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Predictive Analysis of Dengue Outbreak Based on an Improved Salp Swarm Algorithm

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Abstract**:** *The purpose of this study is to enhance the exploration capability of conventional Salp Swarm Algorithm* (*SSA*) *with the inducing of Levy Flight. With such modification, it will assist the SSA from trapping in local optimum. The proposed approach, which is later known as an improved SSA* (*iSSA*) *is employed in monthly dengue outbreak prediction. For that matter, monthly dataset of rainfall, humidity, temperature and number of dengue cases were employed, which render prediction information. The efficiency of the proposed algorithm is evaluated using Root Mean Square Error* (*RMSE*)*, and compared against the conventional SSA and Ant Colony Optimization* (*ACO*)*. The obtained results suggested that the iSSA was not only able to produce lower RMSE, but also capable to converge faster at lower rate as well.*

Keywords**:** *Dengue outbreak prediction, meta-heuristic, optimization, predictive analysis, Salp Swarm Algorithm, swarm intelligence.*

1. Introduction

Prediction issue is one of the fields that has been successfully addressed with the application of meta-heuristic based approach [1, 2]. The importance of prediction is inevitable, regardless of the problem at hand, and this includes finance [3-5], cloud computing [6, 7], electrical engineering [8], oil and gas engineering [9], and medical [10, 11] to name a few. By having accurate prediction, the obtained future values could assist in preparing proper precaution steps and prevention by the interested parties. Consequently, negative impact for certain problem such as loss of profit, excessive load, or increase in infectious disease cases which could lead to possibility of death can be avoided.

In infectious disease, a good number of researches can be found which critically discussed the efficiency of meta-heuristic based approach in dealing with the stated issue. In [10], Particle Swarm Optimization (PSO) was hybrid with Artificial Neural Network (ANN) for early detection of dengue disease. In the research, the employment of PSO was to optimize the values of ANN parameters. Later, with the obtained optimal values, the detection task was carried out by ANN. Findings of the study suggested that PSO-ANN was competent to produce better result compared to other identified approaches. Similarly in [12], a prediction model for dengue is presented based on hybrid Elman Levenberg Neural Network and Genetic Algorithm (GA). Realized on dengue data in Indonesia, the presented model demonstrated a positive performance for the case under study. Other than [12], the work in [13] also employed a hybrid model of GA and Neural Network based model. On the other hand, a study in [14] proposed four hybrid models of Grey Wolf Optimizer (GWO), Moth Flame Optimizer (MFO), Firefly Algorithm (FA) and Artificial Bee Colony (ABC) with Least Squares Support Vector Machines (LSSVM). The identified meta-heuristic algorithms, which were individually hybrid with LSSVM showed competitive results.

Other than dengue cases, recently, the prediction for Coronavirus disease (Covid19) which has been declared as pandemic can be found in [11]. In the presented study, an improved Flower Pollination Algorithm (FPA) based on Salp Swarm Algorithm (SSA) is hybrid with a modified Adaptive Neuro-Fuzzy Inference System (ANFIS). The presented work, which was tested on Covid19 data in USA and China showed good performances.

Even though numerous studies have been published concerning infectious disease prediction, the need to establish a reliable and efficient prediction model always exists, and this includes prediction model for dengue outbreak cases. According to [15], until today, there is no specific treatment offered for dengue fever, in fact, severe dengue disease could lead to dengue hemorrhagic fever, which is much riskier than dengue fever. It is worth noting that dengue is considered as the most widely distributed and rapidly spreading mosquito borne viral disease in the world and the number of incidences for dengue are continuously increasing which caught attention from many parties, including academic community [16, 17]. With respect to that matter, this study proposes a dengue outbreak prediction using a relatively new meta-heurictic alorithm namely Salp Swarm Algorithm (SSA) [18]. SSA is a relatively new meta-heuristic algorithm which has been successfully applied in various areas [19-21]. Nonetheless, the conventional SSA exposes to local optimum [22, 23] and prone to premature convergence [24, 19]. Such situation cannot be ignored since it would demote the prediction performance. Concerning that matter, this work introduces a modification to conventional SSA based on Levy Flight [25]. The modification takes place in exploration phase, which is belived to alleviate its demerits. Later, the proposed model, termed as iSSA is compared againts conventional SSA and Ant Colony Optimization (ACO) for monthly dengue outbreak prediction. Further discussion is provided in the next sections.

The rest of this paper is structured as follow: Sections 2 and 3 provide a description on SSA and Levy Flight respetively. Section 4 discusses the obtained result while the analysis if is gven in Secion 5. Finally, Section 6 concludes the performance of the proposed method and the results obtained.

2. Salp Swarm Algorithm

This section describes the nature of salps and mathematical model of SSA. Detail description of SSA can be found in [18].

2.1. Salps in nature

Salp Swarm Algorithm [18] is a relatively new SI based algorithm which was proposed in 2017. Like any other SI algorithms, SSA is inspired based on intelligent behaviours of animal/insects in nature, where in this case, it is referring to salps. In nature, salps belong to the family of Salpidae, which comes with transparent-barrel shaped physical. Study shows that salps possess similarity with jelly fish in terms of their tissue structure and movement pattern. One of the unique behaviour of salps is their swarming behaviour which forming a salp chain. Fig. 1 shows an example of salp chain.

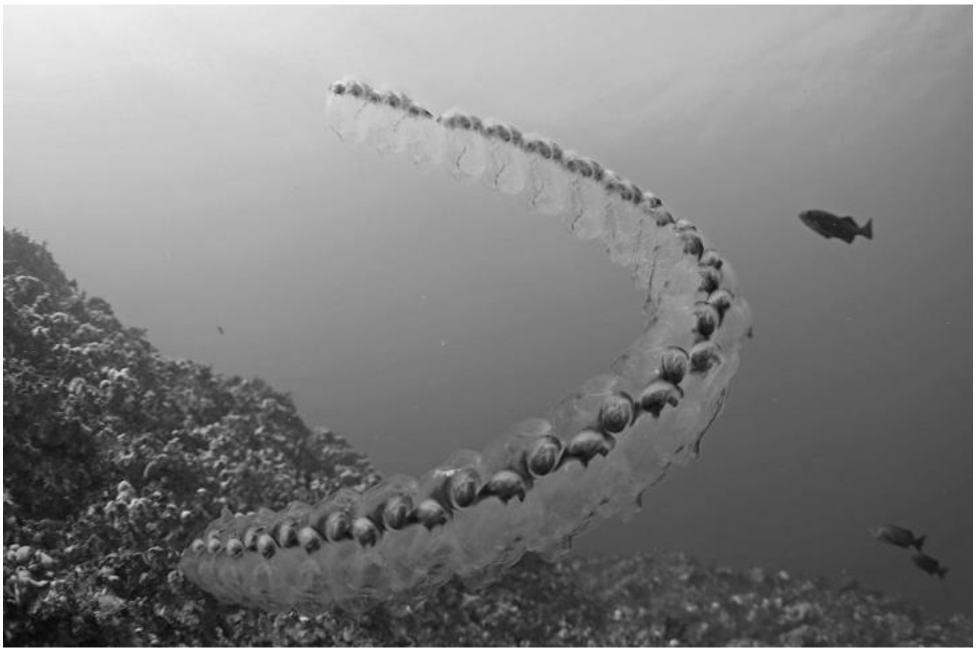

Fig. 1. An example of salp chain [26]

2.2. Mathematical model of SSA

During initialization stage, the salps population is splitted into two parts. The first part is incorporated of leader while the second part consists of followers. In the salp chain, the ones in the front line is designed as leader while the remaining are followers. The leader responsibles to guide the salp swarm while the followers follow each other (and leader directly or indirectly). It is worth noting that, in SSA, it only has one control parameter. The position of salps is defined in an *n*-dimensional space, where *n* is referring to the number of variables for the problem at hands,

$$x_j^i = \begin{cases} F_j + c_1\left[\left(\mathrm{ub}_j - \mathrm{lb}_j\right)c_2 + \mathrm{lb}\right] & c_3 \geq 0, \\ F_j - c_1\left[\left(\mathrm{ub}_j - \mathrm{lb}_j\right)c_2 + \mathrm{lb}\right] & c_3 < 0, \end{cases} \tag{1}$$

where:

x_j^i is the position of the first salp, i.e., the leader,

F_j is the food source position in the *j*-th dimension,

ub_j and lb_j are the **u**pper **b**ound and **l**ower **b**ound of *j*-th dimension, respectively,

c_1, c_2 and c_3 are the random numbers.

As defined in (1), x_j^i only updates its position with respect to the food source. Meanwhile, c_1 plays a vital role in balancing both exploitation and exploration processes. It is defined as

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2}, \tag{2}$$

where l and L indicate the current iteration and maximum number of iterations, respectively. Both c_2 and c_3 are random numbers uniformly generated in the interval of [0,1]. On the other hand, for followers, the position is updated as

$$x_j^i = \frac{1}{2}at^2 + v_0 t, \tag{3}$$

where:

$i \geq 2$,

x_j^i is the position of *i*-th follower salp in *j*-th dimension,

t is the time,

v_0 is the initial speed,

$a = \frac{v_{\mathrm{final}}}{v_0}$, where $v = \frac{x - x_0}{t}$.

In optimization, the time is iteration. Due to that matter, the discrepancy between iteration is equal to 1, and considering $v_0 = 0$, this is defined as

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}), \quad i \geq 2, \tag{4}$$

x_j^i is the position of *i*-th follower salp in *j*-th dimension.

The simulation on salp chain can be simulated using Equations (1)-(4).

The pseudo cod of SSA is shown in Fig. 2.

```
Start
Initialize the salp population x_i (i=1, 2, …, n), considering ub and lb
While (end condition is not satisfied)
Calculate fitness function of each agent (salp)
F=the best search agent
Update c_i using (2)
    for x_i (each salp)
        if(i==1)
            Update the position of the leading salp by (1)
        else
            Update the position of the follower salp by (4)
        end
    end
Update the salps based on ub and lb
Return F
```

Fig. 2. SSA pseudo code

3. Levy Flight

The inducing of Levy Flight (LF) [25] to alleviate meta-heuristic algorithms is well-known with its outstanding outcomes [27-29]. Mainly, the merits of LF depends on its variable namely β where different values of β will provide different random distribution. This unique characteristic leads to outstanding searching behaviour since it will lead to wider searching space, hence the incident of revisiting the similar location can be reduced. Fig. 3 shows pseudo code of LF that is implemented in this study.

```
Input function Min f(x) and β
Select x_i in swarm that will modify the position
Initialize τ = 1 and σ_h = 1
Compute c_u with equation (1)
While (τ < ∈)
        Compute step_size with equation (2)
        Generate new solution x_i' with (3)
        Calculate f( x_i' ) then
        x_i = x_i'
        End if
        τ = τ +1
End
```

Fig. 3. Pseudo code of Levy Flight

(5) $$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\beta\Gamma\left[(1+\beta)/2\right]2^{\beta-1)/2}} \right\},$$

(6) $$\text{step\_size}(\tau) = 0.01 \times s(\tau),$$

(7) $$x_{ij}^{'}(\tau+1)=x_{ij}(\tau)+\text{step\_size}(\tau)\times U(0,1)\ .$$

The step size by using Levy distribution of search area is calculated as in (5). Factor of 0.01 is $L/100$, where L is typical length scale. In (6) where x_{ij} is individual that will modify the position, $U(0, 1)$ is a random number between [0, 1] range and step_size(τ)×U(0, 1) is the random walk from Levy distribution. In this study, the LF is applied to improve the exploration capability of SSA, which consequently lead to global optimum. This is the benefit from the remarkable performance of LF which is able to provide larger step length, i.e., better searching compared to Gaussian process [30].

4. Methodology

The implemented methodology incorporating data collection and pre-processing, experiment setup and evaluation. Fig. 4 shows the simplified form of the proposed methodology.

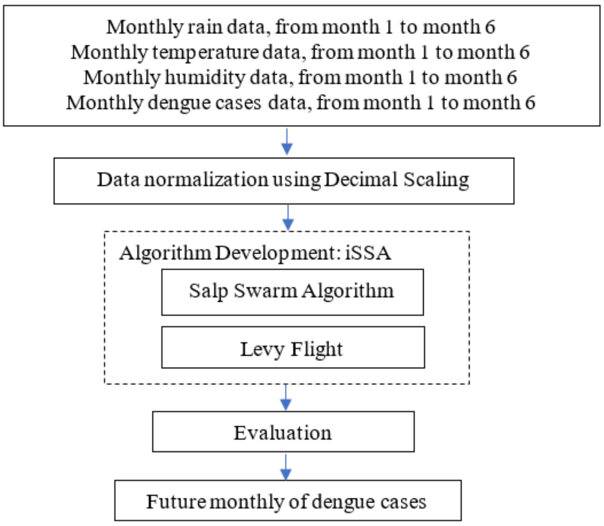

Fig. 4. Schematic of the proposed iSSA for dengue outbreak prediction

4.1. Introducing the dataset

The performance of iSSA was tested on dengue dataset, which is obtained from [31]. Besides the number of dengue incidence data, the data set also consist of three meteorological data which include cumulative rainfall (mm), mean temperature readings (°C), and mean relative humidity (%). These data sets are defined in monthly periodicity, from 2001-2013. From the downloaded data set, several missing values were identified. For that matter, the values were replaced with the average value of before and after the respective row. Table 1 shows the sample of original data recorded in 2013.

Table 1. Sample of original data

Month	Rain	Temperature	Humidity	Dengue cases
January 2012	295.00	26.00	83.00	16
February 2012	388.00	26.00	83.00	39
March 2012	321.00	26.45	87.00	29
April 2012	247.00	26.68	87.00	44
May 2012	63.00	26.79	87.50	42
June 2012	4.00	26.84	87.75	36
July 2012	0.00	26.87	88.38	24
August 2012	33.50	26.89	87.69	16
September 2012	50.25	26.89	87.34	14
October 2012	67.00	26.90	88.17	25
November 2012	222.00	26.90	87.00	25
Dcember 2012	407.00	26.60	88.00	64

4.2. Data normalization

Prior to training the inputs, all input and output values were normalized using Decimal Scaling,

(8) $$\upsilon' = (\upsilon/10^j),$$

where:

υ' is the new value of parameter,

υ is the old value,

j is the smallest integer where Max($|\upsilon'|$)<1. The sample of normalized data is tabulated in Table 2.

The normalized input for sample in Table 1 is as tabulated in Table 2.

Table 2. Sample of normalized data

Month	Rain	Temperature	Humidity	Dengue cases
January 2012	0.2950	0.2600	0.8300	0.0160
February 2012	0.3880	0.2600	0.8300	0.0390
March 2012	0.3210	0.2645	0.8700	0.0290
April 2012	0.2470	0.2668	0.8700	0.0440
May 2012	0.0630	0.2679	0.8750	0.0420
June 2012	0.0040	0.2684	0.8775	0.0360
July 2012	0.0000	0.2687	0.8838	0.0240
August 2012	0.0335	0.2689	0.8769	0.0160
September 2012	0.0502	0.2689	0.8734	0.0140
October 2012	0.0670	0.2690	0.8817	0.0250
November 2012	0.2220	0.2690	0.8700	0.0250
December 2012	0.4070	0.2660	0.8800	0.0640

4.3. Experiment structure

This section consists of five sub-sections namely the arrangement of input and output in the iSSA prediction model, data division for training, validation and testing, mathematical model of iSSA, the iSSA prediction model and finally evaluation.

4.3.1. Input-output setup

The input and output variables employed in this study are shown in Table 3 which incorporated of monthly data of rain, temperature, humidity and number of dengue cases. In addition, the derivation of the stated inputs is fed to the prediction model as well.

Table 3. Input and outputs

Input	Variable	Output
Monthly rain data, from month 1 to month 5	rain_m1, rain_m2, rain_m3, rain_m4, rain_m5	Number of dengue cases, from month 6 and onwards, dcases_m6owd
Monthly temperature data, from month 1 to month 5	temp_m1, temp_m2, temp_m3, temp_m4, temp_m5	
Monthly humidity data, from month 1 to month 5	hmdt_m1, hmdt_m2, hmdt_m3, hmdt_m4, hmdt_m5	
Monthly dengue cases number, from month 1 to month 5	dcases_m1, dcases_m2, dcases_m3, dcases_m4, dcases_m5	

4.3.2. Data division: Training, validation and testing

From the employed data, the data is divided into three sets, as described in Table 4.

Table 4. Training, validation and testing

Set	Data arrangement description	Proportion (%)
Training	1-105	70
Validation	106-129	15
Testing	130-151	15

4.3.3. Improved Salp Swarm Algorithm

Similarly like any other meta-heuristic algorithms, SSA consists of exploitation and exploration phases, where both complement with each other in achieving global optimum. Therefore, it is vital for any meta heuristic algorithm to achieve a stability between both phases. In exploitation phase, the objective is to intensify the search in various areas of the increased search experience while in exploration the aim is to identify high quality solution through fragments of the search space.

In this study, an improvement to conventional SSA is introduced, where the objective is to enhance the exploration feature of SSA, hence better optimization performance can be obtained. For that matter, the advantage of Levy Distribution is benefited, which not only leads to better prediction performance but improves the convergence ability as well.

From (1), it is modified by inducing Levy Flight, as

$$x_j^i = \begin{cases} F_j + c_1\left[\left(\mathrm{ub}_j - \mathrm{lb}_j\right)\mathrm{Lv} + \mathrm{lb}_j\right], & c_3 \geq 0, \\ F_j - c_1\left[\left(\mathrm{ub}_j - \mathrm{lb}_j\right)\mathrm{Lv} + \mathrm{lb}_j\right], & c_3 < 0, \end{cases} \tag{9}$$

where:

x_j^i is the position of the first salp, i.e., the leader,

F_j is the food source position in the *j*-th dimension,

ub_j and lb_j are the upper and lower bound of j-th dimension, respectively,

c_1, c_3 are the random numbers,

Lv are the random values generated based on Levy Flight.

The pseudo code of iSSA is given in Fig. 5. The bold line indicates the proposed modification.

```
Start
Initialize the salp population x_i (i=1, 2, ..., n), considering ub and lb
While (end condition is not satisfied)
Calculate fitness function of each agent (salp)
F=the best search agent
Update c_i using (2)
    for x_i (each salp)
        if(i==1)
            Update the position of the leading salp by (9)
        else
            Update the position of the follower salp by (4)
        end
    end
Update the salps based on ub and lb
Return F
```

Fig. 5. Pseudo code of iSSA

4.3.4. iSSA prediction model

In this study, iSSA algorithm will be used as an estimator of parameters for dengue outbreak prediction. The inputs consist of humidity (hmdt), temperature (temp), rainfall (rain) and the dengue incidence number (dcases), in monthly frequency. Besides, the derivation of the stated inputs until month 6 are fed to the prediction model as well. Meanwhile, the output is the dengue cases from month 6 and onwards. The input and output configuration are defined as

$$\begin{aligned} \text{d\_casesm6owd} = {} & (x_1 * \text{rain\_m1}) + \ldots + (x_6 * \text{temp\_m1}) + \ldots + \\ & +(x_{11} * \text{hmdt\_m1}) + \ldots (x_{16} * \text{dcases\_m1}) + \ldots + x_{21}, \end{aligned} \tag{10}$$

where:

d_casesm6owd are the dengue cases from month 6 and onwards;

$x_1, x_2, \ldots, x_{21}$ is the coefficient to the respective employed variables;

m1, m2, ..., m5 – the month 1 to month 5;

x_{25} – constant.

4.3.5. Evaluation

To evaluate the efficiency of the proposed iSSA, two evaluation metrics were utilized namely Root Mean Square Error (RMSE). Both metrics are defined as

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y(x_n) - y_n)^2}{n}}\ , \tag{11}$$

where:

$n = 1, 2, \ldots, N$,
y_n are the target values,
$y(x_n)$ are the predict values,
N is the total number of tests.

The lowest value of RMSE refers to the best method. Upon the prediction task, the normalized data using (8) (see Section 4.2) are denormalized back, based on the reverse of (8). This is important to ensure all evaluations are calculated based on original scale of the data.

5. Results

This section discusses the prediction performance recorded by iSSA and the identified algorithms namely SSA and ACO. In this study, the maximum iteration is set to 300, while the optimized values for parameters of interest produced by iSSA, SSA and ACO are as tabulated in Table 5. Based on the Table 6, the RMSE produced by iSSA is 3.45, which is far smaller compared to SSA which recorded 28.46 of MSE. Meanwhile, ACO yielded 12.6 of RMSE, which is the largest compared to iSSA and SSA.

Table 5. Optimized parameters of interest for iSSA, SSA and ACO

Parameters	iSSA	SSA	ACO
x_1	0.0120	0.0070	0.4533
x_2	0.0105	0.0093	0.6392
x_3	0.0099	0.0156	0.4568
x_4	0.0295	0.0303	0.4571
x_5	0.0230	0.0069	0.4408
x_6	0.0157	0.0144	0.5190
x_7	0.0134	0.0103	0.6570
x_8	0.0075	0.0082	0.4052
x_9	0.0166	0.0156	0.5210
x_{10}	0.0073	0.0176	0.5470
x_{11}	0.0025	0.0091	0.4700
x_{12}	0.0030	0.0244	0.4767
x_{13}	0.0038	0.0207	0.4301
x_{14}	0.0271	0.0174	0.5556
x_{15}	0.0116	0.0163	0.6586
x_{16}	0.0038	0.01963	0.5010
x_{17}	0.0117	0.0165	0.5140
x_{18}	0.0119	0.0047	0.6028
x_{19}	0.0209	0.0147	0.3680
x_{20}	0.0040	0.0122	0.4127
x_{21}	0.0140	0.0104	0.5655

Table 6. Comparison of iSSA vs SSA vs ACO for dengue outbreak prediction

Algorithm	iSSA	SSA	ACO
RMSE	**3.45**	28.46	12.6

The iSSA not only able to produce lowest RMSE of prediction rate, but the proposed iSSA is also competitive to converge faster (see Fig. 6) with lowest value, which is 6.5325 compared to SSA and ACO which recorded 7.8592 and 21.0380 respectively (see Fig. 7). The obtained results are further discussed in Section 6.

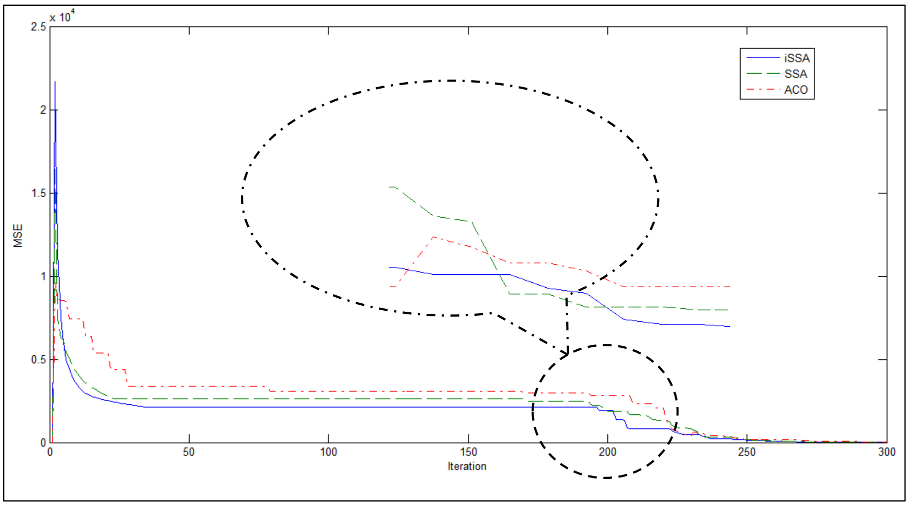

Fig. 6. Comparison of convergence value for iSSA vs SSA vs ACO

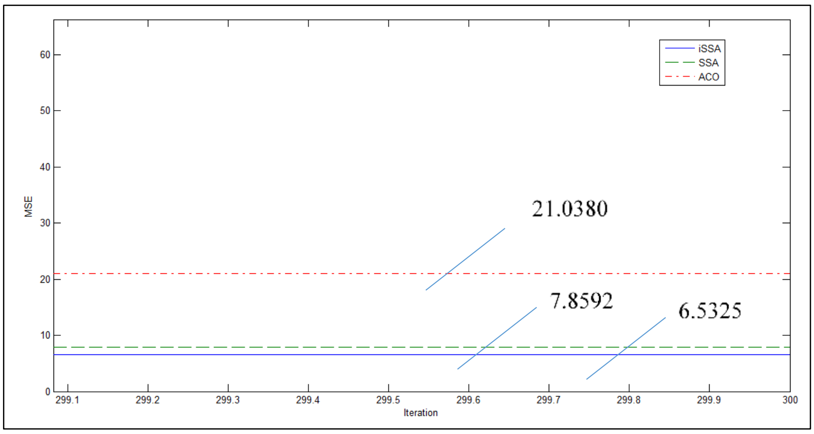

Fig. 7. Close-up of convergence value comparison: iSSA vs SSA vs ACO

6. Discussion

Based on the produced results by iSSA (see Section 5), the induced of Levy Flight to the conventional SSA has assisted the algorithm to have larger step length, which finally assist the algorithm from escaping the local optimum, hence optimal values for parameters of interest can be produced. With such feature, better prediction result can be obtained. The implementation of Levy Flight not only contribute in prediction task, but also significantly prove the convergence rate achieved by the iSSA, both in speed and value. With this capability, the algorithm possesses a great the feature of avoiding local optimum.

7. Conclusion

In this study, an improved SSA based on Levy Flight is proposed, which is later known as iSSA, for monthly dengue outbreak prediction. The aim of inducing the Levy Flight to the SSA is to build up the exploration of SSA, hence global optimum can be obtained. The prediction model was fed with four variables which influence the occurrence of dengue cases namely, rainfall, temperature, humidity and the number of dengue incidence as well. For comparison purposes, the prediction performance of iSSA was compared against SSA and ACO, and guided by RMSE. Findings of the study suggested that the iSSA was not only able to produce lower RMSE, but also capable to converge faster with lower value. In the future, the study on the dengue outbreak prediction will be extended by referring to the methods applied in [32, 33, 34, 35].

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