Energy and Buildings 127 (2016) 360–369

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Applying artificial intelligence modeling to optimize green roof irrigation

S.W. Tsang, C.Y. Jim *

Department of Geography, University of Hong Kong, Pokfulam Road, Hong Kong, China

ARTICLE INFO

Article history:
Received 24 March 2012
Received in revised form 11 May 2016
Accepted 1 June 2016
Available online 2 June 2016

Keywords:
Green roof
Artificial intelligence
Irrigation schedule
Neural network
Fuzzy logic
Water conservation

ABSTRACT

Recent increase in green-roof installation has increased irrigation water consumption which could be wasteful using conventional watering management protocol. The knowledge gap in irrigation optimization to achieve water conservation could be filled. The complicated conventional approach uses weather and soil sensors to calculate watering needs, which is impractical and not cost-effective. This study employs artificial intelligence algorithms composed of artificial neural network and fuzzy logic, using weather data to simulate soil moisture changes to develop an optimal irrigation strategy. The artificial neural network is trained to predict soil moisture based on four daily weather variables: real-time air temperature, relative humidity, solar radiation, and wind speed. Fuzzy-neural network is applied to determine the irrigation time and watering volume. The simulation model successfully mimics the human brain in making irrigation decision. The artificial intelligence irrigation could maintain adequate soil moisture ranging from 0.13 to 0.22 m^3/m^3 and reduce 20% of water use with improved plant coverage. Since the evapotranspiration from living vegetation plays a key role in the passive cooling mechanism, better plant coverage could increase the thermal-energy performance of green roofs. The low-cost and effective technique can motivate the adoption of green roofs by alleviating the water consumption obstacle.

1. Introduction

Green roof offers a passive cooling technology to reduce electricity use for air-conditioning systems [1–4]. Typical green roofs are constituted by component layers laid from bottom to top in the following sequence: root barrier, drainage, filter, water-storage, growing substrate, and vegetation [5]. A wide range of vegetation growth forms, depending largely on substrate depth, can be planted [6,7]. The biomass structure, coverage and density of vegetation characterized by leaf-area index can regulate shading, evapotranspiration rate, and thermal cooling and insulation effect [8]. The role of the substrate in supporting plant growth is supplemented by the water storage layer. Rain or irrigation water is stored in the water-absorbing material to satisfy water demands between irrigation or rainfall episodes. Excess soil moisture can escape from green roof system through the drainage layer.

Modern green roofs can be categorized into extensive and intensive types [9]. They are differentiated by substrate depth and associated vegetation growth form. Intensive green roofs require >20 cm substrate to support shrubs and trees and offer more complex habitats for wildlife. In contrast, herbaceous plants including drought-tolerant species are often chosen for extensive green roofs with <20 cm substrate. Empirical research shows that both green roof types have good thermal insulation performance to reduce penetration of solar energy into buildings. They also offer high-quality green spaces which are often deficient in compact urban areas.

Fresh water has increasingly become a scarce resource in many places, including cities in different climatic zones. The efficient use and conservation of water are important to sustain economic growth and urban development. Despite the multiple economic and ecological benefits of green roofs, using scarce water for irrigation could be controversial particularly in semi-arid and arid regions [10]. There is a common tendency to apply an excessive amount of irrigation water to green roofs even if rain or weather sensors have been installed to regulate the irrigation time and volume. For instance, evapotranspiration is the lowest in warm-humid spring and the highest in cool-dry autumn in Hong Kong [11]. Irrigation schedule regulated by rain sensors without considering evapotranspiration loss may not deliver enough water in autumn. Rainfall data alone cannot tell the amount of available water stored in the soil pores [12], which may bring excessive application and wastage. The optimization of irrigation schedule for green roof remains a knowledge gap yet to be filled by research. It calls for the development of an intelligent irrigation model to improve water-use efficiency.

* Corresponding author.
E-mail address: hragjcy@hku.hk (C.Y. Jim).

http://dx.doi.org/10.1016/j.enbuild.2016.06.005
0378-7788/

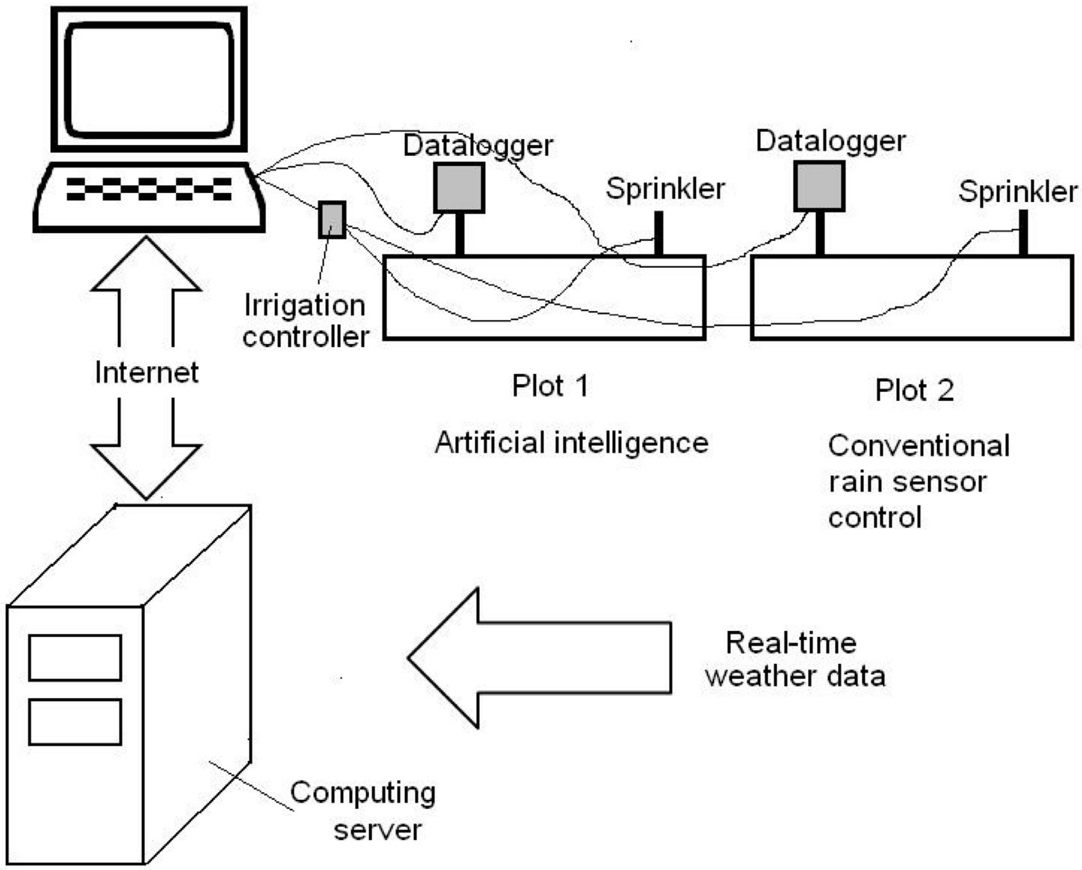

Fig. 1. Schematic drawing of the experimental setup.

2. Artificial intelligence models for irrigation control

Many successful applications of artificial intelligence (AI) models have been reported, such as irrigation scheduling (e.g. [13,14]), water management (e.g. [15,16]), and weather forecast (e.g. [17,18]). The AI computation, namely genetic algorithm (GA), artificial neural network (ANN), and fuzzy logic (FL), could provide flexibility for irrigation researchers to handle real-world complex problems.

GA can be used to optimize the farmland irrigation constraints, such as economic profits, water demand, crop yields, and planted area by minimizing or maximizing objective functions (e.g. [19–22]). The computing flexibility permits researchers to examine many complex problems that are difficult to solve using traditional mathematical and computational methods such as linear and nonlinear programming [23,24]. Analogous to the biological mechanisms of genes, the rules of GA are governed by four basic operations: parent selection, crossover, replacement, and mutation [25,26]. The possible solutions are defined as chromosomes. The objective functions are translated into fitness functions that measure the performance of chromosomes according to the study objectives. New chromosomes are created in crossover and mutation. The chromosomes with the highest fitness values in successive populations can survive. The best set of chromosomes is obtained by iterating the possible solutions until convergence.

ANN is a complex non-linear process that connects the inputs to the outputs of a system. It often provides satisfactory results in scientific and engineering researches. The artificial neurons in ANN resemble the biological ones by forming networks during the learning process. Patterns are recognized from their interactions with the environment [14]. The learning process can be classified into supervised and unsupervised types [13]. ANN acquires knowledge by comparing the simulated output with the real output in supervised learning. The weights associated with neurons at different layers are obtained by training the network [27]. For unsupervised learning, ANN does not require the knowledge of the real output. The weights are found by iterating the network to reflect the output characteristics. Based on the non-linearity properties of ANN, the input-and-output mapping capabilities can be applied to predict water use for green roofs.

ANN is often used with FL in decision making. If the input data are less accurate, ANN would encounter difficulty handling the interactions between inputs and outputs. An integration of ANN with FL (or fuzzy-neural algorithm) presents a better choice to

Table 1
Technical information and accuracy of the soil temperature and moisture sensors installed at the experimental plots.

Sensor position[a]	Sensor model and type	Source	Accuracy & unit
Substrate temperature	8160.TF (PT100)	Lufft, Fellbach, Germany	±0.4 °C
Substrate moisture	S-SMC (Dielectric)	Hobo, Bourne, MA	±3% m^3/m^3
Data logger[b]	Opus 200	Lufft, Fellbach, Germany	n.a.

[a] A weather station was set up near the experimental plots.
[b] The data loggers were programmed to acquire data at 10-min interval.

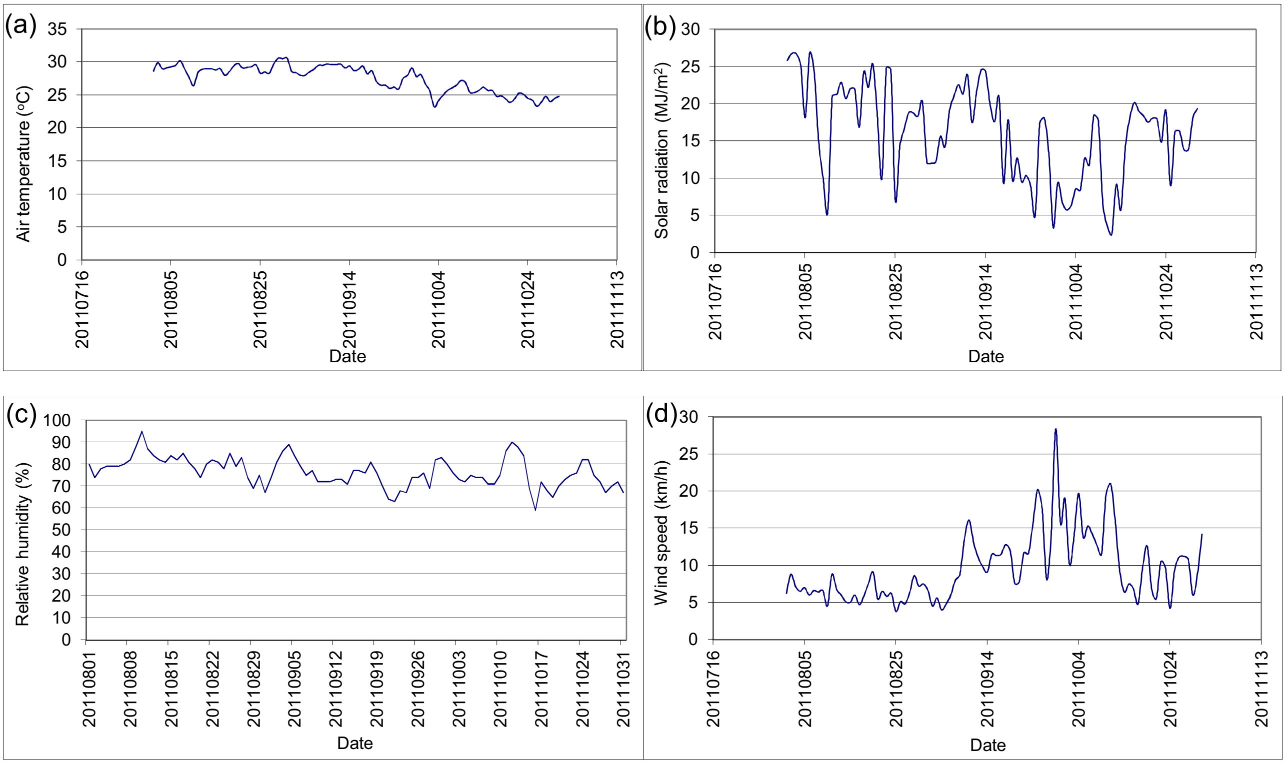

Fig. 2. Diurnal air temperature, relative humidity, solar radiation, and wind speed during the experimental period.

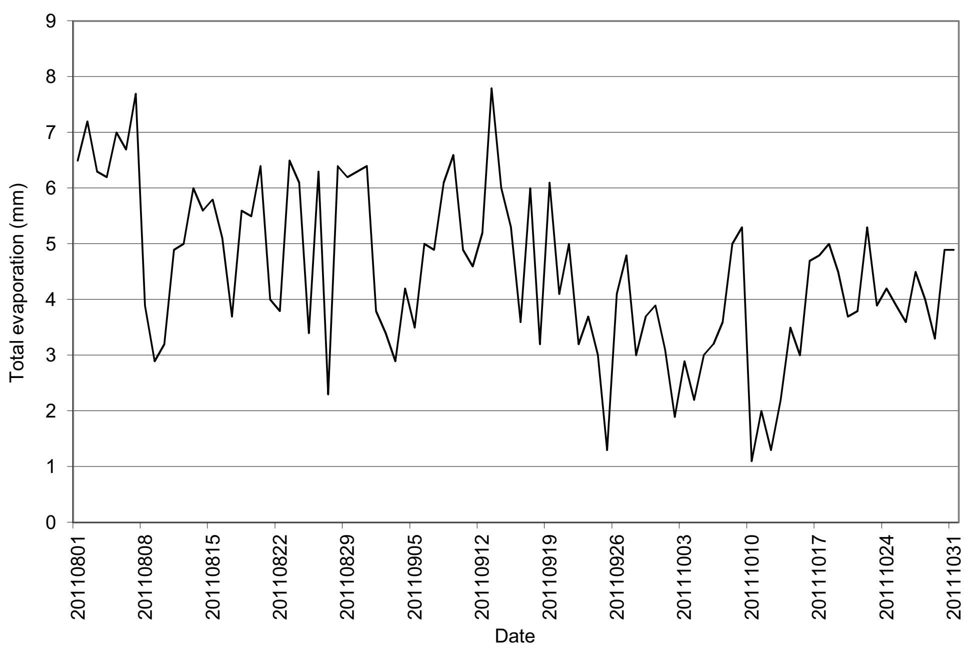

Fig. 3. Diurnal pan evaporation during the experimental period.

tackle complexity (e.g. [28,29]). A set of parameters is identified by adopting hybrid learning rules. For the back-propagated learning, the typical gradient descent methods are used to adjust the weights between neuron layers. This provides a basis to construct fuzzy rules with appropriate membership functions to generate stipulated input-output pairs.

This study examines the potential of integrating soft computing algorithms in predicting irrigation time and watering volume for green roofs. Efficient irrigation scheduling could save a notable amount of water in the long run. An experimental site was set up to assess the performance of the artificial intelligence irrigation system by comparing it with conventional approaches. In order to increase the applicability of artificial intelligence models, a minimum amount of routine weather data should be used [30].

This paper is organized as follows. The next section describes the experimental design. The irrigation scheduling algorithms are explained in the fourth section. The experimental results and performance of artificial intelligence irrigation are examined in the fifth section. Finally, the discussion is followed by conclusion.

3. Experimental design

To assess the performance of artificial intelligence in green roof irrigation, two experimental plots were set up on the roof of the Main Library at the University of Hong Kong. Fig. 1 shows the schematic drawing of the experimental setup. Artificial intelligence was adopted in plot 1 and the conventional approach in plot 2. The experimental plots each of 4 m^2 (2 m × 2 m) were installed in late 2010. The experiment ran from August 2011 to February 2012 to include the highest evapotranspiration rate in autumn [11,31]. The green roof system consists of layers arranged in sequence from top to bottom: vegetation, soil substrate, rockwool (water storage), geotextile filter, plastic drainage, root barrier, and waterproofing membrane. A 15 cm thick soil provided rooting room for plants. The rockwool buffers the water demand of plants between irrigation episodes. PT100 and dielectric sensors were installed at the center of both plots to monitor respectively soil temperature and moisture at 5 and 15 cm depth. The data loggers were programmed to take and store readings at 10-min interval (Table 1). Comprehensive weather data were collected from a nearby weather station of Hong Kong Observatory.

Plot 1 adopted artificial intelligence to schedule irrigation. Watering was turned on and off by an irrigation controller through a valve setup. Based on the computation results, the irrigation time and watering volume were determined. Plot 2, on the other hand, adopted the conventional irrigation approach. A rain sensor was installed to suspend irrigation if the daily cumulative rainfall exceeds 10 mm. The watering duration was programmed using an electronic timer. The plots were equipped with two independent sprinkler irrigation systems with dedicated water meters to compare their water consumption and use efficiency. The data loggers were connected to a computer. Real time experimental monitoring and weather data were transmitted through the internet to a computer server for data analysis. In the next section, we discuss the use of artificial intelligence algorithm in roof greening projects.

4. Irrigation scheduling algorithms

Artificial intelligence algorithms provide simple and useful means of modeling. They are widely reported in optimizing the allocation of scarce water resources. For instance, the multi-objective genetic algorithm has been applied to analyze water use in different sectors in the drought period [22]. Recent researches show that artificial intelligence can be applied to evapotranspiration modeling [32–35].

Weather data near the experimental site covering August 2011 to February 2012 were obtained from the Hong Kong Observatory. Fig. 2 shows the diurnal variation of air temperature, relative humidity, solar radiation, and wind speed collected by a nearby automatic meteorological station at Wong Chuk Hang. Fig. 3 shows the daily pan evaporation data collected at the manned meteorological station at the Observatory's King's Park site.

The purpose of this study is to develop an intelligence irrigation schedule for green roofs with the help of ANN and FL. The experiment was divided into two parts: modeling soil moisture, and obtaining an indication of irrigation duration and watering volume. Fig. 4 presents the methodology flow chart. ANN was used to model the relationships between weather conditions and soil moisture. The mathematical formulation is detailed in the Appendix Section. The model and accuracy of the sensors installed at the experimental plots are listed in Table 1.

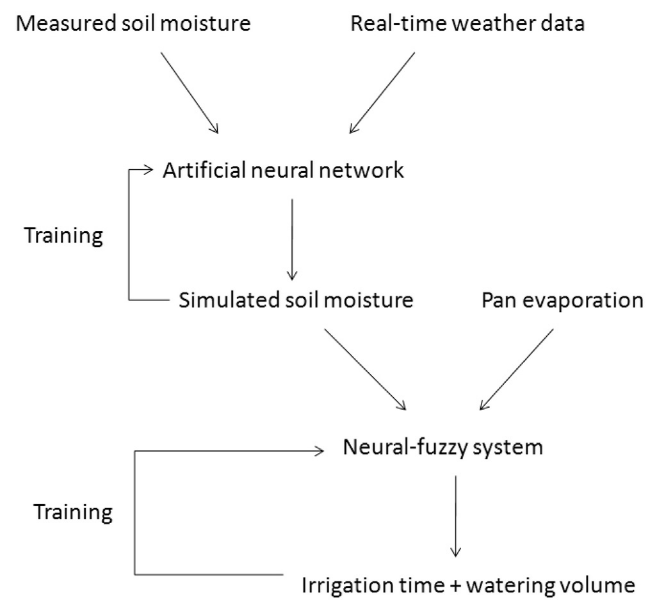

Fig. 4. Flow chart of modeling methodology.

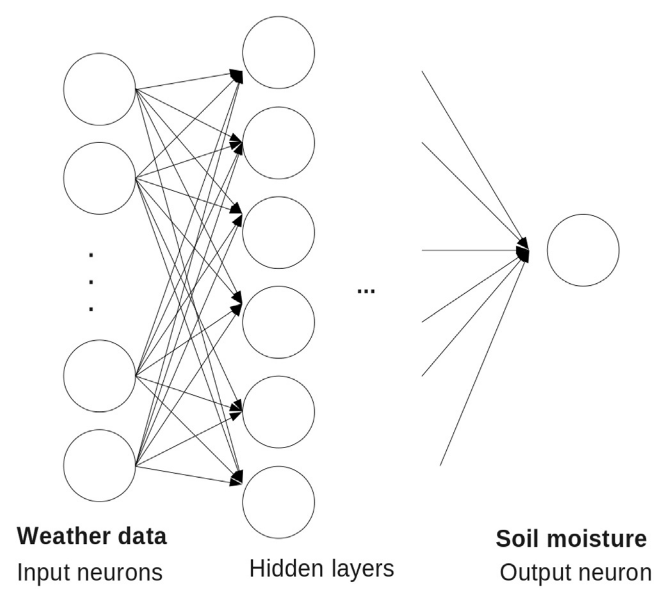

Fig. 5. Architecture of the feed-forward ANN computation method.

In this study, the ANN and FNN (Fuzzy Neural Network) were trained and assessed by removing the soil moisture sensors from the experimental plots during the testing period and reinstalling them for comparing the simulated and measured values. The performance of artificial intelligence irrigation is assessed in the next section.

5. Performance of artificial intelligence irrigation

Water is becoming a scarce and expensive resource in some densely populated areas, including south China where Hong Kong. The recent increase in green roof installation and its anticipated growth in response to enabling government policies have highlighted the issue of irrigation water consumption. Wasteful use of water for irrigation could dampen the green roof initiative and associated long-term benefits.

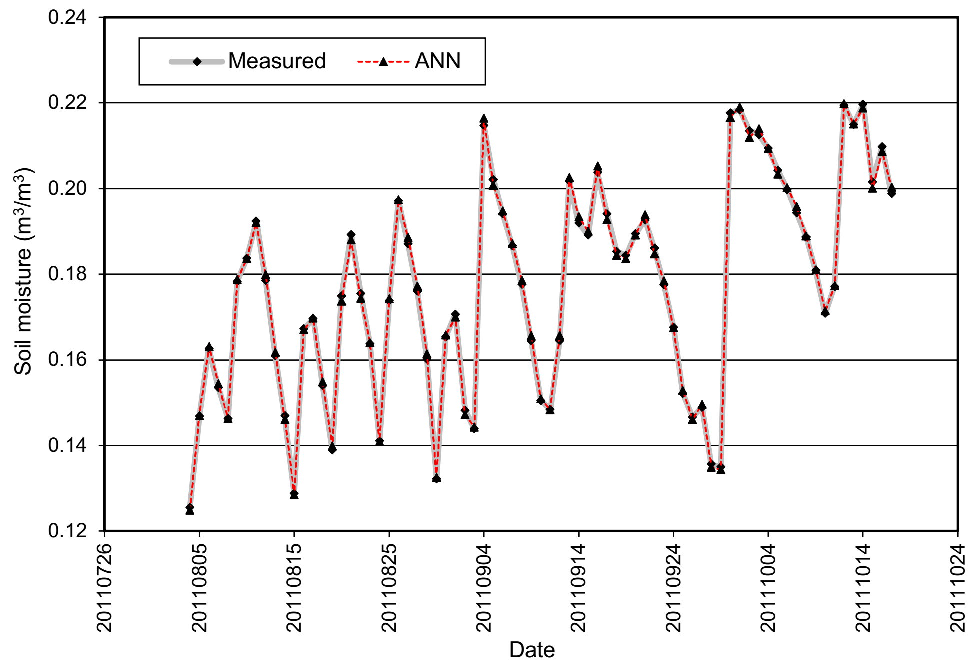

Fig. 6. Simulated and measured soil moisture in the course of training.

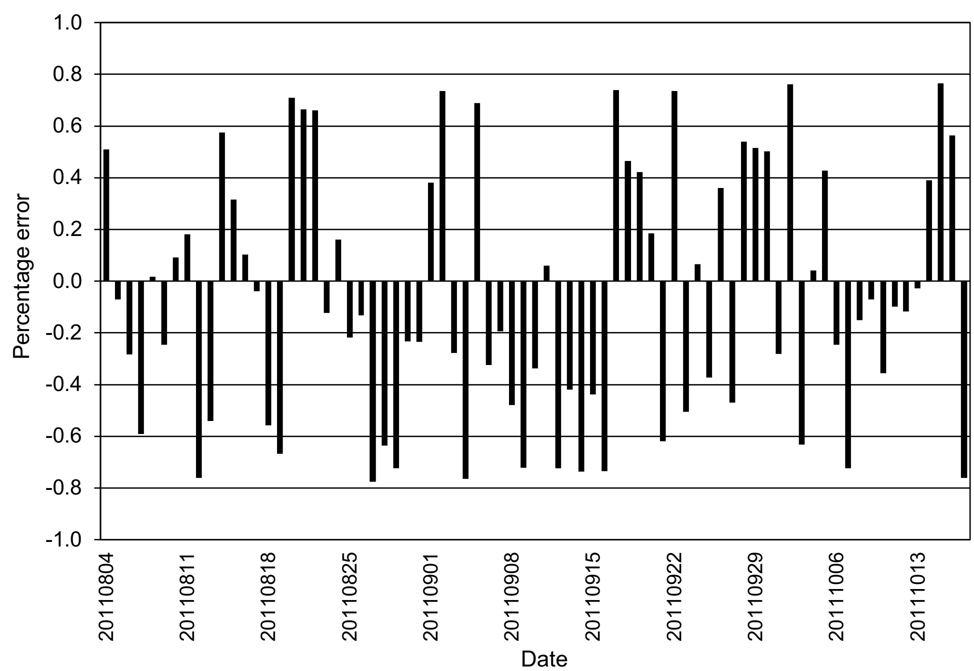

Fig. 7. The percentage error between simulated and measured soil moisture in the course of training.

This study has demonstrated that, the conventional irrigation approach using rain sensors could not perform well in water conservation. The AI irrigation method could outperform the conventional one. Firstly, artificial intelligence algorithms has reduce water consumption at plot 1 by 20%. Secondly, plot 1 has better plant coverage which could be attributed to optimal irrigation management to better match plant needs under different weather conditions. Thirdly, the artificial intelligence algorithm could optimize green roof irrigation by using official and free weather data without costly scientific sensors and monitoring.

ANN can successfully model the relationship between weather data and soil moisture in this study. The relatively simple processing units of ANN have been arranged to estimate soil moisture. Monitoring soil moisture is the primary step in water-resource management because excess water stored in macro-pores (>60 μm diameter) above field capacity point is drained away as gravitational discharge into the stormwater drainage system and hence wasted [12]. Human supervision and scientific sensors are costly for most residents or building users. Artificial intelligence algorithms can reduce the costs involved in irrigation management. Using government weather data, the learning capability of ANN could help to estimate the green-roof soil moisture and recommend irrigation timing and application rate.

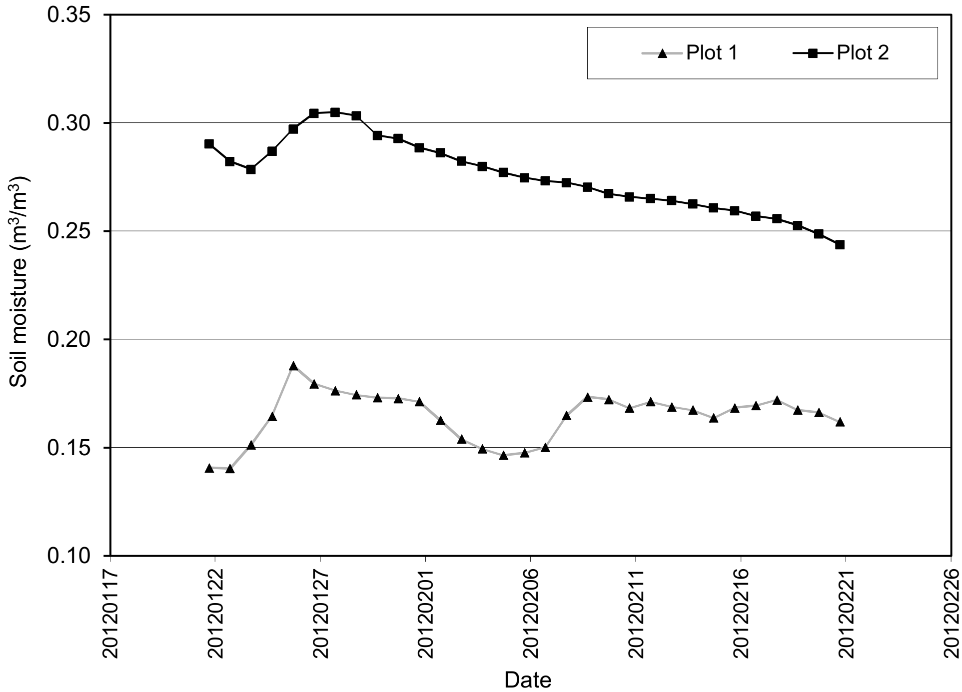

Fig. 8. Simulated and measured soil moisture in model validation.

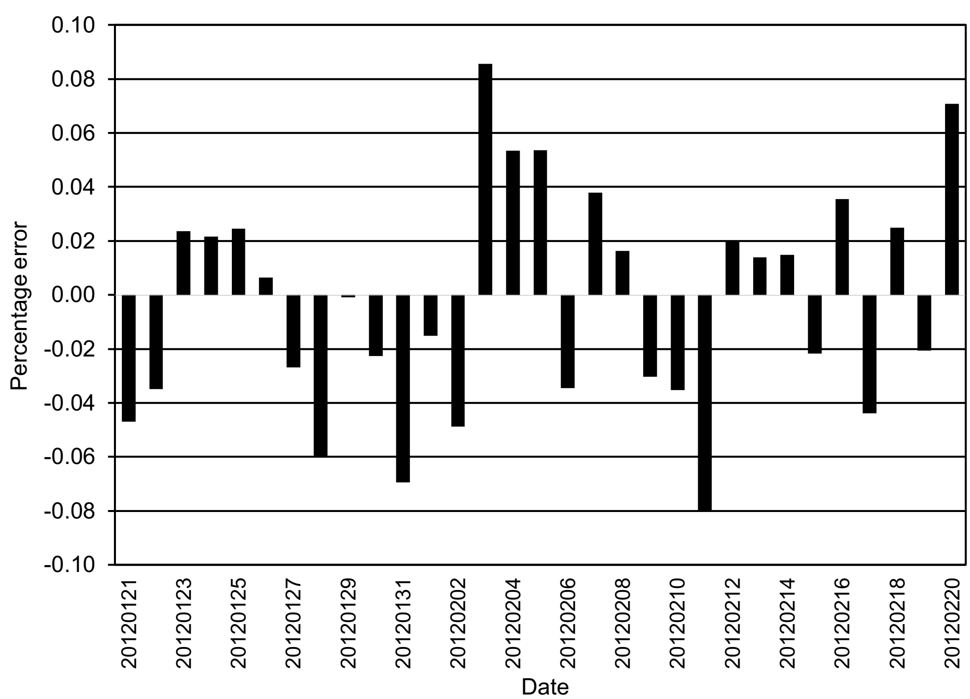

Fig. 9. The percentage error between simulated and measured soil moisture in model validation.

The total volume of water applied to plots 1 and 2 during the whole experimental period were respectively 10.9 m^3 and 13.8 m^3. Using artificial intelligence to schedule irrigation could save about 21% of water, particularly when the relative humidity was high. In Hong Kong, evapotranspiration rate is relatively lower in wet and warm spring [31]. Conventional irrigation approach may apply excess water.

In this study, the soil moisture is simulated and compared with measured values as shown in Fig. 6. It shows that AI generates a good approximation to the measured values and the percentage error between simulation and measured values is shown in Fig. 7. The percentage error is calculated by dividing the differences between simulation and measured values by measured values. An increase in relative humidity can raise soil moisture because of reduced evapotranspiration rate. The soil moisture ranges from 0.13 to 0.22 m^3/m^3. Soil moisture over 0.30 m^3/m^3 can be regarded as applying too much water. However, most plants suffer from water deficit below 0.10 m^3/m^3 of soil moisture. Adequate soil moisture at most times is critical for maintaining plant health. It is worth noting that the real-time ANN could monitor daily soil

Fig. 10. Comparison of plant coverage of the two experimental plots.

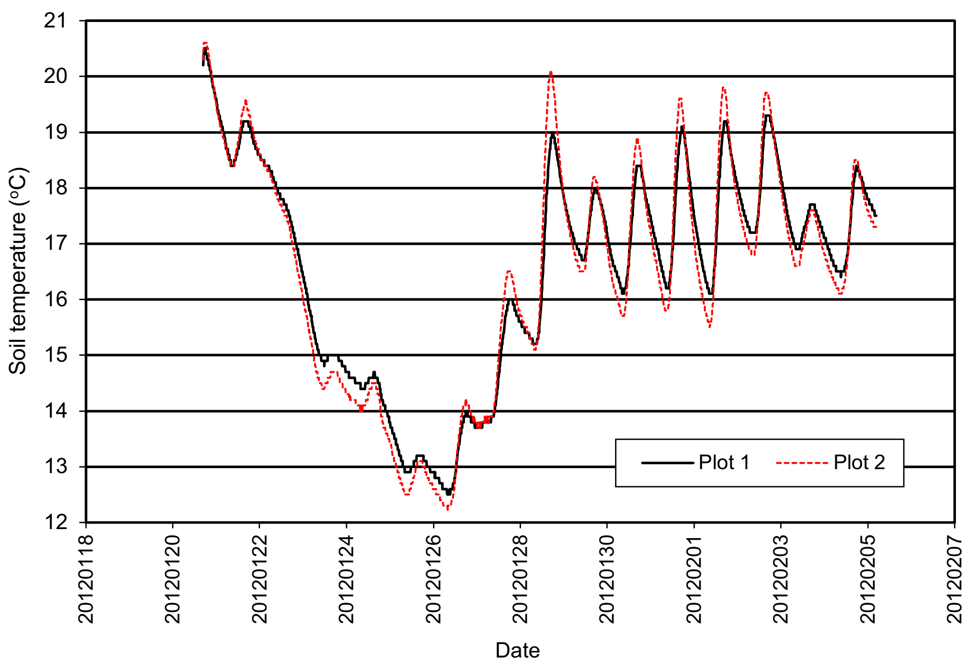

Fig. 11. Soil temperature at 15 cm beneath the soil surface at plots 1 and 2 during the experimental period.

conditions and make irrigation adjustment based on the latest weather information from a nearby weather station. Moreover, the mild weather in Hong Kong also favors the use of AI irrigation because the algorithms could estimate the impact of various weather parameters on the change in soil moisture rather precisely without intensive training process. As a result, a good approximation for the soil moisture is obtained through the learning process of artificial neurons.

Like other irrigation researchers, the iterative method or "trial-and-error" procedure was used to find the optimal weights for ANN (e.g. [32]). One hidden layer with seven neuron nodes was used to describe the relationship between input and output variables. Additional hidden layers and neurons could not further improve the learning capabilities of ANN. In the estimation of irrigation duration and watering volume, FNN, comprising one hidden layer with three nodes, was trained to minimize the mean square error at 0.007 $(m^3/m^3)^2$. The prediction was made on a daily basis. The irrigation signal was sent by the computer server to the sprinkler valves that provided evenly distributed water to plot 1 with a total volume ranging from 3 to 16 L.

In order to validate the artificial intelligence irrigation model, the sensors were removed from 1 November 2011–19 January 2012. Testing model reliability is crucial for practical application. For this purpose, the sensors were reinstalled on 20 January 2012. Fig. 8 shows the actual and simulated soil moisture from 20 January 2012–20 February 2012, and Fig. 9 shows their percentage error. All curves demonstrate a similar pattern of soil moisture variation over time. The soil moisture in plot 1 fluctuated around 0.17 m^3/m^3. The artificial intelligence algorithm was able to respond reliably to drastic weather changes. For instance, irrigation was triggered in response to a sharp drop in relative humidity on 1 February 2012. In contrast, the soil moisture in plot 2 using the conventional approach ranges from 0.25 to 0.31 m^3/m^3. Such high moisture contents imply excessive watering under the conventional irrigation method. The experimental results show that artificial intelligence can maintain an optimal soil moisture level.

Fig. 10 shows the plant coverage of two experimental plots. Plot 1 has higher and denser plant coverage comparing to plot 2 because the effective irrigation management could reduce moisture stress to bring healthy plant growth. It can also dampen the ill effects due to protracted periods of soil wetness. Through evapotranspiration, green roofs play a pivotal role in passive cooling to reduce rooftop heat absorption and ambient air temperature. The movement of soil water from roots to sub-stomatal cavities sustains the evapotranspiration process and contributes to plant thermal regulation.

Fig. 11 compares the soil temperature between plots 1 and 2 at 15 cm beneath the soil surface. The temperature fluctuation in plot 2 is notably wider than plot 1. The maximum absolute difference of soil temperature is about 1.5 °C. Artificial intelligence algorithms could more reliably perceive environmental changes to optimize irrigation parameters. Optimal irrigation could reduce the probability of water-stress extremes due to too much or too little water. With relief from the extreme stresses, plants can achieve better growth and a better coverage to increase transpiration rate and hence passive cooling due to latent heat absorption.

6. Discussion and conclusion

This study adopted artificial intelligence algorithms to mimic the behaviors of the human brain in making irrigation decision. Real-time weather data was used to predict the soil moisture. It could assist green roof managers to estimate the irrigation duration and watering volume. Since the thickness of soil substrate is only around 15 cm for extensive green roofs, adequate soil moisture is required for plants to withstand exposed and extreme rooftop conditions. With the aid of artificial intelligence, the critical irrigation needs of green roofs, particularly on dry and sunny days with high evapotranspiration rate, could be satisfactorily optimized.

Rooftop irrigation differs from farmland irrigation with reference to the scale of cultivation and hence watering. A higher degree of precision in watering volume is expected of green roofs to sustain plant growth, minimize water-deficit damage and reduce water use. The experimental results show that artificial intelligence is capable of simulating the relationship between weather data and soil moisture. Real-time weather data and measured soil moisture can be transmitted to a computing server. Irrigation decision can then be computed and fed back to the irrigation control device. Improvement in ANN performance ceases at a high number of neurons and hidden layers. Reliability has been tested by removing the rainfall sensors from the control plot for three months and then reinstalling them to validate the model. Based upon the research findings, FNN can be applied to green roofs to accurately simulate the water demand. The mean square error has been minimized to 0.007 $(m^3/m^3)^2$ in the training.

In the optimized soil-vegetation-atmosphere continuum of the green roof ecosystem, the bulk of soil moisture should move upwards to evaporate or transpire into the atmosphere. Water moving downward to the drainage layer is wasteful as it does not perform useful ecosystem functions and does not contribute to thermal-energy performance. Irrigation scheduling by artificial intelligence could minimize gravitational drainage of irrigation water, and improve plant growth and associated thermal-energy performance. The environmental benefits per unit of irrigation water consumption can thus be optimized. Because of the significant latent heat of vaporization of water, the evapotranspiration from living vegetation providing an effective cooling mechanism can be sustained.

Water saving for green roof irrigation is very important in Hong Kong and some cities around the world as water scarcity could pose a long-term constraint on urban development. This research attempts to show that AI can be applied effectively to schedule green roof irrigation to reduce water use by 20%. If green roofs are retrofitted on an appreciable proportion of buildings in cities, the amount of water saving is notable.

The application of AI irrigation is not more expensive than the existing systems in the market. It is worth noting that additional hardware requirement is minimal in the present intelligent irrigation system, because the computation tasks are performed by a computing server and the updated irrigation schedules can be delivered to thousands of green roofs simultaneously. In other words, end users who do not have specialist knowledge can find it easy to receive the AI instructions and adjust the irrigation schedule accordingly. However, the following basic equipment items should be installed for irrigation control:

(1) A budget notebook computer: It helps to bridge the irrigation controller and the computing server.
(2) An irrigation controller: It is used to regulate the time to open or close the irrigation valves.
(3) Water pipes and sprinklers: They are used for water conveyance and spread on the green roofs.

The costs for a budget notebook computer is about US$230. The cost of an irrigation controller at about US$260, which in conjunction with water pipes and sprinklers have to be installed anyway in conventional irrigation systems, hence they are not considered as additional costs. The rain sensor is not an essential component in AI irrigation system because the computation can estimate the soil moisture using routine data from a nearby weather station. End users can acquire irrigation schedules through a voluntary organization or a subscription service. The relevant information could be disseminated freely through a website. The water saving in monetary term in the longer run could recover the limited initial hardware expenditures.

The building occupiers can take the advantages of AI irrigation system to enhance the environmental benefits of green roofs. From a fundamental perspective, there is a notable improvement in water-use efficiency. The AI irrigation system could schedule irrigation more efficiently and promptly, and maintain soil moisture above the wilting point but not much above the field capacity point to optimize plant growth. Conventional irrigation approach has difficulty translating uncertain weather conditions to predict water-use trends. In contrast, the AI irrigation system can tackle the uncertainties in precipitation, evaporation, and drainage volume as follows:

(1) Precipitation: Irrigation will be suspended by the conventional rain sensor if the rainfall reaches a threshold. However, AI irrigation system considers a wide range of physical valuables and estimates the next-day water use. During the rainy days, a stronger weight is assigned to the effect of precipitation in the hidden layers of ANN and vice versa.
(2) Evaporation: Evaporation has been considered in the simulation. A higher evaporation rate means the plants demand more water for healthy growth. FNN is used to handle the uncertainties in the relationship between evaporation and simulated soil moisture. AI irrigation system differs from conventional approach in the way that AI algorithms consider nine possible scenarios of irrigation plan instead of one threshold value to mimic the human decision-making process.
(3) Drainage volume: AI algorithms are used to simulate the daily changes of soil moisture and make necessary adjustments in the irrigation plan according to changes in weather conditions. In the ANN training process, a soil moisture sensor has been installed for the measurement of water content. AI algorithms attempt to understand the relationship between weather conditions and soil moisture. Since soil moisture depends on the balance between water input and output, drainage volume has been incorporated in the ANN.

Overall, the objectives of this study have been fulfilled by providing adequate water to green roofs and avoiding superfluous supply whilst sustaining their plant growth and environmental and hence economic benefits. The main research findings can be concluded as follows:

(1) The artificial intelligence irrigation model can capture and predict the most critical features of soil moisture changes. The green roof irrigation regime can be optimized by routine local weather data without costly scientific sensors.
(2) Effective irrigation management can be obtained by enlisting the capabilities of artificial intelligence. The applied water is 20% less than the level estimated by conventional methods. The parsimonious water consumption can maintain plant growth performance and coverage and sustain the thermal-energy performance of the green roof.
(3) For ANN, one hidden layer with seven neurons is sufficient to describe the relationship between weather data and soil moisture. For FNN, three neurons in a single hidden layer can be used to generate the input-and-output pairs.
(4) Minimal hardware installation is required for the intelligent irrigation system. This study has tested and verified a simple and cost-effective practical approach to reduce water consumption in green roof irrigation.

Acknowledgements

We acknowledge the research grant kindly furnished by our university, and the Nophadrain Company through its local agent Cheung Shing Yuk Tong Company for donating the green roof materials for our experiments.

Appendix A. Artificial neural network (ANN)

The application of ANN in modeling soil moisture is based on their capabilities to construct a good approximation of the functional relationships between past and future events. Like the neural structure of human brain, it can process the information and recognize patterns through learning or training. Fig. 5 shows the architecture of multiple layers of feed-forward ANN. In this study, the input of weather data spreads from a layer to the next and the output of soil moisture is back-propagated for error correction [30]. The network consists of multiple inputs and a single output. Mathematically, the output of a node u_j can be expressed by the sum of the inputs x_{ij} with their weights w_{ij} at the *ith* layer as

$$u_i = \sum_{j=1}^{n_i} w_{ij} x_{ij}$$

where N_i is the number of neurons at the *ith* layer.

Standardization is a common procedure in ANN (e.g. [27,32]). The data range is rescaled to the interval [0,1]. The equation for standardization can be expressed as

$$x_{std} = \frac{x_{ij} - x_{\min j}}{x_{\max j} - x_{\min j}}$$

where x_{std} is the standardized value of input x_{ij}, $x_{minj}$and $x_{maxj}$are the minimum and maximum values of observations at the *ith* layer.

The output of a neuron is determined by an activation function. Several activation functions can be used in decision making, such as step or threshold functions. However, the sigmoid function is often used in resource management (e.g. [35]). It is selected for this research. The mathematical expression is given as

$$f(x) = \frac{1}{1 + \exp(-x)}$$

where x is the input variable [32]. The sigmoid function is differentiable and has nonlinear properties [36]. The derivative of the sigmoid function is a simple mathematical function that requires minimal computation time [37].

Artificial learning can be obtained by training the network. The backward propagation training method is employed in this study [27]. It reverses the forward pass of input signals from input to output and estimates the accumulated errors propagated backward within the network. The weights of output neurons w_{ij} are modified from output to input layers. The weights of output and hidden layers can be found by using the following equations:

$$w(k+1) = w(k) - \eta\delta\phi$$

$$w(k+1) = w(k) + \eta x \sum_{q=1}^{r} \delta_i$$

$$\delta = 2\varepsilon_i \frac{\partial\phi}{\partial I}$$

where w is the weight, k is the number of iteration, x is the input variable, η is the learning rate, ϕ is the output, I is the sum of weighted inputs, ε_q is the error signal, and the subscript i represents the layer of neurons [36].

Supervised training is commonly used by irrigation researchers (e.g. [30]). The network architecture can be found by a trial-and-error procedure (e.g. [32]). Sufficient degrees of freedom permit the network to capture major characteristics of a system in the learning process. However, additional flexibility may lead to the overfitting problem [38]. The network with complex architecture may not converge during training [32]. The computation is to begin with one neuron in a hidden layer and it continues the trial by increasing additional neurons. The number of hidden layers is increased if the performance cannot be improved by additional neurons. The accuracy of ANN is often assessed by the value of mean square error (MSE) as

$$MSE = \frac{1}{n} \sum_{j=1}^{n} (y_i - y_i{}')^2$$

where n is the number of observations, y_i is the simulated soil moisture, and $y_i{}'$ is the measured soil moisture [35].

In this study, ANN was used to estimate the soil moisture from weather data provided by Hong Kong Observatory. The inputs of weather data in the network were air temperature (°C), relative humidity (%), solar radiation (MJ/m^2), and wind speed (km/h). Real time weather data and measured soil moisture were transmitted to a computing server and the irrigation decision was determined according to the computation results.

Appendix B. Fuzzy neural network (FNN)

As the literature shows that fuzzy logic is useful in formulating irrigation schedule (e.g. [16]), fuzzy logic modeling has been adopted in the present study to develop an optimal irrigation schedule for green roofs. The advantage of FL lies in its use of simple linguistic statements, such as “High”, “Medium” and “Low”, such that mathematical operations can be simplified and the input uncertainties can be considered in the simulation. The flexibility of FL offers another advantage for irrigation researchers in their attempt to emulate the real world situation. The “if-and-then” rules can be used to process input variables in a complex system [36]. Empirical researches show that the integration of FL and ANN could give a better performance in irrigation scheduling (e.g. [28]).

Neural network could determine the membership functions of fuzzy sets [36]. Membership functions can be used to map each set element into a particular domain. In this study, another neural network model was developed for the implementation of FL. The fuzzy rules were made on the basis of expertise knowledge and experience. The input variables were pan evaporation (E), and simulated soil moisture (M). The irrigation duration (T) as the output was derived by using FNN. As pan evaporation data were not available at the automatic meteorological station in Wong Chuk Hang, the data at the manned meteorological station in King's Park was used instead. The relief variations around the Victoria Harbor might induce local differences in microclimate. The fuzzy-neural model could handle such input uncertainties in mapping the input-and-output relationships. The following fuzzy rules were used in determining the irrigation duration:

Rule 1: IF ("E" is LOW AND "M" is LOW), THEN ("T" is MEDIUM).

Rule 2: IF ("E" is LOW AND "M" is MEDIUM), THEN ("T" is LOW).

Rule 3: IF ("E" is LOW AND "M" is HIGH), THEN ("T" is LOW).

Rule 4: IF ("E" is MEDIUM AND "M" is LOW), THEN ("T" is MEDIUM).

Rule 5: IF ("E" is MEDIUM AND "M" is MEDIUM), THEN ("T" is MEDIUM).

Rule 6: IF ("E" is MEDIUM AND "M" is HIGH), THEN ("T" is LOW).

Rule 7: IF ("E" is HIGH AND "M" is LOW), THEN ("T" is HIGH).

Rule 8: IF ("E" is HIGH AND "M" is MEDIUM), THEN ("T" is MEDIUM).

Rule 9: IF ("E" is HIGH AND "M" is HIGH), THEN ("T" is MEDIUM).

The values of pan evaporation and simulated soil moisture were standardized within the interval [0,1]. The ranges for linguistic statements "HIGH", "MEDIUM", and "LOW" were defined as (0.7,1.0), (0.4,0.7) and (0.0,0.4) respectively. The "mean of maxima" method was applied to defuzzify the output (see Ref. [36] for details).

References

[1] H. Akbari, Shade trees reduce building energy use and CO_2 emissions from power plants, Environ. Pollut. 116 (2002) S119–126.
[2] R. Kumar, S.C. Kaushik, Performance evaluation of green roof and shading for thermal protection of buildings, Build. Environ. 40 (2005) 1505–1511.
[3] H.M. He, C.Y. Jim, Simulation of thermodynamic transmission in green roof ecosystem, Ecol. Model. 221 (2010) 2949–2958.
[4] H.M. He, C.Y. Jim, Coupling model of energy consumption with changes in environmental utility, Energy Policy 43 (2012) 235–243.
[5] S.W. Tsang, C.Y. Jim, Theoretical evaluation of thermal and energy performance of tropical green roofs, Energy 36 (2011) 3590–3598.
[6] K.L. Getter, D.B. Rowe, J.A. Andresen, I.S. Wichman, Seasonal heat flux properties of an extensive green roof in a Midwestern U.S. climate, Energy Build. 43 (2011) 3548–3557.
[7] T.-C. Liu, G.-S. Shyu, W.-T. Fang, S.-Y. Liu, B.-Y. Cheng, Drought tolerance and thermal effect measurements for plants suitable for extensive green roof planting in humid subtropical climates, Energy Build. 47 (2012) 180–188.
[8] S. Parizotto, R. Lamberts, Investigation of green roof thermal performance in temperate climate: a case study of an experimental building in Florianopolis city, Southern Brazil, Energy Build. 43 (2011) 1712–1722.
[9] H.F. Castleton, V. Stovin, S.B.M. Beck, J.B. Davison, Green roofs: building energy savings and the potential for retrofit, Energy Build. 42 (2010) 1582–1591.
[10] A.R. Khoob, Artificial neural network estimation of reference evapotranspiration from pan evaporation in a semi-arid environment, Irrig. Sci. 27 (2008) 35–39.
[11] C.Y. Jim, S.W. Tsang, Modeling the heat diffusion process in the abiotic layers of green roofs, Energy Build. 43 (2011) 1341–1350.
[12] C.Y. Jim, L.L.H. Peng, Substrate moisture effect on water balance and thermal regime of a tropical extensive green roof, Ecol. Eng. 47 (2012) 9–23.
[13] K.S. Raju, D.N. Kumar, L. Duckstein, Artificial neural networks and multicriterion analysis for sustainable irrigation planning, Comput. Oper. Res. 33 (2006) 1138–1153.
[14] I. Pulido-Calvo, J.C. Gutierrez-Estrada, Improved irrigation water demand forecasting using a soft-computing hybrid model, Biosyst. Eng. 102 (2009) 202–218.
[15] C.C. Yang, S.O. Prasher, R. Lacroix, S. Sreekanth, N.K. Patni, L. Masse, Artificial neural network model for subsurface-drained farmlands, J. Irrig. Drain. Eng. 123 (1997) 285–292.
[16] P.C. Deka, V. Chandramouli, Fuzzy neural network modeling of reservoir operation, J. Water Resour. Plan. Manag. 135 (2009) 5–12.
[17] P.E. Thornton, H. Hasenauer, M.A. White, Simultaneous estimation of daily solar radiation and humidity from observed temperature and precipitation: an application over complex terrain in Austria, Agric. For. Meteorol. 104 (2000) 255–271.
[18] O. Kisi, Daily pan evaporation modelling using a neuro-fuzzy computing technique, J. Hydrol. 329 (2006) 636–646.
[19] S.F. Kuo, G.P. Merkley, C.W. Liu, Decision support for irrigation project planning using a genetic algorithm, Agric. Water Manag. 45 (2000) 243–266.
[20] X. Cai, D.C. McKinney, L.S. Lasdon, Solving nonlinear water management models using a combined genetic algorithm and linear programming approach, Adv. Water Resour. 24 (2001) 667–676.
[21] Z.U. Haq, A.A. Anwar, D. Clarke, Evaluation of a genetic algorithm for the irrigation scheduling problem, J. Irrig. Drain. Eng. 134 (2008) 737–744.
[22] L.-C. Chang, C.C. Ho, Y.W. Chen, Applying multiobjective genetic algorithm to analyze the conflict among different water use sectors using drought period, J. Water Resour. Plan. Manag. 136 (2010) 539–546.
[23] W.H. Press, S.A. Teukolsky, W.T. Vetterling, B.P. Flannery, Numerical Recipes in C: The Art of Scientific Computing, 2nd ed., Cambridge University Press, Cambridge, UK, 1992.
[24] O. Hrstka, A. Kucerova, Improvement of real coded genetic algorithms based on differential operators preventing premature convergence, Adv. Eng. Softw. 35 (2004) 237–246.
[25] A. Elferchichi, O. Gharsallah, I. Nouiri, F. Lebdi, N. Lamaddalena, The genetic algorithm approach for identifying the optimal operation of a multi-reservoirs on-demand irrigation system, Biosyst. Eng. 102 (2009) 334–344.
[26] Y.P. Mathur, G. Sharma, A.W. Pawde, Optimal operation scheduling of irrigation canals using genetic algorithm, Int. J. Recent Trends Eng. 1 (2009) 11–15.
[27] M. Kumar, N.S. Raghuwanshi, R. Singh, W.W. Wallender, W.O. Pruitt, Estimating evapotranspiration using artificial neural network, J. Irrig. Drain. Eng. 128 (2002) 224–233.
[28] B. Abolpour, M. Javan, M. Karamouz, Water allocation improvement in river basin using adaptive neural fuzzy reinforcement learning approach, Appl. Soft Comput. 7 (2007) 265–285.
[29] A. Moghaddamnia, M.G. Gousheh, J. Piri, S. Amin, D. Han, Evaporation estimation using artificial neural networks and adaptive neuro-fuzzy inference system techniques, Adv. Water Resour. 32 (2009) 88–97.
[30] S.S. Zanetti, E.F. Sousa, V.P.S. Oliveira, F.T. Almeida, S. Bernardo, Estimating evapotranspiration using artificial neural network and minimum climatological data, J. Irrig. Drain. Eng. 133 (2007) 83–89.
[31] C.Y. Jim, S.W. Tsang, Ecological energetics of tropical intensive green roof, Energy Build. 43 (2011) 2696–2704.
[32] K.P. Sudheer, A.K. Gosain, D.M. Rangan, S.M. Saheb, Modelling evaporation using an artificial neural network algorithm, Hydrol. Process 16 (2002) 3189–3202.
[33] S. Trajkovic, B. Todorovic, M. Stankovic, Forecasting of reference evapotranspiration by artificial neural networks, J. Irrig. Drain. Eng. 129 (2003) 454–457.
[34] S. Trajkovic, Temperature-based approaches for estimating reference evapotranspiration, J. Irrig. Drain. Eng. 131 (2005) 316–323.
[35] M.E. Keskin, O. Terzi, Artificial neural network models of daily pan evaporation, J. Hydrol. Eng. 11 (2006) 65–70.
[36] L.H. Tsoukalas, R.E. Uhrig, Fuzzy and Neural Approach in Engineering, Wiley, New York, 1996.
[37] W.C. Chiang, T.L. Urban, A neural network approach to mutual fund net asset value forecasting, Omega 24 (1996) 205–215.
[38] S.P. Currum, J. Miners, Neural networks, decision tree induction and discriminant analysis: an empirical comparison, J. Oper. Res. Soc. 45 (1994) 440–450.