

FINAL SCIENTIFIC REPORT

The research team and the roles of the members who carried out research activities within the project "**Nonlinear observers-based control structures applied to mechatronics systems**", financing contract no. 164/10.10.2018, with the deposit code PN-III-P1-1.1-PD-2016-0331, <https://szedlak-stinean.wixsite.com/nobsmeecs>, is the one nominated in the funding application: Lect. Dr. Ing. Alexandra-Iulia Szedlak-Stînean, the project leader and Prof. Dr. Ing. Radu-Emil Precup, the mentor.

A. Objectives foreseen/achieved

The 1st Stage of the project – The development of the theoretical framework which allows the implementation of the modern control solutions – carried out during October - December 2018 and continued in 2019 has been fulfilled and is grouped in the form of the following activities:

Act 1.1 – Obtaining current theoretical knowledge regarding observers. To accomplish this activity the analysis of current theoretical research – state-of-the-art on theoretical research – and the possibilities of improving modern control solutions were considered.

Luenberger (Luenberger, 1966) was the first to introduce and solve the problem of designing observers for linear control systems. Thau (Thau, 1973) was first to propose one of the central problems in control systems literature, the problem of designing observers for nonlinear control systems. Many methods of process control use the state reaction principle. In most cases, the only measurements available to the system are the input and output measurements, which is why it is necessary from this information to build the state model chosen to develop the command. A state constructor (Dorf și Bishop, 2005; Preitl și Precup, 2008; Preitl et al., 2009) is a system having as input the inputs and outputs of the real process, and as output an estimate of the state of this process. In the hypothesis of linearity of the process model, the basic structure of the estimator is always the same, but its realization will depend on the chosen context: continuous or discrete, deterministic or stochastic. If the model is deterministic, the state constructor will be called an observer (or estimator). If the model is a stochastic type, then the constructor will be called a filter. The estimation problem requires the construction, for a deterministic model of the process, of a system defined by its state equation, for which the output provides an estimate of the real state of the process. This estimate implies an error that must tend to zero; when this property is satisfied, the estimator or observer is called asymptotic (Dorf and Bishop, 2005; Preitl and Precup, 2008; Preitl et al., 2009). An observer is very useful for implementing feedback stabilization or feedback regulation of nonlinear control systems due to the fact that it is essentially an estimator for the state of the system. The states estimation problem is of important strategic significance for the process of controlling and monitoring of many technological processes. In order to control and optimize a process, knowing some physical state variables provides useful information. This is the case of many widely diffused process control strategies. Therefore by including an appropriate state estimator, the difficulty caused by the presence of unknown states can be solved. For this reason, the development of suitable algorithms to perform the estimation has been the focus of many researchers attention and for this purpose, in order to estimate state variables from the available measurements, several techniques have been developed and introduced. Over the past three decades there has been significant research done on the nonlinear observer design problem. Depending on the mathematical structure of the process model, there is a wide variety of possible estimators that can be used (Soroush, 1997; Mouyon, 1997; Garcia et al., 2000; Aghannan și Rouchon, 2003; Kinsey and Whitcomb, 2007; Ghanes et al., 2013; Magnis and Petit, 2016).

The filtering process aims to determine the estimation of system variables when the environment in which the process takes place presents random perturbations. Two points of view can be used to address this issue: the first one is Wiener's who uses the frequency description and the second one is Kalman's using the temporal description. In both cases, an optimal system (filter) is determined in order to minimize the error variation between the real variable and its estimation (Wiener, 1949; Boulfelfel et al., 1994; Brown and Hwang, 1996). The probabilistic estimation method that is the most well-known and commonly used for linear systems is the **Kalman filter (KF)** and for the nonlinear systems its extension, the **Extended Kalman Filter (EKF)**. Although the KF in the case of highly nonlinear processes becomes unstable and has severe limitations, when employed for linear processes provides an efficient method for estimating the states and thus it also minimizes the mean of the squared error. Even if a precise model of the considered system is unknown the filter supports the estimation of past, present and future states (Biagiola and Solsona, 2006; Lendek et al., 2008; Beyhan et al., 2013; Habibullah and Lu, 2015). Regarding the nonlinear estimation techniques that have been developed until now, the EKF among other nonlinear ones based on linearization techniques is one of the most widely diffused observers. For the EKF approach, in order to obtain the estimator gain a Riccati equation must be solved. Even though the EKF could be a good choice when the assumptions are satisfied, in order to have a good trade-off between the measurement noise and the input uncertainty, it can still fail in many cases. Because of the fact that the noise model is often unknown and it can only be assumed, wrong noise assumptions can lead to biased or even divergent estimates. The purpose of the observer is to process these measurements and any available informations regarding the initial state of the system and to offer an estimate of the current state of the system. The obtained estimation should improve with additional measurements and, ideally, in the absence of noise, it should converge to the true state value. The advantage of using EKF is the lack of stationary error at low speeds. The disadvantage of the method arises from the complexity and large volume of computing, for the implementation the use of processors with high computing power being necessary. Another drawback is the need to fully know the noise sources in the system in order to determine the covariance matrices. For most applications the EKF is still the approach that is more practical and offers the most robustness (Brown and Hwang, 1996; Simon, 2006; Biagiola and Solsona, 2006; Lendek et al., 2008; Beyhan et al., 2013; Habibullah and Lu, 2015).

The estimation of states and of the possible uncertain parameters, based on a dynamic system model and a sequence of noisy measurements, is required by a wide range of problems in decision making, control, and monitoring. The design of an observer for a nonlinear system requires the description of the system in a state-space form. There is no generic method yet developed for the design of an observer valid for all nonlinear system types. From this point of

view *fuzzy control* is more pragmatic due to the specific decision-making mode in the command development. To this end, a rather qualitative linguistic characterization of the situation in which the process evolves and of the intervention decision is developed; this decision is then transposed into an adequate quantitative intervention (Preitl și Precup, 2008; Preitl et al., 2009). Any nonlinear system can be approximated on a compact set with an arbitrary accuracy by the generic nonlinear state-space model that is provided by Takagi-Sugeno (TS) fuzzy systems (Takagi and Sugeno, 1985). The interest of using the approach based on the representation of nonlinear systems through TS models (Takagi and Sugeno, 1985; Taniguchi et al., 2001; Tanaka and Wang, 2001) is built on the fact that once the TS fuzzy models are obtained, some analysis and design tools developed in the theory of linear systems (Huang, 2005; Lee et al., 2013; Li et al., 2014) which facilitates the observation and/or synthesis of the controller for complex nonlinear systems can be used. However, many papers have been done to investigate the problem of nonlinear observers' synthesis and its application to the dynamic systems described by fuzzy TS systems. In (Tanaka et al., 1998; Tanaka and Wang, 2001; Bergsten et al., 2002; Ichalal et al., 2007; Lendek et al., 2010), the problem of the TS fuzzy observer for explicit dynamic models in continuous-time and in discrete-time has been addressed. In implicit cases, there are more continuous-time papers (Taniguchi et al., 2000; Marx et al., 2007; Ilhem et al., 2012; Essabre et al., 2014; Souлами et al., 2015) than for discrete-time (Wang et al., 2012; Estrada-Manzo et al., 2014). Moreover, many other works regarding the explicit design of the observer, called the *Proportional Integral Observer*, have also been proposed for the TS implicit models. These results are based on the singular value decomposition approach and on a generalized inverse matrix and consider the output matrix without nonlinear terms (Marx et al., 2007; Hamdi et al., 2013). The analysis and design for a general nonlinear system represented by a fuzzy model becomes much easier because there are well-established methods and algorithms that can be used to design **fuzzy observers**. For TS fuzzy systems there have been several types of observers developed, such as Thau-Luenberger observers (Beyhan et al., 2013; Tanaka et al., 1998), reduced order observers (Beyhan et al., 2013; Bergsten et al., 2002) and sliding mode observers (Beyhan et al., 2013; Palm și Bergsten, 2000). The observers design methods generally lead to a linear matrix inequalities (LMIs) feasibility problem. The stability analysis for a large number of rules eventually becomes unsolvable because the system complexity grows exponentially with the number of antecedents (Lam et al., 2013). By employing observers, the non-measurable states can be estimated, analyzed, and used for the control of nonlinear systems.

Variable Structure Systems (VSS) are one of the most promising techniques for controlling electrical drives, due to good robustness and performance in case of parametric variations, of perturbations and load variations, respectively due to the compensation of the nonlinearities of the controlled process and their simple implementation. The primary feature that distinguishes the sliding mode systems as an independent class of automatic control systems is the fact that during transient processes the system structure changes. In VSS theory, the most attention is paid to systems with sliding modes. They are based on a specific type of control law that causes a *sliding mode control* or *sliding mode regime* in the system. **Sliding mode observers** use the remarkable VSS properties and are successfully integrated into servosystems. These observers use the equivalent command to estimate the equivalent disturbance. In general, their structures are closely related to the mathematical models used in the controlled process (Spurgeon, 2008; Mercorelli, 2015; Apaza-Perez et al., 2016). These have the ability to minimize the error between the measured process output and the output of the observer that ensures that the observer produces a set of state estimates that are precisely proportional with the actual output of the process. The sliding mode observer design method consists in determining a switching gain. One restriction is the fact that in order to achieve the estimation, the outputs have to lie on specified sliding surface. In addition, performance is rarely guaranteed, particularly when the outputs are corrupted with noise. Similarly to a KF, the sliding mode observers have attractive noise resilience properties. In comparison to linear observers, the principle advantage that the sliding-mode observers have is that they are insensitive to the unknown inputs while in sliding, and additionally they can be utilized in order to reconstruct unknown inputs which could be a combination of system disturbances, faults or nonlinearities (Spurgeon, 2008; Mercorelli, 2015; Apaza-Perez et al., 2016).

The construction of nonlinear observers still provides an open research field because advances in this area often face many obstacles, such as, for example, the very restrictive conditions that have to be satisfied, uncertainty in the performance and robustness and/or poor estimation results. Depending on what type of observer is being used there are other limitations, for example, in case of Luenberger-based observers, design is always based on the perfect knowledge of the system parameters; in case of finite-dimensional system observers, the convergence factor depends strongly on the operating conditions and for artificial intelligence-based observers it may be difficult and time consuming for online implementation and also, the artificial intelligence elements must first be adapted to the system. The control systems should benefit from the advantages of the continued analytical development and implementation of dynamic model-based nonlinear observers that promise to improve the performance of different types of mechatronics systems.

The potential impact to the scientific field may be significant because through new concepts and employed approaches, a new way for the use of highly advanced control designs in mechatronics applications is open, which is very useful for implementing feedback stabilization or feedback regulation of nonlinear control systems. It is clear that nonlinear observer design is still an open area for research, efforts being made to broaden and adapt the proposed techniques in order to widen the classes of nonlinear systems to which they may apply.

The potential impact of the project in the scientific, social, economic or cultural environment is straightforward since the investigated topics can lead to automated tools for controller design and tuning. Although there is a wide range of possibilities for creating new themes for state-of-the-art research, noteworthy is also the impact in the socio-economic environment with directly applicative directions. In the project all mechatronics applications tackled are interdisciplinary and multidisciplinary themselves, with special focus on those applicable cost-effective training systems in the fields of robotics, automation and process control.

Act 1.2 – Studying the practical applications of various types of observers. To accomplish this activity, the realization and classification of observers was studied with focus on mechatronic systems.

Mechatronics systems have experienced a rapid and complex multidisciplinary development as a result of advances in various application areas such as (Bishop, 2007; Gutiérrez-Carvajal et al., 2016; Isermann, 2005): expert

systems, automotive engineering, robotics and automation, systems structural dynamics, control systems, servomechanics, numerical computing systems based on highly integrated microelectronics, consumer products, medical imaging systems, mobile applications, integrated and computer-aided manufacturing systems, transportation systems and vehicles. Mechatronics systems are successfully used in many industrial and non-industrial applications because of their simple and robust structure. By constantly evolving, these systems exhibit increasing performance ensuring functional and applicative versatility, intelligence and flexibility. These features are also provided by the control system which has to be able to adapt to external conditions at all times and to provide the necessary informations to the hierarchical control (Isermann, 2005; Koch et al., 2006; Hehenberger et al., 2006; Pabst, 2006; Bishop, 2007; Dragos, 2011).

The design of control systems is important because of the very good performance specifications imposed in various fields. The specifications become more restrictive if several operating conditions of the processes are involved as the variable parameters (for example, in the case of speed and position control besides the variable moment of inertia situations, the variable reference input, correlated with various particular operating conditions, additional operating conditions may occur, such as oscillations that appear on the mechanical side). These problems can be solved in two ways: by developing advanced nonlinear models or by implementing a robust control based on state observers technique. The implementation of the second solution in servosystems leads to high system performances. In this context, the development of advanced control solutions is a relatively difficult problem which requires a detailed preliminary study of the process, particularly the parameters variability and of its structural properties. As a continuation of previous research, in this project (PD 164/10.10.2018) the approach oriented on the analysis, synthesis, modeling and development of modern control solutions, such as nonlinear observers dedicated to certain mechatronics applications is proposed. Two types of observers can be used: linear and nonlinear. From the category of **linear observers**, the most common are **full-order observers** known as the Luenberger type observers and **reduced-order observers**. Among the nonlinear ones we mention: **extended Kalman filters**, **sliding mode observers**, **fuzzy** and **neural network observers** (Luenberger, 1966; Ackermann, 1972; Friedland, 1996; Gajic și Lelic, 1996; Stefani et al., 2002; Preitl et al., 2009).

Linear and nonlinear observers intended for mechatronics applications within the project

The main research within this project is oriented towards the development of new control solutions dedicated to speed and position control of four mechatronics applications:

1. Electric drive system with DC motor (EDS-DC)

The application considered in this paper is a simple mechanism, a mechatronic system that does not require complex hardware and also exhibits attractive features such as high efficiency, low manufacturing cost, simple construction and operation and linear torque-speed characteristics. In the context of the quality requirements expressed as performance specifications imposed to the operation of EDSs, there are currently several problems, two of which are highlighted: one is to make the control systems robust to variations in parameters and under the influence of disturbances and the other one consists in making the control system adaptable to such changes. The main objectives of these systems are to provide the most accurate following of the reference, smallest possible settling time, reduced overshoot, zero adjustment error (as low as possible) in relation to certain types of references and disturbances and thereby a static character of the system. Given these objectives, the analysis of the state-of-the-art of control theory and applications related to EDSs-DC shows that the solution which involves implementation of robust control techniques based on observers leads to high system performance. For this mechatronics application were proposed and developed, from the category of linear observers: an **extended Luenberger state observer (ELSO)** and a **Kalman filter observer (KFO)** and from the nonlinear category: an **extended Kalman filter observer (EKFO)** and a **sliding mode observer (SMO)**. The details are presented in the study from stage 2 and in the published paper (Szedlak-Stinean et al., 2022a).

2. The electric drive system with time-varying inputs with a brushless motor (EDS-TVI-BLDC)

The electric drive systems with Brushless Direct Current (BLDC) motors (BLDC drives) have experienced a fast and complex multidisciplinary development as a result of advances in various fields such as (Yedamale, 2003; Hansson, 2004; Baldursson, 2005; Nasar and Boldea, 2005): power electronics, modern automated control techniques, powering electric vehicles (e.g., cars, electric bicycles, electric scooters), numerical computing systems based on microelectronics with a high degree of integration, industrial automation, medical equipments and robotic instrumentation (e.g., improving sleep for apnea suffers, providing mobile breathing assistance, preventing blood clots in hospitalized patients), etc. In control applications which involve electric drives, it is often necessary to estimate derivatives of measurable states, for example, estimating the speed (ω) and acceleration (ε) from position information (ϑ_m), which is why, for this mechatronics application were proposed and developed four linear observers – (1), (2), (3) and (4) – and one nonlinear observer (5): (1) **an observer of m^{th} order derivatives with the filtration technique (OFT)**; (2) **an extended Luenberger state observer with ϑ_m and M_e as inputs (ELSO+ M_e)**; (3) **an extended Luenberger state observer having only the ϑ_m as input (ELSO- M_e)**; (4) **a Kalman filter observer (KFO)** and (5) **a sliding mode observer (SMO)**. The details are presented in the study from stage 2 and in the published paper (Szedlak-Stinean et al., 2019a).

3. The electric drive system which wraps a strip with constant linear velocity on a drum - electric drive system with variable parameters (SWS)

For this mechatronics application, two nonlinear estimation approaches were proposed and developed, namely based on **extended Kalman filter (EKF)** and a **Takagi-Sugeno Fuzzy Observer with 32 rules (TSFO-32)**, for a strip winding system (SWS) characterized by variable reference input, variable moment of inertia with constant increasing trend and variable parameters. The SWS is a complex and nonlinear mechatronic system viewed as a controlled process, which wraps a strip with constant linear velocity on a drum and the variable radius modifies both the angular velocity and the moment of inertia. The motivation of using EKF is the zero stationary error at low speeds. The motivation of using TSFO-32 is that once the Takagi-Sugeno fuzzy models are obtained, various analysis and design tools initially developed for linear systems, which facilitate the observation and/or synthesis of the controller for complex nonlinear systems, can be adapted appropriately and used in these nonlinear systems.

Therefore, these tools simplify the design as well-established approaches and algorithms are available. The fuzzy control system stability and observer design conditions are derived and expressed as linear matrix inequalities. The efficiency of TSFO-32 is discussed in this project in terms of setting a certain convergence rate. The details are presented in the study from stage 2 and in a journal accepted to be published (Szedlak-Stinean et al., 2022b).

4. The laboratory equipment - Model 220 Industrial Plant Emulator (M220IPE)

The laboratory application – Model 220 Industrial Plant Emulator (M220IPE) – is a complex, nonlinear equipment, ideal for studying automatic control solutions dedicated to the control of modern industrial equipment, such as: transmission shafts, conveyors, rotary tables, machine tools and machines of automated assembly (ECP, 2010; Szedlak-Stinean et al., 2016; Szedlak-Stinean et al., 2017). The development of suitable algorithms to perform the estimation has been the focus of many researchers' attention and for this purpose, in order to estimate state variables from the available measurements, several techniques have been developed and introduced (Brown and Hwang, 1996; Aghannan and Rouchon, 2003; Marx et al., 2007; Lendek et al., 2008; Spurgeon, 2008; Magnis and Petit, 2016). In this context, from the category of discrete-time linear observers were proposed and developed: an **extended Luenberger state observer (ELSO)** and a **Kalman filter observer (KFO)**, and from the category of continuous-time linear observers was proposed and developed **a controller that can be considered as composed of three subsystems: a subsystem that provides the desired output and from the reference value a feed-forward signal, an observer and a feedback derived from the estimated states**. The interesting structure of the controller allows it to be applied for a wide range of design methods. The defining feature of a state feedback controller and an observer have is the complexity of the controlled system that determines controller's complexity. As such a system model is actually contained by the controller. Thereby the internal model principle that prescribes that an internal model of the controlled system should be contained in the controller is in this project exemplified. From the category of discrete-time nonlinear observers were proposed and developed: an **extended Kalman filter observer (EKFO)** and a **sliding mode observer (SMO)**. The details are presented in the study from stage 7 and in two papers: in a published paper (Szedlak-Stinean et al., 2019b) and in a paper accepted to be published (Szedlak-Stinean et al., 2022c).

The 2nd stage of the project – The design and implementation of the proposed modern control solutions – pursued within the project in 2019 (January - September 2019) and in 2022 (January – April 2022) has been completed and is grouped in the form of the following activity:

Act 2.1 – Development of observers through simulations (digital / simulation results). To carry out this activity, the analysis of theoretical research and the classification of observers specific to mechatronics systems from stage 1, were considered.

1. Electric drive system with DC motor (EDS-DC)

The behavior of the EDS-DC is expressed by the following equations (Isermann, 2005; Nasar and Boldea, 2005; Preitl și Precup, 2008):

$$\begin{cases} \frac{di_a(t)}{dt} = -\frac{1}{T_a}i_a(t) - \frac{k_e}{L_a}\omega(t) + \frac{1}{L_a}u_a(t), \\ \frac{d\omega(t)}{dt} = \frac{k_m}{J}i_a(t) - \frac{k_f}{J}\omega(t) - \frac{1}{J}m_s(t), \\ \frac{du_a(t)}{dt} = -\frac{1}{T_\mu}u_a(t) + \frac{k_E}{T_\mu}u_c(t), \end{cases} \quad (1)$$

where: i_a , u_a – the armature current and voltage [A, V], u_c – the control voltage [V], $T_a=L_a/R_a$, L_a , R_a – the electrical parameters [s, H, Ω], ω – the angular speed [rad/s], k_e , k_m , k_f – the electromagnetic coefficients [V/rad/s, N·m/A, N·m/s], k_E – the actuator gain [V/V], J – the moment of inertia [kg·m²], and m_s – the load torque [N·m]. The characteristic parameters related to EDS-DC used in the informational characterization of the controlled process are: (i) inputs: u_c – the control voltage and m_s – the load torque, (ii) outputs: ω – the angular speed and i_a – the armature current, and (iii) state variables: $\{\omega, i_a, u_a\}$.

The state-space MM of the EDS with DC motor is obtained by inserting the state variables $x_1(t) = i_a(t)$, $x_2(t) = \omega(t)$, $x_3(t) = u_a(t)$:

$$\begin{cases} \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{x}_3(t) \end{bmatrix} = \begin{bmatrix} -\frac{1}{T_a} & -\frac{k_e}{L_a} & \frac{1}{L_a} \\ \frac{k_m}{J} & -\frac{k_f}{J} & 0 \\ 0 & 0 & -\frac{1}{T_\mu} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{J} \\ \frac{k_E}{T_\mu} & 0 \end{bmatrix} \begin{bmatrix} u_c(t) \\ m_s(t) \end{bmatrix}, \\ y(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \end{bmatrix}. \end{cases} \quad (2)$$

In Fig. 1, the block diagram corresponding to the DC electric drive system is shown.

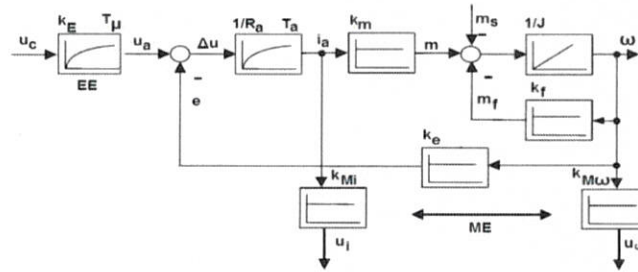


Fig. 1. Block diagram of the EDS-DC

The evaluation of an observer design success is based on its ability to estimate the difficult-to-measure states with acceptable convergence rates and with approximately zero estimation errors. To achieve a comparative study on armature current and angular speed control performance, the four design proposals (observers) presented below will be taken into consideration. The design will use the dynamic model shown in (2).

1.1. Extended Luenberger state observer (ELSO)

A solution to compute the state estimates $\hat{x}_1(t)$, $\hat{x}_2(t)$ and $\hat{x}_3(t)$ is to use two ELSOs having as predictive correction terms the armature current error $\Delta x_1(t) = x_1(t) - \hat{x}_1(t)$ and the angular speed error $\Delta x_2(t) = x_2(t) - \hat{x}_2(t)$. For estimating the armature current, a gain matrix $L = [l_{1ia} \ l_{2ia} \ l_{3ia}]^T \in \mathfrak{R}$ is used (here, T represent the matrix transposition) and the dynamic model of ELSO is (Luenberger, 1966; Preitl și Precup, 2008; Szedlak-Stinean et al., 2019a):

$$\begin{cases} \begin{bmatrix} \dot{\hat{x}}_1(t) \\ \dot{\hat{x}}_2(t) \\ \dot{\hat{x}}_3(t) \end{bmatrix} = \underbrace{\begin{bmatrix} -\frac{1}{T_a} & -\frac{k_e}{L_a} & \frac{1}{L_a} \\ \frac{k_m}{J} & -\frac{k_f}{J} & 0 \\ 0 & 0 & -\frac{1}{T_\mu} \end{bmatrix}}_A \begin{bmatrix} \hat{x}_1(t) \\ \hat{x}_2(t) \\ \hat{x}_3(t) \end{bmatrix} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{J} \\ \frac{k_E}{T_\mu} & 0 \end{bmatrix}}_B \begin{bmatrix} u_c(t) \\ m_s(t) \end{bmatrix} + \underbrace{\begin{bmatrix} l_{1ia} \\ l_{2ia} \\ l_{3ia} \end{bmatrix}}_L (x_1(t) - \hat{x}_1(t)), \\ \hat{y}(t) = \underbrace{\begin{bmatrix} 1 & 0 & 0 \end{bmatrix}}_C \begin{bmatrix} \hat{x}_1(t) \\ \hat{x}_2(t) \\ \hat{x}_3(t) \end{bmatrix} \end{cases} \quad (3)$$

For estimating the angular speed, a gain matrix $L = [l_{1\omega} \ l_{2\omega} \ l_{3\omega}]^T \in \mathfrak{R}$ is used and the dynamic model of ELSO is (Luenberger, 1966; Preitl și Precup, 2008; Szedlak-Stinean et al., 2019a):

$$\begin{cases} \begin{bmatrix} \dot{\hat{x}}_1(t) \\ \dot{\hat{x}}_2(t) \\ \dot{\hat{x}}_3(t) \end{bmatrix} = \underbrace{\begin{bmatrix} -\frac{1}{T_a} & -\frac{k_e}{L_a} & \frac{1}{L_a} \\ \frac{k_m}{J} & -\frac{k_f}{J} & 0 \\ 0 & 0 & -\frac{1}{T_\mu} \end{bmatrix}}_A \begin{bmatrix} \hat{x}_1(t) \\ \hat{x}_2(t) \\ \hat{x}_3(t) \end{bmatrix} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{J} \\ \frac{k_E}{T_\mu} & 0 \end{bmatrix}}_B \begin{bmatrix} u_c(t) \\ m_s(t) \end{bmatrix} + \underbrace{\begin{bmatrix} l_{1\omega} \\ l_{2\omega} \\ l_{3\omega} \end{bmatrix}}_L (x_2(t) - \hat{x}_2(t)), \\ \hat{y}(t) = \underbrace{\begin{bmatrix} 0 & 1 & 0 \end{bmatrix}}_C \begin{bmatrix} \hat{x}_1(t) \\ \hat{x}_2(t) \\ \hat{x}_3(t) \end{bmatrix} \end{cases} \quad (4)$$

In both cases $A \in \mathfrak{R}^{3 \times 3}$, $B \in \mathfrak{R}^{3 \times 2}$, $C \in \mathfrak{R}^{1 \times 3}$ are the continuous-time ELSO matrices and for m_s a step signal is utilized. The observer gain matrix L is calculated in terms of the pole placement method, considering the pair (A, C) observable.

1.2. Kalman filter observer (KFO)

KFO is the most popular and often utilized observer for linear systems and it offers a good approach for estimating the states while minimizing the mean square error (Lendek et al., 2008; Habibullah and Lu, 2015; Szedlak-Stinean et al., 2019a; Brown and Hwang, 1996; KF, 2022). The dynamical state-space model is defined by (Szedlak-Stinean et al., 2019a):

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) + Gw(t), \\ y(t) &= Cx(t) + Du(t) + Hv(t) + v(t), \end{aligned} \quad (5)$$

where: x – the state vector, u – the input, v , w – the white measurement noise and white process noise, Q , R , N – the process covariance, the measurement covariance and noise cross covariance and the elements of matrices A , B , C and D (here $D=0$) are gained using (2). The KFO constructs the error covariance as stated by:

$$P = \lim_{t \rightarrow \infty} E \left(\{x(t) - \hat{x}(t)\} \{x(t) - \hat{x}(t)\}^T \right) \quad (6)$$

Taking this into consideration, the equations of the KFO are:

$$\begin{aligned} \dot{\hat{x}}(t) &= A\hat{x}(t) + Bu(t) + L(y(t) - C\hat{x}(t) - Du(t)), \\ \begin{bmatrix} \hat{y}(t) \\ \hat{x}(t) \end{bmatrix} &= \begin{bmatrix} C \\ I \end{bmatrix} \hat{x}(t) + \begin{bmatrix} D \\ 0 \end{bmatrix} u(t). \end{aligned} \quad (7)$$

As far as the KFO is concerned, in order to obtain the filter gain, a Riccati equation must be solved. The filter gain L , R_r and N_n are according to:

$$\begin{aligned} L &= (PC^T + N_n)R_r^{-1}, \\ R_r &= R + HN + N^T H^T + HQH^T, N_n = G(QH^T + N). \end{aligned} \quad (8)$$

1.3. Extended Kalman filter observer (EKFO)

EKFO is the nonlinear version of KFO, and it linearizes around an estimate of the current mean and covariance. It is deemed to be a relevant standard for well-defined transition models, for nonlinear estimation, global positioning systems and navigation systems (Julier and Uhlmann, 2004). Because most engineering systems are nonlinear, it was attempted to use the EKFO for functions approximated by using a linearization process. The dynamical model is represented by the equations (Beyhan et al., 2013; Simon, 2006; EKF, 2022):

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)) + w(t), w(t) \sim \mathcal{N}(0, Q(t)), \\ y(t) &= h(x(t)) + v(t), v(t) \sim \mathcal{N}(0, R(t)), \end{aligned} \quad (9)$$

where: x , u , w , v , Q and R are exactly the same vectors, variables and parameters as in the case of KFO, f – a function utilized for calculating the predicted state from the previous estimate and h – a function utilized for calculating the predicted measurement from the predicted state. The EKFO predict-update equations are (Beyhan et al., 2013; Simon, 2006):

$$\begin{aligned} \dot{\hat{x}}(t) &= f(\hat{x}(t), u(t)) + K(t)(y(t) - h(\hat{x}(t))), \\ \dot{P}(t) &= F(t)P(t) + P(t)F(t)^T - K(t)H(t)P(t) + Q(t), \\ K(t) &= P(t)H(t)^T R(t)^{-1}, \\ F(t) &= \frac{\partial f}{\partial x} \Big|_{\hat{x}(t), u(t)}, \\ H(t) &= \frac{\partial h}{\partial x} \Big|_{\hat{x}(t)}, \end{aligned} \quad (10)$$

where: P – the error covariance matrix, K – the Kalman gain matrix, F , H – the state transition and the state observation matrices. The states of EKFO are revised employing the error $\hat{e}(t) = y(t) - h(\hat{x}(t))$ and also the K matrix.

1.4. Sliding mode observer (SMO)

These observers have the ability to minimize the error between the measured process output and the output of the observer that guarantees that the observer offers a set of state estimates that are exactly proportional to the actual output of the process. For SMO design, the dynamic model given in (2) will be utilized, knowing that the matrix dimensions are $A \in \mathbb{R}^{n \times n}$, $B \in \mathbb{R}^{n \times m}$, $C \in \mathbb{R}^{p \times n}$, $p \geq m$. In this context, the following change of coordinates $x \rightarrow T_c z$, $T_c = [N_c^T C]^T$, was considered, where $\det(T_c) \neq 0$ and the submatrix $N_c \in \mathbb{R}^{n \times (n-p)}$ covers the null space of C (Lendek et al., 2008; Szedlak-Stinean et al., 2019a; Shtessel et al., 2014). The matrices $T_c A T_c^{-1}$, $T_c B$ and $C T_c^{-1}$ are presented in (11).

$$T_c A T_c^{-1} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, T_c B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}, C T_c^{-1} = \begin{bmatrix} 0 & I_p \end{bmatrix} \quad (11)$$

Knowing that $T_c z = [z \ y]^T$, the dynamical model of the SMO is (Lendek et al., 2008; Szedlak-Stinean et al., 2019a; Shtessel et al., 2014):

$$\begin{aligned} \dot{\hat{z}} &= A_{11}\hat{z} + A_{12}\hat{y} + B_1 u + L v_i, \\ \hat{y} &= A_{21}\hat{z} + A_{22}\hat{y} + B_2 u - v_i, \end{aligned} \quad (12)$$

where $L = [L_1 \ L_2] \in \mathbb{R}^{(n-p) \times p}$ is a gain matrix and $v_i = [v_1 \ v_2]^T = M \operatorname{sgn}(\hat{y}_i - y_i)$, $i=2$ is an injection term in which $M \in \mathbb{R}_+$. The error dynamics is expressed as:

$$\begin{aligned} \dot{e}_z &= A_{11}e_z + A_{12}e_{yi} + L v_i, \quad e_z = \hat{z} - z, \\ \dot{e}_{yi} &= A_{21}e_z + A_{22}e_{yi} - v_i, \quad e_{yi} = \hat{y}_i - y_i. \end{aligned} \quad (13)$$

In order to reduce the sliding motion, the error system defined in (13) provides the relation $\dot{e}_z = (A_{11} + LA_{21})e_z$, which reliant on L , describes a stable system, so $e_z \rightarrow 0$ and therefore $\hat{z} \rightarrow z$.

The validation of the control approaches is done by numerical simulation scenarios. Two simulation scenarios were taken into consideration: (i) a step reference input and (ii) a staircase reference input. The digital simulation results are given in Fig. 2 and Fig. 3.

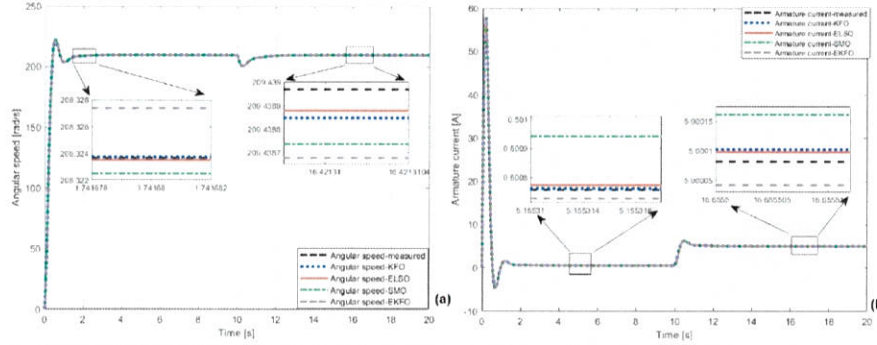


Fig. 1. Digital results for EDS-DC (step reference input): (a) angular speed versus time, (b) armature current versus time

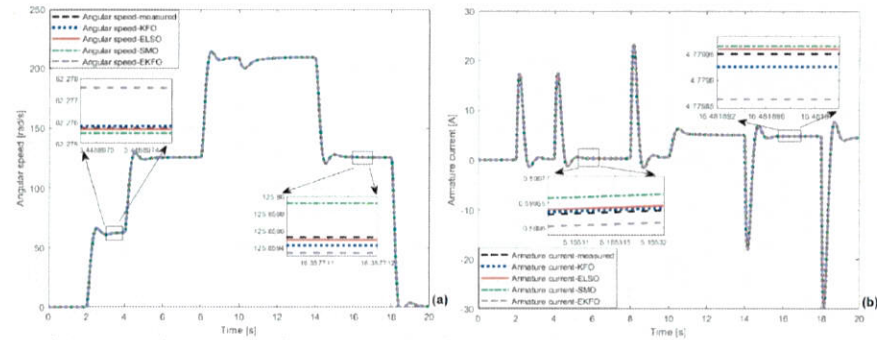


Fig. 2. Digital results for EDS-DC (staircase reference input): (a) angular speed versus time, (b) armature current versus time

Taking into consideration the graphics presented in Fig. 2 and Fig. 3, the following set of conclusions is formulated: (i) the best performances have been obtained by the KFO and by the ELDO due to the fact that they are linear observers and the EDS-DC is a linear system; (ii) the ELDO is less efficient than KFO due to the fact that the process parameters influence the parameters of the observer gain; (iii) the SMO provides better performance than the EKFO due to the fact that similarly to KFO has attractive noise resilience properties and also is insensitive to unknown inputs while in sliding; (iv) the proposed observers are demonstrated to be viable, efficient and guarantee a good reference tracking ability, and (v) the control system should benefit from the advantages of the continued analytical development and implementation of dynamic model-based observers that promise to improve the performance of different types of mechatronics systems. All the information presented in subsection 1 were published in the paper (Szczepanek et al., 2022a).

2. The electric drive system with time-varying inputs with a brushless motor (EDS-TVI-BLDC)

The Matlab/Simulink block diagram of the BLDC drive (Stinean, 2014) is illustrated in Fig. 4.

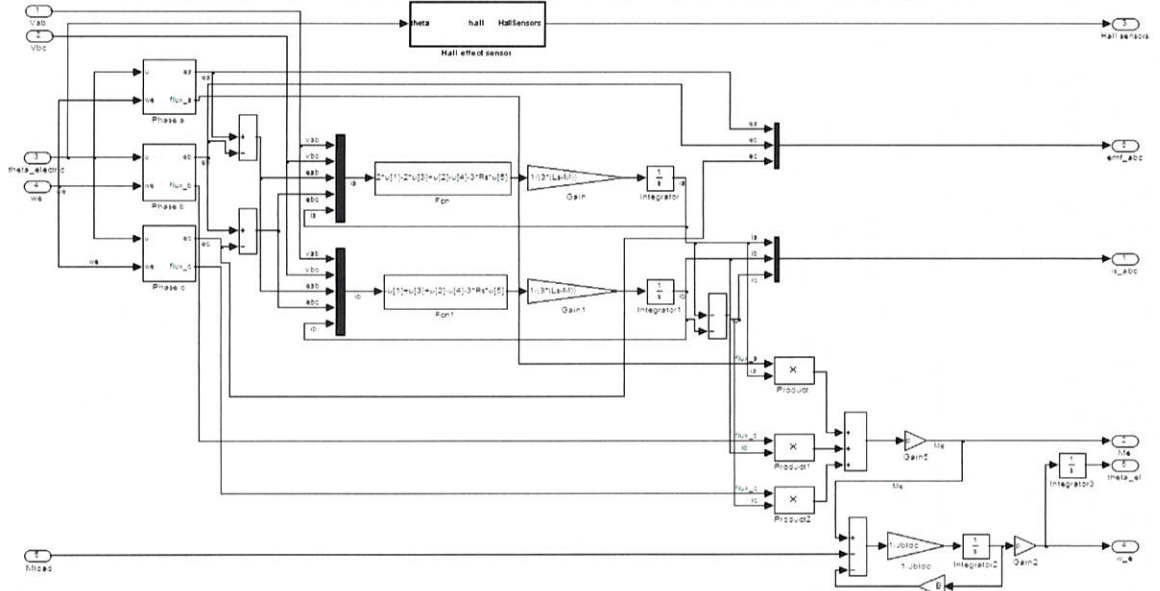


Fig. 4. Matlab/Simulink block diagram of BLDC drive

The MM of the three-phase BLDC motor is of the fourth order, having as states variables i_a , i_b , ϑ_m and ω_m . In this context, the process dynamics can be divided into two subsystems: *the electromagnetic subsystem (ES)* and *the mechanical subsystem (MS)*. The dynamic equations associated with the two subsystems in state-space form are:

$$ES: \begin{bmatrix} \dot{i}_a \\ \dot{i}_b \end{bmatrix} = \begin{bmatrix} \frac{-R}{L-M} & 0 \\ 0 & \frac{-R}{L-M} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \end{bmatrix} + \begin{bmatrix} \frac{2}{3(L-M)} & \frac{1}{3(L-M)} \\ \frac{-1}{3(L-M)} & \frac{1}{3(L-M)} \end{bmatrix} \begin{bmatrix} v_{ab} - e_{ab} \\ v_{bc} - e_{bc} \end{bmatrix} \quad (14)$$

$$Me = \frac{e_a i_a + e_b i_b + e_c i_c}{\omega_m},$$

$$MS: \begin{bmatrix} \dot{\theta}_m \\ \dot{\omega}_m \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & \frac{-B}{J_{BLDC}} \end{bmatrix} \begin{bmatrix} \theta_m \\ \omega_m \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \frac{1}{J_{BLDC}} M_e + \begin{bmatrix} 0 \\ -1 \end{bmatrix} \frac{1}{J_{BLDC}} M_{Load},$$

where $x_{ES} = [i_a \ i_b]^T$ (here, T represents matrix transposition) are the states of the ES and $x_{MS} = [\vartheta_m \ \omega_m]^T$ are the states of the MS. From the five observers developed for this mechatronic application, only three design approaches will be presented below, since the KFO and the SMO were already presented in the subsection above and also in the paper (Szedlak-Stinean et al., 2022a). The three design approaches will only use the dynamic model corresponding to the MS.

2.1. Observer of m^{th} Order Derivatives with Filtration Technique (OFT)

The ideal m^{th} order derivative is characterized by a pure anticipatory dynamic, so it is not practically achievable. A possible solution is to use an n^{th} order low-pass filter for the measured ϑ_m connected in series with a pure derivation operator, respecting the constraint $m \leq n$. The values $m = 2$ and $n = 3$ are set due to the fact that $d^2\vartheta_m/dt^2 = d\omega_m/dt = \varepsilon$, where ε represents the acceleration. Using the substitution $x = [x_1 \ x_2 \ x_3]^T = [\vartheta_m \ \omega_m \ \varepsilon]^T$ the observable canonical form used in the observer structure in Fig. 4 is:

$$\begin{bmatrix} \dot{\hat{\theta}}_m \\ \dot{\hat{\omega}}_m \\ \dot{\hat{\varepsilon}} \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -a_0 & -a_1 & -a_2 \end{bmatrix}}_A \underbrace{\begin{bmatrix} \hat{\theta}_m \\ \hat{\omega}_m \\ \hat{\varepsilon} \end{bmatrix}}_x + \underbrace{\begin{bmatrix} 0 \\ 0 \\ a_0 \end{bmatrix}}_B \theta_m \quad \text{or} \quad \hat{\varepsilon} = \frac{a_0 s^2}{s^3 + a_2 s^2 + a_1 s + a_0} \theta_m \quad (15)$$

Naming this structure an observer is justified since Fig. 5 shows a correction based on the output estimation error, although for the estimation using the filtering technique this idea was not the starting point. It is expected that the dynamic response of the estimate is slower because through the coefficient a_0 there is only one direct correction term based on the position error. The terms a_1 and a_2 appear as state feedbacks and not the estimation error. The observer design uses the pole placement method. For the imposed poles (real negative ones) $P_o = \{p_1, p_2, p_3\}$ the observer coefficients are:

$$a_2 = -(p_1 + p_2 + p_3), a_1 = p_1 p_2 + p_1 p_3 + p_2 p_3, a_0 = -p_1 p_2 p_3. \quad (16)$$

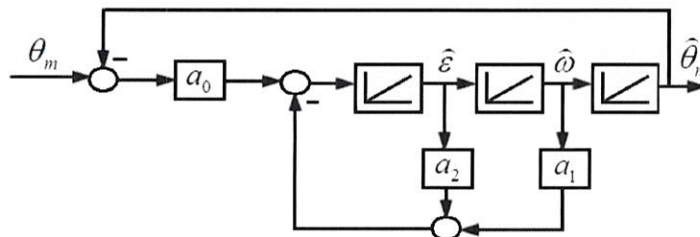


Fig. 5. OFT block diagram

2.2. Extended Luenberger State Observer with θ_m and M_e as Inputs (ELSO+Me)

A solution to compute the state estimates $\hat{\omega}$, $\hat{\varepsilon}$ and \hat{M}_{Load} is to use an extended Luenberger state observer (ELSO) having as predictive correction term the mechanical position error, $\Delta\theta = \theta_m - \hat{\theta}_m$ and as direct input the electromagnetic torque, M_e . For M_{Load} an exogenous model of step signal class is used. In this particular case of ELSO, the state-space equations are (Luenberger, 1966; Andreescu, 1999):

$$\begin{bmatrix} \dot{\hat{\theta}}_m \\ \dot{\hat{\omega}}_m \\ \dot{\hat{M}}_{Load} \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 & 0 \\ 0 & \frac{-B}{J_{BLDC}} & \frac{-1}{J_{BLDC}} \\ 0 & 0 & 0 \end{bmatrix}}_A \underbrace{\begin{bmatrix} \hat{\theta}_m \\ \hat{\omega}_m \\ \hat{M}_{Load} \end{bmatrix}}_x + \underbrace{\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}}_B \frac{1}{J_{BLDC}} \tilde{M}_e + \underbrace{\begin{bmatrix} l_1 \\ l_2 \\ l_3 \end{bmatrix}}_L (\theta_m - \hat{\theta}_m), \quad (17)$$

$$y = \underbrace{\begin{bmatrix} 1 & 0 & 0 \end{bmatrix}}_C \underbrace{\begin{bmatrix} \hat{\theta}_m \\ \hat{\omega}_m \\ \hat{M}_{Load} \end{bmatrix}}_x$$

where $x = [\theta_m \ \omega_m \ M_{Load}]^T$ and the parameters l_1 , l_2 and l_3 of the observer gain are calculated using the pole placement method, knowing that the pair (A,C) is observable. The ELSO+Me structure is presented in Fig. 6 and the observer parameters are:

$$\begin{aligned} l_1 &= -p_1 + p_2 + p_3 - B/J_{BLDC}, \\ l_2 &= p_1 p_2 + p_1 p_3 + p_2 p_3 - l_1(B/J_{BLDC}), \quad l_3 = J_{BLDC} p_1 p_2 p_3. \end{aligned} \quad (18)$$

The observer coefficients depend as expected on the MS parameters (especially on J_{BLDC}). These coefficients determine the dynamics of the observer convergence speed. The idea of using all physical states as observer inputs leads to an observer with improved performance with minimal dynamic delays.

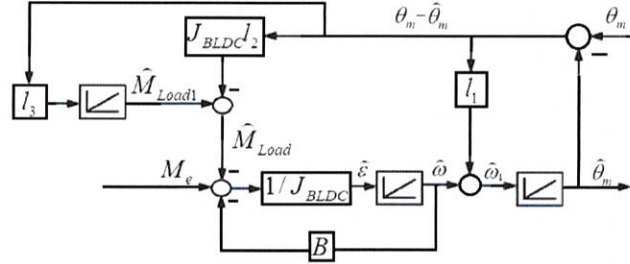


Fig. 6. ELSO+Me block diagram

2.3. Extended Luenberger State Observer with θ_m as Input (ELSO-Me)

Another solution to compute the estimates $\hat{\omega}$ and $\hat{\varepsilon}$ is to use an ELSO considering only the mechanical position error term, without any other input. The motion model is chosen with $\varepsilon = const$, a case commonly encountered in constant acceleration with constant electromagnetic torque and in constant steady-state motion regimes. For this case of ELSO-Me, (here, $x = [\theta_m \ \omega_m \ \varepsilon]^T$) the state-space equations are (Luenberger, 1966; Andreescu, 1999):

$$\begin{aligned} \begin{bmatrix} \dot{\hat{\theta}}_m \\ \dot{\hat{\omega}}_m \\ \dot{\hat{\varepsilon}} \end{bmatrix} &= \underbrace{\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}}_A \begin{bmatrix} \hat{\theta}_m \\ \hat{\omega}_m \\ \hat{\varepsilon} \end{bmatrix} + \underbrace{\begin{bmatrix} l_1 \\ l_2 \\ l_3 \end{bmatrix}}_L (\theta_m - \hat{\theta}_m), \\ y &= \underbrace{\begin{bmatrix} 1 & 0 & 0 \end{bmatrix}}_C \begin{bmatrix} \hat{\theta}_m \\ \hat{\omega}_m \\ \hat{\varepsilon} \end{bmatrix}. \end{aligned} \quad (19)$$

The ELSO-Me block diagram is illustrated in Fig. 7. The observer compensator design $L = [l_1 \ l_2 \ l_3]^T$ is also done with the pole placement method and the observer parameters are:

$$l_1 = -p_1 + p_2 + p_3, \quad l_2 = p_1 p_2 + p_1 p_3 + p_2 p_3, \quad l_3 = -p_1 p_2 p_3. \quad (20)$$

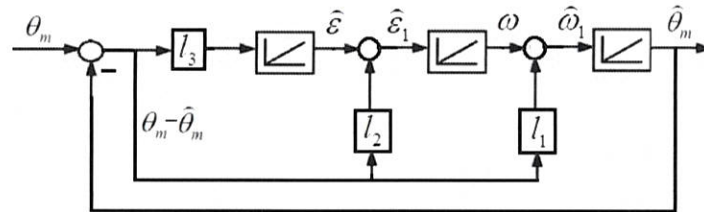


Fig. 7. ELSO-Me block diagram

The validation of the control approaches is done using two simulation scenarios. The digital simulation results are given in Fig. 8 to Fig. 12.

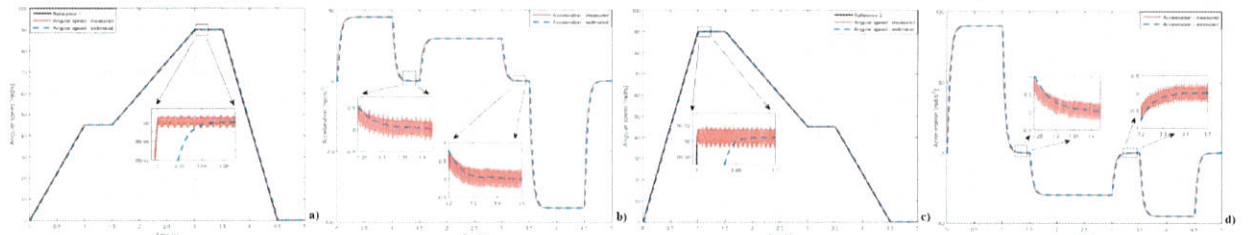


Fig. 8. Digital results for BLDC drive with OTF: a) Angular speed versus time (reference 1), b) Acceleration versus time (reference 1), c) Angular speed versus time (reference 2), b) Acceleration versus time (reference 2)

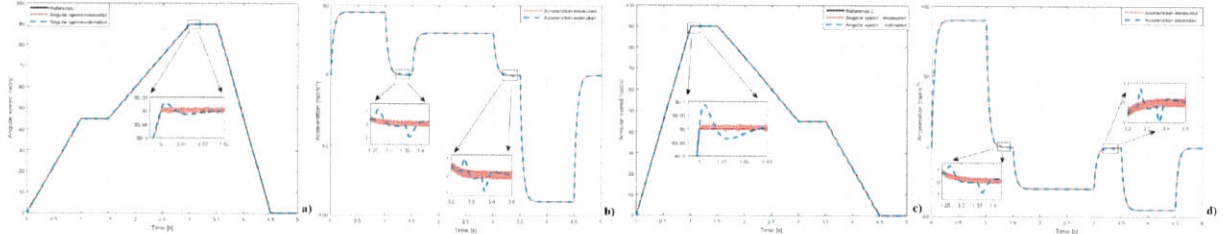


Fig. 9. Digital results for BLDC drive with ELSO+Me: a) Angular speed versus time (reference 1), b) Acceleration versus time (reference 1), c) Angular speed versus time (reference 2), b) Acceleration versus time (reference 2)

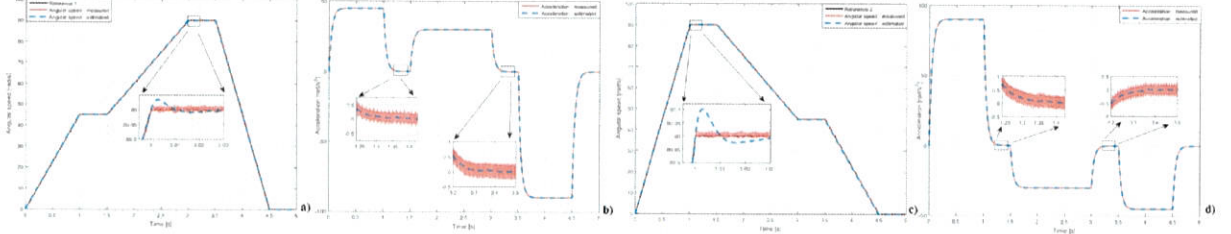


Fig. 10. Digital results for BLDC drive with ELSO-Me: a) Angular speed versus time (reference 1), b) Acceleration versus time (reference 1), c) Angular speed versus time (reference 2), b) Acceleration versus time (reference 2)

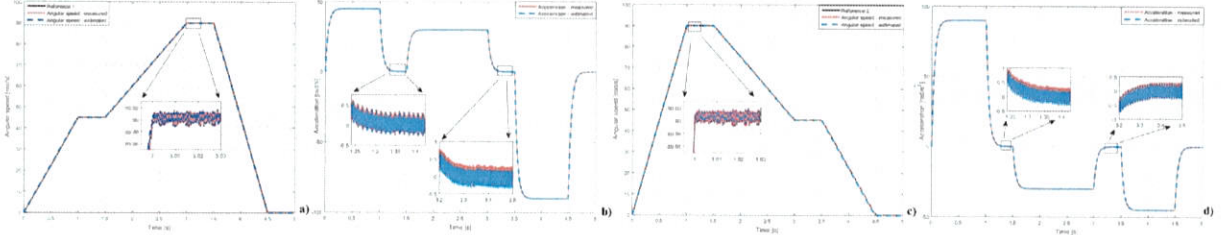


Fig. 11. Digital results for BLDC drive with SMO: a) Angular speed versus time (reference 1), b) Acceleration versus time (reference 1), c) Angular speed versus time (reference 2), b) Acceleration versus time (reference 2)

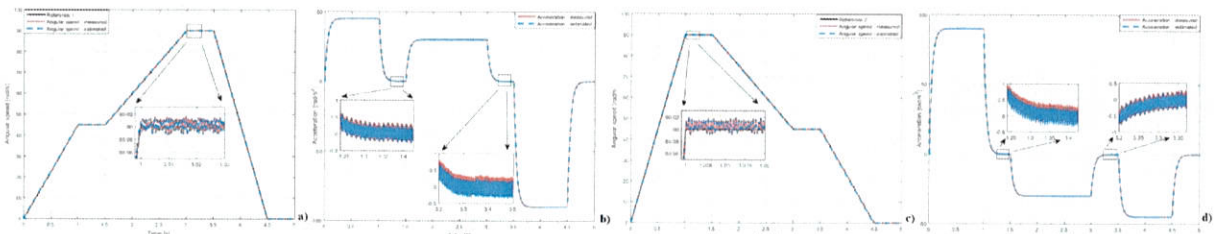


Fig. 12. Digital results for BLDC drive with KFO: a) Angular speed versus time (reference 1), b) Acceleration versus time (reference 1), c) Angular speed versus time (reference 2), b) Acceleration versus time (reference 2)

Considering the graphs illustrated in Fig. 8 to 12, a set of following conclusions is next pointed out: (i) the OTF design approach gives a slower convergence rate and therefore has a large transient error because it uses only one direct correction term by means of the coefficient a_0 ; (ii) the ELSO+M_e uses the electromagnetic torque, resulting in a minimum phase delay. It also ensures that the load torque is estimated but has the disadvantage that the parameters of the observer gain depend on the parameters of the MS; (iii) the ELSO-M_e is more robust to the variation of the MS parameters and does not require the use of the electromagnetic torque; (iv) the estimated states $\hat{\omega}$ and $\hat{\varepsilon}$ obtained with the SMO and KFO techniques are similar to the measured states ω and ε ; (v) based on the comparative analysis of the five design approaches it can be concluded that the proposed observers, namely OTF, ELSO+M_e, ELSO-M_e, SMO and KFO, prove to be viable and ensure a good reference tracking ability and (vi) the use of these observers leads to dynamically and permanently improved performance. All the information presented in subsection 2 were published in the paper (Szczlak-Stinean et al., 2019a).

3. The electric drive system which wraps a strip with constant linear velocity on a drum - electric drive system with variable parameters (SWS)

The mechatronics equipment presents three specific characteristics, (1) to (3): (1) the desired linear speed v_{ref} (m/s) is the product between the angular velocity reference input ω_{ref} (rad/s) and the actual value of the drum radius $r(t)$ (m); (2) due to the winding on the drum made out of brass, the moment of inertia of the rolling drum J_D (kg·m²) will increase in time; (3) the linear velocity of the material v_L (m/s) imposed by the pressing rollers – linear velocity of the drum v_D (m/s) – and the resistance force of the material f_h (N) must remain constant (Stinean, 2014):

$$v_{ref} = \omega_{ref} r(t), \quad v_L(t) = v_D(t) = const, \quad f_h(t) = const. \quad (21)$$

In order to ensure the performance specifications required by the transient regime and the stationary regime, the analysis and synthesis of the afferent control structure requires that the mathematical modeling reproduces as accurately as possible the real operating conditions of the system. In this context, the variation of the angular velocity of the drum ω_f (rad/s) and also the variation of the total moment of inertia of the system $J_{tot}(t)$ (kg·m²) are:

$$\omega_f(t) = a \omega(t), \quad J_{tot}(t) = J_m + J_{empty_drum} + a^2 J_D(t), \quad (22)$$

where: a – the transmission parameter that characterizes the speed reduction unit, ω – the angular velocity of the motor (rotor) (rad/s), J_m – the moment of inertia of the motor (rotor) ($\text{kg}\cdot\text{m}^2$), $J_{\text{empty_drum}}$ – the moment of inertia of the drum without material on it ($\text{kg}\cdot\text{m}^2$). Assuming that the thickness of the material (h , (m)) wrapped on the drum is small enough, the drum radius variation $r(t)$ (m) and the variation of drum's moment of inertia J_D , ($\text{kg}\cdot\text{m}^2$) are approximated as follows:

$$\begin{aligned} \dot{r}(t) &= \frac{h}{2\pi} \omega_f(t) = \frac{h}{2\pi} a \omega(t), \\ J_D &= \frac{\rho \pi l [r(t) - r_0]^4}{2}, \end{aligned} \quad (23)$$

where: ρ – the density of the brass material (kg/m^3), l – the drum width (m), and r_0 – the initial value of the drum radius (m). Taking into consideration these aspects, the behavior of the SWS is described by the following nonlinear state equations (Stinean, 2014):

$$\begin{cases} \dot{i}_a(t) = -\frac{R_a}{L_a} i_a(t) - \frac{k_e}{L_a} \omega(t) + \frac{k_E}{L_a} u_c(t), \\ \dot{\omega}(t) = \frac{k_m}{J_{\text{tot}}(t)} i_a(t) - \frac{1}{J_{\text{tot}}(t)} J_{\text{tot}}(t) \omega(t) - \frac{a r(t)}{J_{\text{tot}}(t)} f_h(t) - \frac{k_f}{J_{\text{tot}}(t)} \omega(t), \\ \dot{f}_h(t) = C a r(t) \omega(t) - C v_L(t), \\ \dot{J}_{\text{tot}}(t) = a^3 \rho l h [r(t) - r_0]^3 \omega(t), \\ \dot{r}(t) = \frac{h}{2\pi} a \omega(t), \end{cases} \quad (24)$$

where: i_a – the armature current intensity (A), L_a , R_a , $T_a = L_a/R_a$ – the electrical parameters (H, Ω , s), k_e , k_m – the electromagnetic parameters (V/rad/s, N·m/A), k_E – the actuator gain (V/V), u_c – the control signal or the control voltage (V), u_a – the armature voltage (V), and C – the elasticity constant of the material (N/m). The state-space model of the SWS is obtained by inserting the state variables $x_1(t) = i_a(t)$, $x_2(t) = \omega(t)$, $x_3(t) = f_h(t)$, $x_4(t) = J_{\text{tot}}(t)$, $x_5(t) = r(t)$:

$$\begin{aligned} \begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{x}_3(t) \\ \dot{x}_4(t) \\ \dot{x}_5(t) \end{bmatrix} &= \begin{bmatrix} -\frac{R_a}{L_a} & -\frac{k_e}{L_a} & 0 & 0 & 0 \\ \frac{k_m}{J_{\text{tot}}(t)} & -\frac{a^3 \rho l h [x_5(t) - r_0]^3 x_2(t) + k_f}{J_{\text{tot}}(t)} & -\frac{a x_5(t)}{J_{\text{tot}}(t)} & 0 & 0 \\ 0 & \frac{C a x_5(t)}{J_{\text{tot}}(t)} & 0 & 0 & 0 \\ 0 & a^3 \rho l h [x_5(t) - r_0]^3 & 0 & 0 & 0 \\ 0 & \frac{h}{2\pi} a & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \\ x_5(t) \end{bmatrix} + \begin{bmatrix} \frac{k_E}{L_a} & 0 \\ 0 & 0 \\ 0 & -C \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} u_c(t) \\ v_L(t) \end{bmatrix}, \\ y(t) &= \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \\ x_5(t) \end{bmatrix} = x_2(t). \end{aligned} \quad (25)$$

The structure and relations between the different subsystems of the controlled process are presented through a nonlinear block diagram in Fig. 13.

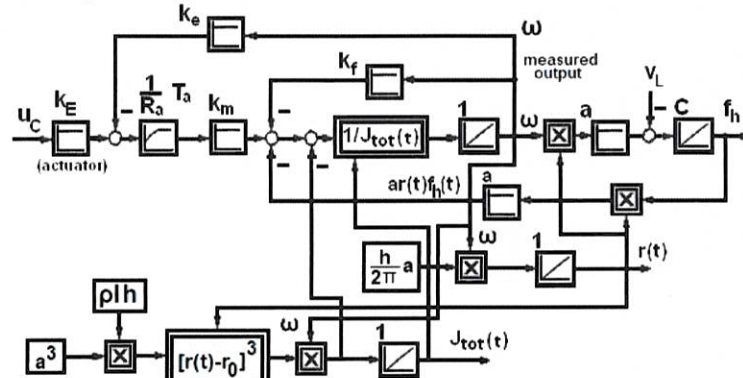


Fig. 13. Block diagram of SWS

3.1. Extended Kalman filter system modeling and design for SWS

The dynamics for the EKF are pointed out as follows in their single input-single output discrete-discrete expression obtained from processing the results reported in (Julier and Uhlmann, 2004; Simon, 2006; Beyhan et al., 2013; EKF, 2022):

1. The nonlinear model of the nonlinear system subjected to nonlinear estimation is represented by the state-space equations:

$$\begin{aligned} \mathbf{x}_{k+1} &= \mathbf{f}(\mathbf{x}_k, u_k) + \mathbf{g} w_k, \\ y_k &= h(\mathbf{x}_k) + v_k, \\ w_k &\sim \mathcal{N}(0, Q), \\ v_k &\sim \mathcal{N}(0, R), \end{aligned} \quad (26)$$

where: $\mathbf{x}_k \in \mathfrak{R}^n$ – the state vector, u_k – the input, $\mathbf{f} : \mathfrak{R}^n \times \mathfrak{R} \rightarrow \mathfrak{R}^n$ – a nonlinear function that gives the predicted state from the previous estimate, $h : \mathfrak{R}^n \rightarrow \mathfrak{R}$ – a nonlinear function that calculates the predicted measurement from the actual state, $w_k \in \mathfrak{R}$, $v_k \in \mathfrak{R}$ – the white noise process and measurement noise, respectively, assumed to be of zero mean and uncorrelated with the initial state vector $\mathbf{x}_{k_0} \in \mathfrak{R}^n$ and with each other, $\mathbf{g} \in \mathfrak{R}^{n \times 1}$ – the process noise matrix assumed to be independent of \mathbf{x}_k , $Q \in \mathfrak{R}$, $R \in \mathfrak{R}$ – the process and measurement covariance, respectively, with $Q > 0$ and $R > 0$.

2. The EKF predict-update equations are:

Predictor update:

$$\begin{aligned} \hat{\mathbf{x}}_{k+1|k} &= \mathbf{f}(\hat{\mathbf{x}}_{k|k}, u_k), \\ \mathbf{P}_{k+1|k} &= \mathbf{F}_k \mathbf{P}_{k|k} \mathbf{F}_k^T + \mathbf{g} Q \mathbf{g}^T, \\ \mathbf{F}_k &= \left. \frac{\partial \mathbf{f}(\mathbf{x}, u)}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k}, u=u_k}, \end{aligned} \quad (27)$$

Filter update:

$$\begin{aligned} \hat{y}_k &= h(\hat{\mathbf{x}}_{k|k-1}), \\ \hat{e}_k &= y_k - \hat{y}_k, \\ S_{k+1} &= \mathbf{H}_{k+1} \mathbf{P}_{k+1|k} \mathbf{H}_{k+1}^T + R, \\ \mathbf{K}_{k+1} &= \frac{\mathbf{P}_{k+1|k} \mathbf{H}_{k+1}^T}{S_{k+1}}, \end{aligned} \quad (28)$$

$$\begin{aligned} \hat{\mathbf{x}}_{k+1|k+1} &= \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1} \hat{e}_{k+1}, \\ \mathbf{P}_{k+1|k+1} &= (\mathbf{I}_n - \mathbf{K}_{k+1} \mathbf{H}_{k+1}) \mathbf{P}_{k+1|k}, \\ \mathbf{H}_{k+1} &= \left. \frac{\partial h(\mathbf{x})}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}_{k+1|k}}, \end{aligned} \quad (29)$$

where: $\hat{\mathbf{x}}_{k|k-1} \in \mathfrak{R}^n$ – the estimated state vector, \hat{y}_k – the estimated output, \hat{e}_k – the error of the estimate, $\mathbf{P}_k \in \mathfrak{R}^{n \times n}$ – the error covariance matrix, $S_k \in \mathfrak{R}$ – the residual covariance, $\mathbf{K}_k \in \mathfrak{R}^{n \times 1}$ – the Kalman gain matrix, $\mathbf{F}_k \in \mathfrak{R}^{n \times n}$ – the state transition matrix, $\mathbf{H}_k \in \mathfrak{R}^{1 \times n}$ – the state observation matrix, and $\mathbf{I}_n = \text{diag}(1, \dots, 1) \in \mathfrak{R}^{n \times n}$ – the n^{th} order identity matrix. As shown in (29), the states of this filtering approach are updated using \mathbf{K}_{k+1} and also \hat{e}_{k+1} . The second equation in (27), the third equation in (28) and the second equation in (29), which make use of the Jacobian matrices \mathbf{F}_k and \mathbf{H}_k , highlight that the \mathbf{P}_k and \mathbf{K}_k matrices are updated using linearized process dynamics around the current estimate.

3. The initial conditions imposed to the dynamic system in (27) are:

$$\begin{aligned} \hat{\mathbf{x}}_{k_0|k_0} &= E(\mathbf{x}_{k_0}), \\ \mathbf{P}_{k_0|k_0} &= \text{Var}(\mathbf{x}_{k_0}), \end{aligned} \quad (30)$$

where E indicates mathematical expectation and Var indicates variance. The initial condition imposed to the dynamic system in (26) is

$$\mathbf{x}_{k_0} \sim \mathcal{N}(\hat{\mathbf{x}}_{k_0|k_0}, \mathbf{P}_{k_0|k_0}). \quad (31)$$

The EKF block diagram is presented in Fig. 14.

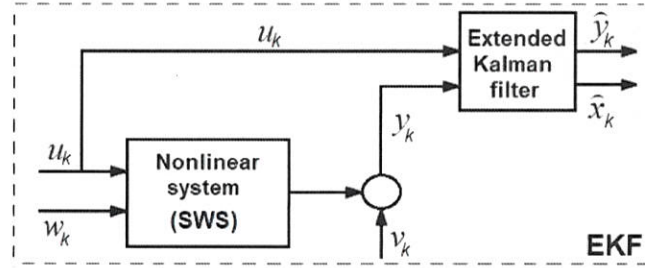


Fig. 14. EKF block diagram

3.2. Takagi-Sugeno fuzzy observer system modeling and design for SWS

To develop a TSFO it is required to have a TS fuzzy model of the nonlinear system subjected to observation. Thus, in this approach, an essential step is the development of a fuzzy model. Generally, there are two ways for obtaining fuzzy models, (1) and (2): (1) Identification (fuzzy modeling) utilizing input-output data, and (2) Derivation from known equations of the nonlinear system.

Using the sector nonlinearity approach ((Kawamoto et al., 1992; Johansen et al., 2000; Mehran, 2008)) is a popular way of obtaining the TS fuzzy models. This approach for the development of fuzzy models was first mentioned in (Kawamoto et al., 1992), and it is based on the following strategy. Considering a simple first order system $\dot{x} = f(x(t))$, with $f(0)=0$, the goal is finding a global sector that fulfills the condition $\dot{x} = f(x(t)) \in [a_1 \ a_2]x(t)$. Following this approach ensures the construction of an exact fuzzy model. Since it is at times challenging to find a global sector for nonlinear systems, local sector nonlinearity can be taken into consideration. This is a valid approach given the fact that the variables of real-world systems are always bounded.

TS fuzzy models

Model rule i :

$$\text{IF } z_1(t) \text{ IS } M_{i1} \text{ AND } \dots \text{ AND } z_q(t) \text{ IS } M_{iq} \text{ THEN } \begin{cases} \dot{\mathbf{x}}(t) = \mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t), \\ \mathbf{y}(t) = \mathbf{C}_i \mathbf{x}(t), \end{cases} \quad i = 1 \dots n_R, \quad (32)$$

where: $z_1(t), z_2(t), \dots, z_q(t)$ – the premise (scheduling) variables, M_{ij} – the fuzzy sets or, more specifically, the linguistic terms of the scheduling variables, $n_R=2^q$ – the number of model rules, $\mathbf{x} \in \mathbb{R}^n$ – the state vector, $\mathbf{u} \in \mathbb{R}^m$ – the input vector, $\mathbf{y} \in \mathbb{R}^p$ – the output vector, $\mathbf{A}_i \in \mathbb{R}^{n \times n}$ – the square state or system matrices, $\mathbf{B}_i \in \mathbb{R}^{n \times m}$ – the input matrices, and $\mathbf{C}_i \in \mathbb{R}^{p \times n}$ – the output matrices. Each linear right-hand term of the state equations in the consequent of (13) represented by the relation $\mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t)$ is labeled as subsystem. Taking into consideration the state vector-input vector pair $(\mathbf{x}(t), \mathbf{u}(t))$, the final outputs of the Takagi-Sugeno fuzzy model are given in the following relations (Johansen et al., 2000; Mehran, 2008; Beyhan et al., 2013):

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \frac{\sum_{i=1}^{n_R} w_i(\mathbf{z}(t)) \{ \mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t) \}}{\sum_{i=1}^{n_R} w_i(\mathbf{z}(t))} = \sum_{i=1}^{n_R} h_i(\mathbf{z}(t)) \{ \mathbf{A}_i \mathbf{x}(t) + \mathbf{B}_i \mathbf{u}(t) \}, \\ \mathbf{y}(t) &= \frac{\sum_{i=1}^{n_R} w_i(\mathbf{z}(t)) \mathbf{C}_i \mathbf{x}(t)}{\sum_{i=1}^{n_R} w_i(\mathbf{z}(t))} = \sum_{i=1}^{n_R} h_i(\mathbf{z}(t)) \mathbf{C}_i \mathbf{x}(t), \end{aligned} \quad (33)$$

where $\mathbf{z}(t)$ and $w_i(t)$ are

$$\begin{aligned} \mathbf{z}(t) &= [z_1(t) \ z_2(t) \ \dots \ z_q(t)]^T, \\ w_i(\mathbf{z}(t)) &= \prod_{j=1}^q M_{ij}(z_j(t)), \quad i = 1 \dots n_R. \end{aligned} \quad (34)$$

In (33) and (34), $w_i(t)$ represents the weight or firing functions and these functions for all t are normalized according to

$$h_i(\mathbf{z}(t)) = \frac{w_i(\mathbf{z}(t))}{\sum_{i=1}^{n_R} w_i(\mathbf{z}(t))}, \quad i = 1 \dots n_R. \quad (35)$$

Knowing that

$$\begin{aligned} \sum_{i=1}^{n_R} w_i(\mathbf{z}(t)) &> 0, \\ w_i(\mathbf{z}(t)) &\geq 0, \quad i = 1 \dots n_R, \end{aligned} \quad (36)$$

for all t , the following relationship is valid:

$$\sum_{i=1}^{n_R} h_i(z(t)) = 1, \quad (37)$$

$$h_i(z(t)) \geq 0, \quad i = 1 \dots n_R.$$

TSFO observer design

The conditions that must be fulfilled for the design of the Takagi-Sugeno fuzzy observer are in fact stability conditions to guarantee the stability of the autonomous dynamic system that corresponds to the state equation in (33), which is the first equation in (33), i.e. that system for $\mathbf{u}(t) = \mathbf{0}$. These conditions are derived using the Lyapunov approach (Tanaka and Sugeno, 1990; Tanaka and Sugeno, 1992; Tanaka and Wang, 2001). The basic stability conditions for an autonomous Takagi-Sugeno fuzzy system are given in Theorem 1 (Tanaka et al., 1998; Beyhan et al., 2013).

Theorem 1: The equilibrium point $\mathbf{x}=\mathbf{0}$ of the continuous-time Takagi-Sugeno fuzzy model described by $\dot{\mathbf{x}}(t) = \sum_{i=1}^{n_R} h_i(z(t)) \mathbf{A}_i \mathbf{x}(t)$ is asymptotically stable, if there exists a positive definite matrix $\mathbf{P}=\mathbf{P}^T$, $\mathbf{P} \in \mathbb{R}^{n \times n}$ such that the following LMIs are fulfilled:

$$\mathbf{A}_i^T \mathbf{P} + \mathbf{P} \mathbf{A}_i < 0, \quad i = 1 \dots n_R. \quad (38)$$

Solving the LMIs in (38) using (Tanaka and Wang, 1997) makes use of the presence of the positive definite matrix \mathbf{P} . The Takagi-Sugeno fuzzy observer is described using

$$\dot{\hat{\mathbf{x}}}(t) = \sum_{i=1}^{n_R} h_i(z(t)) \{ \mathbf{A}_i \hat{\mathbf{x}}(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{L}_i (\mathbf{y}(t) - \hat{\mathbf{y}}(t)) \}, \quad (39)$$

$$\hat{\mathbf{y}}(t) = \sum_{i=1}^{n_R} h_i(z(t)) \mathbf{C}_i \hat{\mathbf{x}}(t),$$

where \mathbf{L}_i , $i = 1 \dots n_R$ are the observer gain matrices, $\mathbf{L}_i \in \mathbb{R}^{n \times p}$. The purpose of this nonlinear observer is to estimate the states of the Takagi-Sugeno fuzzy model (33), which is accomplished if the error dynamics are asymptotically stable. Subtracting (39) from (33) and defining the error of the estimated state vector $\hat{\mathbf{e}}(t) = \mathbf{x}(t) - \hat{\mathbf{x}}(t)$, the error dynamics is expressed as (Tanaka et al., 1998; Beyhan et al., 2013)

$$\dot{\hat{\mathbf{e}}}(t) = \sum_{i=1}^{n_R} \sum_{j=1}^{n_R} h_i(z(t)) h_j(z(t)) (\mathbf{A}_i - \mathbf{L}_i \mathbf{C}_j) \hat{\mathbf{e}}(t). \quad (40)$$

Immeasurable premise variables need to be considered in the design of Takagi-Sugeno fuzzy observers. In this case, according to (Tanaka and Wang, 2001), the premise variables are unknown since they depend on the state variables to be estimated by the fuzzy observer. Therefore, although the Takagi-Sugeno fuzzy observer defined in (39) is defined with respect to the error of the estimated output vector $\mathbf{y}(t) - \hat{\mathbf{y}}(t)$, the error dynamics as presented in (40) is expressed with respect to the estimated state vector are not valid and need to be revised, impacting the observer design.

The stability conditions – with a proper convergence rate – of the Takagi-Sugeno fuzzy observer are given in Theorem 2 and Theorem 3, respectively (Tanaka et al., 1998; Beyhan et al., 2013).

Theorem 2: The error dynamics described by (40) for the Takagi-Sugeno fuzzy model (33) is asymptotically stable, if there exists a positive definite matrix $\mathbf{P}=\mathbf{P}^T$, $\mathbf{P} \in \mathbb{R}^{n \times n}$ such that

$$\begin{aligned} \mathcal{H}(\mathbf{P}(\mathbf{A}_i - \mathbf{L}_i \mathbf{C}_i)) &< 0, \\ \mathcal{H}(\mathbf{G}_{ij} + \mathbf{G}_{ji}) &\leq 0, \\ \mathbf{G}_{ij} &= \mathbf{P}(\mathbf{A}_i - \mathbf{L}_i \mathbf{C}_j), \end{aligned} \quad (41)$$

for all $i, j = 1 \dots n_R$ excepting the pairs (i,j) for which $h_i(z(t))h_j(z(t))=0$.

Theorem 3: The proper convergence rate of the error dynamics described by (40) is at least α , if there exists a positive definite matrix $\mathbf{P}=\mathbf{P}^T$, $\mathbf{P} \in \mathbb{R}^{n \times n}$, such that

$$\begin{aligned} \mathcal{H}(\mathbf{P}(\mathbf{A}_i - \mathbf{L}_i \mathbf{C}_i)) + 2\alpha \mathbf{P} &< 0, \\ \mathcal{H}(\mathbf{G}_{ij} + \mathbf{G}_{ji}) + 4\alpha \mathbf{P} &\leq 0, \end{aligned} \quad (42)$$

for all $i, j = 1 \dots n_R$ excepting the pairs (i,j) for which $h_i(z(t))h_j(z(t))=0$. In the last two theorems, \mathcal{H} denotes the Hermitian matrix, and is defined as $\mathcal{H}(\mathbf{A}) = \mathbf{A} + \mathbf{A}^T$.

In order to obtain high performance of the SWS, two nonlinear estimation approaches, namely EKF and TSFO-32, are developed, tested and validated by means of digital simulation results. The system's responses with respect to the imposed modification of the reference input, which leads to a moment of inertia variation and causes an increased drum radius for the mechatronics application, are illustrated in Fig. 15, Fig. 16 and Fig. 17.

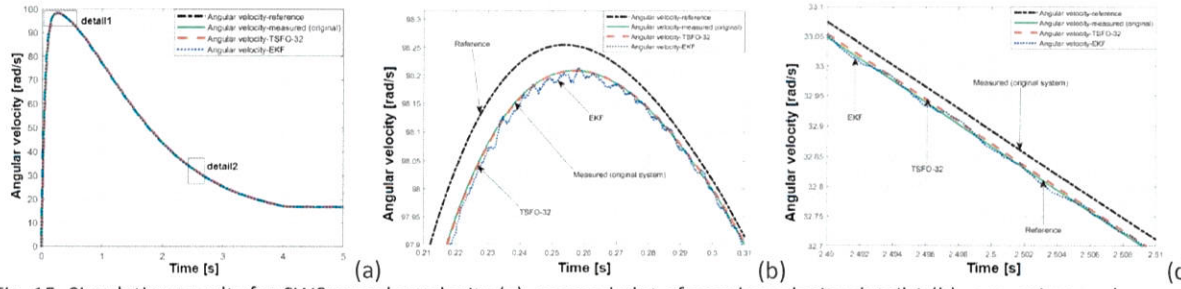


Fig. 15. Simulation results for SWS: angular velocity (a), zoomed plot of angular velocity-detail 1 (b) versus time and zoomed plot of angular velocity-detail 2 (c) versus time

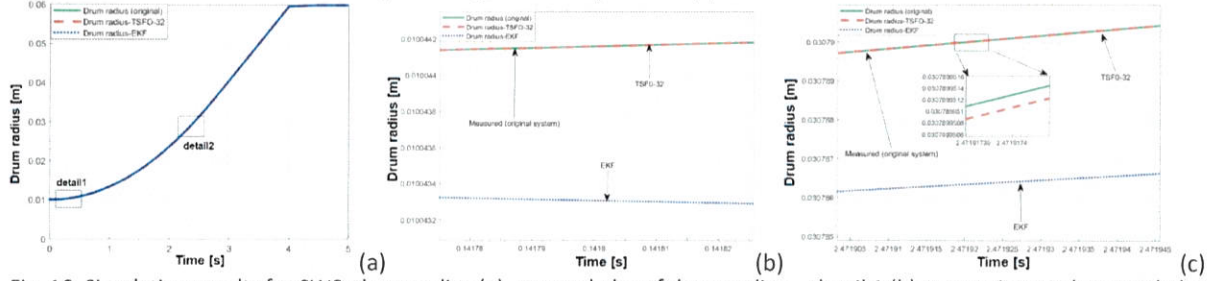


Fig. 16. Simulation results for SWS: drum radius (a), zoomed plot of drum radius – detail 1 (b) versus time and zoomed plot of drum radius – detail 2 (c) versus time

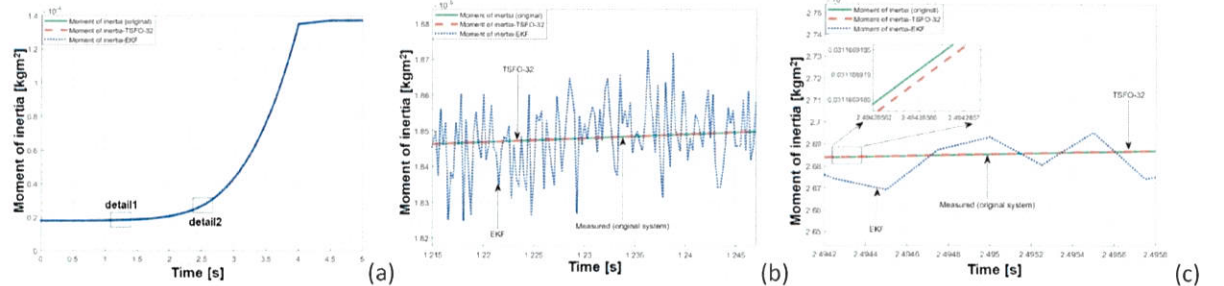


Fig. 17. Simulation results for SWS: moment of inertia (a) and zoomed plot of moment of inertia – detail1 (b) versus time and zoomed plot of moment of inertia – detail2 (c) versus time

Taking into account all the information presented in the previous subsections, the graphs illustrated in Figs. 15 to 17, the following conclusions are expressed: (i) the EKF that linearizes about an estimate of the current mean and covariance uses the linearized dynamics to compute the estimates; (ii) the TSFO-32 uses the sector nonlinearity approach to model the nonlinear process. The system stability and observer design conditions are guaranteed by using LMIs, which are solved by utilizing the Mosek solver within the YALMIP toolbox; (iii) the results illustrated in Figs. 15 to 17 show that the TSFO-32 provides better performance than the EKF due to the fact that the design of the TSFO is based on the exact knowledge of the nonlinear system; (iv) based on the comparative analysis of the two design approaches it can be concluded that the proposed nonlinear observers, namely EKF and TSFO-32, prove to be viable, efficient and ensure a good reference tracking ability and (v) the use of these nonlinear estimation approaches leads to dynamically and permanently improved performance. The results presented support the benefits of controller design approaches and their application to processes with variable parameters. All the information presented in subsection 3 were published in the paper (Szczepanek et al., 2022b).

The 3rd, 4th and 5th stages of the project – Suspended activity - Maternity leave. The suspension of the project starting from 01.10.2019 and until 30.11.2021, the reason for the interruption being the entry into maternity leave and then the entry into child-raising leave.

The 6th and 7th stage of the project – Experimental validation of the proposed modern control solutions – pursued within december 2021 and in 2022 (January – November 2022) has been completed and is grouped in the form of the following activity:

Act 6.1 (7.1) – Validation of observers through experimental results. To carry out this activity, the analysis of theoretical research and the classification of observers specific to mechatronics systems from stage 1, was also considered.

4. The laboratory equipment - Model 220 Industrial Plant Emulator (M220IPE)

The structure of the mechatronics application that represents the controlled process (M220IPE) is presented in Fig. 18. The dynamic equations that describe the mechatronics system in case of rigid (a) and flexible (b) drive dynamics, considering θ_1 as the process output are:

$$\begin{aligned}
 a) \quad & J_{dr} \ddot{\theta}_1 + (c_1 + c_2 g^{-2}) \dot{\theta}_1 = T_D, \\
 b) \quad & J_{dr} \ddot{\theta}_1 + (c_1 + c_{12} g^{-2}) \dot{\theta}_1 - c_{12} g^{-1} \ddot{\theta}_2 + k(g^{-2} \theta_1 - g^{-1} \theta_2) = T_D, \\
 & J_1 \ddot{\theta}_2 + (c_2 + c_{12}) \dot{\theta}_2 - c_{12} g^{-1} \dot{\theta}_1 + k(\theta_2 - g^{-1} \theta_1) = 0.
 \end{aligned} \tag{43}$$

with J_{dr} , J_d , J_p , J_l , g and g' expressed as:

$$\begin{aligned} J_{dr} &= J_d + J_p g'^{-2} + J_l g^{-2}, J_d = J_{ddr} + J_{wdr}, \\ J_p &= J_{pdr} + J_{pld} + J_{backlash}, J_l = J_{lld} + J_{wld}, \\ g &= 6n_{pd} / n_{pl}, g' = n_{pd} / 12. \end{aligned} \quad (44)$$

where J_{dr} – total inertia reflected to the drive disk, J_p , J_d , J_l – pulley, drive disk and load disk inertia, c_1 , c_2 – the drive and load friction, g , g' – drive gear and partial gear system ratio, ϑ_1 , ϑ_2 , ϑ_p – drive disk, load disk and idler pulleys positions where $\vartheta_1 = g\vartheta_2$ or $\vartheta_1 = g'\vartheta_p$.

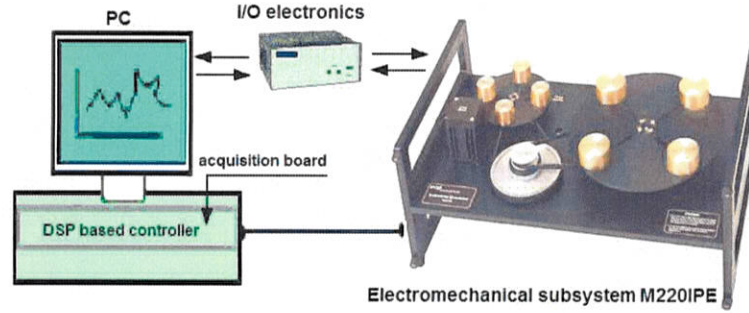


Fig. 18. M220IPE laboratory equipment

Rigid Drive Dynamics: The first principle equations that describe the system in case of rigid drive dynamics are (ECP, 2010; Szedlak-Stinean et al., 2016):

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = \frac{-(c_1 + c_2 g^{-2})x_2}{J_d + J_p g'^{-2} + J_l g^{-2}} + \frac{T_D}{J_d + J_p g'^{-2} + J_l g^{-2}}, \\ y = x_1. \end{cases} \quad (45)$$

The state-space MM (SS-MM) of M220IPE with rigid drive dynamics is:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & \frac{-(c_1 + c_2 g^{-2})}{J_d + J_p g'^{-2} + J_l g^{-2}} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{J_d + J_p g'^{-2} + J_l g^{-2}} \end{bmatrix} T_D, \quad (46)$$

$$y = [1 \ 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T.$$

where T_D is the drive torque ($T_D = u$), $x = [x_1 \ x_2]^T = [\vartheta_1 \ d\vartheta_1/dt]^T$ is the state vector (T indicates matrix transposition) and y is the output. Considering zero initial conditions, the application of the Laplace transform to (43a)) leads to the following transfer function (t.f.):

$$\frac{\theta_1(s)}{T_D(s)} = \frac{1/(J_d + J_p g'^{-2} + J_l g^{-2})}{s[s + (c_1 + c_2 g^{-2})/(J_d + J_p g'^{-2} + J_l g^{-2})]}, \quad (47)$$

Flexible Drive Dynamics: The first principle equations that describe the system in case of flexible drive dynamics are (ECP, 2010):

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = \frac{-(kg^{-2})x_1}{J_{dr}} + \frac{-(c_1 + c_{12}g^{-2})x_2}{J_{dr}} + \frac{kg^{-1}}{J_{dr}} + \frac{c_{12}g^{-1}}{J_{dr}}, \\ \dot{x}_3 = x_4, \\ \dot{x}_4 = \frac{(kg^{-1})x_1}{J_l} + \frac{(c_{12}g^{-1})x_2}{J_l} + \frac{(-k)x_3}{J_l} + \frac{-(c_2 + c_{12})x_4}{J_l}, \\ y = x_1. \end{cases} \quad (48)$$

The SS-MM of M220IPE with flexible drive dynamics is:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -(kg^{-2}) & -(c_1+c_{12}g^{-2}) & kg^{-1} & c_{12}g^{-1} \\ J_{dr} & J_{dr} & J_{dr} & J_{dr} \\ 0 & 0 & 0 & 1 \\ kg^{-1} & c_{12}g^{-1} & -k & -(c_2+c_{12}) \\ J_l & J_l & J_l & J_l \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} 0 \\ I \\ J_d + J_p g^{1/2} + J_l g^2 \\ 0 \\ 0 \end{bmatrix} T_D, \quad (49)$$

$$y = [1 \ 0 \ 0 \ 0][x_1 \ x_2 \ x_3 \ x_4]^T.$$

where T_D is the drive torque ($T_D = u$, u is the input), $x = [x_1 \ x_2 \ x_3 \ x_4]^T = [\vartheta_1 \ d\vartheta_1/dt \ \vartheta_2 \ d\vartheta_2/dt]^T$ is the state vector and y is the output. The following t.f. is attached to (49):

$$\frac{\theta_1(s)}{T_D(s)} = \frac{J_l s^2 + (c_2 + c_{12})s + k}{d_4 s^4 + d_3 s^3 + d_2 s^2 + d_1 s}, \quad (50)$$

where $d_4 = J_d J_l$, $d_3 = J_d(c_2 + c_{12}) + J_l(c_1 + c_{12}/g^2)$, $d_2 = J_d k + J_l k/g^2 + c_1 c_2 + c_1 c_{12} + c_{12} c_2/g^2$, $d_1 = c_1 k + c_2 k/g^2$.

4.1. Continuous-time linear observer - state feedback and observer-based controller design

In cases where the process states are not accessible for measurements or are only partially accessible for measurements and if the process is observable, then it is possible to estimate its states. For this purpose, state estimators or state observers are utilized. The observability test of the linearized SS-MMs (46) and (49) can be done using the matrix:

$$Q_o = [C^T \ C^T A \ C^T A^2 \ C^T A^3 \ C^T A^4 \dots]^T. \quad (51)$$

The starting point in order to specify the relations that describe the functioning of a state observer, is the SS-MM corresponding to the process, assumed known, with the form:

$$\begin{aligned} \dot{x} &= A x + B u, \\ y &= C x. \end{aligned} \quad (52)$$

The variable that is the target of the control process is the output. Firstly, all components of the state vector are assumed as measured. The feedback is constrained to be linear, so it can be considered as (Åström and Murray, 2009):

$$u = -K x + K_{ref} r \quad (53)$$

where r is the reference input, K_{ref} is the feed-forward gain and K is the state feedback gain matrix. The state feedback gain matrix of M220IPE with rigid (a) and flexible (b) drive dynamics are:

$$\begin{aligned} a) \quad K &= [k_{c1} \ k_{c2}], \\ b) \quad K &= [k_{c1} \ k_{c2} \ k_{c3} \ k_{c4}]. \end{aligned} \quad (54)$$

The pole placement method is applied to compute K using three sets of imposed poles, each for three specific load disk inertia values, i.e., J_{l1} , J_{l2} , J_{l3} . The closed loop system obtained when the feedback (53) is applied to the system (52) is given by:

$$\dot{x} = (A - BK)x + B K_{ref} r. \quad (55)$$

The SS-MM corresponding to the state observer has the same structure as the process (52) and is completed with a correction relation based on the output error $\tilde{y} = y - \hat{y}$. Consequently, the MM is rewritten in the form (Åström and Murray, 2009):

$$\begin{aligned} \dot{\hat{x}} &= A \hat{x} + B u + L(y - C \hat{x}) = (A - LC)\hat{x} + B u + L y, \\ \hat{y} &= C \hat{x}, \end{aligned} \quad (56)$$

where L is the observer gain. The parameters of the observer gain for M220IPE with rigid (a) and flexible (b) drive dynamics are:

$$\begin{aligned} a) \quad L &= [l_1 \ l_2]^T, \\ b) \quad L &= [l_1 \ l_2 \ l_3 \ l_4]^T. \end{aligned} \quad (57)$$

In order to analyze the observer, the state estimation error is defined as $\tilde{x} = x - \hat{x}$. Differentiating and replacing the expressions of $\dot{\hat{x}}$ and \dot{x} leads to $\dot{\tilde{x}} = (A - LC)\tilde{x}$. The error \tilde{x} will go to zero if the matrix L is chosen such that the matrix $(A - LC)$ has eigenvalues / poles with negative real parts. The appropriate selection of the eigenvalues / poles determines the convergence rate (Åström and Murray, 2009). Taking this into account, the design of the state observer involves solving a poles placement problem and also calculating the parameters of the observer gain. The starting point in designing the state observer is the expression of the characteristic polynomial:

$$\Delta_{ob}(s) = \det(sI - A + LC) = s^n + \alpha_{n-1}s^{n-1} + \dots + \alpha_1 s + \alpha_0. \quad (58)$$

By allocating the poles of the observer, the characteristic polynomial $\Delta_{ob}(s)$ is expressed as:

$$\Delta_{ob}(s) = \prod(s - p_{ov}) = s^n + \beta_{n-1}s^{n-1} + \dots + \beta_0 \quad (59)$$

Because both the system (52) and the observer (56) have the same order n , the order of the closed loop system is $2n$. In order to obtain the state feedback observer, the design of the observer as well as the design of the state feedback can be realized separately. The closed-loop system is defined as:

$$\begin{bmatrix} \dot{\hat{x}} \\ \dot{\tilde{x}} \end{bmatrix} = \begin{bmatrix} A-BK & BK \\ 0 & A-LC \end{bmatrix} \begin{bmatrix} \hat{x} \\ \tilde{x} \end{bmatrix} + \begin{bmatrix} BK_{ref} \\ 0 \end{bmatrix} r \quad (60)$$

Due to the fact that the matrix on the right side is block diagonal, the characteristic polynomial of the closed-loop system has the form:

$$\Delta_{cl}(s) = \det(sI - A + BK) \det(sI - A + LC). \quad (61)$$

This property is called the separation principle (Åström and Murray, 2009). A schematic diagram of the controller is illustrated in Fig. 19. It can be observed that the controller includes a dynamic model of the plant, thus respecting the internal model principle. It can also be noticed that the observer determines the dynamics of the controller. As such, the controller can be regarded as a dynamical system having y as input and u as output:

$$\begin{aligned} \dot{\hat{x}} &= (A - BK - LC)\hat{x} + L y, \\ u &= -K \hat{x} + K_{ref} r. \end{aligned} \quad (62)$$

The t.f. of the controller has the form:

$$H_c(s) = K [sI - A + BK + LC]^{-1} L. \quad (63)$$

The proposed design approaches were tested and validated by real-time experimental results. The system's responses in two experimental scenarios were considered: 1. the proposed control solutions responses were tested first using a step reference and are illustrated in Fig. 20 and 22 and 2. a staircase change for the reference signal was employed and the proposed control solutions were tested again on the time frame of 30s and are illustrated in Fig. 21 and 23.

Taking into account the graphs illustrated in Fig. 20 to 23, a set of following conclusions are pointed out: (i) the motivation to use observers (state observers) is due to the fact that through the predictive negative reaction, these design approaches have the advantage of faster convergence and a reduced sensitivity of estimation to parameter variation; (ii) the controller structure is identical for systems with one input and one output as well as for systems with multiple inputs and outputs with the same form for the controller equations, the only difference being the fact that the feedback gain K and the observer gain L are matrices instead of vectors; (iii) the separation principle – for the output feedback, the eigenvalue assignment can be split into an observer and a state feedback eigenvalue assignment – leads to a simplified design; (iv) with one dynamic system both a controller and an observer can be developed; (v) the proposed approaches offer contributions for the robustness and dynamic performance of the system; (vi) based on the comparative analysis it can be concluded that the proposed design approaches, prove to be viable and ensure a good reference tracking ability; (vii) the use of these state observers leads to dynamically and permanently improved performance. All the information presented in subsection 4.1 were published in the paper (Szedlak-Stinean et al., 2019b).

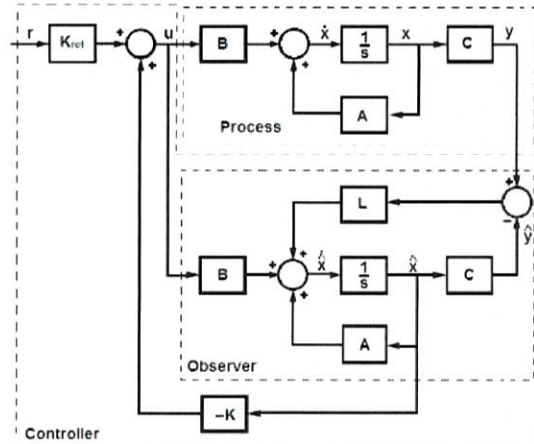


Fig. 19. Schematic diagram of an observer-based controller

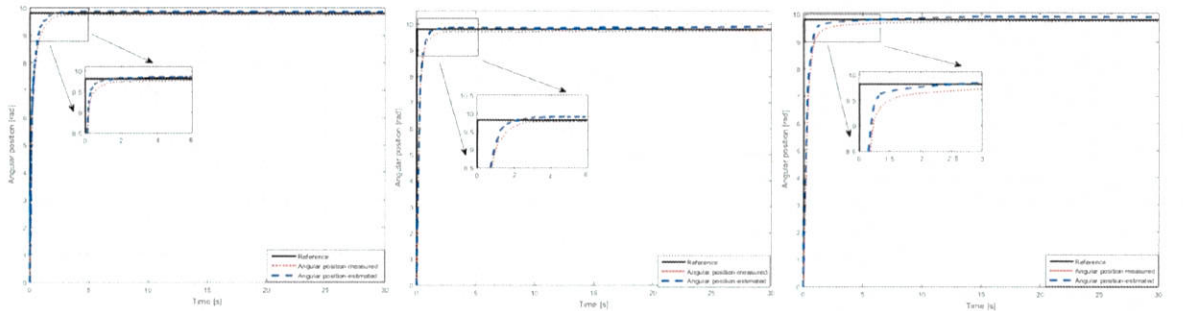


Fig. 20. Experimental results concerning the behaviour of observer-based controller designed for MIPE220 with rigid drive dynamics (step reference): case study 1, 2 and 3

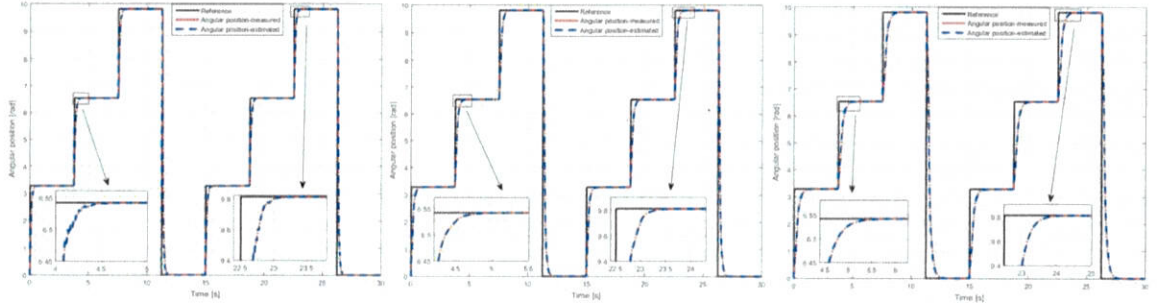


Fig. 21. Experimental results concerning the behaviour of observer-based controller designed for MIPE220 with rigid drive dynamics (staircase reference): case study 1, 2 and 3

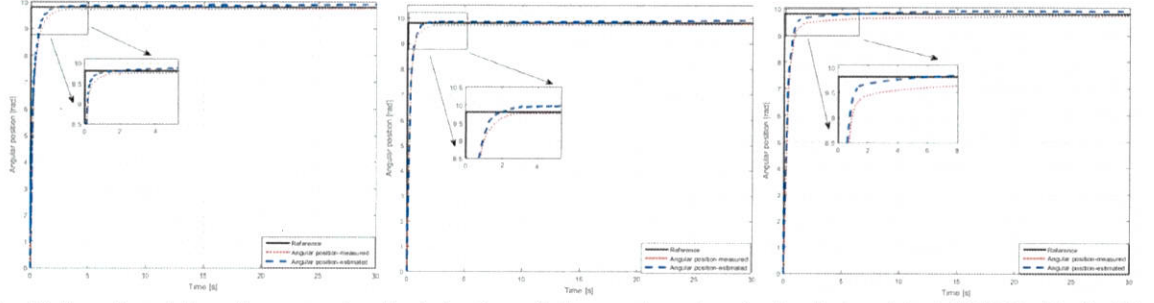


Fig. 22. Experimental results concerning the behaviour of observer-based controller designed for MIPE220 with flexible drive dynamics (step reference): case study 1, 2 and 3

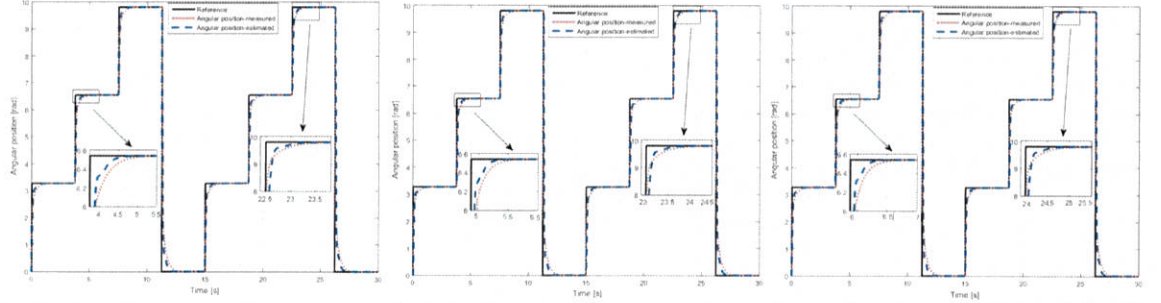


Fig. 23. Experimental results concerning the behaviour of observer-based controller designed for MIPE220 with flexible drive dynamics (staircase reference): case study 1, 2 and 3

4.2. Discrete-time linear and nonlinear observers

In order to carry out a comparative study with the purpose of evaluating their performance and efficiency, the four estimation techniques presented in subsections 4.2.1, 4.2.2, 4.2.3 and 4.2.4 are considered.

4.2.1. Kalman Filter Observer (KFO)

In order to estimate unmeasured states of a process, in control systems engineering for linear systems, KFO which are actually a form of predictor-corrector are widely used. In this context, as part of an approach for designing a control law, the estimated states can be employed (Lendek et al., 2008; Habibullah and Lu, 2015; KF, 2022). The discrete-time dynamical state-space model is defined by (KF, 2022):

$$\begin{aligned} \mathbf{x}_k &= \mathbf{A}_{sd} \mathbf{x}_{k-1} + \mathbf{B}_d u_k + \mathbf{w}_{k-1}, \\ y_k &= \mathbf{C}_d \mathbf{x}_k, \\ \tilde{y}_k &= y_k + v_k, \end{aligned} \quad (64)$$

where k is a discrete point in time (the immediate past time point is $k-1$), \mathbf{x}_k is the state vector, u_k is the input, y_k is the output, \tilde{y}_k is the measured output and \mathbf{w}_k, v_k are the white process and white measurement noise, zero mean Gaussian with covariance \mathbf{Q}_k and R_k , $\mathbf{w}_k \sim \mathcal{N}(0, \mathbf{Q}_k)$, $v_k \sim \mathcal{N}(0, R_k)$. The KFO predictor-corrector equations are (KF, 2022):

Predictor:

$$\begin{aligned} \hat{\mathbf{x}}_k^- &= \mathbf{A}_{sd} \hat{\mathbf{x}}_{k-1} + \mathbf{B}_d u_k, \\ \mathbf{P}_k^- &= \mathbf{A}_{sd} \mathbf{P}_{k-1} \mathbf{A}_{sd}^T + \mathbf{Q}_k, \end{aligned} \quad (65)$$

Corrector:

$$\begin{aligned} \mathbf{K}_k &= \mathbf{P}_k^- \mathbf{C}_d^T (\mathbf{C}_d \mathbf{P}_k^- \mathbf{C}_d^T + R_k)^{-1}, \\ \hat{\mathbf{x}}_k &= \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\tilde{y}_k - \mathbf{C}_d \hat{\mathbf{x}}_k^-), \\ \mathbf{P}_k &= (\mathbf{I} - \mathbf{K}_k \mathbf{C}_d) \mathbf{P}_k^-, \end{aligned} \quad (66)$$

where $\hat{\mathbf{x}}_k$ is the estimated state vector and $\hat{\mathbf{x}}_k^- = E(\mathbf{x}_k | y_1, y_2, \dots, y_{k-1})$, \mathbf{P}_k is the error covariance matrix and $\mathbf{P}_k^- = E(\mathbf{x}_k | y_1, y_2, \dots, y_{k-1})$, \mathbf{I} is the identity matrix, and \mathbf{K}_k is the Kalman gain matrix.

4.2.2. Extended Luenberger State Observer (ELSO)

Another way to compute the estimate states of a process, is to utilize a discrete-time ELSO, a Simulink block, which uses the backward Euler method in the discretization (Luenberger, 1966; Luenberger, 2022; Szedlak-Stinean et al., 2019a). The discrete-time dynamic model of ELSO and the dynamics of the estimation error are:

$$\begin{aligned}\hat{\mathbf{x}}_{k+1} &= \mathbf{A}_{xd} \hat{\mathbf{x}}_k + \mathbf{B}_d u_k + \mathbf{L}_d (y_k - \hat{y}_k), \\ \hat{y}_k &= \mathbf{C}_d \hat{\mathbf{x}}_k, \\ \mathbf{e}_{k+1} &= (\mathbf{A}_{xd} - \mathbf{L}_d \mathbf{C}_d) \mathbf{e}_k,\end{aligned}\tag{67}$$

where $\hat{\mathbf{x}}_k$ is the k^{th} estimated state vector, \hat{y}_k is the estimated output, u_k is the input, y_k is the output, \mathbf{e}_k is the k^{th} error vector, \mathbf{A}_{xd} , \mathbf{B}_d and \mathbf{C}_d are the discretized state, input and output matrices, and \mathbf{L}_d is the discretized observer gain matrix. Considering that the matrix $(\mathbf{A}_{xd} - \mathbf{L}_d \mathbf{C}_d)$ has its eigenvalues inside the unit circle, the observer gain matrix \mathbf{L}_d is calculated by solving a Sylvester equation (Luenberger, 2022; Szedlak-Stinean et al., 2019a)

$$\mathbf{L}_d^T = \mathbf{G} \mathbf{X}^{-1},\tag{68}$$

where \mathbf{X} is the matrix resulting in terms of solving

$$\mathbf{A}_{xd}^T \mathbf{X} - \mathbf{X} \mathbf{A}_{xd} = \mathbf{C}_d^T \mathbf{G},\tag{69}$$

\mathbf{G} is an arbitrary matrix, \mathbf{A} is a matrix with the desired eigenvalues, which are different to the eigenvalues of \mathbf{A}_{xd} .

4.2.3. Extended Kalman Filter Observer (EKFO)

EKFO is the nonlinear version of KFO, and it is the most commonly used observer at this time in the category of those based on nonlinear estimation (Beyhan et al., 2013; Simon, 2006; EKF, 2022). The discrete-time dynamical model is defined by the equations

$$\begin{aligned}\mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}, u_k, k) + w_{k-1}, \\ y_k &= h(\mathbf{x}_k, u_k, k) \\ \tilde{y}_k &= y_k + v_k,\end{aligned}\tag{70}$$

where \mathbf{x}_k , u_k , y_k , \tilde{y}_k , w_k and v_k are exactly the same vectors, variables and parameters as in the case of KFO and \mathbf{f} and h are nonlinear functions connecting the past state, current input and current time to the next state and current output. The equations for the EKFO predictor-corrector are (Beyhan et al., 2013; Simon, 2006; EKF, 2022)

Predictor:

$$\begin{aligned}\hat{\mathbf{x}}_k^- &= \mathbf{f}(\hat{\mathbf{x}}_{k-1}, u_k, k), \\ \mathbf{P}_k^- &= \mathbf{F}_{k-1} \mathbf{P}_{k-1} \mathbf{F}_{k-1}^T + \mathbf{Q}_k, \\ \mathbf{F}_k &= \left. \frac{\partial \mathbf{f}}{\partial \mathbf{x}} \right|_{(\hat{\mathbf{x}}_k, u_k, k)},\end{aligned}\tag{71}$$

Corrector:

$$\begin{aligned}\mathbf{K}_k &= \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{-1}, \\ \hat{\mathbf{x}}_k &= \hat{\mathbf{x}}_k^- + \mathbf{K}_k (\tilde{y}_k - h(\hat{\mathbf{x}}_k^-, u_k, k)), \\ \mathbf{P}_k &= (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^-, \\ \mathbf{H}_k &= \left. \frac{\partial h}{\partial \mathbf{x}} \right|_{(\hat{\mathbf{x}}_k, u_k, k)}.\end{aligned}\tag{72}$$

4.2.4. Sliding Mode Observer (SMO)

SMOs are successfully integrated into mechatronic systems and generally their structures are closely related to the MMs used in the controlled process. In comparison to linear observers, the main (principal) advantage that the SMOs have is that in the case of unknown inputs they are insensitive while in sliding. They can, additionally, be utilized in order to reconstitute unknown inputs that could be a mixture of system disturbances, errors or nonlinearities (Spurgeon, 2008; Mercorelli, 2015; Shtessel et al., 2014). Considering the discrete-time dynamic system

$$\begin{aligned}\mathbf{x}_{k+1} &= \mathbf{A}_{xd} \mathbf{x}_k + \mathbf{B}_d u_k, \\ y_k &= \mathbf{C}_d \mathbf{x}_k,\end{aligned}\tag{73}$$

and omitting the subscript k that indicates the discrete point in time for the sake of simplicity, $\mathbf{x} \in \mathbb{R}^n$, $\mathbf{u} \in \mathbb{R}^p$, $\mathbf{y} \in \mathbb{R}^m$, $\mathbf{y} = [y_1 \dots y_m]^T$, it is assumed that the pair $(\mathbf{A}_{xd}, \mathbf{C}_d)$ is observable, and \mathbf{C}_d has full rank.

Transforming the system in (73) into

$$\begin{aligned}\mathbf{x}_{1,k+1} &= \mathbf{A}_{xd_11} \mathbf{x}_{1,k} + \mathbf{A}_{xd_12} \mathbf{y}_k + \mathbf{B}_{d_1} u_k, \\ \mathbf{y}_{k+1} &= \mathbf{A}_{xd_21} \mathbf{x}_{1,k} + \mathbf{A}_{xd_22} \mathbf{y}_k + \mathbf{B}_{d_2} u_k,\end{aligned}\tag{74}$$

the discrete-time dynamic model of SMO is [(Spurgeon, 2008; Mercorelli, 2015; Shtessel et al., 2014)

$$\begin{aligned}\hat{\mathbf{x}}_{1,k+1} &= \mathbf{A}_{xd_11} \hat{\mathbf{x}}_{1,k} + \mathbf{A}_{xd_12} \hat{\mathbf{y}}_k + \mathbf{B}_{d_1} u_k + \mathbf{L}_s v_k, \\ \hat{\mathbf{y}}_{k+1} &= \mathbf{A}_{xd_21} \hat{\mathbf{x}}_{1,k} + \mathbf{A}_{xd_22} \hat{\mathbf{y}}_k + \mathbf{B}_{d_2} u_k - v_k,\end{aligned}\tag{75}$$

where $\hat{\mathbf{y}} \in \mathbb{R}^m$, $\hat{\mathbf{y}} = [\hat{y}_1 \dots \hat{y}_m]^T$, is the estimated output vector, and $\hat{\mathbf{v}} \in \mathbb{R}^m$, $\hat{\mathbf{v}} = [\hat{v}_1 \dots \hat{v}_m]^T$, is an injection term specific to sliding mode control but employed here in SMO. Using the notation $\mathbf{e}_y = \hat{\mathbf{y}} - \mathbf{y} = [e_y^1 \dots e_y^m]^T$ for the output estimation error, the expression of the injection term is

$$\mathbf{v}_k = [v_{1,k} \dots v_{m,k}]^T = [M \operatorname{sgn}(e_y^1) \dots M \operatorname{sgn}(e_y^m)]^T, \quad (76)$$

where the value of the scalar parameter $M \in \mathbb{R}_+$ is set to $M=1$ as follows.

The error dynamics is expressed as

$$\mathbf{e}_{x1,k+1} = \mathbf{A}_{xd_11} \mathbf{e}_{x1,k} + \mathbf{A}_{xd_12} \mathbf{e}_{y,k} + \mathbf{L}_s \mathbf{v}_k, \quad (77)$$

$$\mathbf{e}_{y,k+1} = \mathbf{A}_{xd_21} \mathbf{e}_{x1,k} + \mathbf{A}_{xd_22} \mathbf{e}_{y,k} - \mathbf{v}_k,$$

where $\mathbf{e}_{x1,k} = \hat{\mathbf{x}}_{1,k} - \mathbf{x}_{1,k}$, $\mathbf{e}_{y,k} = \hat{\mathbf{y}}_k - \mathbf{y}_k$, and \mathbf{L}_s is a gain value / matrix. The expression of the equivalent injection term, $\mathbf{v}_{k,eq} = \mathbf{A}_{xd_21} \mathbf{e}_{x1,k} + \mathbf{A}_{xd_22} \mathbf{e}_{y,k}$, is obtained by solving $\mathbf{e}_{y,k+1} = \mathbf{0}$, and allows the convenient analysis and design of SMO on the sliding manifold. A sliding motion occurs on $\mathbf{e}_{x1} = \mathbf{0}$ in finite step if $\mathbf{v}_k = \mathbf{v}_{k,eq}$, and $\mathbf{e}_{x1,k+1} = (\mathbf{A}_{xd_11} + \mathbf{L}_s \mathbf{A}_{xd_21}) \mathbf{e}_{x1,k}$ holds in sliding mode. By replacing the eigenvalues of $(\mathbf{A}_{xd_11} + \mathbf{L}_s \mathbf{A}_{xd_21})$ at the origin, $\mathbf{e}_{x1} \rightarrow \mathbf{0}$ in finite step.

The validation of the control techniques will be done through real-time experimental and digital simulation results with respect to position control of M220IPE. A part of the digital simulation results is given in Fig. 24 and a part of the real-time experimental results is shown in Fig. 25.

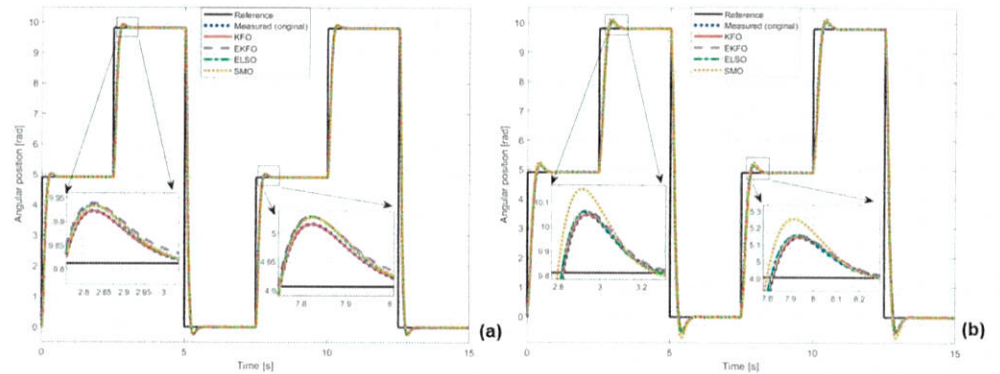


Fig. 24. Digital results for M220IPE with SFCS and four estimation techniques: (a) RDD, (b) FDD

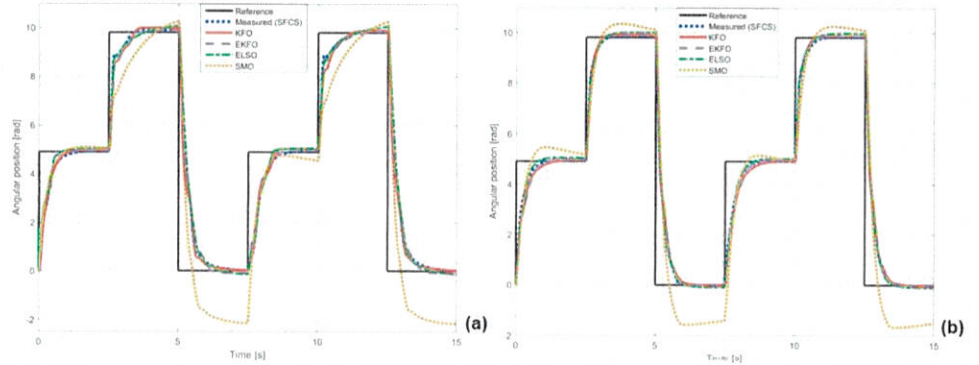


Fig. 25. Real-time experimental results for M220IPE with SFCS and four estimation techniques: (a) RDD, (b) FDD

Considering the graphics presented in Fig. 24 and Fig. 25, the following conclusions can be highlighted: (i) the two situations taken into consideration – rigid drive dynamics (RDD) and flexible drive dynamics (FDD) – showed that the best efficiencies and performance have been obtained by the SMOs developed for M220IPE with FDD; (ii) from the performance point of view the best results have been achieved by the KFO and by the EKFO due to the fact that these observers are simple to define and realize having basic knowledge and they also give satisfactory results in operation due to optimality and structure; (iii) the ELSO is less efficient than KFO due to the fact that the process parameters influence those of the observer gain; (iv) the SMO provides the worst performance given that in order to provide an estimation, the output has to rest on a designated sliding surface and in addition, performance is rarely guaranteed, particularly when the output are corrupted with noise; (v) the proposed estimation techniques are demonstrated to be efficient, practical and guarantee a proper reference tracing capacity, and (vi) the control system should benefit from the advantages of the ongoing analytical progress and realization of dynamic model-based observers that promise to enhance the performance of different types of mechatronics systems. All the information presented in subsection 4.2 were detailed in a paper accepted to be published (Szedlak-Stinean et al., 2022c).

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B. Presentation of the results obtained, of the achieved result indicators; of the recorded non-achievements compared to the results estimated by the financing request (if applicable), with their justification;

The main results obtained in the 1st Stage of the project:

- **1 scientific report:** for 2018, the scientific report is the only deliverable of the project.

The main results obtained in the 2nd Stage of the project:

- **1 paper in Refereed Journals / Contributions to Books** published in conference proceedings indexed in Clarivate Analytics Web of Science (formerly ISI Web of Knowledge) (Roman et al., 2019): a mix of two data-driven algorithms is proposed in (Roman et al., 2019a). The mix of the algorithms aims to exploit the main advantage of data-driven Virtual Reference Feedback Tuning (VRFT) algorithm, that is represented by the automatic computation of the optimal parameters using a metaheuristic Grey Wolf Optimizer (GWO) for the Compact Form Dynamic Linearization (CFDL) version of the authors' Model-Free Adaptive Control Takagi-Sugeno Fuzzy Algorithm (CFDLPDTSFA), so the parameters of the CFDL-PDTSFA are optimally tuned in a model-free manner via VRFT.
- **2 papers** published in conference proceedings indexed in Clarivate Analytics Web of Science (formerly ISI Web of Knowledge) (Szedlak-Stinean et al., 2019a; Szedlak-Stinean et al., 2019b): five design approaches for the speed and acceleration control of an electric drive system with time-varying inputs built around a brushless direct current motor are developed in (Szedlak-Stinean et al., 2019a). Five observers are developed and tested in the context of a cascade control structure with two control loops, which uses a variable structure controller in the inner loop (the current loop) and a classical PI controller in the outer loop (the speed loop); A controller with a novel structure, which is composed of three subsystems: a subsystem that provides the desired output and from the reference input a feed-forward signal, an observer and a feedback derived from the estimated states is developed and validated in (Szedlak-Stinean et al., 2019b).
- **1 paper worked and edited in 2019 but published in 2020** in a Clarivate Analytics Web of Science (formerly ISI

Web of Knowledge) journal with high impact factor (Precup et al., 2020): two applications of Grey Wolf Optimizer (GWO) algorithms to a path planning (PaPl) problem and a Proportional-Integral (PI)-fuzzy controller tuning problem are developed in (Precup et al., 2020a). Both optimization problems solved by GWO algorithms are explained in detail. An off-line GWO-based PaPl approach for Nonholonomic Wheeled Mobile Robots (NWMRs) in static environments is proposed.

- **1 paper written in 2019 but published in 2020** in conference proceedings indexed in Clarivate Analytics Web of Science (formerly ISI Web of Knowledge) (David et al., 2020): a novel application of Whale Optimization Algorithm (WOA) as solution for solving a complex control design and tuning problem concerning fuzzy control systems that control processes modeled as second-order servo systems with an integral component and variable parameters is developed in (David et al., 2020).

- **1 scientific report.**

The main results obtained in the 3rd, 4th and 5th stage of the project: Suspension of the project starting from 01.10.2019 and until 30.11.2021, the reason for the interruption being the entry into maternity leave and then the entry into child-raising leave.

The main results obtained in the 6th stage of the project:

- **1 scientific report:** for the year 2021, more precisely for the month of December, the scientific report is the only deliverable of the project.

The main results obtained in the 7th Stage of the project:

- **1 paper** accepted and published in a Clarivate Analytics Web of Science (formerly ISI Web of Knowledge) journal with high impact factor (Szedlak Stinean et al., 2022b): two nonlinear estimation approaches, namely based on Extended Kalman Filter (EKF) and a Takagi-Sugeno Fuzzy Observer with 32 rules (TSFO-32), for a Strip Winding System (SWS) characterized by variable reference input, variable moment of inertia with constant increasing tendency and variable parameters.

- **9 papers** presented in conference proceedings currently indexed and in the phase of being indexed in international databases (IEEE Xplore, INSPEC, Scopus, DBLP) (Szedlak-Stinean et al., 2022a; Bojan-Dragos et al., 2022a; Precup et al., 2022a; Roman et al., 2022a; Precup et al., 2022b; Hedrea et al., 2022; Roman et al., 2022b; Szedlak-Stinean et al., 2022c; Gale-Cazan et al., 2022): four estimation approaches, namely two linear and two nonlinear ones: Extended Luenberger State Observer (ELSO), Kalman Filter Observer (KFO), Extended Kalman Filter Observer (EKFO) and Sliding Mode Observer (SMO) are developed in (Szedlak-Stinean et al., 2022a) for electric drive systems (EDSs) with direct current (DC) motor; two Proportional-Integral-Derivative controllers, a type-1 fuzzy controller and an interval type-2 fuzzy controller are optimally tuned in (Bojan-Dragos et al., 2022b) using metaheuristic Grey Wolf Optimizer algorithm to control the nonlinear processes with Shape Memory Alloy (SMA) wire actuators; the African Vultures Optimization Algorithm (AVOA)-based tuning of low-cost fuzzy controllers (first order discrete-time intelligent Proportional-Integral controllers with Takagi-Sugeno-Kang Proportional-Derivative fuzzy terms) is proposed in (Precup et al., 2022a) to control the payload position of tower crane systems with SMA actuators; three data-driven control algorithms, namely Active Disturbance Rejection Control, Model-Free Adaptive Control and Model Free Control are optimally tuned in terms of solving an optimization problem in (Roman et al., 2022a) to the position control of shape memory alloy; three categories of nonlinear models of tower crane systems: a first principles state-space model with GWO-based optimally tuned parameters, evolving TSK fuzzy models and a TP-based model are developed and validated in (Precup et al., 2022b); 20 control system structures are designed in (Hedrea et al., 2022) for the level control of vertical three tank systems using Tensor Product (TP)-based model transformation in the framework of state feedback control; the paper (Roman et al., 2022b) proposes to compare the performances of a proportional-integral controller whose parameters are determined in a model-based way using a metaheuristic search algorithm, with the performances of a PI determined in a mode-free way by using virtual reference feedback tuning algorithm and using iterative feedback tuning algorithm to control the position of a shape memory alloy (SMA) laboratory equipment; in (Szedlak-Stinean et al., 2022c) is provided a guide for the development and implementation of four observers for estimating the angular position for Model 220 Industrial Plant Emulator with state feedback control; the computation of the optimal values of a part of the nonlinear model of an unstable transport (UnTrans) system are treated in (Gale-Cazan et al., 2022). Adequate optimization problems were defined and next solved by the recent metaheuristic GWO algorithms.

Remarks:

- Some of the papers presented in Section C contain more than one project in the Acknowledgements section. Several projects contributed to the creation of these papers because the same processes are controlled, different controllers developed in different projects were proposed, and their fair comparison was necessary.
- All published papers or accepted to be published which contains research results obtained under this project mentioned the support of UEFISCDI in the Acknowledgments section, together with the specification of the submitting code of the funding application.
- In the scientific report related to 2019 and in the EvoC platform in the scientific results section related to 2nd stage, the work entitled "MIMO Fuzzy Control Solutions for the Level Control of Vertical Two Tank Systems" is also included, but due to the fact that this work does not contain in the *Acknowledgments* section the submission code PN-III-P1-1.1-PD-2016-0331, it will not be included in this report nor on the project web page
- The obtained results are also mentioned in the web page of the project, <https://szedlak-stinean.wixsite.com/nobsmeecs>, where all the information related to the development of the project will be included.

C. The estimated impact of the results obtained, emphasizing the most significant result obtained.

The main results obtained in the project:

- ***Papers in Refereed Journals / Contributions to Books***

R.-C. Roman, R.-E. Precup, C.-A. Bojan-Dragos and **A.-I. Szedlak-Stinean**. Combined Model-Free Adaptive Control with Fuzzy Component by Virtual Reference Feedback Tuning for Tower Crane Systems, *Procedia Computer Science* (Elsevier Science), vol. 162, pp. 267-274, 2019.

- ***Journal Papers:***

A.-I. Szedlak-Stinean, R.-E. Precup, E. M. Petriu, R.-C. Roman, E.-L. Hedrea and C.-A. Bojan-Dragos (2022b). Extended Kalman Filter and Takagi-Sugeno Fuzzy Observer for a Strip Winding System, accepted to be published in *Expert Systems with Applications*, vol. 208, pp. 118-215, impact factor (IF) = 8.665, IF according to 2021 Journal Citation Reports (JCR) released by Clarivate Analytics in 2022 = 8.665.

- ***Conference Proceedings papers***

A.-I. Szedlak-Stinean, R.-E. Precup and R.-C. David (2019a). Speed and Acceleration Control of BLDC Drives Using Different Types of Observers, 13th International Symposium on Applied Computational Intelligence and Informatics (SACI 2019), Timisoara, Romania, pp. 229-236, 2019.

A.-I. Szedlak-Stinean, R.-E. Precup and R.-C. David (2019b). State Observers for Mechatronics Systems with Rigid and Flexible Drive Dynamics, 16th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2019), Prague, Czech Republic, vol. 2, pp. 387-394, 2019.

A.-I. Szedlak-Stinean, R.-E. Precup and R.-C. Roman (2022a). Linear and nonlinear observers developed for direct current electric drive systems, 9th International Conference on Computers Communications and Control (ICCC 2022), Baile Felix, Romania, pp. 1-14.

C.-A. Bojan-Dragos, R.-E. Precup, E. M. Petriu, R.-C. Roman, E.-L. Hedrea and **A.-I. Szedlak-Stinean**. GWO-Based Optimal Tuning of Controllers for Shape Memory Alloy Wire Actuators, 6th IFAC Conference on Intelligent Control and Automation Sciences (ICONS 2022), Cluj-Napoca, Romania, pp. 39-44, 2022.

R.-E. Precup, E.-L. Hedrea, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragos, **A.-I. Szedlak-Stinean** and F.-A. Paulescu (2022a). AVOA-Based Tuning of Low-Cost Fuzzy Controllers for Tower Crane Systems, 2022 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2022), Padua, Italy, pp. 1-8.

R.-C. Roman, R.-E. Precup, S. Preitl, C.-A. Bojan-Dragos, **A.-I. Szedlak-Stinean** and E.-L. Hedrea (2022a). Data-Driven Control Algorithms for Shape Memory Alloys, 6th IEEE Conference on Control Technology and Applications (CCTA 2022), Trieste, Italy, pp. 1306-1312.

R.-E. Precup, E.-L. Hedrea, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragos, **A.-I. Szedlak-Stinean** and C. Hedrea (2022b). Evolving Fuzzy and Tensor Product-based Models for Tower Crane Systems, IEEE 48th Annual Conference of the Industrial Electronics Society (IECON 2022), Brussels, Belgium, pp. 1-6.

E.-L. Hedrea, R.-E. Precup, R.-C. Roman, C.-A. Bojan-Dragos, **A.-I. Szedlak-Stinean** and C. Hedrea. Tensor Product-based and State Feedback Structures for Level Control of Vertical Three Tank Systems, 26th International Conference on System Theory, Control and Computing (ICSTCC 2022), Sinaia, Romania, pp. 1-6, 2022.

R.-C. Roman, R.-E. Precup, S. Preitl, **A.-I. Szedlak-Stinean**, C.-A. Bojan-Dragos, E.-L. Hedrea and E. M. Petriu (2022b). PI Controller Tuning via Data-Driven Algorithms for Shape Memory Alloy Systems, 1st IFAC Workshop on Control of Complex Systems (COSY 2022), Bologna, Italy, pp. 1-6.

A.-I. Szedlak-Stinean, R.-E. Precup, R.-C. Roman, E. M. Petriu, C.-A. Bojan-Dragos and E.-L. Hedrea (2022c). Discrete-time Linear and Nonlinear Observers for an Electromechanical Plant with State Feedback Control, IEEE Symposium Series on Computational Intelligence (IEEE SSCI 2022), Singapore, Singapore, pp. 1-8.

C. -B. Gale-Cazan, C.-A. Bojan-Dragos, R.-E. Precup, R.-C. Roman, E. M. Petriu and **A.-I. Szedlak-Stinean**. GWO-based Modeling of an Unstable Transport System, 9th International Conference on Information Technology and Quantitative Management (ITQM 2022), China, pp. 1-8 (online).

- ***Papers written in 2019 but published in 2020***

R.-C. David, R.-E. Precup, S. Preitl, E. M. Petriu, **A.-I. Szedlak-Stinean** and R.-C. Roman. Whale Optimization Algorithm-Based Tuning of Low-Cost Fuzzy Controllers with Reduced Parametric Sensitivity, *Proceedings of 28th Mediterranean Conference on Control and Automation MED 2020*, Saint-Raphael, France, pp. 440-445, 2020.

R.-E. Precup, E.-I. Voisan, E. M. Petriu, M. L. Tomescu, R.-C. David, **A.-I. Szedlak-Stinean** and R.-C. Roman. Grey Wolf Optimizer-Based Approaches to Path Planning and Fuzzy Logic-based Tracking Control for Mobile Robots, *International Journal of Computers Communications & Control* (Agora University Editing House - CCC Publications), vol. 15, no. 3, 3844, pp. 1-17, 2020, impact factor (IF) = 2.293, IF according to 2020 Journal Citation Reports (JCR) released by Clarivate Analytics in 2021 = 2.293 (univagora.ro/jour/).

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