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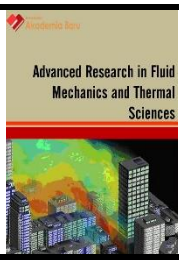

The Application of Particle Swarm Optimization in Estimating Potential Evapotranspiration: A Brief Review

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Nor Farah Atiqah Ahmad[1,*], Sobri Harun[2], Haza Nuzly Abdull Hamed[3], Suhaila Sahat[1], Siti Nooraiin Mohd Razali[1], Masiri Kaamin[1]

[1] Department of Civil Engineering, Centre for Diploma Studies, Universiti Tun Hussein Onn Malaysia, Edu Hub Pagoh, Johor, Malaysia
[2] School of Civil Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia
[3] School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Skudai, Johor, Malaysia

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ABSTRACT

In hydrological cycle, evapotranspiration (ET) is one of the tedious processes to measure. This has caused a massive development of empirical estimation models and the most accurate is Food and Agricultural Organization-56 Penman-Montieth model (FPM-56). The setback of this model is its data demanding which is not applicable at data scarce region and more simple models are preferable. To that avail, evolution of optimization from soft computing, enhancing the performance of simpler empirical models in estimating ET. This paper highlights the application of particle swarm optimization (PSO) in catering the estimation for potential evapotranspiration (ET_p). Although the number of papers in literature related to PSO application in hydrology or any other areas increases exponentially, the concerns is soft computing models keep advancing gambling the validity of today's model improvement such ET estimation empirical model. To have a model that pertinent for a long time still needs a calibration from physical direct measurement. Despite all the arguments, a comprehensive AI algorithm is yet to come.

Keywords:
Hydrological process; artificial intelligence; potential evapotranspiration; particle swarm optimization

1. Introduction

Water scarcity has become the main concern to the most of study area throughout the world. For a small region like Malaysia which received approximately 2000 to 3000 mm annual precipitation, the country still facing the water scarcity issue as the distribution of precipitation is not uniform let alone throughout the globe. Therefore, the increased of competition on preserving, managing and optimizing water resources are noticeable from various field of study. From the hydrological community, the fundamental understanding behind water vulnerability is the struggling in maintaining the water balance system. Evapotranspiration (ET) is one of the essential processes in

* *Corresponding author.*
E-mail address: norfarah@uthm.edu.my (Nor Farah Atiqah Ahmad)

hydrological cycle amongst precipitation, evaporation, transpiration as well as infiltration. Unlike precipitation, physical measurement of ET is tedious nearly impossible for certain region.

Lysimeter, Bowen-ratio energy, eddy covariance system and scintillometers are among the topnotch method in estimating ET as it gives the precise results of ET and very useful for calibration and validation [1] despite its setback in high maintenance. Direct measurement such lysimeter proves to be the prominent apparatus to measure actual ET though it consumes cost, time and labour [2]. As for indirect measurement can be either by empirical models, eddy covariance and remote sensing. Nevertheless, the empirical model has caught researchers' attention as it is based on the statistical approach of relating dependent parameter to its independent parameter.

2. Evapotranspiration

ET is a combination of two processes named evaporation (E), the water evaporates to the atmosphere from water surface on the Earth and transpiration (T) from plants. Together, ET process has been identified as crucial parameter in hydrological cycle as it takes into account the total consumption uses of water lost from plants and water bodies simultaneously. ET can be divided into three main fractions as illustrates in Figure 1; actual ET (ET_a), reference ET (ET_0) and potential ET (ET_p).

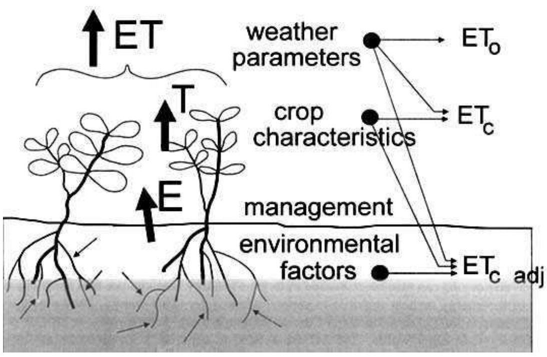

Fig. 1. Evapotranspiration process (FAO)

ET_a can be collected by using lysimeter (Figure 2) a measuring device that records the amount of precipitation of an area and the amount of water loss due to infiltration so that the amount of water lost to the ET can be calculated.

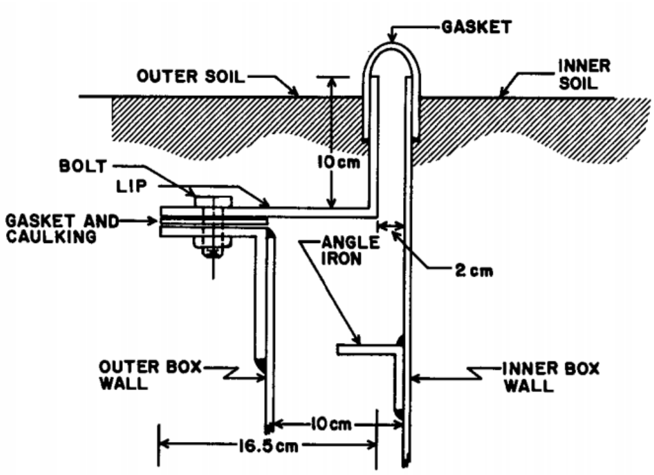

Fig. 2. Standard setup of lysimeter

2.1 Empirical Model for ET Estimation

The empirical model development has started since 1802 by John Dalton where the author derived an equation for estimating evaporation based on the water balance system [3]. Years later in 1945, Blaney and Criddle derived another formula estimating consumptive use for agricultural crops and this formula has been extensively used for estimating water requirements [4]. Although there are lots of empirical models been developed since Blaney and Criddle (1945), these models need calibration on its parameter before its application and it is not standardized to be used globally. Models that are based ranging from mass-transfer to temperature, radiation, aerodynamic concepts and combination-based models can be found for about more than 50 models till dates. FAO-PM takes place as the leading empirical model to be used worldwide. However, these physical principles model requires all the meteorological parameters where at certain region this could be the hindrance in developing country and scarce data situation regions.

The FPM-56 model has been introduced by Allen *et al.,* [5] and has been used globally since then. With over 10000 citations, the accuracy of this model proved to be as observed ET. Knowing it's setback, the updated publication by Pereira *et al.,* [6] suggested that instead of simplify the FPM-56 model, user should estimate the missing data and use the Penman-Monteith [7] instead. Nevertheless, estimating physically-based processes can produce significant error as these processes are highly non-linear [8] and Almedeij [9] suggested that the estimation for hydrological parameters should be done by established forecasting methods in order to accurately predict these parameters.

Numerous methods have been introduced to estimates ET either by physical or computational. FPM-56 has been recognized in hydrologist world as the most prominent empirical model that gives close to accurate estimation of ET. However, note that this is also a data demanding model which is not applicable at some region. Despite that, estimation of ET_p from FPM-56 is used as the observed data for analysis [10-15]. The mathematical equation is presented as in Eq. (1).

$$FAO-PM=\frac{0.408(R_n-G)+\gamma\dfrac{900}{T_a+273}u_2(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)} \tag{1}$$

In which R_n is the net radiation (MJ/m^2/day), G is the soil heat flux (MJ/m^2/day), γ is the psychrometric constant (kPa/°C), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), Δ is the slope of the saturation vapor pressure-temperature curve (kPa/°C), T_a is the average daily air temperature (°C) and u_2 is the average daily wind speed at 2m height (m/s). Therefore, grass height and bulk canopy resistance were assumed to be 0.12m and 70m/s respectively.

More simple method is by empirical models [13, 15-17], remote sensing method [18-20] and lately adapting to the technology application, estimation by using artificial intelligence (AI) [21-23] as well as standardized precipitation evapotranspiration index (SPEI) [24] starting widely used around the world.

ET empirical models can be classified as mass-transfer-based, temperature-based, radiation-based, pan-evaporation-based and combination. The example of simpler empirical models such Turc [25], Hargreaves-Samani [26], Priestley-Taylor [27] and Makkink [28] is used at almost any region around the globe. These models though simple yet need calibration before it can be used at other region since it is a site specific model. By taking Hargreaves as example, the model shows overestimates ET_0 under humid locations humid locations [29] and underestimates under arid locations [30] in [31]. Conclusively, Tabari *et al.,* [15] found that the radiation-based and temperature-based models are more suitable in estimating ET in humid climate in Iran. As according to Ahmad *et al.,* [32], mean temperature and solar radiation variables are the most influential parameters of ET_p for Peninsular Malaysia.

2.2 Temperature-Based Empirical Model

Temperature-based model is one of the simplest empirical based method in estimating ET. Back in early 1920s, ET is estimated by only based on temperature parameter [15]. Temperature based model could either take maximum, minimum and average air temperature as its data input or just the combination of temperature and other parameter such as wind speed and relative humidity. This based model is less popular among engineers with the presence of dew point temperature as its inputs [33]. The general form of this model is;

$$ET = c \times T^{n} \text{ or } ET = c \times d \times T\left(c_1 - c_2 h\right) \tag{2}$$

where c, c_1 and c_2 are constant, d is time duration parameter, T is air temperature (°C) and h is humidity.

2.3 Radiation-Based Empirical Model

Radiation based models are based on the solar radiation which has major influence in ET compares to temperature and humidity. Radiation based models are based on the simplified principle of energy balance and the general form of the model is;

$$ET = \frac{C_r}{\lambda}\left(wR_s\right) \text{ or } ET = \frac{C_r}{\lambda}\left(wR_n\right) \tag{3}$$

where C_r is generated empirical coefficient based on relative humidity and wind speed, λ is latent heat of evaporation (MJ/kg), w is generated empirical coefficient in accordance with temperature and latitude, R_s and R_n is solar radiation (MJ/m^2/day) and net radiation (W/m^2/day) respectively.

2.4 Pan-Evaporation-Based Model

This empirical-based method is simple, low cost and ease of application makes it suitable for data scarcity region. With the Class A pan evaporation (E_{pan}) data and its coefficient (K_{pan}), ET can be determined. The model can be define as in Eq. (4).

$$E = E_{pan} \cdot K_{pan} \tag{4}$$

The K_{pan} varies depending on the models and this parameter calibrate with wind speed and relative humidity [34-36]. This may due to the factor that pan evaporation is being placed on the ground and wind speed measurement must be taken at 2m height above the ground and relative humidity tends to fluctuate as it closer to the ground. Doorenbos and Pruitt [37] is the pioneer for empirical based model;

$$E_{t0} = c[WR_n + (1-W)0.27(1+0.01u)(e_a - e_d)] \tag{5}$$

$$W = \Delta(\Delta+\gamma)^{-1} = (1+\gamma/\Delta)^{-1} \tag{6}$$

where ET_0 is grass reference ET (mm/day), W is the psychometric weigh function, Δ is slope of saturation vapor pressure-temperature relationship (mb/C), γ is the psychometric constant (mb/C), R_n is net radiation (MJ/m^2/day) and u is wind speed a t 2m height from ground level (m/s).

2.5 Mass Transfer-Based Model

Mass transfer-based model is based on the concept of eddy transfer of water vapor from evaporating surface to the atmosphere which directly based Dalton's law (Eq. (7)). Penman [38] stated that Eq. (7) is a radiation-aerodynamic combination equation that later been used as another based for development of other empirical model.

$$E_{pen} = E_{rad} + E_{aero} = \frac{\Delta}{\Delta+\gamma}\cdot\frac{R_n}{\lambda} + \frac{\gamma}{\Delta+\gamma}\cdot\frac{6.43 f_u D}{\lambda} \tag{7}$$

where E_{rad} is radiation term, E_{aero} is aerodynamic component and f_u is wind function by Penman [38].

3. Particle Swarm Optimization

The emerging of artificial intelligence (AI) in solving optimization problem such genetic algorithm (GA), genetic programming (GP), simulated annealing (SA) and more and more biologically-inspired methods been proposed by Chen *et al.,* [39] such as particle swarm optimization (PSO) by Eberhart and Kennedy [40], artificial bee ant colony (ABC) by Karaboga [41] and ant lion optimizer (ALO) by Mirjalili [42] and whale optimizer algorithm (WOA) by Mirjalili and Lewis [43]. The most notable advantage of adapting soft computing technique in hydrological analyzing is it can be applied at local scales and applicable for physical implementation substitution such as evaporation rate and ET rate estimation [44].

The application of (PSO) is no longer a stranger for computer science community. This based on the social behavior of animals theory model [40] may have not yet established but its evolutionary algorithm that can be used to find optimal solutions to numerical and qualitative problems [45] prevails to another field of study such hydrology [46, 47].

Based on the theory of animal social behavior, a certain number of individuals known as particles are collecting information from each other through their respective positions. Each particle has their own p_{best} and will update their position and velocity to their neighbors in order to obtain the objective function. The new velocity and position of the swarm is called as g_{best} that can be represent by using Eq. (8) and (9). This process iterates until the termination criteria is satisfied.

$$\overrightarrow{v_{new}} = \vec{v} + C_1 \times \left(\overrightarrow{p_{best}} - \vec{p}\right) + C_2 \times \left(\overrightarrow{g_{best}} - \vec{p}\right) \tag{8}$$

$$\overrightarrow{p_{new}} = \vec{p} + \overrightarrow{v_{new}} \tag{9}$$

where $\overrightarrow{v_{new}}$, $\vec{v}$, $\overrightarrow{p_{new}}$ and $\vec{p}$ are new velocity, current velocity, new position and current position of particles respectively. Unlike the basic PSO proposed by Eberhart and Kennedy [40] where no inertia weight (w) is included, Shi and Eberhart [48] has introduced initial weight as it helps in balancing the both local and global search. The suggested range of initial weight is from 0.9 to 1.2 for a better performance. According to Gill *et al.,* [47] and Chaturvedi *et al.,* [49] a large inertia weight contributes in good global search while a smaller value aid in local exploration. The practice is to use larger initial weight during the initial exploration and gradual reduction of its values as the search proceeds in further iterations.

The equation to update the velocity can be expressed as in Eq. (10).

$$\overrightarrow{v_{new}} = w \cdot \vec{v} + C_1 \times \left(\overrightarrow{p_{best}} - \vec{p}\right) + C_2 \times \left(\overrightarrow{g_{best}} - \vec{p}\right) \tag{10}$$

where c_1 and c_2 are the cognitive and social coefficients respectively. The summary of standard process of PSO is presented in Figure 3.

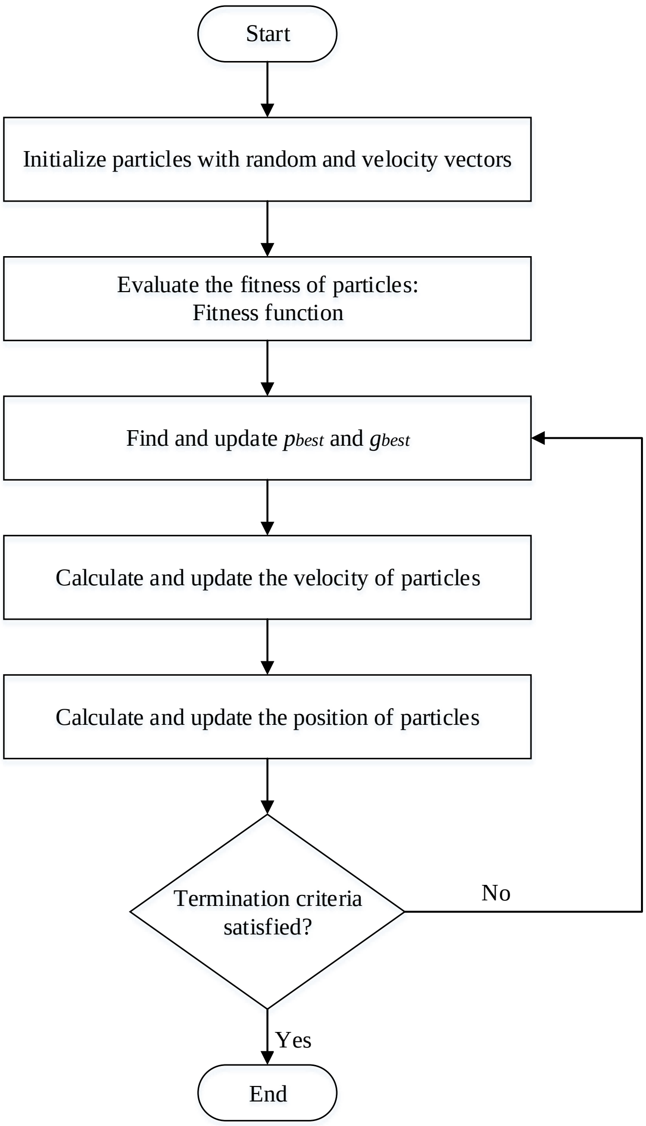

Fig. 3. Standard PSO flowchart [57]

The non-parametric and assumption free of AI has a major advantage on estimation process non-linear process like ET [50]. The specialty of PSO in developing solution for continuous variables and now with discrete variables [51] makes it one of the favorable optimization method for hydrologists. Many researchers have demonstrated the usefulness of PSO in hydrological analysis such Chau [52] applied the PSO algorithm in Artificial Neural Network (ANN) training perceptrons to predict river water level, Sudheer *et al.,* [53] has improvised the support vector machine by using PSO in predicting the monthly streamflow, Chen *et al.,* [54] exhibited the application of PSO in large-scale flood forecasting, Fereidoon and Koch [55] developed a complex multi-crop planning derived from SWAT-MODSIM with the adaptation of PSO and Nabinejad *et al.,* [56] demonstrated the application of PSO-MODSIM model in determining the optimal basin-scale water allocation. To date, the application of PSO in analyzing ET is still limited.

4. Discussion

The idea of adapting AI methods in analyzing hydrological problem is no longer a stranger to the research community. Commonly the AI is applied to improvise the existing hydrological model especially for situation where direct measurement is nearly impossible; ET measurement, evaporation measurement, groundwater analysis, reservoir operation along with others. Nevertheless, the uncertainty of the AI model itself can influence the output. Till dates, no standard algorithm parameters of PSO can be used directly without trial and error. Although AI has lots of potential in easing the analysis, the main concerns when applying AI is the evolution of soft computing models keep advancing. Hence for example, an improved empirical model of ET might not be applicable for the next few years. To have a model that pertinent for a long time still needs a calibration from physical direct measurement.

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