A Comparison of Nonstationary Fuzzy Logic for Cyber-Physical Systems

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***Abstract*—The popularity of cyber-physical systems, which has a wide application area from military to medicine, is increasing day by day. It is practice and common to implement control algorithms such as fuzzy logic in the cyber layer in these systems where the cyber and physical layers are separate. Reliability and consistency are very important for cyber-physical systems, which is often used in large and critical jobs. Uncertainties, which is hard to be modelled, are the greatest threat to the consistency of a system. Type 2 fuzzy logic is a method developed to deal with uncertainties in fuzzy systems. However, computational complexity has prevented the widespread use of this method and has led to the emergence of non-stationary fuzzy logic. In this study, in order to see the appropriateness of using non-stationary fuzzy logic in cyber physical systems, where consistency and reliability are important, various effects on the system have been investigated.Different membership functions are represented by non-stationary fuzzy logic and comparative results are given.**

***Keywords*—cyber-physical system; fuzzy systems; non-stationary fuzzy; uncertainity.**

I. Introduction

Cyber-physical systems (*CPS*) are the systems whose physical elements -such as sensor, actuator, etc.- and cyber elements -such as algorithms- are not in the same place [1]. The integration and communication of these distinct layers are actualized thanks to communication technologies. Fig. 1 represents a basic diagram for CPS structure.

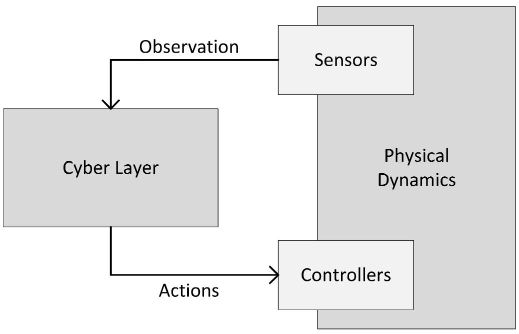

Fig. 1. Basic cyber-physical system structure.

In a cyber-physical system, data obtained by sensors are transported to cyber layer to be processed. As a result of the necessary operations which are actualized in cyber layer, it is calculated how the machines must move. The commands, which tell how the machines must behave, are transported to actuators in physical layer. At the end of the process, the machines know how to act and the systems work within this loop basically. As you can see from the basic principles of CPS working mechanism, the correctness of the system is directly related to the accuracy of the data obtained and transmitted. Uncertainty, which may have occurred unexpected times, is the major factor that affects the consistency of the system. In order to implement a robust CPS, uncertainties should be handled [2].

Fuzzy logic is used many times for solution of many different problems since it was introduced by Zadeh in 1965 [3]. In order to overcome the shortage of fuzzy sets in expressing uncertainties, the type 2 fuzzy logic was introduced by him after 10 years. Although the type 2 fuzzy sets make able to handle uncertainty, it is not common in real because of its complex computation requirements. The complexity of interval type 2 sets is reasonable for implementation in real problems, but such systems are not appropriate to represent variation in time [4]. Thus, non-stationary fuzzy sets are emerged to handle uncertainties with low computational efforts [5].

CPS has a wide application area from agriculture to medicine [6-8]. Lee et al. represented a CPS architecture for Industry 4.0 based manufacturing, which is new production trend of era [6]. Rad et al. established a system for monitoring potato crop with the help of CPS. The data obtained by sensors at field can be observed by user and farmer can make decisions based on other farmers' experiences according to that study [7]. Another study using CPS architecture is done in medicine by Pahlavan et al. They used micro cameras for taking pictures by endoscopy. The captured images sent to a computer by wireless technologies and the images are used to construct 3D map of human internal organs [8]. There are also studies about uncertainties and CPS under uncertainties in literature [9-11].

On the other hand, studies are done about fuzzy systems and handling uncertainties in fuzzy systems [12-16]. In this study, we investigated the effect of change in non-stationary fuzzy inputs to systems for being used in CPS. Different combines of non-stationary and type-1 inputs are given to system. Furthermore, randomly and uniformly created non-stationary sets are used and comparative results are given.

II. Fuzzy Systems

A. Type-1 Fuzzy Systems

Fuzzy systems are emerged from the need of emulating human decision mechanism. Fuzzy sets, the sets used in fuzzy systems, is different from classical set theory. For further information about fuzzy sets, readers are advised to read fuzzy sets **[A]**. This paper will continue with the general steps of fuzzy systems. A type-1 fuzzy system consist of fuzzification, inference, and defuzzification steps. A block diagram of these steps are given by fig. 2.

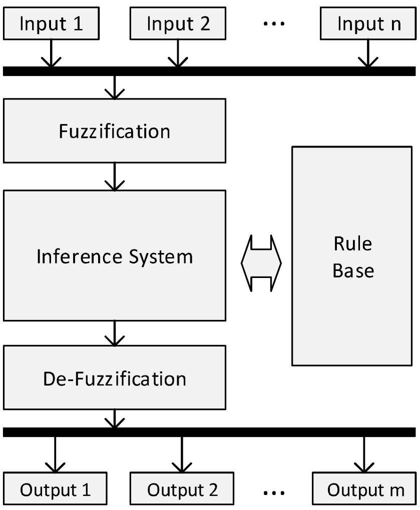

Fig. 2. Type-1 fuzzy system block diagram [17].

As seen in fig. 2, crisp inputs are given to fuzzy systems and crisp outputs are obtained. In fuzzification step, the crisp inputs are fuzzified by the help of membership functions. Most used membership functions in fuzzy systems are triangular, trapezoid, sigmoid, and gaussian functions [18].

After the fuzzification step, inference system come into work by the help of rule base. Rule base is the collection of if-else statements which are detected by experts. The result of cartesian product of the linguistic expressions in the separate entries which are obtained as the result of the fuzzification phase is determined according to this rule base. After that, the results are calculated according to inference mechanism. One of the most used inference mechanism in the literature is min-max method. Defuzzification is the step that makes crisp the variables again which are fuzzified. After output membership functions are limited by the inference results, a method, which is called defuzzification method, is employed to obtain crisp output values. Center of area, center of gravity, first of maximum, last of maximum, indexed center of gravity, mean of maxima, and middle of maximum are some of the most used defuzzification methods [19].

B. Type-2 Fuzzy Systems

Type-2 fuzzy systems, which is introduced 10 years later from its first version by Zadeh, are developed to handle to uncertainties. Type-1 fuzzy sets are not able to represent uncertainties by single membership function. In order to handle them, in type-2 fuzzy systems there are two membership function which are upper and lower membership function. In type-2 systems, unlike type-1 systems, there is type reducer step before de-fuzzification step. A block diagram belongs to type-2 systems are given by fig. 3.

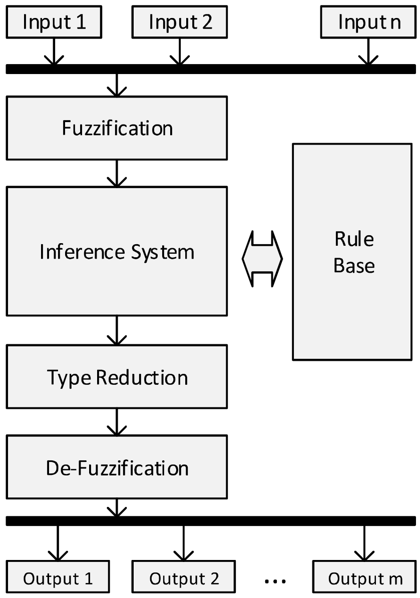

Fig. 3. Type-2 fuzzy system block diagram [17].

Because there are two membership function for each linguistic variable in type-2 fuzzy system, membership degrees cannot be specified by single value. Instead of this, a function which is called secondary membership function is used to express memberships.

The secondary is a constant function. Such systems which has constant secondary membership functions are called interval type-2 systems. Because of its complex computational requirements, interval type-2 systems are more preferable than general type-2 systems. But there still was a need for a new method due to the lack of representation of change over time.

C. Non-stationary Fuzzy Systems

Non-stationary fuzzy systems have emerged to eliminate the disadvantages of type-1 and type-2 systems. It represents the change in time by low computational burden. In non-stationary systems, sub-type-1 systems are used to model type-2 fuzzy systems. A block diagram that shows the mechanism of non-stationary fuzzy system is shown by fig. 4.

As seen by fig. 4, type-2 system is represented by collection of sub-type-1 systems. Each sub-system is calculated and at the end of the processes, final de-fuzzification operation is applied to obtain single value for each output.

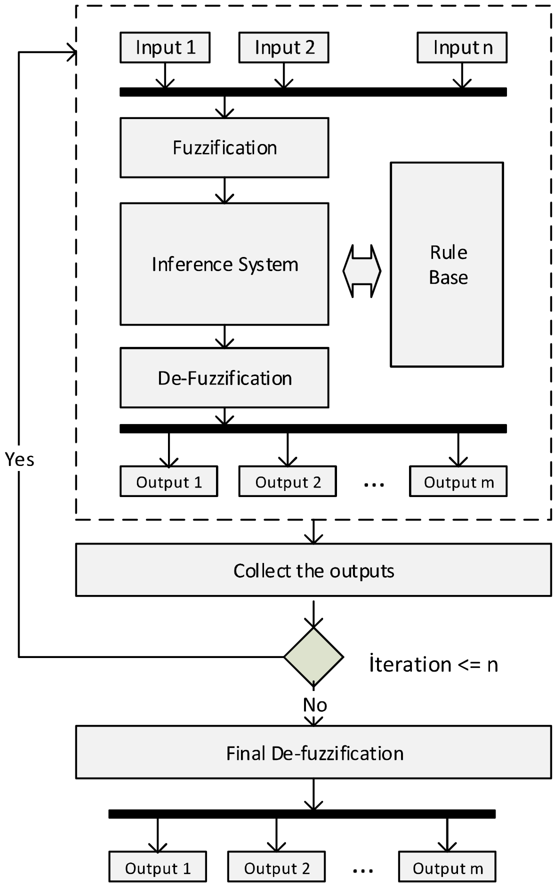

Fig. 4. Non-stationary fuzzy system block diagram [17].

III. COMPARATIVE RESULTS

In this study, in order to demonstrate the effect of non-stationary inputs a comparative study is done. A study that makes non-stationary the inputs for XOR operation done by Garibaldi before [4]. We aimed to take this one step further and see the consequences for different variations of entries in practice. XOR operation consist of two inputs and one output. The three functions have the same formula and there are two linguistic variables for each one. The linguistic variables and triangular type-1 membership function for the problem is given by fig. 5.

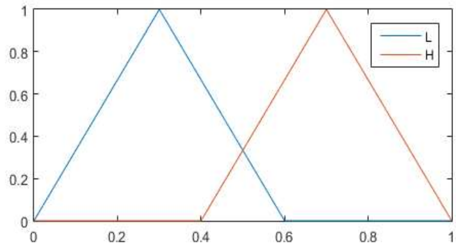

Fig. 5. Triangular membership functions for type-1 [4].

The general formula for triangular functions are given by (1). The a,b,c parameters are 0, 0.3, 0.6 respectively for linguistic variable ‘low’; and 0.4, 0.7, 1 respectively for linguistic variable ‘high’.

$$\max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \qquad (1)$$

The truth table and fuzzy input values for this problem, which consist the rules, is given by table 1. While the values written in brackets in table 1 is fuzzy input values; 0 means low (L), 1 means high (H). A sample linguistic rule of the system is such that ‘if input 1 is L and input 2 is L then output is L’ for case 1.

TABLE I. XOR TRUTH TABLE AND INPUT VALUES

	Input 1	*Input 2*	*Output*
Case 1	0 (0.25)	0 (0.25)	0
Case 2	0 (0.25)	0 (0.75)	1
Case 3	1 (0.75)	0 (0.25)	1
Case 4	1 (0.75)	0 (0.75)	0

For comparison, 4 different scenarios have been implemented. The scenarios are given by table 2. The inputs for type-1 is like given in fig 5. Uniform and normal perturbation are employed to make the inputs non-stationary respectively. Non-stationary inputs are given by fig. 6 and fig. 7. While the amplitude remains constant, changes are made in the center within 0.1 (± 0.05) tolerance.

TABLE II. SCENARIOS TO BE USED IN COMPARATION

	Input 1	*Input 2*	*Output*
S1	type-1	type-1	type-1
S2	type-1	non-stationary	type-1
S3	non-stationary	non-stationary	type-1
S4	non-stationary	non-stationary	non-stationary

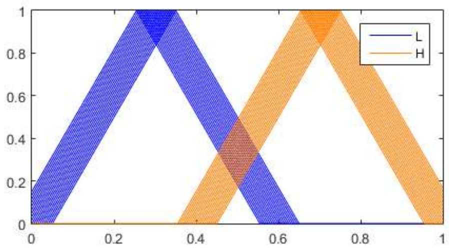

Fig. 6. Uniformly 20-times repeated non-stationary sets

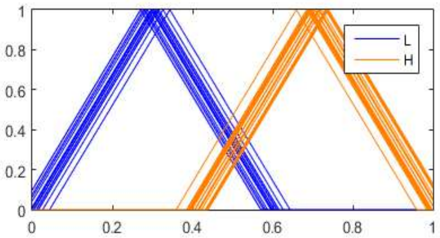

Fig. 7. Randomly 20-times repeated non-stationary sets

TABLE III. TEST INPUTS AND OUTPUTS FOR EACH SCENERIO WITH UNIFORMLY CREATED NON-STATIONARY

Input1	Input2	S1	S2	S3	S4
0.25	0.75	0.7	0.7	0.7	0.7
0.32	0.72	0.7	0.7	0.7	0.7
0.69	0.81	0.3	0.3	0.3	0.3
0.27	0.79	0.7	0.7	0.7	0.7
0.45	0.6	0.591	0.567	0.567	0.571
0.55	0.67	0.409	0.433	0.433	0.429
0.44	0.60	0.611	0.582	0.582	0.586
0.47	0.53	0.554	0.527	0.539	0.542
0.3	0.57	0.632	0.632	0.597	0.601
0.44	0.27	0.389	0.418	0.418	0.41

TABLE IV. TEST INPUTS AND OUTPUTS FOR EACH SCENERIO WITH RANDOMLY CREATED NON-STATIONARY

Input1	Input2	S1	S2	S3	S4
0.25	0.75	0.7	0.7	0.7	0.696
0.32	0.72	0.7	0.7	0.7	0.695
0.69	0.81	0.3	0.3	0.3	0.294
0.27	0.79	0.7	0.7	0.7	0.695
0.45	0.6	0.591	0.547	0.547	0.557
0.55	0.67	0.409	0.418	0.418	0.413
0.44	0.60	0.611	0.561	0.561	0.571
0.47	0.53	0.554	0.513	0.522	0.527
0.3	0.57	0.632	0.632	0.613	0.619
0.44	0.27	0.389	0.439	0.439	0.423

IV. CONCLUSIONS

Different combinations of type-1 and non-stationary fuzzy sets for XOR operation used to compare the results. The results with uniformly created non-stationary and randomly (normal) created non-stationary are given by table 3 and table 4. When we look the results, we can see that there is no difference or a few difference between scenarios when the inputs near to peak values (0.3 for low, 0.7 for high). But when the inputs near the middle value (0.5), the outputs for each case differs from each other. The results indicate that non-stationary makes the results softer. Thus, changes due to uncertainties don't affect the results too much as type-1 systems. And they can be used for CPS, when the effect of uncertainties must be declined.

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