Abstract— Fuzzy systems based on the interval type-2 fuzzy set have many advantages in processing uncertain data compared with the fuzzy systems based on the type-1 fuzzy set. The design of optimal interval type-2 fuzzy systems is often difficult due to many parameters. The selection and construction of membership functions used to map the crisp inputs to fuzzifier data play an important role and greatly influence the accuracy of the fuzzy system. The paper proposes a hybrid optimization model using swarm optimization algorithms to find the parameters for the membership function of the interval type-2 fuzzy logic system (IT2FLS). For the experiment, the paper uses optimization techniques such as particle swarm optimization (PSO), genetic algorithm (GA), ant colony optimization (ACO) to find the optimal parameter for IT2FLS applied to the classification problem. Experimental results on datasets from the UCI machine learning library and satellite image data show that hybrid optimization models between the optimization algorithm and IT2FLS can help IT2FLS achieve higher accuracy in data classification problems.

Keywords— Fuzzy system, Interval type-2 fuzzy set, Evolutionary algorithm, Membership function

I. INTRODUCTION

Fuzzy logic was first introduced in 1965. Since then, it has been widely applied in many different fields. The methods based on the type-1 fuzzy set (T1FS) have the advantage of low computational complexity. However, the membership function (MF) of T1FS is a crisp value, so they cannot handle adequately or restrictively with highly uncertain data [1].

Type-2 fuzzy set (T2FS) is an extension from T1FS, which is characterized by the fuzzy MF [2], unlike T1FS, MF values are a scrips number of [0, 1], MF values of T2FS are a fuzzy set of [0, 1] [3]. One of the applications of T2FS is the interval type-2 fuzzy clustering algorithm [4], which has been used in many practical problems [5], [6]. However, this is an unsupervised clustering algorithm. They have low accuracy and have difficulty in automatic classification. T2FSs are characterized by a three-dimensional fuzzy MF, including the footprint of uncertainty (FOU) that can directly model and handle the uncertainty [7]. Once the type-1 MF is selected, all uncertainties will disappear because the type-1 MFs are entirely correct [8]. The type-2 fuzzy logic system based on T2FS has been used in many practical applications such as predictive problems [9], industrial control [10], [11], data classification [12], [13].

T2FS can handle uncertain data better than T1FS. It has high computational complexity, which should be limited in practical applications. One of the cases of T2FS is more widely used, which is an interval type-2 fuzzy set (IT2FS) [14]. Fuzzy systems based on IT2FS are the interval type-2 fuzzy logic systems (IT2FLSs). Fuzzy systems are characterized by rules and MFs [15]. The extension of T1 FSs to IT2 FSs can effectively describe uncertainties in situations where the available information is uncertain. Some commonly used MFs are Triangular, Trapezoidal, Gaussian, Cauchy, Laplace, so on [8]. Determining these parameters for fuzzy systems is very important and significantly affects the accuracy of fuzzy systems. However, it is challenging to decide on the exact shape of these MFs [16].

A number of studies have proposed solutions to find optimal parameters for fuzzy systems. However, the applications in classification are still limited; whereby most of the research on fuzzy systems is for fuzzy control systems for industrial applications. Unlike type 1 fuzzy systems, the design of type 2 fuzzy systems is much more difficult due to more parameters. Hagras designed the hierarchical type-2 fuzzy control system architecture to increase computational speed for fuzzy control systems for real-time applications [10-11] such as Autonomous Mobile Robots. Das et al. [12] proposed an extended interval type-2 fuzzy system based on the Kalman filter algorithm for motor-imagery task classification. Initially, the fuzzy system starts without rules and automatically develops and corrects the parameters for the fuzzy system. In the study [13], Nguyen and colleagues used the AHP model to select genes and classify cancer patients. Mai et al. [17] have proposed an optimal fuzzy system model using the PSO technique for forecasting problems. In some other studies [18-20], the authors have proposed a solution to design the optimal interval type 2 fuzzy logic controller using evolutionary algorithms.

From some of the above evaluations, it can be seen that the study of using hybrid fuzzy systems can help improve the accuracy of conventional fuzzy systems. This paper presents some Interval type-2 fuzzy logic systems optimization techniques based on swarm algorithms for data classification. The paper consists of five parts: Section 1, Introduction; Section 2, Background; Section 3, Interval type-2 fuzzy logic systems optimization; Section 4, Experimental and Section 5, Conclusion.

II. BACKGROUND

In this section, the paper will introduce an overview of the interval type-2 fuzzy logic system and some optimization techniques used in the paper.

A. Interval type-2 fuzzy logic system

The interval type-2 fuzzy logic system is described in Figure 1, consisting of 5 main parts fuzzifier, inference, rule base, type-reducer, and fuzzifier [8]. IT2FLS works as follows; the crisp inputs are the initial data attributes, which fuzzifier into the input IT2FSs and then activate the inference engine and rule base to maps input IT2FSs into output IT2FSs. These output IT2FSs are then processed by the type-reducer to obtain T1FSs (type reducers). Then T1FSs defuzzifier to create the crisp output.

The generalized Interval type-2 fuzzy logic system architecture includes the following steps:
the method to build rules for fuzzy system using IF...THEN...

\[ R_i : IF x_{i1}IS A_{i1} AND...AND x_{ip}IS A'_{ip} \text{ THEN } y = G' \]

where, \( R_i \) is the \( i \)th rule, \( A_i \) and \( G' \) are the language variables of input and output data. \( X = \{x_{i1}, x_{i2}, ..., x_{in}\} \) is the input data.

+ **Fuzzy inference**: The result of the fuzzy inference process is to produce interval type-2 fuzzy sets.

+ **Type-reducer and defuzzifier**: There are 2 ways to defuzzify as shown in figure 1: Convert the interval type-2 fuzzy sets to the type-1 fuzzy sets, then defuzzify from the type-1 fuzzy sets to get crisp output (1a) and defuzzify directly from the interval type-2 fuzzy sets to get crisp output (1b).

![Interval type-2 fuzzy logic system architecture](image)

Fig. 1. Interval type-2 fuzzy logic system architecture [8]

The difference between the two interval type-2 fuzzy logic system architectures can be seen in the output processing. For the IT2FLS architecture as shown in Figure 1a, the output processing consists of two steps: Downgrading from interval type-2 to type-1, then defuzzification from type-1 to crisp value. Meanwhile, with the IT2FLS architecture in Figure 1b, the output processing consists of only one step, which is defuzzification directly from interval type-2 to the crisp value.

### B. Optimization techniques

There are many different optimization techniques. Within the scope of this paper, we only experiment on three optimization techniques, including PSO, GA, and ACO.

PSO is a technique to find the optimal solution for the population based on swarm intelligence. Each state of the population in the search space is considered a candidate solution; the optimal solution is found by moving particles in the search space according to the particle’s position and velocity [22].

GA is a search-based optimization technique based on the principles of genetics and natural selection [23]. The genetic algorithm uses three main types of rules to create the next generation from the current population: Selection rules select the individuals, called parents, that contribute to the population at the next generation. Crossover rules combine two parents to form children for the next generation [24]. Mutation rules apply random changes to individual parents to create children.

ACO is a well-known bio-inspired technique for solving combinatorial optimization problems and inspired by the foraging behavior of natural ants, where a colony of ants seeks the shortest path between the food source and their nest. Each ant starts its journey from the nest searching for food sources and comes back to the nest, completing an iteration. During the journey, each ant lay a substance known as pheromone on the path they travel. The pheromone concentration on each path depends on the distance of the path and the quality of the food source available. Each ant probabilistically selects a path that depends on the pheromone concentration and some heuristic value, such as the objective function value [25].

### III. THE OPTIMAL MODEL FOR INTERVAL TYPE-2 FUZZY LOGIC SYSTEM

The Gaussian MF model (GMF) is a universal distribution model with good computational performance. In this study, we use the Gaussian MF to build interval type-2 fuzzy MFs. Two very popular FOUs are for a Gaussian MF with uncertain standard deviation (USD) and a Gaussian MF with uncertain mean (UM).

![Interval type-2 Gaussian membership function](image)

Fig. 2. Interval type-2 Gaussian membership function

+ **Gaussian MF with uncertain mean (UM)**: Consider the case of a Gaussian MF having a fixed standard deviation, \( \sigma' \), and an uncertain mean that takes on values in \([m'_{j1}, m'_{j2}]\). Corresponding to each value of \( m'_{j} \) a different membership curve is obtained [8].

\[
\mu_{f_j}(x_j) = \exp\left(-\frac{1}{2} \left(\frac{x_j - m'_{j}}{\sigma'_{j}}\right)^2\right) \cdot N(x_j, m'_{j}, \sigma'_{j}) \quad \text{with} \quad m'_{j} \in [m'_{j1}, m'_{j2}] \tag{1}
\]

The curve in Figure 2.a denotes the Upper MF and the Lower MF; they can be expressed as:

\[
\Pi_{f_j}(x_j) = \begin{cases} 
N(x_j, m'_{j1}, \sigma'_{j}) & x_j < m'_{j1} \\
1 & m'_{j1} \leq x_j \leq m'_{j2} \\
N(x_j, m'_{j2}, \sigma'_{j}) & x_j \geq m'_{j2} 
\end{cases}
\]

\[
\mu_{f_j}(x_j) = \begin{cases} 
N(x_j, m'_{j1}, \sigma'_{j}) & x_j \leq \frac{m'_{j1} + m'_{j2}}{2} \\
N(x_j, m'_{j2}, \sigma'_{j}) & x_j > \frac{m'_{j1} + m'_{j2}}{2} 
\end{cases}
\]

+ **Gaussian MF with uncertain standard deviation (USD)**: Consider the case of a Gaussian MF having a fixed
mean, \( m^j \), and an uncertain standard deviation that takes on values in \([\sigma^j_{\text{L}}, \sigma^j_{\text{U}}]\). Corresponding to each value of \( \sigma^j \), a different membership curve is obtained.

\[
\mu_{\text{MF}}^j(x) = \exp\left(-\frac{1}{2}\left(\frac{x - m^j}{\sigma^j}\right)^2\right) = (x, m^j, \sigma^j)
\]  

(3)

with \( \sigma^j \in [\sigma^j_{\text{L}}, \sigma^j_{\text{U}}] \).

The Gaussian MF with \( \sigma^j_{\text{L}}, \sigma^j_{\text{U}} \) is standard deviation of the interval output and \( m^j \) is the center of the Gaussian MF and also the center of the \( i \)th cluster [8]. The curve in Figure 2.b denotes the UMIF and the LMF; they can be expressed as:

\[
\overline{\mu}_{\text{MF}}^j(x) = \mathcal{N}(x, m^j, \sigma^j_{\text{L}})
\]

\[
\underline{\mu}_{\text{MF}}^j(x) = \mathcal{N}(x, m^j, \sigma^j_{\text{U}})
\]

(4)

Note that both the upper and lower MFs do not change over \( x \in X \) and they are differentiable over \( x \in X \).

The latter is important when an optimization algorithm is used to optimize MF parameters during the design of an interval type-2 fuzzy system.

The parameters \( m^j_{\text{L}}, m^j_{\text{U}}, \sigma^j \) for Gaussian MF with uncertain mean; \( \sigma^j_{\text{L}}, \sigma^j_{\text{U}} \) and \( m^j \) for Gaussian MF with uncertain standard deviation, need to be estimated for the construction of an interval type-2 fuzzy MF model. It can be seen that the Gaussian MF is characterized by three parameters \((m^j, \sigma^j_{\text{L}}, \sigma^j_{\text{U}})\) or \((m^j_{\text{L}}, m^j_{\text{U}}, \sigma^j)\). In this study, we consider a type of membership function that characterizes both types of Gaussian functions by using 4 parameters \(m^j_{\text{L}}, m^j_{\text{U}}, \sigma^j_{\text{L}}, \sigma^j_{\text{U}}\) for each Gaussian function.

GaussianMF\(^j = f(m^j_{\text{L}}, m^j_{\text{U}}, \sigma^j_{\text{L}}, \sigma^j_{\text{U}})
\)

(5)

Upper MF and the Lower MF; they can be expressed as:

\[
\overline{\mu}_{\text{MF}}^j(x) = \begin{cases} 
\mathcal{N}(x, m^j_{\text{L}}, \sigma^j_{\text{L}}) & x < m^j_{\text{L}} \\
\mathcal{N}(x, m^j_{\text{U}}, \sigma^j_{\text{U}}) & m^j_{\text{L}} \leq x \leq m^j_{\text{U}} \\
\mathcal{N}(x, m^j_{\text{L}} + m^j_{\text{U}}) & x \geq m^j_{\text{U}} 
\end{cases}
\]

(6)

\[
\underline{\mu}_{\text{MF}}^j(x) = \begin{cases} 
\mathcal{N}(x, m^j_{\text{L}}, \sigma^j_{\text{L}}) & x < m^j_{\text{L}} \\
\mathcal{N}(x, m^j_{\text{U}}, \sigma^j_{\text{U}}) & m^j_{\text{L}} \leq x \leq m^j_{\text{U}} \\
\mathcal{N}(x, m^j_{\text{L}} + m^j_{\text{U}}) & x \geq m^j_{\text{U}} 
\end{cases}
\]

If \( c \) is the number of Gaussian MFs, then the number of parameters is \( 4c \). The adjustment parameters are determined by using optimization techniques, including FCM, PSO, GA, and ACO. The aim is to find the optimal parameters of MFs for the IT2FLS model. Accordingly, the data is divided into a training set and a validation set. Optimization techniques use training data sets to train the IT2FLS model. Validation data set used for testing the correctness of the model IT2FLS.

To evaluate the proposed method’s effectiveness, we measure the difference between the actual output and the desired output on the data sets labeled by the following formula:

\[
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \overline{y}_i)^2
\]

(7)

where \( y_i, \overline{y}_i \) are the desired output and the actual output of the fuzzy system and \( n \) is the number of input pixels.

### IV. RESULTS AND DISCUSSION

Testing is done with algorithms IT2FLS-FCM, IT2FLS-PSO, IT2FLS-GA và IT2FLS-ACO. The maximum number of iterations for the PSO, GA and ACO algorithms is set to 1000. The classification performance is evaluated by determining True Positive Rate (TPR) and False Positive Rate (FPR) defined as follows:

\[
\text{TPR} = \frac{TP}{TP + FN} \quad \text{and} \quad \text{FPR} = \frac{FP}{TN + FP}
\]

(8)

TP is the number of correctly classified data and FN is the number of incorrectly misclassified data. FP is the number of incorrectly classified data, and TN is the number of correctly misclassified data. A good model will give a large TPR value and a small FTR value. Experiment is developed based on the interval type-2 fuzzy logic system toolbox [21].

#### A. Data classification

Three test data sets are downloaded from the UCI Machine Learning Repository (https://archive.ics.uci.edu). Data is randomly divided into 70% for training and 30% for testing. Table 1 shows the details of the 3 data sets.

The classification results in 3 data sets are shown in Table 2. Training time is averaged over ten runs. Use the fuzzy c-means clustering (FCM) algorithm to initialize parameters for IT2FLS (IT2FLS-FCM).

### RESULTS AND DISCUSSION

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The classification results in 3 data sets are shown in Table 2. Training time is averaged over ten runs. Use the fuzzy c-means clustering (FCM) algorithm to initialize parameters for IT2FLS (IT2FLS-FCM).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Number of Instances</th>
<th>Number of Attributes</th>
<th>Date Donated</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data1: Paper Reviews Data Set</td>
<td>405</td>
<td>10</td>
<td>2017-10-23</td>
</tr>
<tr>
<td>Data2: Travel Reviews Data Set</td>
<td>170</td>
<td>54</td>
<td>2019-07-24</td>
</tr>
</tbody>
</table>

#### TABLE II. ACCURACY OF ALGORITHMS ON TRAINING DATASET

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Alg.</th>
<th>IT2FLS-FCM</th>
<th>IT2FLS-PSO</th>
<th>IT2FLS-GA</th>
<th>IT2FLS-ACO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data1</td>
<td>Time</td>
<td>159s</td>
<td>383s</td>
<td>477s</td>
<td>498s</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.563</td>
<td>0.472</td>
<td>0.281</td>
<td>0.378</td>
</tr>
<tr>
<td></td>
<td>TPR</td>
<td>91.98%</td>
<td>98.91%</td>
<td>99.43%</td>
<td>99.12%</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>1.67%</td>
<td>1.21%</td>
<td>1.15%</td>
<td>1.05%</td>
</tr>
<tr>
<td>Data2</td>
<td>Time</td>
<td>241s</td>
<td>564s</td>
<td>787s</td>
<td>695s</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.693</td>
<td>0.574</td>
<td>0.265</td>
<td>0.273</td>
</tr>
<tr>
<td></td>
<td>TPR</td>
<td>92.53%</td>
<td>98.76%</td>
<td>98.89%</td>
<td>98.92%</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>1.38%</td>
<td>1.13%</td>
<td>0.86%</td>
<td>1.02%</td>
</tr>
<tr>
<td>Data3</td>
<td>Time</td>
<td>98s</td>
<td>178s</td>
<td>238s</td>
<td>269s</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.597</td>
<td>0.475</td>
<td>0.334</td>
<td>0.352</td>
</tr>
<tr>
<td></td>
<td>TPR</td>
<td>89.0%</td>
<td>99.03%</td>
<td>99.31%</td>
<td>99.11</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>2.02%</td>
<td>1.41%</td>
<td>0.98%</td>
<td>1.26%</td>
</tr>
</tbody>
</table>

Table II shows that the models that use the optimal technique are much more accurate than the model not used. On the training dataset, the MSE value reached the smallest for IT2FLS-FCM on all three datasets, followed by IT2FLS-ACO and IT2FLS-PSO. Meanwhile, IT2FLS-FCM gave the worst results among them. Moreover, the IT2FLS-PSO, IT2FLS-GA, IT2FLS-ACO models all showed over 98% accuracy for all three datasets. And model IT2FLS-FCM for
accuracy below 93% for all 3 data sets. While the models IT2FLS-GA, IT2FLS-ACO were more accurate than IT2FLS-PSO, training time was also more significant than IT2FLS-PSO. When using FCM, the time to train the IT2FLS is the smallest on all three data sets.

**TABLE III. ACCURACY OF ALGORITHMS ON TESTING DATASET**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Alg.</th>
<th>IT2FLS-FCM</th>
<th>IT2FLS-PSO</th>
<th>IT2FLS-GA</th>
<th>IT2FLS-ACO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MSE</td>
<td>0.273</td>
<td>0.259</td>
<td>0.188</td>
<td>0.187</td>
</tr>
<tr>
<td>Data1</td>
<td>TPR</td>
<td>92.35%</td>
<td>96.83%</td>
<td>99.07%</td>
<td>98.56%</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>1.45%</td>
<td>1.32%</td>
<td>0.98%</td>
<td>1.11%</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.673</td>
<td>0.524</td>
<td>0.199</td>
<td>0.223</td>
</tr>
<tr>
<td>Data2</td>
<td>TPR</td>
<td>91.76%</td>
<td>97.99%</td>
<td>98.72%</td>
<td>98.36%</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>1.54%</td>
<td>1.23%</td>
<td>0.91%</td>
<td>0.91%</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>0.274</td>
<td>0.826</td>
<td>0.277</td>
<td>0.398</td>
</tr>
<tr>
<td>Data3</td>
<td>TPR</td>
<td>90.14%</td>
<td>98.33%</td>
<td>98.86%</td>
<td>99.79</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>1.85%</td>
<td>1.61%</td>
<td>1.02%</td>
<td>1.01%</td>
</tr>
</tbody>
</table>

Table III shows the results of the accuracy assessment on the testing dataset. The IT2FLS-GA model gives the best results with the TPR index on all three experimental data sets. Both IT2FLS-GA and IT2FLS-ACO provide the best results in 2/3 datasets for the FPR index. For the MSE index, the IT2FLS-GA model gives the best results in 2/3 of the dataset. The IT2FLS-ACO model provides the best results in 1/3 of the data set. The IT2FLS-FCM model gave the worst results among the four experimental models.

**B. Satellite image landcover classification**

Experimental data are Sentinel-2A satellite images of the downtown area of Hanoi, Vietnam on May 18, 2018. The image data has a size of 2,000 x 2,000, the image resolution is 10 meters. The entire dataset has a pixel count of 4,000,000 pixels. The proposed model will classify remote sensing image data according to 6 different landcovers: Class 1: Surface water; Class 2: Bare land; Class 3: Grass, shrubs; Class 4: Planted forests, low woods; Class 5: Perennial tree crops; Class 6: Dense vegetation.

To test models IT2FLS-FCM, IT2FLS-PSO, IT2FLS-GA and IT2FLS-ACO on satellite image data. Labeling data was obtained directly from the image using Erdas Imagine software with 500 samples per landcover. The number of samples (pixels) used for training and testing is 3,000 divided by 70% for training and 30% for testing. The parameters obtained after the optimization process of IT2FLS will be used to classify satellite image data in the central area of Hanoi (Figure 3).

**TABLE IV. ACCURACY OF ALGORITHMS ON SATELLITE IMAGE DATASET**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Alg.</th>
<th>IT2FLS-FCM</th>
<th>IT2FLS-PSO</th>
<th>IT2FLS-GA</th>
<th>IT2FLS-ACO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>Time</td>
<td>945 s</td>
<td>1168 s</td>
<td>2579 s</td>
<td>2281 s</td>
</tr>
<tr>
<td></td>
<td>MSE</td>
<td>8.634</td>
<td>7.548</td>
<td>6.652</td>
<td>6.899</td>
</tr>
<tr>
<td></td>
<td>TPR</td>
<td>94.67%</td>
<td>96.61%</td>
<td>98.54%</td>
<td>97.92%</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>2.15%</td>
<td>2.03%</td>
<td>1.54%</td>
<td>1.89%</td>
</tr>
<tr>
<td>Testing</td>
<td>MSE</td>
<td>7.628</td>
<td>7.081</td>
<td>6.256</td>
<td>6.299</td>
</tr>
<tr>
<td></td>
<td>TPR</td>
<td>93.58%</td>
<td>97.02%</td>
<td>98.23%</td>
<td>97.62%</td>
</tr>
<tr>
<td></td>
<td>FPR</td>
<td>1.99%</td>
<td>1.67%</td>
<td>1.62%</td>
<td>1.53%</td>
</tr>
</tbody>
</table>

Table 4 gives results of the accuracy assessment on the training and testing datasets and time used for training. It can be seen that the training time on the IT2FLS-FCM model is the lowest, with 945(s). The IT2FLS-GA model has the largest training time with 2579(s), followed by the IT2FLS-ACO model and the IT2FLS-PSO model. On the training set, the IT2FLS-GA model gave the best results for all three indexes of MSE, TPR, and FPR. On the testing dataset, the IT2FLS-GA model provides the best results for both MSE and TPR indexes. In comparison, the IT2FLS-ACO model gives the best results on the FPR index. The IT2FLS-FCM model gave the lowest accuracy, followed by the IT2FLS-PSO model.

Figure 4 is the result of classification according to 6 land covers by models IT2FLS-FCM (a), IT2FLS-PSO (b), IT2FLS-GA (c), and IT2FLS-ACO (d), respectively. It can be seen that the classification results by the IT2FLS-FCM model (Figure 4a) give the worst results due to the presence of many surface water layers in the central area of Hanoi. While the results are classified by other models, the urban area in the center of Hanoi shows quite clearly. Especially on Figures 4c
The paper proposes a hybrid optimization model using swarm optimization algorithms to find the optimal parameters for the interval type-2 fuzzy logic system (IT2FLS). The hybrid optimization model consists of 2 phases: Stage 1 uses the swarm optimization technique to find the optimal parameters for the membership function of IT2FLS. Stage 2 is to apply IT2FLS with the set of parameters found above to data classification. The indicators used to evaluate the quality of the model include MSE, TPR, and FPR. Experimental results of hybrid optimization models on data sets from the UCI machine learning library and satellite image data show that using the swarm optimization algorithms to find suitable parameters will help IT2FLS operate more stably and achieve higher accuracy.

The proposed models can be used for many different problem classes, such as classification and prediction. Especially in the field of mapping and assessment and monitoring of landcover changes. In future research, we will experiment with other optimization techniques.

V. CONCLUSION

This result shows the potential of applying optimization techniques to find optimal fuzzy models for classification problems. Furthermore, the proposed model can also be applied to problems with forecasting, regression, so on.

REFERENCES