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The most challenging issue facing developing countries are the cost of inadequate sanitation that is translated into significant economic, social, and environmental burdens. As communities grow, there is no adequate means of waste disposal, which will affect the quality of the waterway. Although most sanitation facilities are valued for their benefit and costs, their long-term performance should be investigated. In this study, we develop a septic sludge treatment plant (SSTP) effluent prediction model. Immune network algorithm (INA) adopted during SSTP modeling. The performance of the SSTP's effluent removal efficiency was examined. INA-based SSTP model fosters effective environmental management tool.

Prediction Analysis of Effluent Removal in a Septic Sludge Treatment Plant: A Biomimetics Engineering Approach

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Abstract

Effluent discharge from septic tanks is affecting the environment in developing countries. The most challenging issue facing these countries is the cost of inadequate sanitation that is translated into significant economic, social, and environmental burdens. Although most sanitation facilities are valued for their benefit and costs, their long-term performance should be investigated. In this study, effluent quality—namely, the biological oxygen demand (BOD), chemical oxygen demand (COD), and total suspended solid (TSS)—was assessed through a biomimetics engineering approach. A novel approach of immune network algorithm (INA) was applied to a septic sludge treatment plant (SSTP) for effluent-removal predictive modelling. The Matang SSTP in the city of Kuching, Sarawak, on the island of Borneo was selected as a case study. Monthly effluent discharges from 2007 to 2011 were used for training, validating, and testing purposes using MATLAB 7.10. The results showed that the BOD effluent-discharge prediction was less than 50% of the specified standard after the 97th month of operation. The COD and TSS effluent- prediction removal were simulated at the 85th and the 121st months, respectively.The study proved that the proposed INA-based SSTP model could be used to achieve an effective SSTP assessment and management technique.

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Keywords: Artificial immune system; effluent quality; immune network algorithm; prediction; septic sludge treatment plant

1.0 Introduction

Environmental issues are of foremost concern today, and they will continue to be in the years ahead. In particular, environmental concerns regarding water and wastewater management in developing countries need to be addressed. As communities grow, there is no adequate means of waste disposal, which will affect the quality of the waterway, and possibly cause a scarcity in the sources of drinking water [1]. Our understanding of environmental development suggests the need to construct an effective and viable infrastructure to protect the ecosystem and public health. Therefore, it is essential to manage waste control and provide better water resource management.

In Malaysia, 97% of the water supply comes from surface water, and the rest comes from groundwater. In 2012, the Malaysian Department of Statistics [2] stated that the major sources of pollution come from improper discharge from sewage treatment plants, agro-based industry, livestock farming, land-clearing activities, and domestic sewage. Urban sewage systems in Malaysia, especially in the state of Sarawak, are poor and deteriorating. Wastewater from domestic and commercial areas is channelled into septic tanks before being discharged to perimeter drains. However, desludging of the septic tanks is often not carried out. Overflowing sewage from septic tanks pollutes waterways. However, constructing a wastewater treatment facility is costly and the benefits are often ambiguous.

Stakeholders and engineers are trying to find solutions that will satisfy both environmental and economic criteria [3]. The State Government of Sarawak has placed a heavy emphasis on sustainable development of wastewater management. In 2005, a septic sludge treatment plant (SSTP) using sequence batch-reactor technology was constructed to treat the septic sludge. The treatment plant began its operations in 2007 when the desludging by-laws were gazetted. Thus, effluent removal from the treatment plant needs to be monitored and controlled in order to achieve the required standards.

This study proposes a new model that utilises a biomimetics engineering approach. Our model can be used by government agencies, local authorities, technical consultants, and contractors in monitoring the SSTP effluent removal.

1.1 Septic Sludge Treatment Plant

The SSTP process can be characterised as a multi-input process. As highlighted by Nielson and Hauschild in 1998 [4], the process is difficult due to the non-linear relationship between the input fraction and the pollution emissions. In addition, constructing a treatment plant is expensive an calibration of SSTP modelling is particularly challenging because of the biology involved. However, the modelling and simulation of an SSTP is valuable [5], especially in forensic analysis. Currently, the use of an activated sludge-model approach is used both in both industry and academia [6][7]. As such, forensic analysis is used to ascertain the characteristic of the current treatment plant so it can be a reference for future SSTP development.

In effluent-removal-model development, INA is applied to reduce redundancy as well as on the input fraction of the data structure [8]. The immune network theory was introduced by Jerne (1974) [9], and the idea has been developed further [10][11][12]. In this study, the effluent removal from the SSTP is predicted using INA.

2.0 Materials and Methods

The forensic analysis for an SSTP was undertaken to assess its compliance with the discharge standards and monitoring requirements for Malaysia's regulation. Although the current SSTP situation satisfies the standards imposed, the current processes need to be closely monitored to ensure that the SSTP development will not significantly increase environmental and public health risks in Kuching. As the study carried out by Ye, Luo, and Xu (2009) [13] showed, effluent quality is the most important criterion of a wastewater treatment plant. In this study, an INA-based SSTP was developed to investigate the compliance of effluent discharge to the standards and monitoring requirements. In light of this previous study, the required monthly effluent samples [14] were collected at the Matang SSTP from 2007 to 2011 by an in-house laboratory.

2.1 Study Area

Sarawak is located on the northwestern part of the island of Borneo (Fig. 1). Kuching is the capital city of Sarawak and it is administered by two distinct entities: a local authority (City Council) and a state government statutory body granted a city hall status. The city is divided into North and South Kuching by the Sarawak River.

In 2010, the total population in Kuching was 617, 887 and that number is projected to increase 35% by the year 2040 [15]. With such a fast-growing city, a clean water supply and efficient wastewater management are necessary. To date, there are about 70,000 septic tanks throughout Kuching. With the stringent requirements imposed by the Malaysia Environmental Quality Act of 1974 and the Environmental Quality (Sewage) Regulation of 2009, septic sludge must be treated before being discharged into the waterways.

In light of these laws, the Local Authority (Compulsory Desludging of Septic Tanks) By-Laws of 1998 were put into effect. The Matang SSTP was built on the upstream tributary of the Sarawak River where effluent was discharged into the river that enters the capital city (Fig. 1). Therefore, forecasting effluent removal from the treatment plant is essential in preserving the ecosystem. This study further confirms that the new infrastructures must be designed to an appropriate standard that would be resilient within urban development.

2.2 Immune Network Algorithms (INA) Prediction Analysis Development

We conducted a prediction study to identify the effectiveness of the designed treatment plant, Matang SSTP. Effluent discharge from the treatment plant was monitored and controlled to achieve the required standards. This study was performed based on a quantitative process using statistical analysis to mimic the end results obtained by an actual SSTP scenario. Collected effluent parameters such as biological oxygen demand (BOD), chemical oxygen demand (COD), and total suspended solid (TSS) were analysed to identify the current performance of the treatment plant.

The efficiency of the post-effluent discharge analysis and management technique depends upon the successful integration of scientific knowledge, data, analysis, risk assessment, and management ideals [16]. In this study, the proposed model could be used to gauge effluent discharge in the future.

This study carried up using self-written pseudocode tailored specifically for the study area with MATLAB 7.10. The proposed algorithm is summarized as follows:

Initialization: Create an initial random set of network antibodies, N
For all patterns in a set of patterns to be recognised, S, do:

1. *Determine the affinity with each antibody in N*
2. *Generate clones of a subset of antibodies in N with the highest affinity that is proportional to its affinity*
3. *Mutate each clone inversely proportional to the affinity as set A, the number of new antibodies established, and the number of highest-affinity clones introduced into a clonal memory set C*
4. *Eliminate all elements of C whose affinity with the antigen is less than a pre-defined threshold*
5. *Incorporate the remaining clones of C into N*
6. *Determine the affinity between each pair of antibodies in N*
7. *Eliminate all antibodies whose affinity is less than the threshold of the network affinity threshold*
8. *Finally, introduce a random number of randomly generated antibodies and place into N.*

These steps will be described in detail as follows:
In Initialization, a random network is created. Antibody is represented by C and receives as input a set of antigens, Ag in the immune network (BOD, COD and TSS). Each antigenic pattern is represented by the following functions:

$$C = [Ab_1, Ab_2, \ldots Ab_n] \quad \text{(Equation 1)}$$

$$Ag = [Ag_1, Ag_2, \ldots Ag_n] \quad \text{(Equation 2)}$$

The affinity is determined using Equation 3 and the n highest affinity antibodies is selected. In CSA principal, the affinity is determined through shape-space concept using real-valued coordinates to measure the distance in the form of Euclidean shape-spaces. The affinity D between an antigen and antibody is identified through Euclidean distance (Equation 3) which indicates the distance between the molecules. From the interaction between the two attribute strings into a nonnegative real number that corresponds to their affinity or degree of match, $S^L \times S^L \rightarrow R^+$.

$$D = \sqrt{\sum_{i=1}^{L} (Ab_i - Ag_i)^2} \quad \text{(Equation 3)}$$

Next, the *n* selected antibodies is going to proliferate (clone) and proportionally to their antigenic affinity generating a set A of clones through the following employed equation:

$$N_c = \sum_{i=1}^{n} round\,(Ab_i - D.Ab_i) \quad \text{(Equation 4)}$$

where N_c is the total clone size generated for each of the antigens

The set A is submitted to a directed maturation process. In the clonal suppression, those memory clones that are less than the threshold are eliminated. In suppression stage, cell similarity mechanism for reducing redundancy.

In the mutation stage, the network, C generates antibodies with higher affinities and enhances the population according to the following equations:

$$C^* = C + \alpha N(0, \sigma) \quad \text{(Equation 5)}$$

$$\alpha = \left(\frac{1}{\beta}\right) e^{(-aff)} \quad \text{(Equation 6)}$$

Where C^* is a mutated cell C, $N(0, \sigma)$ is a vector of independent Gaussian random variables of zero mean and standard deviation $\sigma = 1$, *aff* is the affinity of the antibody, which is normalized in the range [0 1], α is a factor that resizes the value of the Gaussian mutation and it is inversely proportional to the affinity. ρ is a parameter that controls the smoothness of the inverse exponential. β is the control parameter to adjust the mutation range. If C* exceeds the functions specified domain, then it is rejected and removed from the population.

Lastly, the network suppression removes any similar or non-stimulated antibodies and antibodies that fall below the pre-determined suppression threshold.

3.0 Results and Discussion

3.1 Simulation Results

In regards to the INA approach, the effluent discharge is presented in graphical comparisons using a box-and-whisker diagram to investigate the model's reliability. The proposed INA model is calculated through a root mean square error (RMSE) of the Matang SSTP with ten iterations at each detector in BOD, COD, and TSS effluent removal data from 2007 to 2009. From the training process, 200 detectors produced the lowest mean for BOD and 450 detectors for COD and TSS.

Effluent data that were trained were used in the validating and testing processes. The model validation and testing were performed to express the actual SSTP performance. The percentage of accuracy in the validation stage for COD, TSS, and COD are 92.56%, 94.90% and 92.90%, respectively. In the testing stage, COD was recorded at 90.00%, TSS at 88.87%, and 89.96% for BOD. The graphical results obtained from the proposed INA-based SSTP model is shown in Figs. 2, 3, and 4 for BOD, COD and TSS, respectively.

Performance indexes such as RMSE, mean absolute percentage error (MAPE), and correlation coefficient (R) were utilized in the modelling scenario [6]. Therefore, the indexes are further investigated in the INA-based SSTP model. BOD, COD, and TSS effluent removal recorded R^2 as 1. RMSE and MAPE for BOD are found to be 0.031 and 0.3397%, respectively (Fig. 5). COD is about 0.0638 and 0.5141% for RMSE and MAPE, respectively (Fig. 5). For TSS effluent, 0.0748 and 0.6025% are recorded for RMSE and MAPE, respectively (Fig. 5).

The proposed model underwent a cross-validation process in 2011 to obtain new antigens to create new immune networks for prediction purposes. This process further verified the model's improvement and development. The results are tabulated in Table 1. The simulated results were tested in 12 random trials to examine the reliability and performance of the proposed INA-based SSTP model.

On the other hand, to ensure that the SSTP comply with the Malaysia Environmental Quality Act of 1974 and the Environmental Quality (Sewage) Regulation of 2009, Sibu SSTP was tested in order to present SSTPs in Sarawak. Table 2 shows the accuracy of the prediction on both SSTPs. It is also found that the simulation was successfully tested on Sibu SSTP with the accuracy of the prediction were > 80%.

3.2 Effluent Removal Prediction

A new, randomly generated antibody system was used to predict the performance of the proposed INA-based SSTP model. General efficiency indicators of average BOD, COD, and TSS were applied to compare the overall performances of the treatment plant [17]. The results showed that the BOD effluent-discharge prediction was less than 50% of the specified standard after the 97th month (Fig. 6) of operation. The COD and TSS effluent prediction removal were simulated at the 85th (Fig. 7) and the 121st months (Fig. 8), respectively. As a result, this proposed model is found to be useful in: (1) identifying the post-effectiveness of the treatment plant, (2) developing an effluent-removal prediction tool in the treatment plant, and (3) inculcating forensic studies.

4.0 Conclusion

This study presents a forensic analysis framework for a septic sludge treatment plant and a case study on the development and utilisation of the framework for the city of Kuching, Sarawak. The study leads to the development of a novel approach in assessing forensic analysis of treatment plants. The concept of the artificial immune network was adopted and the simulated forensic assessment obtained showed that an effective monitoring method can be produced by developing the quantitative approach in the assessment process. The proposed INA-based SSTP model should be utilised by regulatory authorities for the assessment and management of treatment plants.

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Table 1. A Comparison of Cross-Validation of the Matang SSTP for BOD, COD, and TSS Effluents

No. of Trials	Immune Network Algorithm		
	Validation for BOD (Year 2011)	Validation for COD (Year 2011)	Validation for TSS (Year 2011)
	Average Forecasting Error	Average Forecasting Error	Average Forecasting Error
1	0.84	0.93	0.83
2	0.92	0.88	0.72
3	0.93	0.89	0.80
4	0.85	0.92	0.88
5	0.71	0.85	0.94
6	0.90	1.08	0.90
7	0.62	0.71	0.80
8	1.02	0.95	0.82
9	1.06	1.12	0.64
10	0.80	0.76	0.72
11	0.76	0.77	0.59
12	0.80	0.83	0.57
Average	0.85	0.89	0.77

Table 2. Comparison of predicted effluents removal for Matang and Sibu SSTPs

Effluent	Matang SSTP			Sibu SSTP		
	Sample	RMSE	Accuracy	Sample	RMSE	Accuracy
COD	12	0.834	90.00%	12	0.825	89.54%
TSS	12	0.927	88.87%	12	0.600	87.86%
BOD	12	0.836	89.96%	12	0.628	87.89%

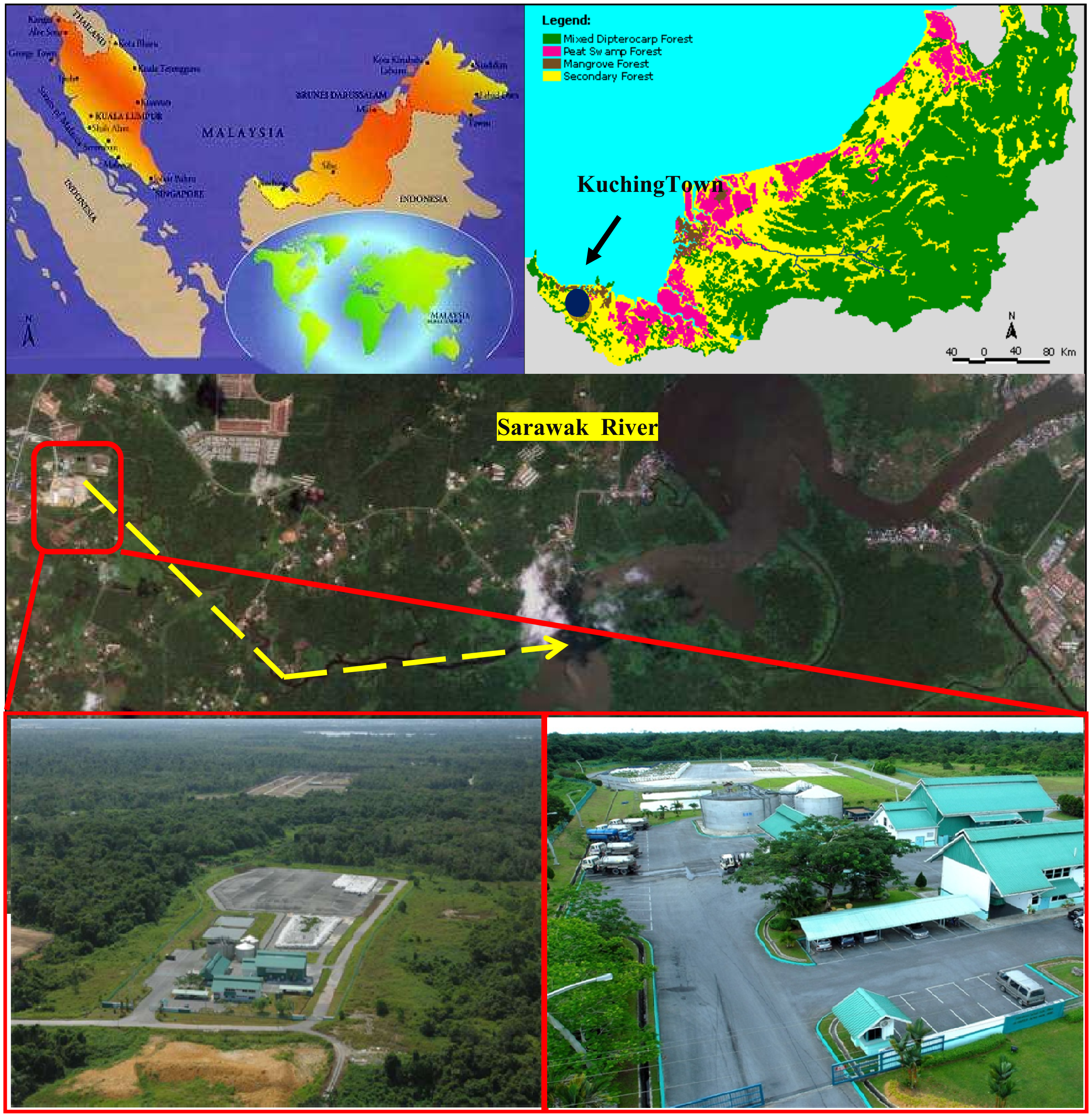

Fig. 1: Septic sludge treatment plant in Matang, Kuching, Sarawak.

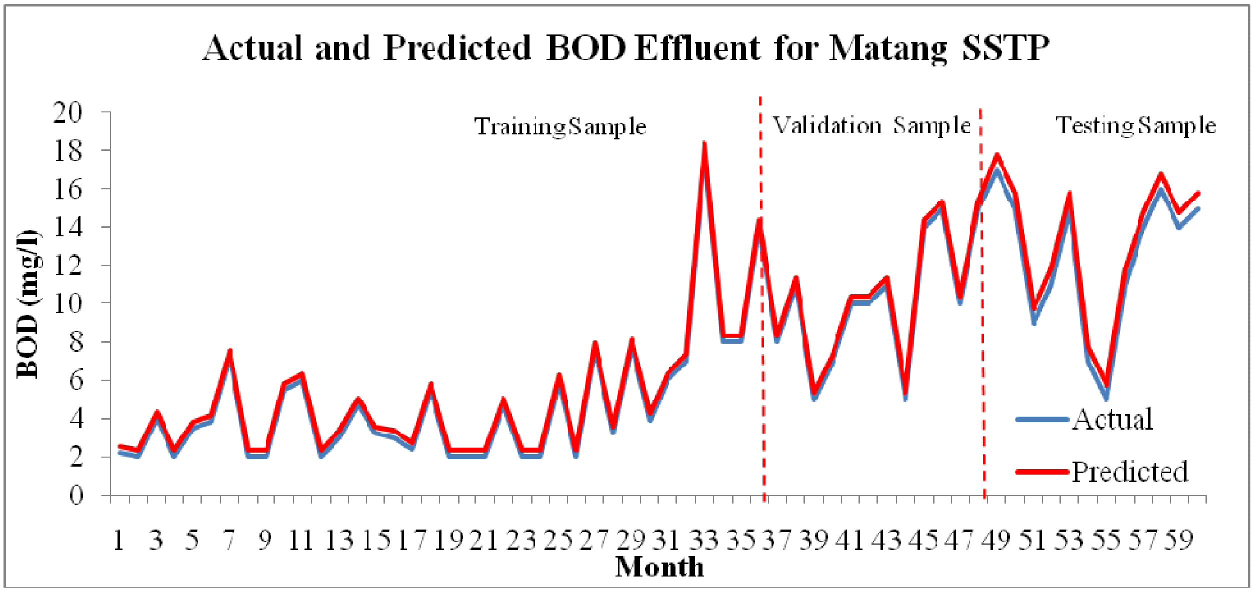

Fig. 2. Pattern recognition of the INA-based SSTP model for BOD effluent removal.

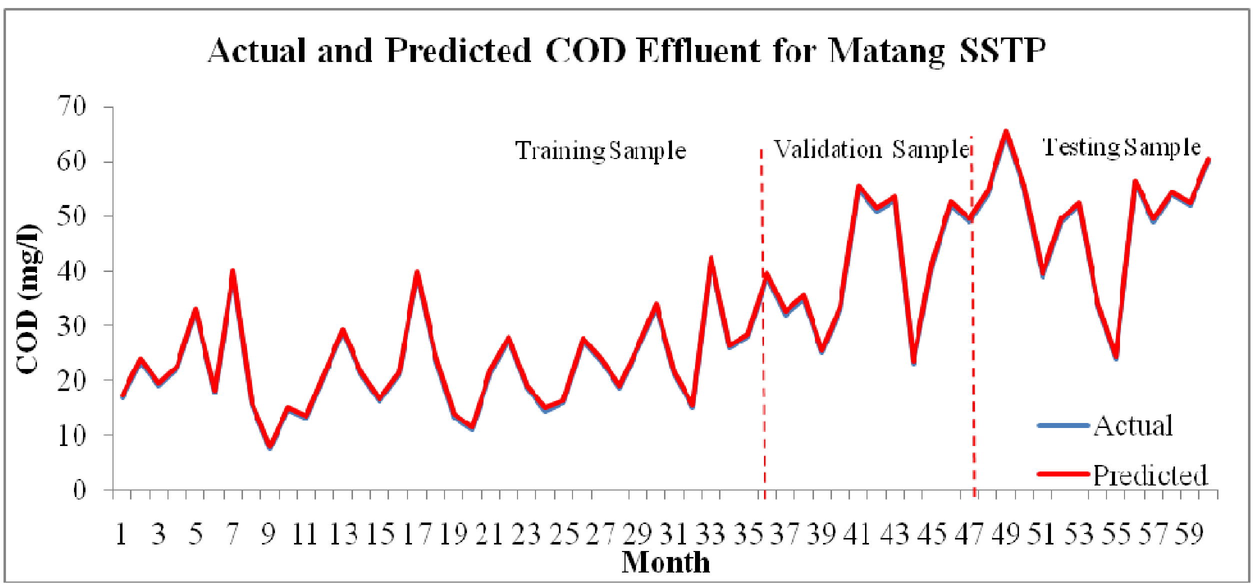

Fig. 3. Pattern recognition of the INA-based SSTP model for COD effluent removal.

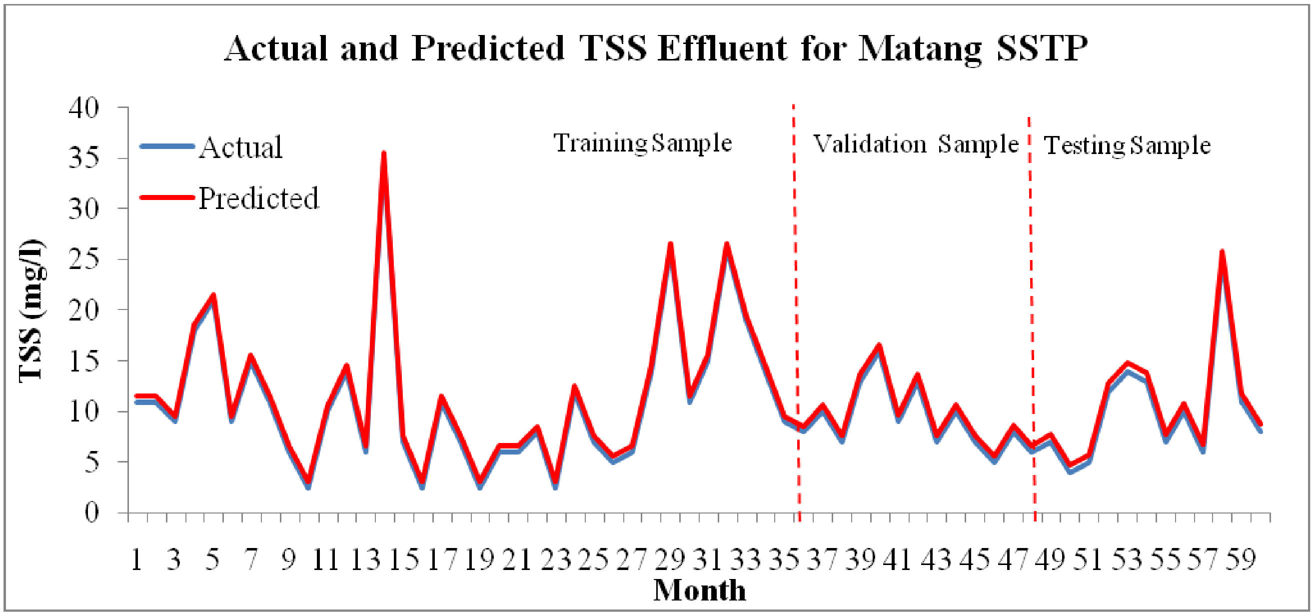

Fig.4. Pattern recognition of the INA-based SSTP model for TSS effluent removal.

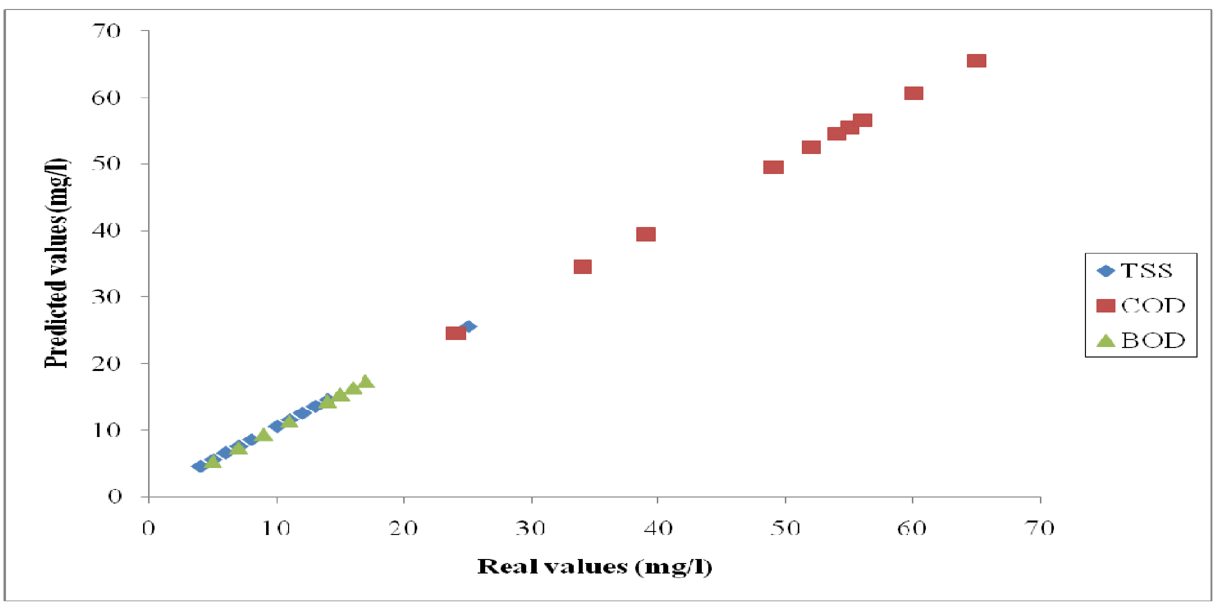

Fig. 5. Test performance of TSS, COD and BOD effluent using the proposed INA model.

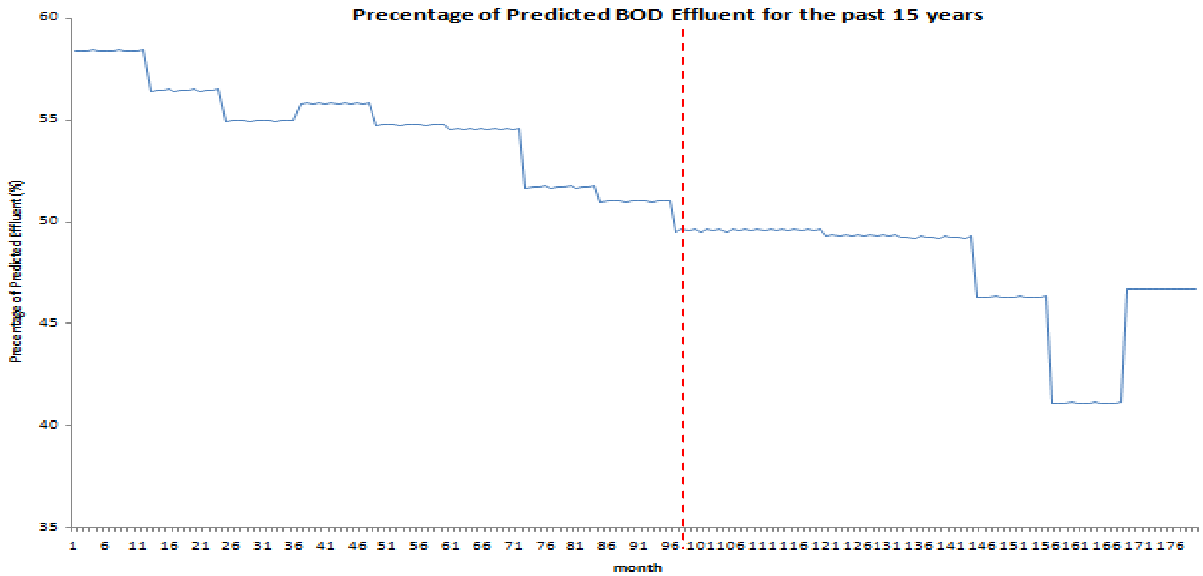

Fig. 6. BOD effluent prediction removal for the next 15 years.

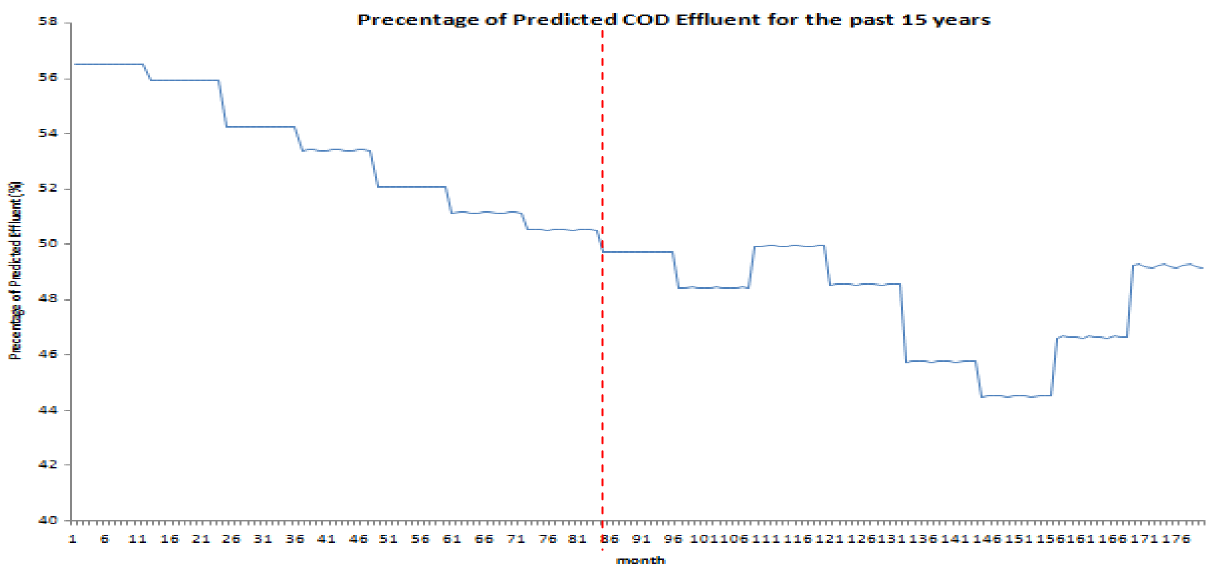

Fig. 7. COD effluent prediction removal for the next 15 years.

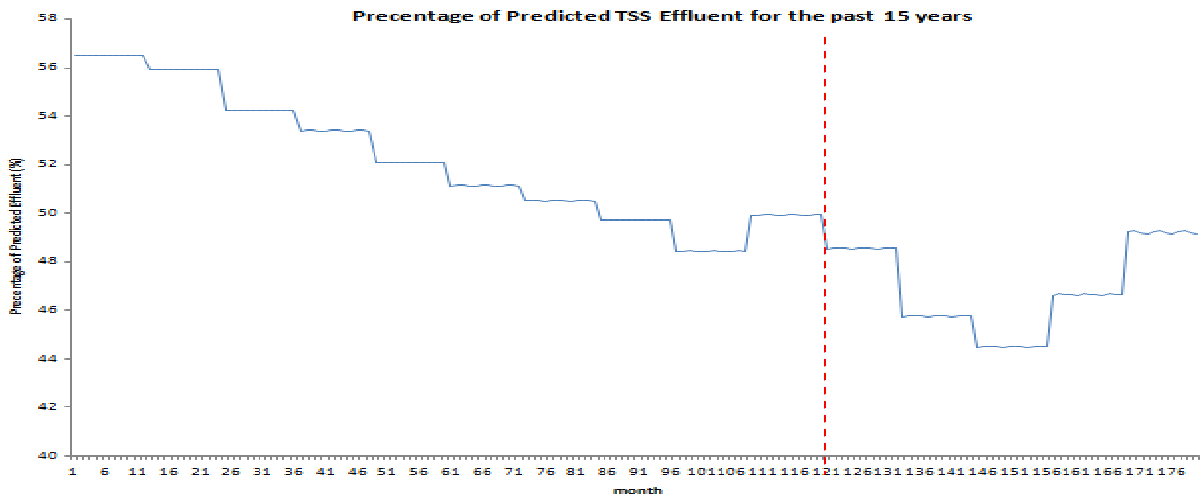

Fig. 8. TSS effluent prediction removal for the next 15 years.