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Article

Introducing a Novel Double Hybrid Algorithm (DHA) and Developing Its Application for Predicting Air Temperature Under Climate Change Conditions (A Case Study of Iran Country)

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Abstract. In the present study, a novel double hybrid algorithm (DHA) based on the least squares support vector machine (LSSVM) and hybrid Aquila optimization-particle swarm optimization (AO-PSO) algorithms, namely LSSVM-AO-PSO for minimum, mean, and maximum monthly air temperature (AT) prediction under climate change for periods (2020-2047) at 30 meteorological stations in Iran is presented. For this purpose, first, four benchmark data sets (BDSs) are used to prove the performance of the DHA. Then, modeling of minimum, mean and maximum AT in different time delays are performed, and the best time delay is selected. The technique for order of preference by similarity to the ideal solution (TOPSIS) method showed reasonable results of the DHA compared to LSSVM, LSSVM-PSO, and LSSVM-AO in modeling AT (in the best time delay). Results of changes in AT parameters under two models, ACCESS-ESM1 and CanESM5 global climate models (GCMs), and SSP scenarios in the future period (2020-2047) showed that AT was increased in all regions of Iran in a pessimistic state, and in an optimistic state were decreased in the northeast of Iran and were increased in other regions.

Keywords: Double hybrid algorithm, new hybrid algorithm, air temperature, climate change, LSSVM, AO algorithm.

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1. Introduction

AT is a primary descriptor of terrestrial environment conditions all over the Earth [1]. AT is the main input in modeling various essential parameters such as evapotranspiration, solar irradiance, runoff, groundwater level, water quality, and wind speed. Conversely, climate change and consequently global warming have recently drawn scientists' attention since it has effects on the rise in AT, growth of extreme events, and global warming, ultimately negatively impacting humans' lives [2],[3].

In past years, different methods have been used for modeling AT. For example, Carson (1963) [4] applied the Fourier technique to analyze and predict AT. In AT estimating, Hipel et al. (1977) [5] used autoregressive, Prihodko and Goward (1997) [6] employed remote sensing, and Blennow (1998) [7] used multiple linear regression. Mihalakakou et al. (1998) [8] modeled AT using artificial neural networks (ANNs), and the results showed that ANNs were significantly better than the autoregressive model. Radhika and Shashi (2009) [9] applied a support vector machine to modeling AT, and the results indicated more support vector machine (SVM) accuracy than ANNs. Salcedo-Sanz et al. (2016) [10] employed ANNs and SVM to estimate AT in Australia and New Zealand, indicating SVM's superiority. Zeng et al. (2021) [11] used random forest (RF) to assess the 8-day and daily maximum and minimum AT, which showed that RF has reasonable accuracy. However, in the mentioned studies prediction of AT under climate change conditions was not considered. While changes in AT in the future period can have negative and positive impacts on the development of agriculture and energy production of countries. Hence, different studies have been conducted in this regard. Nematchoua et al. (2022) [12] employed a linear model (LM), decision tree (DT), SVM, deep learning (DL), RF, and, gradient-boosted trees (GBT) to predict AT of 27 European countries under RCP scenarios. Ghanim and Farhan (2023) [13] investigate the impacts of change AT on change photovoltaic energy potential. In this study, the change of AT was projected based on RCP scenarios. Due to the high importance of AT predicting under climate change conditions, it is important that new and powerful algorithms were used in this regard.

Machine learning (ML) algorithms are among the most accurate algorithms in this field. A suitable selection of hyperparameters can improve these algorithms' final accuracy in modeling using ML algorithms. However, there is no specific method for selecting them in almost conditions. Hence, in recent years optimization algorithms have been used for determining optimal hyperparameters of ML algorithms. Azad et al. (2019) [14] used a hybrid of adaptive neural fuzzy inference system (ANFIS) with genetic algorithm (GA) and particle swarm optimization algorithms (PSO) for modeling minimum, mean and maximum AT, which ANFIS-GA selected as a suitable algorithm. Azad et al. (2020) [15] used GA, PSO, ant colony optimization for continuous domains (ACOR), and differential evolution (DE) for optimal selection of the hyperparameters of ANFIS in modeling AT. The results showed that a hybrid of ANFIS and GA performs better than other algorithms. Farzin et al. (2020) [16] applied the firefly algorithm (FFA) to optimize LSSVM modeling Westwater quality. Results illustrated better accuracy of the hybrid algorithm than ANN, ANFIS, and LSSVM. Mehdizadeh et al. (2020) [17] developed two algorithms, including a hybrid of the Elman neural network (ENN) with a gravitational search algorithm (GSA) and ant colony optimization (ACO) for soil temperature modeling. Results showed that hybrid algorithms improved the accuracy of the standalone algorithm. Anaraki et al. (2021) [18] employed a hybrid of LSSVM and whale optimization algorithm (WOA) for downscaling temperature. Results indicated improving the performance of LSSVM by using WOA. Jamei et al. (2022) [19] employed a hybrid of LSSVM and improved simulated annealing (ISA) for estimating daily global solar radiation. Results showed better performance of mentioned algorithms than multivariate adaptive regression spline (MARS), generalization regression neural network (GRNN), and multivariate linear regression with interactions (MLR). Achite et al. (2022) [20] employed goril troops optimizer for optimizing the M5 algorithm. Results indicate reasonable accuracy of this algorithm in finding optimal parameters of M5.

On the other hand, each optimization algorithm has its strengths and disadvantages [21]. By hybridizing two optimization algorithms, the disadvantages of each algorithm are covered by the strengths of the other algorithm. Therefore, hybrid optimization algorithms can determine machine learning algorithm parameters with more accuracy. Rajabi et al. (2021) [22] employed hybrid of GA and PSO with multiple extreme learning machines (MELM-PSO-GA) for prediction of fracture density. The results indicated that ELM-PSO-GA performed better than standalone MELM, MELM-PSO and MELM-GA. Açıkkar and Altunkol (2023) [23] used a hybrid of PSO and grid search (GS) for tuning SVR parameters. According to the results of this study, in terms of accuracy and speed, PSOGS-SVR was compatible with PSO-SVR and GS-SVR. In the conducted study by (Chaudhari et al. 2024) [24], the hybrid of PSO and Gravitational Search Algorithm (GSA) was used for training enhanced Neural Networks (NN) in the data clustering. Results showed optimal clustering with 71% improved computational time.

Predicting AT under climate change conditions requires accurate algorithms, such as hybrid algorithms. Double hybrid algorithms (DHAs) are a novel hybridization approach for modeling and predicting problems. In this approach, a hybrid of two optimization algorithms determines the parameters of a machine learning algorithm. This increases the speed of machine learning parameter tuning and leads to more accurate problem solving. Although some studies have used DHAs for regression problems. These studies are restricted to using only classical optimization algorithms. Moreover, a literature review indicates that there have been no reports of the use of DHAs in modeling and predicting AT under climate change scenarios. Therefore, for the first time in this study, a novel DHA is proposed using the LSSVM and integrating the AO and PSO algorithms (LSSVM-AO-PSO). The PSO has strong global optimization power and weak local optimization power. While the AO algorithm has strong local and weaker global optimization abilities. By hybridizing these two algorithms, PSO solves the global optimization problem of AO, and AO increases the power of the local optimization of PSO. Furthermore, the hybrid of a PSO and AO with the LSSVM can increase the accuracy and speed of problem-solving compared to simple hybrid algorithms. First, several BDSs will be used to test the performance of the DHA and compare it to LSSVM, LSSVM-PSO, and LSSVM-AO. After comparing the algorithms in BDSs modeling and proving the performance of the DHA, the minimum, mean, and maximum AT modeling will be done in 30 stations in Iran with different climatic conditions with time delays of several months. After selecting the best time delays, the TOPSIS method ranks the algorithms and proves the performance of the novel algorithm. Finally, DHA will predict AT variations in the future period (2020-2047). In this regard, the GCMs and climate-shared socioeconomic pathway scenarios of Coupled model intercomparison project (CMIP6) as new climate change data will be used. The GCMs include ASSESS-ESM1-5 and CanESM5, and climate change scenarios include SSP245 and SSP585. The use of DHA in this field can be a promising tool for modeling and predicting climatological and hydrological parameters.

2. Materials and Methods

2.1. Least Square Support Vector Machine (LSSVM)

LSSVM, which is based on improving the performance of the SVM algorithm, uses linear relationships instead of nonlinear relationships to solve problems [25]. This algorithm is used in regression analysis, classification, and pattern recognition. The use of linear relationships in the structure of this algorithm has improved the accuracy and speed compared to the SVM. The relationship between input (x) and output (Y) in LSSVM is as follows:

$$Y = \alpha_1 k(x, x_1) + \alpha_2 k(x, x_2) + \cdots + \alpha_n k(x, x_n) + b \tag{1}$$

where α_i is i^{th} lagrange multiplier, K is the kernel, and b is biased. Functions such as sigmoid, linear function, polynomial, radial basis function (RBF), etc., are used in nonlinear problems. In this paper, the RBF is used as a kernel function, which is expressed as follows [26]:

$$k(x, x_i) = \exp\left(\frac{-\|x - x_i\|^2}{2\sigma^2}\right) \tag{2}$$

where σ is an effective parameter in the accuracy of the algorithm.

2.2. Particle Swarm Optimization (PSO)

PSO is a population-based algorithm inspired by the social behavior of flocks of birds [27]. Each particle in this algorithm represents a solution in the problem space. In PSO, each particle adjusts its location according to the best site it has ever been and the best location in its entire neighborhood. The position and velocity of the particles are as follows [27]:

$$x_{new} = x + v_{new} \tag{3}$$

$$v_{new} = \omega \times v + c_1 \times r_1 (p_{best} - x) + c_2 r_2 (g_{best} - x) \tag{4}$$

where x_{new} is a new position, x is the previous position, v_{new} is the new velocity, v is the previous velocity, ω is the inertia coefficient, r_1 and r_2 are the random numbers, c_1 and c_2 are the acceleration coefficient, p_{best} is the best personal position, g_{best} is the most appropriate global position.

2.3. Aquila Optimizer (AO)

AO is a new population-based optimization algorithm that Abualigah et al. (2021) [28] proposed. Aquila's behaviors inspire this algorithm during the bait-hunting process. Aquila can behave differently to attack prey and use their legs and claws to hunt prey. The four steps in this algorithm are as follows:

2.3.1. Expanded exploration: High soar with a vertical stoop

In the first method, Aquila is located at a high altitude and monitors the entire area extensively, and after identifying the area, preys on the prey with a vertical curvature. This method is defined as follows:

$$X_{t+1} = X_{best\,(t)} \times \left(1 - \frac{t}{T}\right) + \left(X_{M\,(t)} - X_{best\,(t)} \times rand\right) \tag{5}$$

where $X_{best\,(t)}$ is the best position obtained so far, $X_{M\,(t)}$ is the average position of all Aquila's, t is the current iteration, T is the maximum number of iterations, and rand is a random number.

2.3.2. Narrowed exploration: Contour flight with short glide attack

Aquila uses short flights around the prey to attack after landing in this method. The position update formula is displayed as:

$$X_{t+1} = X_{best\,(t)} \times Levy(D) + X_{R\,(t)} + (y - x) \times rand \tag{6}$$

where $X_{R\,(t)}$ is the random position of the Aquila, D is the dimension size, $Levy(D)$ is the levy flight function, and y and x are used to present the spiral shape.

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2.3.3. Expanded exploitation: Low flight with a slow descent attack

In this method, after determining the prey area, the Aquila lands vertically on the prey to detect the prey reaction. AO exploits the selected area to attack. This behavior is presented as follows:

$$X_{t+1} = X_{best\ (t)} \times Levy(D) + X_{R\ (t)} + (y - x) \times rand \tag{7}$$

where α and δ are the exploitation adjustment parameters equal to 0.1, UB and LB are the upper and lower bounds of the problem.

2.3.4. Narrowed exploitation: Walking and grabbing prey

In the fourth method, Aquila attacks the prey based on its random movements after approaching the prey. The mathematical representation of this behavior is as follows:

$$X_{t+1} = X_{best\ (t)} \times Levy(D) + X_{R\ (t)} + (y - x) \times rand \tag{8}$$

where X_t is the current position, QF is the quality function value, G1 is a random number between [-1,1], G_2 is the flight slope when chasing prey, which decreases linearly from 2 to 0.

Figure S1 (supplementary material) shows Aquila's behavior in different attack modes. For more details, see Abualigah et al. (2021) [28].

2.4. Novel DHA (LSSVM-AO-PSO)

The value of the penalty coefficient (C) and kernel width (σ) parameters in the LSSVM structure has a great effect on the accuracy of this algorithm [29]. This study seeks to find the optimal values of these parameters using optimization algorithms. The DHA is a novel branch of AI algorithms. DHA is generated from two steps of hybridizing ML algorithms. In this paper, first, the two optimization algorithms, AO and PSO, are hybridized together. Then, the AO-PSO optimization algorithm is hybridized with the LSSVM. In this algorithm, training and testing data are first randomly selected. Then, the initial AO and PSO parameters are determined. In this algorithm, 50% of the generated population belongs to the AO, and 50% belongs to the PSO. The initial LSSVM population is initialized to search for C and σ values. In the next step, first, the training data is used to obtain the optimal LSSVM, and finally, the test data is used to evaluate the predictive ability of the LSSVM. The use of the AO-PSO optimization algorithm in optimizing the parameters of the LSSVM makes it possible to use the advantages of both algorithms simultaneously. This factor makes DHA more accurate and faster than hybrid algorithms. Figure 1 shows the structure of the novel DHA. The PSO needs to exit the local optimization to prevent premature convergence. Also, the AO is a powerful local search method, which prevents the PSO from being trapped in local optimizations. In the present study, by combining the two algorithms, AO and PSO, the exploration and operation of the PSO are improved, and a robust hybrid algorithm is constructed. The advantages of DHA can be expresses as follows:

1. Finding the optimal parameters of LSSVM with greater speed than other hybrid algorithms.
2. Covering the drawbacks of each optimization algorithm and using the strengths of each optimization algorithm by hybridizing two optimization algorithms.
3. Finding the global optimal values for LSSVM parameters.
4. Achieving a reasonable accuracy and computable speed in solving regression problems.

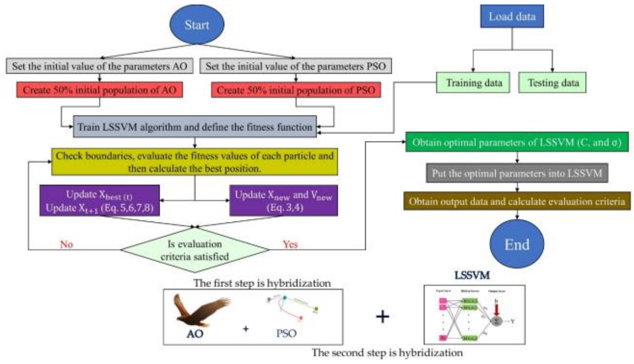

Fig. 1. The schematic structure of the novel DHA.

The objective function for optimization of LSSVM is MSE and computed as follows:

$$Objective\_function = \frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N} \tag{9}$$

where x_i is observed data, y_i is modeled data, and N is the number of samples. Algorithm. 1 demonstrates the pseudocode of DHA.

Algorithm 1. The pseudocode of the novel DHA

```
Define the initial parameters of PSO and AO
Generate the initial population for PSO and AO
Run LSSVM for each search agent (C and σ)
Calculate the objective function for each search agent (Eq. (9))
Update P_best, g_best and X_best
for it=1:MaxIter
%% PSO
    for i=1:N_particle
        Update the position of the particle using Eq. (3) and (4)
        Run LSSVM for each search agent (C and σ)
        Calculate the objective function for each search agent (Eq. (9))
        Update P_best and g_best
    end
%% AO
    for j=1:N_ Aquila
        Update the position of Aquila using Eq. (5) to (8)
```

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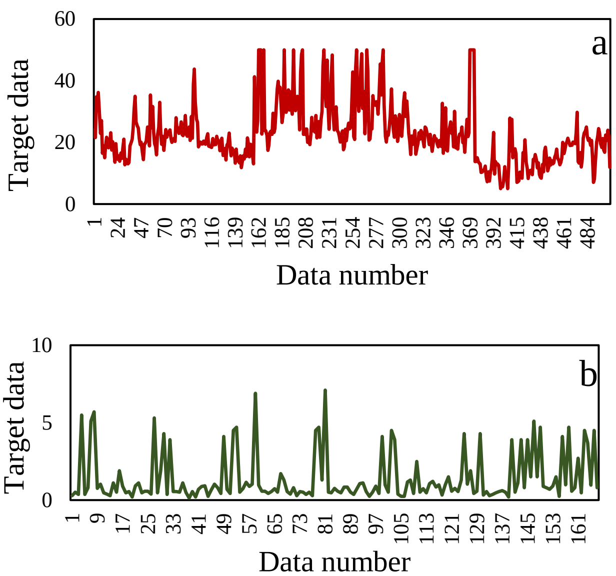
Run LSSVM for each search agent (C and σ)
Calculate the objective function for each search agent (Eq. (9))
Update X_{best}
end
%% Swap results
if mod(it, R)==0
Replace the R best answers of Algorithm PSO with the worst answers of Algorithm AO
Replace the R best answers of Algorithm AO with the worst answers of Algorithm PSO
Update P_{best}, g_{best} and X_{best}
end
end
return the best solution (best C and σ)

2.5. Benchmark Data Set (BDS)

This paper generates a novel algorithm based on two stages of hybridization of LSSVM, AO, and PSO algorithms. To use this algorithm in modeling and predicting various parameters, it is first necessary to prove its performance. BDSs are one of the best tools for verifying the performance of an algorithm and comparing it with other algorithms [30]. In the present study, four BDS, including Housing, Servo, Auto-MPG, and LSVT, are used to validate the performance of the LSSVM-AO-PSO compared with other algorithms. The features of the BDSs are listed in Table S1 (supplementary material). Each BDS is derived from several experiments or studies used in various contexts. Figure 2 shows the process of changing target data in BDSs [31]. For more information about benchmark data sets, please see https://archive.ics.uci.edu/ml/datasets.php.



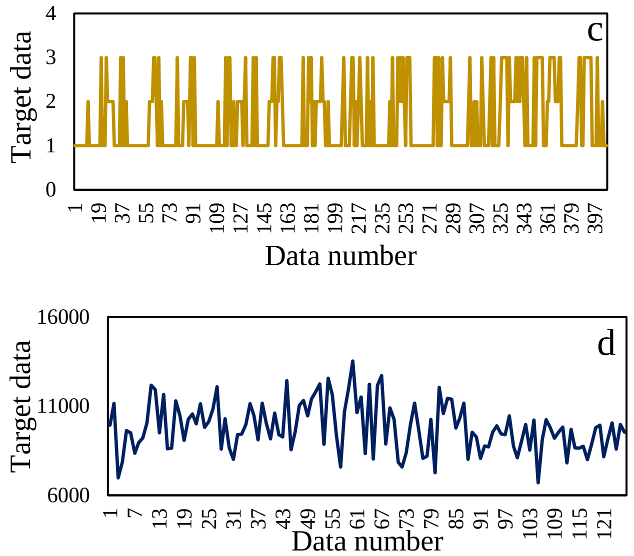


Fig. 2. The process of changing target data in BDSs. a) Housing, b) Servo, c) Auto-MPG, d) LSVT.

2.6. Downscaling AT Parameters

The delta change factor method is used for downscaling GCM's large-scale AT parameters. This method frequently has been used to downscale GCMs outputs [32], [33].

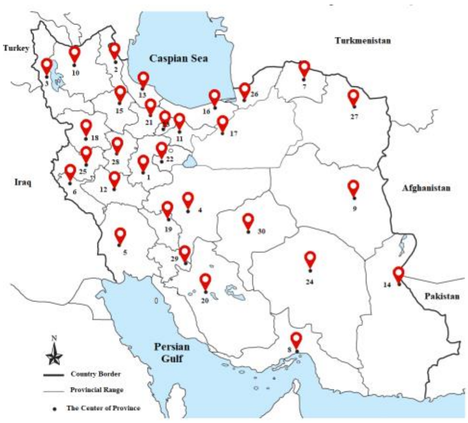
$$\Delta T_{i,t} = \left(\overline{T}\mathrm{GCM}_{future_{i,t}} - \overline{T}\mathrm{GCM}_{historical_{i,t}}\right) \quad (10)$$

The change in monthly AT parameters in the future period, average large-scale AT parameters of GCMs in the future period, and large-scale AT parameters of GCMs in the historical period are represented by $\Delta T_{i,t}$, $\overline{T}\mathrm{GCM}_{future_{i,t}}$, and $\overline{T}\mathrm{GCM}_{historical_{i,t}}$, respectively. The *i* and *t* indicate to *i*th GCM and *j*th month, respectively.

2.7. Case Study and Data Sources

Iran is located in southwest Asia with an area of 1648195 km2. Iran is so big that it has different climates. This makes the AT and spatial and temporal distribution uneven in other cities. Therefore, accurately predict minimum, mean, and maximum AT in cities with different climatic conditions. For this purpose, 30 meteorological stations in different cities of Iran with different climates were used (Fig. 3). The geographical and statistical characteristics of the studied stations are shown in Table S2 (supplementary material). According to Table S2, cities such as Arak, Ardabil, and Zanjan have mountainous climates, and the lowest AT in winter is <-15. Also, cities like Ahvaz, Birjand, Shiraz have dry to semi-arid climates. The mean AT in these areas is high, and they have warmer winters.

Because different combinations of inputs have unique effects on the accuracy of algorithms in predicting minimum, mean, and maximum AT, for this reason, different input combinations with time delays of 1 to 12 months ([1,2], [1,2,3] …, [1,2, 3…,11,12]) are created for algorithm inputs, then, according to increasing or decreasing the accuracy of the algorithms, the best time delays are selected as input.



Station Code	Station Name
1	Arak
2	Ardebil
3	Orumiyeh
4	Esfahan (AirPort)
5	Ahvaz
6	Ilam
7	Bojnurd
8	Bandarabbas
9	Birjand
10	Tabriz
11	Tehran (Mehrabad Airp
12	Khorramabad
13	Rasht
14	Zahedan
15	Zanjan
16	Sari
17	Semnan
18	Sanandaj
19	Shahrekord
20	Shiraz
21	Qazvin
22	Qom
23	Karaj
24	Kerman
25	Kermanshah
26	Gorgan
27	Mashhad
28	Hamedan (Airport)
29	Yasuj
30	Yazd

Fig. 3. Case study area.

Concerning the prediction of AT parameters, the GCMs and SSP scenarios of CMIP6 are used to address this issue. GCMs are included in ASSESS-ESM1-5 and CanESM5, and SSP scenarios consist of SSP245 and SSP585. The ASSESS-ESM1-5 was provided by Commonwealth Scientific and Industrial Research Organization (Australia). The CanESM5 was related to the Canadian Center of Climate Modeling and Analysis (Canada). SSP scenarios are scenarios of projected socioeconomic global changes which are used to derive greenhouse gas emissions scenarios with different climate policies. SSP245 is intermediate GHG emissions, which means CO2 emissions are around current levels until 2050, then falling but not reaching net zero by 2100. The SSP585 is very high GHG emissions so CO2 emissions will triple by 2075.

2.8. Evaluation Criteria

In the present study, various evaluation criteria, MAE, RMSE, MAPE, RRMSE, and R, are employed to evaluate the performance of the ML algorithms [34], [35], [36]. The assessment criteria are given as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \tag{11}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N}} \tag{12}$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_i - y_i}{x_i}\right| \tag{13}$$

$$\mathrm{RRMSE} = \left(\sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N}}\right)/\mathrm{SD}(y) \tag{14}$$

$$R = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})\sum_{i=1}^{N}(x_i - \bar{x})}} \tag{15}$$

where N is the number of data, x is the observed values, y is the predicted values, $\bar{\mathbf{x}}$ is the mean observed values, and $\bar{\mathbf{y}}$ is the mean predicted values.

2.9. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

The TOPSIS method, first introduced by Yoon and Hwang (1995) [37], is one of the most prominent multi-criteria decision-making (MCDM) methods .In this method, the alternative that has the shortest distance to the ideal positive solution (PIS) and the longest distance to the negative ideal solution (NIS) is the best. Decision matrices are created based on n alternative criteria and m as follows [37], [38]:

$$A = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \tag{16}$$

where m, n, and A are the number of criteria, alternatives, and decision matrix. Scores of alternatives are calculated as follows:

$$CC_i^+ = \frac{d_i^-}{d_i^+ + d_i^-} \tag{17}$$

where $\mathbf{d_i^-}$, and $\mathbf{d_i^+}$ are the distance of alternatives from PIS, and NIS. In the final stage, the alternatives are ranked according to their scores. For more information, see [39].

2.10. Presented Framework

Figure 4 shows the general framework for proving the performance of the novel DHA and its application in predicting minimum, mean, and maximum AT. The steps are as follows:

Step1: Proving the performance of the DHA using BDSs

1. Before using the DHA in predicting AT, first, the performance of the proposed algorithm is evaluated in four BDSs (Housing, Servo, Auto-MPG, LSVT) and compared with LSSVM, LSSVM-PSO, and LSSVM-AO.
2. Due to that, in modeling BDSs and comparing algorithms, various factors such as evaluation criteria and calculation time affect the selection of the best algorithm; the TOPSIS method is used to select the best algorithm. This process is as follows:

- Evaluation criteria, including MAE, RMSE, MAPE, RRMSE, R, and the run times of algorithms, are considered as criteria of the TOPSIS method.
- The algorithms are considered alternatives, including LSSVM, LSSVM-PSO, LSSVM-AO, and LSSVM-AO-PSO.

- According to Table 1, the TOPSIS method is used under six scenarios to select the best algorithm. The lambda time weight varies from 0.090 to 0.000, and the lambda weight of the other criteria is the same in all scenarios.
- In the last step in each scenario, the algorithm with the highest score is selected as the best.

Step 2: modeling AT

1. Time delays of 1 to 12 months are created to select the best input combination to model minimum, mean, and maximum AT.
2. Four ML algorithms, including LSSVM, LSSVM-PSO, LSSVM-AO, and LSSVM-AO-PSO, are used to model the minimum, mean, and maximum AT at different time delays in 30 stations in Iran.
3. The best time delays in the minimum, mean, and maximum AT modeling results are selected.
4. Similar to modeling the BDSs, the best algorithm in modeling minimum, mean, and maximum AT is determined by the TOPSIS method.

Step 3: Downscaling AT parameters

At this step, the delta change factor method is used to downscale AT parameters of 30 stations in the historical period using two models (ACCESS-ESM1 and CanESM5), and two scenarios (SSP245 and SSP585) were used.

Step 4: Predicting AT

The DHA predicts AT parameters based on the downscaled AT parameters in the future period (2020-2047).

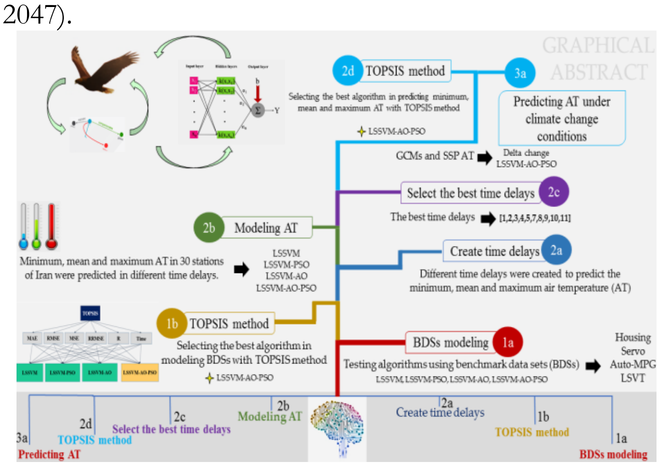


Fig 4. Framework for proving the performance of DHA and AT prediction.

Table 1. Lambda weight in different scenarios for TOPSIS method.

	Scenario ID					
	1	2	3	4	5	6
MAE	0.182	0.195	0.198	0.199	0.199	0.200
RMSE	0.182	0.195	0.198	0.199	0.199	0.200
MAPE	0.182	0.195	0.198	0.199	0.199	0.200
RRMSE	0.182	0.195	0.198	0.199	0.199	0.200
R	0.182	0.195	0.198	0.199	0.199	0.200
Time (s)	0.090	0.025	0.010	0.005	0.003	0.000

3. Results

In all investigated optimization algorithms, the value of population size is ten, and the number of iterations equals 60. Moreover, according to the authors' experiences, the c1 and c2 were considered equal to 2, and w was set to 0.9.

3.1. BDSs Modeling

Before using the novel DHA in predicting the minimum, mean and maximum AT, the performance of the proposed LSSVM-AO-PSO was tested by modeling four BDSs, including, Housing, Servo, Auto-MPG, and LSVT. Then the results of the DHA were compared with the LSSVM, LSSVM-PSO, and LSSVM-AO. According to Table 2, in modeling BDSs, hybrid algorithms and DHA performed well. LSSVM-AO-PSO results were better than LSSVM for four BDSs and better than LSSVM-PSO and LSSVM-AO in most evaluation criteria. Also, the LSSVM-AO-PSO was faster than other algorithms.

Table S3 (supplementary material) shows the average values of the evaluation criteria and run time at BDSs by LSSVM, LSSVM-PSO, LSSVM-AO, and LSSVM-AO-PSO. However, due to differences in criteria and the results obtained, ranking algorithms was difficult. Therefore, the TOPSIS method was used to select the best algorithm.

3.2. TOPSIS Method (in the BDSs Modeling)

According to the average evaluation criteria in modeling four BDSs, Table 1 and the description in the section presented framework, different algorithms were ranked by the TOPSIS method. The scores of the algorithms in the TOPSIS method are given in Table 3. In scenario 1, the weight of all criteria is the same, and the lambda time weight decreases as the scenario identifier increases. Algorithms with maximum scores have better rankings. The LSSVM-AO-PSO scored higher in all scenarios and was recognized as the best algorithm with a sum score of 6.000. In addition, the sum scores of all scenarios show that LSSVM-AO (score 5.571), LSSVM-PSO (score 5.356), and LSSVM (score 0.002) were next in line. The average values of MAE, RMSE, MAPE, RRMSE, and R in modeling the BDSs by the LSSVM-AO-PSO were 20.682, 34.283, 4126.838, 0.576, and 0.733, respectively. According to the results, LSSVM-AO-PSO was skilled in achieving high accuracy and overcoming competitors.

Table 2. Evaluation criteria for measuring precision in the BDSs modeling.

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Housing					
LSSVM	2.965	4.156	0.117	0.493	0.911	5.299	7.507	0.384	0.919	0.436	4.411
LSSVM-PSO	2.994	4.194	0.118	0.497	0.911	5.301	7.504	0.385	0.918	0.437	3.783
LSSVM-AO	2.996	4.196	0.118	0.497	0.911	5.301	7.503	0.384	0.918	0.435	5.831
LSSVM-AO-PSO	2.995	4.196	0.118	0.497	0.911	5.300	7.503	0.384	0.918	0.437	3.861
						Servo					
LSSVM	0.247	0.454	0.258	0.294	0.963	0.475	0.673	0.450	0.428	0.903	1.341
LSSVM-PSO	0.308	0.525	0.341	0.340	0.941	0.476	0.665	0.447	0.422	0.911	1.133
LSSVM-AO	0.314	0.526	0.363	0.337	0.942	0.487	0.669	0.475	0.425	0.912	2.118
LSSVM-AO-PSO	0.310	0.521	0.345	0.340	0.941	0.477	0.664	0.450	0.422	0.912	1.114
						Auto-MPG					
LSSVM	0.306	0.463	0.209	0.626	0.780	0.615	0.717	0.396	0.812	0.586	5.389
LSSVM-PSO	0.307	0.460	0.211	0.622	0.782	0.610	0.714	0.393	0.808	0.589	3.438
LSSVM-AO	0.307	0.459	0.211	0.621	0.784	0.608	0.713	0.391	0.807	0.591	4.136
LSSVM-AO-PSO	0.310	0.462	0.214	0.626	0.779	0.595	0.707	0.377	0.807	0.594	3.315
						LSVT					
LSSVM	47.908	65.017	0.005	0.044	0.999	113.745	209.383	0.013	0.259	0.973	1.968
LSSVM-PSO	17.852	23.477	0.001	0.016	0.999	83.735	139.241	0.009	0.173	0.986	1.596
LSSVM-AO	6.968	9.017	0.000	0.006	1.000	80.275	135.679	0.009	0.168	0.986	1.494
LSSVM-AO-PSO	6.108	8.119	0.000	0.006	1.000	76.354	128.258	0.008	0.157	0.988	1.346

Table 3. Scores of TOPSIS method for ranking of algorithms in the BDSs modeling.

	Scenario ID						**Sum**	**Average**	**Rank**
	1	2	3	4	5	6			
LSSVM	0.003	0.001	0.000	0.000	0.000	0.000	0.002	0.000	4
LSSVM-PSO	0.852	0.852	0.852	0.852	0.852	0.852	5.113	0.852	3
LSSVM-AO	0.904	0.906	0.906	0.906	0.906	0.906	5.433	0.906	2
LSSVM-AO-PSO	1.000	1.000	1.000	1.000	1.000	1.000	6.000	1.000	1

3.3. Modeling AT

In this section, the performance of the LSSVM, hybrid algorithms (LSSVM-PSO, LSSVM-AO), and novel DHA (LSSVM-AO-PSO) were evaluated to model the minimum, mean, and maximum AT. For this purpose, time delays of 1 to 12 months were created, and the best time-delays combination (1,2,3,4,5,7,8,9,10,11) was selected to model the AT in different stations. In addition, each algorithm was run ten times for each station and AT parameters. The range of standard deviation for investigated algorithms is tabulated in Table 4.

Due to the large number of stations studied, the results of six stations (Ahvaz, Tabriz, Tehran, Semnan, Shiraz, and Mashhad) with different climatic conditions to model the minimum, mean and maximum AT and proof of DHA performance are given in Table 4, and the results of other stations are included in the supplementary material (Table S4-S27).

According to Table 4 and Table S4-S27, all three investigated algorithm was trained with reasonable accuracy. Therefore, the accuracy of the testing period and training time are analyzed to select the best algorithm. LSSVM-AO-PSO for modeling min AT has less MAE and RMSE than other investigated algorithms in 22 out of 30 stations. Besides, LSSVM-AO-PSO was more accurate than LSSVM-AO, LSSVM-PSO, and LSSVM. LSSVM-AO-PSO estimate Min AT in Ardabil, Urmia, Isfahan, Bandar Abbas, Birjand, Khorramabad, Qazvin, Qom, Kermanshah, Hamedan, Yazd, with up to 97% lower MAPE than other investigated algorithms. The R-value for LSSVM-AO-PSO varied from 0.951 to 0.989, while these values for LSSVM-AO, LSSVM-PSO, and LSSVM were in the range of 0.943 to 0.988. Therefore, for modeling min AT, LSSVM-AO-PSO in almost stations has better accuracy than LSSVM-AO, LSSVM-PSO, and LSSVM. Moreover, the computation time of LSSVM-AO-PSO was up to 80% less than LSSVM-AO, LSSVM-PSO, and LSSVM.

According to other results of Table 4 and Tables S4-S27, in modeling mean AT, LSSVM-AO-PSO has less MAE than different investigated algorithms in 26 stations out of 30 stations. Regarding RMSE, LSSVM-AO-PSO has more accuracy than LSSVM-AO, LSSVM-PSO, and LSSVM in all 30 stations. The computed values of MAPE for LSSVM-AO-PSO in all stations except Urmia, Zanjan, Shahrekord, and Hamedan were lower than those for other assessed algorithms. RRMSE value for LSSVM-AO-PSO was between 0.107 and 0.295, for LSSVM-AO and LSSVM-PSO were between 0.126 and 0.304, for LSSVM was between 0.128 and 0.304. R values for all investigated algorithms were in the range of 0.974 to 0.994. Also, LSSVM-AO-PSO has up to 83% less computation time than LSSVM-AO, LSSVM-PSO, and LSSVM.

Regarding maximum AT, the MAE of LSSVM-AO-PSO was in the range of 0.918 to 2.039. These criteria for

LSSVM-AO and LSSVM-PSO were between 0.982 to 2.045, and for LSSVM were in the range of 0.976 to 2.046. The values of RMSE for LSSVM-AO-PSO, LSSVM-AO, LSSVM-PSO, and LSSVM varied from 1.122 to 1.869, 1.238 to 2.263, 1.210 to 2.263, 1.212 to 2.263, respectively. The estimated MAPE for investigated algorithms showed that LSSVM-AO-PSO in all stations except Urmia and Sari has up to 90% lower MAPE. The RRMSE value for LSSVM-AO-PSO was between 0.165 to 0.329, for LSSVM-AO was between 0.181 to 0.331, for LSSVM-PSO and LSSVM varied from 0.177 to 0.331. R values for estimating maximum AT using LSSVM-AO-PSO were between 0.946 to 0.987, and using LSVM-AO, LSSVM-PSO, and LSSVM were between 0.945 to 0.984. Therefore, LSSVM-AO-PSO was more accurate than other investigated algorithms. Besides, LSSVM-AO-PSO reduced computation time by up to 79%.

According to Table 4, the standard deviation of the evaluation criteria is very small and close to zero. These low values of standard deviation are because the LSSVM algorithm uses the least squares optimization method, a global optimization algorithm that does not fall into the trap of local optima, and its answer is deterministic. The standard deviation of standalone LSSVM in all stations was equal to zero and, therefore, not shown in Table 4.

Another issue that can be understood from these standard deviation values is that the optimization algorithms (PSO, AO, and AO-PSO) have reached convergence in 60 iterations and their answers have high quality.

According to obtained results, the LSSVM was less accurate in almost stations than the combined LSSVM-PSO and LSSVM-AO. Also, the performance of LSSVM-PSO and LSSVM-AO hybrid algorithms was very close in most evaluation criteria. The modeling results showed that using AO and PSO to optimize important LSSVM parameters improved LSSVM performance. Also, the results obtained in 30 stations showed that combining AO and PSO optimization algorithms (AO-PSO) and using them simultaneously in optimizing LSSVM parameters led to increased accuracy in hybrid algorithms and significantly decreased the computation time. Hybridizing AO and PSO and using a DHA makes simultaneous use of the advantages of both algorithms in improving the performance of the LSSVM, and this factor makes this type of algorithm perform better than classical models and other hybrid algorithms.

Table 4. The modeling results of the minimum, mean and maximum AT in the different station.

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
	Ahvaz										
	Minimum AT										
LSSVM	0.839	1.069	0.059	0.140	0.990	0.999	1.274	0.072	0.157	0.988	8.694
LSSVM-PSO	0.832	1.063	0.059	0.139	0.990	0.980	1.258	0.070	0.155	0.988	5.643
Std	2E-07	2E-07	1E-08	3E-08	1E-09	8E-08	1E-12	3E-09	1E-13	4E-11	
LSSVM-AO	0.832	1.064	0.059	0.139	0.990	0.979	1.258	0.063	0.155	0.988	8.285
Std	1E-03	2E-03	8E-05	2E-04	9E-06	1E-03	9E-05	4E-05	9E-06	8E-07	
LSSVM-AO-PSO	0.820	1.054	0.059	0.137	0.991	0.918	1.127	0.063	0.139	0.990	4.251
Std	1E-04	1E-04	9E-06	2E-05	1E-06	1E-04	4E-07	7E-06	5E-08	4E-08	
	Mean AT										
LSSVM	0.805	1.042	0.039	0.111	0.994	0.892	1.158	0.043	0.122	0.992	8.693
LSSVM-PSO	0.803	1.041	0.039	0.111	0.994	0.884	1.140	0.043	0.120	0.993	5.109
Std	1E-06	2.E-06	1E-07	3E-07	2E-08	1E-06	3E-10	1E-07	4E-11	1E-09	
LSSVM-AO	0.806	1.043	0.039	0.111	0.994	0.886	1.139	0.043	0.120	0.993	8.238
Std	1E-03	1E-03	9E-05	2E-04	1E-05	1E-03	1E-04	1E-04	2E-05	2E-06	
LSSVM-AO-PSO	0.838	1.087	0.041	0.116	0.993	0.766	0.963	0.034	0.102	0.995	2.957
Std	7E-06	9E-06	3E-07	9E-07	4E-08	2E-06	1E-09	1E-07	1E-10	1E-09	
	Maximum AT										
LSSVM	1.007	1.282	0.036	0.120	0.993	1.189	1.520	0.042	0.146	0.989	7.641
LSSVM-PSO	0.997	1.261	0.036	0.118	0.993	1.172	1.502	0.042	0.144	0.990	5.174
Std	3E-07	4E-07	1E-08	4E-08	1E-09	2E-07	2E-12	6E-09	2E-13	9E-11	
LSSVM-AO	0.996	1.257	0.036	0.117	0.993	1.166	1.498	0.041	0.144	0.990	7.212
Std	1E-03	2E-03	6E-05	1E-04	7E-06	1E-03	7E-05	3E-05	6E-06	8E-07	
LSSVM-AO-PSO	1.046	1.334	0.038	0.125	0.992	1.027	1.328	0.035	0.130	0.992	2.917
Std	2E-04	3E-04	9E-06	2E-05	1E-06	1E-04	1E-06	4E-06	1E-07	5E-08	
	Tabriz										
	Minimum AT										
LSSVM	1.218	1.582	0.508	0.208	0.980	1.536	1.885	0.436	0.234	0.972	7.986
LSSVM-PSO	1.219	1.583	0.508	0.208	0.980	1.536	1.885	0.436	0.234	0.972	5.830
Std	2E-07	3E-07	2E-08	4E-08	2E-09	1E-07	1E-12	2E-08	1E-13	1E-12	
LSSVM-AO	1.216	1.580	0.507	0.208	0.980	1.537	1.885	0.496	0.234	0.972	7.835
Std	2E-03	3E-03	2E-04	3E-04	2E-05	1E-03	8E-05	2E-04	9E-06	8E-07	

LSSVM-AO-PSO	1.277	1.681	0.493	0.220	0.978	1.466	1.788	0.496	0.222	0.975	4.215
Std	2E-05	1E-05	1E-05	1E-06	2E-07	3E-06	8E-09	4E-07	1E-09	1E-09	
Mean AT											
LSSVM	1.063	1.328	0.124	0.154	0.988	1.372	1.777	0.159	0.200	0.980	8.386
LSSVM-PSO	1.061	1.326	0.123	0.154	0.988	1.372	1.777	0.159	0.200	0.980	6.718
Std	4E-07	2E-07	2E-07	2E-08	4E-09	5E-08	1E-12	8E-09	1E-13	2E-11	
LSSVM-AO	1.062	1.326	0.123	0.154	0.988	1.372	1.777	0.159	0.200	0.980	7.544
Std	1E-03	6E-04	5E-04	8E-05	1E-05	1E-04	2E-05	3E-05	3E-06	2E-07	
LSSVM-AO-PSO	1.129	1.426	0.134	0.165	0.986	1.249	1.590	0.115	0.180	0.984	2.996
Std	8E-04	1E-03	8E-05	1E-04	6E-06	3E-04	1E-05	8E-05	1E-06	1E-07	
Maximum AT											
LSSVM	1.413	1.747	0.074	0.199	0.980	1.577	2.152	0.087	0.242	0.971	9.116
LSSVM-PSO	1.412	1.745	0.074	0.199	0.980	1.578	2.152	0.087	0.242	0.971	5.580
Std	2E-07	2E-07	1E-08	3E-08	1E-09	1E-08	1E-12	5E-09	1E-13	1E-11	
LSSVM-AO	1.412	1.745	0.074	0.199	0.980	1.578	2.152	0.087	0.242	0.971	7.965
Std	2E-03	3E-03	1E-04	4E-04	2E-05	3E-04	1E-04	7E-05	1E-05	1E-06	
LSSVM-AO-PSO	1.613	2.024	0.088	0.230	0.973	1.462	1.973	0.069	0.222	0.975	3.456
Std	4E-05	5E-05	2E-06	6E-06	3E-07	2E-06	3E-08	1E-06	3E-09	2E-09	
Tehran											
Minimum AT											
LSSVM	1.575	2.268	2155	0.263	0.973	1.464	1.886	1.171	0.207	0.978	8.146
LSSVM-PSO	1.586	2.272	2185	0.264	0.973	1.466	1.883	1.163	0.207	0.978	5.677
Std	2E-07	1E-07	5E-08	1E-08	1E-09	1E-07	1E-12	4E-08	1E-13	9E-11	
LSSVM-AO	1.586	2.271	2219	0.264	0.973	1.465	1.883	1.177	0.207	0.978	7.220
Std	4E-03	2E-03	6E-04	2E-04	2E-05	3E-03	6E-03	1E-03	6E-04	8E-05	
LSSVM-AO-PSO	1.692	2.457	2249	0.281	0.969	1.328	1.757	1.177	0.198	0.980	4.156
Std	5E-05	2E-05	1E+10	2E-06	7E-07	5E-05	1E-07	1E-04	1E-08	2E-08	
Mean AT											
LSSVM	1.332	1.854	0.358	0.188	0.983	1.537	1.956	0.395	0.194	0.981	8.641
LSSVM-PSO	1.313	1.827	0.350	0.185	0.983	1.535	1.942	0.383	0.193	0.981	6.463
Std	1E-07	7E-08	3E+07	8E-09	2E-09	1E-07	2E-12	3E-07	2E-13	6E-11	
LSSVM-AO	1.296	1.812	0.347	0.184	0.983	1.533	1.936	0.376	0.192	0.981	7.139
Std	1E-03	6E-04	3E+11	7E-05	2E-05	1E-03	8E-05	3E-03	9E-06	2E-06	
LSSVM-AO-PSO	1.279	1.819	0.319	0.183	0.984	1.434	1.822	0.317	0.186	0.983	2.974
Std	1E-03	8E-04	3E-04	8E-05	9E-06	8E-04	4E-04	3E-04	4E-05	4E-06	
Maximum AT											
LSSVM	1.466	1.979	0.424	0.183	0.983	1.714	2.161	1.626	0.202	0.980	9.314
LSSVM-PSO	1.429	1.925	0.406	0.178	0.984	1.706	2.144	1.629	0.200	0.980	5.177
Std	2E-07	3E-07	3E-08	3E-08	1E-09	1E-07	2E-12	1E-06	2E-13	4E-11	
LSSVM-AO	1.416	1.908	0.400	0.177	0.984	1.704	2.141	1.630	0.200	0.980	7.090
Std	2E-03	2E-03	2E-04	2E-04	1E-05	1E-03	5E-04	1E-02	5E-05	6E-06	
LSSVM-AO-PSO	1.421	1.916	0.395	0.177	0.984	1.663	2.050	2.107	0.196	0.981	3.496
Std	2E-04	2E-04	2E-05	2E-05	1E-06	1E-04	1E-06	1E-03	1E-07	5E-08	
Semnan											
Minimum AT											
LSSVM	1.059	1.329	0.710	0.144	0.990	1.105	1.511	0.473	0.159	0.987	8.344
LSSVM-PSO	1.059	1.330	0.709	0.144	0.989	1.105	1.511	0.474	0.159	0.987	5.754
Std	2E-07	3E-07	2E-08	3E-08	1E-09	3E-08	2E-12	7E-09	1E-13	2E-11	
LSSVM-AO	1.060	1.330	0.710	0.144	0.989	1.105	1.511	0.341	0.159	0.987	7.308
Std	2E-03	3E-03	2E-04	3E-04	1E-05	3E-04	2E-04	8E-05	2E-05	1E-06	
LSSVM-AO-PSO	1.083	1.383	0.655	0.149	0.989	0.952	1.284	0.341	0.136	0.991	4.528
Std	4E-05	4E-05	2E-05	5E-06	2E-07	9E-06	2E-08	3E-06	2E-09	9E-10	
Mean AT											
LSSVM	1.178	1.475	0.135	0.148	0.989	1.251	1.713	0.148	0.167	0.986	9.368
LSSVM-PSO	1.179	1.476	0.135	0.148	0.989	1.251	1.713	0.148	0.167	0.986	5.948
Std	3E-07	3E-07	1E-07	3E-08	2E-09	7E-08	1E-12	2E-08	1E-13	6E-12	
LSSVM-AO	1.179	1.474	0.134	0.148	0.989	1.252	1.714	0.148	0.167	0.986	9.147
Std	4E-03	5E-03	2E-03	6E-04	3E-05	1E-03	3E-04	1E-04	4E-05	3E-06	
LSSVM-AO-PSO	1.218	1.537	0.143	0.153	0.988	1.084	1.490	0.101	0.147	0.989	3.802
Std	2E-03	2E-03	1E-04	2E-04	1E-05	2E-04	2E-04	7E-05	2E-05	1E-06	
Maximum AT											
LSSVM	1.323	1.676	0.081	0.161	0.987	1.449	2.001	0.110	0.188	0.982	7.876
LSSVM-PSO	1.321	1.674	0.081	0.160	0.987	1.449	2.001	0.110	0.188	0.982	5.360
Std	2E-07	3E-07	1E-08	2E-08	1E-09	2E-08	1E-12	1E-09	1E-13	6E-13	
LSSVM-AO	1.321	1.672	0.081	0.160	0.987	1.448	2.002	0.110	0.188	0.982	7.514

Std	5E-03	6E-03	2E-04	6E-04	2E-05	1E-04	8E-04	1E-04	8E-05	6E-06	
LSSVM-AO-PSO	1.374	1.757	0.081	0.167	0.986	1.312	1.821	0.074	0.174	0.985	2.927
Std	4E-04	5E-04	2E-05	5E-05	2E-06	4E-05	5E-06	2E-06	5E-07	3E-08	
Shiraz											
Minimum AT											
LSSVM	0.723	0.959	0.405	0.131	0.991	0.879	1.144	0.437	0.155	0.989	8.361
LSSVM-PSO	0.724	0.960	0.406	0.131	0.991	0.879	1.144	0.437	0.155	0.989	5.791
Std	2E-07	2E-07	1E-08	2E-08	1E-09	6E-08	1E-12	4E-09	1E-13	1E-11	
LSSVM-AO	0.724	0.961	0.406	0.131	0.991	0.879	1.144	0.310	0.155	0.989	9.039
Std	1E-03	1E-03	1E-04	1E-04	7E-06	3E-04	4E-05	2E-05	5E-06	4E-07	
LSSVM-AO-PSO	0.702	0.933	0.390	0.127	0.992	0.896	1.152	0.310	0.154	0.988	4.188
Std	2E-06	3E-06	1E-06	5E-07	2E-08	1E-06	2E-10	7E-07	4E-11	1E-09	
Mean AT											
LSSVM	0.762	0.998	0.063	0.114	0.993	0.915	1.194	0.076	0.136	0.991	8.663
LSSVM-PSO	0.769	1.006	0.064	0.115	0.993	0.914	1.194	0.076	0.136	0.991	5.595
Std	1E-07	2E-07	7E-08	3E-08	1E-09	7E-08	1E-12	5E-08	1E-13	7E-11	
LSSVM-AO	0.771	1.007	0.064	0.115	0.993	0.914	1.194	0.076	0.136	0.991	8.668
Std	8E-04	1E-03	3E-04	1E-04	8E-06	3E-04	3E-05	2E-04	4E-06	1E-07	
LSSVM-AO-PSO	0.741	0.969	0.062	0.111	0.994	0.872	1.096	0.063	0.125	0.992	3.659
Std	1E-05	1E-05	1E-06	1E-06	7E-08	3E-06	2E-09	2E-07	3E-10	7E-10	
Maximum AT											
LSSVM	1.026	1.349	0.051	0.145	0.989	1.237	1.591	0.057	0.176	0.985	9.631
LSSVM-PSO	1.028	1.351	0.051	0.145	0.989	1.237	1.591	0.057	0.176	0.985	6.494
Std	1E-07	1E-07	4E-09	1E-08	3E-10	9E-09	7E-13	1E-09	8E-14	9E-12	
LSSVM-AO	1.030	1.354	0.051	0.145	0.989	1.238	1.591	0.057	0.176	0.985	7.927
Std	3E-02	4E-02	1E-03	5E-03	1E-04	6E-03	1E-03	3E-04	1E-04	1E-05	
LSSVM-AO-PSO	1.058	1.395	0.053	0.151	0.989	1.219	1.529	0.055	0.169	0.986	2.964
Std	2E-03	3E-03	1E-04	3E-04	8E-06	2E-04	2E-04	2E-05	2E-05	1E-06	
Mashhad											
Minimum AT											
LSSVM	1.068	1.434	0.469	0.188	0.983	1.348	1.878	0.550	0.230	0.974	7.968
LSSVM-PSO	1.047	1.400	0.475	0.184	0.984	1.336	1.861	0.564	0.228	0.974	5.130
Std	2E-07	2E-07	3E-08	2E-08	1E-09	2E-08	8E-13	4E-09	9E-14	1E-11	
LSSVM-AO	1.045	1.397	0.477	0.183	0.984	1.338	1.861	0.381	0.228	0.974	7.780
Std	3E-03	3E-03	6E-04	4E-04	2E-05	7E-04	2E-04	2E-04	2E-05	2E-06	
LSSVM-AO-PSO	1.218	1.724	0.590	0.223	0.976	1.093	1.373	0.380	0.170	0.986	4.257
Std	1E-05	5E-06	6E-06	7E-07	1E-07	1E-06	1E-09	3E-06	1E-10	2E-10	
Mean AT											
LSSVM	1.226	1.580	0.264	0.174	0.985	1.427	2.009	0.257	0.213	0.977	8.114
LSSVM-PSO	1.213	1.557	0.257	0.171	0.985	1.440	2.005	0.251	0.212	0.977	5.361
Std	2E-07	1E-07	1E-07	2E-08	2E-09	5E-08	7E-13	9E-08	9E-14	6E-12	
LSSVM-AO	1.214	1.558	0.257	0.172	0.985	1.440	2.005	0.251	0.212	0.977	7.180
Std	1E-03	9E-04	8E-04	1E-04	1E-05	5E-04	4E-05	4E-04	5E-06	5E-07	
LSSVM-AO-PSO	1.366	1.836	0.292	0.200	0.980	1.176	1.598	0.138	0.172	0.986	2.984
Std	4E-04	4E-04	7E-05	4E-05	2E-06	5E-05	2E-06	1E-05	2E-07	5E-08	
Maximum AT											
LSSVM	1.579	1.984	0.114	0.210	0.978	1.693	2.447	0.150	0.246	0.969	8.369
LSSVM-PSO	1.586	1.986	0.114	0.210	0.978	1.696	2.445	0.149	0.246	0.969	5.171
Std	1E-06	1E-06	7E-08	1E-07	7E-09	5E-07	2E-11	9E-08	2E-12	1E-09	
LSSVM-AO	1.585	1.984	0.114	0.210	0.978	1.697	2.445	0.149	0.246	0.969	7.454
Std	4E-03	5E-03	2E-04	5E-04	2E-05	3E-03	5E-04	3E-04	5E-05	7E-06	
LSSVM-AO-PSO	1.690	2.177	0.135	0.228	0.973	1.541	2.107	0.091	0.214	0.977	2.879
Std	2E-03	2E-03	1E-04	3E-04	1E-05	5E-04	7E-05	1E-04	7E-06	2E-06	

Table 5 shows the average evaluation criteria values and run time in modeling the minimum, mean, and maximum AT in the 30 stations. Despite the better performance of the LSSVM-AO-PSO, due to the different results in 30 stations, the TOPSIS method was used to select the best algorithm and rank the algorithms.

Table 5. Average results model the minimum, mean and maximum AT during the testing period.

	MAE	RMSE	MAPE	RRMSE	R	Time (s)
			Minimum AT			
LSSVM	1.208	1.617	0.738	0.210	0.977	8.445
LSSVM-PSO	1.210	1.616	0.788	0.210	0.977	5.314
LSSVM-AO	1.208	1.613	0.799	0.210	0.977	7.441
LSSVM-AO-PSO	1.128	1.429	0.799	0.190	0.981	4.199
			Mean AT			
LSSVM	1.235	1.640	0.447	0.184	0.982	8.441
LSSVM-PSO	1.235	1.636	0.458	0.184	0.982	5.683
LSSVM-AO	1.236	1.637	0.466	0.184	0.982	7.568
LSSVM-AO-PSO	1.134	1.439	0.432	0.165	0.986	3.154
			Maximum AT			
LSSVM	1.539	2.047	0.346	0.218	0.976	8.334
LSSVM-PSO	1.536	2.045	0.346	0.218	0.976	5.651
LSSVM-AO	1.538	2.046	0.345	0.218	0.976	7.749
LSSVM-AO-PSO	1.434	1.863	0.315	0.203	0.979	3.064

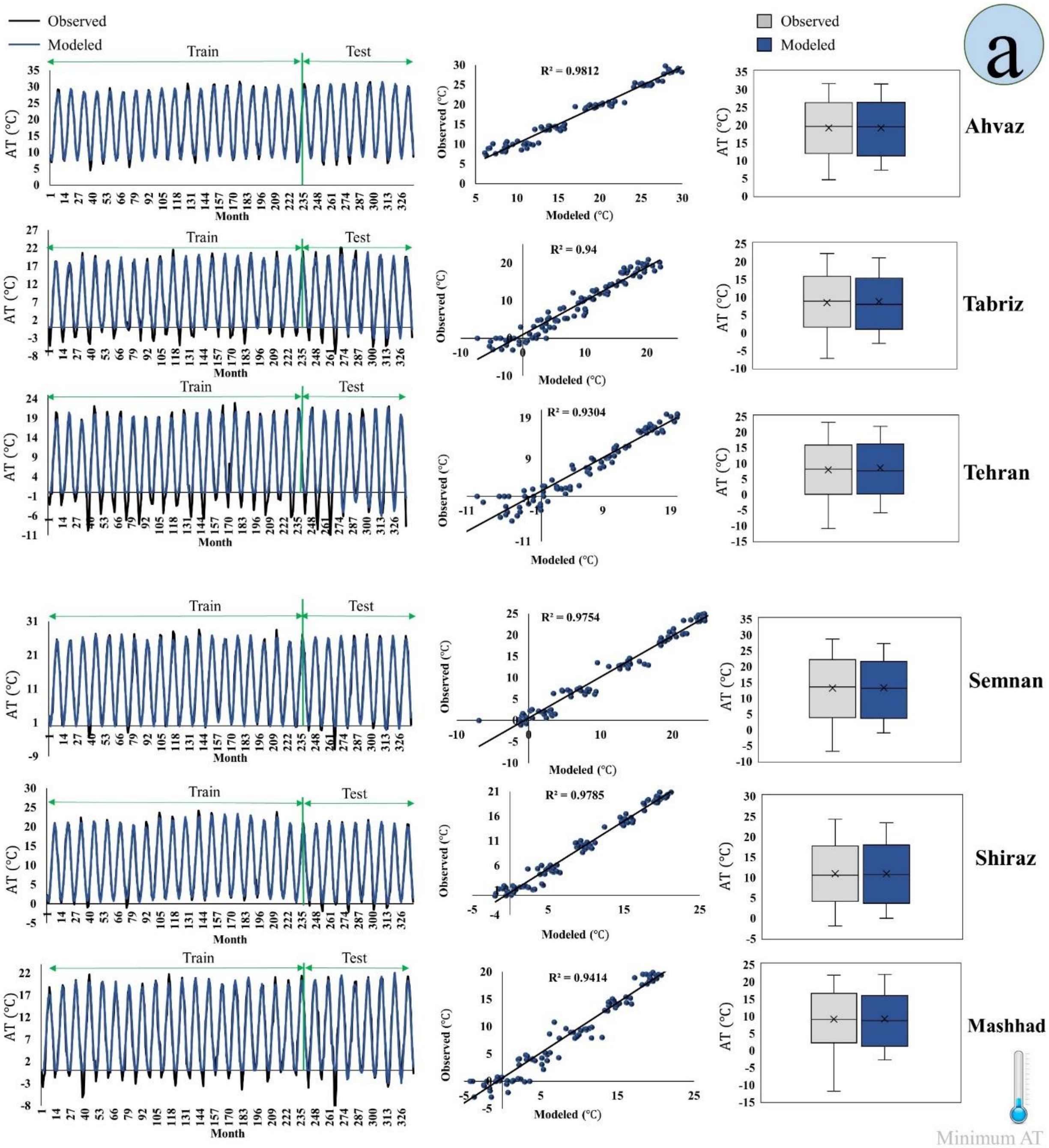
3.4. TOPSIS Method (in the AT Modeling)

In this section, according to Table 1 and the explanations given in the section presented framework, the scores of the algorithms are given in Table 6. In modeling the minimum AT, the sum of the scores of all the scenarios showed that the LSSVM-AO-PSO performed better than the hybrid and classical algorithms, with a score of 6.000. LSSVM-PSO (score 1.398), LSSVM-AO (score 0.525), and LSSVM (score 0.022) were ranked second to fourth. In modeling the mean AT at 30 stations, LSSVM-AO-PSO (score 6.000), LSSVM-PSO (score 1.156), LSSVM-AO (score 0.411), and LSSVM (score 0.008), respectively ranked first to fourth. In modeling the maximum AT by different algorithms, the results of the TOPSIS method showed that the DHA has the best performance (score 6.000). According to the results obtained by the algorithms in different scenarios, the DHA score was very different from other algorithms, which showed that the DHA works better in speed and accuracy than hybrid algorithms. LSSVM-PSO (score 1.058), LSSVM-AO (score 0.256), and LSSVM (score 0.000) were ranked second to fourth.

Figure 5 shows the time series, box plot diagrams, and scatter plots in modeling the minimum, mean and maximum AT during the testing period with the best algorithm (LSSVM-AO-PSO) in the stations of Ahvaz, Tabriz, Tehran, Semnan, Shiraz, and Mashhad. According to Figure 5, the LSSVM-AO-PSO showed high accuracy in modeling the values at all stations, so in most cases, the difference between the modeled and the observed values is minimal. A high R-value means a positive effect of AO-PSO on improving LSSVM performance. Also, since most values were grouped around the semiconductor line, the accuracy of the DHA is high. Also, according to the box plot diagrams, the median, maximum and minimum values observed and modeled were very close due to the high accuracy of the novel DHA. The high accuracy of the DHA in stations with different climatic conditions shows the strength of this algorithm because it had a remarkable performance in all climatic conditions.

Table 6. Scores of TOPSIS method for ranking of algorithms in the AT modeling.

	Scenario ID						Sum	Average	Rank
	1	2	3	4	5	6			
				Minimum AT					
LSSVM	0.028	0.095	0.171	0.209	0.221	0.229	0.952	0.159	3
LSSVM-PSO	0.724	0.612	0.420	0.272	0.186	0.050	2.263	0.377	2
LSSVM-AO	0.235	0.217	0.160	0.102	0.068	0.021	0.802	0.134	4
LSSVM-AO-PSO	0.972	0.905	0.830	0.792	0.780	0.772	5.050	0.842	1
				Mean AT					
LSSVM	0.007	0.026	0.052	0.068	0.073	0.078	0.303	0.051	4
LSSVM-PSO	0.518	0.473	0.351	0.231	0.158	0.039	1.770	0.295	2
LSSVM-AO	0.164	0.155	0.122	0.081	0.054	0.013	0.590	0.098	3
LSSVM-AO-PSO	1.000	1.000	1.000	1.000	1.000	1.000	6.000	1.000	1
				Maximum AT					
LSSVM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	4
LSSVM-PSO	0.506	0.467	0.353	0.234	0.159	0.017	1.735	0.289	2
LSSVM-AO	0.111	0.105	0.085	0.057	0.038	0.008	0.405	0.067	3
LSSVM-AO-PSO	1.000	1.000	1.000	1.000	1.000	1.000	6.000	1.000	1


Observed
Modeled
Train
Test
a
Ahvaz
Tabriz
Tehran
Semnan
Shiraz
Mashhad
AT (°C)
Month
Observed (°C)
Modeled (°C)
R² = 0.9812
R² = 0.94
R² = 0.9304
R² = 0.9754
R² = 0.9785
R² = 0.9414
Minimum AT

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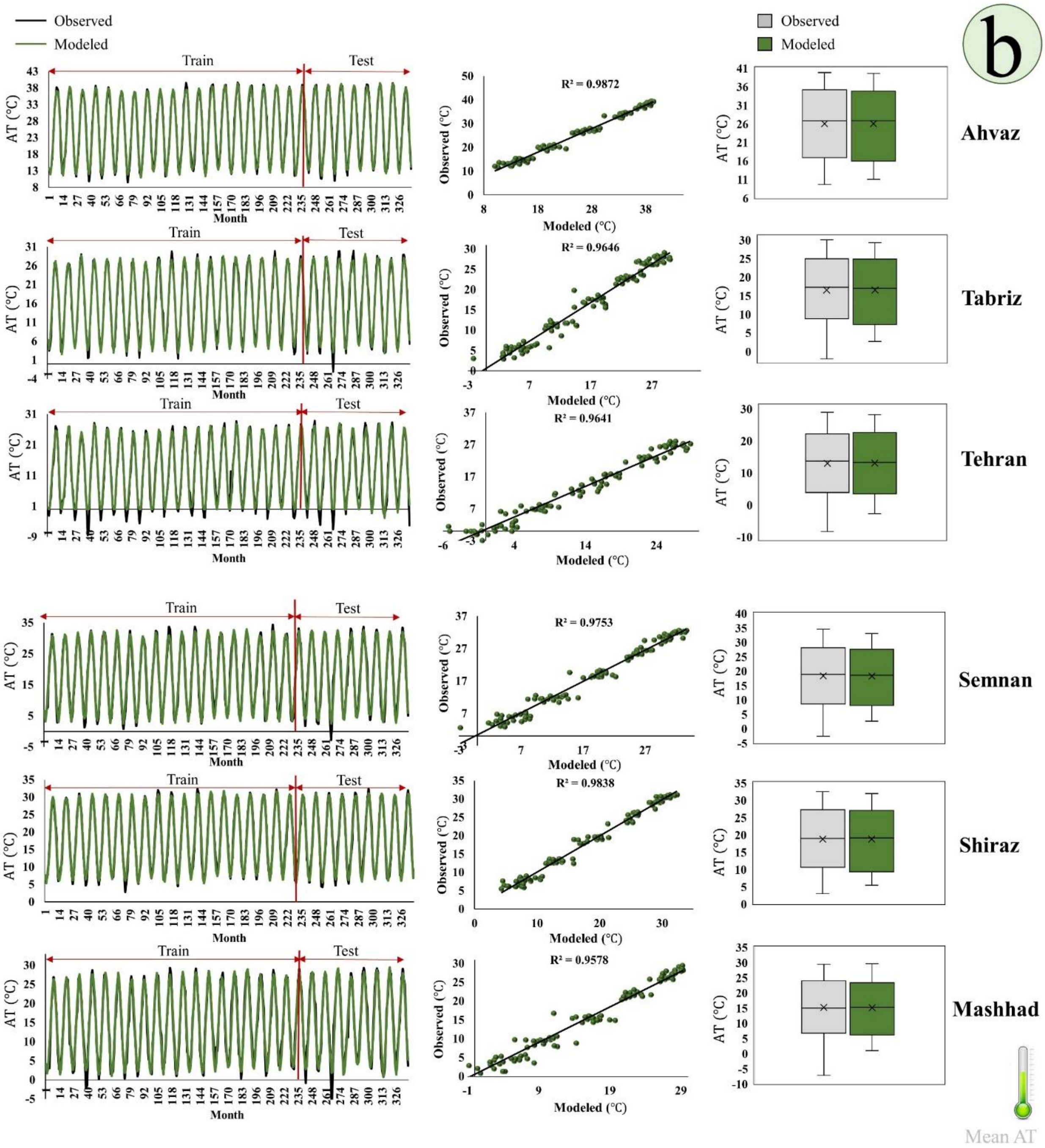

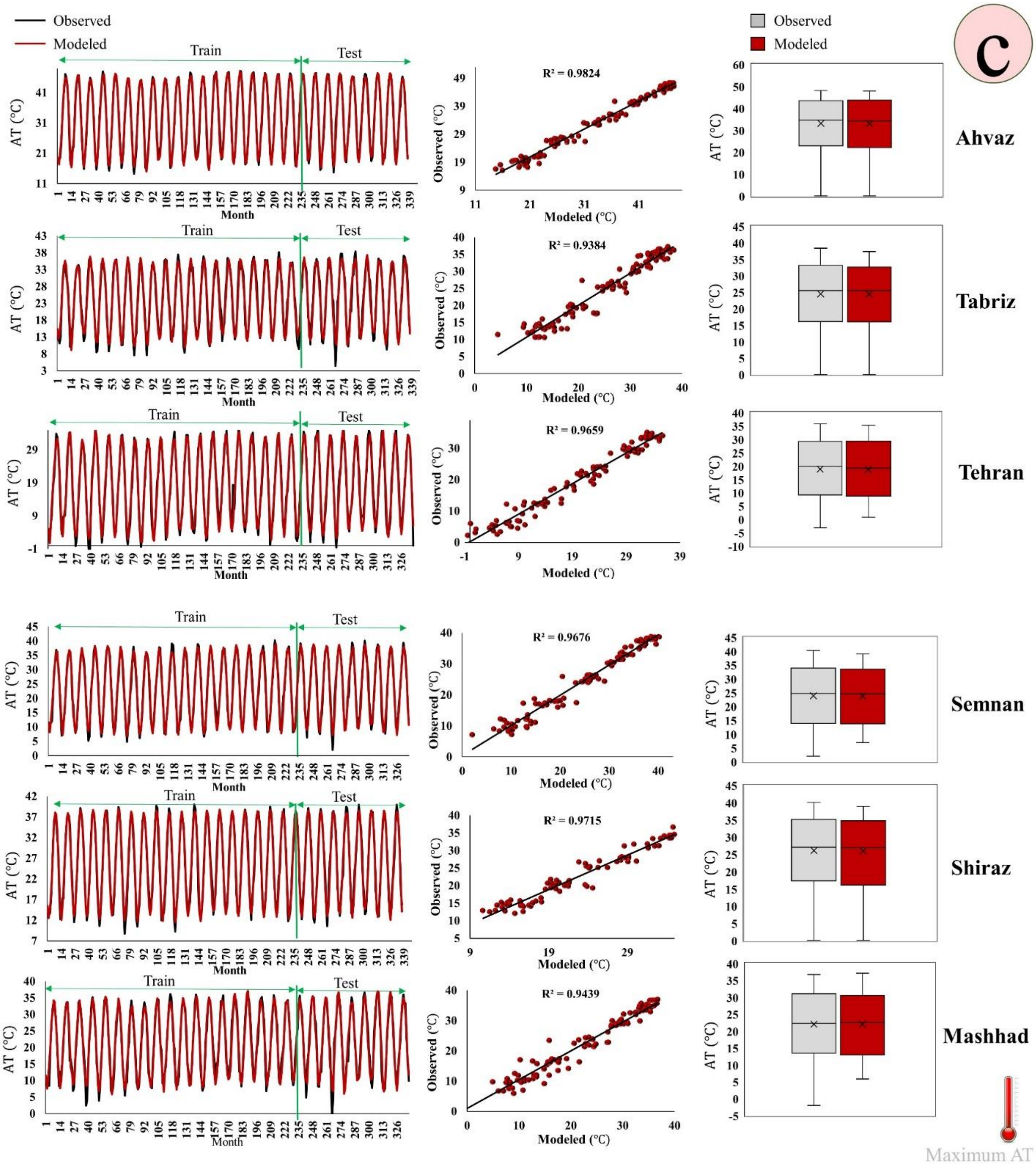

Fig. 5. Observed and modeled results of the AT by the LSSVM-AO-PSO algorithm in six stations. a) minimum AT, b) mean AT, c) maximum AT.

The results of the testing period in modeling the minimum, mean, and maximum AT in 30 stations with the best algorithm are shown in Fig. 6. According to these figures, the evaluation criteria obtained by the DHA were in a very good range. The coefficient R in the minimum, mean, and maximum AT in 30 stations was in the range of 0.946 to 0.995, which shows DHA's reasonable accuracy. According to Fig. 6, the LSSVM-AO-PSO had the best performance in modeling minimum and maximum AT. The average values of MAE, RMSE, MAPE, RRMSE, and R in modeling the minimum AT were 1.128, 1.429, 2.089, 0.190, and 0.981, respectively. Based on the results, in modeling minimum and average AT, the highest modeling accuracy was obtained in the Bandar Abbas station. The R-value in this station for minimum and mean AT were 0.989 and 0.992, respectively. Also, according to the evaluation criteria, Ahvaz and Birjand stations had the highest accuracy in modeling the maximum temperature. The R-values at these stations were 0.992 and 0.987, respectively.

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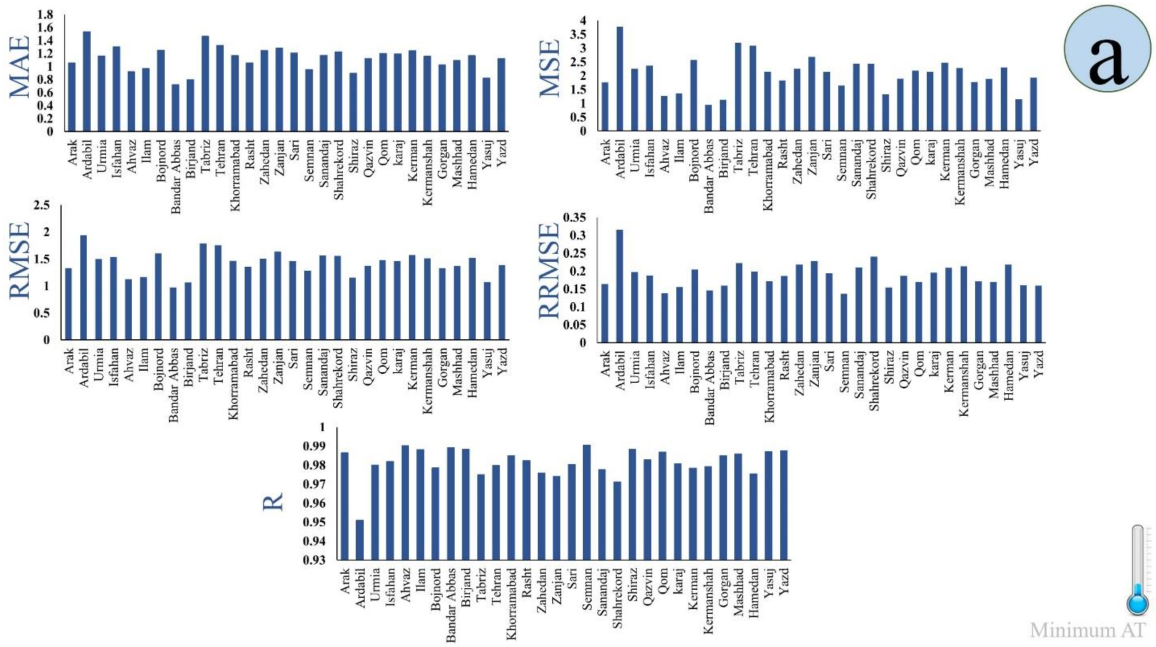
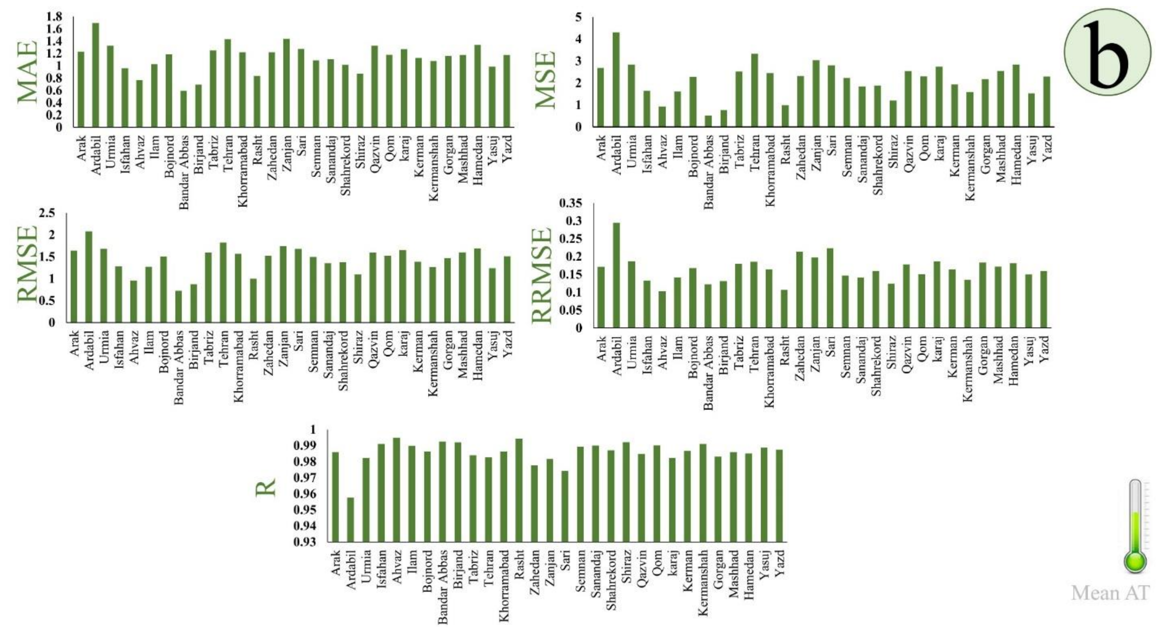




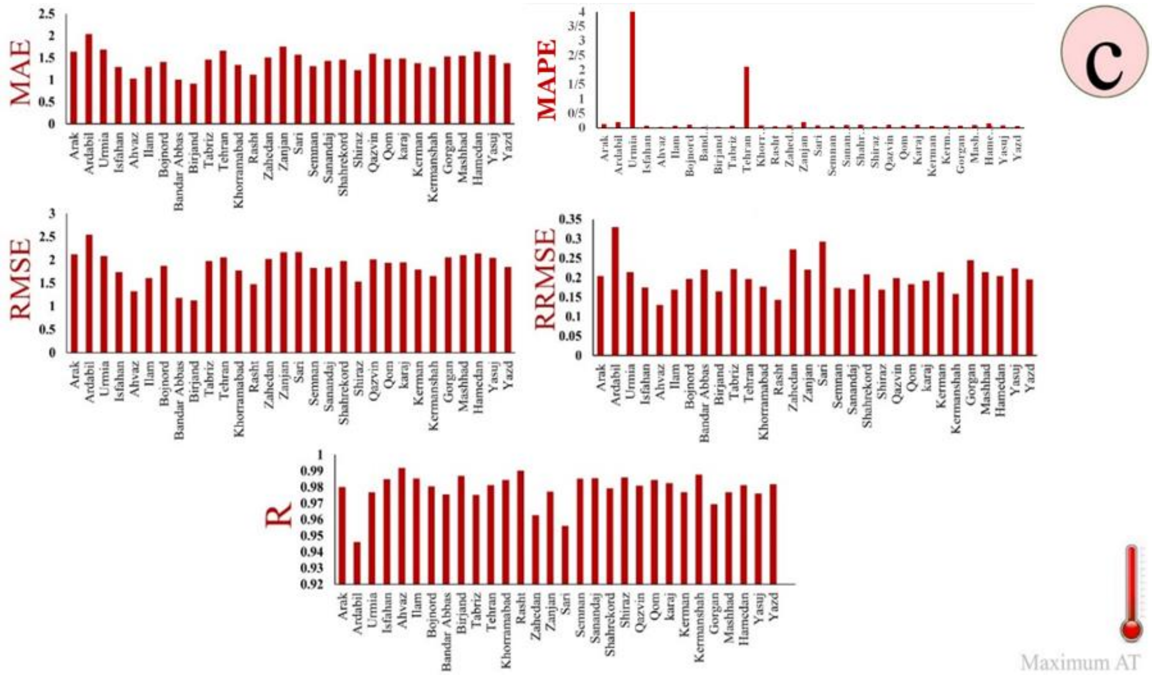
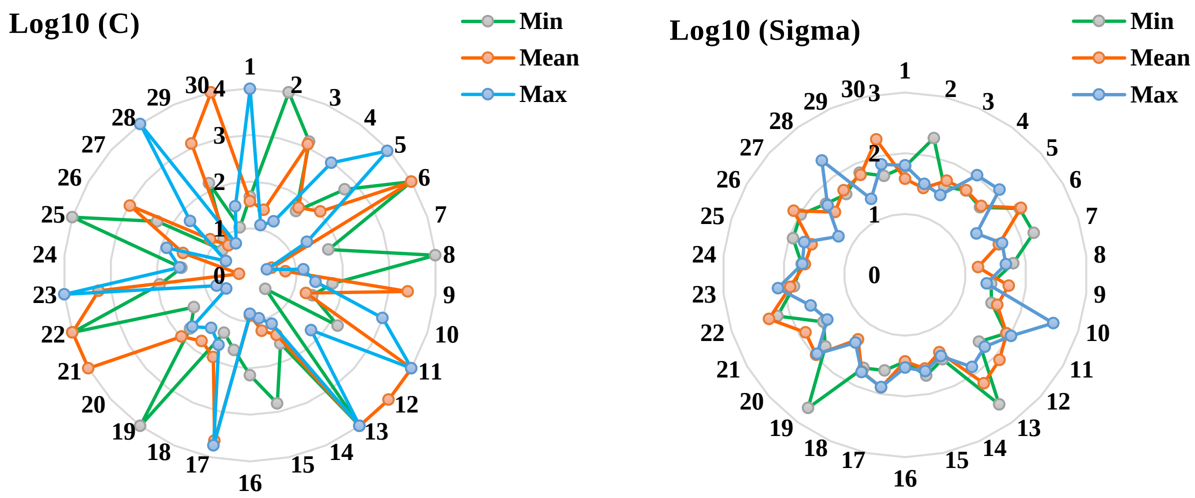


Fig. 6. Modeling of the AT of different weather stations of Iran by LSSVM-AO-PSO. a) minimum AT, b) mean AT, c) maximum AT.



a) b)

Fig. 7. The optimal parameters of DHA in logarithmic scale for the modeling Min, Mean and Max AT a) C and b Sigma.

3.5. Best Parameters of DHA

The optimal parameters of DHA including C and Sigma are depicted in Fig. 7. In this figure, for clear illustration of these parameters, the values are presented in logarithmic scale. As seen, the logarithmic values of C and Sigma were in the range of 0 to 4 and 0 to 3, respectively. Moreover, the values of C and Sigma were different in each station. This issue is for different statistical characteristics of AT time series in each station.

3.6. Predicting AT

3.6.1. Temporal changes over AT in the future horizon (2020-2047)

The temporal changes over AT in the future period (2020-2047) are shown in Fig. 8. As seen, all AT parameters under CanESM5-SSP245 and CanESM5-SSP585 were increased. However, changes in AT parameters for ACCESS-ESM1-SSP245 and ACESS-ESM1-SSP585 fluctuated. The maximum values, minimum, and mean AT in future periods were related to the 2039 year and ACCESS-ESM1-SSP245. The maximum values maximum AT in the future period was

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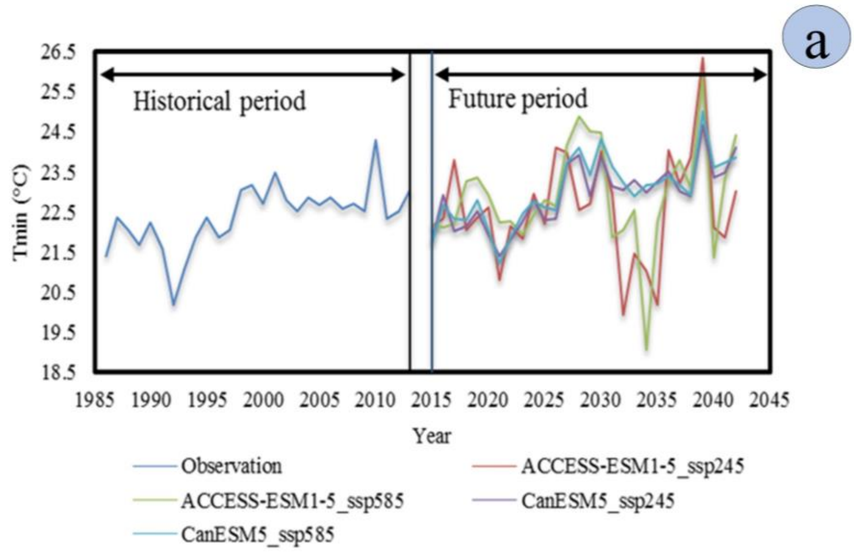
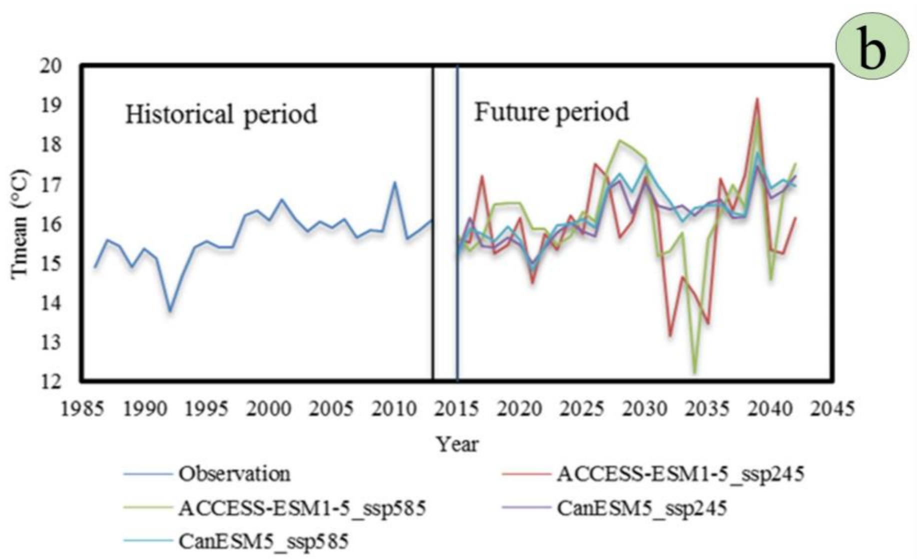
related to the 2044 year and ACCESS-ESM1-SSP245. The minimum values of future minimum and mean AT were estimated for the 2034 year and ACCESS-ESM1-SSP585. The maximum value of maximum AT in the future period was estimated for the 2039 year and ACCESS-ESM1-SSP585.





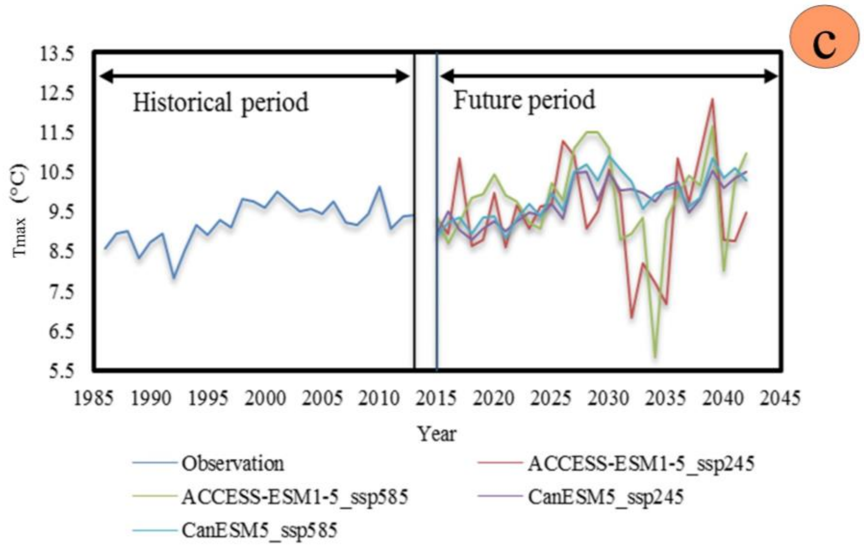


Fig. 8. Temporal changes in AT of Iran for different climate change models and scenarios. a) minimum AT, b) mean AT, c) maximum AT.

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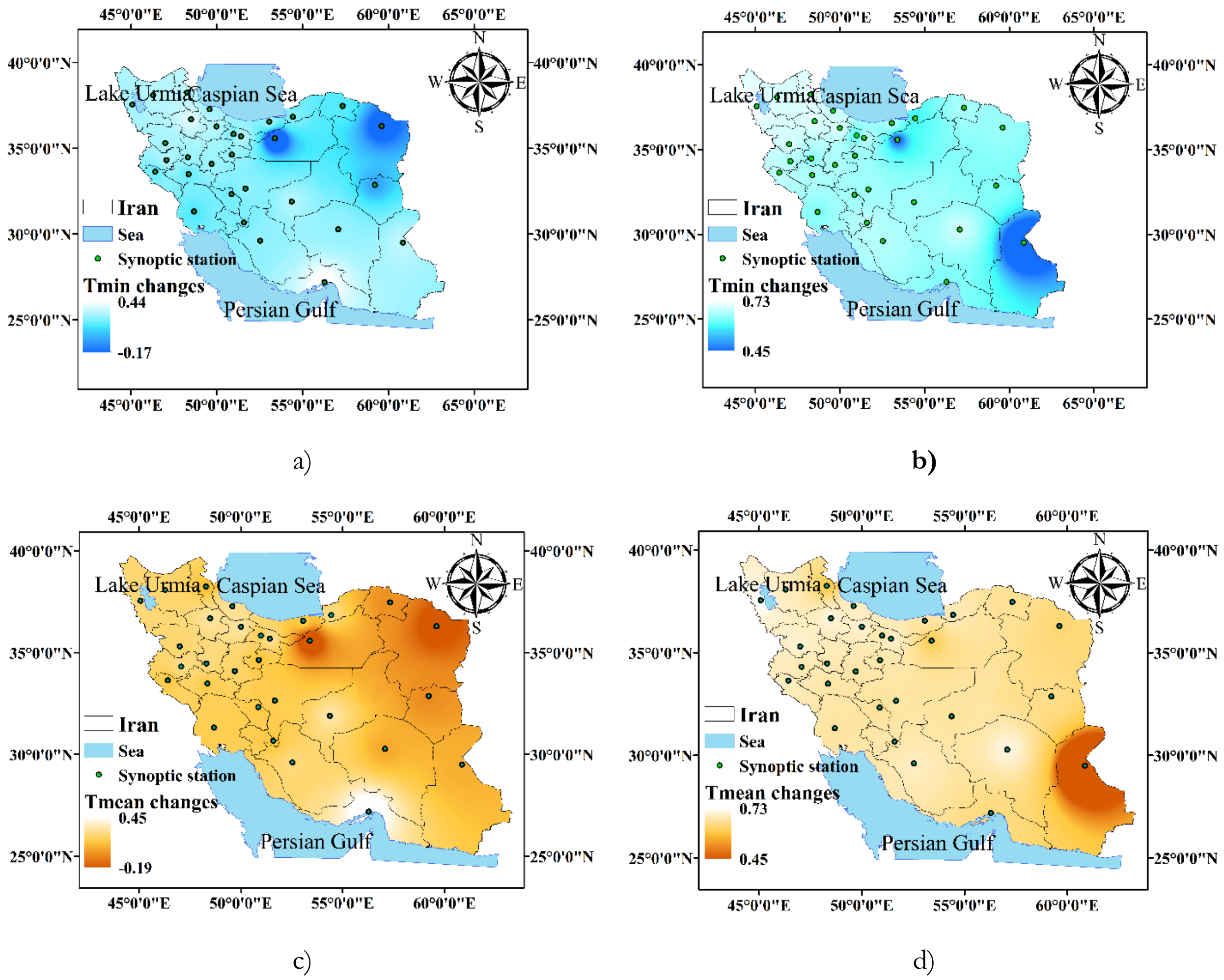
In order to clear the trend of AT changes, the Mann-Kendall test was used. The P-values of this test for observed and predicted AT parameters are presented in Table 7. In this table, if the p-value is less than 0.05, the time series of AT has an increasing trend at a 5% significant level; otherwise, the increasing trend is not significant. According to this table, all AT parameters in the observation period significantly increased. In the future period, all AT parameters under CanESM5-SSP245 and CanESM5-SSP585 had a significant increasing trend. The increasing trend in the future period for CanESM5-SSP245 and CanESM5-SSP585 was more than the observation period.

Table 7. Mann-Kendall trend test for prediction AT under climate change conditions.

Model (Scenario)	P-value		
	Tmin	Tmean	Tmax
Observation	0.004	0.002	0.002
ACCESS-ESM1-5 (ssp245)	0.830	0.71	0.469
ACCESS-ESM1-5 (ssp585)	0.281	0.281	0.175
CanESM5 (ssp245)	0.0001	0.0001	0.0001
CanESM5 (ssp585)	0.0001	0.0001	0.0001

3.7. Spatial changes over AT in the future horizon (2020-2047)

The spatial distribution of changes over AT in the future horizon is shown in Fig. 9. In this figure, the spatial changes of AT parameters are varied in different regions. According to the prediction results, ACCESS-ESM1-SSP245 and CanESM5-SSP585 were considered optimistic and pessimistic predictions, respectively. In general, the AT parameters were increased in the northwest of Iran. In optimistic prediction, the AT parameters were decreased in the northeast of Iran. While, in pessimistic prediction, all AT parameters were increased in all regions of Iran. The lowest changes of AT parameters in pessimistic prediction were related to the southeast of Iran.



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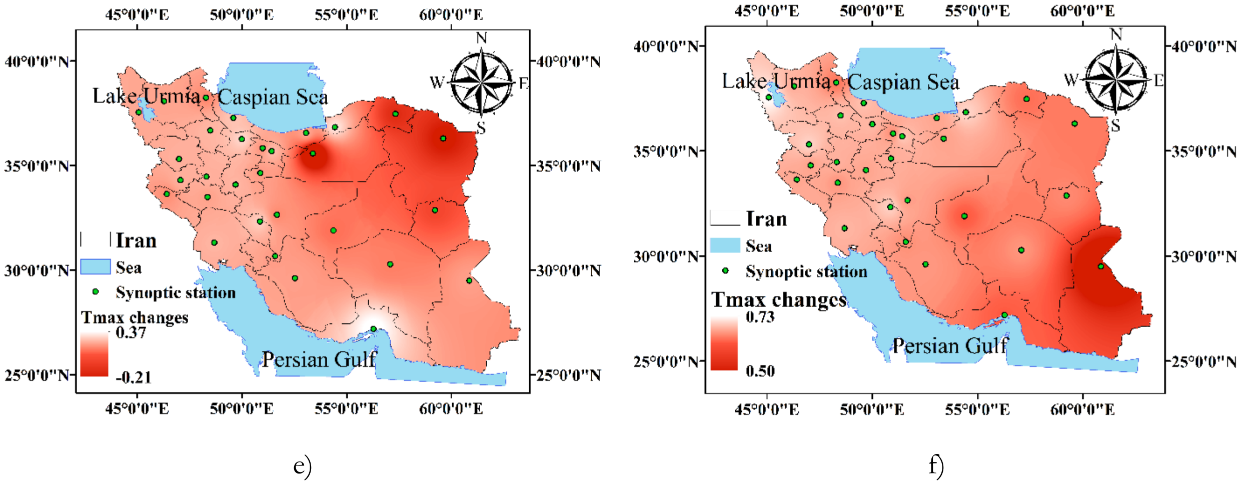

Fig. 9. Spatial changes in AT of Iran under climate change conditions for a) optimistic prediction of minimum AT, b) pessimistic prediction of minimum AT, c) optimistic prediction of mean AT, d) pessimistic prediction of mean AT , e) optimistic prediction of maximum AT, and f) pessimistic prediction of maximum AT.

4. Discussion

According to the results of the TOPSIS method in the modeling of four BDS and the prediction of minimum, mean and maximum AT in 30 meteorological stations of Iran by the classical algorithm (LSSVM), hybrid algorithms (LSSVM-PSO, and LSSVM-AO) and DHA (LSSVM-AO-PSO), the LSSVM-AO-PSO was recognized as the best algorithm. The better performance of the LSSVM-AO-PSO compared to other algorithms is due to the simultaneous use of two optimization algorithms, PSO and AO. The combination of PSO and AO algorithms allows you to use their advantages simultaneously in finding the optimal values of essential parameters of LSSVM. The simultaneous use of two optimization algorithms significantly increased the accuracy of LSSVM. AO is a powerful local search method that prevents PSO from getting trapped in local optimizations, and finding optimal values of LSSVM leads to estimating various parameters with maximum accuracy. Also, the results showed hybrid algorithms have higher accuracy and speed than classical ones. The superiority of hybrid algorithms over classical algorithms has been proven in various studies [39]. The predicting AT parameters by different GCMs and climate change scenarios show different results; this issue is for uncertainty in GCMs, and climate changes scenarios. Besides, spatial variation of AT parameters prediction is for different climates of Iran country. Also, the increase in AT in most parts of Iran will increase evaporation and transpiration and reduce water resources. The presented DHA in this study, has the greatest potential for solving other problems such as short and long term prediction of other meteorological and hydrological parameters such as precipitation, evapotranspiration, solar radiations, wind speed and river streamflow. However, to make a reliable prediction of the mentioned parameters, it is necessary to have accurate observation data with sufficient length. Moreover, the input data should be in a linear or nonlinear relation to the target data. Hence, feature engineering is essential before using DHA to solve problems.

5. Conclusion

Increasing the accuracy of ML algorithms increases the accuracy in predicting the results of meteorological parameters. For this reason, a novel DHA based on LSSVM, AO, and PSO was introduced for the first time to increase the accuracy of hybrid and classical algorithms. In DHA, the two optimization algorithms were hybridized together in the first stage and formed the AO-PSO. Then, the AO-PSO was combined with the LSSVM in the second hybridization stage. First, in this study, four BDSs, including Housing, Servo, Auto-MPG, and LSVT, were used to evaluate the novel algorithm's performance and compare it with other algorithms (LSSVM, LSSVM-PSO, and LSSVM-AO). Next, the application of the novel DHA to predict and model the minimum, mean and maximum AT in 30 meteorological stations in Iran with different climatic conditions was investigated for the first time. For accurate modeling of minimum, mean, and maximum AT, time delays of 1 to 12 months were generated in the input data. Then the minimum, mean and maximum AT modeling results at different time delays were compared with LSSVM, LSSVM-PSO, and LSSVM-AO. The TOPSIS selected the more accurate algorithm. Finally, AT parameters were predicted based on the best algorithm, ACCES-ESM1, and CanESM5 GCMs, SSP245, and SSP585 scenarios. The main results are as follows:

- The results of the TOPSIS method in modeling the BDSs showed that the DHA, with a score of 6.000, has the best performance among other algorithms.
- The average values of MAE, RMSE, MAPE, RRMSE, and R in modeling the BDSs were 20.682, 34.283, 4126.838, 0.576, and 0.733, respectively.

- The results of the TOPSIS method in modeling the minimum, mean and maximum AT showed that the LSSVM-AO-PSO, with a score of 6.000, has the best performance among other algorithms.
- The novel DHA performed best in modeling at minimum AT. The mean values of MAE, RMSE, MAPE, RRMSE, and R in modeling the minimum AT were 1.128, 1.429, 2.089, 0.190, and 0.981, respectively.
- According to the results, the double hybrid technique significantly increased the accuracy and speed of ML algorithms. In the first step, hybridizing the two AO and PSO optimization algorithms and then hybridizing them with the LSSVM resulted in the simultaneous use of the powers and benefits of both optimization algorithms.
- The results of the LSSVM-PSO and the LSSVM-AO were very close in modeling BDSs and AT.
- The temporal variation in AT parameters under climate changes indicated that ASSES-ESM1-SSP245 has optimistic results. However, CanESM-SSP585 has pessimistic results. Also, the temporal changes of AT parameters showed that prediction by the CanESM5 model led to results by increasing trend. This trend for the ACCESS-ESM1 model was not significant.
- The prediction AT parameters under climate change showed variation in values for AT parameters. However, in optimal conditions, the AT parameters in the northeast of Iran were decreased, and in other sections, they were increased. While in pessimistic conditions, the AT parameters were increased in all regions.
- The novel DHA can be used in modeling and accurate forecasting of various parameters and engineering issues. Also, other algorithms can be used in the structure of DHAs. As a result, we achieved the desired goals in presenting a novel DHA.

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Competing Interests

The authors declare that they have no conflict of interest.

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Appendix: Suppmentary Materials

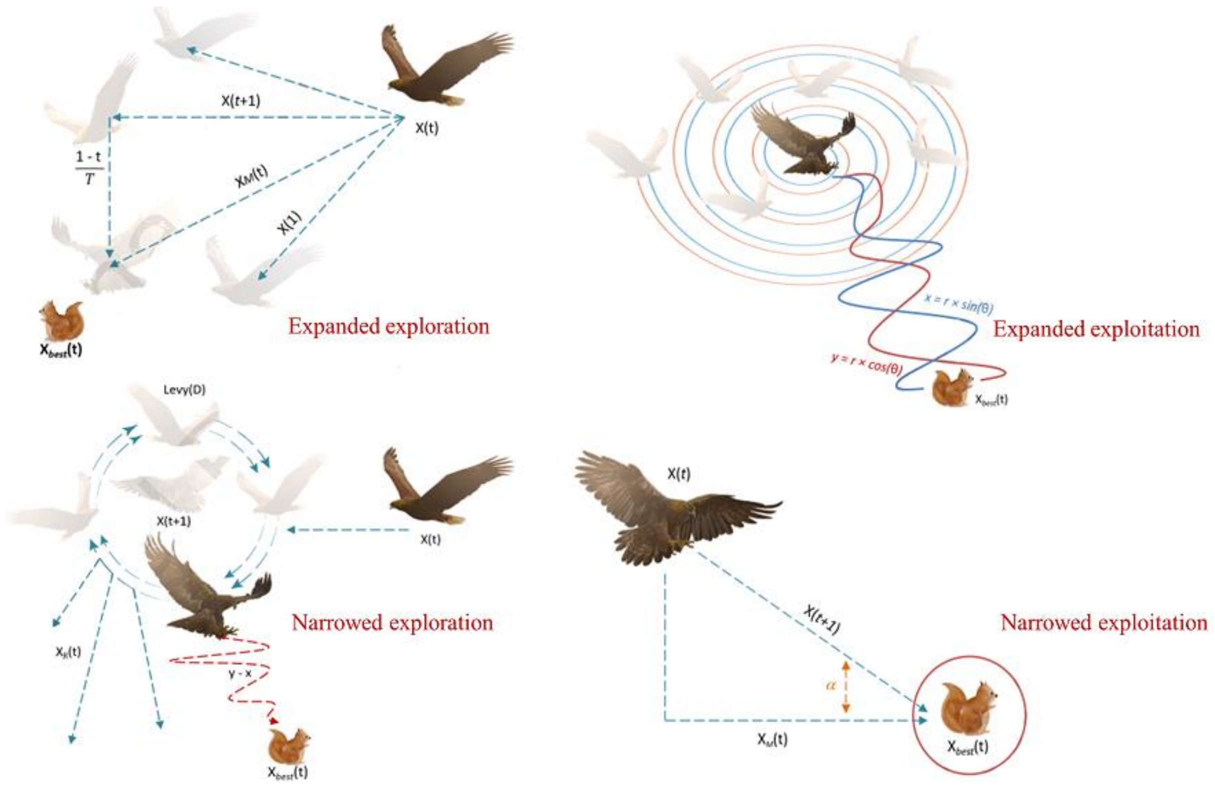

Fig S1
Aquila behavior in various attacks

Table S1
Specification of the BDSs

	Data set characteristics	Attribute characteristics	Number of instances	Number of attributes
Housing	Multivariate	Real	506	13
Servo	Multivariate	Categorical, Integer	167	4
Auto-MPG	Multivariate	Categorical, Real	398	8
LSVT	Multivariate	Real	126	309

Table S2

Geographical and AT information of study area

			Minimum AT			Mean AT			Maximum AT		
	Longitude	Latitude	Min	Average	Max	Min	Average	Max	Min	Average	Max
Arak	49.70	34.09	-15.47	7.40	21.15	-10.99	13.88	29.50	-5.88	20.77	37.90
Ardabil	48.29	38.25	-16.23	3.31	13.86	-11.62	8.93	21.97	-4.14	15.72	30.65
Urmia	45.08	37.55	-7.26	5.35	18.98	-7.26	11.33	26.32	-1.58	17.94	33.70
Isfahan	51.67	32.65	-8.38	6.56	21.36	-2.68	15.50	31.69	3.38	24.02	39.81
Ahvaz	48.68	31.32	4.48	19.05	31.52	9.50	25.93	39.67	14.28	33.21	48.15
Ilam	46.42	33.64	-3.79	11.28	25.76	0.15	17.07	34.44	3.94	22.93	37.97
Bojnord	57.33	37.47	-13.30	7.27	19.31	-7.66	12.99	27.81	-0.50	20.15	34.65
Bandar Abbas	56.28	27.19	9.74	21.78	31.63	14.79	26.84	35.61	19.32	32.19	41.29
Birjand	59.22	32.87	-7.34	8.32	22.15	-2.12	16.46	29.96	4.40	24.57	38.37
Tabriz	46.29	38.08	-11.09	7.78	22.97	-8.44	12.84	28.77	-3.15	18.84	35.76
Tehran	51.42	35.69	-5.70	13.23	26.58	-2.76	18.09	32.65	1.54	23.11	38.44
Khorramabad	48.36	33.49	-3.91	8.42	21.99	0.52	16.69	31.65	5.93	25.06	41.42
Rasht	49.59	37.28	-2.17	12.33	23.34	1.28	15.97	27.70	4.87	20.93	34.09
Zahedan	60.86	29.50	-3.70	10.75	22.31	1.89	19.17	31.58	7.50	26.97	38.62
Zanjan	48.50	36.68	-18.30	4.08	17.13	-11.36	10.89	25.87	-3.88	18.09	35.13
Sari	53.06	36.56	-0.87	13.50	25.06	3.49	17.55	29.57	8.93	22.68	35.37
Semnan	53.39	35.58	-6.94	13.11	28.54	-2.76	18.20	34.33	1.99	23.85	40.17
Sanandaj	47.00	35.31	-10.87	6.16	20.48	-7.65	13.94	30.03	-0.22	22.17	39.33
Shahrekord	50.86	32.33	-19.04	2.67	15.35	-10.19	11.56	25.95	0.03	19.96	35.98
Shiraz	52.53	29.61	-2.03	10.76	24.16	2.86	18.69	32.35	8.74	26.18	40.06
Qazvin	50.00	36.27	-12.05	7.20	19.67	-7.66	13.78	28.30	-1.62	21.45	37.38
Qom	50.88	34.64	-11.35	10.63	25.91	-6.28	18.41	34.24	0.20	26.25	42.63
karaj	50.99	35.83	-9.95	9.09	21.56	-6.12	15.77	30.69	-1.55	21.45	37.20
Kerman	57.08	30.28	-6.87	7.36	20.46	1.33	16.85	30.25	7.81	25.20	38.06
Kermanshah	47.07	34.31	-10.42	6.85	20.31	-5.43	15.36	31.04	0.27	23.44	40.14
Gorgan	54.44	36.84	-3.90	12.60	24.95	1.70	17.31	30.34	8.19	23.25	36.67
Mashhad	59.61	36.30	-11.99	8.89	21.75	-7.34	15.10	29.33	-2.01	22.06	36.70
Hamedan	48.31	34.47	-16.91	4.10	15.99	-11.80	11.72	26.98	-5.00	19.69	37.01
Yasuj	51.59	30.67	-4.97	7.76	19.86	-0.79	14.96	29.05	4.20	22.61	37.37
Yazd	54.37	31.90	-4.84	12.82	28.29	-1.06	19.90	35.89	3.95	27.04	42.63

Table S3

Average results BDSs modeling during the testing period

	MAE	RMSE	MAPE	RRMSE	R	Time (s)
LSSVM	30.034	54.570	0.311	0.605	0.725	3.277
LSSVM-PSO	22.531	37.031	0.308	0.580	0.731	2.488
LSSVM-AO	21.668	36.141	0.315	0.580	0.731	3.395
LSSVM-AO-PSO	20.682	34.283	0.305	0.576	0.733	2.409

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Table S4

The modeling results of the minimum, mean and maximum AT of Arak station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.332	2.224	0.486	0.278	0.968	1.185	1.878	0.930	0.226	0.974	8.394
LSSVM-PSO	1.332	2.224	0.486	0.278	0.968	1.185	1.878	0.930	0.226	0.974	6.582
Std	1.E-07	1E-07	4E-08	1E-08	1E-09	9E-08	1E-12	2 E-08	1E-13	8E-11	
LSSVM-AO	1.331	2.224	0.486	0.278	0.968	1.185	1.878	1.082	0.226	0.974	7.554
Std	2E-03	1E-03	6E-04	1E-04	1E-05	1E-03	2E-04	2E-04	2E-05	2E-06	
LSSVM-AO-PSO	1.424	2.432	0.488	0.301	0.962	1.056	1.327	1.082	0.164	0.986	4.467
Std	6E-06	2E-06	2E-06	2E-07	5E-08	2E-06	1E-09	7E-06	1E-10	2E-09	
						Mean AT					
LSSVM	1.308	2.012	0.488	0.201	0.980	1.408	2.053	0.230	0.206	0.979	8.483
LSSVM-PSO	1.306	2.010	0.487	0.201	0.980	1.409	2.053	0.230	0.206	0.979	6.661
Std	1E-07	6E-08	7E-08	8E-09	1E-09	5E-08	1E-12	2E-07	2E-13	7E-11	
LSSVM-AO	1.306	2.011	0.487	0.201	0.980	1.409	2.053	0.230	0.206	0.979	8.087
Std	7E-04	2E-04	3E-04	3E-05	6E-06	3E-04	1E-05	9E-04	2E-06	5E-07	
LSSVM-AO-PSO	1.357	2.098	0.441	0.209	0.978	1.233	1.639	0.225	0.171	0.986	3.680
Std	3E-05	2E-05	9E-06	2E-06	2E-07	1E-05	2E-08	3E-06	3E-09	1E-08	
						Maximum AT					
LSSVM	1.532	2.174	0.215	0.201	0.980	1.824	2.513	0.175	0.233	0.973	8.663
LSSVM-PSO	1.538	2.184	0.217	0.202	0.979	1.826	2.513	0.174	0.233	0.974	6.745
Std	3E-07	3E-07	3E-08	3E-08	2E-09	1E-07	1E-12	2E-08	1E-13	1E-10	
LSSVM-AO	1.416	1.970	0.195	0.182	0.983	1.874	2.514	0.176	0.233	0.974	9.752
Std	7E-03	9E-03	7E-04	8E-04	5E-05	4E-03	8E-04	6E-04	7E-05	8E-06	
LSSVM-AO-PSO	1.327	1.890	0.171	0.173	0.985	1.639	2.117	0.126	0.204	0.980	3.021
Std	1E-04	2E-04	1E-05	1E-05	1E-06	8E-05	2E-07	1E-05	2E-08	6E-08	

Table S5

The modeling results of the minimum, mean and maximum AT of Ardabil station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	2.208	3.363	0.656	0.525	0.913	1.523	2.167	1.619	0.335	0.943	8.318
LSSVM-PSO	2.217	3.367	0.661	0.526	0.912	1.516	2.161	1.631	0.334	0.943	6.205
Std	1E-06	2E-07	1E-06	3E-08	8E-09	9E-07	4E-11	2E-05	5E-12	1E-09	
LSSVM-AO	2.218	3.367	0.661	0.526	0.912	1.515	2.161	1.551	0.334	0.943	7.104
Std	3E-03	6E-04	3E-03	7E-05	1E-05	2E-03	2E-04	4E-02	3E-05	9E-06	
LSSVM-AO-PSO	2.236	3.438	0.696	0.530	0.907	1.535	1.944	1.550	0.315	0.951	4.566
Std	2E-05	5E-06	1E-05	8E-07	6E-07	3E-05	6E-09	4E-05	9E-10	3E-09	
						Mean AT					
LSSVM	1.699	2.400	1.535	0.311	0.955	1.719	2.268	2.413	0.304	0.953	7.932
LSSVM-PSO	1.705	2.404	1.554	0.311	0.955	1.715	2.266	2.660	0.304	0.953	5.392
Std	3E-07	6E-08	1E-07	9E-09	8E-09	4E-07	1E-12	5E-07	2E-13	3E-11	
LSSVM-AO	1.715	2.411	1.571	0.312	0.955	1.710	2.267	2.896	0.304	0.953	8.481
Std	8E-04	1E-04	3E-04	2E-05	2E-05	1E-03	8E-06	1E-03	1E-06	1E-07	
LSSVM-AO-PSO	1.663	2.389	1.306	0.307	0.956	1.695	2.076	2.370	0.295	0.958	3.576
Std	1E-04	2E-05	1E-04	3E-06	8E-07	1E-04	1E-06	1E-03	2E-07	2E-07	
						Maximum AT					
LSSVM	1.746	2.299	0.638	0.288	0.957	2.046	2.663	0.204	0.331	0.945	8.462
LSSVM-PSO	1.745	2.298	0.638	0.288	0.957	2.046	2.663	0.204	0.331	0.945	6.259
Std	9E-06	1E-05	1E-06	1E-06	7E-08	6E-05	4E-08	3E-06	5E-09	3E-08	
LSSVM-AO	1.744	2.296	0.636	0.288	0.957	2.045	2.663	0.204	0.331	0.945	7.449
Std	3E-03	4E-03	2E-04	5E-04	3E-05	5E-03	5E-04	3E-04	6E-05	1E-05	
LSSVM-AO-PSO	1.747	2.323	0.546	0.288	0.957	2.039	2.545	0.190	0.329	0.946	3.032
Std	2E-03	2E-03	1E-04	3E-04	1E-05	4E-03	4E-04	3E-04	5E-05	1E-05	

Table S6

The modeling results of the minimum, mean and maximum AT of Urmia station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.555	2.324	0.477	0.316	0.968	1.215	1.623	0.379	0.209	0.978	8.477
LSSVM-PSO	1.554	2.323	0.477	0.316	0.968	1.215	1.623	0.379	0.209	0.978	6.309
Std	2E-07	1E-07	3E-08	1E-08	2E-09	2E-07	1E-12	8E-08	2E-13	3E-11	
LSSVM-AO	1.552	2.322	0.477	0.316	0.968	1.215	1.623	0.343	0.209	0.978	7.880
Std	2E-03	1E-03	2E-04	1E-04	2E-05	2E-03	2E-04	7E-04	2E-05	4E-06	
LSSVM-AO-PSO	1.565	2.459	0.483	0.330	0.966	1.164	1.500	0.343	0.198	0.980	4.825
Std	8E-05	1E-05	4E-05	2E-06	7E-07	8E-05	1E-07	1E-06	1E-08	6E-09	
						Mean AT					
LSSVM	1.110	1.550	0.320	0.170	0.986	1.348	1.735	0.390	0.189	0.982	9.892
LSSVM-PSO	1.085	1.529	0.316	0.168	0.987	1.359	1.726	0.412	0.188	0.982	5.175
Std	3E-07	6E-08	1E-07	8E-09	2E-09	2E-07	1E-12	4E-09	2E-13	3E-11	
LSSVM-AO	1.078	1.521	0.314	0.167	0.987	1.358	1.724	0.420	0.188	0.982	8.488
Std	1E-03	3E-04	8E-04	4E-05	1E-05	1E-03	4E-05	3E-05	5E-06	6E-07	
LSSVM-AO-PSO	1.109	1.589	0.315	0.174	0.986	1.325	1.685	0.392	0.188	0.982	3.429
Std	6E-06	3E-06	9E-07	4E-07	6E-08	7E-06	1E-09	2E-06	1E-10	1E-09	
						Maximum AT					
LSSVM	1.313	1.690	0.761	0.172	0.985	1.695	2.154	3.685	0.218	0.976	8.972
LSSVM-PSO	1.293	1.665	0.745	0.170	0.985	1.697	2.145	3.667	0.217	0.976	6.301
Std	1E-07	2E-07	1E-08	2E-08	9E-10	8E-08	2E-12	1E-06	2E-13	1E-11	
LSSVM-AO	1.292	1.665	0.744	0.169	0.985	1.697	2.145	3.667	0.217	0.976	7.161
Std	1E-03	2E-03	1E-04	2E-04	8E-06	6E-04	2E-04	1E-02	2E-05	3E-06	
LSSVM-AO-PSO	1.292	1.691	0.666	0.171	0.985	1.687	2.080	3.918	0.214	0.977	3.041
Std	3E-05	4E-05	3E-06	4E-06	1E-07	1E-05	7E-08	2E-04	7E-09	3E-09	

Table S7

The modeling results of the minimum, mean and maximum AT of Isfahan station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.499	2.156	1.336	0.270	0.977	1.270	1.550	0.470	0.191	0.982	8.444
LSSVM-PSO	1.499	2.156	1.336	0.270	0.977	1.270	1.550	0.470	0.191	0.982	6.606
Std	3E-07	3E-07	1E-07	3E-08	1E-09	3E-08	1E-12	4E-08	1E-13	1E-11	
LSSVM-AO	1.500	2.157	1.339	0.270	0.977	1.270	1.550	0.426	0.191	0.982	8.835
Std	2E-03	2E-03	8E-04	3E-04	1E-05	4E-04	1E-04	3E-04	1E-05	1E-06	
LSSVM-AO-PSO	1.529	2.195	1.171	0.275	0.975	1.302	1.538	0.426	0.188	0.982	4.465
Std	3E-05	8E-06	6E-05	1E-06	2E-07	3E-05	6E-08	1E-05	8E-09	1E-09	
						Mean AT					
LSSVM	0.873	1.116	0.247	0.117	0.993	1.070	1.433	0.246	0.149	0.989	9.372
LSSVM-PSO	0.874	1.116	0.247	0.117	0.993	1.069	1.433	0.246	0.149	0.989	5.530
Std	1E-07	3E-08	2E-07	4E-09	9E-10	1E-07	1E-12	6E-08	1E-13	8E-12	
LSSVM-AO	0.870	1.109	0.245	0.116	0.993	1.070	1.434	0.246	0.149	0.989	9.327
Std	1E-03	3E-04	2E-03	4E-05	1E-05	1E-03	1E-04	7E-04	1E-05	2E-06	
LSSVM-AO-PSO	0.956	1.222	0.255	0.128	0.992	0.960	1.281	0.127	0.133	0.991	2.989
Std	1E-04	1E-04	3E-05	1E-05	6E-07	1E-05	2E-07	1E-05	2E-08	1E-09	
						Maximum AT					
LSSVM	1.169	1.537	0.073	0.154	0.988	1.374	1.833	0.084	0.183	0.983	7.894
LSSVM-PSO	1.168	1.536	0.073	0.154	0.988	1.373	1.833	0.084	0.183	0.983	6.512
Std	4E-07	5E-07	2E-08	5E-08	2E-09	4E-08	1E-12	1E-08	1E-13	1E-11	
LSSVM-AO	1.169	1.537	0.073	0.154	0.988	1.374	1.833	0.084	0.183	0.983	7.302
Std	7E-04	9E-04	5E-05	9E-05	4E-06	8E-05	4E-06	2E-05	4E-07	4E-08	
LSSVM-AO-PSO	1.243	1.630	0.078	0.163	0.987	1.292	1.738	0.071	0.175	0.985	2.895
Std	1E-04	2E-04	1E-05	2E-05	1E-06	2E-05	3E-07	5E-06	3E-08	7E-09	

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Table S8

The modeling results of the minimum, mean and maximum AT of Ilam station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.023	1.285	1.793	0.162	0.987	1.162	1.425	1.057	0.185	0.984	7.869
LSSVM-PSO	1.014	1.279	1.736	0.162	0.987	1.145	1.419	0.961	0.184	0.984	5.192
Std	1E-07	1E-07	1E-08	1E-08	8E-10	2E-08	9E-13	2E-09	1E-13	1E-11	
LSSVM-AO	1.014	1.278	1.737	0.162	0.987	1.145	1.419	1.013	0.184	0.984	7.994
Std	3E-03	3E-03	3E-04	3E-04	1E-05	8E-04	3E-04	4E-05	3E-05	2E-06	
LSSVM-AO-PSO	1.096	1.404	1.373	0.177	0.984	0.966	1.168	1.013	0.155	0.988	4.046
Std	8E-04	9E-04	3E-04	1E-04	6E-06	5E-04	3E-05	1E-03	4E-06	6E-07	
						Mean AT					
LSSVM	1.031	1.333	0.229	0.142	0.990	1.142	1.442	0.173	0.157	0.988	8.441
LSSVM-PSO	1.035	1.334	0.232	0.142	0.990	1.136	1.427	0.169	0.155	0.988	4.803
Std	3E-06	3E-06	4E-06	3E-07	2E-08	8E-06	5E-09	2E-05	6E-10	4E-09	
LSSVM-AO	1.039	1.338	0.233	0.143	0.990	1.137	1.425	0.169	0.155	0.988	6.624
Std	2E-03	2E-03	1E-03	2E-04	1E-05	2E-03	1E-04	3E-03	2E-05	1E-06	
LSSVM-AO-PSO	1.089	1.406	0.242	0.149	0.989	1.025	1.266	0.099	0.142	0.990	2.743
Std	3E-05	4E-05	4E-06	4E-06	1E-07	6E-06	5E-08	5E-07	5E-09	3E-09	
						Maximum AT					
LSSVM	1.099	1.415	0.077	0.146	0.989	1.389	1.791	0.080	0.183	0.983	8.453
LSSVM-PSO	1.110	1.424	0.078	0.147	0.989	1.368	1.774	0.078	0.181	0.984	4.819
Std	1E-07	2E-07	1E-08	2E-08	1E-09	5E-08	1E-12	1E-09	1E-13	4E-11	
LSSVM-AO	1.111	1.425	0.078	0.147	0.989	1.366	1.774	0.078	0.181	0.984	7.575
Std	2E-03	3E-03	1E-04	3E-04	1E-05	8E-04	2E-04	2E-05	2E-05	2E-06	
LSSVM-AO-PSO	1.053	1.371	0.072	0.140	0.990	1.295	1.609	0.071	0.169	0.985	2.937
Std	2E-04	3E-04	1E-05	3E-05	1E-06	8E-05	4E-06	2E-06	4E-07	3E-08	

Table S9

The modeling results of the minimum, mean and maximum AT of Bojnord station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.215	1.588	0.530	0.227	0.976	1.439	2.019	3.889	0.256	0.967	8.778
LSSVM-PSO	1.279	1.647	0.526	0.235	0.975	1.425	2.008	5.441	0.254	0.967	5.404
Std	3E-06	2E-06	5E-06	3E-07	1E-08	2E-06	3E-09	2E-05	3E-10	1E-09	
LSSVM-AO	1.279	1.647	0.525	0.235	0.975	1.424	2.008	5.064	0.254	0.967	8.697
Std	2E-03	2E-03	1E-03	2E-04	1E-05	6E-04	2E-04	7E-03	2E-05	2E-06	
LSSVM-AO-PSO	1.353	1.898	0.516	0.266	0.968	1.252	1.607	5.064	0.205	0.979	4.137
Std	1E-06	1E-06	1E-06	1E-07	2E-08	2E-06	1E-10	6E-06	2E-11	4E-10	
						Mean AT					
LSSVM	1.168	1.500	0.785	0.171	0.985	1.340	1.831	2.539	0.201	0.980	7.653
LSSVM-PSO	1.163	1.491	0.785	0.170	0.985	1.344	1.830	2.544	0.201	0.980	5.375
Std	1E-07	7E-08	6E-08	1E-08	1E-09	1E-07	8E-13	4E-07	1E-13	2E-11	
LSSVM-AO	1.163	1.491	0.785	0.170	0.985	1.344	1.830	2.543	0.201	0.980	7.222
Std	6E-04	4E-04	3E-04	6E-05	1E-05	8E-04	2E-05	2E-03	3E-06	5E-07	
LSSVM-AO-PSO	1.294	1.725	0.847	0.195	0.981	1.183	1.507	2.237	0.168	0.986	2.955
Std	3E-04	2E-04	1E-04	3E-05	1E-06	7E-05	6E-06	1E-03	6E-07	1E-07	
						Maximum AT					
LSSVM	1.530	1.989	0.143	0.218	0.976	1.634	2.263	0.272	0.238	0.972	8.746
LSSVM-PSO	1.530	1.989	0.143	0.218	0.976	1.633	2.263	0.272	0.238	0.972	5.371
Std	1E-04	1E-04	8E-06	1E-05	7E-07	1E-06	2E-08	1E-06	2E-09	7E-08	
LSSVM-AO	1.531	1.990	0.143	0.218	0.976	1.633	2.263	0.272	0.238	0.972	9.215
Std	1E-03	2E-03	1E-04	2E-04	1E-05	7E-05	1E-05	1E-05	1E-06	1E-06	
LSSVM-AO-PSO	1.616	2.149	0.204	0.234	0.972	1.405	1.869	0.106	0.197	0.980	3.095
Std	1E-03	2E-03	1E-04	2E-04	1E-05	5E-05	4E-06	1E-05	5E-07	1.E-06	

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Table S10

The modeling results of the minimum, mean and maximum AT of Bandar Abbas station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.688	0.899	0.037	0.139	0.990	0.809	1.105	0.046	0.165	0.986	8.699
LSSVM-PSO	0.689	0.900	0.037	0.139	0.990	0.809	1.105	0.046	0.165	0.986	5.962
Std	1E-07	2E-07	7E-09	3E-08	1E-09	7E-08	1E-12	3E-09	1E-13	5E-11	
LSSVM-AO	0.688	0.899	0.037	0.139	0.990	0.809	1.105	0.039	0.165	0.986	8.393
Std	2E-03	3E-03	1E-04	5E-04	2E-05	1E-03	2E-04	5E-05	4E-05	3E-06	
LSSVM-AO-PSO	0.699	0.916	0.039	0.141	0.990	0.721	0.973	0.039	0.146	0.989	4.178
Std	1E-05	1E-05	6E-07	2E-06	1E-07	2E-06	2E-09	2E-07	4E-10	2E-09	
						Mean AT					
LSSVM	0.569	0.740	0.023	0.123	0.992	0.629	0.862	0.026	0.142	0.990	8.133
LSSVM-PSO	0.569	0.740	0.023	0.123	0.992	0.629	0.862	0.026	0.142	0.990	6.368
Std	1E-07	2E-07	9E-09	3E-08	1E-09	3E-08	1E-12	3E-09	1E-13	2E-11	
LSSVM-AO	0.568	0.739	0.023	0.123	0.992	0.628	0.862	0.026	0.142	0.990	7.260
Std	2E-03	2E-03	1E-04	4E-04	2E-05	4E-04	6E-05	3E-05	9E-06	1E-06	
LSSVM-AO-PSO	0.584	0.787	0.024	0.130	0.992	0.594	0.723	0.023	0.122	0.992	3.030
Std	1E-04	1E-04	4E-06	2E-05	1E-06	4E-05	2E-07	2E-06	4E-08	3E-08	
						Maximum AT					
LSSVM	0.844	1.076	0.027	0.191	0.982	0.996	1.246	0.032	0.226	0.974	7.368
LSSVM-PSO	0.849	1.086	0.028	0.193	0.981	0.999	1.245	0.032	0.226	0.975	5.286
Std	2E-07	2E-07	6E-09	4E-08	2E-09	4E-08	6E-13	9E-10	1E-13	1E-11	
LSSVM-AO	0.850	1.088	0.027	0.193	0.981	0.999	1.245	0.032	0.226	0.975	9.300
Std	2E-03	3E-03	9E-05	6E-04	3E-05	3E-04	1E-04	6E-06	2E-05	2E-06	
LSSVM-AO-PSO	0.944	1.195	0.031	0.212	0.977	1.008	1.179	0.031	0.221	0.975	3.442
Std	1E-05	2E-05	6E-07	4E-06	2E-07	4E-06	4E-09	8E-08	8E-10	1E-09	

Table S11

The modeling results of the minimum, mean and maximum AT of Birjand station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.674	0.871	0.040	0.132	0.991	0.850	1.090	0.047	0.165	0.988	10.314
LSSVM-PSO	0.674	0.870	0.040	0.131	0.991	0.848	1.090	0.047	0.165	0.988	5.837
Std	1E-07	1E-07	5E-09	1E-08	8E-10	3E-08	7E-13	1E-09	1E-13	2E-12	
LSSVM-AO	0.675	0.871	0.040	0.132	0.991	0.847	1.090	0.043	0.165	0.988	7.714
Std	2E-03	2E-03	1E-04	3E-04	1E-05	6E-04	5E-04	3E-05	8E-05	6E-06	
LSSVM-AO-PSO	0.679	0.877	0.040	0.133	0.991	0.795	1.067	0.043	0.160	0.988	4.372
Std	3E-06	4E-06	2E-07	6E-07	3E-08	9E-07	2E-10	3E-08	4E-11	1E-09	
						Mean AT					
LSSVM	0.665	0.862	0.030	0.123	0.992	0.775	1.014	0.035	0.150	0.989	9.364
LSSVM-PSO	0.665	0.862	0.030	0.123	0.992	0.775	1.014	0.035	0.150	0.989	6.658
Std	2E-07	2E-07	1E-08	4E-08	2E-09	5E-08	4E-13	2E-09	6E-14	8E-11	
LSSVM-AO	0.663	0.857	0.030	0.122	0.992	0.779	1.016	0.036	0.150	0.989	7.597
Std	2E-04	2E-04	1E-05	3E-05	1E-06	5E-05	1E-06	1E-06	1E-07	6E-08	
LSSVM-AO-PSO	0.692	0.902	0.032	0.129	0.992	0.691	0.878	0.030	0.131	0.992	2.987
Std	1E-05	2E-05	8E-07	3E-06	1E-07	5E-06	2E-08	1E-07	3E-09	7E-10	
						Maximum AT					
LSSVM	1.040	1.309	0.037	0.181	0.984	0.976	1.212	0.036	0.177	0.984	8.887
LSSVM-PSO	1.068	1.352	0.038	0.187	0.984	0.970	1.210	0.036	0.177	0.984	5.635
Std	1E-07	1E-07	3E-09	1E-08	7E-10	8E-09	8E-13	1E-10	1E-13	9E-12	
LSSVM-AO	0.861	1.093	0.031	0.152	0.988	0.982	1.238	0.036	0.181	0.984	8.950
Std	1E-03	2E-03	6E-05	3E-04	1E-05	4E-04	2E-04	1E-05	3E-05	2E-06	
LSSVM-AO-PSO	0.908	1.153	0.033	0.161	0.987	0.918	1.122	0.032	0.165	0.987	3.598
Std	3E-06	3E-06	1E-07	5E-07	2E-08	2E-07	4E-10	3E-09	6E-11	2E-10	

Table S12

The modeling results of the minimum, mean and maximum AT of Khorramabad station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.135	1.422	0.299	0.166	0.986	1.243	1.632	0.765	0.188	0.982	8.641
LSSVM-PSO	1.134	1.422	0.299	0.166	0.986	1.243	1.632	0.765	0.188	0.982	5.764
Std	2E-07	3E-07	1E-08	3E-08	1E-09	4E-09	6E-13	4E-09	7E-14	4E-12	
LSSVM-AO	1.131	1.418	0.296	0.165	0.986	1.245	1.632	0.637	0.188	0.982	7.194
Std	2E-03	2E-03	1E-04	3E-04	1E-05	8E-05	6E-05	5.E-05	7E-06	6E-07	
LSSVM-AO-PSO	1.227	1.566	0.414	0.181	0.983	1.168	1.466	0.637	0.172	0.985	4.274
Std	5E-04	5E-04	1E-04	6E-05	3E-06	7E-05	7E-06	2E-04	8E-07	7E-08	
						Mean AT					
LSSVM	1.253	1.572	0.183	0.163	0.987	1.319	1.802	0.141	0.186	0.983	8.149
LSSVM-PSO	1.252	1.571	0.183	0.163	0.987	1.319	1.802	0.141	0.186	0.983	7.692
Std	2E-07	2E-07	7E-08	3E-08	1E-09	3E-08	1E-12	9E-08	1E-13	2E-12	
LSSVM-AO	1.252	1.571	0.183	0.163	0.987	1.320	1.802	0.141	0.186	0.983	7.447
Std	1E-03	1E-03	4E-04	1E-04	9E-06	1E-04	3E-05	5E-04	3E-06	3E-07	
LSSVM-AO-PSO	1.295	1.646	0.183	0.170	0.985	1.218	1.563	0.108	0.165	0.986	2.911
Std	1E-04	1E-04	8E-06	1E-05	6E-07	2E-06	1E-07	2E-06	1E-08	1E-09	
						Maximum AT					
LSSVM	1.384	1.763	0.092	0.172	0.985	1.515	2.052	0.129	0.201	0.980	9.134
LSSVM-PSO	1.384	1.763	0.092	0.172	0.985	1.515	2.052	0.129	0.201	0.980	5.492
Std	4E-07	6E-07	2E-08	5E-08	2E-09	2E-08	1E-12	1E-08	1E-13	7E-12	
LSSVM-AO	1.384	1.764	0.092	0.172	0.985	1.515	2.052	0.129	0.201	0.980	7.550
Std	1E-03	1E-03	7E-05	1E-04	7E-06	6E-05	1E-05	3E-05	1E-06	1E-07	
LSSVM-AO-PSO	1.439	1.856	0.106	0.181	0.984	1.336	1.771	0.079	0.177	0.984	3.560
Std	7E-06	8E-06	3E-07	8E-07	3E-08	3E-07	2E-10	1E-07	2E-11	4E-10	

Table S13

The modeling results of the minimum, mean and maximum AT of Rasht station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.059	1.373	0.778	0.166	0.986	1.243	1.632	0.457	0.188	0.982	7.896
LSSVM-PSO	1.058	1.373	0.778	0.166	0.986	1.243	1.632	0.456	0.188	0.982	5.764
Std	2E-07	3E-07	3E-08	3E-08	1E-09	1E-07	1E-12	9E-09	1E-13	1E-12	
LSSVM-AO	1.055	1.368	0.776	0.165	0.986	1.245	1.632	0.643	0.188	0.982	7.194
Std	1E-03	2E-03	2E-04	2E-04	1E-05	8E-04	5E-05	6E-05	6E-06	3E-07	
LSSVM-AO-PSO	1.172	1.490	0.789	0.181	0.983	1.168	1.466	0.643	0.172	0.985	4.274
Std	1E-03	9E-04	4E-04	1E-04	1E-05	4E-04	1E-04	5E-05	2E-05	3E-06	
						Mean AT					
LSSVM	0.799	1.043	0.122	0.163	0.987	1.319	1.802	0.101	0.186	0.983	7.698
LSSVM-PSO	0.795	1.032	0.121	0.163	0.987	1.319	1.802	0.099	0.186	0.983	7.692
Std	1E-07	1E-07	5E-08	1E-08	1E-09	4E-08	1E-12	1E-08	1E-13	1E-10	
LSSVM-AO	0.796	1.032	0.121	0.163	0.987	1.320	1.802	0.099	0.186	0.983	7.447
Std	2E-03	1E-03	8E-04	2E-04	2E-05	1E-03	7E-04	5E-04	9E-05	1E-05	
LSSVM-AO-PSO	0.863	1.120	0.130	0.170	0.985	1.218	1.563	0.0671	0.165	0.986	2.911
Std	4E-06	6E-06	6E-07	6E-07	3E-08	2E-06	4E-10	1E-07	5E-11	1E-11	
						Maximum AT					
LSSVM	1.075	1.434	0.062	0.172	0.985	1.515	2.052	0.069	0.201	0.980	8.348
LSSVM-PSO	1.075	1.434	0.062	0.172	0.985	1.515	2.052	0.069	0.201	0.980	5.492
Std	1E-07	2E-07	9E-09	2E-08	7E-10	1E-08	1E-12	2E-09	9E-14	2E-11	
LSSVM-AO	1.074	1.432	0.061	0.172	0.985	1.515	2.052	0.069	0.201	0.980	7.550
Std	4E-03	6E-03	2E-04	6E-04	2E-05	1E-03	1E-03	1E-04	1E-04	1E-05	
LSSVM-AO-PSO	1.051	1.395	0.061	0.181	0.984	1.336	1.771	0.052	0.177	0.984	3.560
Std	2E-05	3E-05	1E-06	3E-06	1E-07	2E-06	1E-08	3E-07	1E-09	4E-09	

Table S14

The modeling results of the minimum, mean and maximum AT of Zahedan station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.892	1.133	0.177	0.174	0.985	1.179	1.494	0.188	0.216	0.977	7.968
LSSVM-PSO	0.894	1.134	0.177	0.174	0.985	1.171	1.489	0.184	0.215	0.977	5.521
Std	2E-06	2E-06	1E-07	3E-07	1E-08	3E-06	4E-10	5E-07	6E-11	5E-09	
LSSVM-AO	0.895	1.134	0.177	0.174	0.985	1.171	1.489	0.186	0.215	0.977	7.105
Std	3E-03	4E-03	2E-04	6E-04	2E-05	2E-03	3E-04	6E-04	4E-05	6E-06	
LSSVM-AO-PSO	0.900	1.171	0.177	0.178	0.984	1.247	1.502	0.186	0.219	0.976	4.292
Std	3E-03	4E-03	3E-04	6E-04	2E-05	1E-03	1E-03	7E-04	1E-04	2E-05	
						Mean AT					
LSSVM	1.051	1.361	0.098	0.194	0.981	1.217	1.582	0.133	0.220	0.977	7.876
LSSVM-PSO	1.048	1.357	0.097	0.194	0.981	1.212	1.580	0.132	0.220	0.977	5.234
Std	2E-06	3E-06	4E-07	5E-07	2E-08	4E-07	2E-10	2E-07	3E-11	2E-09	
LSSVM-AO	1.048	1.357	0.097	0.193	0.981	1.212	1.580	0.132	0.220	0.977	7.117
Std	5E-03	6E-03	5E-04	9E-04	3E-05	2E-03	2E-03	1E-03	3E-04	4E-05	
LSSVM-AO-PSO	1.027	1.358	0.107	0.193	0.981	1.218	1.521	0.092	0.214	0.978	3.591
Std	2E-03	2E-03	1E-04	3E-04	1E-05	1E-03	1E-04	3E-04	2E-05	4E-06	
						Maximum AT					
LSSVM	1.379	1.774	0.081	0.254	0.967	1.614	2.198	0.097	0.298	0.956	8.111
LSSVM-PSO	1.381	1.776	0.082	0.255	0.967	1.610	2.198	0.097	0.298	0.956	5.431
Std	2E-07	3E-07	1E-08	4E-08	2E-09	3E-08	9E-13	1E-09	1E-13	6E-12	
LSSVM-AO	1.380	1.775	0.081	0.254	0.967	1.611	2.198	0.097	0.298	0.956	7.396
Std	3E-03	5E-03	2E-04	7E-04	4E-05	8E-04	4E-04	4E-05	5E-05	6E-06	
LSSVM-AO-PSO	1.383	1.818	0.084	0.259	0.966	1.508	2.017	0.081	0.272	0.963	3.598
Std	7E-05	1E-04	4E-06	1.E-05	9E-07	1E-05	1E-07	6E-07	1E-08	5E-10	

Table S15

The modeling results of the minimum, mean and maximum AT of Zanjan station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	2.183	3.520	1.018	0.473	0.933	1.381	1.815	0.5426	0.242	0.971	8.996
LSSVM-PSO	2.183	3.520	1.021	0.473	0.933	1.380	1.815	0.5434	0.242	0.971	6.031
Std	2E-07	6E-08	3E-07	7E-09	1E-09	2E-08	2E-12	1E-07	2E-13	3E-11	2E-07
LSSVM-AO	2.184	3.520	1.018	0.473	0.933	1.380	1.815	0.593	0.242	0.971	7.149
LSSVM-AO-PSO	2.113	3.565	1.060	0.474	0.932	1.282	1.636	0.593	0.228	0.974	4.882
Std	6E-05	1E-05	1E-05	1E-06	9E-07	6E-05	1E-07	2.21E-05	2E-08	3E-08	
						Mean AT					
LSSVM	1.385	2.004	0.840	0.216	0.978	1.515	1.895	1.091	0.208	0.979	9.364
LSSVM-PSO	1.399	2.021	0.753	0.218	0.978	1.512	1.893	1.186	0.207	0.979	5.338
Std	1E-07	3E-08	4E-08	4E-09	2E-09	1E-07	2E-12	5E-08	3E-13	9E-11	
LSSVM-AO	1.399	2.021	0.753	0.218	0.978	1.512	1.893	1.188	0.207	0.979	7.162
LSSVM-AO-PSO	1.387	2.042	0.897	0.219	0.978	1.435	1.744	1.384	0.197	0.982	3.574
Std	5E-05	1E-05	8E-05	1E-06	3E-07	6E-06	1E-07	4E-05	1E-08	7E-09	
						Maximum AT					
LSSVM	1.507	1.925	0.933	0.183	0.983	1.800	2.255	0.512	0.223	0.976	7.314
LSSVM-PSO	1.506	1.923	0.928	0.183	0.983	1.799	2.255	0.511	0.223	0.976	5.414
Std	2E-07	2E-07	3E-08	2E-08	1E-09	1E-08	1E-12	8E-08	1E-13	2E-11	
LSSVM-AO	1.506	1.922	0.928	0.183	0.983	1.799	2.255	0.512	0.223	0.976	7.165
LSSVM-AO-PSO	1.513	1.952	0.900	0.185	0.983	1.752	2.164	0.199	0.220	0.977	3.677
Std	7E-07	7E-07	1E-07	7E-08	3E-09	5E-08	8E-12	2E-07	8E-13	6E-11	

Table S16

The modeling results of the minimum, mean and maximum AT of Sari station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.815	1.034	0.134	0.145	0.989	1.129	1.400	0.1671	0.188	0.983	9.348
LSSVM-PSO	0.809	1.026	0.133	0.144	0.990	1.128	1.398	0.166	0.188	0.983	2.373
Std	1E-07	1E-07	1E-08	2E-08	1E-09	8E-09	6E-13	5E-10	8E-14	2E-11	
LSSVM-AO	0.807	1.025	0.133	0.143	0.990	1.128	1.398	0.194	0.188	0.983	2.933
Std	7E-03	7E-03	5E-04	1E-03	6E-05	3E-04	7E-04	1E-05	1E-04	1E-05	
LSSVM-AO-PSO	0.843	1.082	0.133	0.151	0.988	1.208	1.462	0.194	0.194	0.980	1.840
Std	1E-05	1E-05	2E-06	2E-06	1E-07	9E-06	3E-09	1E-06	4E-10	1E-08	
						Mean AT					
LSSVM	0.922	1.200	0.075	0.169	0.986	1.365	1.727	0.099	0.230	0.975	9.336
LSSVM-PSO	1.081	1.427	0.086	0.201	0.980	1.394	1.738	0.099	0.231	0.975	2.277
Std	1E-07	1E-07	2E-08	2E-08	2E-09	1E-07	6E-13	2E-08	8E-14	1E-10	
LSSVM-AO	0.922	1.200	0.075	0.169	0.986	1.364	1.727	0.099	0.230	0.975	3.866
Std	2E-03	2E-03	4E-04	3E-04	3E-05	1E-03	9E-05	3E-04	1E-05	7E-07	
LSSVM-AO-PSO	0.888	1.207	0.069	0.169	0.986	1.274	1.673	0.099	0.223	0.974	1.557
Std	8E-04	9E-04	5E-05	1E-04	7E-06	4E-05	1E-05	2E-06	1E-06	5E-08	
						Maximum AT					
LSSVM	1.158	1.528	0.061	0.217	0.976	1.627	2.182	0.078	0.289	0.959	7.314
LSSVM-PSO	1.157	1.528	0.061	0.217	0.976	1.627	2.182	0.078	0.289	0.959	2.179
Std	1E-07	1E-07	8E-09	2E-08	1E-09	6E-09	4E-13	6E-10	6E-14	7E-11	
LSSVM-AO	1.154	1.524	0.061	0.216	0.976	1.626	2.183	0.078	0.289	0.959	2.937
Std	7E-03	8E-03	3E-04	1E-03	8E-05	8E-04	1E-03	8E-06	1E-04	2E-05	
LSSVM-AO-PSO	1.105	1.488	0.057	0.208	0.978	1.573	2.168	0.081	0.292	0.956	1.506
Std	1E-04	1E-04	6E-06	2E-05	1E-06	5E-06	3E-07	4E-07	4E-08	6E-08	

Table S17

The modeling results of the minimum, mean and maximum AT of Sanandaj station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.414	2.000	0.573	0.282	0.968	1.268	1.663	1.511	0.223	0.976	7.589
LSSVM-PSO	1.415	2.001	0.573	0.282	0.968	1.268	1.663	1.509	0.223	0.976	5.683
Std	2E-07	1E-07	1E-07	1E-08	1E-09	2E-07	1E-12	1E-08	1E-13	1E-10	
LSSVM-AO	1.416	2.001	0.573	0.282	0.968	1.267	1.663	1.611	0.223	0.976	8.569
Std	1E-03	9E-04	1E-03	9E-05	8E-06	1E-03	1E-04	5E-05	1E-05	2E-06	
LSSVM-AO-PSO	1.594	2.184	0.573	0.306	0.962	1.170	1.563	1.611	0.210	0.978	4.154
Std	3E-05	8E-06	7E-06	1E-06	2E-07	1E-06	5E-08	4E-05	7E-09	3E-08	
						Mean AT					
LSSVM	1.067	1.506	0.903	0.155	0.988	1.245	1.570	0.316	0.161	0.987	7.988
LSSVM-PSO	1.111	1.554	0.941	0.160	0.987	1.228	1.557	0.310	0.160	0.988	5.009
Std	2E-07	6E-08	5E-08	9E-09	2E-09	1E-08	1E-12	3E-07	2E-13	2E-10	
LSSVM-AO	1.112	1.555	0.940	0.160	0.987	1.228	1.557	0.310	0.160	0.988	8.847
Std	3E-03	9E-04	7E-04	1E-04	3E-05	6E-05	4E-04	3E-03	6E-05	1E-05	
LSSVM-AO-PSO	0.941	1.370	0.760	0.141	0.990	1.104	1.356	0.217	0.141	0.990	3.812
Std	7E-06	4E-06	5E-06	4E-07	4E-08	7E-06	3E-09	3.57E-07	3E-10	6E-09	
						Maximum AT					
LSSVM	1.350	1.760	0.298	0.161	0.987	1.679	2.170	0.182	0.198	0.981	9.116
LSSVM-PSO	1.350	1.761	0.298	0.161	0.987	1.680	2.170	0.182	0.198	0.981	5.554
Std	3E-07	4E-07	4E-08	4E-08	1E-09	1E-07	2E-12	2E-08	2E-13	3E-10	
LSSVM-AO	1.351	1.761	0.298	0.161	0.987	1.679	2.170	0.182	0.198	0.981	7.421
Std	1E-03	2E-03	2E-04	2E-04	7E-06	7E-04	4E-05	1E-04	4E-06	1E-06	
LSSVM-AO-PSO	1.291	1.703	0.266	0.156	0.988	1.435	1.838	0.093	0.171	0.985	3.052
Std	1E-04	1E-04	1E-05	1E-05	6E-07	6E-05	4E-07	1E-05	4E-08	1E-07	

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Table S18

The modeling results of the minimum, mean and maximum AT of Shahrekord station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	2.109	3.485	0.527	0.501	0.925	1.367	1.940	2.715	0.280	0.961	8.116
LSSVM-PSO	2.109	3.485	0.527	0.501	0.925	1.368	1.940	2.720	0.280	0.961	5.856
Std	2E-07	7E-08	1E-07	8E-09	1E-09	7E-08	1E-12	1E-07	2E-13	1E-10	
LSSVM-AO	2.103	3.482	0.528	0.500	0.925	1.384	1.944	4.115	0.280	0.960	9.008
Std	1E-03	5E-04	7E-04	5E-05	9E-06	4E-04	4E-05	9E-04	4E-06	1E-06	
LSSVM-AO-PSO	2.307	3.788	0.526	0.535	0.911	1.225	1.558	4.115	0.240	0.971	4.234
Std	2E-05	3E-06	1E-05	5E-07	2E-07	4E-05	2E-07	4E-05	4E-08	3E-08	
						Mean AT					
LSSVM	1.040	1.596	0.326	0.177	0.985	1.157	1.726	0.778	0.193	0.981	8.396
LSSVM-PSO	1.039	1.594	0.326	0.177	0.985	1.157	1.726	0.779	0.193	0.981	5.380
Std	6E-08	7E-09	3E-08	1E-09	4E-10	1E-07	1E-12	1.04E-07	1E-13	7E-11	
LSSVM-AO	1.042	1.596	0.336	0.177	0.985	1.177	1.730	0.801	0.193	0.981	8.909
Std	8E-04	1E-04	4E-04	1E-05	1E-05	3E-03	1E-03	1E-02	2E-04	2E-05	
LSSVM-AO-PSO	1.228	1.868	0.378	0.205	0.979	1.014	1.371	0.843	0.160	0.987	3.616
Std	7E-05	2E-05	3E-05	2E-06	4E-07	2E-05	5E-08	4E-05	6E-09	5E-08	
						Maximum AT					
LSSVM	1.244	1.633	0.357	0.164	0.986	1.546	2.069	1.075	0.211	0.978	7.841
LSSVM-PSO	1.245	1.633	0.357	0.164	0.986	1.545	2.069	1.072	0.211	0.978	5.289
Std	3E-07	3E-07	9E-08	3E-08	1E-09	9E-08	1E-12	E-07	1E-13	2E-11	
LSSVM-AO	1.242	1.629	0.353	0.164	0.986	1.542	2.069	1.055	0.211	0.978	7.175
Std	1E-03	2E-03	5E-04	2E-04	9E-06	5E-04	1E-05	2E-03	1E-06	2E-07	
LSSVM-AO-PSO	1.391	1.827	0.696	0.183	0.983	1.461	1.974	0.103	0.208	0.979	2.876
Std	1E-04	1E-04	4E-05	1E-05	7E-07	4E-05	1E-07	1E-04	1E-08	1E-08	

Table S19

The modeling results of the minimum, mean and maximum AT of Qazvin station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.233	1.777	0.621	0.242	0.977	1.195	1.628	0.493	0.215	0.977	7.386
LSSVM-PSO	1.246	1.789	0.632	0.244	0.976	1.199	1.626	0.498	0.215	0.976	5.286
Std	3E-07	2E-07	5E-08	2E-08	2E-09	5E-08	1E-12	1E-08	1E-13	1E-11	
LSSVM-AO	1.250	1.794	0.638	0.244	0.976	1.203	1.625	0.473	0.215	0.977	8.816
Std	4E-03	3E-03	8E-04	4E-04	3E-05	9E-04	3E-04	2E-04	3E-05	3E-06	
LSSVM-AO-PSO	1.303	1.968	0.634	0.265	0.972	1.123	1.377	0.473	0.187	0.983	4.165
Std	2E-06	1E-06	1E-06	1E-07	3E-08	3E-06	2E-10	8E-07	3E-11	1E-10	
						Mean AT					
LSSVM	1.154	1.503	0.830	0.164	0.986	1.400	1.826	0.397	0.200	0.980	7.314
LSSVM-PSO	1.153	1.502	0.827	0.164	0.986	1.400	1.826	0.398	0.200	0.980	5.493
Std	2E-07	8E-08	1E-07	1E-08	2E-09	2E-07	2E-12	7E-08	3E-13	1E-11	
LSSVM-AO	1.151	1.500	0.793	0.163	0.987	1.410	1.828	0.410	0.200	0.980	7.232
Std	7E-04	2E-04	4E-04	3E-05	8E-06	8E-04	1E-05	2.17E-04	1E-06	2E-07	
LSSVM-AO-PSO	1.270	1.682	0.840	0.182	0.983	1.325	1.592	0.297	0.179	0.985	3.638
Std	3E-05	2E-05	5E-06	2E-06	2E-07	5E-06	1E-08	1E-06	1E-09	1E-09	
						Maximum AT					
LSSVM	1.489	1.919	0.169	0.184	0.983	1.748	2.305	0.163	0.223	0.976	8.314
LSSVM-PSO	1.486	1.915	0.169	0.183	0.983	1.747	2.305	0.163	0.223	0.976	6.869
Std	2E-07	3E-07	2E-08	3E-08	1E-09	2E-08	2E-12	1E-08	2E-13	4E-11	
LSSVM-AO	1.484	1.914	0.168	0.183	0.983	1.746	2.305	0.163	0.223	0.976	9.213
Std	4E-03	5E-03	3E-04	5E-04	2E-05	6E-04	3E-04	2E-04	3E-05	3E-06	
LSSVM-AO-PSO	1.562	2.057	0.177	0.196	0.981	1.595	2.007	0.108	0.199	0.981	2.869
Std	1E-04	1E-04	1E-05	1E-05	7E-07	9E-06	2E-07	5E-06	2E-08	1E-08	

Table S20

The modeling results of the minimum, mean and maximum AT of Qom station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.961	1.356	0.372	0.164	0.987	1.289	1.906	0.391	0.216	0.978	9.486
LSSVM-PSO	1.222	1.656	0.503	0.200	0.980	1.413	1.986	0.374	0.225	0.976	5.678
Std	1E-07	2E-07	1E-08	2E-08	8E-10	7E-08	9E-13	2E-09	9E-14	2E-11	
LSSVM-AO	0.910	1.278	0.346	0.155	0.988	1.315	1.913	0.361	0.217	0.977	7.605
Std	1E-03	2E-03	1E-04	2E-04	9E-06	9E-04	2E-04	3E-05	2E-05	2E-06	
LSSVM-AO-PSO	1.124	1.662	0.474	0.199	0.980	1.200	1.481	0.361	0.170	0.987	4.120
Std	4E-04	3E-04	1E-04	4E-05	4E-06	3E-04	5E-06	2E-04	5E-07	4E-08	
						Mean AT					
LSSVM	1.065	1.480	0.143	0.149	0.989	1.306	1.860	0.127	0.181	0.984	7.996
LSSVM-PSO	1.035	1.424	0.139	0.143	0.990	1.297	1.839	0.126	0.179	0.984	5.260
Std	4E-07	4E-07	1E-07	4E-08	4E-09	3E-07	2E-12	2E-07	2E-13	3E-11	
LSSVM-AO	1.035	1.424	0.139	0.143	0.990	1.297	1.839	0.126	0.179	0.984	7.222
Std	4E-03	4E-03	2E-03	5E-04	5E-05	4E-03	8E-04	2E-03	9E-05	1E-05	
LSSVM-AO-PSO	1.129	1.600	0.146	0.159	0.987	1.178	1.519	0.099	0.151	0.990	3.438
Std	1E-04	2E-04	1E-05	2E-05	9E-07	9E-05	1E-06	3E-06	1E-07	1E-08	
						Maximum AT					
LSSVM	1.464	1.999	0.078	0.190	0.982	1.535	2.199	0.581	0.204	0.979	8.164
LSSVM-PSO	1.464	1.997	0.078	0.190	0.982	1.536	2.199	0.581	0.204	0.979	6.801
Std	3E-07	4E-07	1E-08	4E-08	1E-09	6E-08	2E-12	8E-08	1E-13	1E-12	
LSSVM-AO	1.463	1.995	0.078	0.189	0.982	1.537	2.199	0.581	0.204	0.979	9.348
Std	1E-03	1E-03	7E-05	1E-04	8E-06	5E-04	1E-04	4E-04	1E-05	1E-06	
LSSVM-AO-PSO	1.466	1.982	0.244	0.187	0.982	1.474	1.932	0.072	0.183	0.984	2.900
Std	3E-04	4E-04	1E-05	4E-05	1E-06	5E-05	3E-06	8E-05	3E-07	2E-08	

Table S21

The modeling results of the minimum, mean and maximum AT of Karaj station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.093	1.473	1.065	0.203	0.980	1.291	1.706	0.541	0.223	0.975	9.384
LSSVM-PSO	1.111	1.490	1.050	0.205	0.979	1.283	1.700	0.571	0.222	0.975	5.702
Std	2E-07	1E-07	2E-08	1E-08	1E-09	8E-09	6E-13	2E-08	6E-14	1E-11	
LSSVM-AO	1.121	1.500	1.033	0.206	0.979	1.278	1.696	0.725	0.222	0.975	7.144
Std	4E-03	3E-03	5E-04	3E-04	2E-05	2E-04	4E-04	5E-04	4E-05	4E-06	
LSSVM-AO-PSO	1.171	1.627	0.893	0.221	0.976	1.193	1.463	0.725	0.196	0.981	4.226
Std	3E-05	1E-05	1E-05	2E-06	3E-07	1E-05	4E-08	1E-05	6E-09	2E-09	
						Mean AT					
LSSVM	1.328	1.718	0.357	0.180	0.984	1.474	1.944	0.313	0.213	0.977	9.114
LSSVM-PSO	1.326	1.717	0.358	0.180	0.984	1.475	1.944	0.312	0.213	0.977	5.445
Std	1E-07	1E-07	8E-08	1E-08	1E-09	7E-08	1E-12	6E-08	2E-13	1E-11	
LSSVM-AO	1.323	1.712	0.358	0.180	0.984	1.477	1.944	0.312	0.213	0.977	7.612
Std	2E-03	1E-03	9E-04	1E-04	2E-05	1E-03	4E-04	7.74E-04	6E-05	6E-06	
LSSVM-AO-PSO	1.458	1.932	0.384	0.202	0.979	1.270	1.655	0.235	0.187	0.982	2.900
Std	4E-03	3E-03	5E-04	3E-04	1E-05	1E-04	3E-04	4.99E-04	4E-05	3E-06	
						Maximum AT					
LSSVM	1.410	1.819	0.149	0.176	0.984	1.618	2.234	0.161	0.217	0.978	8.364
LSSVM-PSO	1.412	1.820	0.149	0.176	0.984	1.618	2.234	0.161	0.217	0.978	6.816
Std	2E-07	3E-07	2E-08	3E-08	1E-09	5E-08	1E-12	1E-08	9E-14	4E-12	
LSSVM-AO	1.404	1.806	0.147	0.175	0.985	1.617	2.237	0.163	0.217	0.978	9.705
Std	1E-03	2E-03	1E-04	2E-04	1E-05	3E-04	4E-05	6E-05	4E-06	3E-07	
LSSVM-AO-PSO	1.468	1.930	0.163	0.186	0.982	1.479	1.948	0.102	0.193	0.982	2.920
Std	1E-04	1E-04	1.E-05	1E-05	8E-07	2E-05	3E-07	5E-06	3E-08	9E-10	

Table S22

The modeling results of the minimum, mean and maximum AT of Kerman station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.292	1.709	0.622	0.238	0.976	1.284	1.614	0.335	0.216	0.977	8.368
LSSVM-PSO	1.291	1.708	0.621	0.238	0.976	1.285	1.614	0.3360	0.216	0.977	6.889
Std	1E-07	1E-07	1E-08	2E-08	1E-09	3E-08	1E-12	1E-08	1E-13	5E-12	
LSSVM-AO	1.294	1.710	0.622	0.238	0.976	1.282	1.614	0.3576	0.216	0.977	7.379
Std	2E-03	2E-03	2E-04	3E-04	1E-05	6E-04	2E-04	1E-04	3E-05	2E-06	
LSSVM-AO-PSO	1.310	1.735	0.557	0.241	0.975	1.243	1.573	0.3576	0.210	0.979	4.142
Std	1E-03	4E-04	6E-04	5E-05	1E-05	1E-04	9E-04	1E-04	1E-04	1E-05	
						Mean AT					
LSSVM	0.916	1.154	0.088	0.138	0.990	1.137	1.472	0.121	0.175	0.985	7.318
LSSVM-PSO	0.913	1.151	0.088	0.138	0.990	1.136	1.472	0.120	0.175	0.985	5.506
Std	6E-08	1E-08	2E-08	2E-09	3E-10	1E-08	8E-13	1E-08	1E-13	1E-10	
LSSVM-AO	0.913	1.150	0.088	0.138	0.990	1.137	1.472	0.121	0.175	0.985	7.452
Std	2E-03	6E-04	9E-04	8E-05	1E-05	1E-03	2E-03	4E-04	3E-04	3E-05	
LSSVM-AO-PSO	0.978	1.234	0.103	0.148	0.989	1.126	1.389	0.088	0.165	0.987	2.910
Std	5E-06	6E-06	5E-07	7E-07	3E-08	9E-07	7E-10	3E-07	8E-11	1E-10	
						Maximum AT					
LSSVM	1.228	1.549	0.060	0.183	0.983	1.422	1.865	0.069	0.222	0.975	7.389
LSSVM-PSO	1.232	1.554	0.060	0.184	0.983	1.421	1.865	0.069	0.222	0.975	6.910
Std	1E-07	2E-07	8E-09	3E-08	1E-09	1E-09	1E-12	2E-09	1E-13	4E-11	
LSSVM-AO	1.232	1.554	0.060	0.184	0.983	1.421	1.865	0.069	0.222	0.975	8.789
Std	5E-03	7E-03	2E-04	8E-04	5E-05	2E-04	6E-04	8E-05	8E-05	6E-06	
LSSVM-AO-PSO	1.309	1.666	0.065	0.197	0.980	1.376	1.788	0.061	0.214	0.977	3.253
Std	7E-05	1E-04	3E-06	1E-05	7E-07	8E-07	1E-07	1E-06	1E-08	2E-08	

Table S23

The modeling results of the minimum, mean and maximum AT of Kermanshah station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.330	1.903	0.456	0.272	0.969	1.294	1.688	0.529	0.234	0.976	8.369
LSSVM-PSO	1.331	1.903	0.456	0.272	0.969	1.294	1.688	0.529	0.234	0.976	6.437
Std	1E-07	1E-07	8E-09	1E-08	8E-10	1E-07	2E-12	1E-08	2E-13	2E-11	
LSSVM-AO	1.328	1.901	0.456	0.272	0.969	1.293	1.688	0.499	0.234	0.976	7.457
Std	4E-03	3E-03	2E-04	3E-04	2E-05	3E-03	7E-04	5E-04	7E-05	6E-06	
LSSVM-AO-PSO	1.433	2.003	0.447	0.284	0.966	1.157	1.513	0.499	0.213	0.979	4.153
Std	1E-05	4E-06	8E-06	5E-07	1E-07	1E-05	3E-09	6E-06	5E-10	1E-08	
						Mean AT					
LSSVM	0.955	1.338	0.248	0.141	0.990	1.180	1.473	0.182	0.155	0.988	8.146
LSSVM-PSO	0.980	1.362	0.248	0.143	0.990	1.180	1.467	0.175	0.155	0.988	4.965
Std	2E-07	1E-07	2E-07	1E-08	3E-09	2E-07	1E-12	1E-07	2E-13	4E-10	
LSSVM-AO	0.992	1.374	0.250	0.145	0.989	1.175	1.465	0.172	0.154	0.988	7.021
Std	1E-03	4E-04	8E-04	5E-05	1E-05	9E-04	3E-05	6E-04	4E-06	1E-06	
LSSVM-AO-PSO	1.060	1.458	0.249	0.153	0.988	1.078	1.260	0.132	0.135	0.991	2.880
Std	5E-05	3E-05	2E-06	4E-06	2E-07	3E-05	1E-07	5E-06	1E-08	1E-08	
						Maximum AT					
LSSVM	1.212	1.636	0.225	0.150	0.989	1.425	1.879	0.101	0.176	0.984	9.641
LSSVM-PSO	1.212	1.634	0.225	0.150	0.989	1.424	1.878	0.101	0.176	0.984	6.197
Std	2E-07	3E-07	1E-08	3E-08	1E-09	4E-08	1E-12	1E-08	1E-13	2E-11	
LSSVM-AO	1.212	1.633	0.224	0.150	0.989	1.424	1.878	0.101	0.176	0.984	7.734
Std	2E-03	3E-03	1E-04	3E-04	1E-05	4E-04	1E-04	1E-04	1E-05	8E-07	
LSSVM-AO-PSO	1.249	1.688	0.211	0.155	0.988	1.291	1.656	0.072	0.158	0.988	2.988
Std	5E-05	7E-05	4E-06	7E-06	2E-07	9E-06	5E-08	2E-06	4E-09	6E-09	

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Table S24

The modeling results of the minimum, mean and maximum AT of Gorgan station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.949	1.219	0.199	0.168	0.986	1.104	1.489	0.236	0.191	0.982	8.389
LSSVM-PSO	0.977	1.248	0.200	0.172	0.985	1.099	1.483	0.224	0.190	0.982	4.975
Std	2E-07	2E-07	1E-08	3E-08	1E-09	2E-08	1E-12	8E-09	1E-13	1E-11	
LSSVM-AO	0.977	1.248	0.200	0.172	0.985	1.099	1.483	0.243	0.190	0.982	7.018
Std	1E-03	1E-03	1E-04	2E-04	1E-05	1E-04	9E-05	7E-05	1E-05	1E-06	
LSSVM-AO-PSO	0.998	1.300	0.199	0.177	0.984	1.027	1.331	0.243	0.171	0.985	4.191
Std	4E-05	5E-05	6E-06	8E-06	4E-07	6E-06	4E-08	7E-08	5E-09	1E-10	
						Mean AT					
LSSVM	1.007	1.260	0.081	0.168	0.986	1.173	1.560	0.113	0.194	0.981	7.634
LSSVM-PSO	1.005	1.258	0.081	0.168	0.986	1.175	1.560	0.113	0.194	0.981	5.241
Std	2E-07	3E-07	3E-08	4E-08	2E-09	3E-08	5E-13	4E-10	6E-14	3E-12	
LSSVM-AO	1.005	1.258	0.081	0.168	0.986	1.175	1.560	0.113	0.194	0.981	7.145
Std	2E-03	3E-03	4E-04	5E-04	3E-05	6E-04	2E-04	1E-05	2E-05	2E-06	
LSSVM-AO-PSO	1.036	1.317	0.092	0.174	0.985	1.162	1.471	0.084	0.183	0.983	3.003
Std	7E-05	8E-05	5E-06	1E-05	5E-07	6E-06	1E-07	2E-06	1E-08	4E-09	
						Maximum AT					
LSSVM	1.347	1.700	0.069	0.224	0.974	1.629	2.205	0.079	0.266	0.967	7.369
LSSVM-PSO	1.401	1.767	0.071	0.233	0.972	1.609	2.208	0.079	0.267	0.965	4.875
Std	2E-07	3E-07	1E-08	4E-08	2E-09	2E-08	1E-12	2E-09	2E-13	9E-11	
LSSVM-AO	1.401	1.767	0.071	0.233	0.972	1.606	2.207	0.080	0.267	0.965	7.024
Std	2E-03	2E-03	1E-04	3E-04	1E-05	9E-05	1E-04	2E-05	2E-05	3E-06	
LSSVM-AO-PSO	1.351	1.754	0.070	0.229	0.973	1.529	2.052	0.072	0.245	0.969	2.879
Std	1E-05	1E-05	5E-07	1E-06	8E-08	7E-07	2E-09	8E-08	2E-10	3E-09	

Table S25

The modeling results of the minimum, mean and maximum AT of Hamedan station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	1.721	2.732	0.659	0.408	0.945	1.332	2.079	0.916	0.283	0.960	8.314
LSSVM-PSO	1.720	2.731	0.661	0.408	0.945	1.332	2.079	0.921	0.283	0.960	5.248
Std	1E-07	3E-08	4E-08	3E-09	7E-10	8E-08	1E-12	4E-08	1E-13	2E-10	
LSSVM-AO	1.721	2.732	0.660	0.408	0.945	1.332	2.079	0.425	0.283	0.960	7.436
Std	1E-03	4E-04	5E-04	5E-05	1E-05	1E-03	1E-04	6E-04	1E-05	5E-06	
LSSVM-AO-PSO	1.848	3.041	0.841	0.442	0.933	1.166	1.518	0.425	0.219	0.975	4.206
Std	1E-05	9E-07	8E-06	1E-07	7E-08	1E-05	1E-08	6E-05	2E-09	2E-08	
						Mean AT					
LSSVM	1.301	1.997	0.340	0.209	0.979	1.499	2.045	0.489	0.212	0.978	8.996
LSSVM-PSO	1.300	1.997	0.340	0.209	0.979	1.499	2.045	0.489	0.212	0.978	7.177
Std	1E-07	9E-09	8E-08	1E-09	7E-10	1E-07	1E-12	6E-07	1E-13	2E-10	
LSSVM-AO	1.298	1.995	0.337	0.208	0.979	1.499	2.045	0.497	0.212	0.978	7.718
Std	2E-03	2E-04	1E-03	3E-05	1E-05	E-03	7E-04	1E-02	1E-04	1E-05	
LSSVM-AO-PSO	1.362	2.144	0.328	0.222	0.977	1.339	1.686	0.649	0.182	0.985	2.963
Std	9E-06	2E-06	3E-06	2E-07	5E-08	6E-06	4E-09	3E-06	4E-10	1E-08	
						Maximum AT					
LSSVM	1.492	1.987	1.838	0.183	0.983	1.799	2.388	0.281	0.221	0.978	7.891
LSSVM-PSO	1.498	1.995	1.859	0.184	0.983	1.800	2.388	0.281	0.221	0.978	5.613
Std	2E-07	2E-07	5E-07	2E-08	1E-09	1E-07	1E-12	5E-08	1E-13	1E-10	
LSSVM-AO	1.492	1.987	1.838	0.183	0.983	1.799	2.388	0.280	0.221	0.978	7.550
Std	3E-03	2E-03	5E-03	2E-04	1E-05	1E-03	2E-04	5E-04	2E-05	3E-06	
LSSVM-AO-PSO	1.510	2.011	1.458	0.184	0.983	1.641	2.140	0.155	0.204	0.981	3.144
Std	5E-04	5E-04	1E-03	5E-05	2E-06	3E-04	1E-05	1E-04	9E-07	2E-07	

Table S26

The modeling results of the minimum, mean and maximum AT of Yasuj station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.861	1.173	0.369	0.167	0.987	0.835	1.123	0.3712	0.164	0.987	7.963
LSSVM-PSO	0.868	1.177	0.405	0.168	0.987	0.836	1.122	0.369	0.164	0.987	4.503
Std	1E-07	2E-07	3E-08	2E-08	6E-10	8E-08	8E-13	1E-07	9E-14	8E-11	
LSSVM-AO	0.868	1.177	0.405	0.168	0.987	0.835	1.122	0.383	0.164	0.987	6.491
Std	3E-03	3E-03	6E-04	4E-04	1E-05	1E-03	1E-04	2E-03	2E-05	2E-06	
LSSVM-AO-PSO	0.891	1.240	0.377	0.176	0.986	0.820	1.071	0.383	0.161	0.987	3.762
Std	1E-04	7E-05	1E-04	1E-05	1E-06	2E-05	8E-07	6E-05	1E-07	4E-08	
						Mean AT					
LSSVM	0.829	1.104	0.983	0.128	0.992	1.012	1.335	1.732	0.159	0.987	8.664
LSSVM-PSO	0.827	1.102	0.981	0.128	0.992	1.012	1.335	1.729	0.159	0.987	6.570
Std	1E-07	4E-08	9E-08	6E-09	9E-10	1E-08	5E-13	3E-08	8E-14	2E-11	
LSSVM-AO	0.819	1.086	1.013	0.126	0.992	1.041	1.358	1.686	0.161	0.987	6.511
Std	6E-04	2E-04	5E-04	3E-05	5E-06	9E-05	9E-06	2E-04	1E-06	6E-08	
LSSVM-AO-PSO	0.855	1.139	1.416	0.132	0.991	0.984	1.235	0.111	0.150	0.989	2.573
Std	3E-05	4E-05	6E-06	4E-06	1E-07	1E-05	2E-08	3E-05	2E-09	1E-08	
						Maximum AT					
LSSVM	1.069	1.427	0.070	0.148	0.989	1.584	2.060	0.095	0.220	0.977	8.639
LSSVM-PSO	1.068	1.425	0.070	0.148	0.989	1.583	2.060	0.095	0.220	0.977	5.263
Std	5E-07	7E-07	3E-08	7E-08	2E-09	6E-08	1E-12	5E-10	1E-13	5E-11	
LSSVM-AO	1.070	1.428	0.070	0.148	0.989	1.584	2.060	0.095	0.220	0.977	6.551
Std	1E-03	1E-03	7E-05	1E-04	6E-06	1E-04	8E-06	1E-06	9E-07	5E-08	
LSSVM-AO-PSO	1.182	1.576	0.078	0.163	0.987	1.566	2.040	0.088	0.224	0.976	2.576
Std	6E-05	7E-05	3E-06	8E-06	3E-07	7E-06	4E-08	6E-08	4E-09	6E-09	

Table S27

The modeling results of the minimum, mean and maximum AT of Yazd station

	Train					Test					
	MAE	RMSE	MAPE	RRMSE	R	MAE	RMSE	MAPE	RRMSE	R	Time (s)
						Minimum AT					
LSSVM	0.896	1.145	0.585	0.131	0.991	1.280	1.623	0.415	0.185	0.983	8.364
LSSVM-PSO	0.895	1.145	0.585	0.131	0.991	1.280	1.623	0.416	0.185	0.983	5.516
Std	3E-07	4E-07	2E-08	4E-08	2E-09	8E-08	1E-12	3E-08	1E-13	2E-11	
LSSVM-AO	0.894	1.142	0.580	0.131	0.991	1.279	1.623	0.211	0.185	0.983	8.299
Std	5E-03	7E-03	4E-04	7E-04	3E-05	1E-03	7E-04	5E-04	8E-05	6E-06	
LSSVM-AO-PSO	0.963	1.242	0.467	0.142	0.990	1.123	1.389	0.211	0.160	0.988	4.547
Std	2E-05	2E-05	1E-05	2E-06	1E-07	1E-05	1E-08	7E-06	1E-09	6E-10	
						Mean AT					
LSSVM	0.982	1.253	0.080	0.131	0.991	1.283	1.750	0.151	0.182	0.983	8.114
LSSVM-PSO	0.980	1.251	0.080	0.131	0.991	1.283	1.750	0.151	0.182	0.983	6.936
Std	1E-07	1E-07	1E-07	2E-08	1E-09	1E-07	9E-13	6E-08	1E-13	3E-12	
LSSVM-AO	0.978	1.247	0.080	0.131	0.991	1.284	1.750	0.151	0.182	0.983	7.619
Std	4E-03	5E-03	7E-03	5E-04	3E-05	3E-03	9E-04	1E-03	1E-04	1E-05	
LSSVM-AO-PSO	1.099	1.431	0.107	0.150	0.989	1.175	1.513	0.075	0.160	0.987	3.338
Std	2E-04	3E-04	2E-05	3E-05	1E-06	6E-05	1E-06	2E-05	1E-07	3E-08	
						Maximum AT					
LSSVM	1.273	1.601	0.061	0.167	0.986	1.514	2.101	0.084	0.217	0.976	7.686
LSSVM-PSO	1.272	1.600	0.061	0.167	0.986	1.514	2.101	0.0844	0.217	0.976	5.473
Std	3E-07	4E-07	1E-08	4E-08	2E-09	6E-08	1E-12	1E-08	1E-13	3E-11	
LSSVM-AO	1.273	1.600	0.061	0.167	0.986	1.514	2.102	0.084	0.217	0.976	7.215
Std	1E-03	1E-03	7E-05	2E-04	1E-05	3E-04	3E-05	5E-05	3E-06	1E-07	
LSSVM-AO-PSO	1.381	1.780	0.071	0.185	0.983	1.378	1.851	0.058	0.196	0.982	2.912
Std	4E-04	5E-04	2E-05	5E-05	3E-06	8E-05	2E-06	1E-05	2E-07	1E-08	