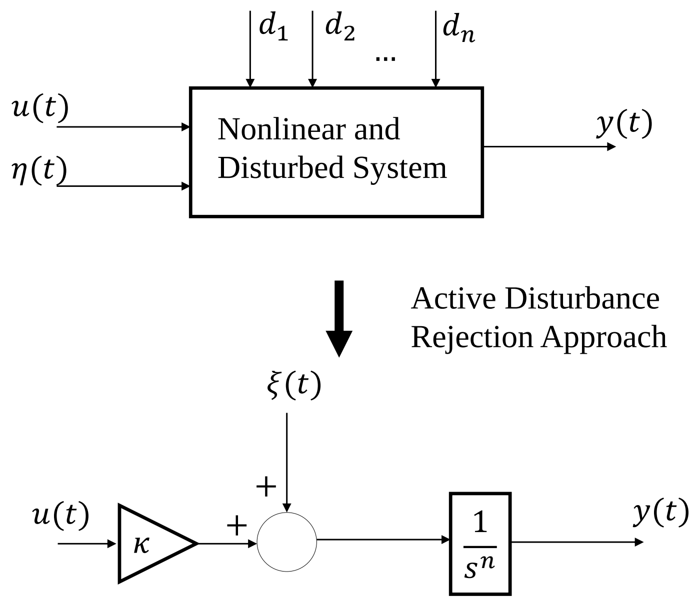


Figure 2-1.: Active Disturbance Rejection Approach

In Figure **2-1**, d_1, ... , d_n are the internal and external disturbances, $u(t)$ is the control signal, $\eta(t)$ is the noise, κ is a constant value, $\xi(t)$ is the unified disturbance and $y(t)$ is the output of the system. According to [25, 53], under the ADRC scheme the nonlinear dynamics, the uncertainties, and the external disturbances can be considered in an unified disturbance $\xi(t)$. Thus, the active disturbance rejection control allows us to consider a nonlinear and perturbed system with uncertainties as a linear disturbed system.

In the first instance, the unified disturbance is considered as a function that depends on the flat output and a finite set of its derivatives. Based on the active disturbance rejection, it is necessary to make the following consideration

$$\xi(y(t), \dot{y}(t), \ldots, y^{(n-1)}(t), t) \to \xi(t). \tag{2-3}$$

According to the equation (2-3), under the ADRC scheme, the unified disturbance only depends on the time, with the purpose of considering locally the Taylor approximation

$$\xi(t) = a_n t^n + a_{n-1} t^{n-1} + \ldots + a_1 t + a_0, \tag{2-4}$$

where the intern model can be considered

$$\frac{d^{n+1}\xi(t)}{dt^{n+1}} \approx 0. \tag{2-5}$$

Based on Figure **2-1**, the case most simple is when $\kappa = 1$. In order to show a particular example, a development with $n = 2$ and $\kappa = 1$ will be shown.

In this case, it is possible to consider

$$y^{(2)}(t) = u(t) + \xi(t), \tag{2-6}$$

where the purpose of the control law will be based on the dynamic of the tracking error. Then the control law is

$$u(t) = y^{(2)*}(t) - k_1(\hat{\dot{y}}(t) - \dot{y}^*(t)) - k_0(y(t) - y^*(t)) - \hat{\xi}(t), \tag{2-7}$$

considering that $\dot{y}(t)$ and $\xi(t)$ are not available but can be estimated. Assuming that $\hat{\dot{y}}(t)$ and $\hat{\xi}(t)$ are good approximations or estimations, the dynamic of the tracking error is given by

$$e_y^{(2)}(t) + k_1 e_y^{(1)}(t) + k_0 e_y(t) = 0, \tag{2-8}$$

where it is possible to observe that the error dynamics are stable if the conditions of the Hurwitz polynomial are met. Additionally, the space state representation of the system if $n = 2$ considering the Figure **2-1**, taking into account that the disturbance is locally constant for the control design is

$$\dot{x}_1(t) = x_2(t), \tag{2-9}$$

$$\dot{x}_2(t) = u(t) + x_3(t), \tag{2-10}$$

$$\dot{x}_3(t) = \dot{\xi}(t). \tag{2-11}$$

For estimating ξ and $\dot{y}$ is used an Extended State Observer, therefore the dynamics are

$$\dot{\hat{x}}_1(t) = \hat{x}_2(t) + l_2(y(t) - \hat{y}(t)), \tag{2-12}$$

$$\dot{\hat{x}}_2(t) = u(t) + l_1(y(t) - \hat{y}(t)), \tag{2-13}$$

$$\dot{\hat{x}}_3(t) = l_0(y(t) - \hat{y}(t)), \tag{2-14}$$

subtracting the equations (2-9) and (2-12), (2-10) and (2-13), and (2-11) and (2-14)

$$\begin{aligned}
\dot{x}_1(t) - \dot{\hat{x}}_1(t) &= x_2(t) - \hat{x}_2(t) - l_2(y(t) - \hat{y}(t)), \\
\dot{x}_2(t) - \dot{\hat{x}}_2(t) &= x_3(t) - l_1(y(t) - \hat{y}(t)), \\
\dot{x}_3(t) - \dot{\hat{x}}_3(t) &= \dot{\xi}(t) - l_0(y(t) - \hat{y}(t)),
\end{aligned}$$

and using the derivatives and the substitutions, the global dynamic is

$$(y(t) - \hat{y}(t))^{(3)} + l_2(y(t) - \hat{y}(t))^{(2)} + l_1((y(t) - \hat{y}(t))^{(1)}) + l_0(y(t) - \hat{y}(t)) = \dot{\xi}(t).$$

Due to the disturbance being approximately locally constant for the control design, it is possible to consider that the error of the estimates and the real states tend asymptotically to zero.

General Case

According to [51, 52, 53], a real system can be represented by the simplified disturbed integrator chain shown in Figure **2-1**. Its corresponding state-space representation is given by

$$\dot{x}_s(t) = A_s x_s(t) + B_s(u(t) + \xi(t)), \tag{2-15}$$

$$y(t) = C_s x_s(t), \tag{2-16}$$

where s denotes the system, and $y(t)$ represents the system output. In this case, the states of the system are

$$x_s(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_n(t) \end{bmatrix}.$$

Now, considering the disturbance model

$$x_{n+1}(t) = \xi(t), \quad x_{n+2}(t) = \dot{\xi}(t), \quad x_{n+3}(t) = \xi^{(2)}(t), \quad x_{n+4}(t) = \xi^{(3)}(t), \quad \ldots, \quad x_{n+m}(t) = \xi^{(m-1)}(t).$$

Then, the disturbance has the following state-space representation

$$\dot{x}_\xi(t) = A_\xi x_\xi(t) + B_\xi \xi^{(m)}(t), \tag{2-17}$$

$$\xi(t) = C_\xi x_\xi(t). \tag{2-18}$$

Considering an extended model using the representations in equations (2-17) and (2-15)

$$\underbrace{\begin{bmatrix} \dot{x}_s(t) \\ \dot{x}_\xi(t) \end{bmatrix}}_{\dot{x}} = \underbrace{\begin{bmatrix} A_s & B_s C_\xi \\ 0 & A_\xi \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} x_s(t) \\ x_\xi(t) \end{bmatrix}}_{x} + \underbrace{\begin{bmatrix} B_s \\ 0 \end{bmatrix}}_{B} u(t) + \underbrace{\begin{bmatrix} 0 \\ B_\xi \end{bmatrix}}_{B_\xi} \xi^{(m)}(t). \tag{2-19}$$

Thus, the global system can be expressed by the representation

$$\dot{x}(t) = Ax(t) + Bu(t) + B_\xi \xi^{(m)}(t), \tag{2-20}$$

and the dynamics of the observer are given by

$$\dot{\hat{x}}(t) = (A - LC)\hat{x}(t) + Bu(t) + Ly(t). \tag{2-21}$$

The dynamics of the error are obtained by subtracting equations (2-20) and (2-21)

$$\dot{e}_x(t) - (A - LC)e_x(t) = B_\xi \xi^{(m)}(t).$$

In the Laplace domain, it is possible to consider

$$\underbrace{(sI - (A - LC))}_{PO} e_x = B_\xi s^{(m)} \xi,$$

where the eigenvalues of the matrix PO (observation matrix) will be stable. Considering the tracking error, it is possible to define the matrices of the state-space representation

$$x_s \in R^{1\times n}, \quad x_\xi \in R^{1\times m},$$

$$A = \begin{bmatrix} 0 & 1 & 0 & \dots 0 \\ 0 & 0 & 1 & \dots 0 \\ \vdots & \vdots & \vdots & \ddots \\ 0 & 0 & 0 & \dots 1 \end{bmatrix} \in R^{m\times n}, \quad B = \begin{bmatrix} 0 \\ \vdots \\ \kappa(\text{nth Position}) \\ \vdots \\ 0 \end{bmatrix} \in R^{1\times(n+m)},$$

$$C = \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix} \in R^{1\times(n+m)}, \quad B_\xi = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \in R^{(n+m)\times 1},$$

where A is the Brunovsky canonical form and κ depends on the structure of the system. Thus, the Active Disturbance Rejection approach allows us to consider the internal and external disturbances, the uncertainties, and the nonlinear and unmodeled dynamics in the unified disturbance $\xi(t)$. The dynamic of the system can be reduced to an integrator chain using the Active Disturbance Rejection scheme. Using an ESO, it is possible to linearize the system considering the disturbance feedback through its estimation. This approach shows a simplification in a control problem due to the complexity of the system can be reduced due to disturbance rejection.

2.2. Optimization

This subsection discusses the optimization problem within the convex scheme. Subsequently, attention is given to the optimal control problem, and considering the structure and complexity of the research problem, various metaheuristic algorithms are proposed. The section describes several algorithms, culminating in the creation of a hybrid algorithm specifically utilized in this research due to its superior performance compared to two traditional algorithms. This superiority is demonstrated through benchmark functions and statistical considerations.

2.2.1. Optimization problem

According to [5, 7, 37], the optimization problem is given by

$$\begin{aligned} &\text{minimize } f(x), \\ &\text{subject to } g_i(x) \leq b_i, \quad i = 1, 2, 3, \dots, m, \end{aligned} \tag{2-22}$$

where x is a vector of decision or optimization variables and

$$f : \mathbf{R}^n \to \mathbf{R} \tag{2-23}$$

is the objective or cost function subject to restrictions of constraint functions g_i that are inequalities.

2.2.2. Convex optimization problem

An optimization problem is convex when a local minimum is also the global minimum. To meet the criteria for convexity, both the cost function and constraints must be convex; in other words, it is necessary to satisfy

$$g_i(\alpha x + \beta y) \leq \alpha g_i(x) + \beta f_i(y), \quad f(\lambda x + (1-\lambda)y) \leq \lambda f(x) + (1-\lambda) f(y), \tag{2-24}$$

where $x, y \in \mathbf{R}^n$ and $\alpha + \beta = 1$, $\lambda \in [0, 1]$ where α and β have to be higher or equal to zero. Otherwise the function is concave. Equation (2-24) considers that the cost function and the constraints are convex [5, 7, 37].

2.2.3. Optimal Control problem

According to [30], the optimal control problem is based on finding a control signal that can minimize the performance criterion, but in general, the classical design is based on linear and time-invariant systems. The optimal control performance is given by the following performance criterion

$$J = h(x(t_f), t_f) + \int_{t_0}^{t_f} g(x(t), u(t), t)dt, \tag{2-25}$$

where $x(t)$ is associated to the state, $u(t)$ is the control signal, t is the time, while g and h are scalar functions, and t_f and t_0 are the final and initial time, respectively. Thus, the optimal control objective is to find an optimal trajectory using an optimal control signal with the purpose of minimizing the J criterion. Considering the problem of electric vehicles, it is possible to create a performance criterion or cost function that considers energy efficiency and the performance of the system taking into account constraints based on the system functioning.

Induction motor case

This research considers the study of the optimal control for the induction motor used in electric vehicles under a nondeterministic cost function J that considers the performance of the system, the energy efficiency and several constraints of the decision variables. Additionally, the induction motor proposes a nonlinear dynamic [15]. Thus, the consideration of the function structure can be taken as a problem due to the complexity of the optimization problem. For this reason, it is considered an optimization problem through metaheuristic algorithms.

2.2.4. Metaheuristic

The Metaheuristic is a subgroup of stochastic optimization, where it is necessary to use a degree of randomness to find an optimal, there are different algorithms that it is possible to consider. These techniques can be applied in a variety of complex problems [3, 47]. When the problem is too complicated such as when the system is nonlinear or multinodal, it is necessary to use other strategies, different from the deterministic strategies due to the problems in resource use. For the example, the problem of the induction motor proposes a high grade of complexity because this system has nonlinear dynamics, and the decision variables are subject to the operation conditions. Then, it is possible to show that the metaheuristic can face an optimization problem in an efficient way [40]. Exist several algorithms as the genetic algorithm that can reach the best results using the local search using other types of algorithms [58]. These types of algorithms produce quality solutions and currently, these algorithms have increased according to the bibliometric analysis [9]. There are several types of these algorithms such as Evolutionary-based, Swarm-based, Physics-based, and Mathematics-based . Additionally, there are many algorithms that are adapted to control strategies such as PID [22].

Simulated annealing

Simulated annealing is an algorithm that is based on the solid annealing principle. In thermodynamics, this procedure is based on the temperature decreasing of an object as metals, this decrease is gradual, whereas the temperature of the object is lower, the object has a lower energy. When the temperature starts to cool, it is possible to reach the crystallization and condensation processes. The system reaches the minimum energy in the crystalline state. But if the cooling is very fast, the level of minimum energy can not be reached [12, 34].
According to [47], the algorithm is derived from the Metropolis algorithm. The principle is based on having a candidate solution S and if R is better than S, it is necessary to replace S with R, but if R is worse than S, it is possible to replace S with R, considering the probability P, where P is based on

$$P = e^{\frac{Q(S)-Q(R)}{t}}, \tag{2-26}$$

where t is the actual temperature $t \geq 0$ while Q represents the cost value. Additionally, taking into account equation (2-26), if $Q(S) - Q(R) < 0$ due to R being worse than S, then

the value of t will determine a high or a low value of P, so it is possible to escape from local minimums. The Simulated Annealing can have advantages in results respecting brute force algorithms [57]. However, this algorithm can have problems respecting the selection of the initial temperature and the annealing rate, if the initial temperature is too high, it is necessary for more iterations requiring greater computational effort, but if the temperature is low, the performance of the algorithm will be reduced. Whereas the annealing rate can change the performance of the algorithm [34].
The simulated annealing is based on the following algorithm

Algorithm 1: Simulated Annealing

Data: Initial Temperature (IT), Energy variation ($\Delta E = Q(S) - Q(R)$), Temperature (t), Candidate Solution (S), Possible Solution (R), Annealing rate (ar)
Result: Best Solution (BS)

```
t ← IT
S ← Random possible solution
while t ≥ 0 do
    R = Tweak of S
    α ← Random number between [0, 1]
    if ΔE < 0 or α < e^((Q(S)−Q(R))/t) then
        S ← R
    if Fitness(S)>Fitness(BS) then
        BS ← S
    t ← t · ar (Temperature decrease)
```

In algorithm 1, in the first instance, it is considered an initial temperature and a random possible solution, then it is considered a variation of S with the name of R, also is proposed a α value, this value allows to compute the probability section. If the fitness of R is better than the fitness of S, S will take the value of R, if the new value of S has a better performance than BS, the value of BS will change, after these processes the temperature of the algorithm will change and all processes will be repeated [34, 47, 57].

Tabu Search

The Tabu Search is a metaheuristic algorithm that has the purpose of mathematical optimization under a local search approach [59]. Despite the algorithm work taking into account a local search, it is possible to find a global optimum, because this algorithm allows one to select one solution with a higher cost. Additionally, this procedure includes a Tabu list to avoid cycles considering restrictions [63]. This algorithm can be a good metaheuristic process for a variety of problems of optimization [35].
According to [47], this algorithm is based on the Steepest Ascent with Replacement. This algorithm considers a tabu list of the candidate solutions. Items in the list cannot be selected as a possible solution, if the list is too large, the oldest solution may be deleted. The tabu

search is based on the following algorithm

Algorithm 2: Tabu Search

Data: Number of tweaks for each sample (n), maximum number of elements of tabu list (l), candidate solution (S) , best solution (BS), tabu list (L)

Result: Best Solution (BS)

$S \leftarrow$ Random Solution Value

$L \leftarrow L \cup S$

for $Iteration \in maxIter$ **do**

  $R =$ Tweak of S

  for $n-1$ *times* **do**

    $W =$ Tweak of S

    if $W \notin L$ *AND Fitness of* $W <$ *Fitness of* R *OR* $R \in L$ **then**

      $R \leftarrow W$

  if $R \notin L$ **then**

    $S \leftarrow R$

    $L \leftarrow L \cup S$

  if *Fitness of* $S <$ *Fitness of* BS **then**

    $BS \leftarrow S$

In algorithm 2, it is possible to observe that in the first instance, a tabu list L with a maximum possible length l is proposed, then a random solution S is given, and this solution is included in the tabu list, if the tabu list reaches the maximum value of elements, the oldest value will be removed. Then, a possible solution R is selected, this solution is based on a variation of S (candidate solution), and this value of R is compared to other variations of S, these new variations will be named W. The different values are compared respecting the fitness value, if R is the new candidate solution, this value of R is included in the tabu list [35, 47].

Particle Swarm Optimization

According to [47], this algorithm is similar to evolution algorithms, but this one is different from these, because it is not modeled based on the evolution process, it is based on swarms or animals behavior. In this process it is not necessary to consider a new sample of the population, then any particle changes taking into account the space of search, that is, it is based on mutated directed. Any particle has two components: The location and the velocity, the location vector is given by $\vec{x}$

$$\vec{x} =< x_1, x_2, \dots x_n >, \tag{2-27}$$

and the velocity vector is given by the expression $\vec{v}$.

$$\vec{v} =< v_1, v_2, \dots, v_n >, \tag{2-28}$$

the velocity is the speed and direction of particles taking into account a time-step. The values of x_i and v_i under $i \in \{1, 2, 3, \ldots n\}$ in the equations (2-27) and (2-28) represent the coordinates in the space considered.
In this algorithm it is necessary to consider several parameters

- $\beta \rightarrow$ A number between $(0, 1]$ that represents the informants best velocity retained.
- $\alpha \rightarrow$ A number between $(0, 1]$ that represents the velocity retained.
- $\gamma \rightarrow$ A number between $(0, 1]$ that represents the informants velocity retained.
- $\delta \rightarrow$ A number between $(0, 1]$ that represents the global best retained.
- $\epsilon \rightarrow$ This number represents the jump-size.

Thus, the PSO is based on the following algorithm

Algorithm 3: Particle Swarm Optimization

```
Data: Population (P)
Result: Best Solution (BS)
P ← {}
P ← P ∪ {Particles with random position and velocity}
for Each particle ∈ P do
    Compute the cost value of x⃗_i
    if cost value of x⃗_i < cost value of BS then
        BS ← x⃗_i
for Iteration < maxIter do
    for Each particle ∈ P do
        x⃗* = Previous fitness location
        x⃗+ = Previous fitness location of informants of x⃗
        x⃗! = Previous fitness location of any particle
        for Each dimension of the problem do
            b = random number [0, β]
            c = random number [0, γ]
            d = random number [0, δ]
        v⃗_i = α v⃗_i + b(x⃗*_i − x⃗_i) + c(x⃗+_i − x⃗_i) + d(x⃗!_i − x⃗_i)
    for Each particle ∈ P do
        x⃗ = x⃗ + c · v⃗
    Iteration ← Iteration + 1
```

In algorithm 3, it is possible to observe that in the first instance is proposed a population of several particles with a random position and speed, then it is necessary to compute the fitness of each particle and select the best one. Then, taking into account a group of previous fitness locations, it is possible to compute the velocity of each particle and compute the new position of each particle. The process finishes when the number of iterations is equal to or higher than the $maxIter$ parameter [19, 47].

Genetic algorithm

This algorithm is based on natural selection, a crossover, and mutation. The algorithm seeks the survival of the fittest candidate. The genetic algorithm allows to escape from the local minimum but requires more iterations [38, 44]. This algorithm takes into account a fitness assessment, the algorithm selects many parents and creates enough children. For reproduction, it is necessary to consider an empty children population, then select several parents of the original population and reproduce them, generate copies, mutations, and cross them. This process generates two children, for this reason, it is necessary to select other parents and repeat the process [47]. According to [47] the procedure of the genetic algorithm is given by

Algorithm 4: Genetic algorithm

```
Data: Population (P), Popsize(ps)
Result: Best Solution (BS)
for popsize times do
    P ← P ∪ {new random individual}
    BS ← BestFitness(P_i)
for Iteration ∈ maxIter do
    for each P_i ∈ P do
        J_i ← CalculateFitness(P_i)
        if J_i > CalculateFitness(BS) then
            BS ← P_i
    Q ← {}
    P_a, P_b ← SelectReplace(P)
    C_a, C_b ← Crossover(Copy(P_a), Copy(P_b))
    Q ← Q ∪ {mutate(C_a), mutate(C_b)}
    P ← Q
    Iteration ← Iteration + 1
```

The algorithm 4 is based on creating an initial random population of pop size members, then it is necessary to compute the fitness of each population member and select the best member through the "BestFitness" function. After, it is necessary for any population member P_i the compute the fitness value and compare the value to the value of the best solution, this process allows to selection of a new best solution according to the actual population. Then, the reproduction process is considered, two members of the population are selected and then these parents are crossed. Finally, the new population is given by the mutation of the result of the crossover of the parents.

2.2.5. Hybrid Algorithm - (PSO,AS,TS)

According to [17, 29, 31, 46], the result of the traditional algorithms can be improved through the combination of many algorithms or the use of techniques such as neural networks, Markov chains, and others, reaching a better performance considering the original algorithm, for example, in terms of accuracy. In this work, is proposed an algorithm that uses the Particle Swarm optimization with an additional local search space through Simulated Annealing and Tabu Search algorithms. The algorithm is given by

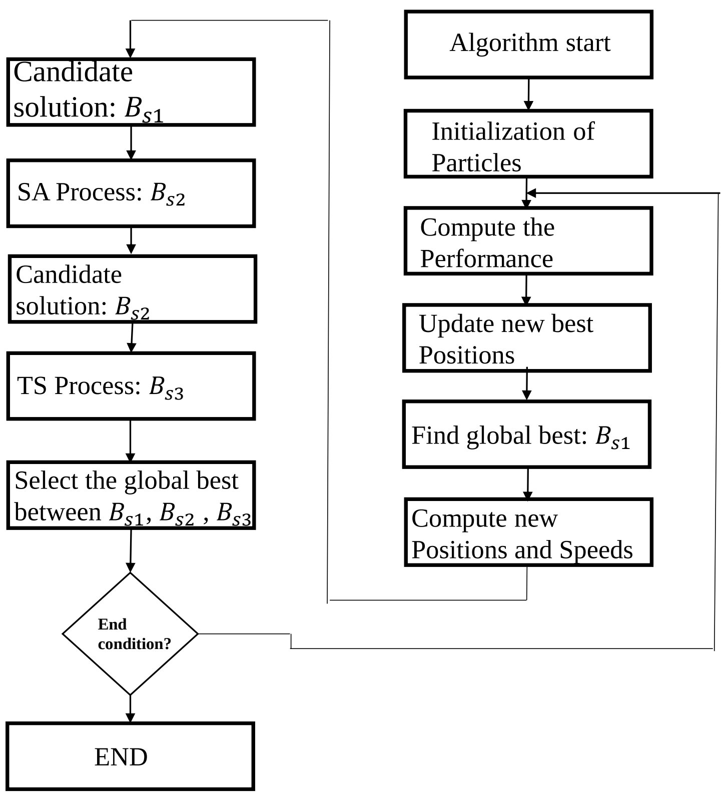


Figure 2-2.: Hybrid algorithm

According to the Figure **2-2** , the hybrid algorithm is based on the following steps

- **Initialization of Particles**: In this step, the particles of the Particle Swarm Optimization are generated.

- **Compute the performance**: In this step, the performance of any particle is computed.

- **Update new Positions**: In this step, the best performances are selected of any particle.

- **Find global best**: In this step, the best position of all particles is selected taking into account the performance.
- **Update new Positions**: In this step, the new positions and speeds are computed.
- **Candidate Solution B_{s1}**: In this step the best solution of PSO is considered as a candidate solution.
- **SA process**: In this step the Simulated annealing is used taking into account the candidate solution.
- **Candidate solution B_{s2}**: In this step, the best solution of the algorithm is selected and considered as a candidate solution.
- **TS Process B_{s3}**: In this step using B_{s2}, it is possible to use the TS algorithm and select a candidate solution B_{s3}, through a local search.
- **Select the global best between B_{s1}, B_{s2}, B_{s3}**: In this step, the globally best solution is selected.

In this process, the Tabu search and simulated annealing algorithms work as a local search to contribute to the search of the Particle Swarm Optimization. The number of iterations of any algorithm depends on the application, the complexity of the problem, and system conditions.

2.2.6. Comparison between algorithms

There are algorithms such as Particle Swarm Optimization and Genetic algorithms that are faster than other algorithms as the simulated annealing, but the quality of the solution of these algorithms depends on the initial solutions. Additionally, these algorithms can use large amounts of memory [32]. For this reason, this research proposes a hybrid algorithm that is composed of three strategies: The Particle Swarm Optimization, the Tabu search, and the simulated annealing algorithms. The performance of the algorithm will be compared to other mature strategies such as genetic algorithm and Particle Swarm Optimization.

Methodology of algorithm comparison

A group of benchmark functions is considered for this comparison. These functions **are non-convex and dependent on six decision variables**. The number of variables considered is related to the number of variables in the induction motor case, because five variables will be tuned. Additionally, the limits considered for each variable will be $(-200, 200)$.
There are three problems using different metaheuristic algorithms. The first algorithm is

Particle Swarm Optimization, the second one is the genetic algorithm, and finally a Hybrid between Particle Swarm Optimization, simulated annealing and Tabu Search. The results of each function are compared to select the best algorithm to use in the nonlinear problem of electric vehicles using an induction motor.

2.2.7. Cost Function

For optimization problems, there are benchmark functions. For these functions, the global minimum and the optimal location of the decision variables are well-known [14, 16, 28, 42, 54]. For the benchmark functions described in the equations (2-29), (2-30) and (2-31), D represents the dimension of the optimization problem, x_i the decision variable i, and $x^* \in \mathbf{R}^D$.

Rosenbrock function

For this function the global minimum is 0, and the optimal location of the decision variables is $x^* = \begin{bmatrix} 1 & 1 & 1 & \ldots & 1 \end{bmatrix}$. The general structure of the function is

$$f(X) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2], \tag{2-29}$$

Ackley function

For this function the global minimum is 0, and the optimal location of the decision variables is $x^* = \begin{bmatrix} 0 & 0 & 0 & \ldots & 0 \end{bmatrix}$. The general structure of the function is

$$f(X) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{D}(x_i^2)}) - \exp(\frac{1}{n}\sum_{i=1}^{D}\cos(2\pi x_i)) + 20 + e, \tag{2-30}$$

where e represents the euler constant.

Schwefel function

For this one the optimal location of the decision variables is $x^* = \begin{bmatrix} 0 & 0 & 0 & \ldots & 0 \end{bmatrix}$. The general structure of the function is

$$f(X) = 418.9829D - \sum_{i=1}^{D} x_i \sin\sqrt{|x_i|}. \tag{2-31}$$

Algorithm parameters

For finding the optimal value for the benchmark functions described in equations (2-31), (2-30) and (2-29), the parameters of each algorithm are given in table **2-1**.

Table 2-1.: Parameters of metaheuristic algorithms

Algorithm	Values
Genetic algorithm	
Number of variables for optimizing	6
Limits (Restrictions of variables)	$(-200, -200, -200, -200, -200, -200)$, $(200, 200, 200, 200, 200, 200)$
Population size	15
Max Iteration ($maxIter$)	30
Crossover probability	0.7
Mutation probability	0.1
Particle Swarm Optimization	
Number of variables for optimizing	6
Limits (Restrictions of variables)	$(-200, -200, -200, -200, -200, -200)$, $(200, 200, 200, 200, 200, 200)$
Number of particles	15
Max Iteration ($maxIter$)	30
C_1, C_2	0.7
W_{max}, W_{min}	0.9 , 0.2
Hybrid Algorithm (PSO, SA, GA)	
Number of variables for optimizing	6
Limits (Restrictions of variables)	$(-200, -200, -200, -200, -200, -200)$, $(200, 200, 200, 200, 200, 200)$
Number of particles	15
Max Iteration ($maxIter$)	30
C_1, C_2	0.7
W_{max}, W_{min}	0.9 , 0.2
Initial Temperature	10
Annealing rate	0.7
Lenght of Tabu list	10

For comparing the algorithms, it is proposed a metric whose purpose is to compare the quality of solutions. For this reason, in the first instance, it is necessary to realize the optimization process for the three algorithms using three different functions, the Rosenbrock, Schwefel, and the Ackley functions. All functions are not convex, which is a challenge for metaheuristic algorithms.

Next, it is possible to observe the results of 100 simulation samples per algorithm, in which the mean, standard deviation, best case and worst case for each algorithm are evaluated. In this case, algorithm 1 corresponds to the genetic algorithm, algorithm 2 to the particle Swarm Optimization, and the third to the hybrid algorithm.

Table 2-2.: Algorithm Comparison - Rosenbrock Function

Variable	Algorithm 1	Algorithm 2	Algorithm 3
Mean	4.4195e+08	1.5785e+05	1.7054e+05
Standard Deviation	8.3583e+08	5.0371e+05	4.6340e+05
Best case	1.9570e+04	458.2053	321.3912
Worst case	4.1665e+09	3.9497e+06	2.8956e+06

Table 2-3.: Algorithm Comparison - Ackley Function

Variable	Algorithm 1	Algorithm 2	Algorithm 3
Mean	20.3653	20.1996	19.9148
Standard Deviation	0.2714	1.2230	2.4069
Best case	18.7648	8.5561	4.8757
Worst case	20.8296	20.6342	20.7743

Table 2-4.: Algorithm Comparison - Schwefel Function

Variable	Algorithm 1	Algorithm 2	Algorithm 3
Mean	2.0155e+03	1.7478e+03	1.7457e+03
Standard Deviation	87.7186	120.8496	137.8671
Best case	1.7915e+03	1.3910e+03	1.3910e+03
Worst case	2.2157e+03	2.0354e+03	1.9982e+03

According to Tables **2-2**, **2-3**, and **2-4**, Algorithm 3 demonstrates superior performance compared to the other algorithms in both the best and worst cases among two of the three functions. This suggests the potential to achieve a global optimum due to the algorithm improvement. The Simulated annealing and Tabu search improve the performance of the Particle Swarm Optimization through the local search.

For this reason, in this thesis, the hybrid algorithm will be used to find the best solution to improve the cost of the performance criterion in electric vehicles that use the induction motor under the ADR scheme.

Thus, if the optimal control problem is considered, it is necessary to contemplate the optimization problem due to the optimal control problem is based on optimization. When the problem becomes overly complex, obtaining a deterministic optimal solution can pose a challenge. For this reason, there exist algorithms that enable us to achieve an efficient solution, taking into account the intricacies of the problem. The combination of multiple algorithms can demonstrate superior performance for the optimization problem compared to traditional algorithms. Now, a motivational example will be considered where a modified Active Disturbance Rejection control is proposed.

2.3. Motivating example

The purpose of this example is to show that regarding the active disturbance rejection scheme, it is possible to consider different approaches considering an optimization problem. In this academic example, it is possible to find that approximate linearization through the standard Active Disturbance Rejection Control is not always necessary. This affirmation depends on the cost function structure or the complexity of the problem. In the simulation results of this section, it will be considered that the disturbance rejection does not represent the optimal cost of an optimization problem, considering the deterministic problem of the Linear Quadratic Regulator cost. It is important to consider that the standard LQR design is based on a stabilization problem. This academic example gives a new control structure based on ADRC where it is considered the disturbance weighting. This approach could improve the performance taking into account a cost function of an optimization problem and the constraints of the decision variables. This motivation example proposes a new methodology where the unified disturbance is not rejected completely. Using the approach of this academic example, where it is considered a partial rejection of the disturbance, it is considered the optimization problem for electric vehicles using an induction motor.

Example

It is considered the following nonlinear system from [8]

$$\begin{gathered}\dot{x_1}(t) = \beta x_1(t), \qquad \dot{x_2}(t) = \lambda x_1^2(t) + \alpha x_2(t) + \zeta u(t) \\ \{\beta, \alpha, \zeta\} \in \mathbf{R}.\end{gathered} \tag{2-32}$$

In this case, it is possible to observe that this representation shows a nonlinear system, and if $\beta \in \mathbf{R}^-$, the state x_1 has a stable dynamic. This stable dynamic can be described by Laplace approach

$$\begin{aligned}\dot{x}_1 &= \beta x_1, \\ sX_1(s) - x_1(0) &= \beta X_1(s), \\ X_1(s) &= \frac{x_1(0)}{s-\beta},\end{aligned}$$

where the dynamic of x_1 is stable, considering the Laplace inverse transformation.

2.3.1. Variations of the motivational example

In this subsection, it will be considered $\alpha = \lambda = \zeta = 1$ and $\beta = -1$ for the example in equation (2-32), the value of β guarantees the stability of the system.

$$\begin{aligned} \dot{x}_1(t) &= -x_1(t), \\ \dot{x}_2(t) &= x_1^2(t) + x_2(t) + u(t). \end{aligned} \tag{2-33}$$

Considering the state-space representation in equation (2-33), the control law $u(t) = -kx(t)$ is proposed, where k is the control vector gains and $x(t)$ is the states vector. Then, considering the following cost function or performance criterion

$$\begin{aligned} J &= \int_{t_0}^{t_f} (x(t)^T Q x(t) + u(t)^T R u(t)) dt, \\ J &= \int_{t_0}^{t_f} (x_1(t)^2 + x_2(t)^2 + u(t)^2) dt. \end{aligned} \tag{2-34}$$

The cost in equation (2-34) represents the Linear Quadratic Regulator Cost [30, 56]. The values of Q and R for this problem are $Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $R = 1$.

Variation 1 - Space state transformation

Considering [8], the nonlinear system that was described in (2-33), can be modeled through space transformation $T : R^2 \rightarrow R^3$ considering the following substitutions $z_3(t) = x_1(t)^2$, $z_1(t) = x_1(t)$ and $z_2(t) = x_2(t)$. Thus, the space state representation of the transformation is given by

$$\begin{bmatrix} \dot{z}_1(t) \\ \dot{z}_2(t) \\ \dot{z}_3(t) \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & -2 \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \\ z_3(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} u(t). \tag{2-35}$$

Regarding the equation given in (2-35), it is possible to find an exact linearization through the space transformation. The control law, considering the performance criterion given in equation (2-34) is

$$u(t) = -kz(t) = -\begin{bmatrix} 0 & 2.41 & 0.7071 \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \\ z_3(t) \end{bmatrix},$$

$$u(t) = -2.41x_2(t) - 0.7071x_1^2(t),$$

where the expression of the control represents a nonlinear control law. However, through space transformation, it is possible to minimize the cost because exact linearization, facilitated by the space transformation, enables a linear control design using a deterministic approach.

Variation 2

In this variation of the example of equation (2-33), the Active Disturbance Rejection Approach is considered

$$\dot{x_2}(t) = x_1^2(t) + x_2(t) + u(t) \quad \equiv \quad \dot{y}(t) = \kappa u(t) + \xi(t).$$

Due to the stable dynamic of the x_1 state, it is possible to consider the state x_2 as the output of the system. In this particular case $\kappa = 1$. Then, the disturbance in this case is given by

$$\xi(t) = x_1^2(t) + x_2(t), \tag{2-36}$$

and computing the dynamics of the disturbance

$$\dot{\xi}(t) = -\xi(t) + 2x_2(t). \tag{2-37}$$

According to equation (2-37), the dynamic of the disturbance depends in a linear way on the states and on itself. Then, the space-state representation of the system is

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{\xi}(t) \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 2 & -1 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ \xi(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} u(t). \tag{2-38}$$

According to the equation (2-38), the dynamic of the disturbance allows the consideration of a linear system. Using the performance criterion of equation (2-34), the optimal control law is given by

$$u(t) = -\begin{bmatrix} 0 & 1.707 & 0.7071 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ \xi(t) \end{bmatrix},$$
$$u(t) = -1.707x_2(t) - 0.7071\xi(t),$$

Where the control law does not consider disturbance rejection, as proposed by traditional active disturbance rejection control. **This illustrates that exact rejection of the disturbance does not always lead to optimal performance.**

Variation 3

In this variation, the active disturbance rejection control will be applied to the system described in (2-33). Taking into account that the control problem is based on the stabilization problem, then, $x_1^*(t) = x_2^*(t) = 0$. Therefore, it is possible to observe

$$\dot{x_2}(t) = x_1^2(t) + x_2(t) + u(t) \equiv \dot{y}(t) = \xi(t) + \kappa u(t),$$

$$\dot{e_{x2}}(t) = x_1^2(t) + e_{x2}(t) + u(t) \equiv \dot{e}_y(t) = \xi(t) + \kappa u(t),$$

where $e_{x2}(t) = x_2(t) - x_2^*(t)$. In this approach, it is feasible to consider the disturbance $\xi(t) = x_1^2(t) + e_{x2}(t)$ and $\kappa = 1$. Considering $\xi(t)$ is constant locally under the Taylor approach for the control design, through an extended state observer, the dynamic of the system can be represented by

$$\begin{aligned}\begin{bmatrix}\dot{e_{x2}}(t)\\ \dot{\xi}(t)\end{bmatrix} &= \underbrace{\begin{bmatrix}0 & 1\\ 0 & 0\end{bmatrix}}_{A}\begin{bmatrix}e_{x2}(t)\\ \xi(t)\end{bmatrix} + \underbrace{\begin{bmatrix}1\\ 0\end{bmatrix}}_{B}u(t) + \begin{bmatrix}0\\ 1\end{bmatrix}\dot{\xi}(t),\\ \dot{e_{x2}}(t) &= \underbrace{\begin{bmatrix}1 & 0\end{bmatrix}}_{C}\begin{bmatrix}e_{x2}(t)\\ \xi(t)\end{bmatrix}.\end{aligned} \tag{2-39}$$

The structure of the extended state observer is given by the following scheme

$$A_o = A - LC, \quad B_o = \begin{bmatrix}B & L\end{bmatrix},$$

$$C_o = \begin{bmatrix}1 & 0\\ 0 & 1\end{bmatrix}, \quad D_o = 0.$$

In this case, the estimation of disturbance will be used to linearize approximately the non-linear system. Additionally, the control law is based on the stabilization of the tracking error dynamics. Then, the control law is

$$u(t) = -\hat{\xi}(t) - k_0\hat{x}_2(t).$$

Here, the dynamics of the controlled state e_{x2} are given by

$$\dot{e}_{x2}(t) = -k_0\hat{e}_{x2}(t). \tag{2-40}$$

Under the S domain and taking into account an approximate estimation, it is considered the following expression

$$(s + k_0)x_2 = 0, \tag{2-41}$$

where k_0 guarantees stability of system.

Variation 4

In this variation, the system considered is the same

$$\begin{aligned}\dot{x_1}(t) &= -x_1(t),\\ \dot{x_2}(t) &= x_1^2(t) + x_2(t) + u(t),\end{aligned} \tag{2-42}$$

but in this case the reference of the output or the state $x_2(t)$ is given by $x_2^*(t) = \mu(t)$, where $\mu(t)$ is the unit step function

$$\mu(t) = \begin{cases} 0 \quad , \quad t < 0 \\ \\ 1 \quad , \quad t \geq 0. \end{cases} \tag{2-43}$$

In this variation, the vector of optimal gains given in Variation 2 is considered

$$k = -\begin{bmatrix} 0 & 1.707 & 0.7071 \end{bmatrix}.$$

For this variation, the tracking error will be analyzed. For this reason, it is necessary to observe the stationary state response

$$\dot{x_2}(t) = x_1^2(t) + x_2(t) - 1.707x_2(t) - 0.7071\hat{\xi}(t),$$
$$\dot{x_2}(t) = \xi(t) - 1.707x_2(t) - 0.7071\hat{\xi}(t).$$

However, in this case the reference is not equal to zero, for this reason

$$\dot{x_2}(t) = x_1^2(t) + x_2(t) + u(t),$$
$$\dot{x_2}(t) - \dot{x_2^*}(t) = x_1^2(t) + x_2(t) + u(t) - \dot{x_2^*}(t) - x_2^*(t) + x_2^*(t).$$

In $t = [t_0, t_f]$, without considering the initial condition of the states of the representation, the dynamic of the of the error of the state x_2 can be given by

$$\dot{e_{x2}}(t) = x_1^2(t) + e_{x2}(t) + 1 + u(t).$$

Thus,

$$\dot{e_{x2}}(t) = x_1^2(t) + e_{x2}(t) + 1 - 1.707x_2(t) - 0.7071\hat{\xi}(t),$$
$$\dot{e_{x2}}(t) = \xi(t) - 1.707e_{x2}(t) - 0.7071\hat{\xi}(t),$$
$$\dot{e_{x2}}(t) = \xi(t) - 1.707e_{x2}(t) - 0.7071\hat{\xi}(t).$$

Using a Laplace transformation or the S domain analysis

$$se_{x2} - e_{x2}(0) = 0.303x_1^2 + 0.303e_{x2} + \frac{0.303}{s} - 1.707e_{x2},$$

$$(s + 1.404)e_{x2} = 0.303x_1^2 + \frac{0.303}{s}.$$

Then, the response in stationary state of error is

$$\lim_{t \to \infty} e_{x2}(t) \neq 0.$$

2.3.2. Simulation Stabilization case

After simulations using ADRC estimation and initial conditions for each one of the states

$$x_1(0) = x_2(0) = 2, \quad k_0 = 1.6459(\text{Equation (2-40)}).^*$$

The results are

Table 2-5.: Results stabilization case - Motivating example

Function cost (J)	Variation 1	Variation 2	Variation 3
$J = \int_0^{100}(x_1^2 + x_2^2 + u^2)dt$	26.63	26.63	40.81

*:*The eigenvalues of the observation matrix are situated at* -10 *(ESO design), and the value of* k_0 *is determined by an optimization algorithm.*

The ADRC results show lower performance than the optimal cost given by the first and the second variations. This result is given by variation 2, this variation supposes that the disturbance is not rejected completely for reaching the minimum cost, while the ADR considers the disturbance rejection.

2.3.3. Conclusion of the motivation example variations

Taking into account the simulation results and the deterministic development through the cost of the linear quadratic regulator, it is possible to conclude that depending on the cost function in an optimization problem, the rejection of the disturbance given in the traditional ADR scheme is not always possible. Disturbance weighting could represent the best solution. However, disturbance weighting implies a compromise in tracking error reduction under a disturbance monitoring and rejection scheme, as the final value of the error differs from zero despite having stable dynamics.
Additionally, it is possible to observe that different substitutions of the nonlinear dynamics through a space transformation, allow us to reach equivalent results for the original nonlinear system. Despite the disturbance weighting can show a better performance than the

traditional ADRC, considering a cost function with restrictions, this new approach increases the complexity of the system because if the control law does not reject the disturbance, it is considered a nonlinear control problem. Furthermore, disturbance weighting should guarantee the stability of the system. For this reason, the value of the disturbance weighting will be closer to 1, generating the constraints of the decision variables. Concluding that disturbance weighting can improve the cost value of a performance criterion but increase the complexity of the control problem. Thus, the control strategy for this research is given in Figure **2-3**.

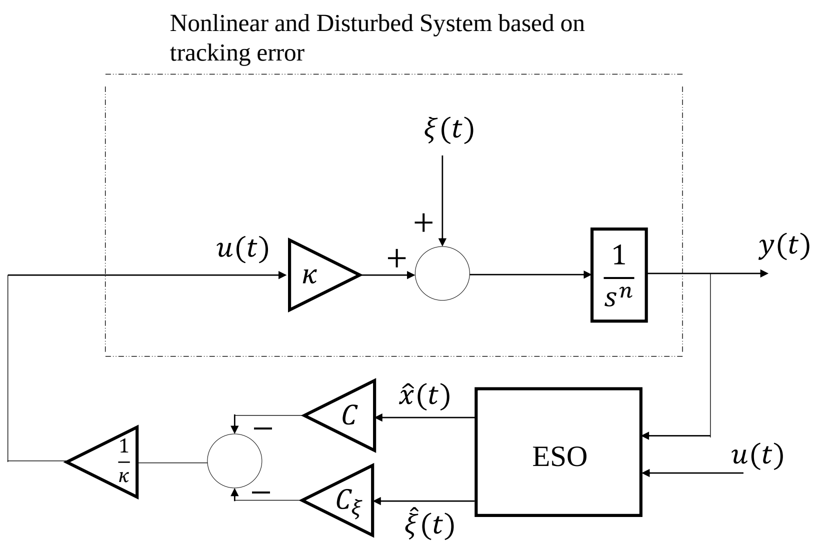


Figure 2-3.: Control strategy proposed

In Figure **2-3**, C represents the control law parameters based on the states of the system taking into account the tracking error, and C_ξ is the disturbance weighting parameter, in this research the objective is to find the values of C and C_ξ considering the hybrid algorithm described in this chapter.

3. Induction motor control under vehicle dynamics

This chapter discusses the dynamics of induction motors and electric vehicles. For the induction motor, the Clarke transformation is considered. Considering the two-phase transformation, the Field-Oriented scheme is described, because this scheme is widely used in the control of electrical machines [15, 18, 56]. Under the FOC scheme, a control strategy based on the active disturbance rejection approach is proposed to estimate the disturbance and error signals. For the control law, two control strategies are proposed taking into account the motivational example of Chapter 2. The first control strategy is based on disturbance rejection and a control based on feedback of the error states, the second strategy considers a disturbance weighting that allows another degree of freedom to be considered. However, this strategy should have restrictions because a nonlinear control problem is considered. Taking into account what was described above, three optimization problems are proposed, comparing disturbance rejection and disturbance weighting, under the hybrid algorithm described in Chapter 2 and an offline simulation, the optimal values are found.

3.1. Vehicle Dynamics

According to [24], [41], and [39], based on the dynamics of the vehicle, it is feasible to consider the energy for the vehicle's functioning. Then, it is possible to consider the road load that is given by several forces that have a relationship with the vehicle characteristics and/or the environmental conditions. In Figure **3-1**, it is possible to find the forces that are applied to a vehicle.

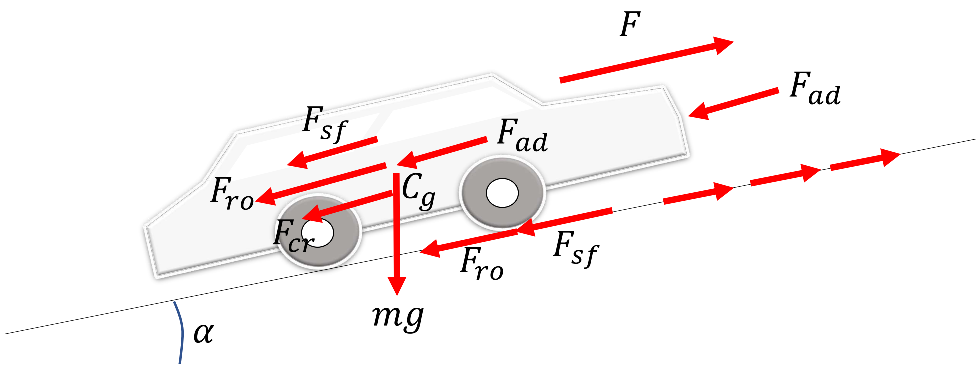


Figure 3-1.: Vehicle Scheme

The road Load under positive speed conditions is based on

$$F_\omega = F_{\textbf{Rolling resistance}} + F_{\textbf{Aerodynamic drag}} + F_{\textbf{Climbing resistance}} + F_{\textbf{sf}}, \tag{3-1}$$

where $F_{\textbf{Rolling resistance}}$ pertains to the resistance force that arises when the vehicle's wheel contacts the road, and its mathematical expression is given by

$$F_{\textbf{Rolling resistance}} = \Omega m g \cos(\alpha), \tag{3-2}$$

where m represents the mass of the vehicle, g is the gravity, and α is the angle of the slope of the road, while Ω is a nonlinear variable that depends on the speed, and the type and the pressure of the tire.

$$F_{\textbf{Aerodynamic drag}} = \frac{1}{2}\phi C_\omega A_f (v + v_0). \tag{3-3}$$

Equation (3-3) represents the aerodynamic drag that shows the influence of the air in the vehicle. A_f is the frontal area of the vehicle, v and v_0 are the speed of the vehicle and the headwind velocity, respectively. While, ϕ is the air density and C_ω is the aerodynamic drag coefficient.

For the climbing resistance expression there are two possibilities. It can be a downgrade force or climbing resistance, depending on the sign of the expression of equation (3-4).

$$F_{\textbf{Climbing resistance}} = \pm \text{ m g } \sin(\alpha). \tag{3-4}$$

Another force can be described in equation (3-5), but this force can be ignored taking into account the $F_{\textbf{Rolling resistance}}$.

$$F_{\mathbf{sf}} = k_A v. \tag{3-5}$$

In equation (3-5), k_A represents the Stokes' coefficient.
Using those forces and [39], the total torque of the motor can be given by

$$\tau_L(t) = \tau_{fL}(t) + \frac{R_\omega}{G_r}\tau_{TL}(t), \tag{3-6}$$

where $\tau_{fL}(t)$ is the friction torque of the motor shaft, R_ω is the radius of the wheel, G_r is the transmission radio, and τ_{TL} is the simplified torque related to the associated all-wheel drive. Regarding the dynamics of the motor, it is possible to define the following expression

$$J_{EV} + \frac{d\omega(t)}{dt} = \tau_e(t) - \tau_L(t), \tag{3-7}$$

where $\tau_e(t)$ is the motor torque and J_{EV} is the total inertia of the motor which can be described by

$$J_{EV} = J + \frac{1}{2}(\frac{R_\omega}{G_r})^2 m_\omega + \frac{1}{2}(\frac{R_\omega}{G_r})^2 m(1 - s_\omega), \tag{3-8}$$

where m and m_ω are the masses of the vehicle and the wheel, respectively. s_ω is the wheel slippage, and J is the inertia of the motor.

3.1.1. Induction motor

The induction motor is an electric machine that is possible to use in electric vehicles [61]. This machine has many types , for example, one of the most important configurations is the three-phase motor. There are two types of three-phase induction motors: the squirrel cage structure and the wound rotor structure [48]. One of the techniques that it is possible to use for controlling an induction motor is the FOC scheme [27, 56]. According to [15], a three-phase induction motor can be analyzed under a two-phase scheme through Clarke's transformation, where it is possible to consider a three to two-phase transformation.

Field Oriented Scheme (FOC)

Taking into account the two-phase transformation for the induction motor, it can be considered the following scheme under the Park transformation [15],

$$\begin{bmatrix} v_d(t) \\ v_q(t) \end{bmatrix} = \begin{bmatrix} \cos(\rho(t)) & \sin(\rho(t)) \\ -\sin(\rho(t)) & \cos(\rho(t)) \end{bmatrix} \begin{bmatrix} v_a(t) \\ v_b(t) \end{bmatrix}, \tag{3-9}$$

where v can represent the currents, the voltages or magnetic fluxes, considering the representation

$$\rho = \tan^{-1}(\frac{\psi_{Rb}}{\psi_{Ra}}), \tag{3-10}$$

$$\psi_d(t) = \sqrt{\psi_{Ra}(t)^2 + \psi_{Rb}(t)^2}. \tag{3-11}$$

Using the transformation d/q described in equation (3-9) to the two-phase transformation, it is possible to consider the dynamics of the induction motor under the FOC scheme

$$\frac{d\theta(t)}{dt} = \omega(t), \tag{3-12}$$

$$\frac{d\omega(t)}{dt} = \mu\psi_d(t)i_q(t) - \frac{1}{J_{EV}}\tau_L, \tag{3-13}$$

$$\frac{d\psi_d(t)}{dt} = -\eta\psi_d(t) + \eta M i_d(t), \tag{3-14}$$

$$\frac{di_d(t)}{dt} = -\gamma i_d(t) + \frac{\eta M}{\sigma L_R L_S}\psi_d(t) + n_p\omega(t)i_q(t) + \eta M\frac{i_q(t)^2}{\psi_d(t)} + \frac{1}{\sigma L_s}u_d(t), \tag{3-15}$$

$$\frac{di_q(t)}{dt} = -\gamma i_q(t) - \frac{n_p M}{\sigma L_R L_S}\omega(t)\psi_d(t) - n_p\omega(t)i_d(t) - \eta M\frac{i_q(t)i_d(t)}{\psi_d(t)} + \frac{1}{\sigma L_s}u_q(t), \tag{3-16}$$

$$\frac{d\rho(t)}{dt} = n_p\omega(t) + \eta M\frac{i_d(t)}{\psi_d(t)}, \tag{3-17}$$

where,

$$\eta = \frac{R_R}{L_R} \quad, \beta = \frac{M}{\sigma L_R L_S} \quad, \gamma = \frac{M^2 R_R}{\sigma L_R^2 L_s} + \frac{R_S}{\sigma L_S}, \quad \sigma = 1 - \frac{M^2}{L_R L_S}.$$

Under the FOC scheme, it is possible to conclude that the Field-Oriented Control scheme shows a decoupling with respect to the magnitude of the rotor flux by means of the direct current. Additionally, a decoupled control design can be considered for three variables, where the direct current is controlled by the voltage u_d, the quadrature current by the voltage u_q, and the speed is controlled by the quadrature current [15].

Optimal Field Weakening

According to the [15], the Field weakening is a product of the purpose of obtaining a higher speed without violating the restriction of voltages and currents. For considering a reference of direct current, it is necessary to consider the torque

$$\tau = \frac{n_p M^2}{L_R} i_d i_q = \frac{n_p M}{L_R} \psi_d i_q. \tag{3-18}$$

In this case, the constraint of the problem is given by

$$i_d^2 + i_q^2 = I^2 \leq I_{max}^2, \tag{3-19}$$

and defining $\delta = \frac{i_q}{i_d}$, the expression of the torque is

$$\tau = \frac{n_p M^2}{L_R^2} I^2 \frac{\delta}{1+\delta}. \tag{3-20}$$

Using the equation (3-20) the maximum torque requires that $I = I_{max}$, and solving the convex optimization problem $\delta = 1$. Thus, the reference of the direct current is given by

$$i_d^* = \frac{I_{max}}{\sqrt{2}}$$

Control of an induction motor under FOC scheme

The general scheme of the control of the induction motor using the FOC scheme is given by Figure **3-2**.

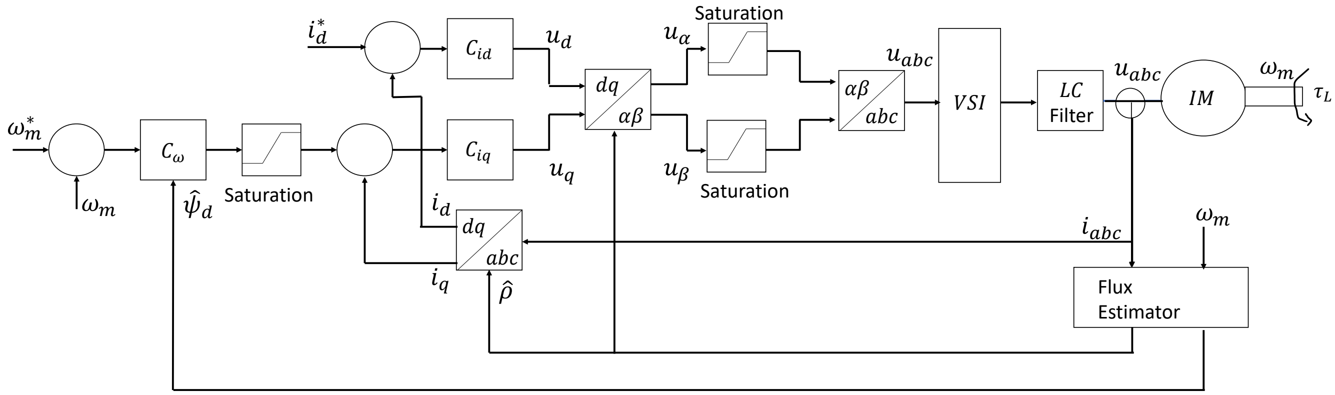


Figure 3-2.: Control under Field Oriented scheme - Induction motor

The induction motor under the Field-oriented scheme needs three controllers, two for the currents and one for the angular velocity of the system [27, 33]. Additionally, it is necessary to consider a flux estimator through the implementation of the dynamics given in equations (3-14) and (3-17). Going into detail in Figure **3-2**, the controller C_{id} is considered, whose objective is to control the dynamics of the direct current where its behavior is in the equation (3-15). The controller C_{iq} seeks to control the dynamic of the quadrature current where its behavior is described in equation (3-16). Finally, the last controller is C_ω, the objective of this controller is to control the dynamics of the angular speed described in equation (3-13). These controllers can be designed based on an Extended State Observer.

Active Disturbance Rejection Control in Induction Motor

For the control of the induction motor, the three controlled variables are ω, i_q and i_d, considering the equations (3-13),(3-15) and (3-16). Their dynamics have the structure

$$\dot{y}(t) = \kappa u(t) + \xi(t), \tag{3-21}$$

where $y(t)$ is the output, $u(t)$ is the control signal, κ is an average value and $\xi(t)$ is the unified disturbance. Additionally, in equation (3-21), it is viable to subtract the reference of the derivative of $y(t)$ to leave the equation in terms of the tracking error $e_y(t)$.

$$\dot{e}_y(t) = \kappa u(t) + \xi_1(t), \quad \xi_1(t) = \xi(t) - \dot{y}^*(t), \tag{3-22}$$

where $\xi_1(t)$ considers the derivative of the reference, but this reference can be considered as an external disturbance. For this control problem, it will be considered an intern model that corresponds to approximately a constant signal for the Extended State Observer design, then it is only considered one extended state for implementing an Extended State Observer. Thus, the design for each variable is given by

$$x_1(t) = e_y(t), \tag{3-23}$$

$$x_2(t) = \xi_1(t). \tag{3-24}$$

Therefore, the space-state representation of the dynamics of the system is given by

$$\begin{bmatrix} \dot{x_1}(t) \\ \dot{x_2}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} \kappa \\ 0 \end{bmatrix} u(t) + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \dot{\xi}(t), \tag{3-25}$$

$$x_1(t) = e_y(t) = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}. \tag{3-26}$$

The control law using the ADR scheme is given by a feedback state control that can be described in equation (3-27)

$$u(t) = \frac{1}{\kappa}(-k_0 \hat{e_y}(t) - k_1 \hat{\xi}(t)), \tag{3-27}$$

where $\hat{e_y}(t)$ and $\hat{\xi}(t)$ are good approximations. The traditional ADRC considers $k_1 = 1$ to linearize approximately the nonlinear system and consider the dynamic of the tracking error

$$\begin{aligned} \dot{e}_y(t) &= \kappa u + \xi(t), \\ \dot{e}_y(t) = \kappa(\frac{1}{\kappa}&(-k_0 \hat{e_y}(t) - \hat{\xi}(t))) + \xi(t), \end{aligned} \tag{3-28}$$

simplifying equation (3-28) under the linear approximation,

$$\dot{e}_y(t) = -k_0 \hat{e_y}(t). \tag{3-29}$$

Using the Laplace transformation in equation (3-29), it is possible to consider the dynamic of the tracking error

$$(s + k_0) e_y = 0, \tag{3-30}$$

where $k_0 > 0$ in equation (3-30) to guarantee the stability of the system. Thus, considering the standard ADR approach, a good estimation of the disturbance and the equations of the dynamics of the induction motor under the intern model considered, it is possible to contemplate the following simplification of the dynamic equations, taking into account the controlled variables

$$\frac{d\omega(t)}{dt} = \mu\psi_d(t)i_q(t) + \xi_w(t), \tag{3-31}$$

$$\frac{di_d(t)}{dt} = \frac{1}{\sigma L_s}u_d(t) + \xi_{id}(t), \tag{3-32}$$

$$\frac{di_q(t)}{dt} = \frac{1}{\sigma L_s}u_q(t) + \xi_{iq}(t). \tag{3-33}$$

The ADR can estimate $\xi_{iq}(t)$, $\xi_{id}(t)$ and $\xi_\omega(t)$, then through a feedback linearization, it is possible to consider the linear approximation of the system that is possible to observe in equations (3-34) , (3-35) and (3-36).

$$\frac{de_{i_d(t)}}{dt} \approx \frac{1}{\sigma L_s}u_d(t), \tag{3-34}$$

$$\frac{de_{i_q(t)}}{dt} \approx \frac{1}{\sigma L_s}u_q(t), \tag{3-35}$$

$$\frac{de_{\omega(t)}}{dt} \approx \mu\psi_d(t)i_q(t). \tag{3-36}$$

The equations are based on the tracking error to consider a stabilization problem. Additionally, the scheme of the linear approximation of the system is given by

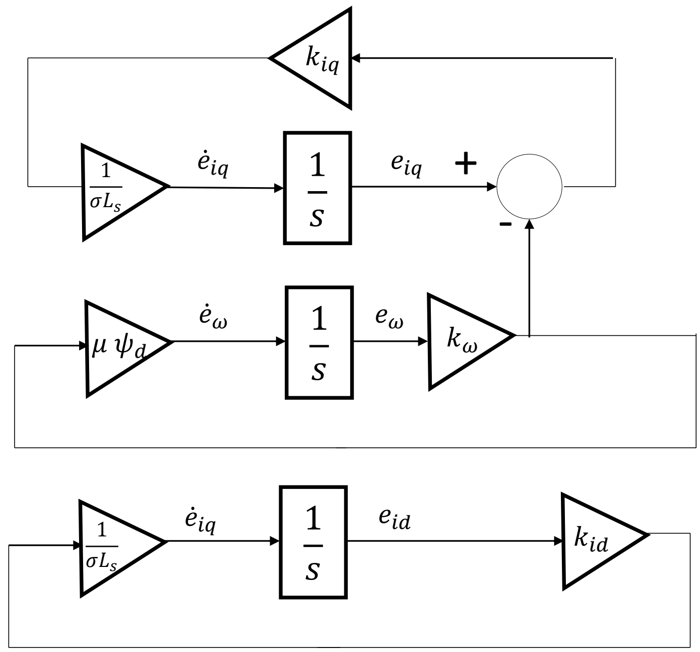


Figure 3-3.: Linear approximation of the induction motor under Active Disturbance Rejection approach

Figure **3-3** shows that is possible to simplify the complexity of the problem using the linear approximation taking into account the disturbance rejection considering a good estimation of the unified disturbance. This approximation allows to design of a control strategy based on the tracking error of a linear system. In the case of the standard Active Disturbance Rejection where the disturbance is rejected, it is possible to observe that the values of k_{iq}, k_{id} and k_ω should guarantee the stability of the system.

3.1.2. Disturbance Weighting in the induction motor

However, according to the motivational example, the value of k_1 in equation (3-27) is not always equal to 1, the value of k_1 depends on the complexity of the optimization problem. Then it is possible to consider

$$\begin{aligned}\frac{de_\omega(t)}{dt} = \mu\psi_d(t)(\frac{1}{\mu\psi_d(t)}(-k_\omega\hat{e}_\omega(t) - k_{\xi\omega}\hat{\xi}_\omega)) + \xi_\omega(t),\\ \frac{de_\omega(t)}{dt} + k_\omega\hat{e}_\omega(t) = \xi_\omega(t) - k_{\xi\omega}\hat{\xi}_\omega(t).\end{aligned} \tag{3-37}$$

Considering that there is not an exact linearization, it is necessary to define

$$e_\omega(t) = \hat{e}_\omega(t) + \Delta e_\omega(t), \quad \hat{e}_\omega(t) = e_\omega(t) - \Delta e_\omega(t),$$
$$\xi_\omega(t) = \hat{\xi}_\omega(t) + \Delta \xi_\omega(t), \quad \hat{\xi}_\omega(t) = \xi_\omega(t) - \Delta \xi_\omega(t),$$

where $\Delta e_\omega(t)$ and $\Delta \xi_\omega(t)$ represent the estimation error of the tracking error and the disturbance, respectively. Then, it is possible to consider

$$\begin{aligned} \frac{de_\omega(t)}{dt} + k_\omega e_\omega(t) - k_\omega \Delta e_\omega(t) &= \xi_\omega(t) - k_{\xi\omega}\xi_\omega(t) + k_{\xi\omega}\Delta\xi_\omega(t), \\ (s + k_\omega)e_\omega &= (1 - k_{\xi\omega})\xi_\omega + k_\omega \Delta e_\omega + k_{\xi\omega}\Delta\xi_\omega. \end{aligned} \tag{3-38}$$

Equation (3-38) shows that the dynamic of the tracking error is based on the error of estimation and the value of $k_{\xi\omega}$. If it is considered a good approximation, where $\Delta e_\omega \approx 0$ and $\Delta\xi_\omega \approx 0$, the dynamic of the tracking error will depend principally on the value of $k_{\xi\omega}$. In a similar way for currents it is possible to observe

$$\begin{aligned} \frac{de_{id}(t)}{dt} &= \frac{1}{\sigma L_s}(\sigma L_s(-k_{id}\hat{e}_{id}(t) - k_{\xi id}\hat{\xi}_{id})) + \xi_{id}(t), \\ \frac{de_{id}(t)}{dt} + k_{id}\hat{e}_{id}(t) &= \xi_{id}(t) - k_{\xi id}\hat{\xi}_{id}(t). \end{aligned} \tag{3-39}$$

Defining

$$e_{id}(t) = \hat{e}_{id}(t) + \Delta e_{id}(t), \quad \hat{e}_{id}(t) = e_{id}(t) - \Delta e_{id}(t),$$
$$\xi_{id}(t) = \hat{\xi}_{id}(t) + \Delta \xi_{id}(t), \quad \hat{\xi}_{id}(t) = \xi_{id}(t) - \Delta \xi_{id}(t),$$

where $\Delta e_{id}(t)$ and $\Delta\xi_{id}(t)$ represent the estimation error of the tracking error and the disturbance according to the direct current. Thus,

$$\begin{aligned} \frac{de_{id}(t)}{dt} + k_{id}e_{id}(t) - k_{id}\Delta e_{id}(t) &= \xi_{id}(t) - k_{\xi id}\xi_{id}(t) + k_{\xi id}\Delta\xi_{id}(t), \\ (s + k_{id})e_{id} &= (1 - k_{\xi id})\xi_{id} + k_{id}\Delta e_{id} + k_{\xi id}\Delta\xi_{id}. \end{aligned} \tag{3-40}$$

Equation (3-40) shows that if $\Delta e_{id} \approx 0$ and $\Delta\xi_{id} \approx 0$, the dynamic of the error depends principally on the parameter $k_{\xi id}$. Finally, for the quadrature current, it is possible to consider

$$\begin{aligned} \frac{de_{iq}(t)}{dt} &= \frac{1}{\sigma L_s}(\sigma L_s(-k_{iq}\hat{e}_{iq}(t) - k_{\xi iq}\hat{\xi}_{iq})) + \xi_{iq}(t), \\ \frac{de_{iq}(t)}{dt} + k_{iq}\hat{e}_{iq}(t) &= \xi_{iq}(t) - k_{\xi iq}\hat{\xi}_{iq}(t). \end{aligned} \tag{3-41}$$

Defining

$$e_{iq}(t) = \hat{e}_{iq}(t) + \Delta e_{iq}(t), \quad \hat{e}_{iq}(t) = e_{iq}(t) - \Delta e_{iq}(t),$$
$$\xi_{iq}(t) = \hat{\xi}_{iq}(t) + \Delta \xi_{iq}(t), \quad \hat{\xi}_{iq}(t) = \xi_{iq}(t) - \Delta \xi_{iq}(t),$$

where $\Delta e_{iq}(t)$ and $\Delta \xi_{iq}(t)$ represent the estimation error of the tracking error and the disturbance according to the quadrature current. Thus,

$$\begin{aligned} \frac{de_{iq}(t)}{dt} + k_{iq}e_{iq}(t) - k_{iq}\Delta e_{iq}(t) &= \xi_{iq}(t) - k_{\xi iq}\xi_{iq}(t) + k_{\xi iq}\Delta\xi_{iq}(t), \\ (s + k_{iq})e_{iq} &= (1 - k_{\xi iq})\xi_{iq} + k_{iq}\Delta e_{iq} + k_{\xi iq}\Delta\xi_{iq}. \end{aligned} \tag{3-42}$$

In equation (3-42), it is possible to conclude that if $\Delta e_{iq} \approx 0$ and $\Delta\xi_{iq} \approx 0$ due to a good approximation is considered, the dynamic of the error will be based on the parameter $k_{\xi id}$. The equations (3-40), (3-42), and (3-38) show that it does not exist a rejection of the disturbance but it is assumed a good approximation of the estimation, the dynamic of the error can be stable, but the weighting of the unified disturbance can produce an increasing in a complexity of the problem because the system continues to be a nonlinear system and the control strategy depends on the model and the variations of the system can be unknown then they are not considered. For this research on the induction motor case, to avoid many problems with respect to the variations of the parameters and nonlinear conditions

$$k_{\xi\omega} = 1, \tag{3-43}$$

for equation (3-38).

Electric Vehicles have a dynamic related to the environmental conditions and their structure, this dynamic can be applied to the induction motor. The induction motor is one of the machines that is possible to use in electric vehicles, and using the FOC scheme, it is possible to design three controllers based on Extended State Observers. Under the ADR approach, two control strategies can be considered, the first one is based on disturbance rejection and an approximate linearization, and the second one is based on disturbance weighting taking into account the motivational example described in Chapter 2. The disturbance weighting case shows that the weighting parameter can handle tracking error dynamics, for this reason, this value should be close to 1. Additionally, the disturbance weighting increases the complexity of the problem due to the control design is based on a nonlinear system. Finally, for the tracking of the reference, the disturbance rejection of the angular speed variable is considered. Now, it is important how the disturbance weighting can be related to the optimization problem and compared to the traditional Active Disturbance Rejection scheme.

3.2. Optimization problem - Induction motor case

In this section, it is possible to consider an optimization problem for the induction motor under the dynamics of an electric vehicle, then the simulations are proposed considering cost functions that take into account the settling time, the tracking error, and the power used. Additionally, those simulations are elaborated using the hybrid algorithm described in Chapter 2. Three optimization problems are considered with the purpose of comparing the disturbance weighting and the disturbance rejection cases. The reference considered for these problems is based on the acceleration and deceleration processes.

Cost Function for electric vehicles using a FOC scheme in induction motor

Taking into account what was mentioned above, the induction motor has intrinsic losses, and for this reason, it is necessary to improve its performance. However, the ideal performance of the induction motor does not only consider energy use. For this work, there are three components for consideration in the performance criterion, the objective is tuning the parameters of the controller and the weighting of the disturbance. Additionally, three performance criteria will be considered, the comparison of the disturbance weighting and the disturbance rejection, and the tuning only of the parameters of the weighting of the disturbance. For all optimization problems

$$\{K_1, K_2, K_3\} \in \mathbf{R}.$$

Considerations for the performance criterion of optimization problems

In the first instance, it is necessary to define

$$t_{sc} = |e_w(t)|t, \quad t \geq 0, \tag{3-44}$$

where $e_w = \omega - \omega^*$ and t is the execution or work time, this part of the criterion is based on obtaining a value proportional to the tracking error and will be weighted taking into account the execution time. Therefore, it is possible to consider a relationship between the error and the settling time in this part of the criterion.

$$P = |v_\alpha(t)i_\alpha(t)| + |v_\beta(t)i_\beta(t)|, \tag{3-45}$$

where $u_{\alpha/\beta}$ and $i_{\alpha/\beta}$ are the two-phase voltages and currents, respectively. This part has a relationship with the voltage and current that will be applied to the motor, for this reason it is important to consider the minimum value of the voltage considering the tracking error.

$$e = |e_w(t)|. \tag{3-46}$$

Additionally , it is necessary to consider the tracking error of the angular speed, while the voltage and current component in equation (3-45) seeks to minimize the multiplication of the voltage and current used in the motor, the settling time component in equation (3-44) seeks to minimize the time in which the system settles. Thus , it is necessary to minimize the tracking error independently in order to reach the reference in terms of speed.

First optimization problem

The first optimization problem is given by

$$J = \int_{t_0}^{t_f} (K_1 P + K_2 e + K_3 t_{sc}) \quad dt. \tag{3-47}$$

S.t

$$60 \leq k_\omega \leq 300,$$
$$60 \leq k_{id} \leq 300,$$
$$60 \leq k_{iq} \leq 300.$$

The objective of the first problem is to tuning the parameters of the control law k_{iq}, k_{id} and k_ω to guarantee the stability. The disturbance weighting is not considered.

$$k_{\xi iq} = k_{\xi id} = k_{\xi\omega} = 1.$$

In equation (3-47), the constraints of the decision variables have a relationship with the operating conditions and stability due to the values of decision variables have to be greater than zero to guarantee stability. Thus, in this case, disturbance rejection is implemented as traditional Active Disturbance Rejection Control. The objective of this optimization problem is to tune the controller parameters considering prescribed eigenvalues of the observer matrix associated with an Extended State Observer (ESO) design.

Second optimization problem

The second optimization problem is given by

$$J = \int_{t_0}^{t_f} (K_1 P + K_2 e + K_3 t_{sc}) \quad dt. \tag{3-48}$$

S.t

$$60 \leq k_{\omega} \leq 300,$$

$$60 \leq k_{id} \leq 300,$$

$$60 \leq k_{iq} \leq 300,$$

$$0.990 \leq k_{\xi iq} \leq 1.1,$$

$$0.990 \leq k_{\xi id} \leq 1.1.$$

The second problem considers the tuning of the parameters of the control law (k_{iq}, k_{id} and $k_{i\omega}$) and the weighting of the disturbance of the currents. The constraints associated with $k_{\xi iq}$ and $k_{\xi id}$ are related to the analysis described in Appendix D, where stable cases are considered. Additionally, the disturbance rejection of the angular speed is considered

$$k_{\xi iq} \neq k_{\xi id} \neq 1,$$

$$k_{\xi\omega} = 1.$$

In equation (3-48), to improve the performance and for reducing the complexity of the problem, it is considered $k_{\xi\omega} = 1$. Additionally, this assumption is considered due to the uncertainty of the real system can be higher under an implementation considering a parameter change taking into account the operation conditions. However, this problem considers greater complexity than the first optimization problem, because there are five decision variables in the problem.

Finally, the objective of this problem is to show that the disturbance weighting can show a better performance than the traditional Active Disturbance Rejection scheme described in equation (3-47).

Third optimization problem

The third optimization problem is given by

$$J = \int_{t_0}^{t_f} \left(K_1 P + K_2 e + K_3 t_{sc}\right) \quad dt. \tag{3-49}$$

S.t

$$0.9905 \leq k_{\xi id} \leq 1.08,$$

$$0.9905 \leq k_{\xi iq} \leq 1.08,$$

$$k_{\xi\omega} = 1.$$

The third problem is based on optimizing only the weighting of the disturbance of the direct and quadrature currents. The constraints associated with disturbance weighting have a relationship with the real implementation and the analysis described in the Appendix D, where stable cases are considered. The control law is given for arbitrary values that allow the tracking of the angular speed reference considering the disturbance rejection

$$k_\omega = 285,$$

$$k_{id} = 300,$$

$$k_{iq} = 300.$$

The objective of this optimization problem is to show that the disturbance rejection does not represent the best scenario taking into account the performance required in a cost function with restrictions.

Finally , in equations (3-47), (3-48) and (3-49) the constants K_1, K_2, and K_3, are the weightings for considering the importance and the magnitudes of each component of the criterion. In conclusion, in the equation (3-47), it is considered the standard ADRC, where the disturbance is rejected. Whereas, in the performance of the equation (3-48), it is considered a disturbance weighting for the direct and the quadrature currents, the disturbance weighting of the angular speed is not considered due to the performance of the motor operation. The minimum and maximum values of the decision variables are given by conditions of the operating system. The cost in equation (3-49) seeks to find the optimal value of the disturbance weighting with the objective that these parameters can improve the performance of the controller.

Proposed control scheme

For the finding of the optimal value for any optimization problem, it will be considered an offline simulation that uses the hybrid algorithm that is described in Chapter 2 and the dynamics of the induction motor under FOC scheme. Depending on the optimization problem the algorithm will return different values of the parameters. The scheme of the tuning of the parameters for the optimization problems is given by Figure **3-4**.

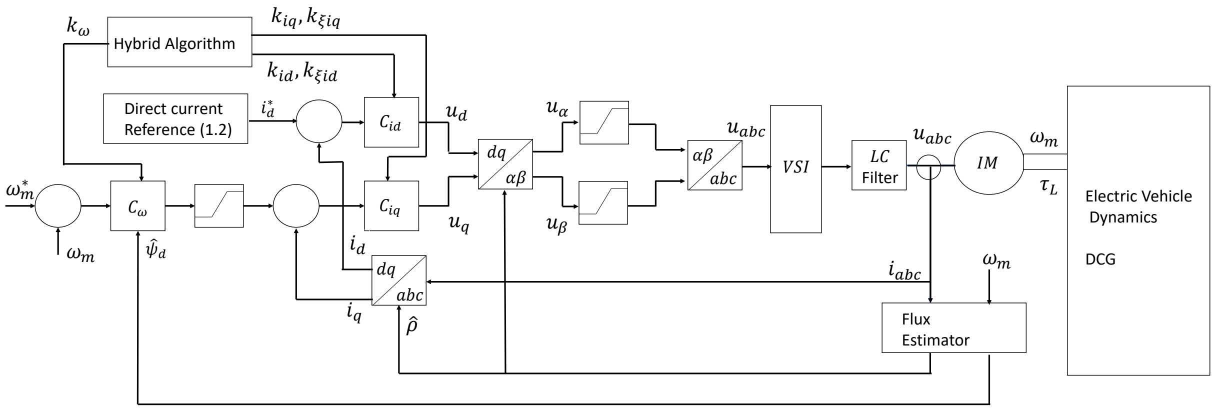


Figure 3-4.: Proposed control scheme - Offline simulation

Thus, according to Figure **3-4**, it is possible to consider three options: The disturbance rejection taking into account the cost and restrictions given by the function of the equation (3-47). The second option considers the weighting of the disturbance as in the motivational example, in this case, it is considered the cost of the equation (3-48), and finally the third option where it is only considered the tuning of the weighting of the disturbance under fixed controller parameters. Additionally, for all optimization problems, it is considered the hybrid algorithm described in Figure **2-2** under the parameters described in Appendix C, depending on each optimization problem.

3.2.1. Simulation results

In this subsection, it is possible to find three offline optimization cases. The first one is based on the comparison of two control strategies, the standard Active disturbance Rejection Control and a nonlinear control strategy based on active disturbance rejection, but the rejection of the disturbance is weighted. For the second case, it is considered the disturbance weighting, but the weights of the cost function in equation (3-48) change. Finally, the third case is based on selecting arbitrary parameters of the control law and comparing the results with the same control law but using a tuning of the weighting disturbance for the quadrature and direct currents. In all cases, the weight of the speed disturbance is equal to 1 to improve the performance.

Experiment conditions

For the experiment, the following conditions are considered

- *For the experiment of this research, the slope of the system is not considered and the dynamics are modeled by a motor DC, where the purpose is to model the reference* *of the current of this machine for describing the torque. Thus, climbing force is not considered $\alpha = 0$ in Figure **3-1** (the angle of the slope of the road is not considered) and, F_{sf} is not considered (Equation (3-5)).*

- *For the ESO design in the induction motor, the eigenvalues associated with the currents are located at -650 and the eigenvalues for the speed are located at -610.*
- *The reference of the direct current is a constant value $i_d^*(t) = 1.2[A]$.*

Consideration of Reference for parameter tuning - First and third optimization case

The reference for the optimization problem for cases one and three is given for a signal given in Figure **3-5**. The form of the angular speed reference is based on a section of the Urban Dynamometer Driving Schedule (UDDS) that allows us to evaluate the performance of the vehicle under urban conditions [21, 23]. The cycle in this section is not considered completely. However, the section considered is based on acceleration and deceleration processes, where it is possible to consider high and low speeds.

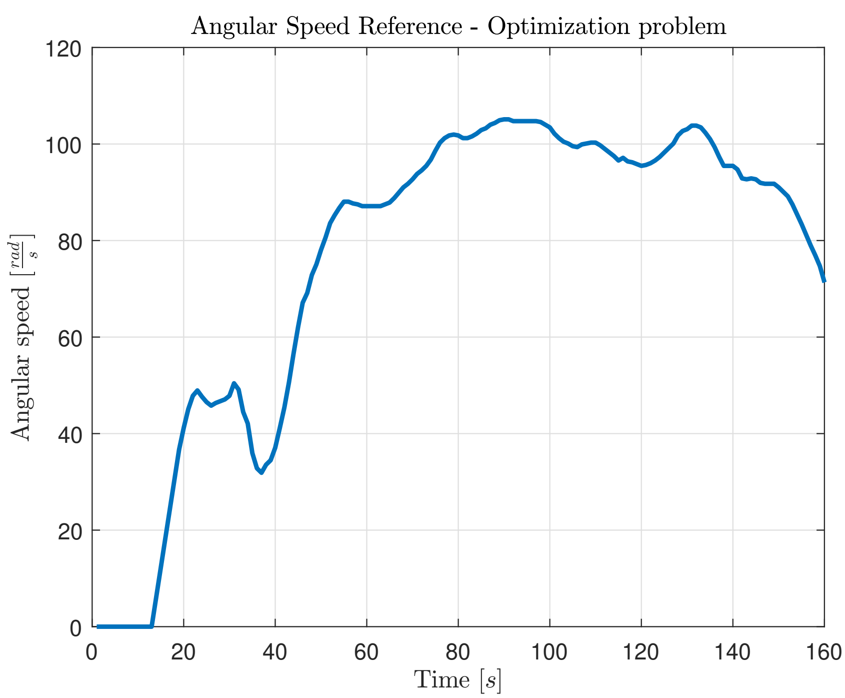


Figure 3-5.: Reference of the optimization problem

Considering Figure **3-5** and the first optimization case, the hybrid algorithm performed 24 iterations in both cases (disturbance rejection and disturbance weighting) because the disturbance weighting find a final value of the cost in this number of iterations. In this case, it is used the performance criterion described in equation (3-48) for the case of the weighting of the disturbance, and the performance criterion described in equation (3-47) for the case of the disturbance rejection. The weights of the performance criteria are given by

$$K_1 = 0.35,$$
$$K_2 = 50,$$
$$K_3 = 500.$$

The values of K_1, K_2 and K_3 are based on the maximum values of the different components of the cost function

- For the value of K_1, it is considered that the maximum value of the power factor P (Equation (3-45)) can be lower than 160 for all intervals of time, this value is considered under simulation conditions, then

$$\begin{aligned} |\text{maximum value of } P| &< 160, \\ K_1|\text{maximum value of } P| &< 160K_1, \\ K_1|\text{maximum value of } P| &< 56, \end{aligned} \tag{3-50}$$

- For the value of K_2, it is considered that the maximum value of the error e (Equation (3-46)) can be lower than one for all intervals of time, then

$$\begin{aligned} |\text{maximum value of } e| &< 1, \\ K_2|\text{maximum value of } e| &< K_2, \\ K_2|\text{maximum value of } e| &< 50, \end{aligned} \tag{3-51}$$

- For the value of K_3, it is considered that the maximum value of the error e (Equation (3-46)) can be lower than one for all intervals of time. Additionally, the work time is considered, then

$$\begin{aligned} t|\text{maximum value of } e| &< t, \\ K_3 t|\text{maximum value of } e| &< K_3 t, \end{aligned} \tag{3-52}$$

  Considering $t = 0.1$ seconds to achieve a low settling time under the given reference

$$\begin{aligned} 0.1K_3|\text{maximum value of } e| &< 0.1K_3, \\ 0.1K_3|\text{maximum value of } e| &< 50, \end{aligned} \tag{3-53}$$

Using these values, the hybrid algorithm is used for tuning the parameters of the controller and the disturbance weighting.

Parameter tuning - Disturbance rejection

According to Figures **3-7**, **3-6** and **3-8**, it is possible to observe that all parameters require three iterations for establishing their final value using the hybrid algorithm. Taking into account the result of the algorithm it is possible to observe that the optimal value of the parameters is given by the limits of each decision variable. In iteration 23, it is possible to find out any value does not change. The result of the tuning of each parameter considering the number of iterations is given by

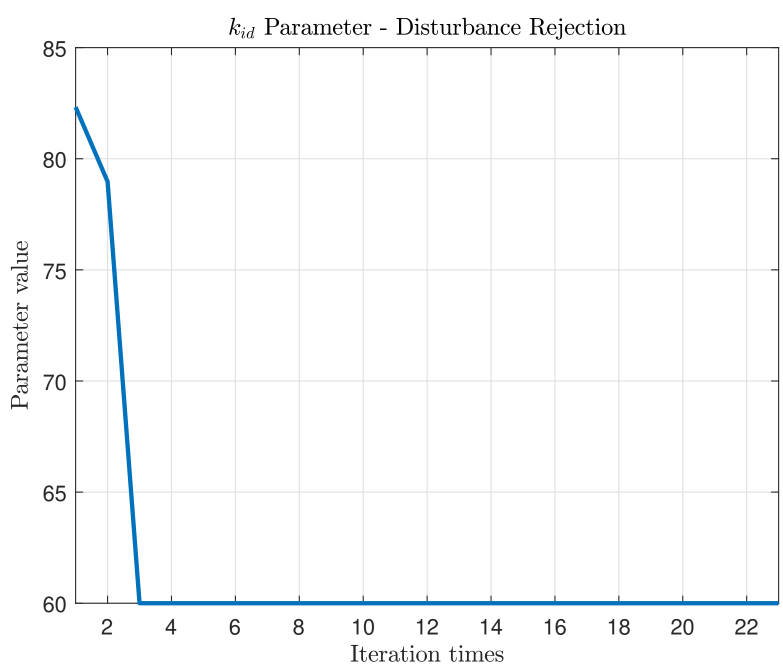


Figure 3-6.: Evolution of the parameter k_{id} - Disturbance Rejection

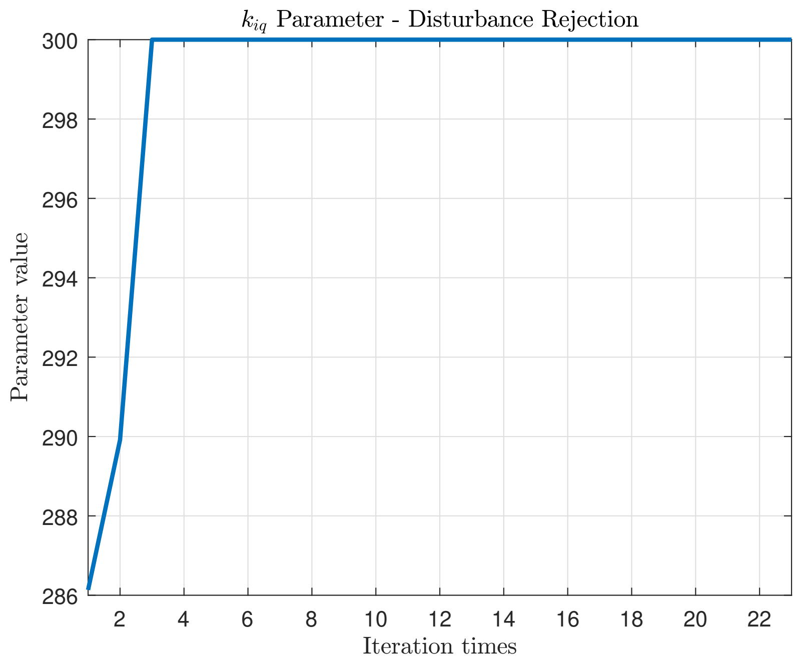


Figure 3-7.: Evolution of the parameter k_{iq} - Disturbance Rejection

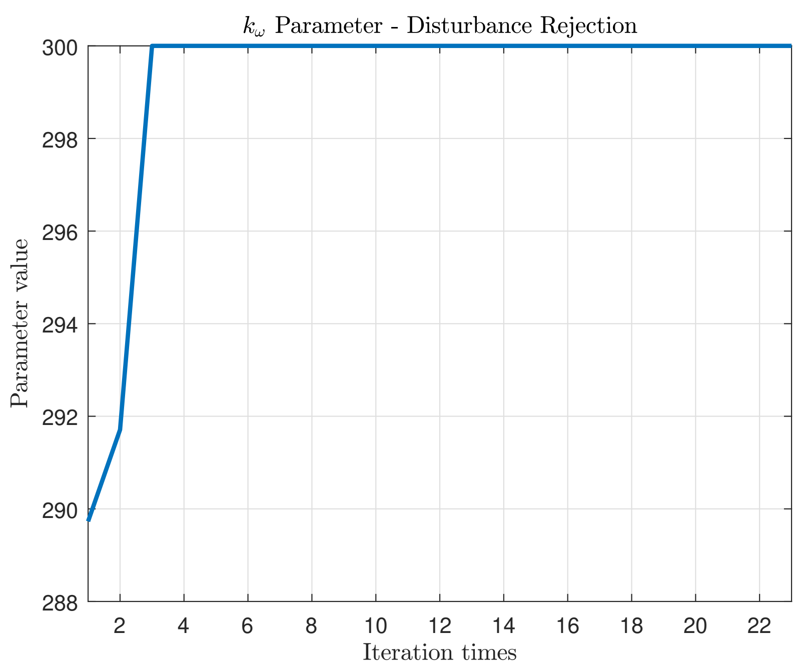


Figure 3-8.: Evolution of the parameter k_{ω} - Disturbance Rejection

It is possible to conclude that all variables find their final values at the same iteration.

Regarding the speed of the controller of motor variables, the control of the current i_d should be slower than the control of the other considered variables.

Parameter tuning - Weighting Disturbance

According to the figures **3-9**, **3-10**, **3-11**, **3-12** and **3-13**, the final value of the parameters is established for iteration 22, but any parameter finds its final value in different value of iteration. This situation represents a greater requirement with respect to the system that considers the approximate linearization of the system through the rejection of the disturbance. However, it is possible to observe that the final values of the weighting of the disturbances of the direct and quadrature currents are not equal to one, allowing us to consider that the standard Active Disturbance Rejection approach does not represent the optimal value of the system taking into account the hybrid algorithm. However, it is necessary to consider that the values of the disturbance weighting should be close to one for the analysis described in Appendix D.

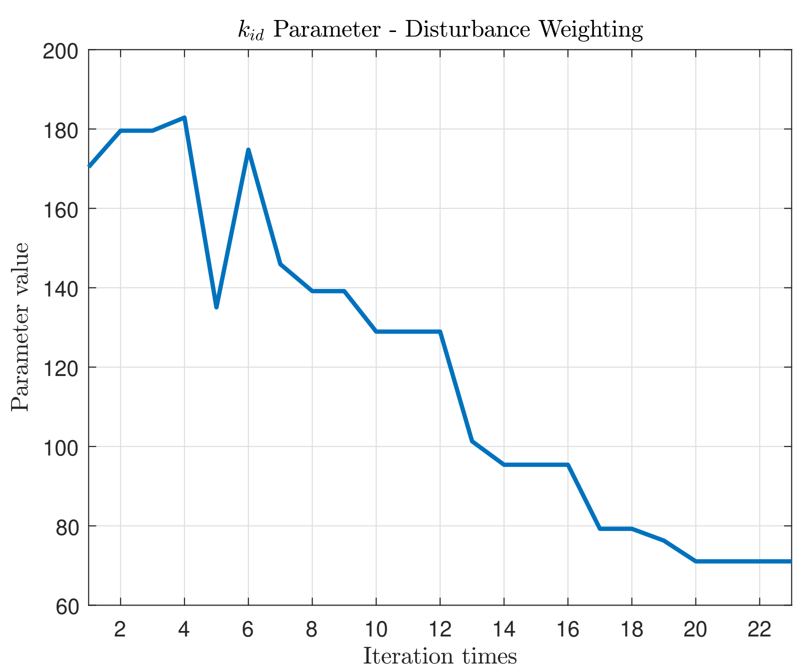


Figure 3-9.: Evolution of the parameter k_{id} -Disturbance Weighting

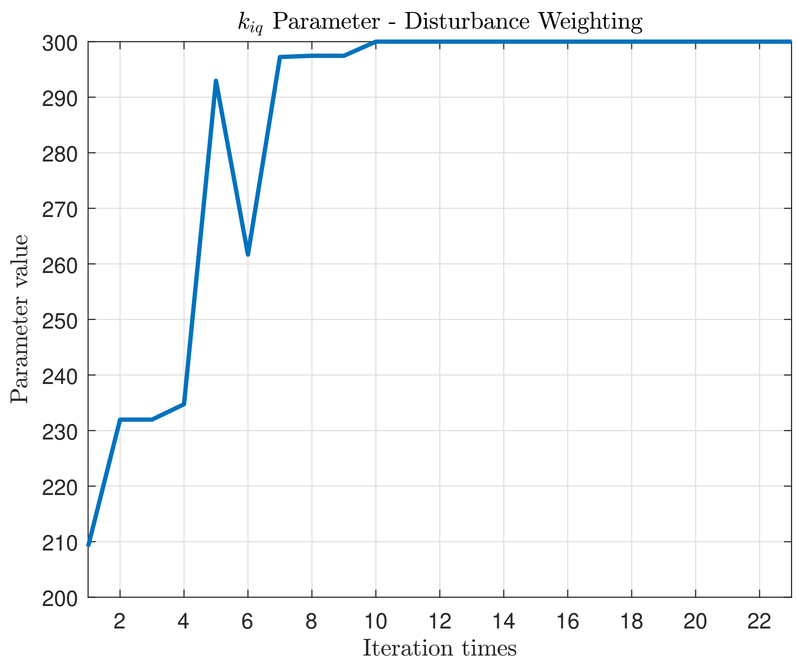


Figure 3-10.: Evolution of the parameter k_{iq} - Disturbance Weighting

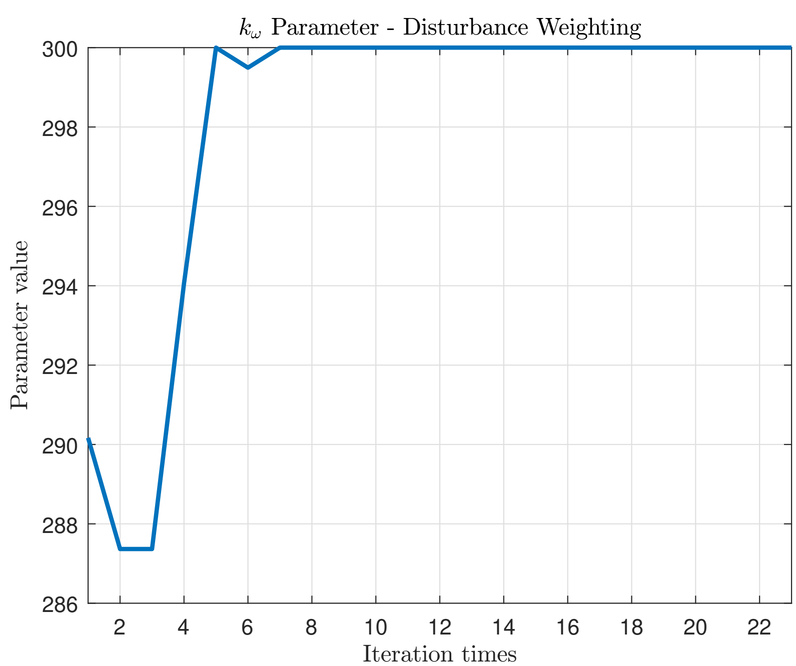


Figure 3-11.: Evolution of the parameter k_{ω} - Disturbance Weighting

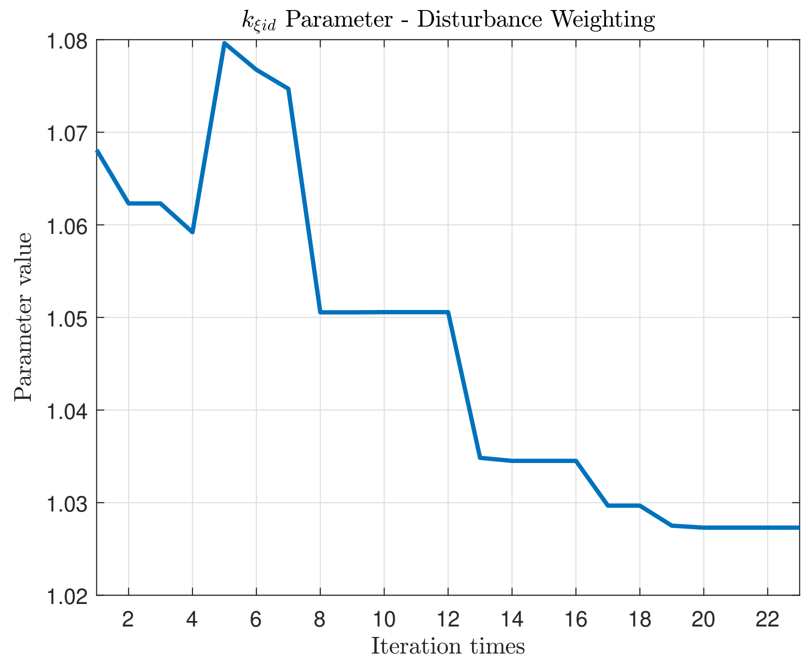


Figure 3-12.: Evolution $k_{\xi id}$ parameter - Disturbance Weighting

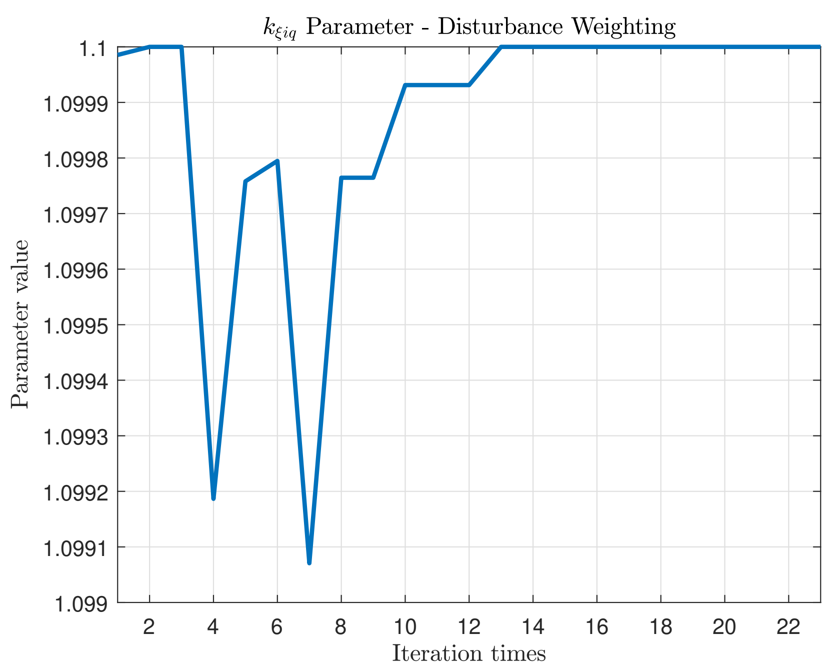


Figure 3-13.: Evolution $k_{\xi iq}$ parameter - Disturbance Weighting

In conclusion the parameter associated to the direct current has a lower value than the other controlled variables, this parameter finds its final value at iteration 20. Regarding Figure **3-13**, it is possible to find out the weighting of the disturbance the quadrature current is equal to the upper value of the decision variable. It is feasible to observe that disturbance weighting proposes two new degrees of freedom. However, the variations of these values propose a nonlinear control strategy where the linearization does not exist. For this reason, the limits of these values should be close to one.

Cost comparison - Disturbance Weighting and Disturbance Rejection

Taking into account the setting of the value of the system parameters, it is possible to see the behavior of the cost for both configurations in which it can be seen that the disturbance weighting approach shows a better performance.

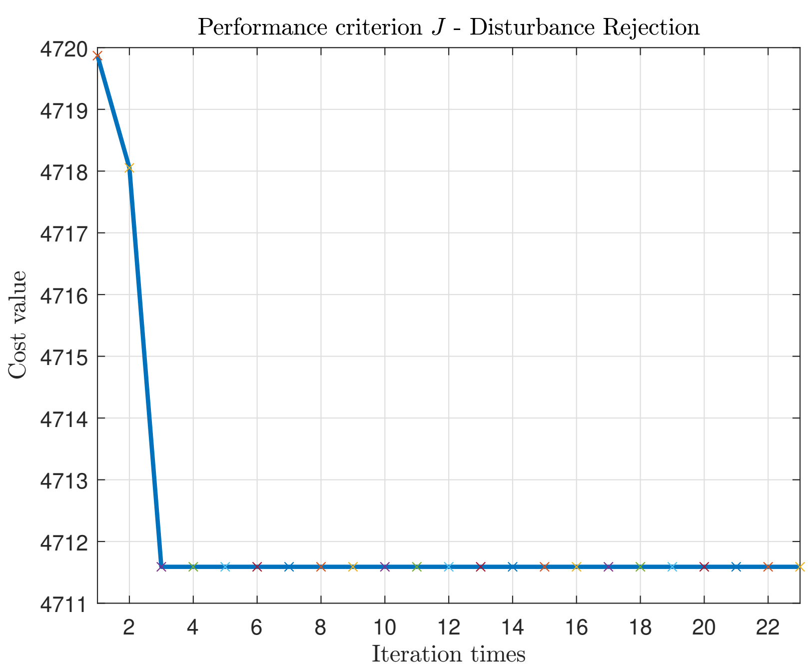


Figure 3-14.: Cost value - Disturbance Rejection

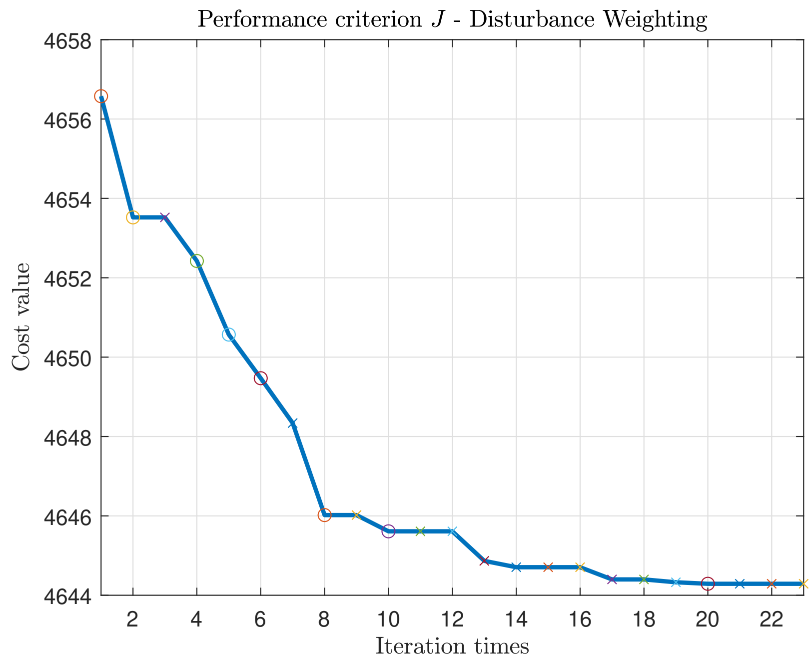


Figure 3-15.: Cost value - Weighting Disturbance

According to the figure **3-14**, the associated cost sits close to iteration 3. Additionally, it is possible to find that the circles represent an optimal value given by the local search given by the modification of the traditional particle swarm optimization algorithm, while the x's represent a given optimal value by traditional search. Thus, the search for the optimal for the disturbance rejection does not depend on the modification of the traditional Particle Swarm Optimization. Regarding Figure **3-15**, the cost associated with the weighting of the disturbance shows that it starts at a lower value than the initial value in the rejection of the disturbance. However, more iterations are required to reach the final value of the cost, the final value is lower than the system that is based on approximate linearization through disturbance rejection. However, these values serve as a guide because the optimization is based on an offline simulation where a time-invariant system is considered. The variation of the traditional Particle Swarm Optimization algorithm is considered to search for the optimal value of the cost.

Summary of the parameters found by hybrid algorithm

The summary of the parameter tuning and its respective costs can be seen in table **3-1**

Table 3-1.: Results of tuning - Disturbance Rejection and Disturbance Weighting

Parameter	**Disturbance Weighting**	**Disturbance Rejection**
k_{id}	71.0542	60
k_{iq}	300	300
k_{ω}	300	300
$k_{\xi id}$	1.0273	Not Considered
$k_{\xi iq}$	1.100	Not Considered
Cost	4644.3	4711.6

The weighting of the disturbance proposes a lower cost than the disturbance rejection case under the reference considered. However, not considering the disturbance rejection proposes a higher grade of uncertainty due to a nonlinear control problem is considered. Additionally, despite both strategies having similar final costs. It is important to observe that the cost function depends on the work time and the tracking error, this situation implies a grade of uncertainty due to the reference can include other forms or the time duration can be different, then the values of the cost can change. Additionally, as was previously mentioned, the values of the disturbance weighting imply a higher grade of uncertainty then it is necessary to implement these values in an experimental setup.

Sensibility analysis

In this section, it is possible to observe two cases of analysis of the variations of the parameters, the first experiment is based on varying the parameters K_1, K_2 and K_3 independently, of the cost given in the equation (3-48). The second experiment of the sensitivity analysis is given by the consideration of only one parameter of the cost function. The reference for this sensibility is given by the reference exposed in Figure **3-16** due to this reference considers the acceleration and deceleration processes, the time of this reference is based the resource use, reducing the complexity of the problem. The results of the parameters can be observed in the tables **3-2** and **3-3**.

Table 3-2.: Consideration of only one parameter

Parameter	$K_1 = 1$ $K_2 = K_3 = 0$	$K_2 = 1$ $K_3 = K_1 = 0$	$K_3 = 1$ $K_2 = K_1 = 0$
k_{id}	70.8016	154.1852	135.6484
k_{iq}	127.4332	243.4036	300
k_{ω}	261.3929	141.1478	300
$k_{\xi id}$	1.0729	1.0291	0.9900
$k_{\xi iq}$	1.0665	1.0841	1.0823

Table 3-3.: Results of tunning - Varying K_1, K_2 and K_3

Parameter	$K_1 = 1$ $K_3 = 500$ $K_2 = 50$	$K_1 = 2$ $K_3 = 500$ $K_2 = 50$	$K_1 = 3$ $K_3 = 500$ $K_2 = 50$
k_{id}	60	91.2667	86.8805
k_{iq}	300	300	266.8140
k_{ω}	300	291.0261	293.1717
$k_{\xi id}$	1.0475	1.0849	1.0828
$k_{\xi iq}$	1.0904	1.0595	1.0599
Parameter	$K_1 = 0.2$ $K_3 = 500$ $K_2 = 250$	$K_1 = 0.2$ $K_3 = 500$ $K_2 = 500$	$K_1 = 0.2$ $K_3 = 500$ $K_2 = 750$
k_{id}	60	247.9713	131.0916
k_{iq}	300	300	291.0297
k_{ω}	300	198.1115	291.0908
$k_{\xi id}$	1.068	1.0996	1.0469
$k_{\xi iq}$	1.0905	1.1	1.0467
Parameter	$K_1 = 1$ $K_3 = 2500$ $K_2 = 50$	$K_1 = 1$ $K_3 = 5000$ $K_2 = 50$	$K_1 = 1$ $K_3 = 7500$ $K_2 = 50$
k_{id}	68.9831	63.1690	206.3902
k_{iq}	299.9103	300	300
k_{ω}	298.1367	299.1652	300
$k_{\xi id}$	0.9905	0.9900	0.9900
$k_{\xi iq}$	1.0860	1.0853	1.0829

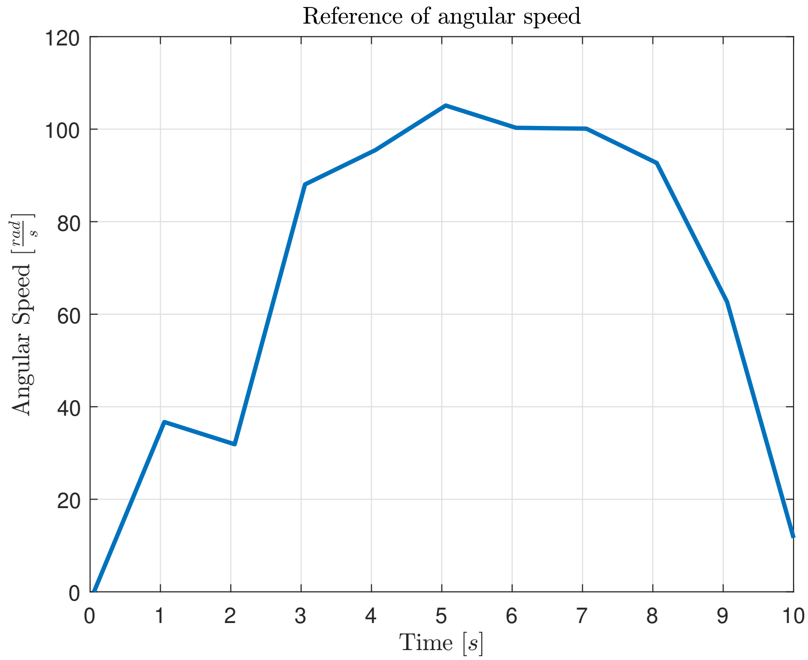


Figure 3-16.: Reference considered - Sensitivity analysis

According to Table **3-2**, if only one of the components of the cost function described in equation (3-48) is considered, the weighting of the disturbance changes its value, subject to the considered reference and other parameters. In the case where only P is considered, the value of the disturbance weighting for the direct current is higher than the values for other configurations considering the other components of the initial performance criterion. When $K_3 = 1$, it can be observed that the value of $k_{\xi id}$ is at the lower bound. It is well known that the disturbance associated with the angular speed is completely rejected to improve the performance of the control strategy. Regarding Table **3-3**, all results consider all components of the cost function described in equation (3-48), but under the optimization process, including the algorithm, the reference, and the complexity of the problem, it is found that the values do not reach the value of one. However, these results are subject to offline simulation due to the exact simulation model having limitations regarding the operation system in a real implementation. It is possible to conclude that the results of all experiments are different. However, in the case of the disturbance weighting of the direct current, the values are close to the lower bound of the decision variable constraint when changes in the settling time weight are considered. Meanwhile, it is possible to observe that the parameter of the disturbance weighting of the quadrature current is close to the upper value. Finally, in the largest number of experiments, the parameters of the quadrature current controller and speed controller are close to the upper bound, while in the case of direct current, the values are close to the lower bound. This leads to the conclusion that the values of the parameters can be different depending on the structure of the optimization problem.

Disturbance Weighting

According to the literature, the selection of the parameters of the controller and observer based on the Active disturbance rejection control are selected by the experience [62], for this reason, the third problem of the optimization of the induction motor is considered under the reference described by the Figure **3-5**. The results of the weighting under the cost of equation (3-49) are

$$K_1 = 0.2$$

$$K_2 = 50$$

$$K_3 = 500.$$

The weighting values are selected taking into account the order of magnitude of each component of the cost function for short simulation times, the selection is based on equations (3-50)*,* (3-51) *and* (3-53)*.*
In this problem, the objective is to compare two control strategies, both strategies have the same controller parameters, but one of the strategies tunes the weighting of the disturbance through the hybrid algorithm. Concluding that the weighting of disturbance can represent a high number of degrees of freedom. However, these values have to be close to one due to the nonlinear dynamics and the control approach. The results of the of the optimization are in Table **3-4**.

Table 3-4.: Results of tuning

Parameter	Disturbance Weighting	Rejected Disturbance
$k_{\xi id}$	0.9905	Not Considered
$k_{\xi iq}$	1.08	Not Considered

Table **3-4** shows the optimal values of the weighting of the disturbance, Figure **3-17** shows that the parameter $k_{\xi id}$ tends to a value close to 0.9905 that represents the lower value of the decision variable, while Figure **3-18** shows that the parameter $k_{\xi iq}$ tends to the upper bound of the decision variable. These constraints of the decision variables are based on the uncertainties and the problems with respect to the variations in the model considering the operating conditions.

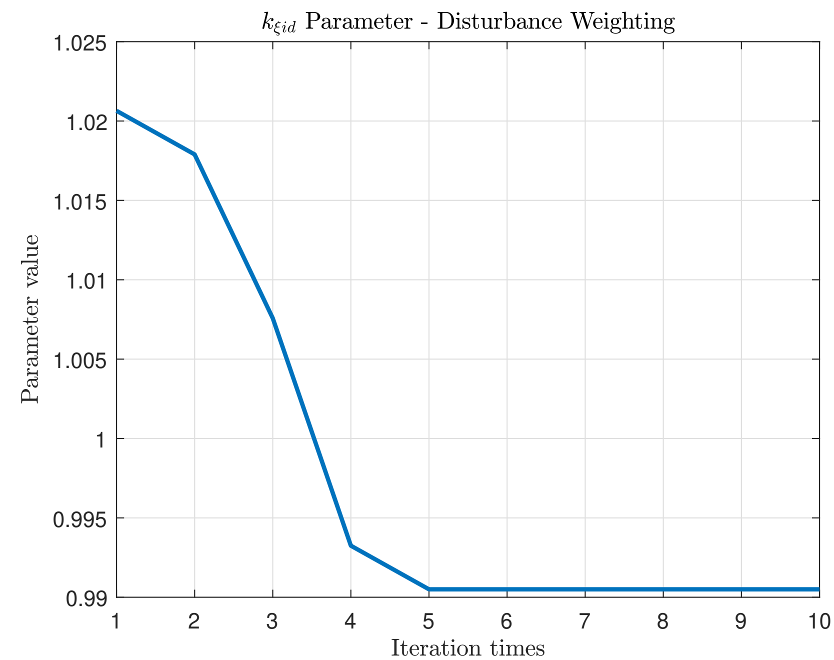


Figure 3-17.: Evolution $k_{\xi id}$ parameter - Disturbance weighting

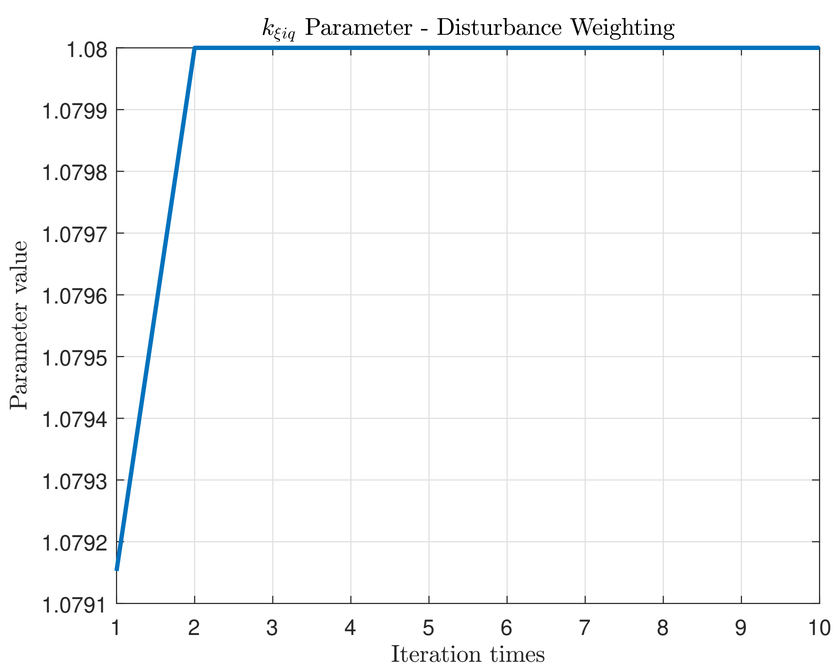


Figure 3-18.: Evolution $k_{\xi iq}$ parameter - Disturbance weighting

Concluding that the disturbance rejection does not represent the optimal performance according to a performance criterion and hybrid algorithm, allowing us to consider the weighting of the disturbance as a degree of freedom subject to decision variables constraints.

The disturbance Weighting scheme proposes a modified Active Disturbance Rejection control. This modified strategy can improve a performance of a cost function but it implies a high grade of uncertainty due to the cost function structure and system dynamic. The values that have a relationship with the weighting disturbance have to be close to 1, to guarantee the control approach. The uncertainties can have a relationship with the nonlinear control approach due to when the disturbance is not rejected the control design is based in a nonlinear scheme and the parameter variations can change the control problem.

4. Experimental setup - Results

This chapter discusses the implementation of the control strategies that were described in Chapter 3 in an experimental setup. Two global experiments are considered. The first experiment takes into account two control strategies: The first one is based on the disturbance rejection, and the second one considers the disturbance weighting. For the first and second control strategies, ten experiments are implemented to decrease the uncertainties due to the measurement equipment or the motor conditions at the moment of the test. After tests, it is computed the arithmetic mean of the system response in terms of the angular speed, and then it is compared the arithmetic mean and standard deviation of the cost of the two strategies. The second global experiment is based on considering another two control strategies that are compared. Both strategies consider the same linear control law based on state-feedback control, but one of these, considers a weighting of the current disturbances, then ten experiments are carried out for any strategy, and the results are compared in terms of cost and the response of the system.

4.1. Experimental setup

For the prototype, it is important to give the specifications for the following components

- **Induction motor:** The parameters of the induction motor and the electric vehicle are in Appendix B.

- **Xpc target:** It is considered a solution to implement a real-time control system using a PC and off-the-shelf l/O boards allowing to consider prototypes in real-time.

- **Three-phase rectifier:** For the implementation, it is considered a rectifier with a rated power of $600[W]$. The nominal values of voltage input and current input are $220[V_{rms}]$ and $3[A_{rms}]$, respectively. This rectifier includes a filter for changes in the voltage. The measurement voltage system works with $\pm 15[V]$.

- **Three-phase inverter:** For the implementation, it is considered a three-phase inverter that works through IGBT modules that have a rated power of $600[W]$. Additionally, it is considered a commercial controller compatible that works with $13.5[V]$ and $2.6[A]$. There are electronic components that work with the PWM signals to control the IGBT firing. To protect the counter it is necessary to implement optocouplers that work with $13.5[V]$ and $2.6[A]$. Finally, there is a filter for connecting the motor that has a cutoff frequency of $800[Hz]$.

- **Induction motor measurement:**

  For the measurement of the voltages and currents of the stator, it is considered an electronic system that works with $\pm 15[V]$ and $0.5[A]$. The nominal values of the input are $220[V_{rms}]$ and $3[A_{rms}]$. Finally, the relationship between the input and the output is $25[V/V]$ for the voltage and $1[A/V]$ for the current.

- **DC-DC converter:** This system gives the energy for the motor DC-DC, the rated power is $500[W]$ and the firing voltage is $12[V]$, and the nominal values for the input are $170[V]$ and $0.5[A]$.

- **Motor DC measurement:** There is a filter that has a a cutoff frequency of 5[kHz] to avoid unwanted harmonics. The nominal values for the voltage and current are 100[V] and 3[A]. This system works with 12 [V].

System operation

The experimental setup of the electric vehicle is given in Figure **4-1**. In the first instance, a three-phase source is connected to a three-phase variac, and the output is connected to a three-phase rectifier that gives a DC voltage, this voltage works as a voltage supply of the inverter, and the objective of the inverter is to change the voltage through an XPC-target via PWM scheme . The output of the inverter is filtered via an LC filter, avoiding high-frequency harmonics from PWM modulation, and giving a sinusoidal signal to the induction machine. The output of the LC filter is connected to the induction motor and the measurement instrumentation. A DC motor is connected mechanically to the induction motor, representing the load. In this case, the DC motor works as a generator, and the mechanical movement of the induction motor generates a current that is controlled via a DC-DC converter that is connected to an LC filter, cleaning the signal, and making it possible to use the PWM scheme. The output is connected to a resistive load. Regarding the electronics associated with the induction motor, there are two measurement instruments, the first one is for the measurement of analog signals and the second is a high-speed counter that gives a PWM signal, controlling the IGBT transistors of the inverter. Now, regarding the signals of voltages and currents, these are connected to one measurement instrument (measurement of analog signals), and the second device sends the control signal associated with the PWM modulation. The control of the system is given by an XPC-target that allows work in real-time. This software is provided by MATLAB. Regarding the DC motor, there is a system that generates a PWM for controlling the DC-DC converter, changing the power in the resistive load. So, both systems work at the same time, it is necessary to connect the systems through a HUB or router that works via TCP/IP protocol.

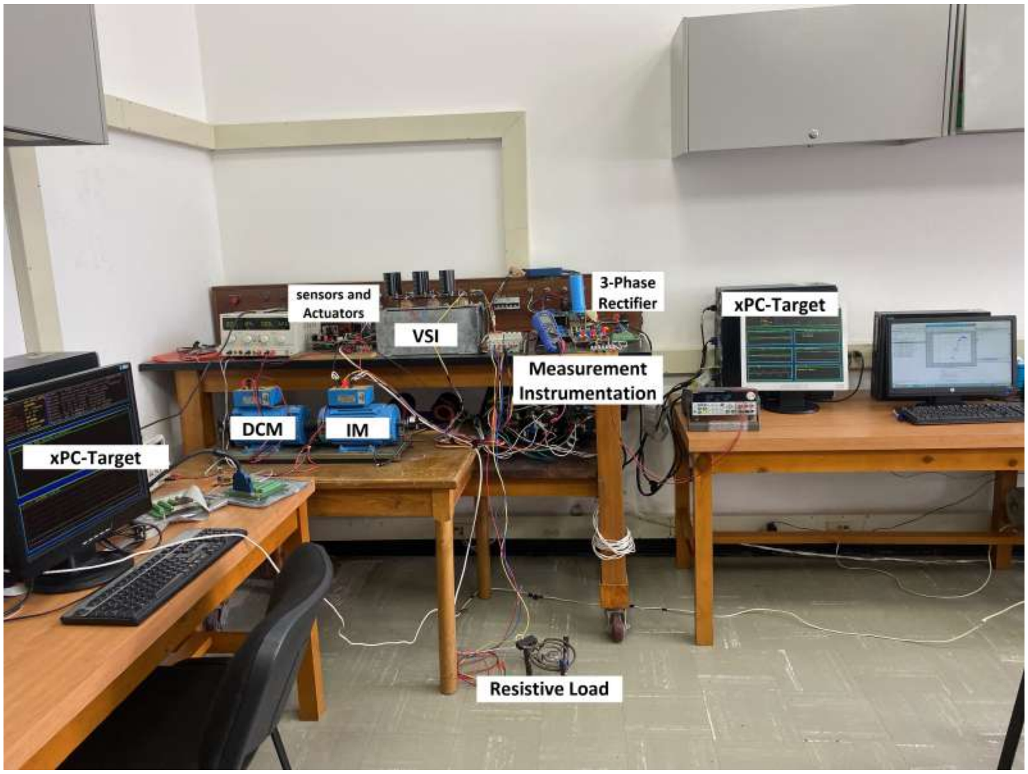


Figure 4-1.: Experimental setup

The diagram illustrating the connections among the various components can be found in Appendix A.

4.1.1. The Robustness of the Experiments

For each global experiment, robustness is determined by assessing changes in the cost under similar operational conditions. The results of any global experiment are evaluated based on both standard deviation and arithmetic mean.

4.1.2. Reference Considered

Various driving cycles can be considered [4]. For this experiment, the UDDS (Urban Dynamometer Driving Schedule) driving cycle is proposed, allowing the evaluation of the performance of the vehicle under urban conditions [21, 23]. The UDDS reference is provided in

Figure **4-2**, where both acceleration and deceleration processes can be observed.

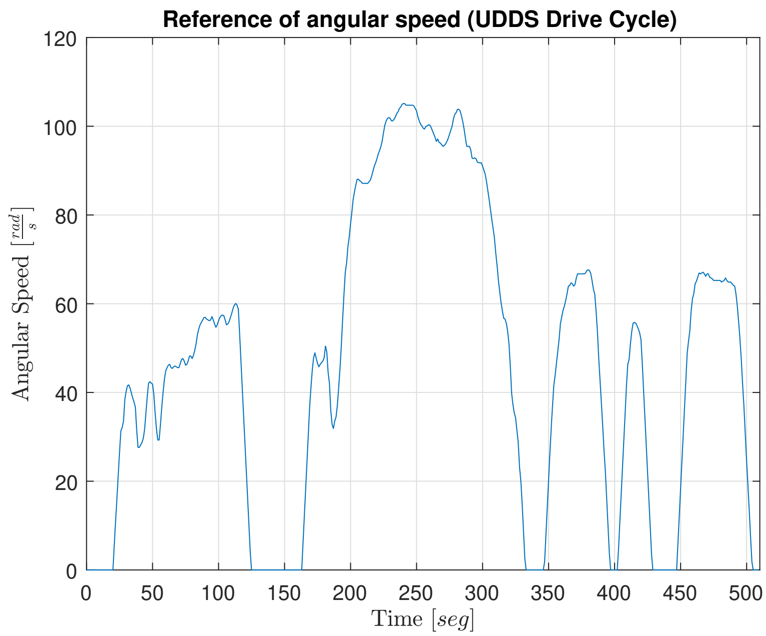


Figure 4-2.: Reference considered

4.1.3. First experiment

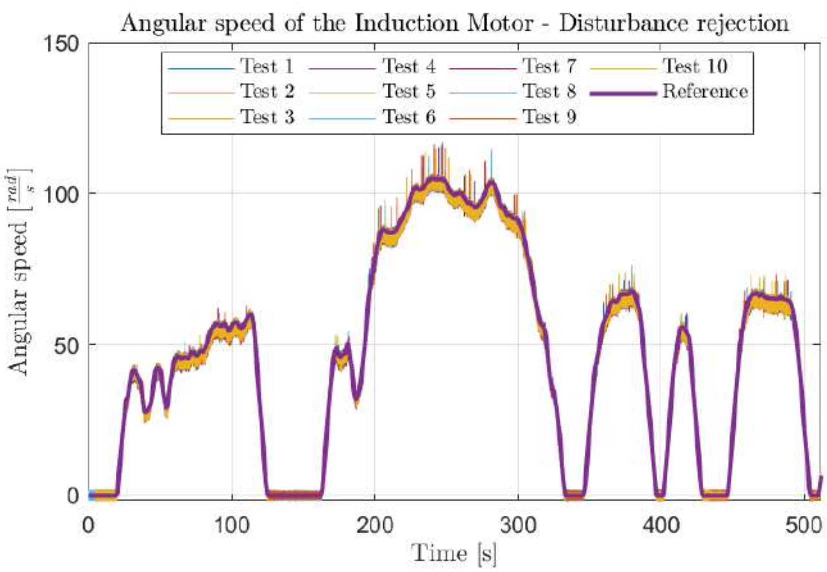
For this experiment, two control strategies are compared, the first one considers the disturbance rejection, while the second strategy is based on the disturbance weighting. The parameters of the control strategies are given by the table **3-1**.

Remark:

For each control strategy, 10 experiments are conducted under similar conditions to account for uncertainties in the system and the measurement process. Moreover, statistical analyses were performed, involving comparisons among the results.

System Response

Figure **4-3** shows the results of the ten experiments for any strategy. According to the results, it is possible to observe that both strategies can allow good reference tracking of the angular speed. However, there are differences between the results for each strategy due to the measurement process, taking into account the limitations of the speed of the experimental setup and the computer communication through the HUB. Thus, it is considered the arithmetic mean of the tests of any control strategy to compare the strategy performance considering the tracking error. The results of the arithmetic mean of the response of any control strategy are given in Figure **4-4**.



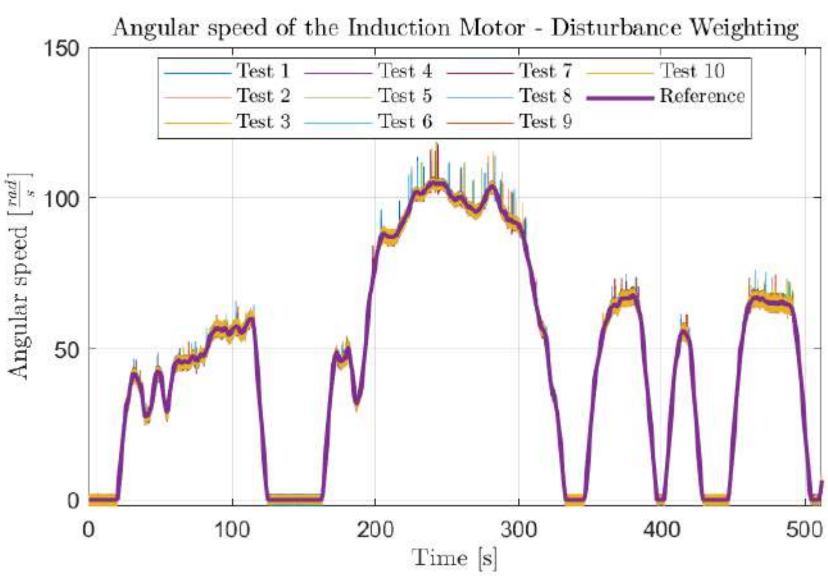


Figure 4-3.: Experimental results (First experiment)

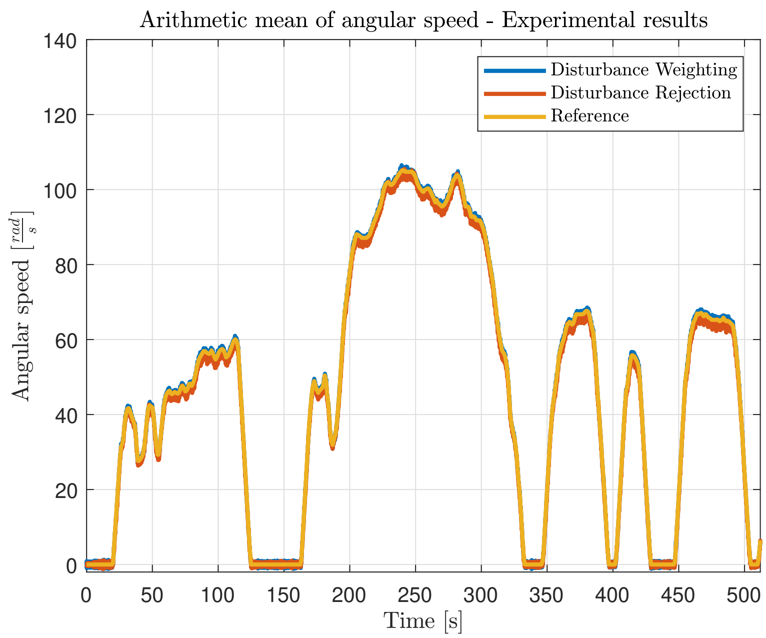


Figure 4-4.: Arithmetic mean of the results - Comparison between Disturbance Rejection and Disturbance Weighting (First experiment)

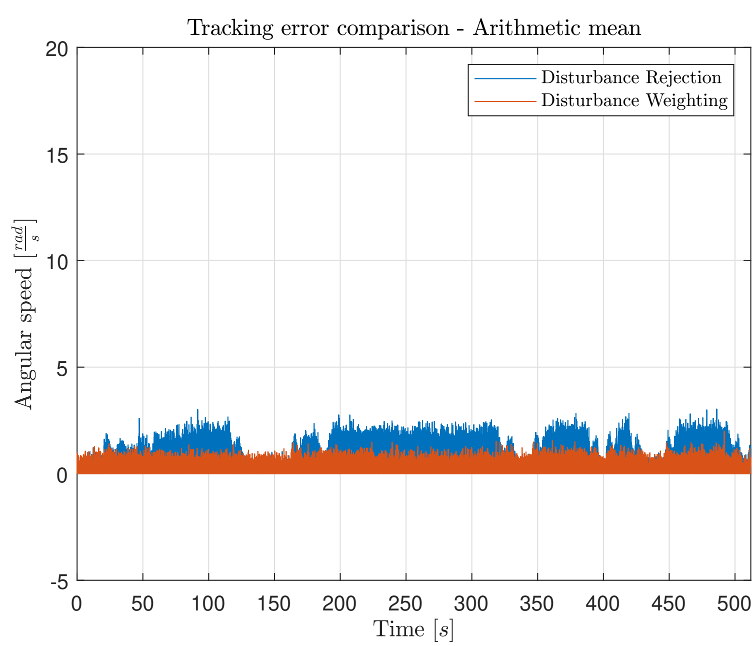


Figure 4-5.: Comparison of tracking error - Arithmetic mean approach (First experiment)

For Figure **4-4**, the following equation is considered

$$\text{Arithmetic mean of angular speed} = \frac{\sum_{i=1}^{10} \omega_i(t)}{10}, \tag{4-1}$$

where $\omega_i(t)$ is the angular speed of the experiment i. Regarding Figure **4-4**, the arithmetic mean of the disturbance weighting process has a higher value than the arithmetic mean of the disturbance rejection process. However, both strategies have the disturbance rejection of the speed-controlled variable to guarantee the tracking of the reference.

For Figure **4-5**, it is considered the following equation for each control strategy

$$\text{Arithmetic mean of Tracking error} = e_m(t) = \frac{\sum_{i=1}^{10} |e_i(t)|}{10}, \quad e_i(t) = \omega_i(t) - \omega^*(t). \tag{4-2}$$

Figure **4-5** shows that the performance taking into account the tracking error is better when exists a disturbance weighting. This result is possible due to other components are considered in the cost functions given by equations (3-47) and (3-48).

Cost Value

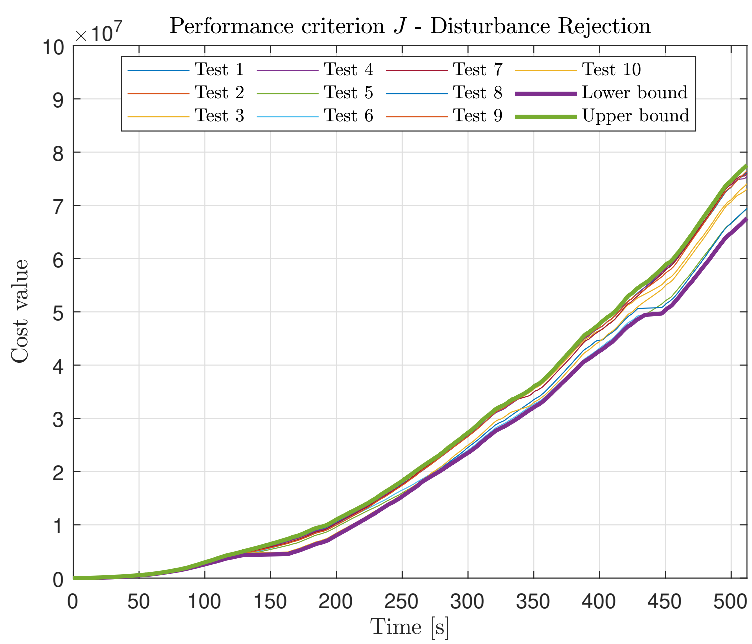


Figure 4-6.: Performance criterion for all test - Disturbance Rejection (First experiment)

Regarding Figure **4-6**, it is possible to find the cost values of the performance criterion using the disturbance rejection approach, while Figure **4-7** shows the cost values using the disturbance weighting approach. Graphically, it is possible to observe that the disturbance rejection case has a lower difference between the different tests, but its best and worst cases have a higher value than the experiments of the weighting of the disturbance case. The summary of the final value of the cost for any experiment is shown in Table **4-1**.

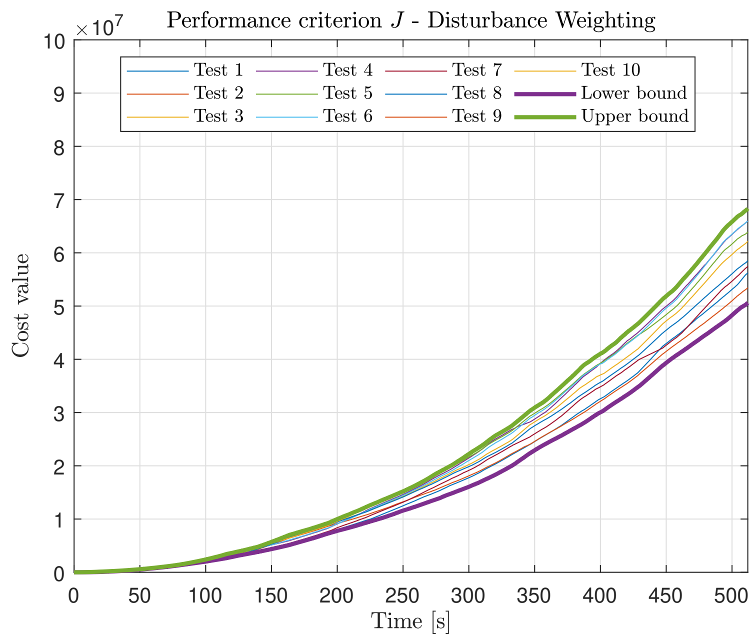


Figure 4-7.: Performance criterion for all test - Disturbance Weighting (First experiment)

In table **4-1**, it is possible to observe the standard deviation and variance of all tests for each control strategy. The arithmetic mean of the cost in the disturbance weighting case represents the 81.96% of the disturbance rejection case, approximately. Additionally, the disturbance rejection case presents a lower standard deviation than the disturbance weighting case. Graphically, it can be observed bigger variations between the values of all the experiments in the disturbance weighting case, these values can be seen in the graphs previously analyzed. The variation in costs is attributed to the fact that the technique based on disturbance weighting loses the linear approach. Additionally, the transient behavior of the cost average of each case can be seen in Figure **4-8**.

Table 4-1.: Cost - Disturbance Rejection and Disturbance Weighting

Test	**Disturbance Weighting**	**Disturbance Rejection**
Test 1	$5.6216e+07$	$7.6265e+07$
Test 2	$5.3445e+07$	$7.7550e+07$
Test 3	$6.2152e+07$	$7.4057e+07$
Test 4	$6.5996e+07$	$7.5427e+07$
Test 5	$6.3923e+07$	$6.9383e+07$
Test 6	$6.5987e+07$	$6.7590e+07$
Test 7	$5.7465e+07$	$7.5999e+07$
Test 8	$5.8502e+07$	$6.9452e+07$
Test 9	$5.0622e+07$	$7.6476e+07$
Test 10	$6.8316e+07$	$7.3108e+07$
Arithmetic mean	$6.0262e+07$	$7.3531e+07$
Variance	$3.4910e+13$	$1.2396e+13$
Standard deviation	$5.9085e+06$	$3.5209e+06$

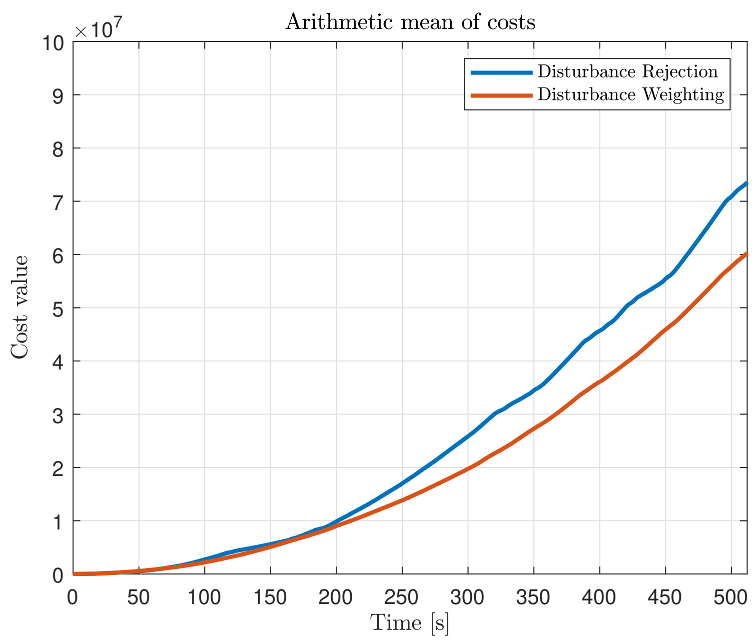


Figure 4-8.: Performance criterion for all test - Arithmetic mean approach (First experiment)

The equation associated with Figure **4-8** is

$$\text{Arithmetic mean of the costs} = \frac{\sum_{i=1}^{10} c_i(t)}{10}, \tag{4-3}$$

where $c_i(t)$ represents a cost for the i experiment.
Figure **4-8** shows that in the first stage of the UDDS cycle, the average values of the costs are similar. However, when a higher speed is requested, the increase in the difference in the costs of both strategies is observed; this situation may be because the tuning of the parameters was carried out with a high-speed reference. Then, considering the mean, it is necessary to consider the best and the worst cases for any control design. This procedure is observed in Figure **4-9**. This figure shows that the best result of the disturbance rejection case shows a similar performance to the worst case of the disturbance weighting case. Finally, the best case of the disturbance weighting case represents about 75% of the disturbance rejection case.

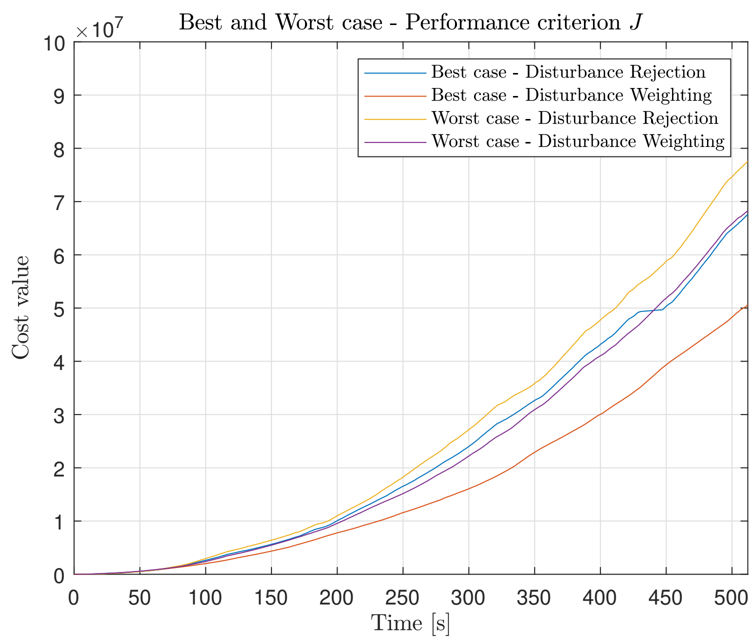


Figure 4-9.: Best and worst cases comparison (First experiment)

4.1.4. Performance evaluation

Remark:

While energy use is considered in the performance criteria described in equations (3-47), (3-48), *and* (3-49), *this analysis was susceptible to tracking errors. Therefore, in this subsec-*

tion, two new parameters are evaluated to enhance the analysis. The first analysis is based on energy, and the second one incorporates a weighting of the energy using the tracking error.

Power and energy analyses

After analyzing the costs associated with the related experiments, two performance criteria will be proposed for evaluation. The first performance criterion is based on the average of energy used $E_m(t)$, considering all experiments. In this case, it is considered the following expression

$$\begin{aligned} p_m(t) &= v_{am}(t)i_{am}(t) + v_{bm}(t)i_{bm}(t) + v_{cm}(t)i_{cm}(t), \\ E_m(t) &= \int_{t_0}^{t_f} p_m(t) \cdot dt, \end{aligned} \tag{4-4}$$

where am, bm, and cm are the averages of the three-phase voltages and currents. The second performance criterion is given by the first criterion but with a weighting by the magnitude of the tracking error

$$E_P(t) = \int_{t_0}^{t_f} |e_m(t)| p_m(t) \cdot dt. \tag{4-5}$$

In equation (4-4), it is possible to observe that it is considered the energy used and in equation (4-5), it is possible to consider the energy of the system and the error at the same time, where it is possible to evaluate the importance of the tracking error in any strategy due to the nonlinear dynamics and the variation of the parameters.

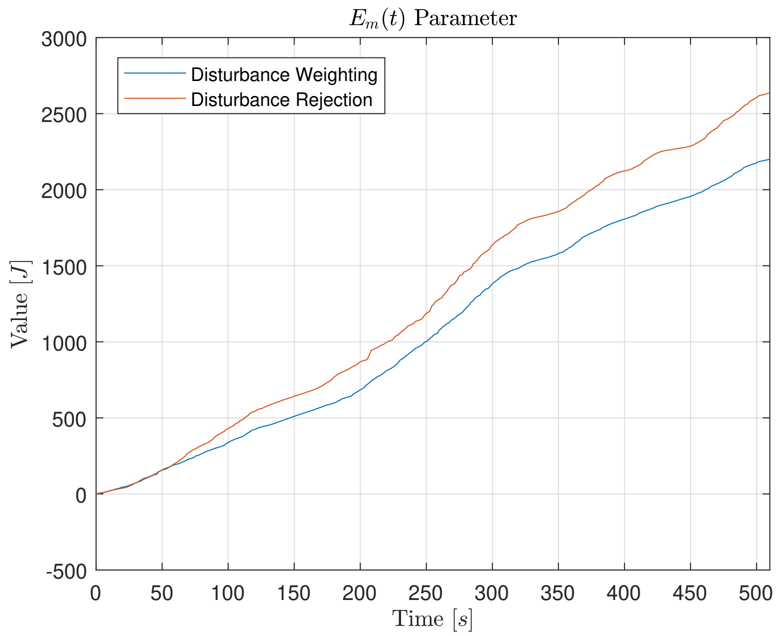


Figure 4-10.: $E_m(t)$ Parameter - Comparison (First experiment)

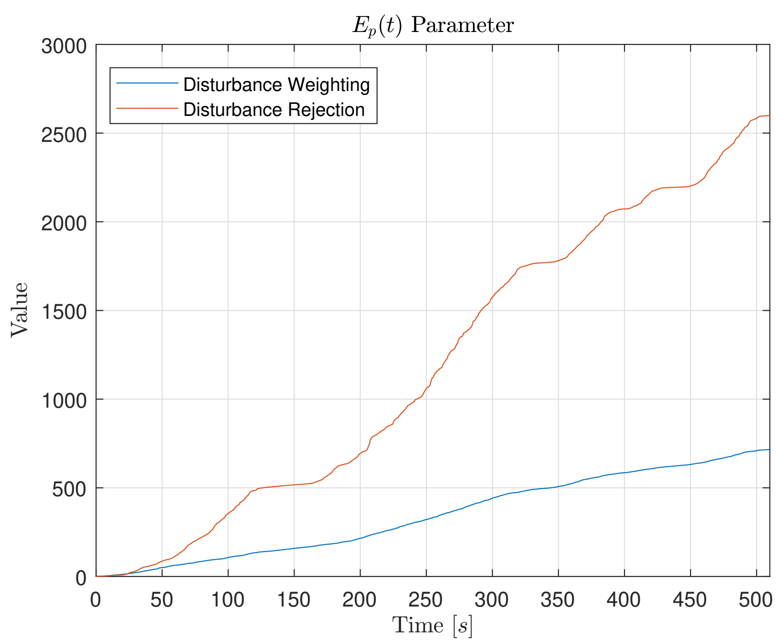


Figure 4-11.: $E_P(t)$ Parameter - Comparison (First experiment)

The energy parameter shown in Figure **4-10** shows a lower value for the disturbance weighting case. Additionally, according to Figure **4-11**, in the case when it is considered the integral where the $p_m(t)$ is weighted by the magnitude of the error, the disturbance weighting shows a better result than the disturbance rejection case. Concluding, a better performance of the disturbance weighting case considering the parameters.

Cost variation analysis (Cost robustness)

Given that the experimental conditions are very important for the experiments, it is proposed an analysis with respect to the statistical variables of arithmetic mean and standard deviation considering the final value of the costs. Figure **4-12** shows the values of the mean and the standard deviation.

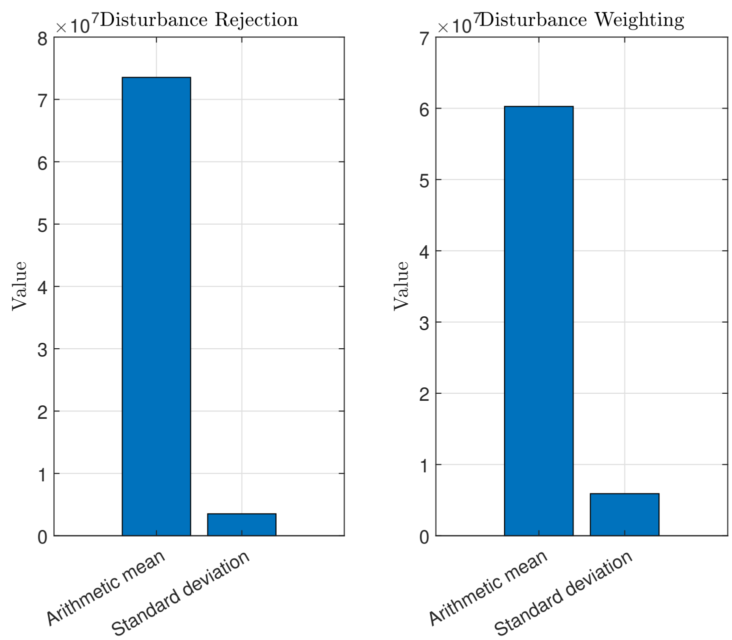


Figure 4-12.: Arithmetic mean and standard deviation (First experiment)

Additionally, to compare the variation of the final value of the experiments, it is proposed the following parameter

$$R = \left(\frac{\text{Standard deviation}}{\text{Arithmetic mean}}\right) \times 100. \tag{4-6}$$

The parameter R is depicted Figure **4-13**.In this figure, it is possible to conclude that the variation of the final value of the experiments is higher in the disturbance weighting case. In conclusion, the disturbance weighting can improve the cost of the performance criterion, but the variation of the experimental results can be higher under operation conditions. The nonlinear control problem of the disturbance weighting case shows if the disturbance is not rejected the variation of the parameters can change the final values of the cost.

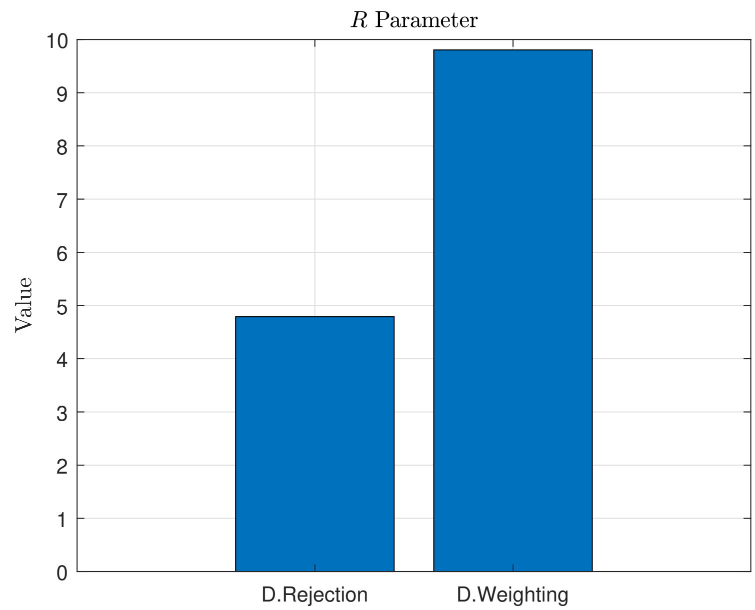


Figure 4-13.: R parameter (First experiment)

4.1.5. Vehicles dynamics - Comparison

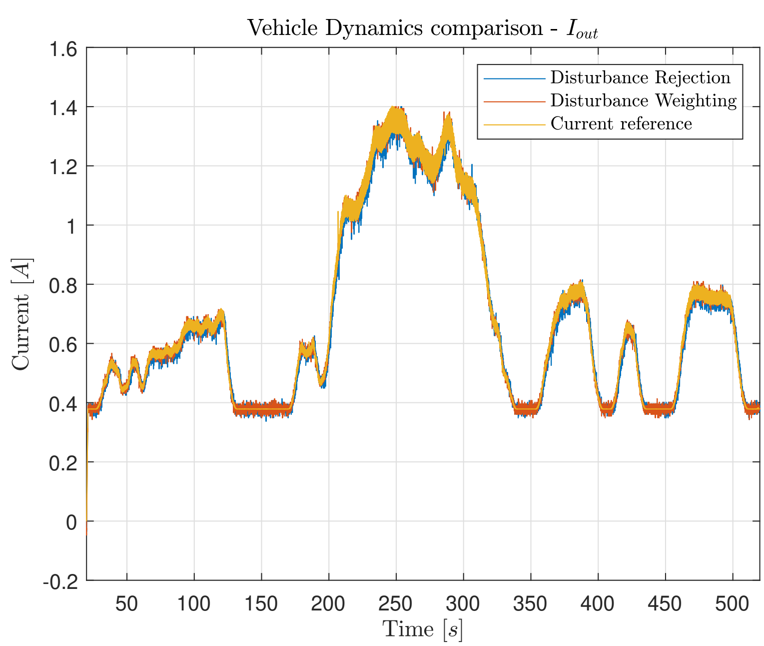


Figure 4-14.: Comparison of the current I_{out} - Vehicle dynamics (First experiment)

To consider the vehicle dynamics, the current reference of the DC generator is considered, the vehicle dynamics and according to the vehicle speed and the conditions of the problem is reflected in the DC motor current reference. For both control strategies the result is similar, the differences depend on the speed of any control strategy.
The current reference and the τ associated to electric vehicles torque for the induction motor have the following relationship

$$\tau = \gamma i_{or}, \tag{4-7}$$

where γ is a constant value and i_{or} is the reference of I_{out}.

Conclusions from the first experiment

It can be concluded that the cost of disturbance rejection is higher than that of the disturbance weighting case, under the constraints of the hybrid algorithm and decision variables. The weighting in the rejection of disturbances in the currents proposes two new degrees of freedom. However, the parameters associated with the weighting of the disturbances are limited to values close to 1. Not considering values close to 1 decreases the robustness of the system regarding the costs due to the simulation and tuning process of the parameters does not consider the variation of the parameters given the operating conditions and uncertainties.

4.1.6. Second experiment

The objective of this experiment is to show the case of the disturbance weighting of Chapter 3 considering the respecting performance criterion under a control parameter condition. In this case, the parameters tuned of the disturbance weighting by the hybrid algorithm are considered, using the values of Table **3-4**, ten experiments are carried out for each control strategy under the electric vehicle conditions, and the reference of Figure **4-2**.

Remark:

For each control strategy, 10 experiments are conducted under similar conditions to account for uncertainties in the system and the measurement process. Moreover, statistical analyses were performed, involving comparisons among the results.

System Response

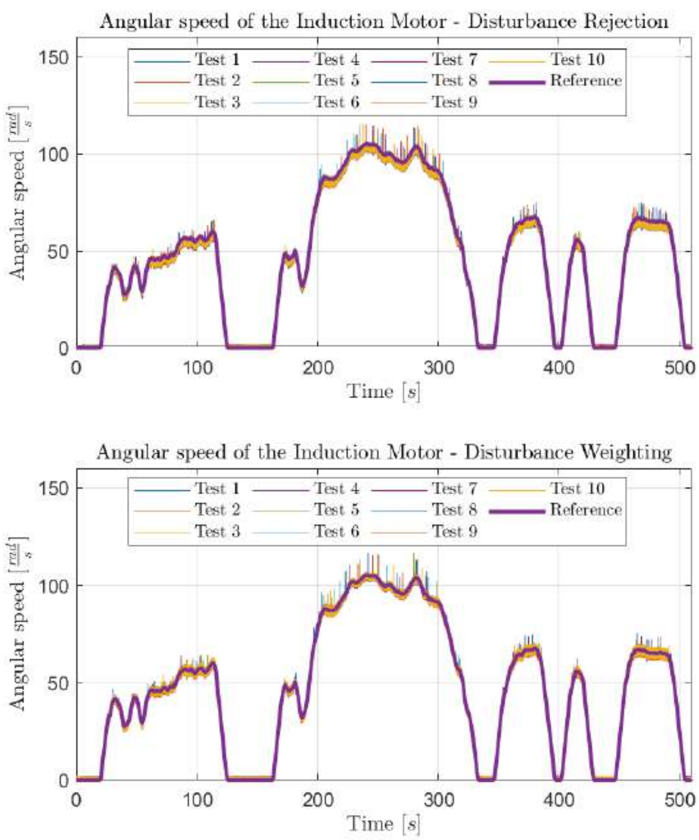


Figure 4-15.: Experimental results (Second experiment)

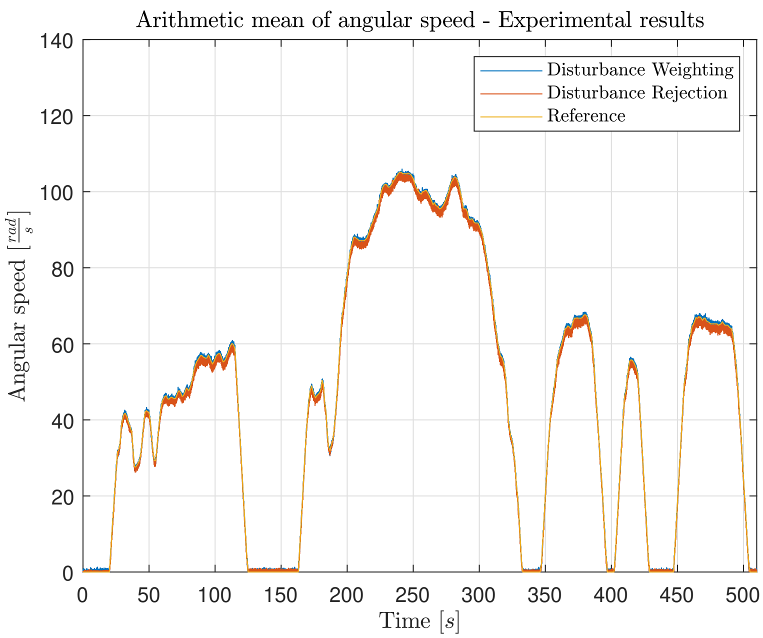


Figure 4-16.: Arithmetic mean of the results - Comparison between Disturbance Rejection and Disturbance Weighting (Second experiment)

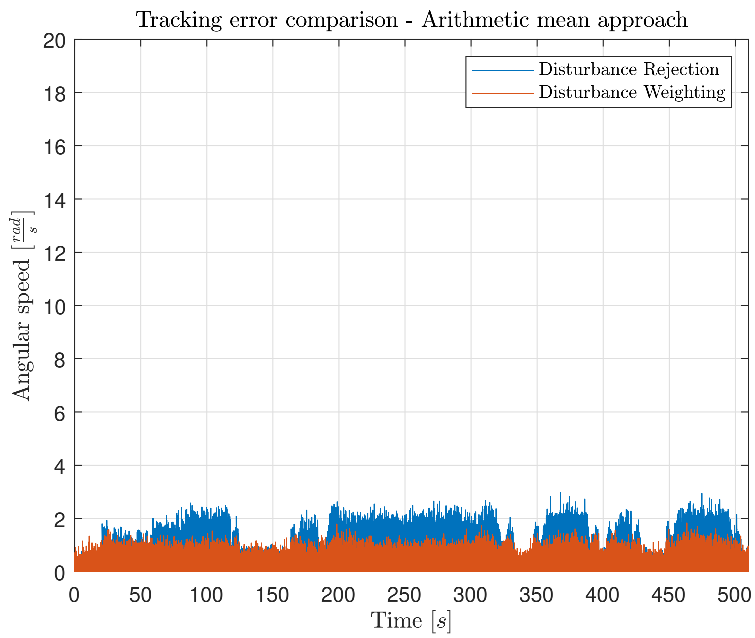


Figure 4-17.: Comparison of tracking error - Arithmetic mean approach (Second experiment)

The results of the figures **4-16** and **4-17** are based on the equations (4-1) and (4-2), respectively. Figure **4-15** shows a tracking of the reference, but as mentioned in the first experiment, there are measurement problems, so it is necessary to carry out several experiments and determine the corresponding statistical values. For this reason, it is possible to observe the arithmetic mean of the response of the system in Figure **4-16**. Figure **4-16** shows that the disturbance rejection has a lower value than the disturbance weighting strategy, the comparison of the tracking error can be observed in Figure **4-17**. This figure shows the magnitude of the error for any case considering the mean of the response of the ten experiments, concluding that the system that considers the disturbance rejection shows a higher value of error than the weighting of the disturbance case. Considering the tracking error it is possible to observe that the weighting of the disturbance proposes a better performance, but taking into account the performance described in equation (3-49).

Cost value

Considering Figures **4-18** and **4-19**, it is possible to conclude that the weighting of the disturbance considers a better performance, but the values present a higher variation of the final value of the costs than the other strategy, the final values an the analysis of the experiments can be seen in table **4-2**.

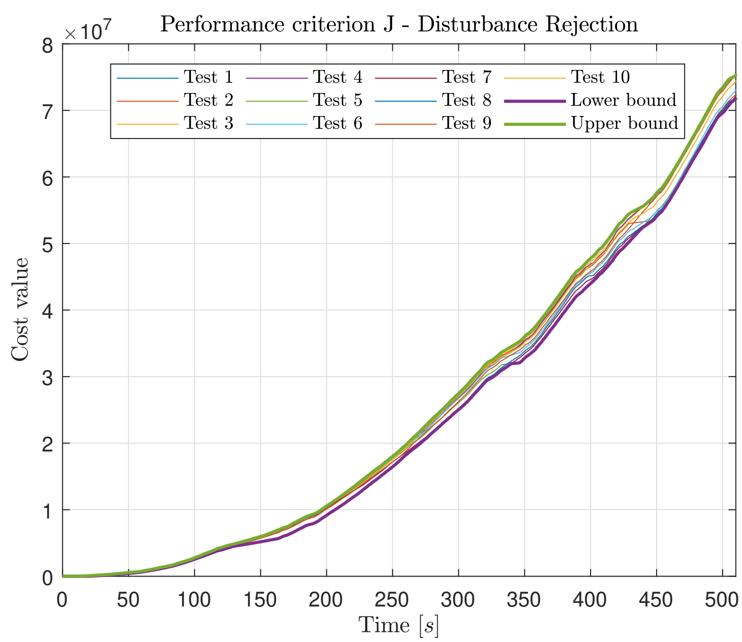


Figure 4-18.: Performance criterion for all test - Disturbance Rejection (Second experiment)

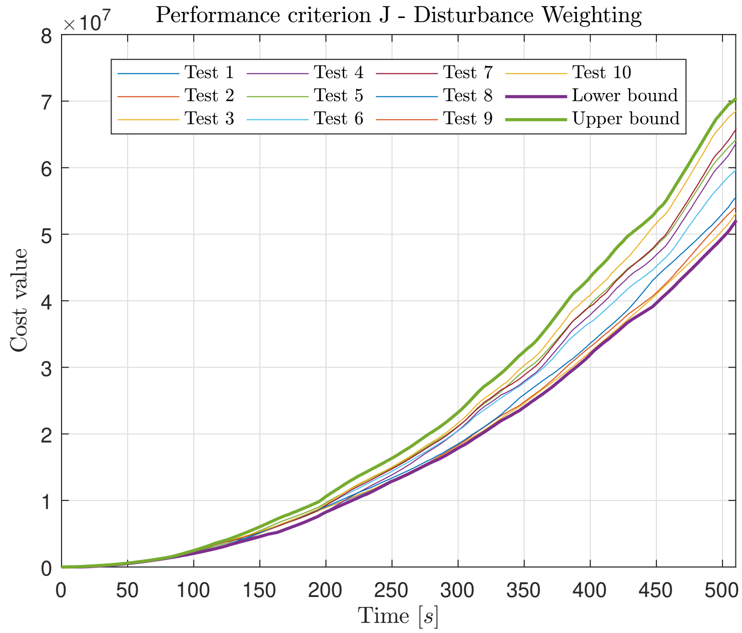


Figure 4-19.: Performance criterion for all test - Disturbance Weighting (Second experiment)

Table 4-2.: Results of tuning - Disturbance Rejection and Disturbance Weighting

Test	Disturbance Weighting	Disturbance Rejection
Test 1	$5.2372e + 07$	$7.5739e + 07$
Test 2	$5.4419e + 07$	$7.2865e + 07$
Test 3	$5.3536e + 07$	$7.5569e + 07$
Test 4	$6.4036e + 07$	$7.5742e + 07$
Test 5	$6.4576e + 07$	$7.2283e + 07$
Test 6	$6.0083e + 07$	$7.3454e + 07$
Test 7	$6.6193e + 07$	$7.2596e + 07$
Test 8	$5.6026e + 07$	$7.2293e + 07$
Test 9	$7.0820e + 07$	$7.5799e + 07$
Test 10	$6.8907e + 07$	$7.4809e + 07$
Arithmetic mean	$6.1097e + 07$	$7.4115e + 07$
Variance	$4.5210e + 13$	$2.4113e + 12$
Standard deviation	$6.7238e + 06$	$1.5528e + 06$

According to the table **4-2** it can be concluded that the weighting of the disturbance presents lower costs taking into account the performance criterion. However, there is a much larger variation in the data compared to the strategy where there is disturbance rejection. This phenomenon is due to the fact that when carrying out a large number of tests the motor presents a variation in the parameters that cause the offline optimization or the problems with the nonlinear approach.

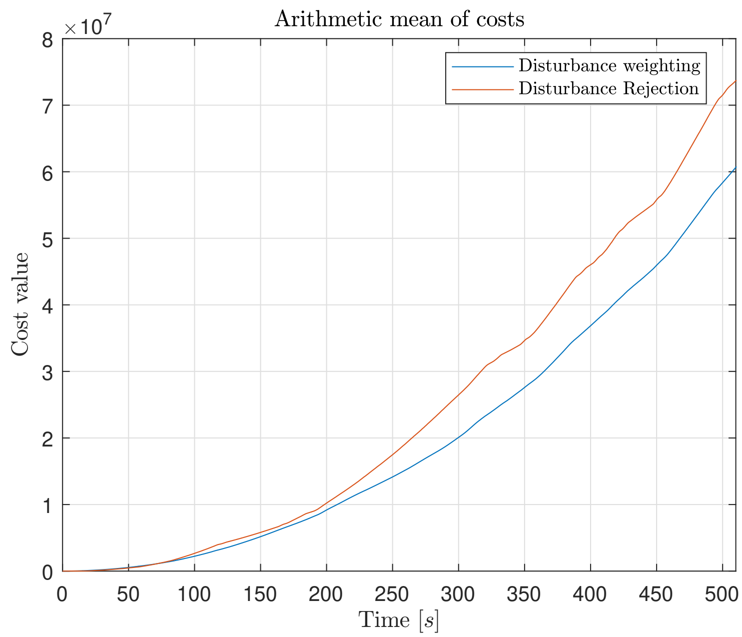


Figure 4-20.: Performance criterion for all test - Arithmetic mean approach (Second experiment)

Figure **4-20** is based in equation (4-3). This figure shows that the mean of the disturbance rejection case begins to have a higher cost when the reference is at a higher speed. The mean value of the disturbance weighting case represents the 82.44% of the mean value of the disturbance rejection case. Additionally, in Figure **4-21**, it is possible to observe a higher standard deviation in the disturbance weighting case. However, the worst case of the disturbance weighting experiment has a lower cost than the best case of the disturbance rejection experiment.

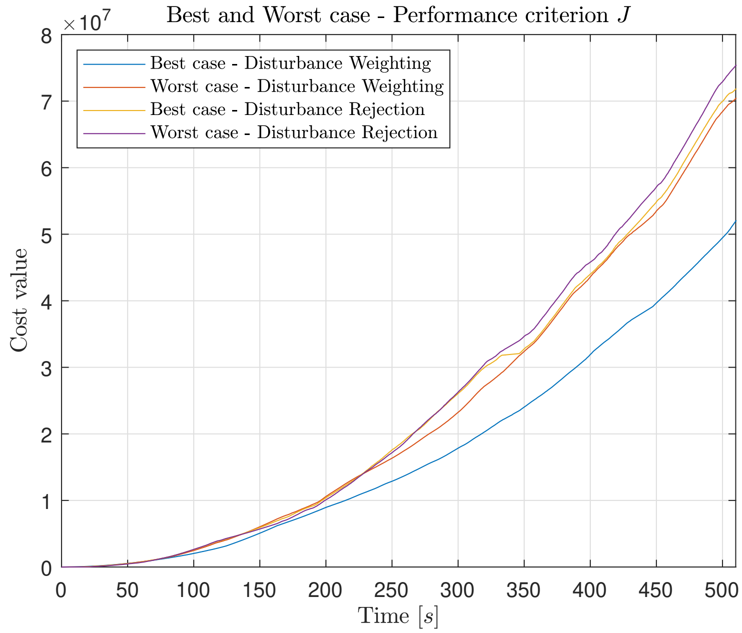


Figure 4-21.: Best and worst cases comparison (Second experiment)

4.1.7. Performance evaluation

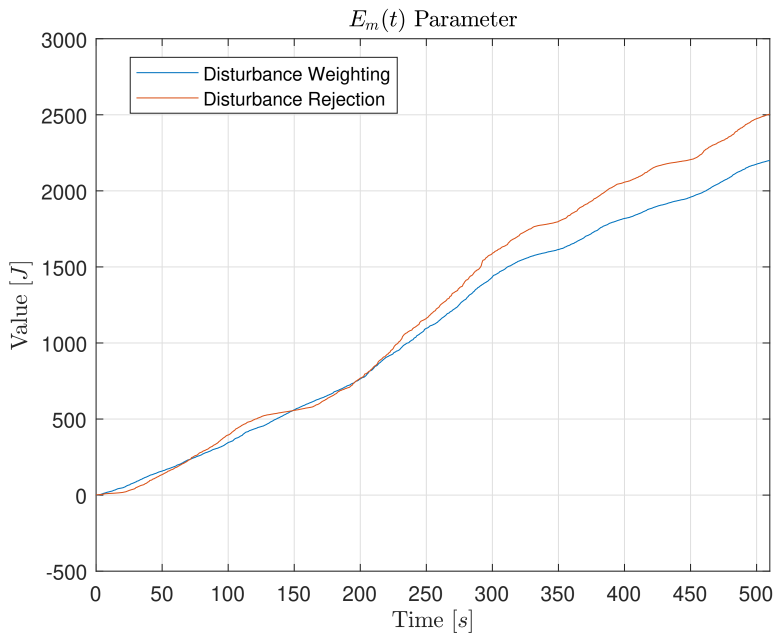


Figure 4-22.: $E_m(t)$ Parameter - Comparison (Second experiment)

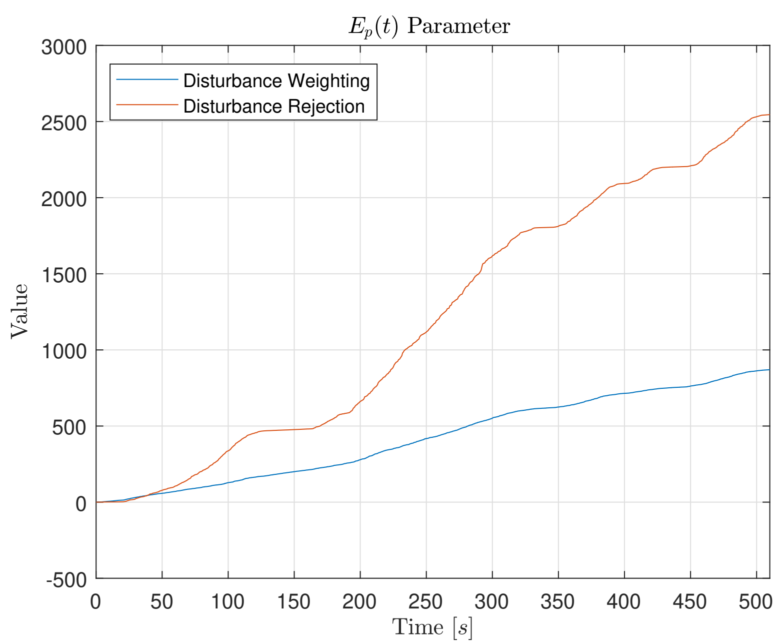


Figure 4-23.: $E_P(t)$ Parameter - Comparison (Second experiment)

For this experiment are considered the same additional performance criteria to evaluate the first experiment. The criteria can be described in equations (4-4) and (4-5). When it is considered the integral of the power parameter $p_m(t)$, it is possible to observe that in the case of disturbance weighting, the result of the energy parameter is given in Figure **4-22**, in this case, a lower final value is evident for the considered interval. When the error weighting is considered, it is contemplated Figure **4-23**, the disturbance weighting shows a better performance.

Analysis cost variation (Cost robustness)

For the cost variation analysis, the same analysis that was used in the first experiment is proposed. Additionally, the same parameter of the equation (4-6) is used to determine the variations of the system under the operating conditions.

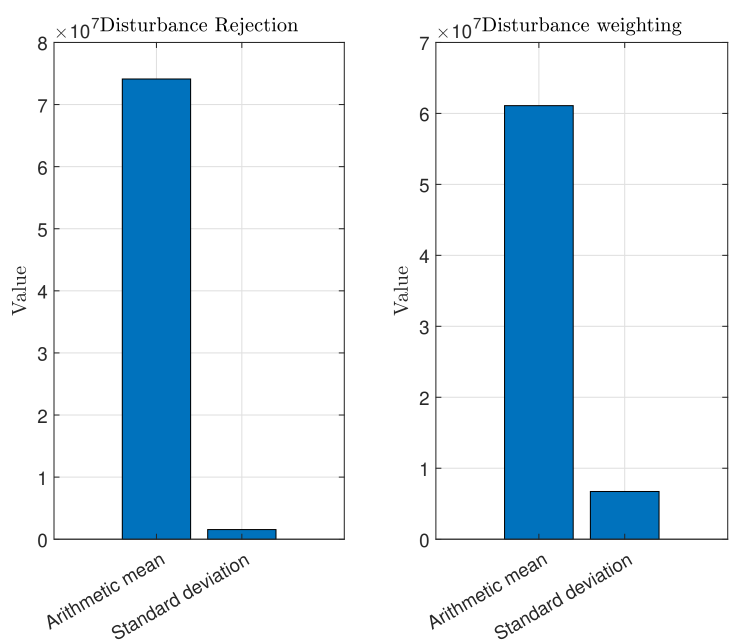


Figure 4-24.: Arithmetic mean and standard deviation (Second experiment)

According to Figures **4-25** and **4-24**, it is possible to conclude, despite the same values for the parameters of the ESO and the controller, the disturbance weighting proposes a higher variation of the results, showing that if the disturbance is not rejected completely, the variation of different experiments is higher than the traditional Active disturbance Rejection Control.

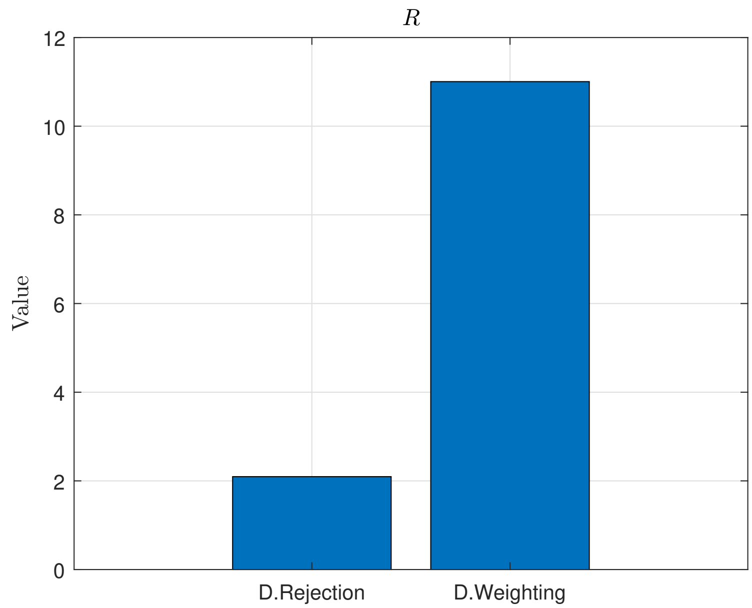


Figure 4-25.: R Parameter (Second experiment)

4.1.8. Vehicles dynamics - Comparison

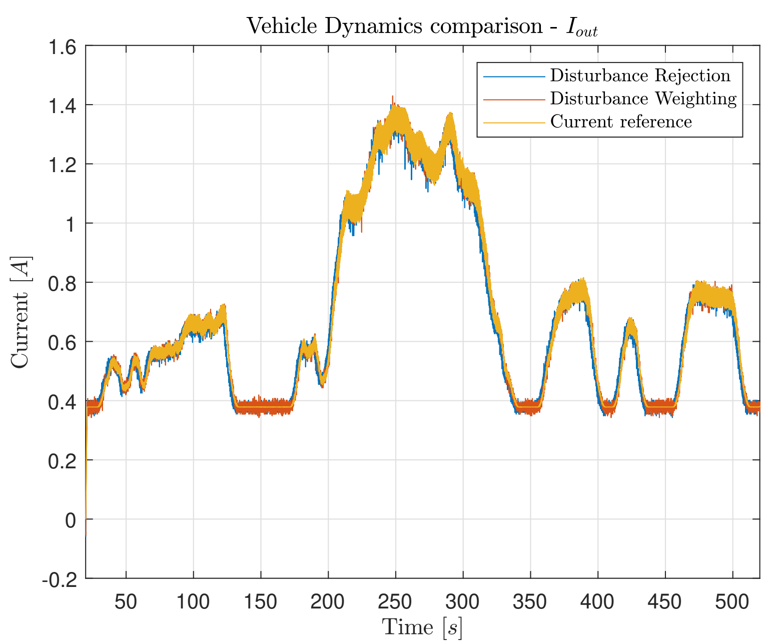


Figure 4-26.: Comparison of the current $I_{out}(t)$ - Vehicle dynamics (Second experiment)

As in the first experiment, the dynamics of the electric vehicle are provided by the reference current of the DC motor. This currents has a direct relationship with the torque. Where it is possible to see that the behavior of the current of both systems is similar and there a tracking of the reference current. The relationship between the reference of current I_{out} and the associated torque is given by equation (4-7).

The disturbance weighting strategy can offer advantages in an optimization problem since it allows for the consideration of new degrees of freedom. However, the absence of an approximate linearization in the standard Active Disturbance Rejection Control leads to a nonlinear control problem. This consideration introduces higher complexity and increases variations in different experiments due to operational conditions that can alter system parameters. These conclusions are validated through experimental results considering the dynamics of an electric vehicle using an induction motor.

5. Additional discussion

5.1. General Comparison Between Approaches

Considering a nonlinear system, it can be described by the following representations

$$\dot{x}(t) = f(x(t)) \equiv e_y(t)^{(n)} = \xi(t) + \kappa u(t), \tag{5-1}$$

where $x(t)$ represents the states, f is a vector field that describes the dynamics of the system, including the control signal, r is a function, κ is an average value, $u(t)$ is the control signal, and $e_y(t)$ is the tracking error of the output of the system. In equation (5-1), it is possible to consider the Koopman approach, Active Disturbance Rejection under disturbance rejection, and ADR under disturbance weighting.

5.1.1. Koopman Approach

Under the Koopman approach described in [8], the objective is to find a vector z to simplify or linearize the system:

$$\dot{z}(t) = Lz(t), \quad x = \phi(z), \quad z = \phi(x) \tag{5-2}$$

where the dynamics of the system are described by the eigendecomposition of L. Additionally, considering that it is possible to access measurement data, the discrete-time representation is considered:

$$x(k+1) = F(x(k)), z(k+1) \quad = K(x(k)), \tag{5-3}$$

where K is equivalent to L but in discrete time. Considering ρ is the Koopman operator, it is possible to define:

$$\rho\phi(x(k)) = g(F(x(k))) = g(F(x(k+1)))\rho\phi(x(k)) \quad = \lambda\phi(x(k)) = \phi(k+1), \tag{5-4}$$

where g is a measurement function that evaluates x. Additionally, ϕ is an eigenfunction of ρ, and λ is the respective eigenvalue. The eigendecomposition of the Koopman operator allows us to decompose the nonlinear dynamics in a linear way or in simpler ways, subject to measurement data. Then the control of the system can be realized under an approximation [8].

5.1.2. ADR Control - Disturbance Rejection

Under Disturbance Rejection control, the design is based on an Extended State Observer (ESO) where the estimation of the states and the disturbance is considered. The linearization of the system is given by the feedback linearization considering the disturbance

$$e_y^{(n)}(t) = v(t) + \xi(t) - \hat{\xi}(t) + \Delta_M, \tag{5-5}$$

where $\kappa u(t) = v(t) - \hat{\xi}(t) + \Delta_M$, Δ_M is the estimation error, and $v(t)$ represents the control law without considering the feedback linearization. A good estimation of the disturbance allows to consider a linear system design [53].

5.1.3. ADR Control - Disturbance Weighting

Under the disturbance weighting approach, it is possible to consider

$$e_y^{(n)}(t) = v(t) + \xi(t) - c\hat{\xi}(t) + \Delta_M, \tag{5-6}$$

where $\kappa u(t) = v(t) - c\hat{\xi}(t) + \Delta_M$, Δ_M represents the estimation error, and $v(t)$ denotes the control law without considering the weighting of the feedback linearization. Concerning traditional Active Disturbance Rejection control, it is possible to find a new degree of freedom given by c parameter. A good estimation of the disturbance can be achieved by considering a linear system with values of c close to 1. However, the design is based on a nonlinear control problem.

5.1.4. Conclusion of Comparison

The traditional Active Disturbance Rejection Control (ADRC) and the modified version presented in this document represent a method for linearizing the system through disturbance estimation. However, the estimation error may not significantly impact the system results with well-tuned parameters. The introduction of disturbance weighting provides an additional degree of freedom, enabling the consideration of various optimization problems to achieve a better result considering a higher level of complexity. In contrast, the Koopman approach offers a linear approximation, but it necessitates measurement data, which can pose an additional challenge. Consequently, both ADR approaches hold advantages over the Koopman approach as they do not require the measurement of data to linearize the system.

Instead, these ADRC approaches achieve system linearization through the differential grade of the system.

6. Conclusions and recommendations

6.1. Conclusions

Taking into account the results of this research, it is possible to conclude

- In optimization problems, under the Active Disturbance Rejection approach and an optimal control problem. Including a weighting of the disturbance rejection may improve the performance of a control design mixing both optimal control and ADRC. However, this weighting also increases the complexity when solving the optimization problem and reduces the ADRC rejection capabilities.

- The use of disturbance weighting considers a higher variety in the results than the traditional Active Disturbance Rejection Control because the disturbance weighting strategy is based on a nonlinear control design and uncertainties are not completely rejected. Additionally, in these cases, it is important to keep disturbance weighting values close to 1 to mitigate the nonlinear and uncertainty aspects and guarantee the stability of the system.

- The traditional Active Disturbance Rejection Control (ADRC) can be considered a more practical design from an optimization problem since it is based on a linear process. Additionally, it does not imply much difference in percentage regarding a considered cost compared to the modified ADRC. The reduction in degrees of freedom decreases the complexity of the optimization problem and confines the stability of the system to the controller parameters.

6.2. Recommendations

For each experiment, it is advisable to operate the system under consistent conditions. Conducting multiple experiments consecutively can introduce variations in the operational conditions of the motor, potentially leading to changes in the dynamic system parameters. It is important to note that the control strategy proposed in this work is based on disturbance weighting. This strategy does not linearize the system, preserving unmodeled dynamics and uncertainties that can vary considerably. Additionally, the disturbance weighting constraints need to be set close to 1 because accurately predicting the behavior of the system is too complex taking into account the stability of the system.

6.3. Future work

After conducting experiments and working on the optimization problem, it is necessary to consider the following issues and topics for future research:

- The metaheuristic method employed in this work operates under offline conditions, which may pose a challenge due to potential changes in system parameters during experiments. The disturbance weighting results in a nonlinear system that might encounter issues when the system dynamics change under operational conditions. Hence, it is necessary to devise an optimal online control strategy that considers the system model continuously, reducing dependency on the model.
- During offline optimization, it is recommended to use other and different algorithms considering the same optimization problem, with the aim of determining which algorithm is superior.
- It is recommended to characterize the induction motor parameters because the use and variations can change the dynamic of the system.
- It is recommended to use other extended states for the disturbance model for the control design to compare the results regarding the tuning of the controller.

A. Experimental setup diagrams

Using the references from tables **0-1**, **0-2**, and **0-4**, the experimental setup can be modeled in Figure **A-1**. Figure **A-1** illustrates the structure of the controller and the implementations, taking into account the xPC-Target. Figure **A-2** shows the control principle of the induction motor, considering the respective electronic components, while Figure **A-3** illustrates the control principle of the DCG, considering the electronics.

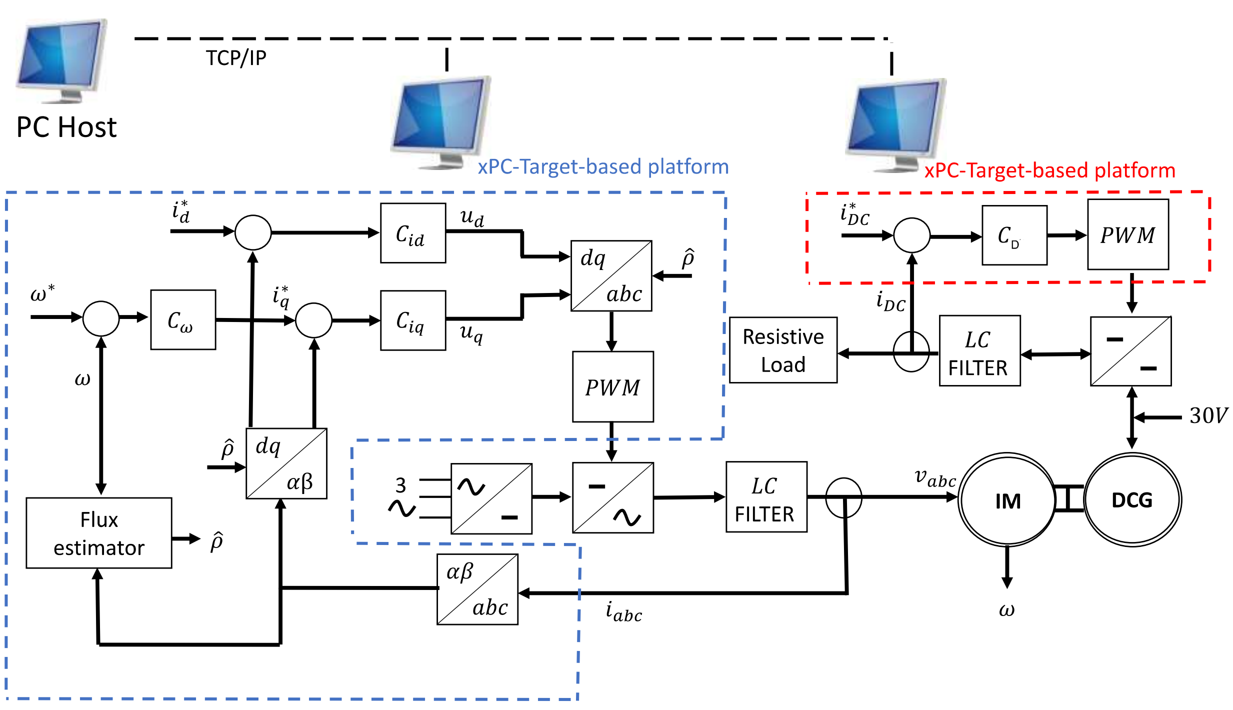


Figure A-1.: Experimental setup - Operating principle

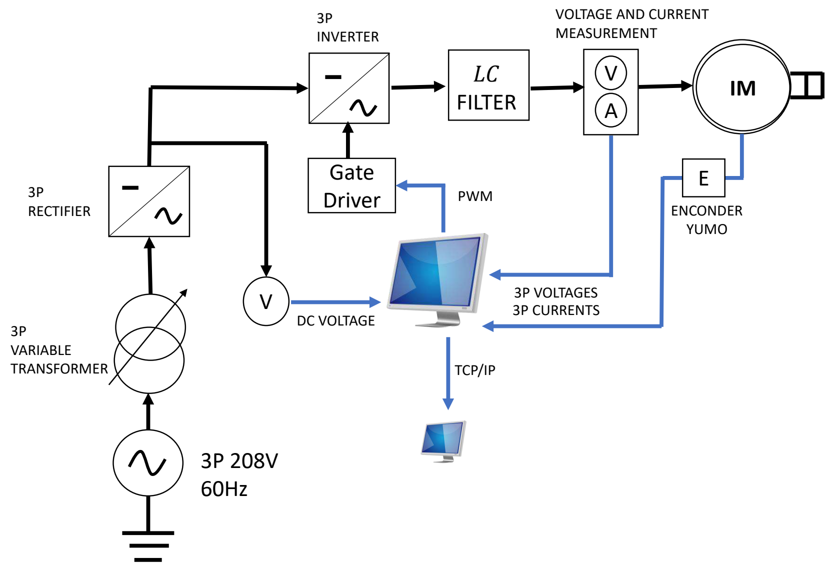


Figure A-2.: Experimental setup - Induction motor control

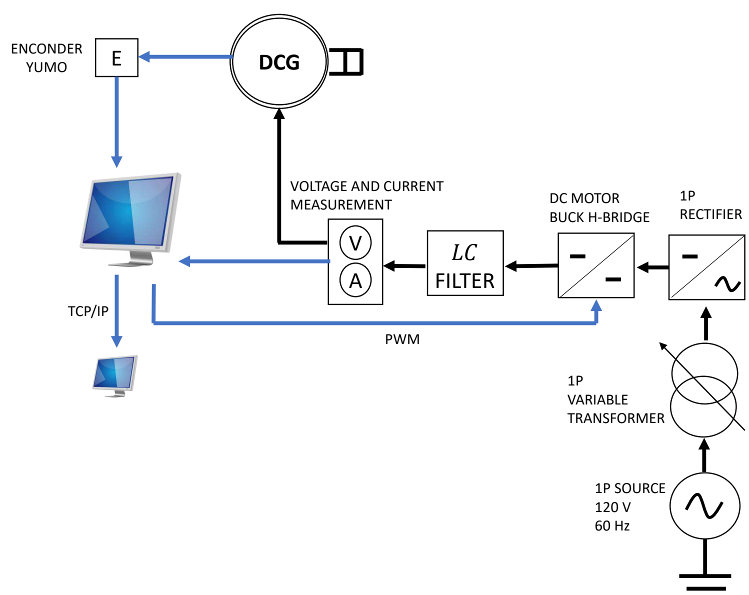


Figure A-3.: Experimental setup - Generator DC control

B. Induction motor and Vehicle parameters

The parameters that will be used for the induction motor can be shown in table **B-1**

Table B-1.: Induction motor and Vehicle parameters

Induction motor	
Parameter	**Value**
Nominal speed/ pair pole	1500rpm/2
Nominal voltage/ Nominal frequency	$70V/50Hz$
Nominal current	$1.2A$
Stator resistor/ Rotor resistance	$6.575\Omega/19.577\Omega$
Nominal torque/Nominal power	$0.6Nm$ / $100W$
Magnetization inductance	$243.4mH$
Rotor leakage inductance	$5.4mH$
Stator leakage inductance	$55.2mH$
Vehicle	
Parameter	**Value**
Vehicle mass	$98Kg$
Wheel Radius/Fixed Gear Ratio	$0.3594m/9.73$
Frontal Area	$2.4m^2$
Air density	$1.1839\frac{kg}{m^3}$
Aerodynamic drag coefficient	0.24
γ	5.3475
Rolling resistance coefficient	0.002

C. Hybrid algorithm parameters

Table C-1.: Parameters of hybrid algorithm - Induction motor case

Algorithm for tuning k_{id} **,** k_{idq} **and** k_{ω} (Disturbance Rejection)	
Number of variables for optimizing	3
Limits (Restrictions of variables)	$(60, 60, 60)$, $(300, 300, 300)$
Number of particles	10
Max Iteration ($maxIter$)	30
C_1, C_2	0.7
W_{max}, W_{min}	0.9 , 0.2
Initial Temperature	10 / 5*
Annealing rate	0.7
Lenght of Tabu list	10
Neigh-board Tabu Search	3
Iterations of tabu Search	3
Algorithm for tuning k_{id} **,** k_{iq}**,** k_{ω} **,** $k_{\xi id}$ **and** $k_{\xi iq}$ **(Disturbance Rejection)**	
Number of variables for optimizing	5
Limits (Restrictions of variables)	$(60, 60, 60, 0.990, 0.990)$, $(300, 300, 300, 1.1, 1.1)$
Number of particles	10
Max Iteration ($maxIter$)	30
C_1, C_2	0.7
W_{max}, W_{min}	0.9 , 0.2
Initial Temperature	10 / 5*
Annealing rate	0.7
Lenght of Tabu list	10
Neigh-board Tabu Search	3
Iterations of tabu Search	3

Table C-2.: Parameters of hybrid algorithm - Induction motor case

Algorithm for tuning $k_{\xi id}$ and $k_{\xi iq}$	
Number of variables for optimizing	2
Limits (Restrictions of variables)	$(0.995, 0.995)$, $(1.08, 1.08)$
Number of particles	10
Max Iteration ($maxIter$)	30
C_1, C_2	0.7
W_{max}, W_{min}	0.9 , 0.2
Initial Temperature	10 / 5*
Annealing rate	0.7
Lenght of Tabu list	10
Neigh-board Tabu Search	3
Iterations of tabu Search	3

$*$: The value of the initial parameter temperature depends on the actual temperature and the comparison between the optimal value of the particle swarm optimization algorithm and the improvements. If the actual temperature is equal to 1 or the hybrid algorithm has a better performance than the traditional PSO, the new initial temperature is equal to 5 to reduce the search space.

D. Selection of the disturbance weighting parameters interval

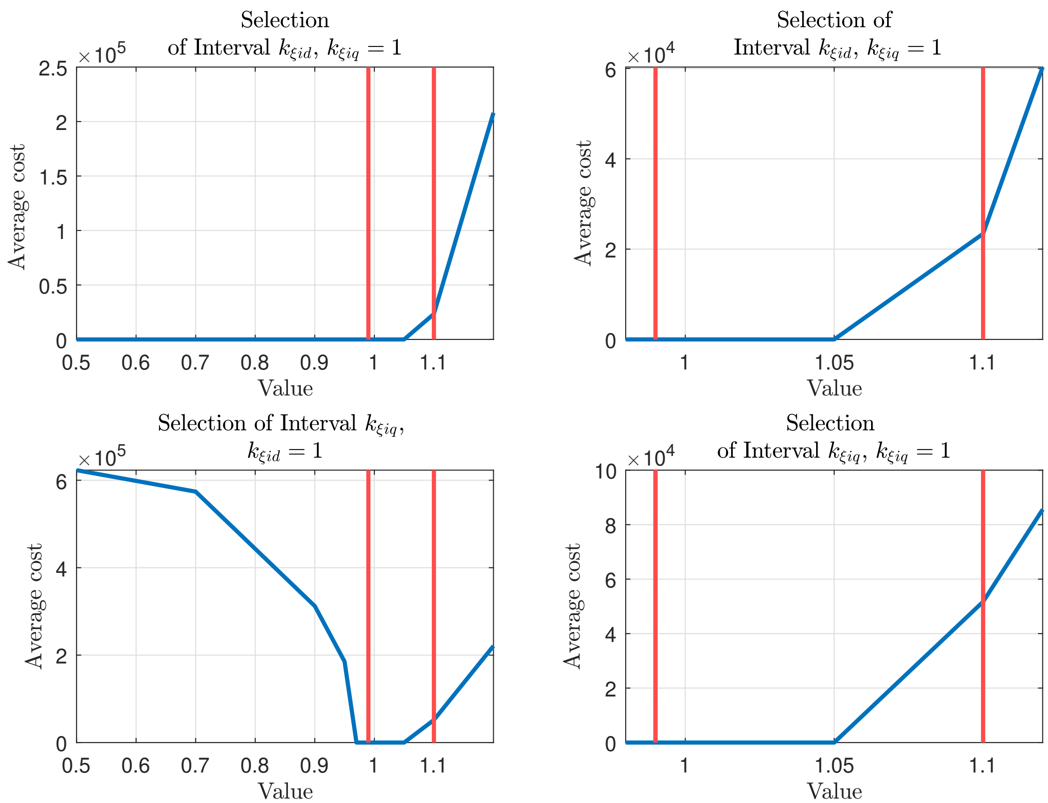


Figure D-1.: Selection of the disturbance weighting parameters interval

For the selection of decision variable constraints related to disturbance weighting parameters, numerical analysis was employed using various values for controller parameters while varying the values of variables associated with disturbance. The cost considered is determined by calculating the average tracking error of the angular speed over the working time across multiple simulations

$$\text{Cost considered} = \int_{t_0}^{t_f} (a|e_\omega(t)|)dt, \quad a \in \mathbf{R}^+, \quad e_\omega(t) = \omega(t) - \omega^*(t). \tag{D-1}$$

The analysis can be observed in Figure **D-1**. The reference considered is that of Figure **3-5**, taking into account the first 100 seconds of operation.

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