engineering proceedings

MDPI

Proceeding Paper

High Gain Observer Based Active Disturbance Estimation ADE for Second Order Nonlinear Uncertain Systems (ex:Induction Motor) †

Saad Kelam [1,*], Mohamed Chennafa [2], Mohamed Belkheiri [3] and Mohamed Amine Zaafrane [4]

1 Automatic Departement, University of Sciences and Technology of Oran—Mohamed-Boudiaf (USTO-MB), El Mnaouar, BP 1505, Bir El Djir 31000, Algeria
2 National Polytechnic School of Oran-Maurice Audin, Route d'Es-Sénia, B.P. 1523, El M'Naouer, Oran 31000, Algeria
3 The Telecommunications, Signals and Systems Laboratory, University Amar Telidji of Laghouat, B.P. 37G, Guardaia Road, Laghouat 03000, Algeria
4 Electrical Engineering Faculty, University of Sciences and Technology of Oran—Mohamed-Boudiaf (USTO-MB), El Mnaouar, BP 1505, Bir El Djir 31000, Algeria
* Correspondence: saad.kelam@univ-usto.dz
† Presented at the 2nd International Conference on Computational Engineering and Intelligent Systems, Online, 18–20 November 2022.

Abstract: The main objective of this paper is to solve state observation and external disturbances estimation for a class of second-order nonlinear systems. The proposed method relies mainly on the high gain observer as an estimator that tries to estimate the state vector and at the same time identifies the system's unknown combined structured and unstructured uncertainties. The efficiency of the proposed method is demonstrated by estimating the flux and the speed of the induction motor by simulation.

Keywords: high-gain observers; estimation; disturbances; second order systems; uncertain systems; active disturbance estimation; flux; speed; induction motor

Citation: Kelam, S.; Chennafa, M.; Belkheiri, M.; Zaafrane, M.A. High Gain Observer Based Active Disturbance Estimation ADE for Second Order Nonlinear Uncertain Systems (ex:Induction Motor). *Eng. Proc.* **2023**, *29*, 14. https://doi.org/10.3390/engproc2023029014

Academic Editors: Abdelmadjid Recioui, Hamid Bentarzi and Fatma Zohra Dekhandji

Published: 17 January 2023

1. Introduction

Dynamic systems are usually exposed to control signals that can be used to drive them to achieve a given objective and solve regulation and tracking control problems based on reliable models and in the presence of external perturbations and disturbances. These disturbances are, generally speaking, unstructured, i.e., they may depend on internal variables of the system in an either unknown or an ignored manner or else, they may also depend on external phenomena affecting the system [1]. They are unknown, unpredictable, or unmodeled. They can affect the controlled system response, its stability and closed-loop performance if they are ignored in the control synthesis phase. Solving this problem is still an open issue for control systems researchers. In the literature, many control methods that rely on a reliable model that approximates the system to be controlled are proposed feedback linearization and backstepping. In this case, some analytic robust terms are included in the derivation of the controller to guarantee stability and performance in the presence of uncertainties [2,3]. Sliding mode control techniques are among the robustifying methods that derive the control law bead on two combined terms, the equivalent control term based on the system model and a switching robustifying term [4]. High-gain observers are first used in the context of linear feedback as a tool for robust observer design for loop transfer recovery achieved by state feedback and in robust H∞ control in [5]. High-gain observers integration in nonlinear feedback control started in the late 1980 [6–9], where researchers in these papers have studied a wide range of nonlinear control issues, including stabilization, regulation, tracking, and adaptive control. They also studied time-varying high-gain observers and related problems [5]. In any case, disturbances are classed into two main categories and referred to as internal uncertainties and disturbances [10–14]. The main idea of this short note is to simplify the prediction of disturbances acting on the plant by grouping all external and internal dynamic disturbances into a single disturbance term and proceed to estimate the effects of this disturbance using High-Gain observers. The rest of the paper is organized as follows: in Section 2, we present the problem statement and state observation scheme with active disturbance estimation (ADE) based on the high-gain observer. The resulting ADE observer is applied to the induction motor system in Section 3 followed by the concluding remarks in Section 4.

2. State Observation Scheme with Active Disturbance Estimation (ADE)

2.1. Problem Statement

Active Disturbance Estimation ADE strategy is based on the possibility of online estimating of unknown disturbance inputs affecting the plant. The feedback control law usually requires full knowledge of the state which can be at the same time reconstructed by the same designed observer. In this section, we consider the following endogenously perturbed second-order system:

$$\left\{\begin{array}{c} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = u(t) + \theta^T\phi(x(t)) + \varepsilon(t) \end{array}\right. \tag{1}$$

where $x(t) = [(x_1(t)\&x_2(t))]^T$ is the state vector and the first element $x_1(t)$ of $x(t)$ is only the measured state or output $y(t) = x_1(t)$ and $\theta^T\phi(x(t))$ known linearly parameterized terms and $\varepsilon(t)$ represents the unmodelled unknown uncertain terms. The system defined in (1) can be used to derive an adaptive high-gain observer that reconstructs the state vector with an adaptive law that estimates the unknown parameter vector θ the observer error is bounded and is ensured to converge given some robustness conditions on the term $\varepsilon(t)$ to be verified. For more information on designing high-gain observers, the readers can refer to reference [5]. In the context of Active Disturbance Estimation ADE disturbances and nonlinearities may be combined in a single term that can be approximated online. This suggests rewriting the second-order uncertain system in the following form:

This is an example of the equation:

$$\left\{\begin{array}{c} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = u(t) + \xi(t) \end{array}\right. \tag{2}$$

where $\xi(t) = \theta^T\phi(x(t)) + \varepsilon(t)$.

The term $\xi(t)$ combines all the unknown exogenous terms. It is assumed that $\xi(t)$ and its first-order time derivative are uniformly absolutely bounded. Note that many mechanical electrically driven systems in robotics and mechatronics can be represented by the system in Equation (1). The objective can then be stated as follows: to design a state observer to estimate the state vector and actively estimates the unknown exogenous terms with converging observation errors.

2.2. High-Gain Observer with Active Disturbance Estimator

Consider the following Extended State Observer (ADE):

$$\left\{\begin{array}{c} \dot{\hat{x}}_1(t) = \hat{x}_2 + \lambda_1(x_1(t) - \hat{x}_1(t)) \\ \dot{\hat{x}}_2(t) = u(t) + \hat{\xi}(t) + \lambda_2(x_1(t) - \hat{x}_1(t)) \\ \dot{\hat{x}}_3(t) = \lambda_3(x_1(t) - \hat{x}_1(t)) \end{array}\right. \tag{3}$$

where λ_1,λ_2 and $\lambda 3$ are (ADE) observer gains and they are chosen to achieve convergence.

$$\lambda_1 = \frac{1}{\varepsilon} \times (p_0 + 2\xi_0\omega_0)$$

$$\lambda_2 = \frac{1}{\varepsilon^2} \times (2p_0\xi_0\omega_0 + \omega_0^2)$$

$$\lambda_3 = \frac{1}{\varepsilon^2} \times (p_0\omega_0^2)$$

with p_0, ξ_0,ω_0 are positive constants and ε being a small parameter bestowing a high-gain character to the ESO design. Here, the variable $\hat{\xi}$ is supposed to estimate the total disturbance input to the system $\xi(t)$, composed of the two terms; the endogenous perturbation input $\theta^T\phi(x(t))$ and the exogenous perturbation input $\varepsilon(t)$.

Defining the estimation error vector as $e_1(t) = x_1(t) - \hat{x}_1(t)$,$e_2(t) = x_2(t) - \hat{x}_2(t)$ and $e_\xi(t) = \xi(t) - \hat{\xi}(t)$, its dynamics evolve according to the linear perturbed dynamics

$$\begin{cases} \dot{e}_1(t) = e_2 - \lambda_1 e_1(t) \\ \dot{e}_2(t) = e_\xi(t) - \lambda_1 e_1(t) \\ \dot{e}_3(t) = \xi - \lambda_3(x_1(t) - \hat{x}_1(t)) \end{cases} \tag{4}$$

The derivative term $\dot{\xi}$ is given by:

$$\dot{\xi} = \theta^T \frac{d(\phi(x(t))}{dt} + \frac{d(\varepsilon(t))}{dt}$$

It is bounded given that the nonlinear terms are continuous and their derivatives are continuous as well. Another methodology based on adaptive control can be used to estimate the term $\theta^T(\phi(x(t))$ rather than $\hat{\xi}(t)$ Defining the error vector as $e^T = (e_1, e_2, e_\xi)$ Equation (4) can be written as

$$\dot{e} = \begin{pmatrix} -\lambda_1 & 1 & 0 \\ -\lambda_2 & 0 & 1 \\ -\lambda_3 & 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \dot{\xi}(t) \tag{5}$$

The right choice of the design parameters λ_i ensure the convergence of the observer error dynamics in (4) for more details on the convergence readers may refer to the book written by Hassan Khalil on High gain observers (5).

3. Ade Observer for the Induction Motor

3.1. Induction Motor System Modeling

The induction motor is one of the most complex dynamical systems due it is difficult to control since this system is considered to be multivariate having properties such as high coupling and high non-linearity. It is generally described by a fifth-order nonlinear differential equation with two inputs. Moreover, the control and the parameters estimation of an induction motor is very complex, because it is subject to unknown disturbances and the variation of motor parameters due to heating and magnetic saturation. We used field-oriented control (FOC) to perform a change of variables to bring the equations into new coordinates that will be simple to work with, where the currents regulating the flux and the speed are decoupled [15,16]. Thus, instead of working with (ψ_{ra},ψ_{rb}), one uses the polar coordinate representation (ρ,ψ_d) [15,16]. IM is represented by the model [15–17].

$$\begin{aligned} \tfrac{d\omega}{dt} &= \mu\psi_d i_q - \tfrac{f}{J}\omega - \tfrac{1}{J}\tau_L \\ \tfrac{\psi_d}{dt} &= -\eta_{rn}\psi_d + \eta_{rn}L_m i_d \\ \tfrac{di_d}{dt} &= -\gamma_n i_d + \eta r_n \beta\psi_d + n_p\omega i_d + \tfrac{\eta_{rn}L_m i_d^2}{\psi_d} \\ &\quad + f_1 + \tfrac{1}{\sigma L_s}u_d + \delta_1 \\ \tfrac{di_q}{dt} &= -\gamma_n i_q - \beta n_p\omega\psi_d - n_p\omega i_d - \tfrac{\eta_{rn}L_m i_d i_q}{\psi_d} \\ &\quad + f_2 + \tfrac{1}{\sigma L_s}u_q + \delta_2 \\ \tfrac{d\rho}{dt} &= n_p\omega + \tfrac{\eta_{rn}L_m i_q}{\psi_d} \\ \tau_e &= J\mu\psi_d i_q \end{aligned} \tag{6}$$

In the above model, the angular speed of the rotor is denoted by ω, ψ_r is the flux in the stator reference frame, and i_S and u_S denote the stator currents and voltages, n_p is the number of pole pairs, R_s and R_r are the stator and rotor resistances, M is the mutual inductance, L_s and L_r are the stator and rotor inductances, and the two mechanical parameters: J is the inertia of the rotor and f is the load torque. The resistances R_s, R_r and the inductances L_s , L_r will be treated as uncertain parameters with R_{sn}, R_{rn} and L_{sn}, L_{rn} as their rated values, respectively. $\eta_{rn} = \frac{R_{rn}}{L_{rn}}$, $\eta_{sn} = \frac{R_{sn}}{L_{sn}}$ $\delta_1 = \delta_R r g_1 + \delta_{Sr} g_2 + \delta_{Lr} g_3 + \delta_{Ls} g_4$, $\delta 2 = \delta_R r g_5 + \delta_{Sr} g_6 + \delta_{Lr} g_7 + \delta_{Ls} g_8$. Where f_1 and f_2 are continuous functions of δ_{Rr}, δ_{Rs}, δ_{Lr}, δ_{Ls} are continuous functions of (ψ_d, i_d, i_q). The electromagnetic torque $\tau_e = J\mu\psi_d i_q$ is now just proportional to the product of two state variables ψ_d and i_q. That is the first four equations of (6) may be written as two decoupled subsystems consisting of the flux subsystem model:

$$\begin{cases} \frac{d\psi_d}{dt} = -\eta_{rn}\psi_d + \eta_{rn} M i_d \\ \frac{di_d}{dt} = f_d + u_d \end{cases} \tag{7}$$

and the speed subsystem model:

$$\begin{cases} \frac{d\omega}{dt} = \mu i_q \psi_d - \frac{f}{J}\omega - \frac{\tau_L}{J} \\ \frac{di_q}{dt} = f_q + u_q \end{cases} \tag{8}$$

where

$$f_d = -\gamma_n i_d + \eta_{rn}\beta\psi_d + n_p\omega i_q + \frac{\eta_{rn} M i_q^2}{\psi_d} + f_1 + \delta_1$$

and

$$f_q = -\gamma_n i_q - n_p\omega\beta\psi_d + n_p\omega i_q - \frac{\eta_{rn} i_d i_q}{\psi_d} + f_2 + \delta_2$$

f_d and f_q are perturbation terms. The field-oriented control consists of using u_d to force ψ_d to track the constant flux reference $\psi_{dn} = M i_{dn}$ in the flux subsystem, and the control of speed in the subsystem is done through the input u_q. Consequently, the flux dynamics are now decoupled from the speed dynamics. However, the differential equations for i_d and i_q still contain quite complicated nonlinearities in both flux (7) and speed subsystems (8). To solve the problem of unknown variations in plant parameters and structure, in this paper a robust ADE observer will be designed to eliminate the effect of unstructured uncertainties in each subsystem of the decoupled dynamics of flux and speed subsystems of the IM .

3.2. High-Gain Observer with Active Disturbance Estimator

Noting that in applying the feedback (6), there is some uncertainty in the knowledge of the motor parameters and the state variables. Furthermore, the motor parameters R_r and R_s can vary significantly due to Ohmic heating while L_r and L_s can also vary due to magnetic saturation [15]. For that, assuming that all neglected terms for each subsystem as an error signal Δ_i (Δ_d and Δ_q) consequently, the dynamics of the output $(y_d = x_1 = \psi_d)$ $(y_q = \xi_1 = \omega)$. Defined by (7) and (8), respectively, will be expressed as:

Flux expressed:

$$\begin{cases} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = f_d(t) + u_d(t) \end{cases} \tag{9}$$

Speed expressed:

$$\begin{cases} \dot{\xi}_1(t) = \xi_2(t) \\ \dot{\xi}_2(t) = f_q(t) + u_q(t) \end{cases} \tag{10}$$

Our objective is to develop a high-gain observer with an active disturbance estimator that is capable of estimating the flux and speed of an induction motor and eliminating the uncertainties effect in the observer law in order to achieve a good estimation of the desired trajectory and to solve the problem of unknown variations in plant parameters and the load torque. In designing an observer law for speed estimation and torque load generation based on a given flux reference signal, for each subsystem, a simpler strategy is followed in this paper where two ADE observers are used to overcome the effects of nonlinear uncertainties and neglected terms in the accuracy of the estimation. The desired torque $\tau_e^* = \mu\psi_d^* i_q$ to be generated with the corresponding reference flux ψ_d^*. In order to the flux tracking, we introduce the state variables $(x_1 = \psi_d)$, $(x_2 = \dot{x_1})$ and $(\zeta_d = f_d)$ the state space model (6) and for the tracking problem of the speed we define the new state vector $(\xi_1 = \omega)$, $(\xi_2 = \dot{\xi}_1)$ and $(\zeta_q = f_\omega)$ the speed subsystem dynamics given in (9) can be written as follows:

$$\begin{cases} \dot{x}_1(t) = x_2(t) \\ \dot{x}_2(t) = \zeta_d(t) + u(t) \\ \dot{\zeta}_d(t) = \dot{f}_d(t) \end{cases} \tag{11}$$

where

$$\zeta_d(t) = f_d(t) = \eta_{rn}^2 \psi_d - \eta_{rn}^2 + \eta_{rn} M F_d, b_d = \frac{\eta_{rn} M}{\sigma L_s}$$

and

$$u(t) = u_d(t)$$

$$\begin{cases} \dot{\xi}_1(t) = \xi_2(t) \\ \dot{\xi}_2(t) = \zeta_q(t) + u(t) \\ \dot{\zeta}_q(t) = \dot{f}_q(t) \end{cases} \tag{12}$$

where

$$\begin{aligned} f_q(t) &= \mu \psi_d \left(-\gamma_n i_q - \beta n_p \omega \varphi_d - n_p \omega i_d - \frac{\eta_{rn} L_m i_d i_q}{\varphi_d} \right) \\ &-\frac{f}{J} \dot{\omega} - \frac{\tau_L}{J} \end{aligned}$$

and

$$u(t) = u_q(t)$$

Note that the objective of the ADE strategy is to obtain proper estimation, minimize the total disturbance and obtain a good estimation of the flux and the speed. The ADE observer law is given by (7) and (8), where λ_i are design parameters chosen as described in Section 2. The observer uses the error between the actual measured flux ψ and the estimated flux $\hat{\psi}$ for correcting the estimated vector.

4. Results

The performance of the high-gain observer with an active disturbance estimator is tested by a differential simulation model under Matlab/Simulink environment. The simulated motor is a six-pole $(n_p = 3)$, 1/12 horsepower two-phase IM and the rated parameters of the motor were taken from [15] as $R_s = 1.7\ \Omega$, $R_r = 3.9\ \Omega$, $L_s = 0.0014$ H, $L_r = 0.0014$ H, $M = 0.0117$ H , $J = 0.00011$ K·gm^2, $f = 0.00014$ N·m/rad/s.

The speed and flux estimation performance of ADE is illustrated in graphs (a) and (b) in Figure 1, respectively, which shows that the ADE observer is robust to parametric uncertainties and external disturbance variation. Although the references peed is changed from 100 rad/s to 20 rad/s and the torque load is kept constant with variations. The ADE observer has not encountered a tracking problem to follow the reference speed and flux as illustrated in Figure 1 This result shows the achieved performance of the ADE strategy for the perfect speed and flux esteeming.

For the last simulation scenario, a highly varying load torque is applied with parametric uncertainty to show the power of ADE to achieve perfect speed tracking for highly varying load illustrated in the Figure 2. Obviously, the ADE observer can estimate the speed, flux and disturbance despite a change in the torque simulation scenario as demonstrated in Figure 3.

Figure 4 illustrates the ADE observer system's U_{ABC} and d, q-axes control voltage waveform, respectively.

The external and internal disturbances are grouped in a single term and estimated by the observer it is highlighted in Figure 5. This signal can be usefull in designing feedback controllers for induction motor. The above shows the power and robustness of the observer to estimate the speed and flux in spite of the highly varying load torque and parametric uncertainty.

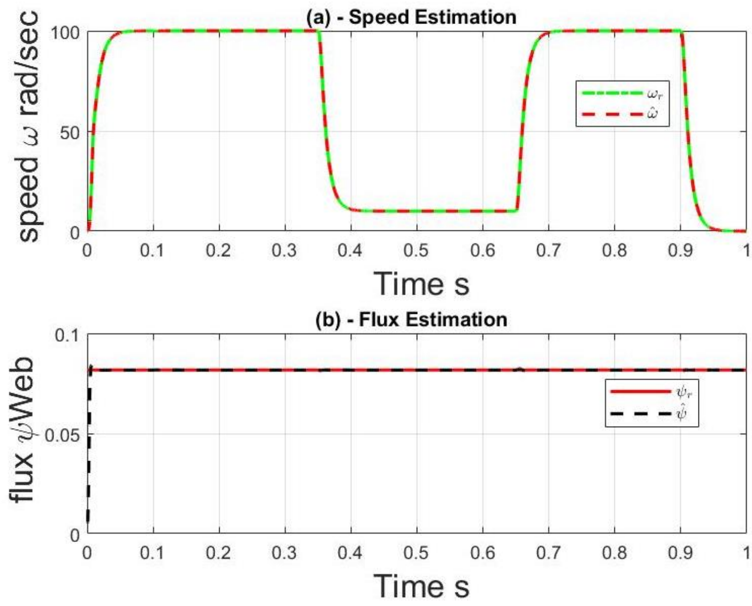

Figure 1. Simulation results with constant load and variation of parametric uncertainties with ADE Observer.

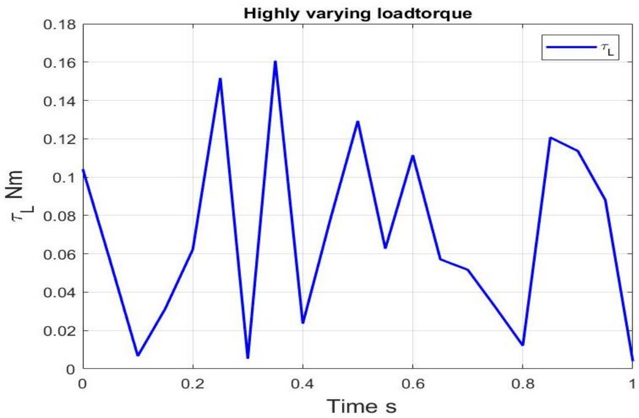

Figure 2. The applied of varying load.

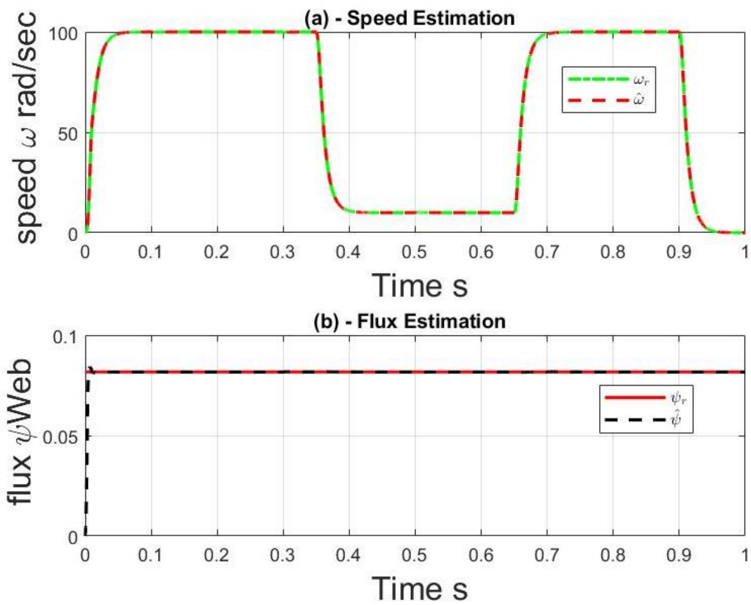

Figure 3. Simulation results with varying load and parametric uncertainties with ADE Observer.

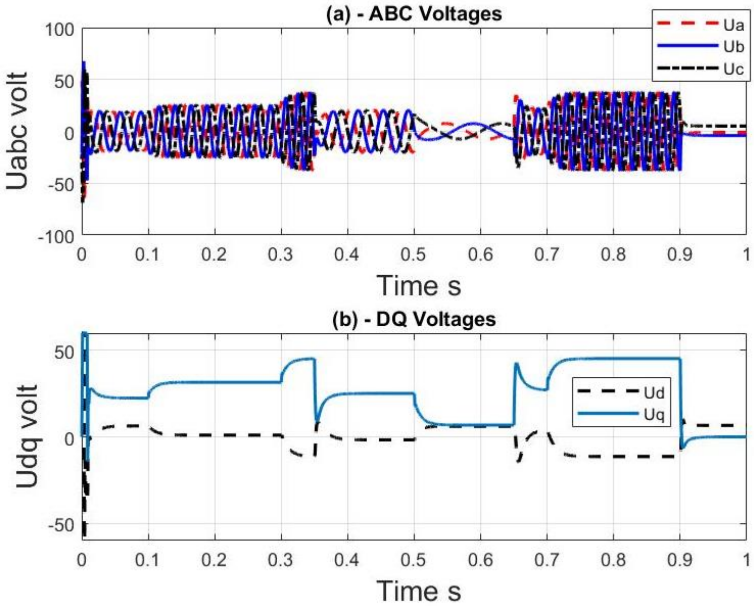

Figure 4. Simulation results with varying load and parametric uncertainties with ADE Observer.

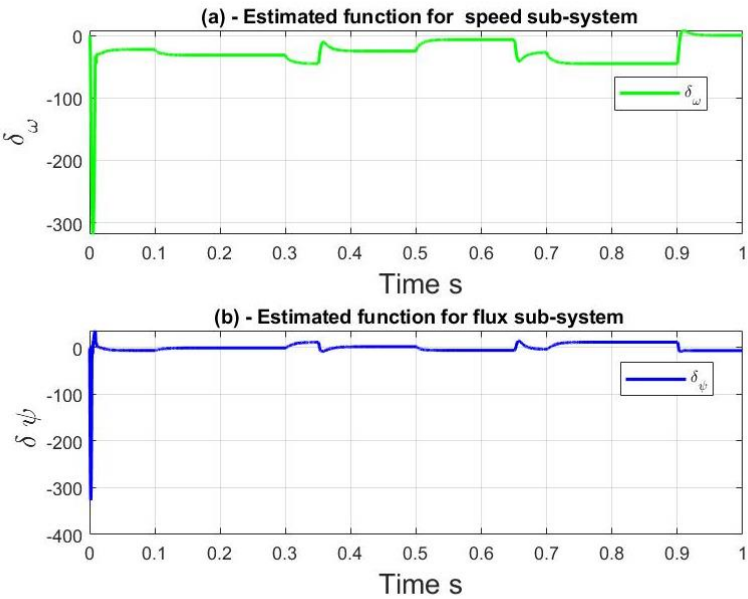

Figure 5. Simulation results with varying load and parametric uncertainties with ADE Observer.

5. Conclusions

An active disturbance estimator combined with a high gain state observer is presented in this paper to address the problem of unmodelled and external disturbances for a second-order nonlinear system. The convergence of the state estimation disturbances is guaranteed by the right choice of observer gains. We have applied this method to an induction motor to show the design choices and the achieved performance although we have assumed a partly known model of the system to be estimated. In future research, we will try to include the ADE in designing robust observers to compensate for the unknown terms.

Author Contributions: Conceptualization, S.K.; methodology, S.K.; software, S.K., M.C. and M.B.; writing—original draft preparation, S.K.; writing—review and editing, S.K., CH.M., M.B. and M.A.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Directorate-General for Scientific Research and Technological Development/Ministry of High Education and Scientific Research of Algeria (DGRSDT/MESRS).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

FOC	Field-Oriented Control
IM	Induction motor
ADE	Active Disturbance Estimation

References

1. Sira-Ramírez, H.; Luviano-Juárez, A.; Ramírez-Neria, M.; Zurita-Bustamante, E.W. *Active Disturbance Rejection Control of Dynamic Systems: A Flatness-Based Approach*; Elsevier Ergonomics Book Series; Butterworth-Heinemann: Amsterdam, The Netherlands, 2017.
2. Ammar, A.; Kheldoun, A.; Metidji, B.; Ameid, T.; Azzoug, Y. Feedback linearization based sensorless direct torque control using stator flux MRAS-sliding mode observer for induction motor drive. *ISA Trans.* **2020**, *98*, 382–392. [CrossRef] [PubMed]
3. Regaya, C.B.; Farhani, F.; Zaafouri, A.; Chaari, A. A novel adaptive control method for induction motor based on Backstepping approach using dSpace DS 1104 control board. *Mech. Syst. Signal Process.* **2018**, *100*, 466–481. [CrossRef]
4. Regaya, C.B.; Farhani, F.; Zaafouri, A.; Chaari, A. An adaptive sliding-mode speed observer for induction motor under backstepping control. *Int. J. Innov. Comput. I* **2017**, *11*, 763–771.
5. Khalil, H.K. *High-Gain Observers in Nonlinear Feedback Control*; Society for Industrial and Applied Mathematics: Philadelphia, PA, USA, 2017.
6. Petersen, I.R.; Holot, C.V. High-gain observers applied to problems in disturbance attenuation, H-infinity optimization and the stabilization of uncertain linear systems. In Proceedings of the 1988 American Control Conference, Atlanta, GA, USA, 15–17 June 1988; pp. 2490–2496.
7. Esfandiari, F.; Khalil, H.K. Observer-based design of uncertain systems: Recovering state feedback robustness under matching conditions. In Proceedings of the 1989 American Control Conference, Pittsburgh, PA, USA, 21–23 June 1989.
8. Khalil, H.; Saberi, A. Adaptive stabilization of a class of nonlinear systems using high-gain feedback. *IEEE Trans. Autom. Contr.* **1987**, *32*, 1031–1035. [CrossRef]
9. Saberi, A.; Sannuti, P. Observer design for loop transfer recovery and for uncertain dynamical systems. *IEEE Trans. Autom. Contr.* **1990**, *35*, 878–897. [CrossRef]
10. Tornambe, A. Use of asymptotic observers having high-gains in the state and parameter estimation. In Proceedings of the 28th IEEE Conference on Decision and Control, Tampa, FL, USA, 13–15 December 1989; pp. 1792–1794.
11. Yin, Z.; Zhang, Y.; Du, C.; Liu, J.; Sun, X.; Zhong, Y. Research on Anti-Error Performance of Speed and Flux Estimation for Induction Motors Based on Robust Adaptive State Observer. *IEEE Trans. Ind. Electron.* **2016**, *63*, 3499–3510. [CrossRef]
12. Guo, B.-Z.; Zhao, Z.-L. On convergence of the nonlinear active disturbance rejection control for MIMO systems. *SIAM J. Control Optim.* **2013**, *51*, 1727–1757. [CrossRef]
13. Guo, B.-Z.; Zhao, Z.-L. On the convergence of an extended state observer for nonlinear systems with uncertainty. *Syst. Control Lett.* **2011**, *60*, 420–430. [CrossRef]
14. Zheng, Q.; Gao, L.; Gao, Z. On stability analysis of active disturbance rejection control for nonlinear time-varying plants with unknown dynamics. In Proceedings of the 2007 46th IEEE Conference on Decision and Control, New Orleans, LA, USA, 12–14 December 2007; pp. 12–14.
15. Chiasson, J. *: Modeling and High Performance Control of Electric Machines*; John Wiley and Sons: Hoboken, NJ, USA, 2005.
16. Abbas, H.A.; Belkheiri, M.; Zegnini, B. Feedback Linearization Control of an Induction Machine Augmented by Single Hidden Layer Neural Networks. *Int. J. Control* **2016**, *89*, 140–155. [CrossRef]
17. Zhang, Y.; Jiang, Z.; Yu, X. Indirect Field-Oriented Control of Induction Machines Based on Synergetic Control Theory. In Proceedings of the IEEE Power and Energy Society General Meeting—Conversion and Delivery of Electrical Energy in the 21st Century, Pittsburgh, PA, USA, 20–24 July 2008; pp. 1–7. [CrossRef]