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PERFORMANCE ASSESSMENT OF PSO AND GA IN ESTIMATING SOIL HYDRAULIC PROPERTIES USING NEAR-SURFACE SOIL MOISTURE OBSERVATIONS

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Abstract: Quantification of soil moisture movement and water uptake dynamics in the vadose zone for sound irrigation management requires the knowledge of soil hydraulic properties. Non-availability of complex and expensive instrumentation hinders identification of soil hydraulic and retention characteristics. The study presents the application of Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) in identifying soil moisture retention θ(h) and hydraulic conductivity K(h) functions by inverting a SWAP model using observed near-surface soil moisture (0-10 cm). Two hydrologic cases, i.e. homogenous soil column with free drainage and with Shallow Groundwater Table (SGT) at the lower boundary, are considered. Study takes into account the agro-climatic data of Palampur (Himachal Pradesh), India. Results for both cases establish the applicability of GA and PSO in identifying soil hydraulic parameters. The identification of soil hydraulic parameters is more accurate when the soil column is draining in comparison to that with SGT. The comparative evaluation of simulated to the field observed soil moisture content indicates root mean square error of 0.0163 and 0.0297 for GA and PSO respectively. GA provides an effective alternative to estimate soil hydraulic properties using inverse approach in absence of experimental values.

Keywords: Genetic algorithm, Particle Swarm Optimization, soil properties.

I. INTRODUCTION

Numerous geophysical, agricultural and hydrologic applications necessitate information of the soil hydraulic properties (SHP) of vadose zone as they indicate soil ability to transmit or retain moisture [1, 2]. For instance, they influence the segregation of precipitation and irrigation into runoff and infiltration at the soil surface, the available moisture in the plant root zone, the rate and amount of redistribution of moisture in a soil profile, the moisture uptake by roots, and capillary rise from shallow groundwater table (SGT), among numerous different processes between SGT and the soil surface [3, 4]. The SHP is additionally basic segments of mathematical and scientific models for foreseeing solute movement and site-specific moisture flow in the subsurface [5].

Proper water balance assessment in the vadose zone is dependent on the suitable characterization of the soil hydraulic function [6,7]. Extensive in-situ and laboratory based methods are developed to determine the SHP [8,9]. However, the measurement of SHP is often difficult and complex because of time and instrumentation constraints [10]. Pedo-transfer functions approach uses bulk density, soil texture and carbon content for estimating SHP [11]. [12] focused on the need for developing a robust methodology that can be effectively utilized to estimate SHP for field applications. The inverse modelling approach is widely used in groundwater studies [13].

The assumption in inverse modelling method is that, any change in near surface soil moisture (NSSM) affects the soil moisture dynamics at the subsurface and, henceforth recommend the investigation of subsurface SHP. In general, observed soil moisture is used as a basis in inverse modelling using Soil Water Atmosphere and Plant (SWAP) model [14]. The simulation utilizes maximum and minimum base values of the Mualem-Van Genuchten (MVG) parameters [15,16]. Robust search algorithms and powerful optimization techniques, e.g. GA and PSO are suitable for investigating such problems [17,18].

[19] used Genetic Algorithm (GA) to identify the SHP, through the inversion of a SWAP model using soil moisture data from airborne remote sensing. The approach is however unsuccessful for the layered soil system with only certain parameters identified, where the identifiable SHP are the shape parameters of the Mualem-Van Genuchten functions and the vadose soil moisture content. SHP of van Genuchten equation have been estimated using Particle Swarm Optimization (PSO) [20,21]. Most of the studies used standard soil databases to SHP and validate their findings. In present study, experimental values of soil hydraulic functions and soil moisture characteristics (SMC) will be used for comparing and validating the simulated results.

Given the prominence of SHP in assessing various soil-water-plant related problems and the difficulties in estimating experimental values of these parameters, the present study aims at evaluating the performance of GA and PSO in determining the SHP using NSSM observations based on the inverse modelling approach. The objectives of the study are: (1) to investigate the potential of GA and PSO in solving inverse problem for estimating SHP, and (2) to evaluate comparative efficacy of methods by comparing simulated values with field observed soil moisture content values.

II. MATERIAL AND METHODS

2.1 Framework

Study employs inverse modelling and utilizes the NSSM θ(t) data to estimate hydraulic conductivity K(h) functions and soil moisture retention θ(h) at the same time by considering the soil hydrologic model, utilizing GA and PSO. Inverse modelling necessitates a soil hydrologic model to perform iteratively until the solutions of θ(h) and K(h) get congregated [22]. NSSM at 10 cm depth is used for estimation of the SHP. The relation between the near surface and subsurface processes, allows the estimation of SHP in the root zone. This co-dependency is the principal assumption utilized as a part of near surface data assimilation studies.

Mathematically, the SHP can be obtained by finding a set of SHP 'p' such that the differences between simulated $\theta_i(t, p)$ and observed $\theta_i(t)$ NSSM at soil layers i are minimized, where 't' is running indices for soil layers with time, and 'p' corresponds to the SHP (MVG parameters). Parameter p = ($p_{j=1. \ . \ . \ m}$) where p_j = corresponding SHP in the individual soil layer having 'j' as an index of parameter position and 'm' as the maximum no. of parameters. Additive absolute form (equation 1) is selected as objective function because it produces better results than other forms (e.g., multiplicative and additive squared delta) considered for the particular problem [17].

$$Minimize\{Z(k)\} = \frac{1}{N}\frac{1}{M}\sum_{t=1}^{N}\sum_{t=1}^{M}\left|\theta_i(k,t) - \theta_i(t)\right|$$

Where, Z(k) = objective function with $k = \{p_{j=1,m}\}$, N = time domain, M = number of soil layers, and t = index for time.

2.1.1 SWAP Model. The SWAP model, [14] is defined as a physically based agro-hydrological model that simulates the complex interactions among soil, water, atmosphere and plants. The core of the model is the Richards' Equation [23] (equation 2) incorporating a sink term. SWAP model uses implicit finite difference scheme for the numerical solution of Richard's equation [24],

$$\frac{\partial\theta(h)}{\partial t} = C(h)\frac{\partial h}{\partial t} = \frac{\partial}{\partial z}\left[\left(\frac{\partial h}{\partial z}+1\right)K(h)\right] - S(h) \qquad (2)$$

Where, K = hydraulic conductivity (cm d‑1), z = vertical soil depth (cm) taken positive upwards, h = soil moisture pressure head (cm), C = differential water capacity (cm‑1), and S = sink term representing moisture extraction rate by plant roots (cm3 cm‑3 d‑1) computed using equation 3 [25],

$$S(h) = a_w(h)\frac{T_{pot}}{|z_r|} \qquad (3)$$

Where, Zr = rooting depth (cm), Tpot = potential transpiration (cm d‑1), and aw = reduction factor as function of (h) accounting for water stress. The soil hydraulic functions in SWAP are the MVG constitutive relationships as given in equations 4 and 5.

$$S_e = \left[\frac{1}{1+\|\alpha h\|^n}\right]^m = \frac{\theta(h)-\theta_{res}}{\theta_{sat}-\theta_{res}} \qquad (4)$$

$$K(h) = K_{sat} S_e^{\lambda} [1-(1-S_e^{1/m})^m]^2 \qquad (5)$$

Where, Se = effective saturation, n = shape parameter accounting pore size distribution, m = 1 – 1/n, α (cm^{-1}) = shape parameter accounting the bubbling pressure, K_{sat} (cm d^{-1}) = saturated hydraulic conductivity, θ_{res} ($cm^3\ cm^{-3}$) = residual moisture content, θ_{sat} ($cm^3\ cm^{-3}$) = saturated soil moisture content, and λ = shape parameter accounting tortuosity in the soil generally taken as 0.5 [15]. The values of these parameters depend on the soil texture and are supplied as inputs to the simulation model.

Hysteresis, soil swelling, moisture repellence and shrinkage also affect soil moisture and solute transport, though, in the present work these options are not incorporated. The water balance is solved by considering top and bottom boundary conditions that are either flux or head controlled. The reference evapotranspiration (ET_0) is estimated with FAO-56 Penman-Monteith equation [26]. SWAP uses the leaf area index (LAI) for partitioning ET_0 into the transpiration and evaporation from a cropped soil.

2.1.2 Genetic Algorithm. The GA works on the mechanism of natural selection to explore decision search space for optimal solutions [27]. It has wide applicability in water resources systems and unsaturated moisture dynamics in porous media [28]. Application of GA in hydrologic sciences is comprehensively studied by [29].

In present study, GA is used as a tool to find the solution of the unknown parameter set for the inverse-modelling-based on NSSM observations, considering the SHP of the MVG functions as unknowns stated as k = {α, n, θ_{res}, θ_{sat}, K_{sat}, λ}. Since λ = 0.5 (assumption) [Mualem 1976]; and defining $p_{j = 1, m-1}$ = {α, n, θ_{res}, θ_{sat}, K_{sat}} (refer to equation 1), hence k = {$p_{j = 1, m-1}$, λ}. The parameters p'($p_{j = 1,m-1}$) are the only ones disseminated in GA. The maximum range of the parameter values is designed to indulge a variety of soils textures [30]. The fitness function is $f(p') = 1/(Z(k))$.

2.1.3 Particle Swarm Optimization. The PSO is a "population based stochastic global optimization method" [31]. [32] Comprehensively reviewed the application/ability of PSO for resolving optimization problems in different fields of engineering and sciences. A PSO problems consist in finding the optimal solution vector **X,** which corresponds to the minimum value of a nonlinear objective function f(**X**), with $\mathbf{X} = [x_1, x_2, \ldots, x_r]^T$ where r is the dimension. The objective function domain is limited to the interval $\mathbf{X} \in [\mathbf{X}_{min}, \mathbf{X}_{max}]$ where $\mathbf{X}_{max} = [x_{1max}, \ldots, x_{rmax}]^T$ and $\mathbf{X}_{min} = [x_{1min}, \ldots, x_{rmin}]^T$ are the upper and lower bounds of the interval [33].

The goal for objective function (see equation 1) which resembles to the current position of a certain particle is to be placed in the best position (i.e. the global minima). During the process, each particle is processed through an iterative process where the current position $\mathbf{X}_i^k$ is simplified to the new position as $\mathbf{X}i^{k+1} = \mathbf{X}_i^k + \mathbf{V}_i^{k+1}$, based on updated velocity of particle given as $\mathbf{V}_i^{k+1} = w_k \mathbf{V}_i^k + c_1 r_1(\mathbf{P}_i - \mathbf{X}_i^k) + c_2 r_2(\mathbf{P}_g - \mathbf{X}_i^k)$. Here, k and i represents the iteration and particle numbers respectively. $\mathbf{P}_i$ represents the best location attained till now by the particle, $\mathbf{P}_g$ is the best location attained by neighboring particles, r_1 and r_2 are two random causes in the (0, 1) interval which generates variety of the swarm, w_k = inertia weight and c_1 and c_2 = constants weighting the "cognitive" and "social" component of the method respectively.

In present study, PSO is applied to solve the sets of unknown parameter. The SHP of the MVG functions are the unknowns expressed as k = {α, n, θ_{res}, θ_{sat}, K_{sat}, λ}. The first search is done for all parameters for a wide range of values (Table 1). The process continues with gradually smaller ranges for n, α, θ_{res}, θ_{sat}, and K_{sat}. It is probable, that for each iteration, the final value of objective function is smaller than in the previous one.

Table 1. Range of the Mualem-Van Genuchten Parameters for GA and PSO [30]

Parameters	Search Space	
	Minimum value	Maximum value
α	0.0060	0.0330
n	1.200	1.610
θ_{res}	0.061	0.163
θ_{sat}	0.37	0.550
K_{sat}	1.84	55.70

2.2 Model domain and Flow conditions

In the present study, estimation of the SHP in a soil column adopting the NSSM assimilation technique is performed based on the inverse modelling approach [19, 34]. The numerical simulation is performed for two cases, i.e., case 1 i.e. soil column with free drainage and case 2 i.e. soil column with a SGT (i.e., -100 cm and -150 cm from the ground surface). In case 1 (Figure 2), the initial pressure head distribution in the soil profile, is recommended uniformly at -150 cm. For the case 2 (Figure 2), profile is recommended with initial pressure head distribution in hydrostatic equilibrium with the initial SGT depths. The bottom flux (positive upward) is estimated using h (z = -100 & z = -150, t > 0) = 0 cm. The soil type considered for simulations in SWAP model is silt loam. From these data, simulated values of daily soil moisture are generated using SWAP (forward mode). All SWAP simulations are performed across the crop-growing season for a period of 175 days, as detailed in field experiments section.

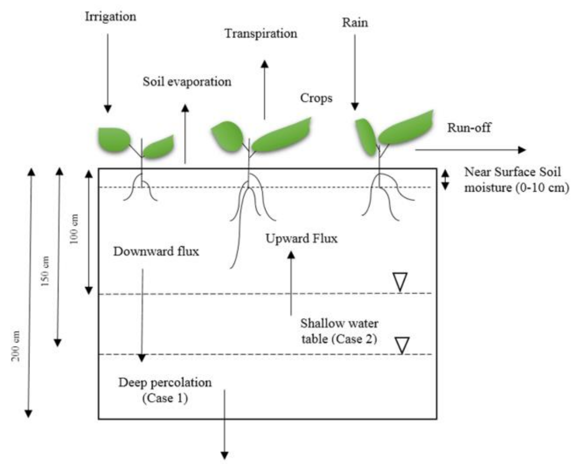


Figure 1. Location of the experimental site CSK Agriculture University Palampur, India

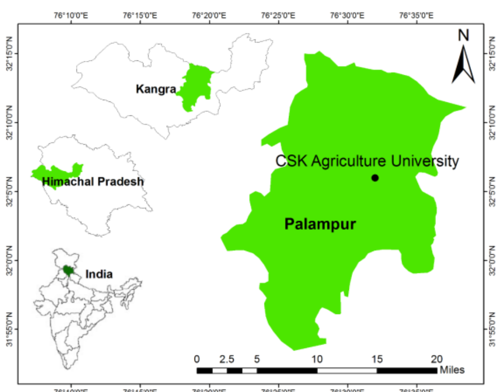


Figure 2. Flow conditions and Model domain incorporated in the field experiments

2.3 Study Area and Field Experiments

Field investigations were carried out in CSK Agriculture University, at Palampur in the Indian state of Himachal Pradesh (Figure 1), located at Latitude 32°6' North; Longitude 76°32' East with an average height of 1250 meters (above mean sea level). Study area has wet-temperate agro climate, having average annual rainfall of 250 cm and average temperature ranging from 15 to 19^{0}C. The soil is classified as mountainous soil with texture predominantly varying from loam to silt loam.

The field experiments were conducted on wheat crop (Triticum aestivum) from 20th November 2014 to 14th May 2015 for a period of 175 days under controlled conditions and were repeated during next crop season for validation purpose. The NSSM (0-10 cm) data is obtained daily using a Time Domain Reflectometer from a lysimeter setup. The Lysimeters (200 cm deep with surface area of 1m^2) were installed in an open field to neglect boundary effects and to simulate actual field conditions. The soil in lysimeter is similar to adjoining soil strata. Daily meteorological parameters i.e., air temperature, precipitation, solar radiation, wind speed and humidity used in the study are recorded by the weather station installed at CSK Agricultural University Palampur (HP).

2.3.1 Soil Parameters. Samples of Soil are obtained from different depths in the experimental site for detailed soil investigations. Grain size analysis [35] reveals that the soil texture as silt loam. Bulk particle density, density and porosity (saturated moisture content θ_{sat}) are 2.65 g cm^{-3}, 1.51 g cm^{-3} and 0.43, respectively. The residual moisture content (θ_{res}) is obtained using pressure plate apparatus and is equal to 0.061 corresponding to the moisture content at 1500 centibars. MVG parameters α and n are estimated as 0.012 cm^{-1} and 1.39, respectively, using a nonlinear optimization algorithm E04FDF [36]. Field value of saturated hydraulic conductivity (K_{sat}) determined through Guelph permeameter is 30.5 cm d^{-1}. In the present study, experimental SMC curve is obtained using the pressure plate apparatus.

2.3.2 Crop Parameters. LAI, an important input for SWAP model was observed by the direct method suggested by [37]. LAI varied from 0 to 2.15 (m^2/m^2) on last day of crop period with a maximum value of 4.26 (m^2/m^2) on 88th day after sowing the crop. Entire crop period is divided into initial, mid-season and end season crop stages based on LAI. Crop coefficient (K_c) values are 0.28, 1.12 and 0.36 for initial, mid-season and end season crop growth stages, respectively. Daily K_c is deduced from stage specific values using graphical interpolation. Crop evapotranspiration (ET_c) is estimated as the product of daily K_c and ET_0 [26].

III. Results and Discussion

3.1 Case 1: Homogenous Free-Draining Column

Table 2 presents the summarized results of the GA and PSO solutions for Case (1). The values of SHP are computed and compared with the experimental values of the parameters. In case of GA, the shape parameters i.e., α and n are closely identified, while the scale parameters i.e, θ_{res}, θ_{sat}, and K_{sat}, exhibited small variations. It is observed that shape parameters which describe nonlinearity, have better predictability as compared to the scale parameters which describe the relative magnitude, for explaining the moisture retention and hydraulic conductivity functions for silt loam soil considered in the study.

Table 2. Solutions of the GA and PSO to the NSSM Observations for Silt loam for Case 1: Homogenous, Free-Draining soil Column

Parameter	Experimental Values	Obtained Value	
		GA results	PSO results

α	0.012	0.013	0.016
n	1.39	1.42	1.46
θ_{res}	0.061	0.069	0.073
θ_{sat}	0.430	0.452	0.48
K_{sat}	30.5	31.62	35.138

As evident from Table 2, solution of PSO for the NSSM observations for Case (1) indicates that the estimated values of SHP followed almost similar pattern, as in case of GA, but with greater variations from the experimental values as compared to GA based values. In comparison to estimated values of α, n, θ_{res}, and θ_{sat}, estimated K_{sat} shows larger variation to experimental value, which indicates the general insensitivity of PSO in K_{sat} estimation.

Comparative evaluation of GA and PSO based solutions indicate that for Case (1), parameter assessment using GA is found to be relatively effective in estimating the parameter mean values of α, n, θ_{res}, and θ_{sat}. The estimated K_{sat} is relatively variable for present case but falls within the acceptable range. The effect of variability of estimated parameters on θ(h) and K(h) functions is studied by plotting SMC and hydraulic conductivity curve.

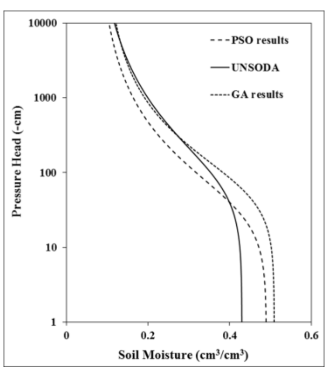


Figure 3. Soil moisture retention curve θ(h) for Homogenous, Free-Draining soil Column

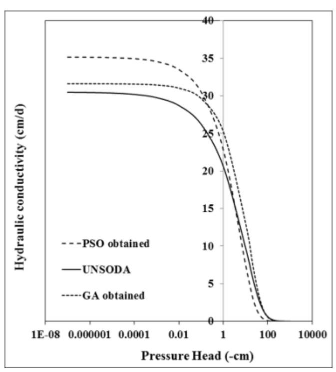


Figure 4. Hydraulic conductivity function K(h) for Homogenous, Free-Draining soil Column

The derived SHP are used as inputs in the SWAP (forward simulations) to translate them into soil hydrologic states. Figures 3 and 4 show the derived θ(h) and K(h) functions for a silt loam soil. The GA estimated θ(h) values match well with the experimental values (SMC), and indicate strong agreement at the drier end of the SMC curve. PSO estimated θ(h) values, however show poor agreement with experimental values for larger range. The GA estimated K(h) agreed well with experimental values for a larger range, as compared to PSO estimated K(h) values. However, both GA and PSO estimated K(h) values in the saturated range, i.e., K_{sat} values, does not match much accurately with the average K_{sat}, since the macro-pore effect is not considered in the inverse analyses. Nevertheless, the derived θ(h) and K(h) reproduced the NSSM variation dynamics well, when used in the forward modelling with SWAP.

3.2 Case 2: Homogenous Column with Shallow Groundwater Table

Tables 3 and 4 show the summarized results of the NSSM observations using GA and PSO, in the presence of SGT at a depth of 150 cm [Case 2 (a)] and 100 cm [Case 2 (b)] from the ground surface, respectively. It is clearly visible from Tables 2, 3 and 4 that estimated parameters using GA and PSO follow the same pattern of agreement with the experimental values for Cases (1), (2a) and (2b) i.e., GA estimated values show better agreement with the experimental values as compared to PSO estimated values. However, a visible trend can be clearly noticed that the SHP in free draining soil column are identified better, than those estimated for the scenarios with SGT at -150 and -100 cm. Additionally, as the SGT is lowered, the GA and PSO estimated values of the parameters at the -150 cm are identified better than those at the -100 cm, signifying that the parameter estimations is influenced by the upward flows from SGT.

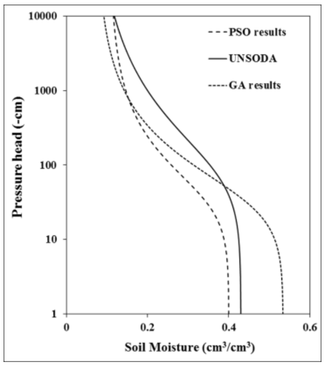
Table 3. Solutions of the GA and PSO to the NSSM Observations for Silt loam for Case 2 (a): Homogenous Soil Column with SGT (-150 cm)

Parameter	Experimental Values	Obtained Value	
		GA results	PSO results
α	0.012	0.015	0.018
n	1.39	1.47	1.57
θ_{res}	0.061	0.074	0.089
θ_{sat}	0.430	0.48	0.52
K_{sat}	30.5	34.91	40.140

Table 4. Solutions of the GA and PSO to the NSSM Observations for Silt loam for Case 2 (b): Homogenous Soil Column with SGT (-100 cm)

Parameter	Experimental Values	Obtained Value	
		GA results	PSO results
α	0.012	0.018	0.02
n	1.39	1.53	1.60
θ_{res}	0.061	0.081	0.102
θ_{sat}	0.430	0.50	0.54
K_{sat}	30.5	38.40	47.21

It is drawn from the above analysis that GA estimated values of SHP show better agreement with experimental values as compared to PSO estimated values for deep as well as SGT, indicating that GA as a method is more effective for such investigations. However, the agreement between estimated and experimental values shows a decline with the rise of SGT at the bottom boundary, which characterizes generation of upward flows. The θ(h) and K(h) curves are plotted for Case 2 (a) and 2 (b), to analyze the effect of variability of estimated parameters.



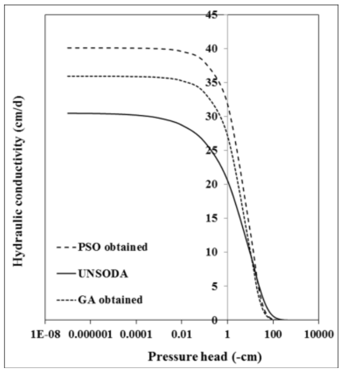
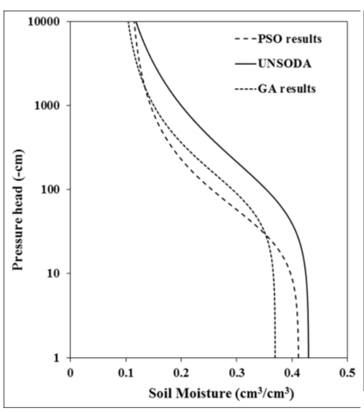


Figure 5. Soil moisture retention curve θ(h) for Homogenous Column with SGT (150 cm)

Figure 6. Hydraulic conductivity function K(h) for Homogenous Column with SGT (150 cm)



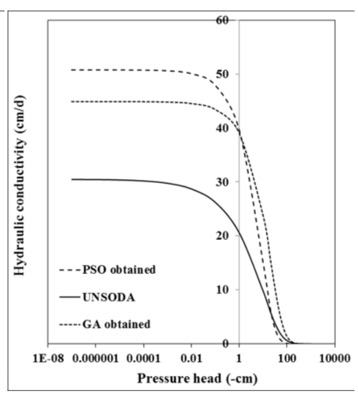


Figure 7. Soil water retention curve θ(h) for Homogenous Column with SGT (100 cm)

Figure 8. Hydraulic conductivity function K(h) for Homogenous Column with SGT (100 cm)

The pattern of derived θ(h) and K(h) curves agreed well with experimental values for the NSSM dynamics under the presence of SGT. The GA estimated θ(h) curve matched fairly with the corresponding experimental SMC, and showed substantial agreement at the drier end of the retention curve for both the cases, i.e., with SGT at a depth of 150 cm and 100 cm (Figures 5 and 7). In case of PSO, the moisture retention curve shows deviation from the experimental values based SMC for larger range. GA and PSO based hydraulic conductivity function shows unsatisfactory agreement with the experimental curve at the wetter end, whereas, it shows satisfactory agreement at the drier end (Figures 6 and 8) for both the cases, i.e., 2(a) and 2(b), though agreement is better for case 2 (a). The difference is larger for estimated K(h), particularly in the range signifying K_{sat}, where GA and PSO based curves do not match well with the experimental curve, as is also indicated by the relatively high difference between the estimated values of parameter K_{sat} and that of the experimental value of K_{sat} (Tables 3 and 4). While comparing GA and PSO based K(h) curves, GA based curves agree better with experimental curve.

3.3 Field Validation

For validation, field crop experiments on wheat were conducted from December 2015 to May 2016. Moisture content at the depth of 10 cm is measured using a TDR. GA and PSO estimated SHP for case 1 only, are considered for validation of simulated soil moisture content. NSSM observed in field for depth 0 – 10 cm is used for field validation of SWAP simulated soil moisture [17]. The comparison between the SWAP simulated and observed soil moisture is carried out in order to assess the performance of GA and PSO in estimating SHP. Two statistical parameters, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are calculated for quantitative evaluation of the comparison. The parameters RMSE and MAE are calculated as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left|\theta_{obs} - \theta_{sim}\right|^2} \quad (8)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\theta_{obs} - \theta_{sim}\right| \quad (9)$$

Where, θ_{obs} is the observed soil moisture for the time (t), θ_{sim} is the simulated soil moisture with time index (t) and n is maximum number of observations.

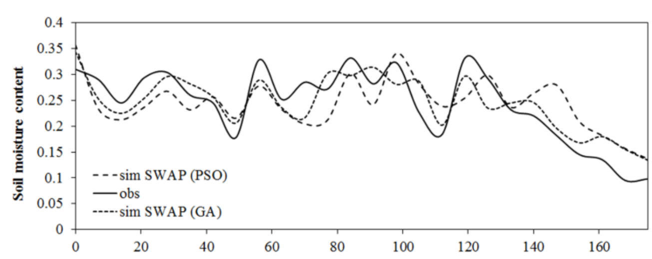


Figure 9: GA and PSO Simulated soil moisture vs Observed soil moisture at 10 cm depth

The variation of simulated soil moisture to the field observed moisture for 0-10 cm depth is shown in Figure 9. Qualitative analysis indicates that the simulated NSSM (SWAP) in case of GA agree closely with the observed soil moisture, as compared to PSO. In quantitative evaluation of GA and PSO based simulations, the values of statistical parameters are found to be MAE = 0.0127 and RMSE = 0.0163 in case of GA, and MAE = 0.0245 and RMSE = 0.0297 for PSO based results. This indicates qualitative as well as quantitative superiority of GA based results over PSO. It is drawn from above discussion that GA based estimation of SHP using NSSM observations is a dependable alternative to complex and costly experimental procedures.

IV. Conclusion

Algorithms such as GA and PSO have vast applicability in determining soil hydraulic properties (SHP). Study investigates an indirect approach of utilizing near-surface soil moisture observations into an inverted SWAP model for deriving SHP in vadose zone, in absence of experimental values. In the study, GA is able to represent the optimization problem very well and SHP estimated agree reasonably well with experimental values as compared to that of PSO. The GA estimated shape parameters α and n of the Mualem-Van Genuchten function are well identifiable parameters in free draining soil column. There are difficulties in the estimation of the SHP when the soil profile is significantly controlled by the upward flux from SGT. The quantitative evaluation between observed and simulated soil moisture over the crop period, for free draining soil, implies the efficacy of GA based approach over PSO based approach for estimating SHP based on near surface observed soil moisture data. The approach can be extended to other crops since the subsurface moisture dynamics are highly governed by crop root growth.

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