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Fuzzy-Based Parameter Optimization of Adaptive Unscented Kalman Filter: Methodology and Experimental Validation

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ABSTRACT This study introduces a fuzzy based optimal state estimation approach. The new method is based on two principles: Adaptive Unscented Kalman filter, and Fuzzy Adaptive Grasshopper Optimization Algorithm. The approach is designed for the optimization of an adaptive Unscented Kalman Filter. To find the optimal parameters for the filter, a fuzzy based evolutionary algorithm, named Fuzzy Adaptive Grasshopper Optimization Algorithm, is developed where its efficiency is verified by application to different benchmark functions. The proposed optimal adaptive unscented Kalman filter is applied to two nonlinear systems: a robotic manipulator, and a servo-hydraulic system. Different simulation tests are conducted to verify the performance of the filter. The results of simulations are presented and compared with a previous version of the unscented Kalman filter. For a realistic test, the proposed filter is applied on the practical servo-hydraulic system. Practical results are discussed, and presented results approve the capability of the presented method for practical applications.

INDEX TERMS Adaptive unscented Kalman filter, state estimation, fuzzy adaptive grasshopper optimization algorithm (FAGOA), time variant noise, robot manipulator.

I. INTRODUCTION

State estimation is one of the most important parts of industrial system control. In practical systems, it is difficult to measure some of their states. To design a proper controller for these systems, it is necessary to develop methods to identify the states. In recent years, two main ideas have been mentioned to solve the problem. The first method is using sensors to estimate/detect different states. This method has some disadvantages: high cost, difficulty of implementation, storage requirement, and some equipment for transferring data. These problems require developing new methods which can compensate for the disadvantages of the first method. The other method is the usage of state estimators which have been investigated during recent years. The state estimator refers to a series of equations which try to estimate their propagation [1], [2]. Many studies have focused on this topic, and different methods have been investigated for proposing a new state estimator. For instance, a new estimator has been developed based on the concept of moving horizon estimation in [3]. The research has been focused on outstretching the estimation method based on the combination of networked navigation system and locally relative measurements. In another research, a state estimation approach has been designed for dynamical systems for development of a satisfiability modulo theory [4]. The method was developed to achieve a good result in noisy and contradictory measurement conditions. In [5], a high-order sliding mode observer has been investigated to detect the states of the system under control. The proposed method has been applied to an experimental system to demonstrate its efficiency. As a well-known method to estimate linear systems, the Kalman Filter has been introduced in previous years [6]. Different versions of Kalman filters have been developed, which attempt to enhance the performance of the basic approach. Despite the proper result of the Kalman filter for the estimation of linear systems, the method does not lead to good results for nonlinear systems. To solve this problem, various versions of the Kalman Filter have been developed to deal with nonlinear systems [7], [8]. Extended Kalman

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Filter (EKF) [9], Unscented Kalman Filter (UKF) [10], and Square-root unscented Kalman filter (Sr-UKF) [11] are most popular versions of the basic Kalman Filter, which have been introduced to estimate the behaviour of nonlinear dynamics. In [12], an invariant extended Kalman filter (IEKF) has been developed to estimate the states of a nonlinear system. The IEKF method has been designed in such a way that the dynamics of the estimation error are autonomous. This was obtained by using Lie algorithm. In another research, a consensus-based networked estimation method has been developed [13]. In this research, distributed extended Kalman filters have been employed to estimate states of nonlinear dynamic system. A robust extended Kalman filter has been implemented to estimate the states of stochastic systems [14]. The filter can estimate the system with Bernoulli distributed random noise and delays and packet dropout. The unscented Kalman Filter is one of the strong versions of the Kalman filter which has been used to predict the states of nonlinear systems. The filter has various uses for state estimation [15] and fault detection [16]. Based on this aspect, a robust double-gain unscented Kalman filter has been introduced. This proposed filter has been developed to estimate the attitude of a satellite [17]. In [18], an integrated unscented Kalman filter has been introduced and is applied to control an underwater vehicle.

On the other hand, different methods of artificial intelligence, which can be listed as neural networks [19], fuzzy logic [20]–[22], and evolutionary algorithms [23]–[26], have wide uses in solving engineering problems. For this purpose, different combinations of conventional approaches and artificial intelligence methods have been investigated to find new methods to sufficiently address the problem. For instance, a neural network-based method has been developed to approximate the states of nonlinear systems in [27]. The updating rules for the involved observer are obtained using the Lyapunov design. The presented method has employed to estimate the states of a robotic system. In [28], an active seat suspension is controlled by a TS fuzzy controller which is based on a disturbance observer. In further research, an adaptive control has been introduced, using the principles of neural networks [29], which is designed to manage uncertainties of the system effectively. Evolutionary algorithms, as one of the strongest representations of artificial intelligence, have been employed to find suitable solutions for different engineering problems [30]. For instance, a so-called Biogeography-based optimization (BBO) algorithm has been combined with a traditional PID controller to control a five-link robotic manipulator [31]. The algorithm is used to optimize the controller by tuning its parameters. In [32], particle swarm optimization (PSO) is used to control a pneumatic surgical robot. In this research, a high-performance H_∞ controller with two degrees of freedom (DOF) and guaranteed robustness is optimized using a PSO algorithm. A new and efficient algorithm which has been recently introduced is the Grasshopper Optimization Algorithm (GOA) [33]. Using special benchmark functions, it is found to be a reliable approach for solving nonlinear optimization problems. Despite the good performance of the basic GOA algorithm, new improvements to the algorithm can increase its efficiency.

In this study, a new intelligent adaptive unscented Kalman filter is introduced to estimate the states of nonlinear systems. The proposed approach is a combination of an adaptive unscented Kalman filter with an evolutionary algorithm, named Fuzzy Adaptive Grasshopper Optimization Algorithm (FAGOA). The algorithm uses fuzzy logic to update the candidate solutions. The proposed optimization Algorithm is applied to the adaptive unscented Kalman filter to tune its parameters. The proposed approach is implemented to detect/estimate the states of two nonlinear systems: a robotic manipulator, and a servo-hydraulic system. Simulations are run wherein two scenarios are planned for the systems. In the first scenario, the systems are affected by a time-varying noise with constant statistics, and in second scenario, they are affected by a time varying noise with time-varying statistics. The proposed method is compared with a previous version of the Kalman filter. The simulation results demonstrate the improvement of the performance of the filter. At the end, the result of application of the proposed method on a practical servo-hydraulic system are discussed. Experimental results prove the ability of the proposed method in a real-world application.

The rest of this paper is organized as follows. The methods and materials section, used to design the proposed intelligent unscented Kalman filter, is reviewed in section II. Section III shows the results of the application of the proposed method on a robotic system. Results of the simulation are analysed and discussed in section IV. Finally, section V concludes the paper.

II. METHODS AND MATERIALS

In this section, an overall review of the methods used to design the proposed method is given. First, a general description of the adaptive Unscented Kalman Filter is presented. Then, the Fuzzy Adaptive Grasshopper Optimization Algorithm (FAGOA) is described, and its validation process is reviewed.

A. ADAPTIVE UNSCENTED KALMAN FILTER

In many practical system, some of states of the system are not reachable or can not be measured. In these cases, state observers are employed to estimate the missed states. Unscented Kalman filter is one of well-known methods for this purpose. The filter uses unscented transformation to estimate states. The general description of the filter is given in the following. The general model of a nonlinear system can be expressed as follows:

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t)) + w(t) \\ y(t) &= g(x(t)) + v(t) \end{aligned} \tag{1}$$

where $x \in R^n$ is the vector of states, $y \in R^m$ represents measured outputs and $u \in R^d$ shows control inputs. f and g

are nonlinear dynamics and measurement functions, respectively. Gaussian white noises are given by w and v. Each step of the filter is calculated at each time step $k * T_s$, where T_s presents the sampling time. For simplification, "k" will stand for $k * T_s$. The covariance matrices of noises are expressed as R and Q.

The main drawback of the basic UKF is that it is necessary to possess *a-priori* knowledge about the noise covariance. In cases that there is not any knowledge about the noise, the filter will not be able to work properly and can be diverged. In many real cases, the statistics of the noises which affect the system, are not accessible. Regarding this fact, a new adaptive version of the basic filter is developed. The new filter can estimate the states of a nonlinear system without *a-priori* knowledge about noises. The procedure of obtaining the formula for estimating the covariance of noises is shown as follows.

By considering equation (1), and assuming that the mean of the noises can be shown by r and q, the problem of the estimation of $\hat{Q}$ and $\hat{R}$ can be regarded as a optimization problem as in [34]:

$$\begin{aligned} J^* &= p\left[X(k), q, Q, r, R|Y(k)\right] \\ &= \frac{p\left[Y(k)|X(k), q, Q, r, R\right] p\left[X(k), q, Q, r, R\right]}{p\left[Y(k)\right]} \end{aligned} \tag{2}$$

is a description for an *a-posteriori* density function, $X(k) = [x_0, x_1, \ldots, x_k]$ and $Y(k) = [y_0, y_1, \ldots, y_k]$. It is obvious that the parameter $p\left[Y(k)\right]$ cannot have any effect on the problem, and the function can be rewritten as follows [35]:

$$\begin{aligned} J = p\left[Y(k)|X(k), q, Q, r, R\right] \\ \times p\left[X(k)|q, Q, r, R\right] \times p\left[q, Q, r, R\right] \end{aligned} \tag{3}$$

Now, the equation (3) can be regarded as a optimization problem. By calculating different parts of (3) regarding equation (1), and basic unscented Kalman filter, the formula of the proposed problem can be given as

$$\begin{aligned} J &= C|Q|^{-k/2}|R|^{-k/2} \times exp\left\{-\frac{1}{2}\left[\sum_{j=1}^{k} \|x_j - f_{j-1}(x_{j-1})\right.\right. \\ &\qquad \left.\left. - q\|^2_{Q^{-1}} + \sum_{j=1}^{k} \|y_j - g_j(x_j) - r\|^2_{R^{-1}}\right]\right\} \\ C &= \frac{1}{2\pi^{n(k+1)/2}} \frac{1}{2\pi^{mk/2}} |P_0|^{-1/2} \\ &\quad \times p\left[Q, R\right].exp\left\{\frac{-1}{2}||x_0 - \hat{x}_0||^2_{P_0^{-1}}\right\} \end{aligned} \tag{4}$$

by considering the derivative of the optimization function with respect to different parameters, including r, q, R and Q, and the new updating formula for the estimation of the covariance matrices can be drawn as in [34]: To have a new formula to estimate the statistics of measurement and process noises, it is necessary to introduce its parameters in iterative form. To reach this form, first two new values are defined:

$$\begin{aligned} \xi_k &= y_k - \hat{y}_{k|k-1} - \hat{r}_k \\ \Gamma_k &= \frac{1-\varrho}{1-\varrho^k} \quad 0 < \varrho < 1 \end{aligned} \tag{5}$$

where Γ is forgetting factor, ϱ is the parameter which determines the value of the forgetting factor, and ξ is the residual value. To get the formula to calculate the mean and covariance of the measurement noise, the derivative of Eq. (4) with respect to q, and Q, respectively, should be calculated. The formula can be obtained as follows:

$$\begin{aligned} \hat{Q}_K &= (1-\Gamma_k)\,\hat{Q}_{k-1} + \Gamma_k\left[K_k\xi_k\xi_k^T K_k^T + P_k\right. \\ &\qquad \left. - \sum_{i=0}^{2n}\left\{w_i^{(c)} \times \left(\gamma_{k|k-1}^{(i)} - \hat{x}_{k|k-1}\right)\left(\gamma_{k|k-1}^{(i)} - \hat{x}_{k|k-1}\right)^T\right\}\right] \\ \hat{q}_k &= (1-\Gamma_k)\,\hat{q}_{k-1} + \Gamma_k\left[\hat{x}_k - \sum_{i=0}^{2n} w_i^{(m)} f\left(\mathcal{X}_{k-1}^{(i)}\right)\right] \end{aligned} \tag{6}$$

and same procedure can be applied for statistics of process noise. By considering the derivative of the optimization function with respect to parameters r, and R, the new updating formula for the estimation of mean and covariance can be gotten as

$$\begin{aligned} \hat{R}_k &= (1-\Gamma_k)\,\hat{R}_{k-1} + \Gamma_k\left[\xi_k\xi_k^T - \sum_{i=0}^{2n}\left\{w_i^{(c)}\right.\right. \\ &\qquad \left.\left.\left(\mathcal{Y}_{k|k-1}^{(i)} - \hat{y}_{k|k-1}\right) \times \left(\mathcal{Y}_{k|k-1}^{(i)} - \hat{y}_{k|k-1}\right)^T\right\}\right] \\ \hat{r}_k &= (1-\Gamma_k)\,\hat{r}_{k-1} + \Gamma_k\left[y_k - \sum_{i=0}^{2n} w_i^{(m)} \times g\left(\mathcal{X}_{k|k-1}^{(i)}, u_k\right)\right] \end{aligned} \tag{7}$$

Based on these new formulations, the overall procedure of the adaptive unscented Kalman filter is presented in Alg. 1. To optimize the procedure of the estimation, a fuzzy logic based evolutionary algorithm is employed to find the best solution. The proposed algorithm is introduced in the next section.

B. FUZZY ADAPTIVE GRASSHOPPER OPTIMIZATION ALGORITHM (FAGOA)

In this section, a new version of the GOA is presented. The GOA is a swarm-based optimization algorithm. In previous studies, different algorithms have been presented regarding the behaviour of swarm animals, such as ants and bees. The algorithm was developed with respect to the behaviour of grasshoppers in natural environment [33]. Usually, grasshoppers live alone but sometimes they are gathered to build the biggest swarms. The biggest swarms gather for exploration and exploitation. The grasshoppers can search an area, based on which the GOA has been developed. In the proposed Fuzzy Adaptive Grasshopper Optimization Algorithm (FAGOA),

Algorithm 1 Adaptive Unscented Kalman Filter (AUKF)

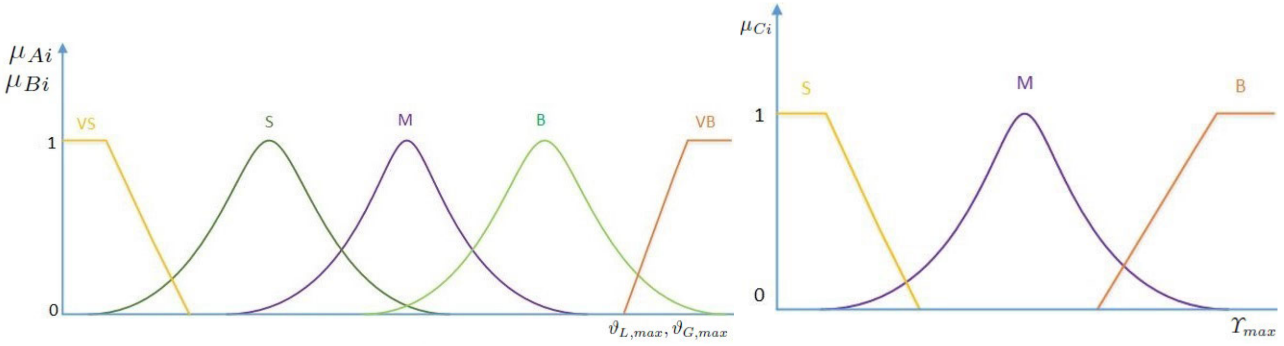
```
Initialization:    $\hat{x}_0 = E[x_0],\ P_0 = E\left[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T\right]$
for all samples do
    Time Updating:
        $\mathcal{X}^{(i)}_{k-1|k-1} = \left[\hat{x}_{k-1|k-1},\ \hat{x}_{k-1|k-1} + \sqrt{n+\lambda}\sqrt{P_{k-1|k-1}}, \hat{x}_{k-1|k-1} - \sqrt{n+\lambda}\sqrt{P_{k-1|k-1}}\right],\quad i = 1, 2, \ldots, 2n$
        $\gamma^{(i)}_{k|k-1} = f\left(\mathcal{X}^{(i)}_{k-1|k-1}, u_{k-1}\right) + \hat{q}_{k-1}$
        $\hat{x}_{k|k-1} = \sum_{i=0}^{2n} w_i^{(m)} \gamma^{(i)}_{k|k-1}$
        $P_{k|k-1} = \sum_{i=0}^{2n} \left\{ w_i^{(c)} \left(\gamma^{(i)}_{k|k-1} - \hat{x}_{k|k-1}\right)\left(\gamma^{(i)}_{k|k-1} - \hat{x}_{k|k-1}\right)^T \right\} + \hat{Q}_{k-1}$
        $\mathcal{X}^{(i)}_{k|k-1} = [\hat{x}_{k|k-1},\ \hat{x}_{k|k-1} + \sqrt{n+\lambda}\sqrt{P_{k|k-1}}, \hat{x}_{k|k-1} - \sqrt{n+\lambda}\sqrt{P_{k|k-1}}\ ],\quad i = 1, 2, \ldots, 2n$
        $\mathcal{Y}^{(i)}_{k|k-1} = g\left(\mathcal{X}^{(i)}_{k|k-1}\right) + \hat{r}_k \qquad \hat{y}_{k|k-1} = \sum_{i=0}^{2n} w_i^{(m)} \mathcal{Y}^{(i)}_{k|k-1}$
    Measurement Update:
        $P_k^{yy} = \sum_{i=0}^{2n} \left\{ w_i^{(c)} \left(\mathcal{Y}^{(i)}_{k|k-1} - \hat{y}_{k|k-1}\right)\left(\mathcal{Y}^{(i)}_{k|k-1} - \hat{y}_{k|k-1}\right)^T \right\} + \hat{R}_k$
        $P_k^{xy} = \sum_{i=0}^{2n} \left\{ w_i^{(c)} \left(\gamma^{(i)}_{k|k-1} - \hat{x}_{k|k-1}\right)\left(\mathcal{Y}^{(i)}_{k|k-1} - \hat{y}_{k|k-1}\right)^T \right\}$
        $K_k = P_k^{xy} \left(P_k^{yy}\right)^{-1}$
        $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(y_k - \hat{y}_{k|k-1}\right) \qquad P_{k|k} = P_{k|k-1} - K_k P_k^{yy} K_k^T$
    Noise Estimation:
        $\xi_k = y_k - \hat{y}_{k|k-1} - \hat{r}_k$
        $\Gamma_k = \frac{1-\varrho}{1-\varrho^k} \qquad 0 < \varrho < 1$
        $\hat{R}_k = (1 - \Gamma_k)\hat{R}_{k-1} + \Gamma_k \left[\xi_k \xi_k^T - \sum_{i=0}^{2n} \left\{ w_i^{(c)} \left(\mathcal{Y}^{(i)}_{k|k-1} - \hat{y}_{k|k-1}\right)\left(\mathcal{Y}^{(i)}_{k|k-1} - \hat{y}_{k|k-1}\right)^T \right\}\right]$
        $\hat{Q}_K = (1 - \Gamma_k)\hat{Q}_{k-1} + \Gamma_k \left[K_k \xi_k \xi_k^T K_k^T + P_k - \sum_{i=0}^{2n} \left\{ w_i^{(c)} \left(\gamma^{(i)}_{k|k-1} - \hat{x}_{k|k-1}\right)\left(\gamma^{(i)}_{k|k-1} - \hat{x}_{k|k-1}\right)^T \right\}\right]$
        $\hat{r}_k = (1 - \Gamma_k)\hat{r}_{k-1} + \Gamma_k \left[y_k - \sum_{i=0}^{2n} w_i^{(m)} g\left(\mathcal{X}^{(i)}_{k|k-1}, u_k\right)\right]$
        $\hat{q}_k = (1 - \Gamma_k)\hat{q}_{k-1} + \Gamma_k \left[\hat{x}_k - \sum_{i=0}^{2n} w_i^{(m)} f\left(\mathcal{X}^{(i)}_{k-1}\right)\right]$
end for
```

a fuzzy logic is implemented to calculate the updating factor for each candidate solution. Suppose a task is to find the optimal solution G^* to minimize a function, the basic GOA can be summarized as per the following steps:

Step 1 Initialization: Initialize the grasshoppers as follows:

$$G_t = L_b + rand \times (U_b - L_b), \quad t = 1, \ldots, N \tag{8}$$

where the i-th grasshopper candidate is presented by G_i. The lower and upper bounds of the search space are shown by L_b and U_b, respectively. These bounds show the possible minimum and maximum values for the solution to the proposed problem. The parameter, $rand$, is a random number in (0, 1). The integer N is the number of grasshoppers.



(a) The membership functions of inputs (b) The membership functions of output

FIGURE 1. **The typical form of the membership functions of fuzzy logic switching system.**

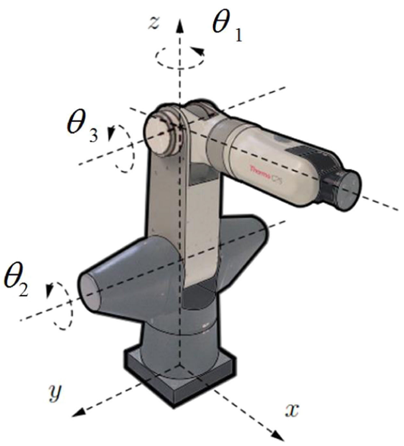


FIGURE 2. **Schematic of robot manipulator [34].**

Step 2 Decreasing factor: Calculate the decreasing factor for new generation as follows:

$$\Upsilon = \Upsilon_M - \frac{It \times (\Upsilon_M - \Upsilon_m)}{Max_{It}} \tag{9}$$

where the current and maximum iterations are shown by "It", and Max_{It}, respectively. The minimum and maximum values of the parameter Υ are given by Υ_m, and Υ_M, respectively.

Step 3 Updating: Generate new agents using the following equation:

$$G_t^{new} = \left[\sum_{k=1,k\neq t}^{N} \left(\frac{\Upsilon(U_b - L_b)}{2d_{tk}} \times (G_k^{old} - G_t^{old}) \right.\right.$$
$$\left.\left. \times\, \delta\left(G_k^{old} - G_t^{old}\right)\right)\right] + \psi$$
$$\delta\,(m) = \alpha \times \exp(\frac{-m}{\beta}) - \exp(-m) \tag{10}$$
$$d_{tk} = \left|G_k^{old} - G_t^{old}\right|$$

where parameters ψ, α, and β represent the effects of wind on the real environment, intensity of attraction, and attractive length scale, respectively. The function, $\delta(.)$, shows the social forces between individuals [33]. The distance between t-th and k-th agents is given by d_{tk}.

Step 4 Updating best solution: Reorder candidate solution regarding their performance and choose the best one between them

Step 5 Termination: If the termination criteria is satisfied, the best solution is returned, otherwise go to step 2.

To introduce a new fuzzy adaptive grasshopper optimization algorithm, each agent will have two new features:

$$\vartheta_{G,t}^f = \vartheta_G^f = fit_{t-1}^{best} - fit_t^{best}$$
$$\vartheta_{L,t}^f = fit_{t-1} - fit_t \tag{11}$$

where $\vartheta_{G,t}^f$ and $\vartheta_{L,t}^f$ show the global and local priority factor for $t-$th agent at iteration f, respectively. If the local and global priority factors are small/big, then the decreasing factor should also be small/big. All other combinations of local/global priority factors lead to a medium decreasing factor. Fuzzy logic has the advantage of enabling calculation of the input-output behaviour of a static process with smooth transitions inside an operating area or a control surface, which can be listed as: determining the proper decreasing factor with finite inputs, working with a rule-based model to be controlled, and tolerating uncertainties. In our case, these advantages can be summarized: the system should determine the output with two inputs, there is only a linguistic rule-based model between the inputs and output, and there are different uncertainties between the inputs and output. Considering these explanations, it is inferred that a fuzzy logic-based module is a good approach by which to determine the decreasing factor. Regarding $\vartheta_{G,t}^f$ and $\vartheta_{L,t}^f$, a fuzzy logic module is applied to calculate the factor which will be used to update agents. The proposed updating factor is replaced in equation (10), and the formula can be written as follows:

$$G_t^{new} = \left[\sum_{k=1,k\neq t}^{N} \left(\frac{\Upsilon_{F,t} \times (U_b - L_b)}{2d_{tk}} \times (G_k^{old} - G_t^{old}) \right.\right.$$
$$\left.\left. \times\ \delta\left(G_k^{old} - G_t^{old}\right)\right)\right] + \psi \tag{12}$$

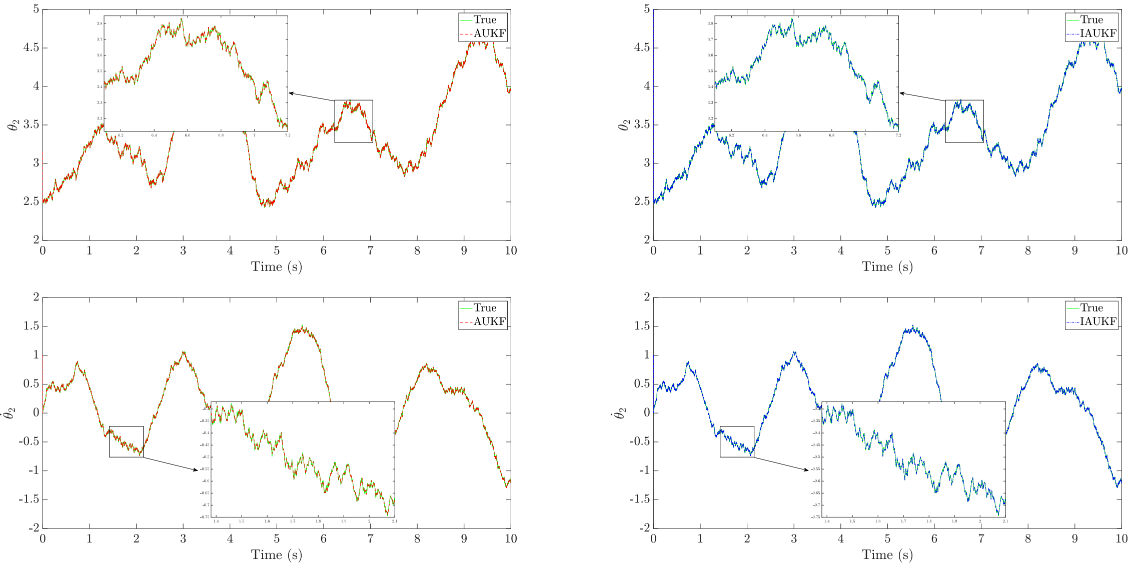


FIGURE 3. The estimation of second joint's parameters of the robotic system under time varying noises with constant statistics.

where Υ_F represents the new fuzzy updating factor, which is calculated by the fuzzy logic module. It is supposed that the fuzzy module receives global and local priority factors as inputs, with the decreasing factor as the output. The fuzzy module is expressed by a set of Mamdani fuzzy rules [36]. Define rule $R_i, i = 1, \ldots, N$, where N is number of rules, which is represented by:

$$R_i: \text{ IF } \vartheta_L = A_i \text{ AND } \vartheta_G = B_i \text{ THEN } \Upsilon_F = C_i \quad (13)$$

where A_i, B_i, and C_i are fuzzy sets.

$$\begin{aligned} A, B &= \{VS, S, M, B, VB\} \\ C &= \{S, M, B\} \\ VS &= \text{Very Small}, \quad S = \text{Small}, M = \text{Medium}, \\ B &= \text{Big}, \quad VB = \text{Very Big} \end{aligned} \quad (14)$$

μ_{Ai}, μ_{Bi}, and μ_{Ci} are the corresponding membership functions (MFs). $\mu_{Ai}(\vartheta_L), \mu_{Bi}(\vartheta_G)$, and $\mu_{Ci}(\Upsilon_F)$ are crisp degrees of membership of ϑ_L, ϑ_G, and Υ_F to their respective term sets. Each rule leads to a clipped membership function

$$\mu_{R_i} = min\left(min\left(\mu_{Ai}(\vartheta_L), \mu_{Bi}(\vartheta_G)\right), \mu_{Ci}(\Upsilon_F)\right) \quad (15)$$

where $min\left(\mu_{Ai}(\vartheta_L), \mu_{Bi}(\vartheta_G)\right)$ is crisp and μ_{Ci} is fuzzy. The aggregation over all rules R_i leads to

$$\mu_r = \bigcup_{i=1}^{N} \mu_{r_i} \quad (16)$$

Table 1 shows a module of the corresponding fuzzy rules, which is used to determine the decreasing factor. Figure 1 gives the structure of the membership functions of the fuzzy module. To have a clear understanding about the rules in the table, examples for its rules can be given as follows:

TABLE 1. The rules of the fuzzy module.

Υ_F ϑ_L ϑ_G	VS	S	M	B	VB
VS	S	S	S	M	M
S	S	S	M	M	M
M	S	M	M	M	B
B	M	M	M	B	B
VB	M	M	B	B	B

$$\begin{aligned} &Ex.1: \text{ IF “}\vartheta_L = VS\text{” AND “}\vartheta_G = M\text{” THEN “}\Upsilon_F = S\text{”} \\ &Ex.2: \text{ IF “}\vartheta_B = VS\text{” AND “}\vartheta_G = VB\text{” THEN “}\Upsilon_F = B\text{”} \end{aligned} \quad (17)$$

Since the result of the aggregation (16) is still a fuzzy membership function, we need to defuzzify (16) to achieve a crisp decreasing factor.

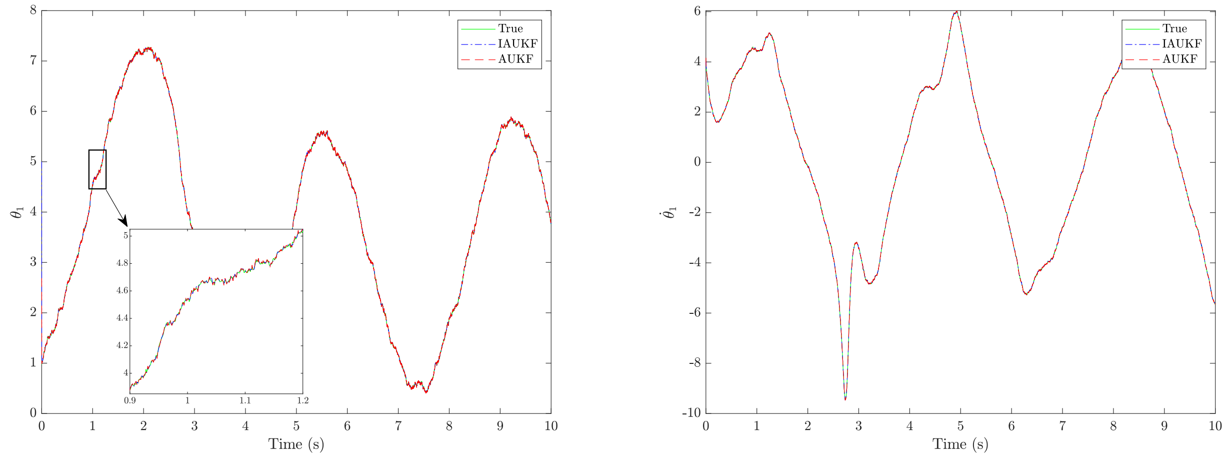
Defuzzification leads to

$$\Upsilon_F = \frac{\int \mu_r(\Upsilon)\,\Upsilon\,d\Upsilon}{\int \mu_r(\Upsilon)\,d\Upsilon} \quad (18)$$

where the integrals in (14) run from 0 to Υ_{max}. Let us assume that the calculated factor, which is determined by the fuzzy module, has the maximum value which is presented by ϖ. It then follows that the maximum values should be decreased with time, because the algorithm will converge toward the best solution. This reduction will enable the algorithm to explore the search area precisely. The maximum value, ϖ, is set in such a way that $Max\ Iteration = q\varsigma$, $q \in \mathbb{N}$. The value of ϖ_i will be updated as follows:

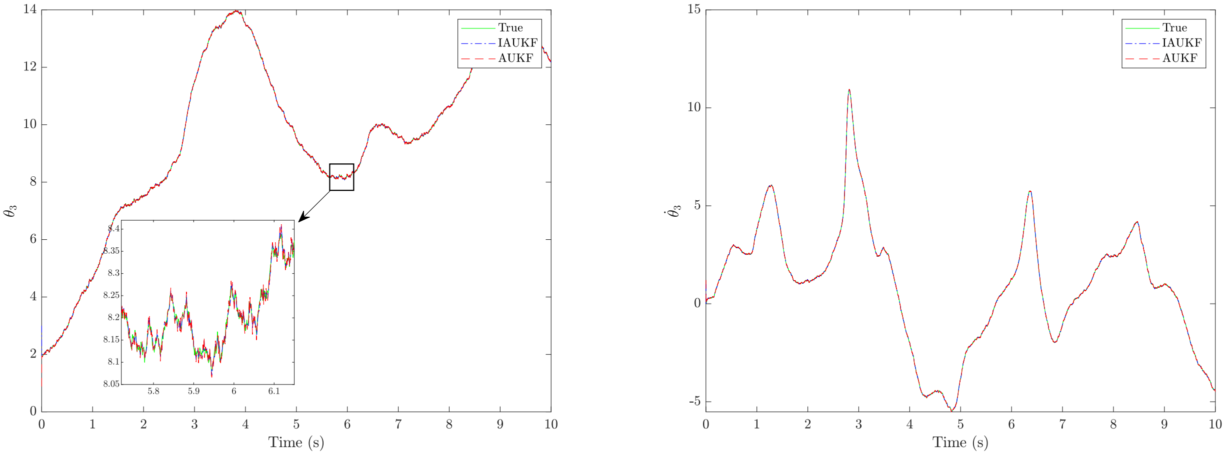
$$\varpi_i = \Delta \times \varpi_{i-1}, \quad i = 1, \ldots, q \quad (19)$$

where $0 < \Delta < 1$. By using the formula (19), the parameter ϖ will attain a smaller value with time, and it can help to improve the efficiency of the basic algorithm by reducing search step. Alg. 2 shows the pseudo code of the



(a) The position of first joint

(b) The velocity of first joint



(c) The position of third joint

(d) The velocity of third joint

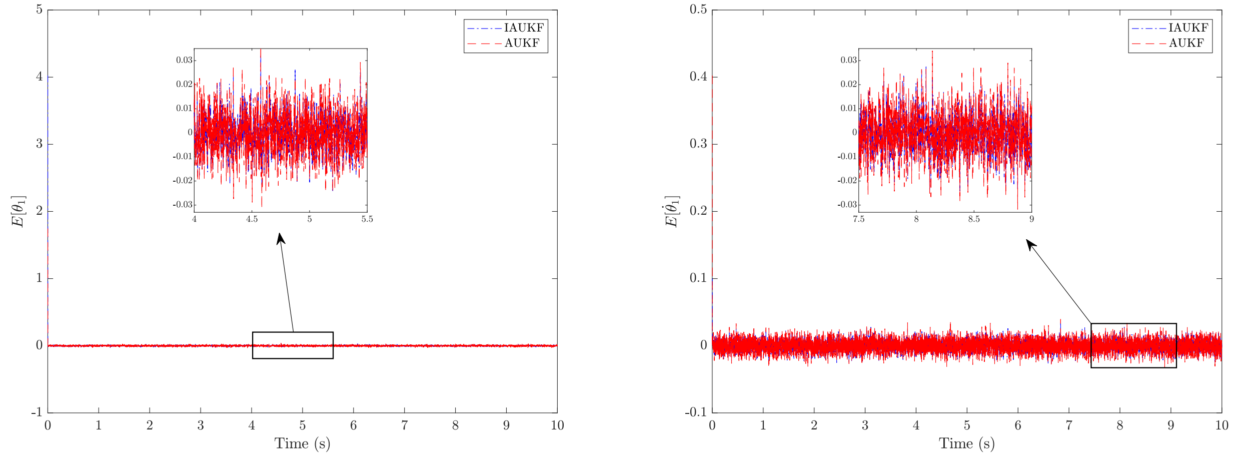
FIGURE 4. The estimation error of the states of the robotic system under time varying noises with constant statistic.

Algorithm 2 Fuzzy Adaptive Grasshopper Optimization Algorithm (FAGOA)

```
Initialization: Create the first generation of grasshoppers,
and calculate fitness function for each one
Determine the best agent and name it as "$G_{best}$"
while $m <$ Max iteration do
    for each search agent do
        Calculate global and local priority factors using Eq. (11)
        Use fuzzy logic to calculate decreasing factor ($\Upsilon_{F,t}$) based on global and local priority factors
        Update search agent using Eq. (12)
    end for
    Update "$G_{best}$"
    $m = m + 1$
end while
Return "$G_{best}$"
```

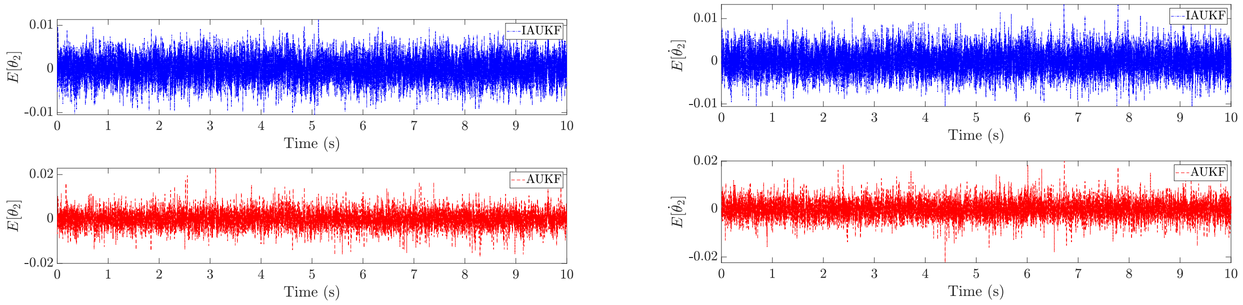
new fuzzy adaptive algorithm. As it can be seen in the algorithm, the fuzzy logic is added to basic algorithm to calculate the decreasing factor. The fuzzy logic uses information from previous step which helps algorithm to find better solutions for optimization problems in comparison with the basic algorithm.

The new proposed algorithm should be tested on different benchmark functions to validate its proficiency. To test the newly introduced algorithm, it is applied to find the solution for various benchmark functions. The results of the proposed FAGOA are compared with those of well-known algorithms, including Particle Swarm Optimization (PSO) [37], Genetic Algorithm (GA) [38], Differential Evolution (DE) [39], and basic Grasshopper Optimization Algorithm (GOA) [33]. The parameters of these algorithms, which are used for simulation, are presented in table 2. On the other hand, to show the effect of fuzzy rules on the performance of the proposed fuzzy adaptive algorithm, two fuzzy sets are defined for fuzzy logic as Tabs. 3, and 4. In the first table, it is supposed that most of rules lead to a big output and in the other one it is supposed that the fuzzy logic will produce small output for most cases. The benchmark functions are selected to be of various types, including unimodal, multimodal, and composite, details of which can be found in table 5. The results of applying different algorithms to optimize the functions are shown in table 6. As can be seen in the table 6, for unimodal



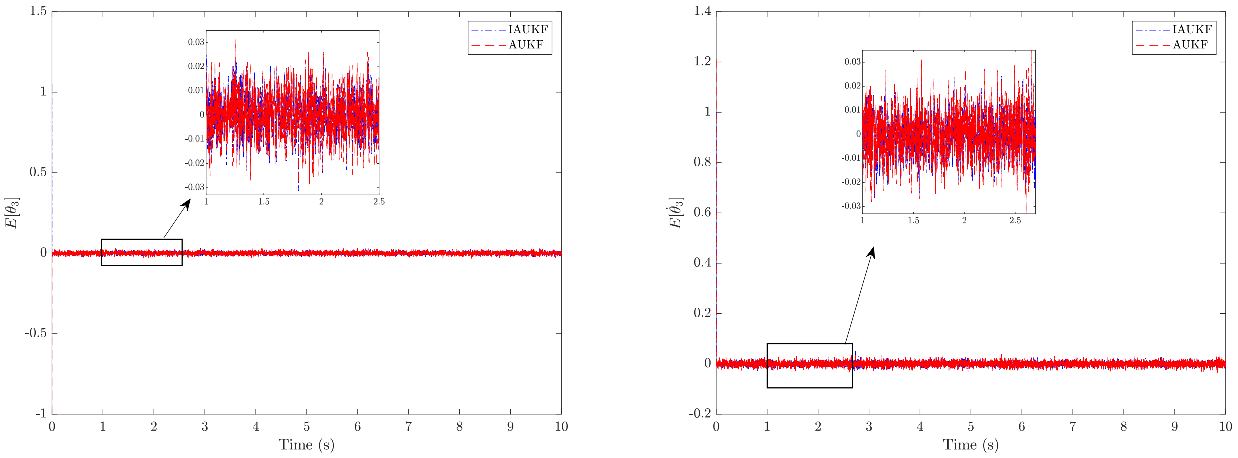
(a) The position of first joint

(b) The velocity of first joint



(c) The position of second joint

(d) The velocity of second joint



(e) The position of third joint

(f) The velocity of third joint

FIGURE 5. **The estimation error of the states of the robotic system under time varying noises with constant statistics.**

TABLE 2. **Parameters of algorithms.**

PSO	GA	DE	GOA	FAGOA
$N = 30$	$N = 30$	$N = 30$	$N = 30$	$N = 30$
$w = 0.9$	$P_c = 0.8$	$P_c = 0.95$		$\varpi_0 = 2.5$
$G_{max} = 50$	$P_m = 0.2$	$P_m = 0.85$		$q = Max\ Iteration/5$

N : Number of agents, P_c : The rate of crossover, P_m : The rate of mutation, G_{max} : Number of max generation

benchmark functions ($F_1 - F_4$), the proposed fuzzy adaptive algorithm demonstrates better results in comparison with those of other algorithms. Regarding multimodal functions ($F_5 - F_7$), the proposed optimization algorithm demonstrates better results in comparison with those of the basic algorithm. This can be regarded as a proper choice to find the

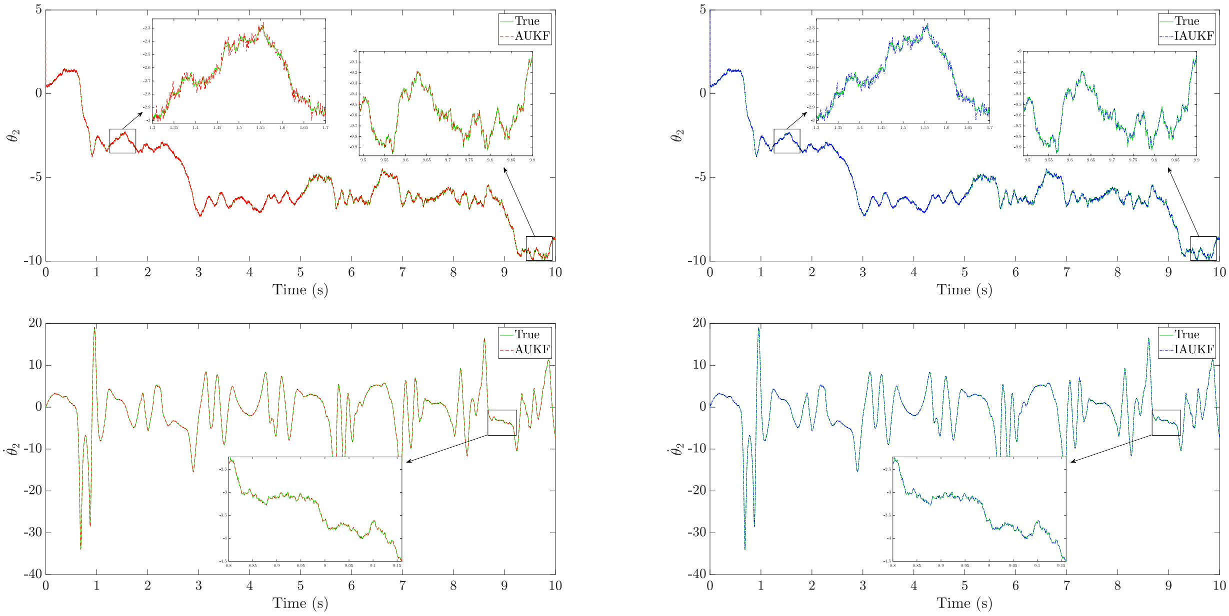


FIGURE 6. The estimation of the position of the second joint of the robotic system under time varying noises with time varying statistics.

TABLE 3. The fuzzy set No. 1.

Υ_F ϑ_L ϑ_G	VS	S	M	B	VB
VS	S	M	B	B	B
S	M	B	B	B	B
M	B	B	B	B	B
B	B	B	B	B	B
VB	B	B	B	B	B

TABLE 4. The fuzzy set No. 2.

Υ_F ϑ_L ϑ_G	VS	S	M	B	VB
VS	S	S	S	S	S
S	S	S	S	S	S
M	S	S	S	S	S
B	S	S	S	S	M
VB	S	S	S	M	B

optimal solution among the other traditional algorithms. Finally, the results of applying the algorithm on composite functions ($F_8 - F_{10}$) show that the developed fuzzy based algorithm demonstrates a big improvement in comparison with the basic algorithm. The results for the algorithm with insufficient fuzzy logic show the its effect on the performance of the algorithm. Based on these results, it can be easily drawn that the fuzzy set should be defined properly to have reliable performance. Regarding the overall results shown in table 6, it can be easily inferred that the proposed algorithm can be regarded as a strong optimization instrument to find the optimal solution for different problems.

III. SIMULATION AND RESULTS

In this section, the optimized intelligent filter, which is a combination of previously introduced methods, AUKF and FAGOA, will applied on two different systems: a robotic manipulator and a servo-hydraulic system. Simulations are conducted for two different conditions: the first where the system is affected by a time varying noise with constant statistics, and the second where it is affected by time-varying statistics. At the end, the results of experimental application of the proposed method on a practical servo-hydraulic system are discussed.

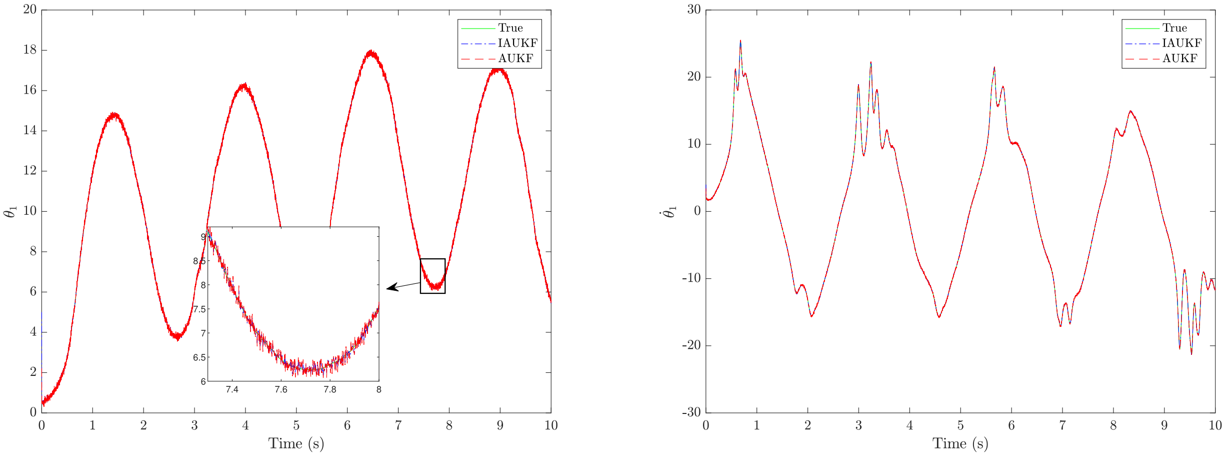
As a mandatory factor for evolutionary algorithms, the fitness function is proposed as

$$Fitness = \sum_{i=1}^{n} \int_{0}^{t_o} e\left(\tau\right) d\tau$$
$$e_i(t) = \hat{x}_i(t) - x_i(t) \tag{20}$$

where n is the number of states of the nonlinear system, and t_o is the simulation time step. The newly proposed algorithm is employed to find optimal parameter simultaneously during the working period of the robot. The algorithm tries to find the best solution for optimizing the adaptive filter, and whenever a new value is found and a better parameter exists in comparison to the existing value, then the previous amount is replaced by the new one.

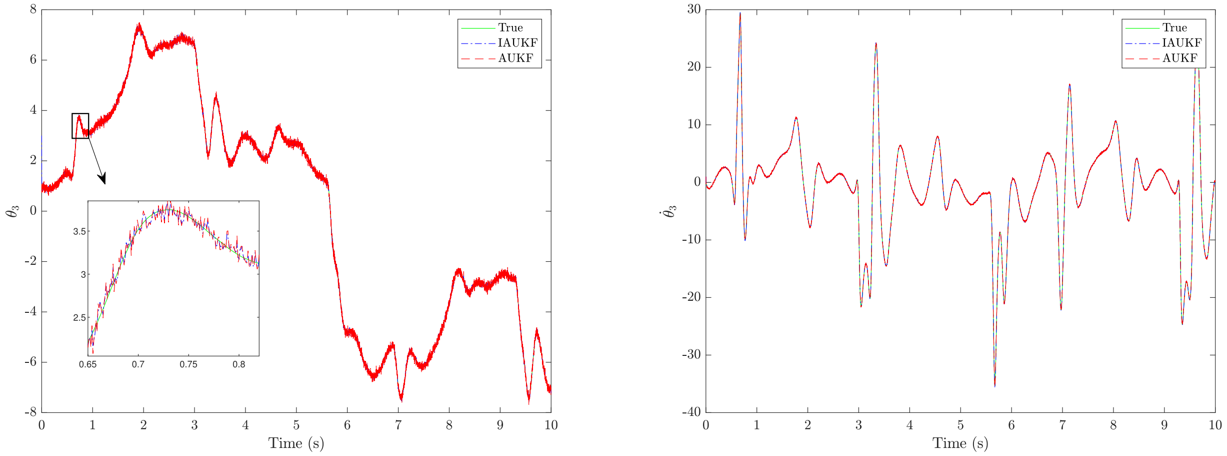
A. ROBOTIC MANIPULATOR

The schematic of a manipulator is shown in Fig. 2. Its dynamics can be summarized as per equation (21), as shown at the bottom of the next page.



(a) The position of first joint

(b) The velocity of first joint



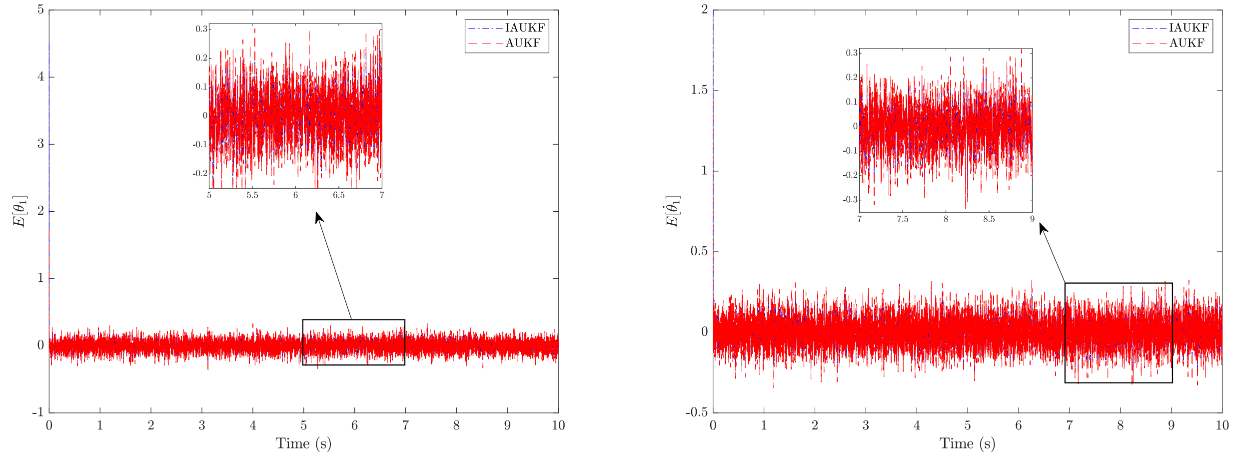
(c) The position of third joint

(d) The velocity of third joint

FIGURE 7. The estimation of the states of the robotic system under time varying noises with time varying statistics.

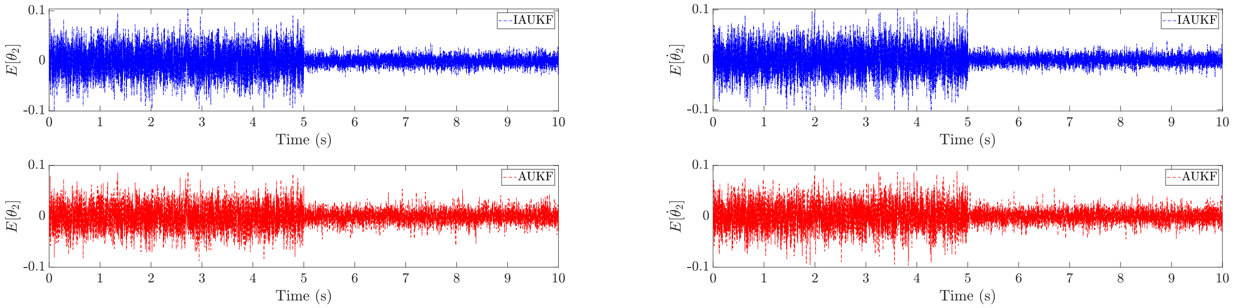
In equation (21), $s_i = \sin(\theta_i)$ and $c_i = \cos(\theta_i)$. The parameters of the model, b_i, can be found in [40]. In the presented model, the states and input of the system, which are introduced in equation (1), can be assumed as $x(t) = [x_1, x_2, x_3, x_4, x_5, x_6]^T = \left[\theta_1, \theta_2, \theta_3, \dot{\theta}_1, \dot{\theta}_2, \dot{\theta}_3\right]^T$, and $u(t) = [\tau_1, \tau_2, \tau_3]^T$, respectively. Regarding these definitions and simplification of the equation (21), the state space of the robotic will be changed into state space equation (1), and the proposed methods can be applied to the system. The proposed method is applied to different scenarios, and the results of these simulations are presented in the following.

$$\begin{aligned}&\begin{bmatrix} b_3 s_2 c_3 + b_6 c_2^2 + b_7 c_3^2 + b_5 & 0 & 0 \\ 0 & 0.5 b_3 (c_2 c_3 + s_2 s_3) + b_{13} & 0.5 b_3 (c_2 c_3 + s_2 s_3) + b_{14} \\ 0 & 0.5 b_3 (c_2 c_3 + s_2 s_3) + b_{17} & b_{16} \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \end{bmatrix} \\ &+ \begin{bmatrix} b_1 & b_2 \dot{\theta}_1 s_2 c_2 + b_3 \dot{\theta}_1 c_2 s_3 & b_3 \dot{\theta}_1 s_2 c_3 + b_4 \dot{\theta}_1 s_3 c_3 \\ 2 b_{11} \dot{\theta}_1 s_2 c_2 + 2 b_{12} \dot{\theta}_1 s_3 c_3 - 0.5 b_3 \dot{\theta}_1 (s_2 c_3 + c_2 s_3) & 0.5 b_3 \dot{\theta}_2 (c_2 s_3 - s_2 c_3) + b_{10} & 0.5 b_3 \dot{\theta}_3 (s_2 c_3 - c_2 s_3) \\ 2 b_{12} \dot{\theta}_1 s_3 c_3 - 0.5 b_3 \dot{\theta}_1 s_2 c_3 & 0.5 b_3 \dot{\theta}_2 (c_2 s_3 - s_2 c_3) - b_{15} & b_{15} \end{bmatrix} \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \\ \dot{\theta}_3 \end{bmatrix} \\ &+ \begin{bmatrix} 0 \\ b_8 s_2 + b_9 s_3 \\ b_9 s_3 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \end{bmatrix} \end{aligned} \quad (21)$$



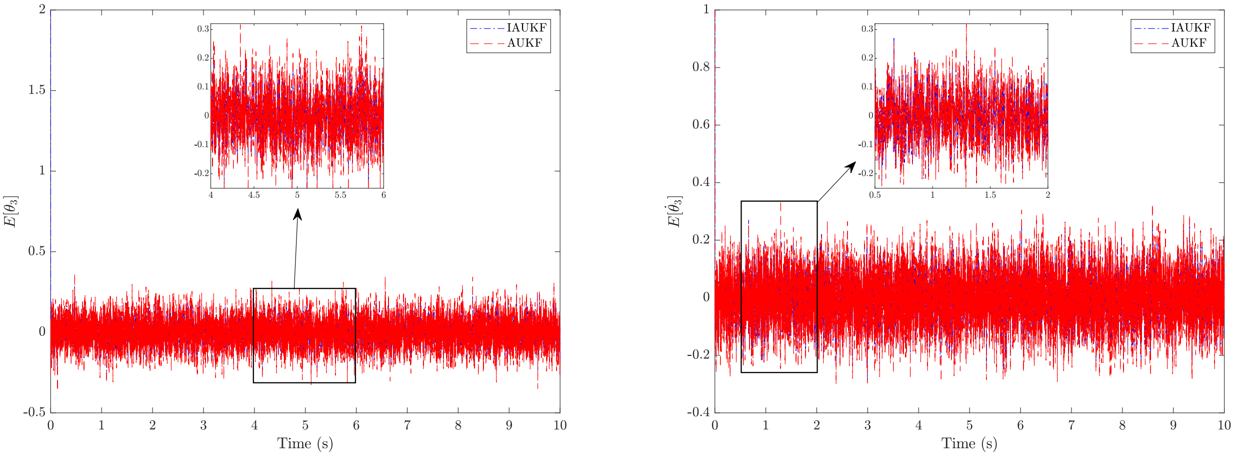
(a) The position of first joint

(b) The velocity of first joint



(c) The position of second joint

(d) The velocity of second joint



(e) The position of third joint

(f) The velocity of third joint

FIGURE 8. **The estimation error of the states of the robotic system under time varying noises with time varying statistics.**

1) CONSTANT NOISE STATISTICS

To define the simulation conditions, it is considered that the covariance matrices of the noises are constant. The covariance matrices are set to $Q = 10^{-6} \times I_{6\times6}$ and $R = 10^{-6} \times I_{6\times6}$. The starting point of the estimation of the matrices is initialized as $\hat{Q} = 10^{-3} \times I_{6\times6}$ and $\hat{R} = 10^{-4} \times I_{6\times6}$. This is simulated by considering $\boldsymbol{\tau}(t) = [1.14 \times \sin(2.25 \times t), 0.85\times \cos(2.7 \times t), 2.32 \times \sin(3.4 \times t)]$ as the input vector for the system. To obtain an understandable comparison, the results are given in Fig. 3, and 4. The errors of this estimation are given in figure 5. As can be observed from these results, the proposed intelligent filter demonstrates better results in comparison to the traditional filter.

TABLE 5. The benchmark functions [33].

Function No.	Formulation	Dimensions (D)
F_1	$f(x)=\sum_{i=1}^{D} x_i^2$	10
F_2	$f(x)=\sum_{i=1}^{D} \lvert x_i\rvert+\Pi_{i=1}^{n}\lvert x_i\rvert$	10
F_3	$f(x)=\sum_{i=1}^{D}\left([x_i+0.5]\right)^2$	10
F_4	$f(x)=\sum_{i=1}^{D-1}\left\{100\left(x_{i+1}-x_i^2\right)^2+(x_i-1)^2\right\}$	10
F_5	$f(x)=\sum_{i=1}^{D}\left\{x_i^2-10\cos(2\pi x_i)+10\right\}$	30
F_6	$f(x)=\sum_{i=1}^{D}\left\{-x_i\sin\left(\sqrt{\lvert x_i\rvert}\right)\right\}$	30
F_7	$f\left(x\right)=-20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{D}x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{D}\cos\left(2\pi x_i\right)\right)+20+e$	30
F_8	$f(x)=\frac{1}{4000}\left(\sum_{i=1}^{D}\left(x_i-100\right)^2\right)-\left(\Pi_{i=1}^{D}\cos\left(\frac{x_i-100}{\sqrt{i}}\right)\right)+1$	30
F_9	$f(x)=f\left(x\right)=\sum_{i=1}^{D}\left(x_i^2-10\cos\left(2\pi x_i\right)+10\right)$	30
F_{10}	$f(x)=\frac{1}{4000}\left(\sum_{i=1}^{D}\left(x_i-x^*-100\right)^2\right)-\left(\Pi_{i=1}^{D}\cos\left(\frac{x_i-x^*-100}{\sqrt{i}}\right)\right)+1$	30

TABLE 6. Comparative results of FAGOA with GA, DE, PSO, and GOA.

Function	Minimum value	GA	DE	PSO	GOA	FAGOA (Fuzzy set No.1)	FAGOA (Fuzzy set No.2)	FAGOA
F_1	0	0	0	0	0	0	0	0
F_2	0	0	0	0	0	0	0	0
F_3	0	0.0416	2.7E-09	0	0.0374	0		
F_4	0	0	1.7E-8	0	7.8E-08	6.9E-09	3.7E-07	6.4E-09
F_5	0	0	0	0	0	4.1E-09	5.3E-06	0
F_6	0	0.0051	9.2E-05	2.1E-7	0.0166	0.008	8E-06	3.5E-07
F_7	0	0.0011	0.0843	4.1E-07	0.0175	1.8E-03	1.4E-03	5.2E-06
F_8	0	3.3E-08	3.9E-08	6.1E-09	1.5E-07	5.2E-08	2E-08	2.2E-09
F_9	0	8.3E-07	2.6E-07	3.4E-07	7.2E-04	6.7E-06	3.5E-03	1.1E-07
F_{10}	0	4.2E-09	4.7E-07	4.3E-07	0.0097	0.07	0.006	9.1E-08

TABLE 7. Definition of variables and parameters of the servo hydraulic system in SI units.

Variable	Definition	Value
x_p	Piston position	-
$\dot{x}_p$	Piston speed	-
$p_{1,2}$	Pressure on different side of the cylinder	-
$Q_{1,2}$	Flows on different side of the cylinder	-
$A_{1,2}$	Area of different side of the cylinder	8.04×10^{-4}, 4.24×10^{-4}
$v_{01,02}$	pipeline volume	2.13×10^{-4}, 1.07×10^{-4}
M	Load mass	270
F_e	External force	0
b	Friction	418.33
β_e	Bulk modulus	7×10^{8}
C_s	flow coefficient	2.36×10^{-5}
$k_{E1,E2}$	external leakage flow coefficient	2.4×10^{-12}, 1.02×10^{-13}
k_i	Internal leakage flow coefficient	1724×10^{-13}
P_s	Supply pressure	14
P_a	Tank pressure	0.9

2) TIME VARYING NOISE STATISTICS

This section presents the results of simulating the changing statistics of the noises over time. To test the reliability of the proposed filter in a harsh condition, strong noises are applied to the robotic system. At the beginning, noises covariance matrices show the values $Q = 10^{-3} \times I_{6\times6}$ and $R = 10^{-3} \times I_{6\times6}$. After five seconds, the matrices are changed to $Q = 10^{-3} \times I_{6\times6}$ and $R = 10^{-4} \times I_{6\times6}$. The initialization of the estimated matrices are assumed to be $\hat{Q} = 10^{-6} \times I_{6\times6}$ and $\hat{R} = 10^{-5} \times I_{6\times6}$. The input of the system is assumed to be $\boldsymbol{\tau}(t) = [6.75 \times \sin(2.5 \times t), 6.75 \times \cos(t), 4.5 \times \sin(t)]$.

Figures 6 and 7 give the result of this section. The estimation error for states can be found in Fig. 8.

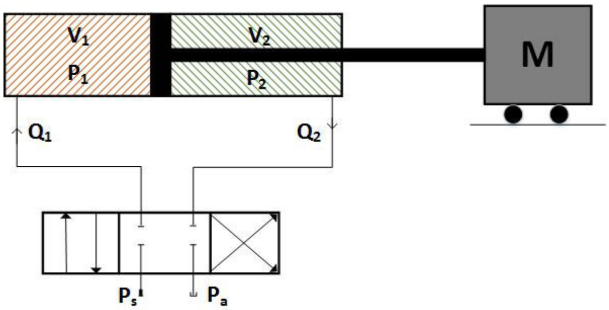
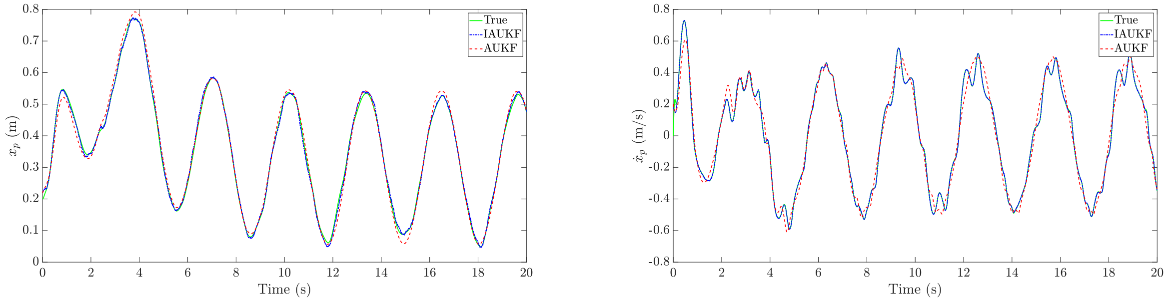


FIGURE 9. The schematic of servo-hydraulic system [11].

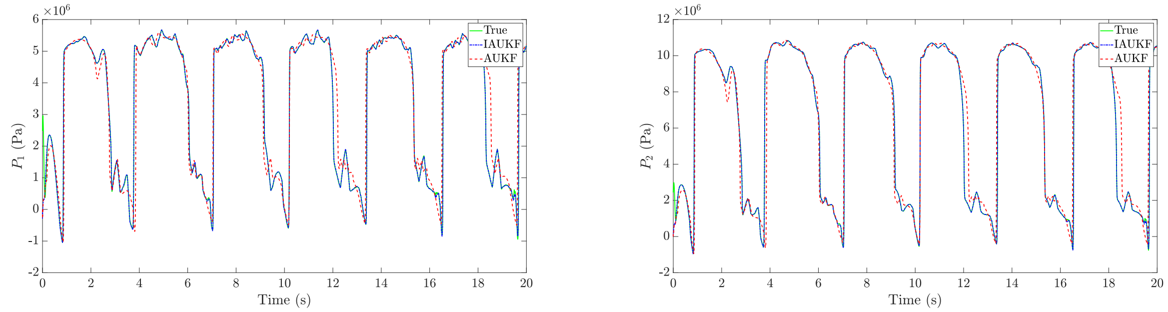
B. SERVO-HYDRAULIC SYSTEM

A servo-hydraulic system is used to test the proficiency of the proposed optimized Kalman filter. The schematic of the proposed servo-hydraulic system is shown in Fig. 9. Considering Newton's law for the load mass the and basic hydraulic circuit laws, the state space of the presented hydraulic system is drawn as follows [41]:

$$
\begin{aligned}
\dot{x}_1 &= x_2\\
\dot{x}_2 &= \frac{1}{M}\left(-bx_2 + A_1x_3 - A_2x_4 - F_e\right)\\
\dot{x}_3 &= \begin{cases}
\dfrac{\beta_e}{A_1x_P + v_{01}}\left[C_su\sqrt{p_s - x_3} - A_1x_2\right.\\
\left.+K_i\left(x_4 - x_3\right) - K_{E1}\left(x_3 - p_a\right)\right] & u \geq 0\\
\dfrac{\beta_e}{A_1x_P + v_{01}}\left[C_su\sqrt{x_3 - p_a} - A_1x_2\right.\\
\left.+K_i\left(x_4 - x_3\right) - K_{E1}\left(x_3 - p_a\right)\right] & u < 0
\end{cases}
\end{aligned}
$$

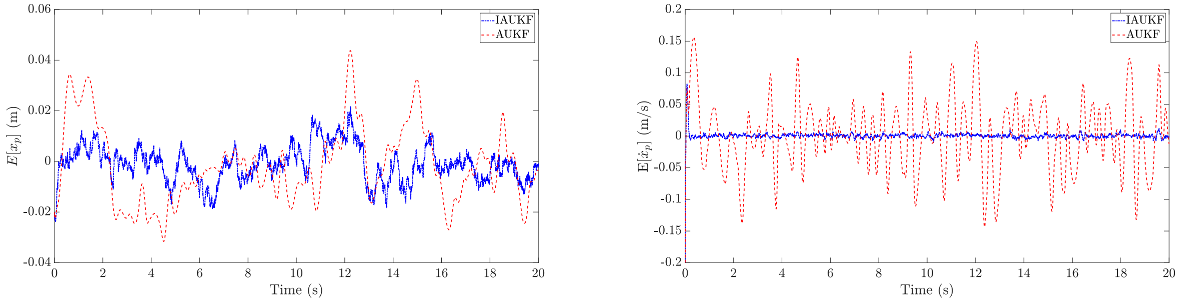


(a) x_p (b) $\hat{x}_p$

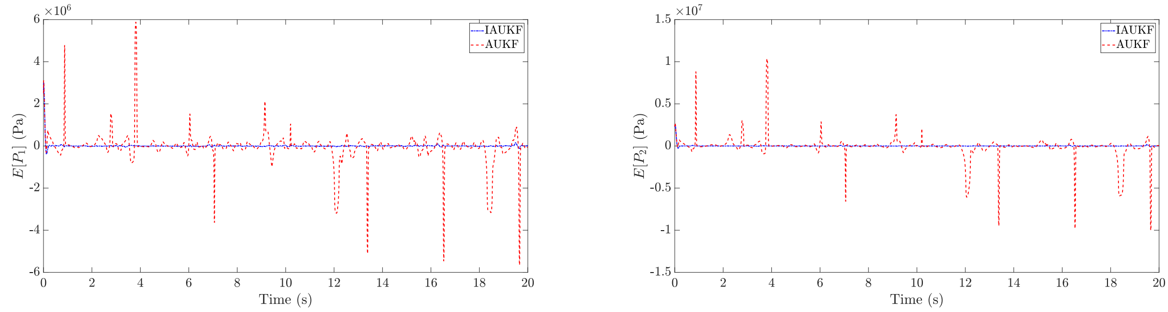


(c) P_1 (d) P_2

FIGURE 10. The estimation of the states of the servo-hydraulic system under time varying noises with constant statistics.



(a) $E[x_p]$ (b) $E[\hat{x}_p]$

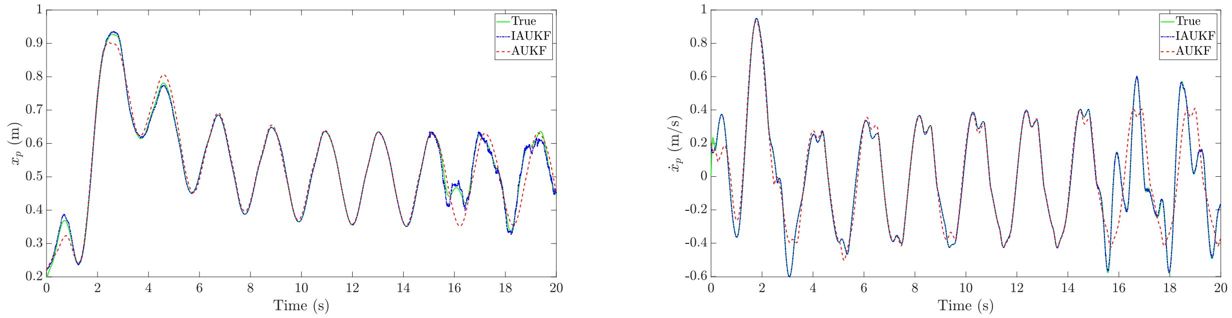


(c) $E[P_1]$ (d) $E[P_2]$

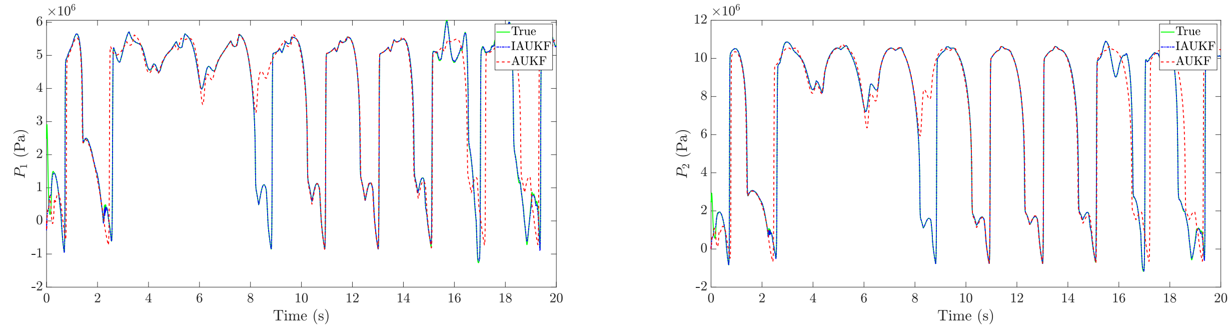
FIGURE 11. The estimation error of the states of the servo-hydraulic system under time varying noises with constant statistics.

$$\dot{x}_4 = \begin{cases} \dfrac{\beta_e}{A_2\left(L - x_P\right) + v_{02}} \left[C_s u \sqrt{x_4 - p_a} - A_2 x_2\right. & \\ \left. - K_i\left(x_4 - x_3\right) - K_{E2}\left(x_4 - p_a\right)\right] & u \geq 0 \\ \dfrac{\beta_e}{A_2\left(L - x_P\right) + v_{02}} \left[C_s u \sqrt{p_s - x_4} - A_2 x_2\right. & \\ \left. - K_i\left(x_4 - x_3\right) - K_{E2}\left(x_4 - p_a\right)\right] & u < 0 \end{cases} \tag{22}$$

where state variables are defined as $X = [x_1, x_2, x_3, x_4]^T = \left[x_p, \dot{x}_p, p_1, p_2\right]^T$. All variables and parameters of the servo-hydraulic system are defined in Tab. 7. As in the case of the robotic manipulator, different tests are conducted on the hydraulic system, and the results are presented. Finally, to obtain a realistic view of the performance of the presented method, the developed algorithm is applied on a practical servo-hydraulic system.

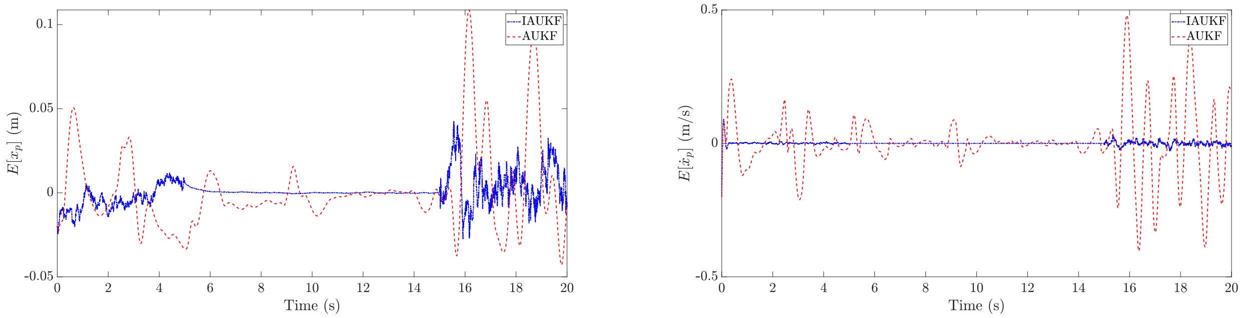


(a) x_p (b) $\hat{x}_p$

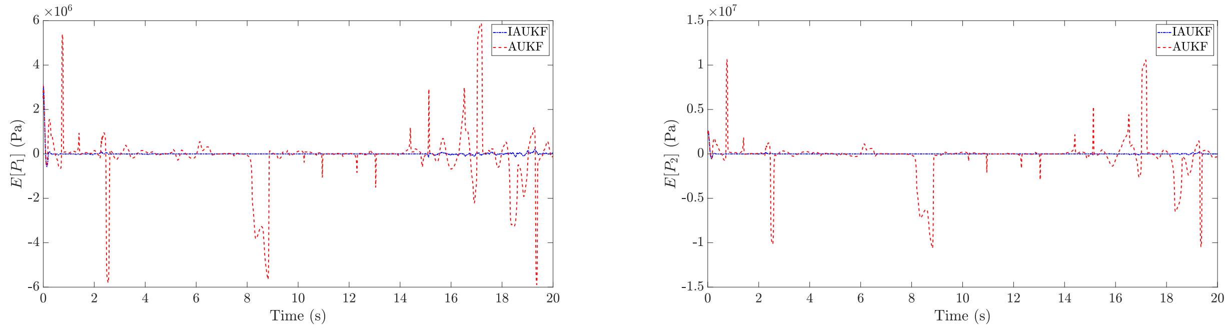


(c) P_1 (d) P_2

FIGURE 12. The estimation of the states of the servo-hydraulic system under time varying noises with time-varying.



(a) $E[x_p]$ (b) $E[\hat{x}_p]$



(c) $E[P_1]$ (d) $E[P_2]$

FIGURE 13. The estimation error of the states of the servo-hydraulic system under time varying noises with time-varying statistics.

1) CONSTANT NOISE STATISTICS

The proposed method is applied on a servo-hydraulic system in the presence of time-varying noise with constant statistics. To conduct the simulation, the initial start point is selected as $X_0 = \left[x_{p0}, \dot{x}_{p0}, p_{10}, p_{20}\right]^T = [0.2, 0.0002, 2.5 \times 10^6, 2.5 \times 10^6]^T$, and the start point for the filter is set to

(a) Hydraulic test setup (b) Servo-hydraulic actuator

FIGURE 14. Practical servo-hydraulic actuator system in the Laboratory of intelligent Machines at LUT University [11].

$\hat{X}_0 = \left[\hat{x}_{p0}, \hat{\dot{x}}_{p0}, \hat{p}_{10}, \hat{p}_{20}\right]^T = [0.22, 0.2, 100, 10]^T$. In this section, the covariance of noises, which affect the states of the system and measurement, are assumed to be constant during the simulation, and are chosen as $Q = 2\times 10^{-4}$ and $R = 0.01$, for states and measurement noises, respectively. The initial values of covariances are $\hat{Q} = 10^{-12}$, and $R = 10^{-9}$. Considering the proposed conditions, the simulation results are collected as shown in Figs. 10, and 11. An analysis of the results shows the proficiency of the presented intelligent filter for a system with high nonlinearity. Tab. 10 shows the mean square error of the estimation.

2) TIME VARYING NOISE STATISTICS

In this section, the proposed algorithm is applied on the servo-hydraulic system which is affected by a time-varying noise with time-varying statistics. The starting points of the system and the filter are set as per the previous section. It is assumed that the hydraulic system is affected by noises whose statistics changed with time. The changes are applied as

$$Q = \begin{cases} 5 \times 10^{-4} * I_{4\times4}, & t < 4s, t > 16 \\ 10^{-6} * I_{4\times4}, & 4 \le t \le 16, \end{cases}$$
$$R = \begin{cases} 10^{-2} * I_{4\times4}, & t < 4s, t > 16 \\ 2 \times 10^{-4} * I_{4\times4} & 4 \le t \le 16, \end{cases} \tag{23}$$

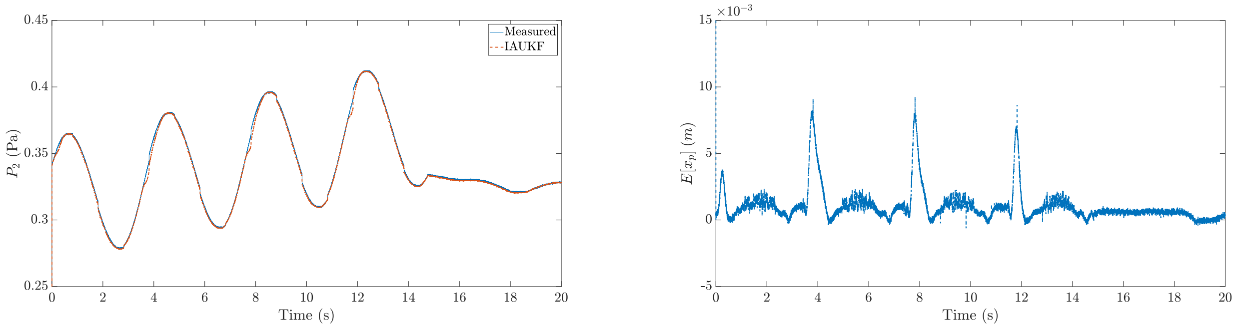
The initial value of noise covariances are set as $\hat{Q} = 10^{-10}$, and $R = 10^{-4}$. Results of the estimation of states of the system are given in Fig. 12. The estimation error and mean square error (MSE) of the estimation, which are given in Fig. 13, and Tab. 11, show that the proposed filter is an acceptable solution and can be applied to different nonlinear systems while employing the proposed conditions.

3) EXPERIMENTAL VALIDATION

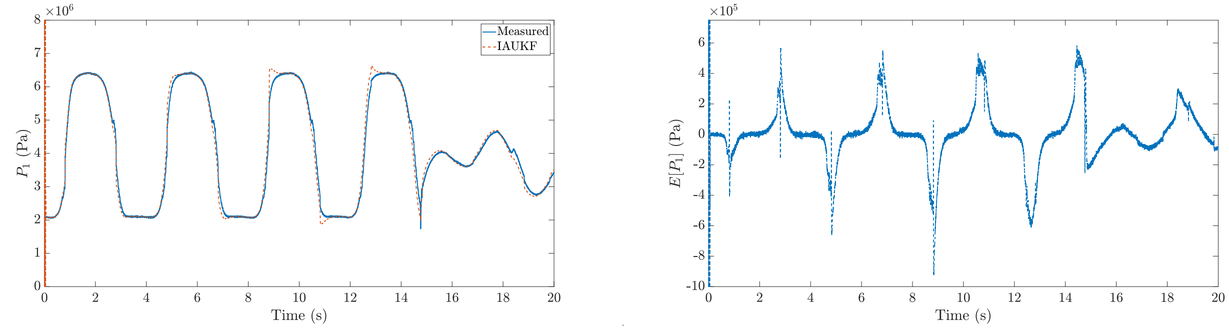
To obtain an idea of a realistic behaviour of the developed method, it is applied on a practical servo-hydraulic system. The system are shown in Fig. 14 is located at the Laboratory of Intelligent Machines at LUT University. The practical data is collected from the system. The proposed method is applied on it, and results are presented in Fig. 15.

IV. ANALYSIS AND DISCUSSION

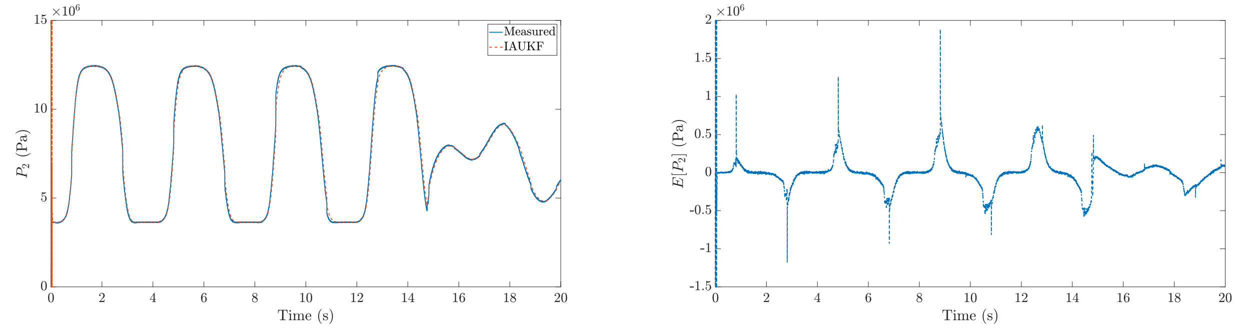
The analysis should be separated into two different parts. First, it is necessary to discuss the proposed fuzzy adaptive evolutionary algorithm. The proposed algorithm was developed by implementing fuzzy logic to determine the updating factor for the new candidate solutions. The proposed approach was applied to different benchmark functions, and the results are given in Tab. 6. Results show that the presented method demonstrates better performance in comparison to the basic algorithm. The algorithm was compared with other traditional algorithms, and its effectiveness in solving different kinds of problems is clearly demonstrated. The second part of the analysis should deal with the application of the presented algorithm to an adaptive unscented Kalman filter for optimization. The proposed method was applied to a robotic manipulator, and a servo-hydraulic system, to estimate the states of nonlinear systems under time varying noise. To obtain a more comprehensive comparison between the proposed method and the traditional method, more numerical results are given in this section. For each system, the



(a) x_p (b) $E[x_p]$



(c) P_1 (d) $E[P_1]$



(e) P_2 (f) $E[P_2]$

FIGURE 15. State estimation of the experimental hydraulic actuator affected by noises with unknown statistics.

TABLE 8. MSE of robotic system estimation under time varying noises with constant statistics.

Variable / Method	θ_1	$\dot{\theta}_1$	θ_2	$\dot{\theta}_2$	θ_3	$\dot{\theta}_3$
IAUKF	0.047	0.046	0.031	0.022	0.03	0.025
UKF	0.074	0.067	0.164	0.059	0.068	0.052

TABLE 9. MSE of robotic system estimation under time varying noises with time varying statistics.

Variable / Method	θ_1	$\dot{\theta}_1$	θ_2	$\dot{\theta}_2$	θ_3	$\dot{\theta}_3$
IAUKF	0.093	0.077	0.081	0.095	0.079	0.086
UKF	0.144	0.121	0.138	0.158	0.142	0.136

simulation was separated into two parts. First, the approach was applied to a nonlinear system subjected to a time varying noise with constant covariances. The MSE of the state estimation is given in table 8. As the table shows, the proposed method demonstrates better performance in comparison with the traditional one. The difference between the performance of the methods can be seen in the estimation error of the position and velocity of the second joint. The second simulation was conducted on the condition that the robot was influenced by a time varying noise with time varying covariances. The MSE of the simulation is presented in table 9.

The servo-hydraulic system has been simulated as per two different conditions as well. First the simulation was conducted when the system was affected by a time-varying noise with constant statistics. Then, the simulation was conducted in presence of a time-varying noise with time-varying statistics. The results were obtained, and the MSE of the estimation of states of this system can be found in Tabs. 10, and 11 for two scenarios. The method was applied on a practical system to obtain an understanding of its behaviour in a real-world scenario, and the results were reported.

TABLE 10. MSE of the estimation of servo-hydraulic system under time varying noises with constant statistics.

Variable / Method	x_p	$\dot{x}_p$	P_1	P_2
IAUKF	0.006	0.007	1.33×10^5	1.27×10^5
AUKF	0.018	0.0078	9.23×10^5	1.69×10^6

TABLE 11. MSE of the estimation of servo-hydraulic system under time varying noises with time varying statistics.

Variable / Method	x_p	$\dot{x}_p$	P_1	P_2
IAUKF	0.011	0.007	1.49×10^5	1.37×10^5
AUKF	0.023	0.067	9.24×10^5	1.67×10^6

Based on all simulations and experimental tests, it can be inferred that the proposed intelligent method is a reliable method for applying to different nonlinear systems and even practical scenarios.

V. CONCLUSION

This study presents a new and intelligent adaptive unscented Kalman filter. The proposed filter has been developed using two aspects: Adaptive unscented Kalman filter (AUKF) and Fuzzy adaptive grasshopper optimization algorithm (FAGOA). The evolutionary algorithm is a developed version of the basic algorithm. A fuzzy logic-based module has been employed to determine the updating factor of the algorithm. The new algorithm has been applied to optimize the adaptive unscented Kalman filter. The proposed filter was used to estimate the states of a robotic manipulator, and a servo-hydraulic system where a time varying noise influenced the system. To demonstrate the efficiency of the proposed approach, the simulation has been conducted under different conditions, and promising results have been obtained. Finally, the applicability of the proposed method to real-world application was demonstrated by the experimental results. As our future work, the proposed evolutionary algorithm will be modified for multi-objective optimization problems.

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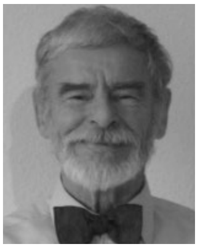

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